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Portfolio rebalancing with respect to market psychology in a fuzzy environment: A case study in Tehran Stock Exchange

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ABSTRACT

While a vast amount of literature shows that psychological factors are major pricing determinants, portfolio optimization models ignore the emotional aspects of financial markets. Accordingly, this paper presents a two-stage portfolio rebalancing method to integrate mean-variance theory with market psychology. At the first stage, the psychological state of market participants is translated into a set of criteria to evaluate stocks, and then, in a fuzzy environment, the process of ratiocination used by technical analysts is simulated to assess the status of these criteria and determine under- and overvaluation possibilities of stocks. At the second stage, a fuzzy programming approach utilizes the calculated possibilities to revise an existing portfolio considering investor profile, transaction costs, and risk-free rate of return. An empirical study using the obtained data from Tehran Stock Exchange is employed to validate the designed method and compare it against several other investment strategies, including Buy-and-Hold strategy and a conventional portfolio rebalancing model. The results show that the proposed fuzzy method responds appropriately to the psychological component of the market. In addition, for all investor profiles, the recommended strategy completely outperforms the market and the remaining strategies.

1. Introduction

Stock market prices are affected by a wide variety of factors ranging from business fundamentals and company events to political situations and human psychology. This makes financial markets complicated to analyze. Modern Portfolio Theory (MPT) considers some basic assumptions including “Efficient Market Hypothesis” (EMH) and “absolute rationality of investors” to overcome the complexities of markets [1]. But in recent years, both empirical and theoretical studies have cast great doubts on these assumptions.

On the other hand, social psychology concentrates on interpersonal behavior and suggests that social forces play a major role in controlling human behavior. Also, the term “mass psychology” or “market psychology” refers to the general mentality, sentiment or feeling (e.g., fear, greed, hope, regret, etc.) that market participants are experiencing at any specific time [2].

Accordingly, this paper extends MPT by considering the irrational behavior of the market. More specifically, the presented method analyzes the possible future performance of stocks using the mass psychology of the market, and revises an existent portfolio according to the obtained results. Implementation of the presented method has led to remarkable results in Tehran Stock Exchange (TSE). However, since the efficiency of the proposed method depends on how much the target market is emotional, these results must be considered carefully and they may not be generalizable.

One of the basic assumptions of MPT is the EMH. According to EMH, prices quickly reflect all available information and are the best estimation of fair values of assets [3,4]. Moreover, absolute rationality of investors is another assumption indicating that completely rational agents are the driving force of markets. In other words, market prices are not influenced by human emotions (note that although absolute rationality of investors is essential for market efficiency, markets can still be inefficient even if investors are rational). These assumptions suggest that assets can only be traded at their fair values (i.e., there is no under/overvalued asset). As a result, no analytical method can help an investor outperform the market and the only possible way to obtain higher returns is by buying riskier assets. Therefore, MPT ignores emotional aspects and maintains that statistical properties of stock returns, which are used to measure a portfolio’s risk and return, are sufficient for portfolio optimization.

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Behavioral Finance (BF) is one of the domains that has strongly challenged the EMH and absolute rationality of investors during the last few decades. This field of study focuses on the interaction between psychology and financial performance of market practitioners [5]. As BF theorists argue, in the formation of prices, the psychological state of traders is much more crucial than the statistical properties of the stock returns [6]. Human psychology offers a promising explanation of return abnormalities [7] and justifies why stock price patterns (which provide profitable investment opportunities for traders) appear. BF explains how investors create market inefficiencies by making systematic errors and how other participants take advantage of such errors (i.e., errors that are not random and don't have a zero mean).

Also, BF presents alternative models that assume a lower level of rationality [8]. Simon [9] describes humans as bounded rational agents that use simple rules-of-thumb, and believes that this description is more realistic than perfect rationality. Kahneman [10] emphasizes that rational models are unrealistic from the psychological point of view. Shiller [11] argues as well that theoretical models representing everyone as rational optimizers are nothing more than metaphors for the real world and that it is absurd to claim that everyone knows how to solve optimization models. Likewise, there are other studies in which similar results have been indicated (e.g., [12,13]). All in all, increasing attention to BF over the past few years has led to the awarding of the Nobel Prize to Smith and Kahneman in 2002 and Shiller in 2013.

Besides, there is a relationship between behavioral biases (i.e., systematic errors in judgment) and market prices. BF theorists distinguish a long list of specific biases including representativeness, availability, anchoring, etc. (for more details, see Shefrin [5]). As a concrete example, consider representativeness bias according to which people usually have a tendency to overreact to unexpected news. Also, they put too much emphasis on the latest information they have received. As a result, if an earnings report is better/worse than what market participants expected, they will become excessively optimistic/pessimistic. As BF theorists argue, the net effect of this issue is that prices strongly deviate from their fair values. This provides an opportunity to exploit market misvaluation and those participants who take advantage of it may even be able to outperform the market. Representativeness bias can also cause underreaction to new information and can lead to market misvaluation in a similar way.

In contrast, despite admitting that some investors facing new information may overreact and some other may underreact, EMH believes that their reactions are random and follow a normal distribution so that the net effect on market prices is not considerable. Nevertheless, while there is no consensus among scientists on this issue, the literature contains a large body of convincing evidence that behavioral biases affect the market prices significantly [14,2,5]. For instance, [15] shows that market participants overweight new information and, as a result of their overreaction to earnings, stock prices deviate from their fair values.

As investors make major systematic errors and their financial behavior is affected by environment in which they are socially embedded [16], they cannot be those rational agents that traditional portfolio models assume [17]. Furthermore, since MPT relies heavily on past data to measure a portfolio's risk and return, it involves the assumption that past data can truly reflect future state of markets. But this assumption is also hard to confirm for the real-world ever-changing markets [18]. Unrealistic assumptions about market behavior have led to a substantial gap between academic models of portfolio selection and what market practitioners actually need [19]. Thus, with a mass of studies questioning the EMH [20], and ample evidence that investors do not always behave in rational ways [21], this study aims to present a method to integrate MPT with market psychology.

In summary, the main reason why it is logical to consider emotional aspects along with standard methods in portfolio selection is that markets may not be efficient and market prices, instead of indicating the actual values of assets, usually represent consensus among investors about the values of assets. Social and environmental factors as well as human psychological biases can affect this consensus dramatically and cause market prices to depart from fair values of assets. From this perspective, emotional aspects can act as a potential risk for a portfolio that ignores them. In addition, systematic behavioral errors (whose impact on prices is somewhat predictable) lead to misvaluation of assets, and buying/selling such under/over-valued assets can help investors achieve above-average gains. Therefore, it is expected that considering market psychology will lead to a better portfolio management strategy, which makes it possible to exploit market misvaluation.

If it is accepted that market psychology is not negligible in portfolio decision-making [22], the important question that will come to mind is that how the psychological component of market can be realistically utilized to improve portfolio performance.

The well-known mean-variance (M-V) model [1], assumes that the economic conditions are static over the investment horizon while investment opportunities expectedly change over time and adjustment of the portfolio composition is necessary to increase the investor's utility [23]. Incidentally, in practice it is common to rebalance a portfolio [24]. In addition, the inconsistencies and irrational behavior of investors provide profitable opportunities, which are identifiable by using some tools like Technical Analysis (TA) and Fundamental Analysis (FA) [17]. Consequently, it is sensible to divide the investment period into sub-periods and re-establish a portfolio at the beginning of each sub-period considering the use of such tools to improve portfolio performance.

This study makes use of TA to analyze the market's psychological component. Generally, TA is based upon the mass psychology of the market [19] and provides a broad set of methods that try to exploit market fluctuations [25]. As BF assumes (e.g., [26,11]), irrational behavior is not chaotic but rather has a systematic component that affects market trends and fluctuations. Since TA also emphasizes on the trends and fluctuations, it can be an acceptable tool to analyze the market's psychological component [27]. Besides, TA is widely accepted among brokerage firms and financial economists [28], and has been used by practitioners for many decades [29]. Moreover, there is a vast amount of literature supporting the predictive power of TA (e.g., [30,31]). Although FA can also be used to identify under/over-valued assets, it concentrates on economic reasons like the supply/demand situations, price/earnings ratios, etc., and naturally, there is no psychological component involved in the analysis of this type [27]. Accordingly, this paper develops an artificial intelligence to think like a technical analyst and identify under- and overvalued stocks.

This study utilizes fuzzy logic and possibility theory to cover the uncertainty inherent in the human mental processes. As an example, imagine a technical indicator the ideal value of which to send an undervaluation signal is 30. Nevertheless, an analyst may still perceive the value of 40 as an acceptable undervaluation signal while values more than 35 may not be convincing enough for another analyst to lead him/her to such a conclusion. In such an uncertain situation, fuzzy methods are more suitable than stochastic methods to take human's subjective decisions into consideration [22].

The remainder of this paper is organized as follows: the next section introduces related work. Section 3 presents a complete description of the proposed method for finding under- and overvalued stocks, and further, proposes a multi-objective mixed-integer non-linear programming model for portfolio rebalancing. Afterward, a fuzzy programming approach is introduced to identify a revised portfolio in accordance with the investor profile. In Section 4, performance of the proposed method is validated by using the

Table 1
Comparable studies.

Study	Problem	Method(s)	MPT	TA	FA	TC	IP
Escobar et al. [42]	Stock recommendation	Fuzzy logic		*			*
Wei et al. [43]	Stock price prediction	Fuzzy inference system		*			
Gradojevic and Gençay [44]	Stock market timing	Fuzzy logic		*			
Esfahanipour and Mousavi [25]	Stock market timing	Genetic programming		*		*	
Chavarnakul and Enke [28]	Stock trading	Neural networks		*			
Lincy and John [45]	Stock trading	Fuzzy inference system		*	*		*
Yunusoglu and Selim [46]	Stock evaluation and portfolio construction	Fuzzy expert system		*	*		*
Gorgulho et al. [47]	Portfolio management	Genetic algorithm		*		*	
Fu et al. [48]	Portfolio selection	Genetic algorithm	*	*			
Dastkhan et al. [49]	Portfolio selection	Fuzzy programming	*				*
Jana et al. [50]	Portfolio selection	Possibility theory, Fuzzy programming	*			*	*
Paranjape-Voditel and Deshpande [51]	Portfolio rebalancing	ARM, Fuzzy logic					
Ruiz-Torrubiano and Suárez [52]	Portfolio rebalancing	Memetic algorithm	*			*	
Yu and Lee [53]	Portfolio rebalancing	Fuzzy programming	*			*	
Samaras and Matsatsinis [54]	Portfolio management considering market psychology	Multi-criteria DSS		*	*		*
Jasemi et al. [19]	Portfolio management considering market psychology	Conceptual model	*	*			
This study	Portfolio rebalancing considering market psychology	Fuzzy logic, Possibility theory, Fuzzy programming	*	*		*	*

data derived from TSE in cases of different investor profiles. Conclusions and further research suggestions complete the structure of the paper in Section 5.

2. Literature review

Although MPT has been widely studied and acknowledged (see e.g., Kolm et al. [32]), criticism on its assumptions has increased during the recent years. For instance, Petty et al. [33] remark that the market price of an asset deviates from its fair value and does not always reflect all available information. Black [34] and Shleifer and Summers [35] also highlight the irrational behavior of the market and declare that traders who act on the basis of imperfect information cause prices and their fair values deviate from each other.

In addition, the empirical evidence doesn't always support the assumptions of MPT [36]. In fact, much evidence exists for a strong relationship between market prices and emotions of investors [37]. For example, Maymin [38] asserts that popular music can predict market conditions. His research demonstrates a significant negative correlation between the standard deviation of returns of the S&P 500 index to the beat variance (a measure that has a direct relationship to complexity of music) of the songs in the U.S. Billboard. Take the following as another good example; Edmans et al. [39] investigates the effect of international soccer results on the stock market and show that losses cause low returns in the defeated country. Lo and Repin [40] and Chang et al. [41] also show other instances representing a connection between moods of market participants and market prices. Finally, Ramiah et al. [2] review the literature on the consequences of the presence of noise traders (i.e. irrational traders and traders who make their financial decisions based on imperfect information) in the market and show how markets are likely to trade at irrational values.

Accordingly, this study makes use of TA to analyze the irrational behavior of market. As reported in Table 1, TA already has been successfully used for stock price prediction, stock market timing, stock evaluation and portfolio selection.

We deal with the problem in a fuzzy environment, in which a decision maker cannot sharply define the constraints and/or objectives. Zadeh [55] introduced the concept of fuzzy sets to provide a quantitative framework for considering the vagueness of human thought processes. Zadeh [56] asserts that much of the information on which human judgments are based is possibilistic rather than probabilistic in nature. Moreover, possibility theory, presented by Zadeh [56] and expanded by Dubois and Prade [57], is used in many decision-making problems that deal with imprecise knowledge. Considering that the fair values of assets are hard to measure and can be estimated only approximately (due to the everyday uncertainty of financial markets), and regarding that the process of identifying the fair values of assets relies on analyst's subjective judgments, it is worthwhile to use fuzzy logic and possibility theory to cover the uncertainty in the problem.

Different types of soft computing techniques have been efficiently applied in the financial domain so far (see e.g., Bahrammirzaee [58] and Hu et al. [59]). Fuzzy systems, neural networks and evolutionary computation are among the subjects growing rapidly in this field. In a recent work, Paranjape-Voditel and Deshpande [51] developed a portfolio rebalancing system using association rule mining (ARM) and fuzzy logic. In a more related work to this study, Jasemi et al. [19] suggested a conceptual portfolio management model sensitive to market psychology. This model combines MPT with TA. Market psychology is also considered by Samaras and Matsatsinis [54]. They have developed a decision support system (DSS) to determine the market psychology by describing current financial conjuncture. Considering the related body of knowledge, it can be stated that there is a lack of a portfolio model that incorporates both MPT and market psychology in a practical and realistic manner.

The present study advances the literature by proposing a novel method to involve the irrational behavior of the market in the portfolio optimization process and closes the gap between portfolio model and real investment world. In a fuzzy environment, the reasoning and deduction process of thinking used by technical analysts of financial markets is simulated to determine the under- and overvaluation possibilities of stocks. After that, a fuzzy programming approach is introduced to rebalance an existent portfolio considering investor profile (IP) and transaction costs (TC).

3. A fuzzy method to rebalance a portfolio considering market psychology

This section proposes an adaptive method for stock evaluation and portfolio rebalancing with respect to the mass psychology of

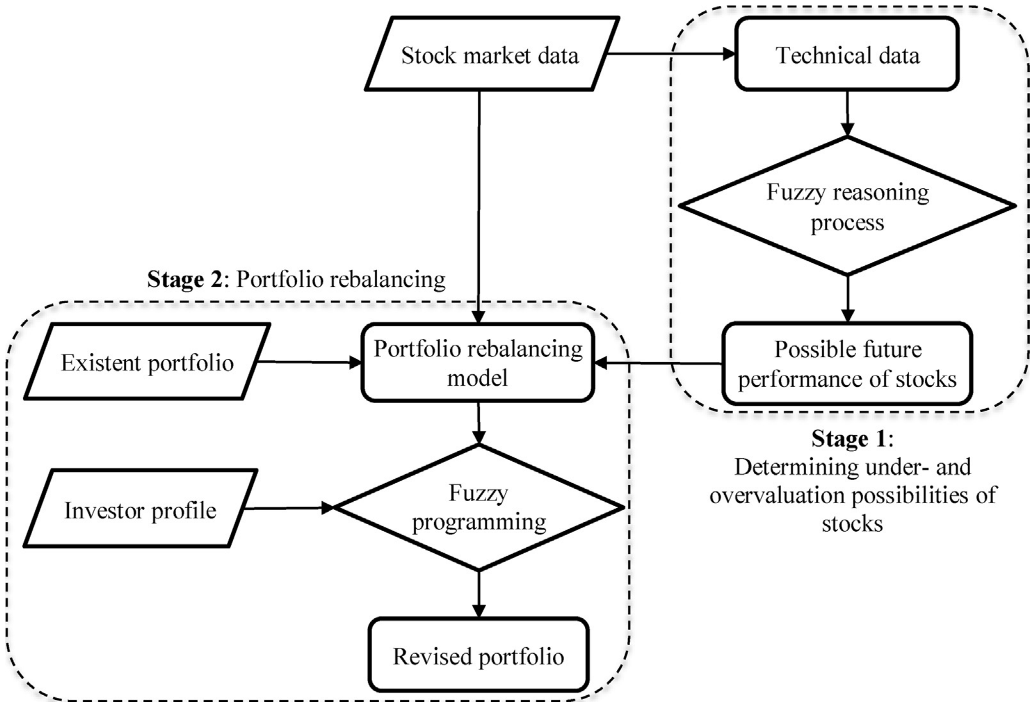


Fig. 1. Process flow diagram of the proposed investment strategy.

market. The purpose of surveying market psychology is to identify under- and overvalued stocks on the basis of mental and behavioral patterns of traders and rebalancing a portfolio to take advantage of misvaluation of stocks. Accordingly, the presented method consists of two stages as illustrated in Fig. 1. At the first stage, under- and overvaluation possibility degrees of stocks are calculated by modeling the reasoning process used by technical analysts. At the second stage, a real-world portfolio rebalancing model utilizes the calculated possibility degrees to find an optimal revised portfolio according to the investor profile.

3.1. Stage 1: determining under- and overvaluation possibilities

This stage presents a fuzzy reasoning process to evaluate stocks, which determines under- and overvaluation possibilities of stocks using market psychology. Considering a set of n stocks, which are supposed to be evaluated, called $S = \{S_1, S_2, \ldots, S_n\}$, the presented approach can be summarized in the following steps:

Step 1: Translate mass psychology of market into a set of criteria, called $C = \{C_1, C_2, \ldots, C_m\}$, to evaluate stocks.

Step 2: Define one or more quantities using the mathematical formulas of TA indicators to measure each criterion. Hence, criterion C_j, ($j = 1, 2, \ldots, m$) is measured by a set of quantities called $Q_j = \{Q_{j1}, Q_{j2}, \ldots, Q_{jk_j}\}$.

Step 3: Define a possibility distribution function of undervaluation signal for each quantity in the following way (for detailed information, see Zimmermann [60]):

Let X_{jl} be the universe of the numerical values of quantity Q_{jl}, ($j = 1, 2, \ldots, m$, $l = 1, 2, \ldots, k_j$), and x_{jl} be a variable of X_{jl}.

Also, let $\tilde{U}_{jl}$ be the fuzzy set of values of quantity Q_{jl} that signal the undervaluation, then $\pi_{x_{jl}}$ is interpreted as the possibility degree of the proposition 'x_{jl} is an undervaluation signal'.

Consequently, a set of k_j possibility distribution functions, $P_{x_j} = \{\pi_{x_{j1}}, \pi_{x_{j2}}, \ldots, \pi_{x_{jk_j}}\}$, is related to criterion C_j, ($j = 1, 2, \ldots, m$).

Step 4: Compute a joint undervaluation signal possibility distribution function for each criterion according to the following relation:

$$\pi_{x_j} = \pi_{x_{j1},\ldots,x_{jk_j}} = \min_l \left(\pi_{x_{j1}}, \ldots, \pi_{x_{jl}}\right), \quad j = 1, 2, \ldots, m, \; l = 1, 2, \ldots, k_j \tag{1}$$

where π_{x_j} denotes the k_j-ary possibility distribution function of undervaluation signal for criterion C_j, ($j = 1, 2, \ldots, m$), over the Cartesian product $X_{j1} \times \ldots \times X_{jk_j}$.

Step 5: Compute the aggregated undervaluation possibility degree of each stock by

$$\pi_{u_i} = \prod_{j=1}^{m} \pi_{x_j}, \quad i = 1, 2, \ldots, n \tag{2}$$

where π_{u_i} represents the undervaluation possibility degree of stock S_i, ($i = 1, 2, \ldots, n$).

Step 6: Similarly, take steps 3–5 to compute the overvaluation possibility degree of each stock (π_{o_i}).

Finally, the under- and overvaluation possibility degrees of stocks are calculated using market data.

It is recommended to select the set of criteria and corresponding technical indicators based on the specific characteristics of target market. We should mention that there is no best set of criteria or even best technical indicators and it may differ from one market to another. It should be specified that what psychological criteria have the most impact on prices in target market and what technical indicators can more efficiently analyze each specified psychological factor.

In this regard, the first phase is to identify common psychological criteria and the related technical indicators by studying the literature. Murphy [61], Nison [62], and Pring [63] are TA manuals introducing different kinds of technical indicators and their relation to market prices, which are affected by psychological factors. Moreover, Van Bergen [64] and Van Bergen [65] introduce some of the most common psychological factors and the related indicators. They also explain how those criteria can drive the indicators. Additionally, Table 1 gathers some studies in which different sets

Table 2
A representative set of criteria.

Steps	Market psychology				
S1:	Trading volume	Price moving average		Speed of price movements	
S2:	Vd_t	M_t	Md_t	S_t	Sd_t
S3:	"Values more than 1 are undervaluation signal"	"0 is an undervaluation signal"	"Positive values are undervaluation signal"	"30 is an undervaluation signal"	"Values more than 1 are undervaluation signal"
	"Values less than 1 are overvaluation signal"	"0 is an overvaluation signal"	"Negative values are overvaluation signal"	"70 is an overvaluation signal"	"Values less than 1 are overvaluation signal"

step 1 translates market psychology into a set of criteria, step 2 defines one or more quantities to measure each criterion and step 3 expresses the relation between each quantity and under- and overvaluation signals using a fuzzy proposition.

of technical indicators are applied in various target markets around the world.

The second phase is to consult experts who are familiar with the target market to identify criteria and corresponding technical indicators that efficiently can analyze the target market. Notice that TA indicators predictive power can be completely dissimilar in different markets. Although there is a large number of criteria and various technical indicators (like Japanese Candlestick, Elliot Waves, ROC oscillator, stochastic oscillator, etc.) introduced in TA manuals and the related literature, usually each technical analyst in a certain market uses a very limited number of them in practice. The key point is that each analyst, based on his/her experience, progressively has reached to a specific set of criteria and indicators that seems useful to him/her and he/she using his/her reasoning and deduction method can make good profits in his/her target market. This reasoning and deduction process of thinking is what Stage 1 also tries to simulate. Therefore, enough time should be dedicated to talk to a number of experienced analysts in target market to find a practical set of criteria and corresponding indicators.

In this current study, we wanted the set of criteria and indicators to be as similar as possible to what most analysts use in the TSE. Obviously, this will not guarantee to have a carefully optimized set of criteria and related indicators. However, it is an efficient way for us (and presumably for others implementing this method in other markets) to describe and evaluate our main methodology. Because this study mainly aims to present a method for making use of criteria and the corresponding indicators (which provide the inputs of our proposed model) to improve portfolio performance by taking market psychology into account. The proposed methodology has enough flexibility to work with various criteria and technical indicators. Therefore, different types of indicators for use in other markets can be selected, optimized, or even specifically developed (see Escobar et al. [42] as an example of developing a unique technical indicator using target market data).

Table 2 suggests a representative set of criteria and corresponding technical indicators, which are generated in collaboration with a number of technical analysts at TSE. Our typical sample set of criteria includes trading volume, price moving averages and speed of price movements. In fact, trading volume indicates investors' emotional state; moving averages determine shifts in consensus of value among investors; and speed of price movements can suggest the rate of emotional trades (for detailed information, refer [63,64]).

Note that 0 can be both an overvaluation and an undervaluation signal for M_t; i.e., M_t alone can only send a misvaluation signal. However, if Md_t is positive and M_t is 0, then it will be considered as an undervaluation signal. But, if Md_t is negative and M_t is 0, then it will be an overvaluation signal sent from the criterion of price moving averages. In fact, the quantities measuring a common criterion should be considered together.

Technical indicators try to find if a stock is under or overpriced by investigating the psychology of investment [47]. Therefore, we use mathematical formulas of technical indicators to measure each criterion in the second step (see Table 2). On-Balance Volume (OBV), Moving Average Convergence/Divergence (MACD) and Relative Strength Index (RSI) are the technical indicators employed in this study.

OBV, calculated by Eq. (3), relates trading volume to price change and shows whether volume is flowing in or flowing out of a stock. Quantity Vd_t, calculated by Eq. (4), is defined to measure trading volume based on the OBV change.

$$\mathrm{OBV}_t = \begin{cases} \mathrm{OBV}_{t-1} + V_t, & P_t \geq P_{t-1} \\ \mathrm{OBV}_{t-1}, & P_t = P_{t-1} \\ \mathrm{OBV}_{t-1} - V_t, & P_t \leq P_{t-1} \end{cases} \tag{3}$$

$$Vd_t = \frac{OBV_t}{OBV_{t-1}} \tag{4}$$

where V_t denotes volume traded during period t and P_t is stock's close price.

MACD-Histogram is a trend-following indicator based on the relation between two different moving averages. We define two quantities using MACD-Histogram as follows:

$$M_t = MACD_t - EMAm(9) \tag{5}$$

$$Md_t = M_t - M_{t-1} \tag{6}$$

where $MACD_t$ is the difference between a 12-period and 26-period exponential moving average of price and $EMAm(9)$ is a 9-period moving average of $MACD_t$. MACD-Histogram change is represented by Md_t.

RSI is a momentum oscillator that measures the speed of price movements. The following equations represent the quantities defined according to RSI.

$$S_t = RSI_t = 100 - \frac{100}{1 - RS_{14}} \tag{7}$$

$$Sd_t = \frac{RSI_t}{RSI_{t-1}} \tag{8}$$

where RS_{14} is *Average gains/Average losses* over the last 14 periods and Sd_t corresponds to the RSI change.

The relations between numerical values of quantities and under/over-valuation signal are imprecise and depend on an analyst's subjective interpretation. For this reason, as reported in Table 2, these relations are expressed using approximate (fuzzy) propositions. In addition, each quantity has a certain relation with under/over-valuation signal. Actually, the type of this relation is not necessarily similar for different quantities. For example, the values of Vd_t have a direct relationship to undervaluation possibility while the values of M_t suggest higher undervaluation possibilities when they are closer to zero. Accordingly, we have to use different types of possibility functions to describe the relations between quantities and under/over-valuation possibility.

Fig. 2 illustrates possibility distribution functions used in this study. For a better understanding of how to build possibility distribution functions, consider the structure of the function related to the quantity St (Fig. 2(d)) as an example. Almost all analysts

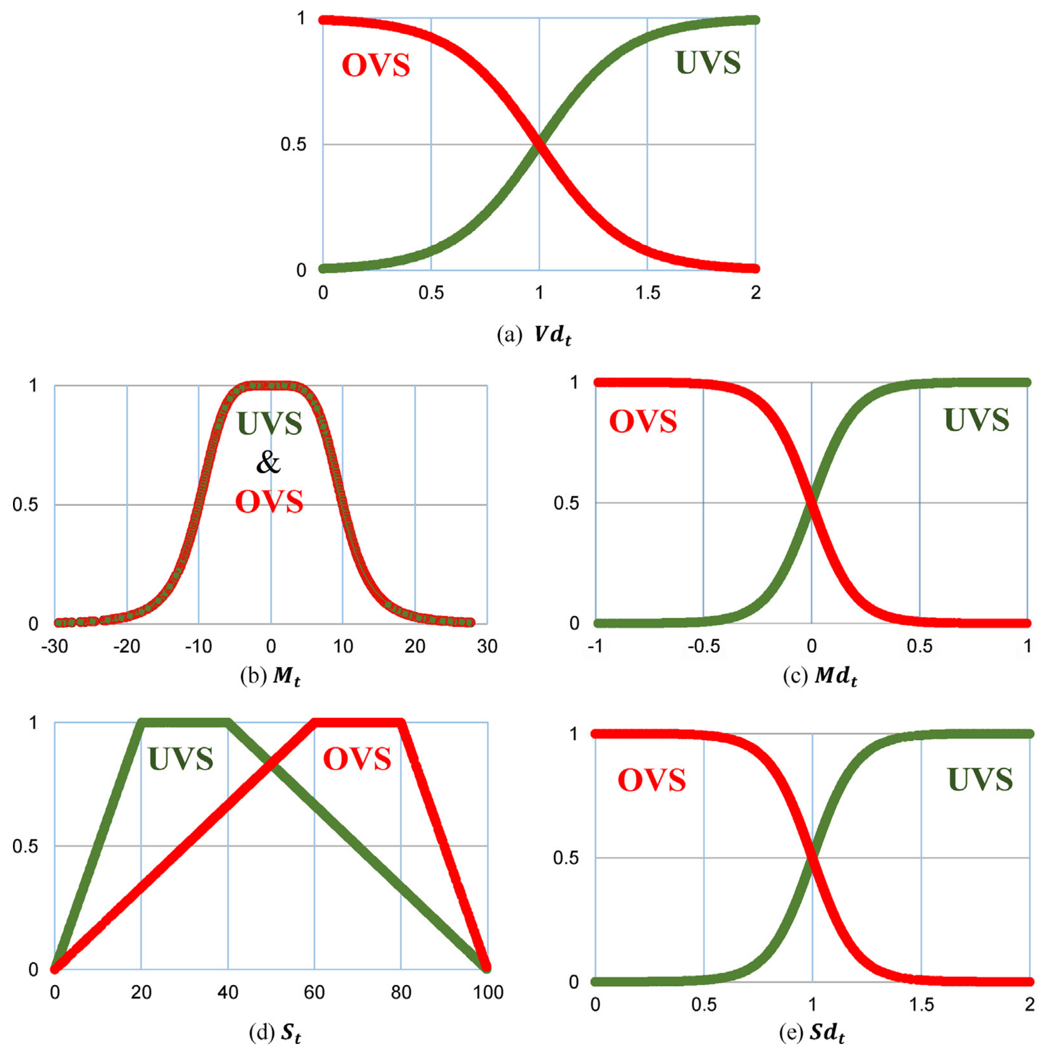


Fig. 2. Possibility distributions of under- (UVS) and overvaluation signals (OVS).

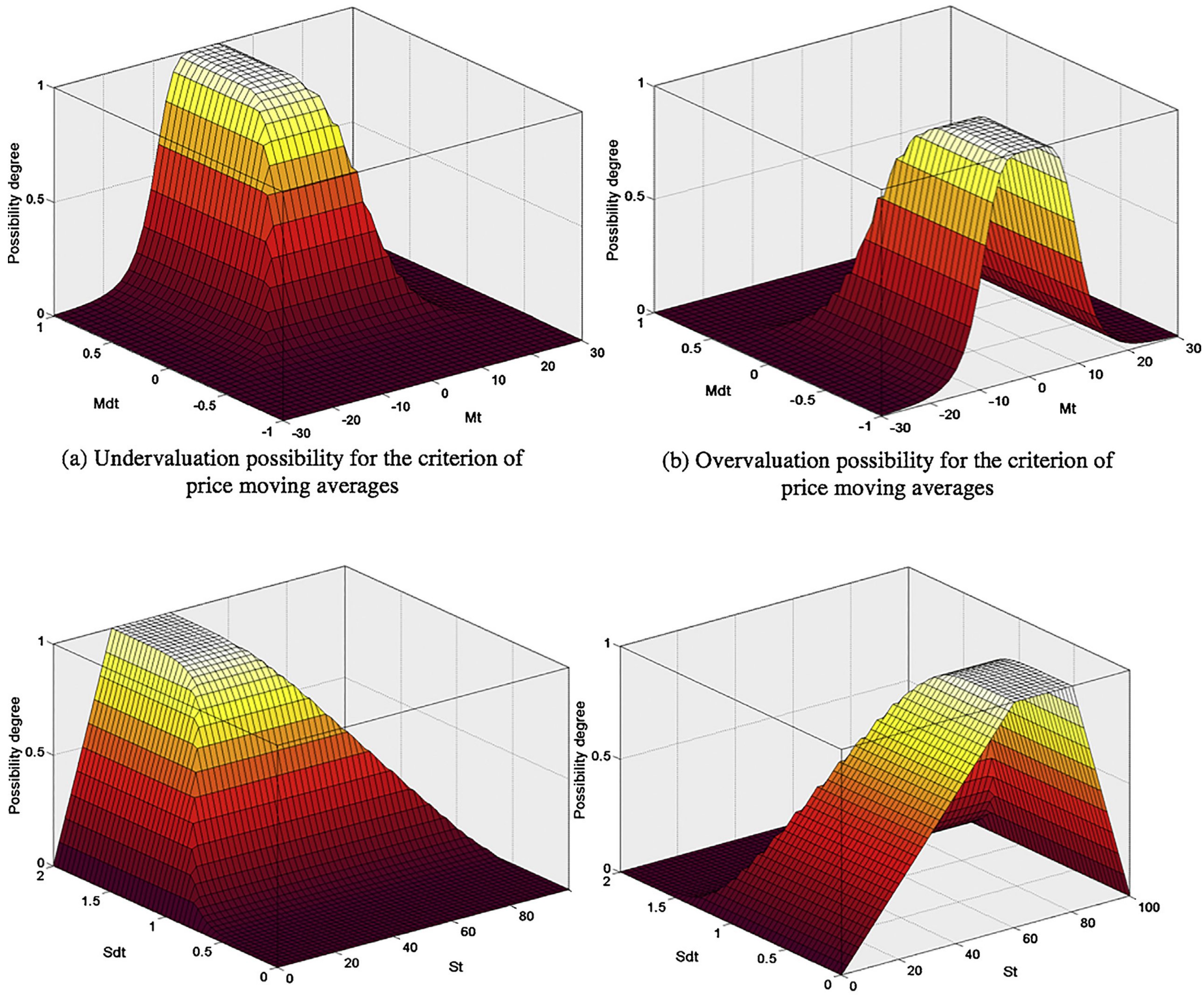
acknowledge that 30 is the best value for sending an undervaluation signal. Also, the value of 70 shows the best state of St for sending an overvaluation signal. But, the key point is that a better possibility distribution function is a function that can more precisely represents the analysts' viewpoint about the values around 30 and 70. For example, is the value of 35 still good for sending an undervaluation signal? What about the value of 40? Actually, an analyst may believe 45 is even good. While, another one may not. We consulted to a number of experienced analysts in TSE to gather their opinions. Consequently, we build the possibility distribution functions to demonstrate the consequent upon the analysts' opinions as accurate as possible in a fuzzy environment. Trapezoidal, bell-shaped and sigmoidal possibility distribution functions are used in this study. However, the purpose of this study is to introduce a flexible method that is not depended on a special kind of quantity or special form of fuzzy function. Therefore, it should be mentioned that there are other various methodologies in the literature to find accurate descriptions about the relation between each quantity and under/over-valuation signals.

Describing the relation between each quantity and under/over-valuation signal needs the domain knowledge. Generally, there are two universal methods for knowledge acquisition in the literature [66]: (a) by application of inductive learning methods (e.g., [67]) and (b) right from the experts (e.g., [68]). In this study, propositions and possibility distributions are generated in consultation with experts. Furthermore, TA manuals (e.g., [61]) and its related literature (e.g., [47]) have been taken into account.

As we mentioned before, the quantities that measure the same criterion should be considered together and each criterion is expected to give one single under/over-valuation possibility degree. Therefore, somehow, we have to join possibility distribution functions of different quantities measuring a common criterion so that we can calculate only one under/over-valuation possibility degree for each criterion. In our study, both quantities M_t and Md_t are defined to measure the criterion of price moving averages. Therefore, we have to join them. Also, S_t and Sd_t together measure the criterion of speed of price movements and we need to join them together, too. Although possibility distributions of different quantities have completely different universes of discourse, variables of different quantities are non-interactive under their k_j-ary fuzzy restrictions.

Zadeh [56] defines non-interactive variables in the following way:

Suppose that $x_1, \ldots, x_n$ are generic elements taking values in universes of discourse $X_1, \ldots, X_n$ respectively. Let variables $V_1, \ldots, V_n$ be associated with the restriction $\tilde{R}(V_1, \ldots, V_n)$, which induces the restrictions $\tilde{R}(V_1), \ldots, \tilde{R}(V_n)$ on $x_1, \ldots, x_n$, respectively (for more information about fuzzy restrictions, refer [60]). Then $V_1, \ldots, V_n$ are said to be non-interactive if and only if $\tilde{R} = (V_1, \ldots, V_n) = \tilde{R}(V_1) \times \ldots \times \tilde{R}(V_n)$, Correspondingly, $\pi_{x_1,\ldots,x_n} = min_i(\pi_{x_1}, \ldots, \pi_{x_n})$.



(a) Undervaluation possibility for the criterion of price moving averages

(b) Overvaluation possibility for the criterion of price moving averages

(c) Undervaluation possibility for the criterion of speed of price movements

(d) Overvaluation possibility for the criterion of speed of price movements

Fig. 3. Two-ary possibility distributions for the criteria measured by two quantities.

Thus, we can calculate a joint possibility distribution function for each criterion using Eq. (1). Zadeh [56] defines a joint possibility distribution function as follows:

Let $x_1, \ldots, x_n$ take values in $X_1, \ldots, X_n$ respectively. Also, let proposition 'x is$\tilde{A}$' include n variables $V_1, \ldots, V_n$ that take values in $X_1, \ldots, X_n$ respectively. Then $\tilde{A}$ is a fuzzy relation in the Cartesian product $X = X_1 \times \ldots \times X_n$ with the form$\tilde{R}(V_1, \ldots, V_n) = \tilde{A}$, where $\tilde{R}(V_1, \ldots, V_n)$ is an n-ary fuzzy restriction. Also, $\pi_{x_1,\ldots,x_n}$ is an n-ary possibility distribution function induced by 'x is $\tilde{A}$'. Finally, $\pi_{x_1,\ldots,x_n}$ is numerically equal to$\mu_{\tilde{A}}(x_1, \ldots, x_n)$.

Therefore, in step 4, an under/over-valuation joint possibility distribution for each criterion is calculated using the Cartesian product of possibility functions of quantities measuring it. Fig. 3 illustrates the possibility distributions for the criteria measured by more than one quantity in our study.

After step 4, each criterion can calculate under- and overvaluation possibility degrees of a stock using its related market data. However, an under/overvalued stock must meet all the criteria. Since technical indicators are best used when they complement each other [61], the product of possibility degrees corresponding to different criteria (modeling the logical "and") computes the aggregated possibility degree in the last step.

3.2. Stage 2: portfolio rebalancing

3.2.1. The proposed model

M-V model suggests that an investor should allocate his/her wealth on the basis of a trade-off between the portfolio's expected return and its variance as risk. This stage presents a portfolio rebalancing model in the M-V framework. We add two extra objective functions to the M-V model to utilize the possibility degrees specified in the previous stage.

The portfolio revision process is likely to incur transaction costs, which cannot be ignored when employing an active trading strategy [69]. We consider different transfer costs for buying and selling and it is supposed that the costs are paid at the beginning of the investment period. The problem is solved in the presence of a riskless asset. In addition, cardinality constraints and bounds on holdings, which are practical constraints necessary for generating a well-diversified portfolio, are taken into account. Mathematically, the real-world portfolio rebalancing model can be written as:

Model 1

$$\text{Max}\ \ M(x) = \sum_{i \in S} x_i r_i + x_f r_f \tag{9}$$

$$\text{Max}\ \ U(x) = \sum_{i \in S} x_i \pi_{u_i} \tag{10}$$

$$\text{Min}\ \ O\ \ (x) = \sum_{i \in S} x_i \pi_{o_i} \tag{11}$$

$$\text{Min}\ \ V(x) = \sum_{i \in S} \sum_{j \in S} x_i x_j \sigma_{ij} \tag{12}$$

$$\text{Min}\ \ C(x) = \sum_{i \in S} (x_i^b C_i^b + x_i^s C_i^s) \tag{13}$$

$$\text{s.t.}\quad \sum_{i \in S} x_i + \sum_{i \in S} (x_i^b C_i^b + x_i^s C_i^s) \le 1 \tag{14}$$

$$x_f = 1 - \sum_{i \in S} x_i - \sum_{i \in S} (x_i^b C_i^b + x_i^s C_i^s) \tag{15}$$

$$m \le \sum_{i \in S} z_i \le M \tag{16}$$

$$z_i l_i \le x_i \le z_i u_i, \quad i \in S \tag{17}$$

$$x_i = x_i^0 + x_i^b - x_i^s, \quad i \in S \tag{18}$$

$$x_i^b, x_i^s \ge 0, x_i^s \le x_i^0, \quad z_i \in \left\{0, 1\right\}, \quad i \in S$$

where x_i is the proportion of the total budget invested in stock i after revision. Also, x_i^0 is the proportion of stock i owned by the investor before revision.x_i^b denotes the proportion of stock i bought by investor. x_i^s is the proportion of stock i sold by investor and x_f is the amount invested in riskless asset. r_f is risk-free rate of interest. $r_i = E(R_i)$ is the expected return of stock i and R_i is a random variable representing the return of stock i. Also, σ_{ij} denotes the covariance between R_i and R_j. Moreover, z_i is a binary variable, which is 1 if any of stock i is held, and 0 otherwise. l_i and u_i are the lower and the upper bound on investment on stock i. Furthermore, m and M are the minimum and the maximum number of assets in the portfolio, respectively. Finally, C_i^b and C_i^s indicate buying and selling transaction costs, respectively. The distribution of variable R_i can be characterized using historical data of stock i in T periods as follows:

$$r_i = E(R_i) = \frac{\sum_{t=1}^{T} r_{it}}{T} \tag{20}$$

where r_{it} is the realization of stock i in period$t$.

There are five competing objectives in the model: maximizing the portfolio expected return $M(x)$ while minimizing both the portfolio risk $V(x)$ and the transaction costs $C(x)$, and finally, maximizing the possibility of undervaluation of portfolio $U(x)$, while minimizing the possibility of its overvaluation $O(x)$. The original objective functions $U(x)$ and $O(x)$ form the psychological component of the model trying to increase future returns and prevent possible losses by exploiting market misvaluation.

Constraint (14) is the budget constraint; constraint (15) specifies the amount invested in risk-free asset; constraint (16) controls the number of stocks in the portfolio; constraint (17) sets upper and lower bounds to the amount invested in each stock; constraint (18) indicates that the portfolio position x is selected through adjustments to the initial holding x° that are sales x^s and purchase x^b; and constraint (19) is the non-negative constraint. It is assumed that short position is not allowed and the transaction of risk-free asset does not incur any costs.

Using a practical situation, we briefly demonstrate how behavioral biases influence the model and the market as a whole. Suppose that corporation XYZ announces an earnings report that is substantially above expectations. According to representativeness bias, investors may overweight such a report and become too optimistic about XYZ's prospect. Consequently, in a relatively short period of time, they push XYZ's price to abnormally high levels. The fast upward changes in XYZ's price cause S_t to increase up to the values around 70 and above. Also, M_t, which is the difference between a fast and a slow moving average, increases. However, after a while, the speed of price movements reduces and S_t starts decreasing ($Sd_t < 1$). Moreover, M_t reduces to values around zero ($Md_t < 0$). Hence, $\pi_{o_{XYZ}}$ rises and the model minimizes the weight of XYZ in the portfolio. In other words, the model sells XYZ, which is overpriced due to market's overreaction. Unsurprisingly, XYZ's stock price will correct itself downward after the sharp price increase that motivated the model to sell XYZ.

3.2.2. Fuzzy programming approach

Besides having different attitudes toward their financial goals, real investors usually cannot fix the aspiration levels for their goals. In an uncertain financial environment, the desired level of return, the preferred sensitivity level to market behavior, and the acceptable level of risk and transaction costs are vague; therefore, we deal with them in fuzzy terms.

The fuzzy programming is primarily developed by Bellman and Zadeh [70], Tanaka et al. [71], Zimmermann [72,73]. It treats decision-making problems under fuzzy goals and constraints. The fuzzy goals denote the flexibility of the target values of objective functions. Zimmermann [74] provides an overview of the development of this method. Also, Inuiguchi and Ramik [81] draw a comparison between fuzzy programming and stochastic programming in portfolio selection problem. Table 1 shows some comparable studies employing fuzzy programming.

Following Zimmermann [73], a membership function is defined for each objective function using ideal and anti-ideal solutions. These solutions are initially determined by solving Model (1), considering one objective at a time while ignoring the others and calculating pay-off matrix (for more details, see Jana et al. [50]). Consequently, the multi-objective Model (1) translates into a single-objective problem as:

Model 2

$$\text{Max}\ \ F = w_m\left(\frac{M(x) - M_l}{M_u - M_l}\right) + \frac{w_p}{2}\left(\frac{U(x) - U_l}{U_u - U_l}\right) + \frac{w_p}{2}\left(\frac{O(x) - O_l}{O_u - O_l}\right) + w_v\left(\frac{V(x) - V_l}{V_u - V_l}\right) + w_c\left(\frac{C(x) - C_l}{C_u - C_l}\right) \tag{21}$$

$$\text{s.t.}\quad \text{M}(x) = \sum_{i \in S} x_i r_i + x_f r_f \tag{22}$$

$$U(x) = \sum_{i \in S} x_i \pi_{u_i} \tag{23}$$

$$O(x) = \sum_{i \in S} x_i \pi_{o_i} \tag{24}$$

$$V(x) = \sum_{i \in S} \sum_{j \in S} x_i x_j \sigma_{ij} \tag{25}$$

$$C(x) = \sum_{i \in S} (x_i^b C_i^b + x_i^s C_i^s) \tag{26}$$

$$w_m + w_p + w_v + w_c = 1 \tag{27}$$

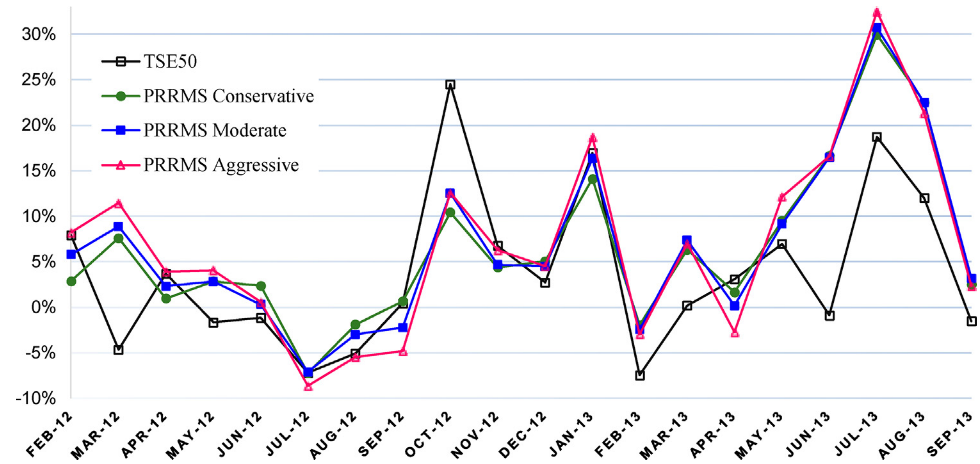


Fig. 4. The sub-periodic returns.

Table 3
Weights (percentage) of fuzzy objectives according to different IPs for the two rebalancing strategies.

PRRMS												PR								
Conservative				Moderate				Aggressive				Conservative			Moderate			Aggressive		
w_m	w_v	w_c	w_p	w_m	w_v	w_c	w_p	w_m	w_v	w_c	w_p	w_m	w_v	w_c	w_m	w_v	w_c	w_m	w_v	w_c
10	35	5	50	10	25	5	60	5	10	5	80	35	60	5	50	45	5	60	35	5

PRRMS: portfolio rebalancing with respect to market psychology, PR: conventional portfolio rebalancing strategy.

s.t.constraint (14) ~ (19)

where M_u, V_u, C_u, U_u and O_u are the utopia values for goals of return, risk, transaction costs, the undervaluation possibility, and the overvaluation possibility, respectively. In contrast, M_l, V_l, C_l, U_l and O_l are the respective anti-ideal values of the goals. w_m, w_v and w_c are the respective weights of the objectives of return, risk, and transfer costs. Also, w_p is the weight of psychological component of the model and specifies the sensitivity level to market misvaluation. Finally, constraint (27) ensures that the weights add to one.

Higher values of w_p give more importance to the possible future performance of stocks estimated on the basis of market psychology. On the other hand, higher values of w_m cause more reliance of the portfolio to past performance of stocks. Considering that TA is more profitable in shorter-term horizons and its predictive power varies from one market to another [27], w_p and w_m can be determined depending on the target market and portfolio rebalancing frequency. In addition, w_v and w_c respectively indicate risk aversion and cost aversion preferences of the investor. Obviously, in a hypothetical efficient market, w_p is equal to zero and the model reduces to a conventional portfolio rebalancing model with transaction costs (M-V-C model).

4. Implementation and evaluation of the proposed method

This section includes an empirical study using 30 stocks listed on TSE to evaluate the performance of the proposed method. The stocks are selected from different activity sectors based on their liquidity during the validation period. The quarterly announcements appearing in the official website of TSE (www.tse.ir) introduce the most liquid stocks. The details of considered stocks and their industry class are reported in Appendix A, Table A1. The historical data, containing the dividend and splits adjusted daily closing prices and transaction volumes, are provided using *Mofid Securities online trading platform* (www.emofid.com).

In order to validate the method, a time interval including both bear and bull markets, from January 1, 2012 to august 31, 2013, is considered. An initial portfolio x° consisting of 10 stocks with equal weights is endowed to the investor. The selected stocks are the top 10 most profitable ones, based on their historical data from January 1, 2010 to December 31, 2011. The investment horizon is divided into 20 sub-periods and the investor is assumed to rebalance his/her portfolio on the first day of each month using Model (2). As specified by TSE's regulation, the investor pays the transfer costs $C_i^b = 0.486\%$ and $C_i^s = 1.029\%$. Also, according to the central bank of Iran, the monthly interest on the investor's money from a risk-free investment is $r_f = 0.583\%$. The desired number of stocks in the portfolio ranges from 6 to 14 in constraint (16). Additionally, in constraint (17), the lower and upper bounds on the weight of each stock in the portfolio are determined as 0.05 and 0.2, respectively.

As we mentioned in Section 3.1., steps 1–6 are taken to calculate the under- and overvaluation possibility distributions of stocks. The calculated possibility degrees are shown in Appendix B, Fig. B1. Depending on the portfolio rebalancing frequency, generally, the period t in Eqs. (3)–(8) can take various timeframes, such as an hour, a day, a week, etc. Considering the duration of sub-periods, we have used the daily stock data to measure the quantities.

The expected returns of stocks and covariances among various assets are calculated using their historical monthly returns. Particularly, the last 10 observations leading up to the scheduled rebalancing date are considered, i.e. $T = 10$ in Eq. (20).

The performance measures used in this study are: end of period portfolio value (EPV), minimum and maximum monthly returns (MR), average monthly return (AMR), Sharp ratio (SR) and information ratio (IR). The proposed approach is compared against the Buy-and-Hold (B&H) strategy, where the initial portfolio is held for a long time, regardless of market conditions. In addition to

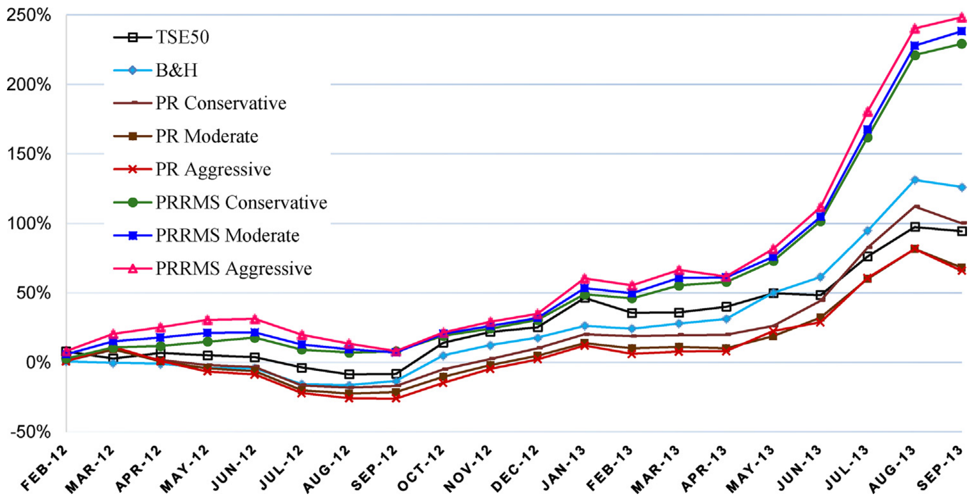


Fig. 5. The cumulative returns.

Table 4
Performance evaluation results.

Strategy	IP	EPV	Min. MR	AMR	Max. MR	SD	SR	IR	$\bar{x}_f$
TSE50	–	1.944	−7.46	3.72	24.50	8.53	0.299	NA	NA
B&H	–	2.262	−11.92	4.49	21.23	8.37	0.397	0.164	NA
PR	Conservative	2.001	−13.97	3.92	26.42	9.10	0.303	0.030	24.10
	Moderate	1.682	−14.66	3.00	21.25	8.65	0.212	−0.112	9.18
	Aggressive	1.659	−14.73	3.03	24.72	9.77	0.190	−0.103	3.03
PRRMS	Conservative	3.291	−7.24	6.47	29.96	8.59	0.616	0.404	10.90
	Moderate	3.382	−7.11	6.65	30.73	9.07	0.604	0.445	4.86
	Aggressive	3.485	−8.64	6.89	32.49	9.95	0.574	0.449	2.69

this passive strategy, a conventional portfolio rebalancing strategy, where the market is assumed to be efficient, i.e. $w_p = 0$, is taken into account. Above all, TSE50 Index is considered as the benchmark.

Since IP has a major effect on the portfolio composition, we compare the performance of the proposed method in cases of 3 different IPs: conservative, moderate and aggressive. As reported in Table 3, the weights of fuzzy goals are determined for both the proposed method and the comparative conventional portfolio rebalancing model in accordance with different IPs. In order to support the investor in the short-term rebalancing horizons, the psychological component of the model, which utilizes the TA processed data, is given relatively a greater weight than the portfolio expected return. Finally, the model has been run on an Intel CPU Q6600 2.4 GHz and 4 GB RAM desktop computer, using Lingo 11 software.

Fig. 4 represents the sub-periodic returns obtained from our proposed strategy in comparison with TSE50 Index. Normally, the sub-periodic returns, more or less, follow the benchmark index. However, a remarkable difference has emerged in a specific time interval around June 2013. Interestingly, this period corresponds to the country's presidential election, which causes extraordinary psychological effects on the market prices ([75] provides more details about the impact of such events on TSE returns). The proposed strategy has benefited well from this. In a similar but less significant manner, this situation has also happened before the parliamentary elections held on march 2, 2012. As expected, the presented method shows superior performance relative to the benchmark index when the psychological state of market participants affects the market dramatically. These results are in parallel to the study of Yahyazadehfar et al. [76] who show that political factors have the most influence on the financial behavior of investors in TSE. Regarding this matter, it can be concluded that the proposed method has managed to respond appropriately to the market's psychological component in the evaluation period.

At the end of the period, the aggressive portfolio has the highest market value among the three portfolios generated by the proposed method. However, as reported in Table 4, it has tolerated the highest standard deviation (SD) of returns over the investment horizon. Conversely, the conservative investor is the one with the slowest but the most stable capital growth. Moreover, as Table 4 shows, there is a meaningful relationship between the average weight of riskless asset ($\bar{x}_f$) in the portfolio and the investor risk profile. This results reveal that the introduced fuzzy approach efficiently reflects the IP in the portfolio composition.

As illustrated by Fig. 5, in the cases of all IPs, the presented method yields a higher cumulative return compared to TSE50 and other evaluated strategies. As well, the suggested strategy outperforms the market and the Buy-and-Hold strategy in terms of risk-adjusted return measures, namely SR and IR (see Table 4). But the conventional rebalancing approach (M-V-C model) has shown noticeably inferior results. In particular, the presented model's average portfolio value is over 90% above the M-V-C model's average portfolio value at the end of the period. However, a closer look at Fig. 5 reveals the substantial fact that the performance of the PRRMS strategy is only around 20% higher than the performance of PR strategy before June 2013, which is corresponding to the presidential election. In other words, ignoring the results obtained in the last 3 month of the investment horizon causes a significant decrease in the difference between the results obtained by two comparable strategies.

Confirming our empirical results, Kolm et al. [32] indicate that equally weighted portfolios often outperform the M-V portfolios in practical applications. Jobson and Korkie [77] and Jorion [78] and DeMiguel et al. [79] also report similar results. After analyzing the performance of more than 200 professional portfolio managers, Goodwin [80] finds that the median IR is positive, although it usually does not exceed 0.5. The portfolios constructed by the proposed strategy have achieved the highest IR of 0.449, which is consistent with Goodwin's study.

5. Conclusions and further research

Considering the importance of mass psychology of financial markets and the dearth of literature on the use of market psychology in portfolio selection, this paper presents a novel portfolio rebalancing method combining MPT and market psychology. The main advantages of the proposed method can be summarized as follows: (a) eliminating the restricting assumptions of EMH and absolute rationality of investors; (b) simulating the reasoning process used by technical analysts to evaluate the psychological component of financial markets; (c) designing a novel portfolio rebalancing method to exploit market misvaluation of assets; (d) developing a portfolio model that is not only sensitive to market psychology, but the sensitivity level of which is adjustable; (e) reducing the dependency on simple historical data by entering the data processed by a fuzzy artificial intelligence; (f) involving the IP and transaction costs into the model to better reflect the reality; and (g) adaptability and ability of evaluating a significantly large number of stocks (due to the computational simplicity), which is a critical issue in financial markets.

Empirical results suggest that the proposed method has enormous potential to help real-world investors and portfolio managers, especially during difficult market conditions. However, some important topics like applying various optimization methods to build more efficient fuzzy distribution functions, considering uncertain rebalancing time intervals, more sophisticated risk management methods and employing various TA tools (e.g., support and resistance levels, Elliot wave theory and Japanese candlestick) remain for future researches.

Acknowledgement

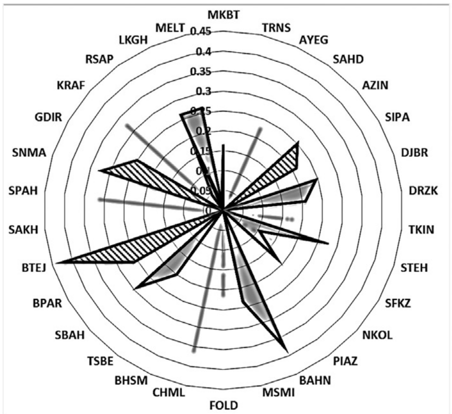
We would like to give special thanks to our colleague Mr. Arman Khayamim for his contribution to this study that greatly assisted us.

Appendix A.

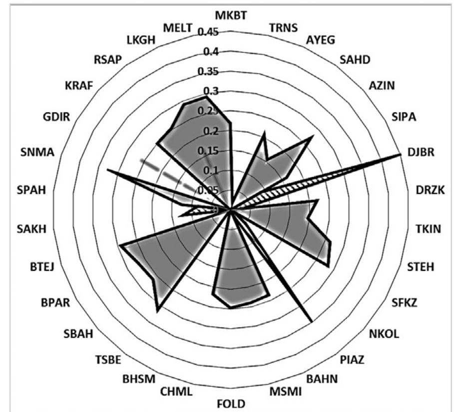
Table A1
Activity sector classification and symbol of the 30 selected companies.

Industry sector	Number of companies	Company	Symbol
Real estate and construction	2	Shahed Investment Co.;	SAHD
		Iran Construction Investment Co.	SAKH
Motor vehicles and auto parts	2	Saipa Azin Co.	AZIN
		Saipa Co.	SIPA
Financial intermediary	2	Ghadir Khodro Leasing Co.	LKGH
		Rayan Saipa Co.	RSAP
Banks and credit institutions	3	Parsian Bank	BPAR
		Tejarat Bank	BTEJ
		Karafarin Bank	KRAF
Pharmaceuticals	2	Jaber Hayan Pharmaceutical Co.	DJBR
		Razak Labs Co.	DRZK
Cement, lime and plaster	2	Tehran Cement Co.	STEH
		Fars and Khuzestan Cement Co.	SFKZ
Basic metals	3	Bahonar Copper Co.	BAHN
		Mobarakeh Steel Co.	FOLD
		National Iranian copper Ind. Co.	MSMI
Food and Beverage	2	Piazar Agro Co.	PIAZ
		Behshahr Industrial Co.	TSBE
Telecommunication	1	Iran Telecommunication Co.	MKBT
Technical and engineering services	1	Techinco Co.	TKIN
Holdings	1	Ghadir Investment Co.	GDIR
Investments	5	Bahman Investment Co.	SBAH
		Melat Investment Co.	MELT
		Sepah Investment Co.	SPAH
		Pardis Investment Co.	AYEG
		Industrial and Mine Investment Co.	SNMA
Metal ores mining	1	Chadormalu Co.	CHML
Electric machinery and apparatus	1	Iran Transfo Co.	TRNS
Tiles and ceramics	1	Behceram Co.	BHSM
Chemical products	1	NiroCholor Co.	NKOL

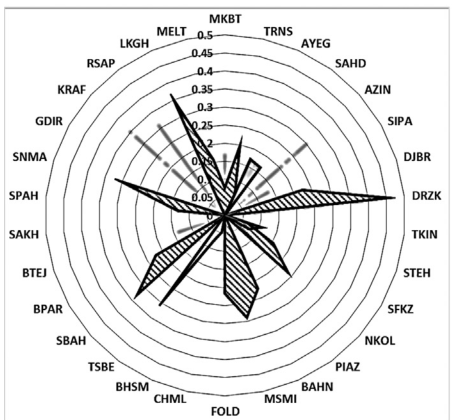
Appendix B.



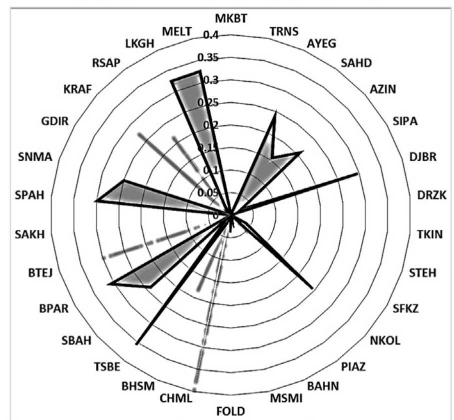
(a) Sub-period 1.



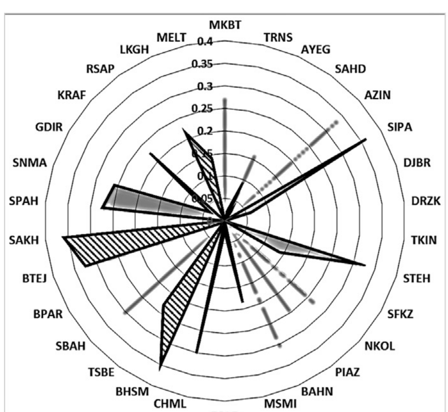
(b) Sub-period 2.



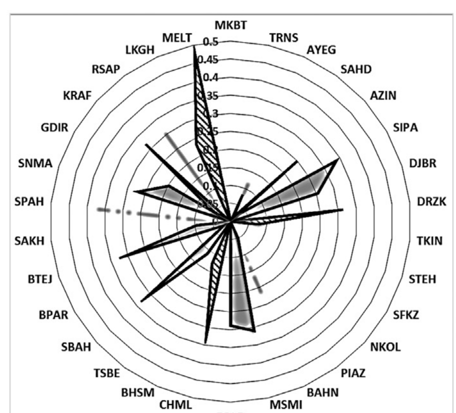
(c) Sub-period 3.



(d) Sub-period 4.

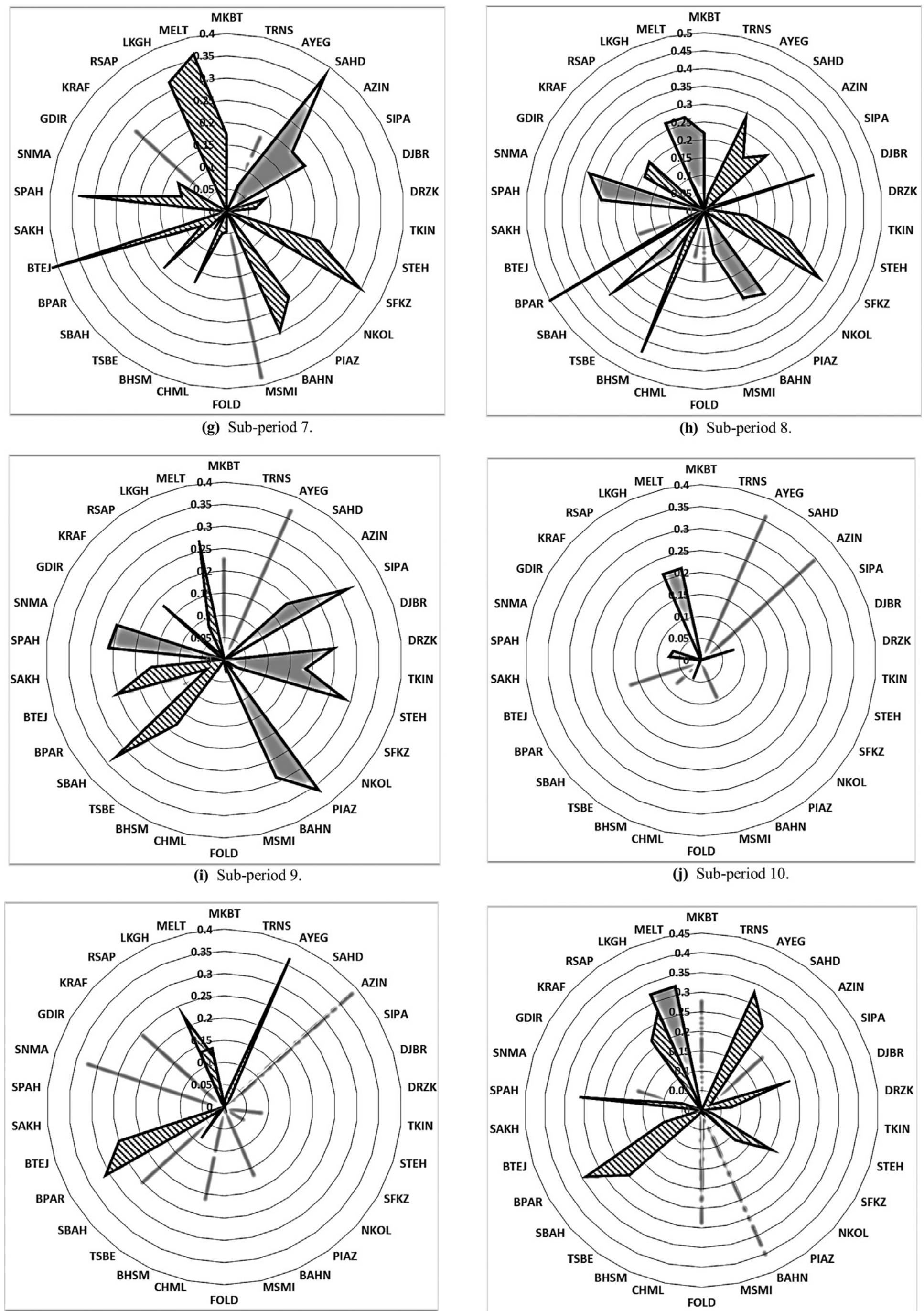


(e) Sub-period 5.



(f) Sub-period 6.

Fig. B1. illustrates under- and overvaluation possibility degrees of stocks for the 20 sub-periods. The solid area shows overvaluation possibility degrees while the area with diagonal lines shows undervaluation possibility degrees of stocks for each sub-period.



(g) Sub-period 7.

(h) Sub-period 8.

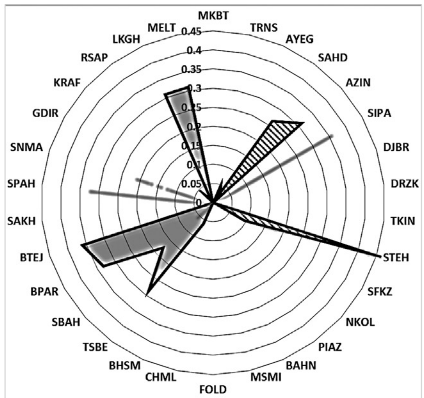
(i) Sub-period 9.

(j) Sub-period 10.

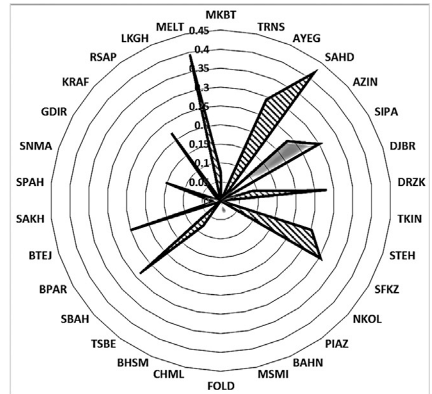
(k) Sub-period 11.

(l) Sub-period 12.

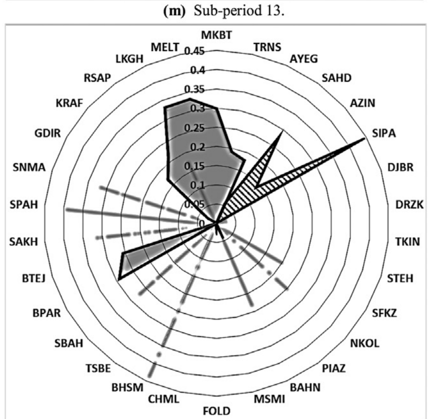
Fig. B1. *Continued*



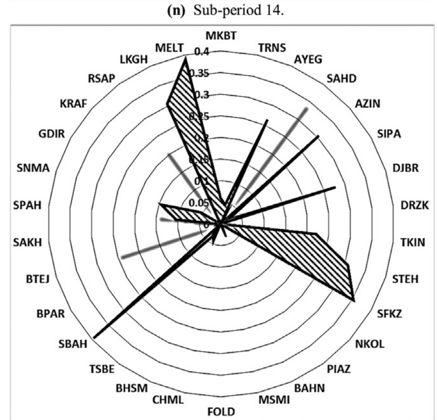
(m) Sub-period 13.



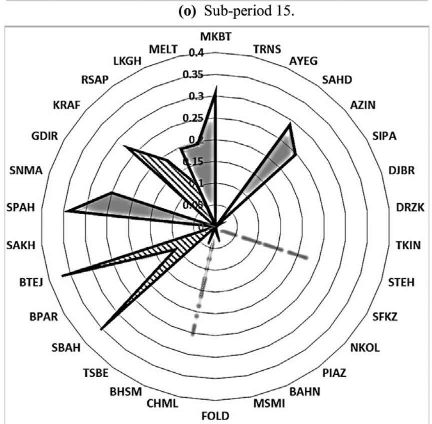
(n) Sub-period 14.



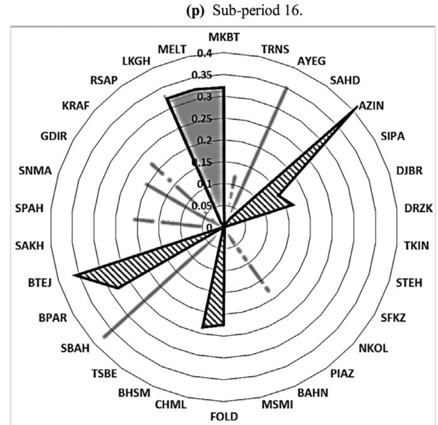
(o) Sub-period 15.



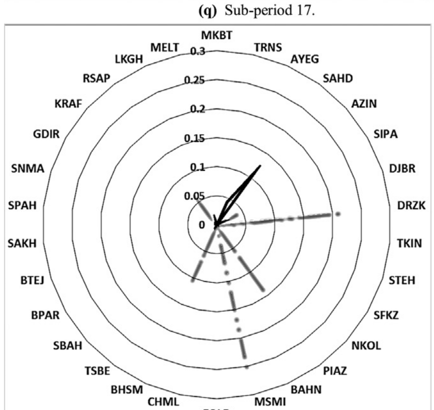
(p) Sub-period 16.



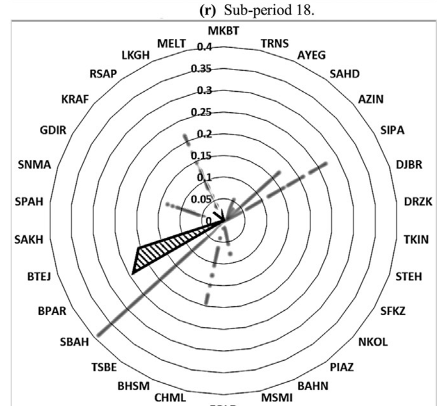
(q) Sub-period 17.



(r) Sub-period 18.



(s) Sub-period 19.



(t) Sub-period 20.

Fig. B1. *Continued*

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