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Research Paper

Designing and Evaluating the Profitability of Linear Trading System Based on the Technical Analysis and Correctional Property

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ABSTRACT

Traders in the capital market always seek methods to make full use of available information and combine them to find the best buying and selling strategy. The present study uses a linear hybrid system to combine 106 signals from moving averages oscillators and RSI signals in the technical analysis along with two buy and sell bounds. In addition, the system has correctional property and modifies its parameters over time and according to new information. The result of the research on Tehran Exchange overall index in the period 2011/03/21 to 2019/03/20 indicates that the system after the optimal training on training data, has an average of daily returns of 0/0025, 0/0048 risk and a daily Sharp ratio of 0/52, which is better than the individual performance of each signal and market performance in daily average return and sharp ratio criterion. Therefore, the linear trading system with correctional property presented in the study has a better performance than individual systems and its applicability is recommended for productivity and integration of technical information.

1 Introduction

Investing in stock markets as a way to earn money is of particular importance to investors. Therefore, investors are interested in creating and developing different trading systems with the ability to combine information to identify profitable trading situations [17]. For this reason, it is necessary to develop a trading system to help investors in the capital market, which will increase the return on their investment (ROI) and reduce the investment risk as much as possible. Many trading systems (at least theoretically and in the research literature) have been developed, each with its own methodology and purpose. For example, a pair trading system has been developed with the aim of utilizing statistical arbitrage and is based on aggregate tools between two-time series, or the momentum trading system with the aim of taking advantage of the momentum property based on the tendency of prices to maintain the previous profitability trend [21]. Technical analysis is one of the major approaches in market analysis and many

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trading strategies have been developed based on the tools available in this analysis. In technical analysis, the trend of stock changes is examined, using price and trading volume data. The two main tools in this approach are the use of charts and oscillators [20]. Oscillators are perceived of as a function of price and trading volume, and their changes send signals for buying and selling. In the technical analysis literature, different oscillators are defined, each with one or more trading systems. It should be noted that each technical indicator examines an aspect of the market, and certainly their proper combination can provide more comprehensive and useful information about market complexities. Therefore, the design of systems combining individual technical information and sending trading signals is of particular importance [25]. In addition, due to the expansion of algorithmic trading, they can be applied in the field of automated trading systems. Each trading system has parameters that are often estimated and optimized based on historical data or experts' opinions. Due to the dynamic nature of the market, these parameters must be monitored and updated in accordance with new information. This process is called correctional properties of trading systems.

The correctional properties indicate that adjustable parameters of trading systems should be updated in what time periods and according to how much historical information. In this way, the automated trading system regularly updates itself and adapts to new information. The innovation of the present study is to create a framework for the correctional properties in a linear trading system in order to combine technical inputs. The aim of the present study is to present a generalizable trading system with correctional properties (correcting parameters over time) in order to combine these tools and achieve a combined trading system with the aim of making full use of the information of individual tools. For this purpose, a linear system is developed based on technical oscillators, including moving averages and relative strength indices in different time periods, which combines the weighted inputs and finally combines them into a single signal. The calculated weights are updated at regular intervals based on specific historical information to keep the system up to date. The present research includes the different sections of theoretical foundations and research background, research methodology, statistics and conclusions.

2 Theoretical Foundations and Literature Review

Technical analysis examines past price changes to predict changes in future prices. The technical analyst believes that the market itself stands as the best source of information and information about future stock price fluctuations can be obtained by studying previous price changes. Financial information is recorded using charts and oscillators, and this information is carefully examined to achieve repetitive patterns [14]. One of the tools used in technical analysis are indicators, which are a function of price and trading volume and often fluctuate between two levels. One of these popular indicators is the relative strength or RSI. The 14-day adjustment is generally used for this indicator. This indicator is based on victories and defeats (victory and defeat are not repeated continuously). To calculate this indicator the following formula is used [11]:

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

The RS numerator is equal to all average gains in the last 14 days and the denominator is the sum of the absolute value of all average losses in that period. Since RS is always a positive number, RSI will stand between zero and one. The two key levels 30 and 70 (or 20 and 80) are frequently used as sales saturation (defeat occurs and the moment of purchase) and purchase saturation [14] (victory occurs and the moment of sale). Moving averages are also among the most basic and simple indicators used in technical analysis. N-day moving average is calculated using the mean (arithmetic or geometric) of the previous N period. If arithmetic mean is used, the moving average obtained is called the simple moving average or SMA, and if exponential average is used, it is called the exponential moving average or EMA. The difference between EMA and SMA is that EMA gives more importance to recent data by giving a larger coefficient [6]. averages smooth charts to discover the trends. One of the trading methods is the simultaneous uses of two averages. In this method, two moving averages with different time periods are plotted on the price chart. In this case, whenever the moving average with a shorter period (which is more sensitive to recent prices) cuts the moving average with a larger period (which shows the historical trend) upwards, it means the possibility of climbing in the market. Whenever the opposite happens (that is, the moving average with a shorter period of time cuts the moving average with a larger period of time downwards) it means the probability of the beginning of a downtrend [9]. So far, we have been familiar with two indicators, each of which can be used individually to determine a trading strategy and can easily be converted into an automated and algorithmic transaction with the help of computer programs. Algorithmic trading in financial markets means using computer programs to enter trade orders. To select and apply these orders one or more algorithms are decided and implemented from various aspects such as timing, price or volume without human intervention.

Much research has been conducted on the profitability of trading strategies based on technical tools and signals. Tadi et al. [4] in a study applied pair strategy. After post-test they showed that assuming the existence of a borrowing sales system within the desired threshold, the return on pair transactions will be higher than the buying and holding strategy. Fallahpour and Hakimian [3] in a study calculated Sortino return and ratio, showing that the performance of pair trading system as a neutral trading system to market changes and trends, has a significant return compared to normal stock returns in the same period. Molaee et al. [5] evaluated the usefulness of momentum price strategy (prices tend to continue the previous trend and a concept derived from technical analysis) in the Iranian stock market. The results show that this strategy brings about excess returns after considering the risk. Abbasi et al. [1] introduced an automated trading system that uses a combination of technical analysis and adaptive neural fuzzy inference system to predict stock price trends and increase returns. The results show that by adjusting the parameters of technical indicators, the accuracy of predicting stock price changes can be increased. Nasrollahi et al. [7] in their research evaluated the profitability of Japanese candlestick patterns. The results show that most of the studied patterns (18 patterns) -without considering the transaction fee- have achieved significantly more profit than the buy and hold method. Nabavi and Hassanzadeh [6] showed that the exponential moving average method has a higher validity for predicting stock prices in terms of validation measures (mean absolute errors and signal tracker).

Feng et al. [11] designed an adaptive trading system based on reinforcement learning and technical tools of Japanese candles in which prices are fuzzy. They examined the system on futures contracts and evaluated the results with high accuracy. De Souza et al. [10] examined the usefulness of trading systems using the moving average technical technique in the stock markets of the BRICS countries and concluded that this trading system has a higher return on buying and maintaining, especially in India and Russia. Stubinger and Bredthauer [21] examined the profitability of a variety of pair trading strategies on the New York Stock Exchange from 1998 to 2015. The research shows that although the profitability of pair strategies has diminished over time, it can still be a good option for trade transactions. Elsherbini [19] in a study entitled “Time Cycle Oscillators” examined the profitability of using oscillators that determine market turning points, including simple harmonic oscillators and wave frequency oscillators on the Egyptian stock exchange between 2006 and 2015. The results of his research showed that both oscillators performed better in terms of Sharp ratio than market performance. Brown [9] in a study examines the profitability of using the divergence trading system in the US stock market. The oscillators used in this study are the relative strength index and the MACD. Brown concludes that the MACD-based divergence system is more profitable than when the system is based on relative strength. Lim et al. [14] examined the profitability of the Ichimoku cloud in the US and Japanese stock markets between 2005 and 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. Naranjo and Santos [17] proposed a new prediction method 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. Finally, the proposed hybrid algorithm is implemented on 15 stocks. Volna et al [23]. 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 oscillator or index alone contains specific information and illuminates an aspect of the market, and it seems that the right combination of them can provide better information to the investor. 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, Yang et al. [26] designed a combined trading system using deep learning. First, with the help of convolutional neural networks, they extracted features from the inputs, including a three-dimensional tensor of the technical inputs, prices and indicators, and then, with the help of long short-term memory networks, they started to predict.

Shalini et al. [18] have examined the productivity of trading systems based on technical signals on the Indian Stock Exchange from 2012 to 2017. The systems used have been designed based on relative strength index, convergence-divergence and average directional movement index. The results show that the use of combined systems and especially the combined system of moving averages with different time ranges has better performance than individual systems. Banga and Brorsen [8] in a study examined the profitability of systems combining technical signals with statistical approaches such as logistic regression and artificial intelligence methods such as neural networks. Findings indicate that the combination of signals increases profitability and statistical methods and artificial intelligence have different functions dealing with different assets. Silva [20] used machine learning with a long-short term memory approach with technical inputs along with risk management and concluded that the combined system has a higher profitability than individual systems and the buy-and-hold technique. Xucheng and Zhihao [25] introduced a hybrid trading system based on classical reinforcement learning with technical inputs aimed at maximizing user profits and evaluated its profitability in the Forex market. Wang et al [24] 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. Ijegwal et al [11] 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. Magda et al [15] 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 [22] 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 the better conclusion than using an individual index. Hirabayashi et al [19] 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.

There are various methods for combining technical analysis signals. These methods include decision tree, random forest, neural networks, Bayesian networks, support vector regression, and fuzzy inference systems [24]. The approach used in this research is the optimized weighted sum with sell and buy threshold levels. Therefore, different signals, including moving average and relative strength with different time periods, are multiplied by their optimal specific weight and finally combined to form a final signal. This signal contains the information of all signals in a linear fashion. The final linear signal produced by the combination of moving averages and trading bands is used by the two trading threshold levels in the stock market. In addition, the basic property of the designed trading system is its ability to be corrected. The implication is that the calculated coefficients for the linear composition of the weights in the final signal are not constant and are corrected over time. For this purpose, a value is specified as the inspection period, and when the time is due, the system weights are updated with the help of a certain amount of data leading up to that date (inspection data) through the optimization process.

3 Methodology

Moving averages are a set of smoothing operators that calculate and replace average prices at a given time interval instead of the main price signal at any given time. Moving averages show the movement trend more objectively by smoothing the price charts[18]. If the series $\{p(t)\}_{t=1}^{T}$ would be a stock price, the simple moving average series of length n is equal to Equation (1):

$$MA_n(t) = \frac{p(t) + p(t-1) + p(t-n+1)}{n} \tag{1}$$

Table 1: 90 Time Pairs For Combining Two Moving Averages

n	m	N	M	n	m	n	m	n	m	n	m	n	M	n	m	n	M
5	1	20	2	30	1	40	10	50	20	75	25	100	25	125	20	150	10
5	2	20	5	30	2	40	15	50	25	75	30	100	30	125	25	150	15
10	1	20	10	30	5	40	20	50	30	75	40	100	40	125	30	150	20
10	2	20	15	30	10	40	25	50	40	75	50	100	50	125	40	150	25
10	5	25	1	30	15	40	30	75	1	100	1	100	75	125	50	150	30
15	1	25	2	30	20	50	1	75	2	100	2	125	1	125	75	150	40
15	2	25	5	30	25	50	2	75	5	100	5	125	2	125	100	150	50
15	5	25	10	40	1	50	5	75	10	100	10	125	5	150	1	150	75
15	10	25	15	40	2	50	10	75	15	100	15	125	10	150	2	150	100
20	1	25	20	40	5	50	15	75	20	100	20	125	15	150	5	150	125

If n is a large number, the moving average better reflects the historical trend, and the smaller the *n*, the more sensitive it is to newer data [9]. By using a combination of moving averages, new oscillators-divergence-convergence oscillators- are created, which are used to generate buy and sell signals. So if $\{MA_n(\mathrm{t})\},\{MA_m(\mathrm{t})\}$ are two sets of moving averages and $n>m$, then if $MA_n(\mathrm{t})<MA_m(\mathrm{t})$, then a signal is received for buying that is $S_t=1$, and if $MA_n(\mathrm{t})>MA_m(\mathrm{t})$, then a signal is received for selling that is $S_t=-1$. In the present study, 90 pairs of moving averages are used, which are presented in Table 1. Each pair is introduced with *n* and *m* and *m* is the smaller member. Each pair has a number in a column. For example, in Table 1, pair (1,5) has been attributed number one and pair (5,2) number two. The relative strength index oscillator was previously introduced. This indicator is based on victories and defeats (victory and defeat are not repeated continuously). To calculate this indicator, the following formula is used [10]:

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

The RS numerator is equal to all average gains in the last 14 days and the denominator is the sum of the absolute value of all average losses in that period. Since RS is always a positive number, RSI will stand between zero and one. The two key levels 30 and 70 (or 20 and 80) are frequently used as sales saturation (defeat occurs and the moment of purchase) and purchase saturation [10] (victory occurs and the moment of sale). 16 relative strength oscillators based on 16 time periods according to Table 2 will be used in the linear system of the research.

Table 2: Time Periods Used for Relative Strength Oscillators

Oscillator no.	**value**	**Oscillator no.**	**value**	**Oscillator no.**	**value**	**Oscillator no.**	**value**
1	5	5	25	9	45	13	75
2	10	6	30	10	50	14	80
3	15	7	35	11	60	15	90
4	20	8	40	12	70	16	100

Therefore, at any given time, 106 signals

$$\{S_1(\mathrm{t})\},\{S_2(\mathrm{t})\},\{S_3(\mathrm{t})\},\{S_4(\mathrm{t})\},...,\{S_{90}(\mathrm{t})\},\{S_{91}(\mathrm{t})\},...,\{S_{106}(\mathrm{t})\} \tag{2}$$

are provided to the trading system, of which the first 90 signals are related to the moving averages and the rest are related to relative strengths. All linear signals are converted into a single signal by the following convex linear relation.

$$S(\mathrm{t})=\mathrm{w}_1 S_1(\mathrm{t})+\mathrm{w}_2 S_2(\mathrm{t})+...+\mathrm{w}_{106} S_{106}(\mathrm{t})=\sum_{i=1}^{106}\mathrm{w}_i S_i(\mathrm{t}) \tag{3}$$

Imagine $\sum w_i=1$. The convexity condition causes the combined signal to remain between zero and one. To determine the time of buying and selling, two thresholds of θ_1,θ_2 are defined for the total signal. By crossing the upper threshold buying takes place while selling would occur if passing down the low threshold. So,

$$S(\mathrm{t})>\theta_1\Rightarrow buy,\qquad S(\mathrm{t})<\theta_2\Rightarrow sell \tag{4}$$

Fig. 1 shows what has been done so far. The proposed system includes correctional properties. For this purpose, the system turns backwards in size θ_3 by reaching certain times, which are determined by numerical multiples such as θ_4, and examines the profitability of 106 signals separately.

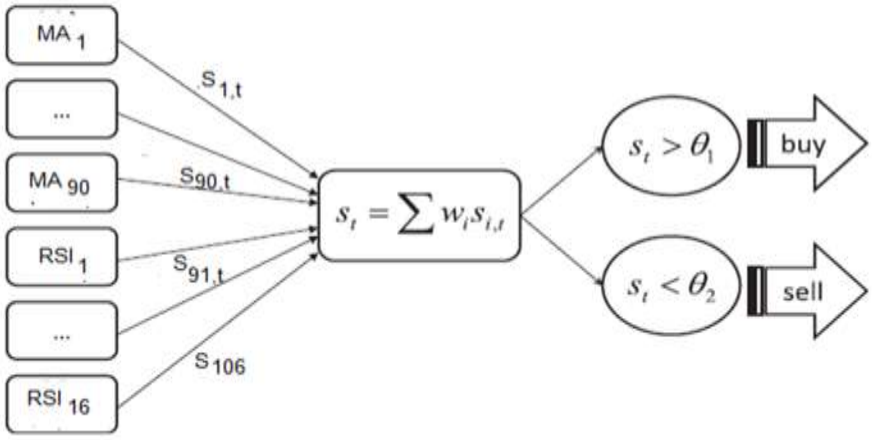

Fig. 1: Trading System View

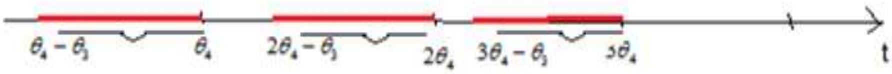

Fig. 2: Correctional Concept

For example, in the time period $[n\theta_4 - \theta_3, n\theta_4]$ profitability of each signal is calculated. Profitable signals are encouraged. On the other hand, harmful signals are punished. Taking these two cases into consideration, the signal coefficient in the combined signal increases and decreases, respectively. For this purpose, for the harmful signal *i*, the coefficient change is equal to

$$w_i \leftarrow w_i - \frac{\theta_5}{106} \tag{5}$$

in which θ_5 is one parameter and for the profitable signal *i*, the coefficient change is equal to

$$w_i \leftarrow w_i + \frac{e\theta_5}{116(116-e)} \tag{6}$$

in which *e* equals to the total of harmful signals. Thus the corrected coefficients are still convex, ie their sum equals to one. The meta-heuristic algorithm of particle swarm optimization is used to optimize the unknowns of the designed system (weights and $\theta_1, \theta_2, \theta_3, \theta_4, \theta_5$). Particle swarm optimization or PSO is a meta-heuristic algorithm inspired by the group behavior of birds and fish. In this method, the randomly generated initial solution leads to the production of new solutions in a collaborative process to further optimize the model. The basis of cooperation in this algorithm is based on the concepts of inertia, best personal experience and best group experience, which uses the linear combination of these factors to calculate newer answers. The objective or fitness function in the process of optimizing the linear trading system with correctional property is the average daily return of the trading positions discovered by the trading system. After designing and optimizing the system on educational data, its performance in Tehran Stock Exchange market on test data is examined.

4 Statistics

The profitability of the research trading system was examined on the overall index of Tehran Stock Exchange as a market representative. Fig. 3 represents the overall index of Tehran Stock Exchange from 2001/03/21 to 2019/03/20 and it includes 4398 daily data. Also, descriptive statistics of the daily return of the indices are presented in Table 3.

Table 3: Statistical Description of Overall Index

Statistical measures	**value**
Average daily return	0.000955
median	0.000406
maximum	0.07217
minimum	-0.055125
Standard deviation	0.006943

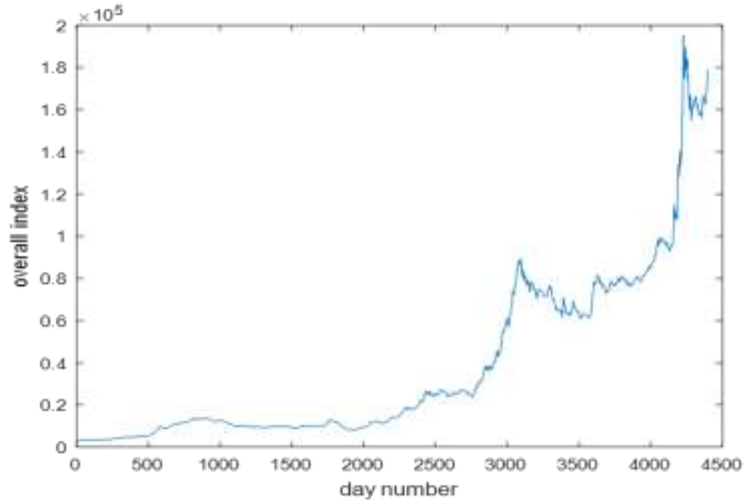

Fig. 3: Overall Index from 2001 to 2019

4.1 The Performance of Combined Research Model

Coding in MATLAB software was used to design and optimize the linear trading system with correctional properties. To optimize the unknown parameters of the system, the particle or bird swarm optimization algorithm with 200 repetitions and 100 particles per generation was used on 2398 primary data as educational data. In terms of optimization, transaction fees are also included and in total, 0.015 (according to Tehran Stock Exchange) as transaction fee is reduced from trading return. The objective function of the system was defined as maximizing the average daily return from trading positions. Limitations applied in optimizing system parameters include:

$$\begin{gathered} 0 < \theta_1 < 0.9, \quad -0.9 < \theta_2 < 0, \quad 150 < \theta_3 < 300 \\ 20 < \theta_4 < 120, \quad 0 < \theta_5 < 1 \end{gathered} \tag{7}$$

Accordingly, the optimal values were calculated as follows:

$$\left[\theta_1 = 0.0106, \theta_2 = -0.3372, \theta_3 = 231, \theta_3 = 231, \theta_4 = 58, \theta_5 = 0.3322\right] \tag{8}$$

Therefore, by passing above the linear signal, the overall index is purchased from $\theta_1 = 0.0106$. By crossing down the linear signal the overall index is sold from $\theta_2 = -0.3372$. Once every 231 days, the weights of the correctional system are re-optimized and updated with the help of data from the previous 58 days. An example of the first set of convex linear system coefficients combining 106 signals used for the first 231 days of test data is presented in Fig. 4.

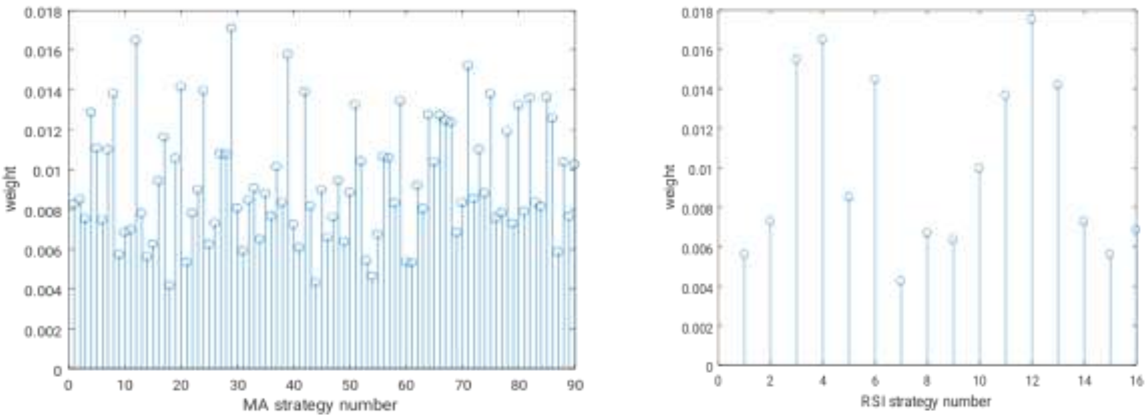

Fig. 4: Optimal Coefficients of the Linear System for The First Run on the First 231 Days

The correctional trading system on the 2000 test data has opened and closed 43 trading positions, each trading situation being at place for a period of time (in terms of days). The returns of trading situations have been converted into equivalent daily returns with the help of the trading period, which are presented in Fig. 5 and Fig. 6.

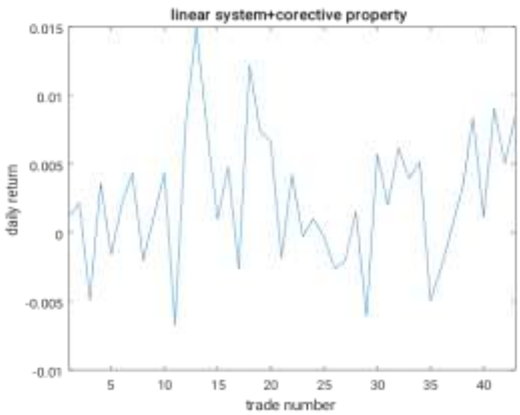

Fig. 6: Equivalent to the Daily Return of Each Trading Situation

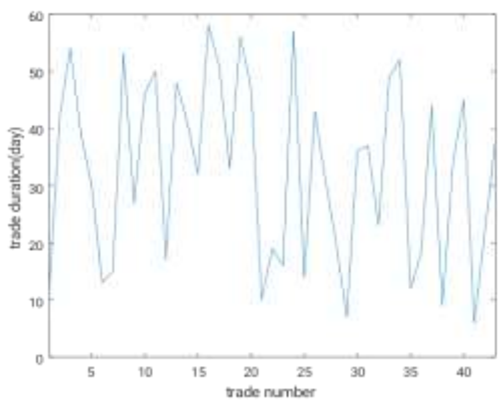

Fig. 5: Duration of Each Trading Situation

Descriptive statistics for the 43 discovered situations are presented in Table 4. According to the results of Table 4, the average daily return of the correctional linear system is 0.0025, to obtain which you must bear the risk equal to 0.0048. In addition, the adjusted return to risk (Sharpe ratio) equals to 0.52 which means that for one-unit additional risk the return grows with rate 0/52.

Table 4: descriptive statistics for 43 transactions discoverd by linear system

Statistical measure of performance	value
mean	0.0025
Standard deviation	0.0048
maximum	0.0150
minimum	-0.0068
Average duration of each transaction	27
sharp	0.52

4.2 The performance of trading systems based on moving averages

As stated earlier, one of the goals of hybrid systems is to make better use of information for higher profitability than individual signals. In addition, the profitability of 90 moving average indices was studied individually and the number of trades discovered per pair is presented in Fig. 7.

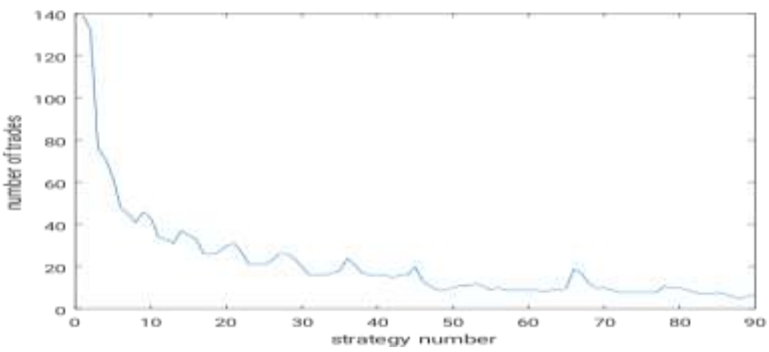

Fig. 7: The Number of Trading Situations Discovered by Moving Average Pairs in Table 1

Average daily returns, daily risk, average trading duration and Sharp ratio of each strategy are presented in the Fig. 8 to Fig. 11.

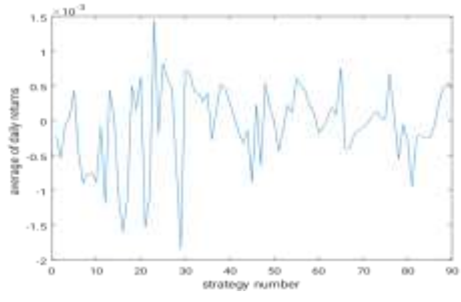

Fig. 8: Average of Daily Returns

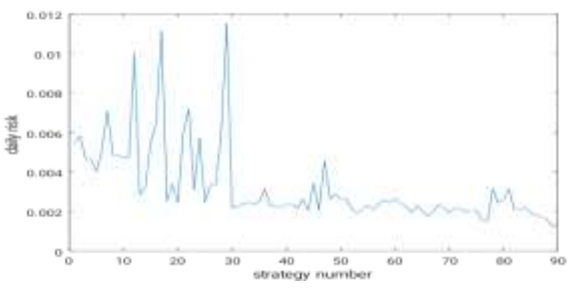

Fig. 9: Daily Risk

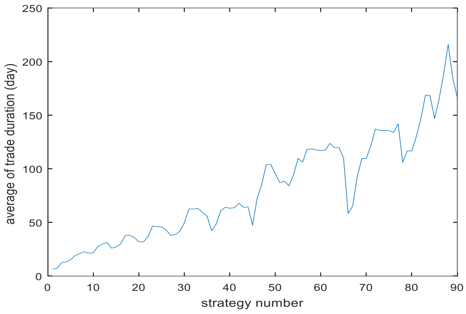

Fig. 10: Average of Trade Duration

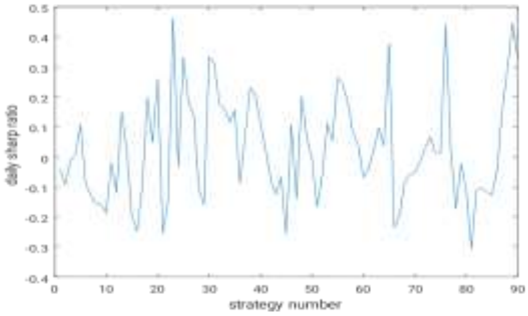

Fig. 11: Daily Sharp Ratio

Finally, statistical description of 90 strategies based on the moving averages is presented in Table 5. As an example, the average in Table 5 means the average daily return of 90 strategies.

Table 5: Statistical description of 90 moving average strategies

Statistical measure of performance	Daily returns	Sharp ratio
mean	0.0000625	0.026286
median	0.0000264	0.010786
maximum	0.001429	0.461104
minimum	-0.00183	-0.304882
Standard deviation	0.000579	0.174337

According to the results of Table 5, the average daily returns of 90 moving average strategies is 0.0000625 with risk 0.000579 and the average daily sharp ratios of 90 moving average strategies is 0.026286 with risk 0.174337.

4.3 The Performance of Trading Systems Based on Relative Strength Indices

Then, the profitability of 16 moving average indices was studied individually, and the number of trading positions is presented in Fig. 12.

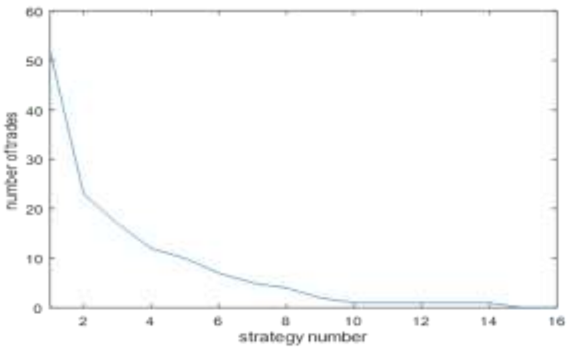

Fig. 12: The Number of Trading Situations Discovered by Relative Strength Indices in Table 2

According to Fig. 12 from the seventh strategy onwards, the number of trading situations is small and has little statistical significance. Therefore, in the following, only strategies number one to six will be examined.

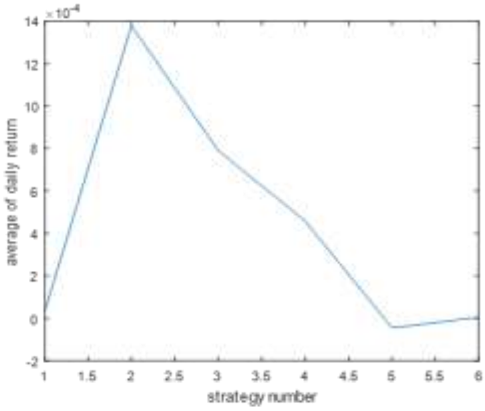

Fig. 13: Average Daily Returns

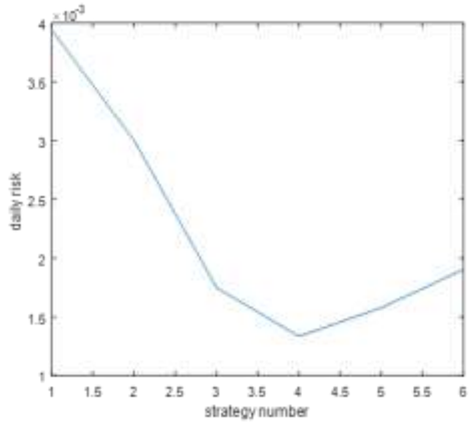

Fig. 14: Daily Risk

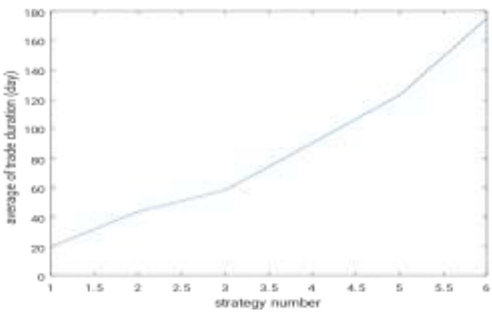

Fig. 15: Average of Trade Duration

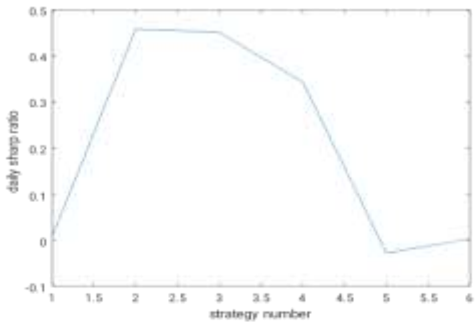

Fig. 16: Sharp Ratio

Finally, a statistical description of the first 6 strategies based on relative strengths indices at different time horizons is presented in Table 6. As an example, the average in Table 6 means the average daily return of 6 strategies.

Table 6: Statistical Description of 6 Strategies Based on Relative Strength

Statistical measure of performance	Daily returns	Sharp ratio
mean	0.000436	0.206
Median	0.000242	0.1756
maximum	0.0014	0.549
minimum	-0.000045	-0.0286
Standard deviation	0.000564	0.236

According to the results of Table 6, the average daily return of 6 RSI strategies is 0.000436 with risk 0.000564 and the average daily sharp ratios of 90 RSI is 00.206with risk 0.236.

4.4 Market Performance

Market performance refers to a random selection involving buying and selling on a random day, the statistical characteristics of which are presented in Table 7.

Table 7: Statistical description of market performance

Measure of performance	value
Average of daily returns	0.0012
Standard deviation of daily returns	0.0081
Daily sharp ratio	0.1481

As Table 7 shows, the daily return of the market is equal to 0.0012, to obtain which you must bear the risk of 0.0081. Sharpe ratio is equal to 0.1481 and shows that for one more risk unit, an increase of 0.1481 in return can be expected.

5 Conclusion

The purpose of this study was to present an algorithmic trading system based on the linear system approach with correctional properties. The linear system is optimized and harmonized with the buy-and-sell threshold levels. Therefore, different signals, including moving averages and relative strengths with different time periods, are multiplied by their optimum specific gravity and finally added to form a final signal. This signal contains the information of all linear signals. In addition, the basic property of the designed trading system is its ability to be corrected. The implication is that the coefficients calculated for the linear composition of the weights in the final signal are not constant and are corrected over time. For this purpose, a value is specified as the inspection period, and upon reaching the time multipliers of this value, the system weights are updated with the help of a certain amount of data leading up to that date (inspection data) through the optimization process. MATLAB coding was used to implement and evaluate performance.

The results show that in the study period, the average daily return of the modified hybrid method, with a value of 0.0025, is superior to individual systems (relative and random strength alone) and market performance and is approximately 0.0013 more than the best return produced by these systems. In the case of risk-adjusted returns or sharp ratios, the combined method has a value of 0.52, which is almost twice the best sharp ratio created by individual systems and the market. Therefore, in general, it can be said that the results of our model performance evaluation in Tehran Stock Exchange show that the system in the average daily return, risk and daily sharp ratio has a significant advantage over strategies based on individual signals and market performance. Like Silva et al. [20], Xucheng and Zhihao [25], Wang et al. [24], Magda et al. [15], Theodorus and Dimitrus [22], Hirabayashi et al. [12], the present study confirms the higher returns of hybrid systems over individual trading systems. Therefore, those interested in automated and algorithmic trading systems are recommended to design and optimize hybrid trading systems and use them by testing them on experimental data and observing appropriate results. By combining individual signals, these systems can take advantage of the beneficial aspects of each signal and create a more reliable hybrid one. The present study also dynamizes the trading system by introducing the concept of conventionalization. In this way, investors can have trading systems that can be updated according to market conditions. Those interested in algorithmic trading are also advised to test other oscillators and indicators in their systems so that they can choose the right combination with the help of profitability testing on test data. The general structure of the correctional property that was investigated in the present study can be combined with other artificial intelligence systems such as neural networks to estimate the parameters dynamically. Therefore, it is recommended that the parameters of trading systems be updated over time with the help of the correctional properties. Finally, it should be noted that in calculating trading situations based on a linear system with correctional property, it has always been assumed that there is a possibility of buying and selling at any price. It should be noted that this assumption is possible for stocks with high liquidity, and therefore this should be taken into account for practical use and generalization of system results.

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