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Using ELECTRE-TRI and FlowSort methods in a stock portfolio selection context

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Abstract

In recent years, multi-criteria sorting problems have become an interesting topic for researchers working on multi-criteria decision-making. ELimination and Choice Expressing REality (ELECTRE)-TRI and FlowSort are well-known approaches suggested for such a classification. The current study aimed to implement ELECTRE-TRI and FlowSort methods in the stock portfolio selection (SPS) as one of the most popular and important decision-making subjects and compare the outcomes of each method to understand how these methods perform in SPS problems. In this study, the best–worst method was applied to determine the weights of criteria. Four approaches for ELECTRE-TRI and 15 approaches for FlowSort were considered. Finally, 19 different approaches were considered to select stocks from a large pool of stocks. Results indicated that the model parameter should be properly defined to minimize inconsistencies and improve the power of the model.

Keywords: Multi-criteria decision-making, ELECTRE-TRI, FlowSort, Best–worst method, Finance

Introduction

Currently, multi-criteria decision-making (MCDM) is an integral part of operations research and occupies a prominent position within the field owing to significant theoretical and practical developments during the past five decades. MCDM methods can provide the decision-maker (DM) with a countable number of alternative decisions with several criteria attached to each decision (Qu et al. 2018). MCDM can be considered a decision tool for helping DMs maximize their satisfaction (Vanani and Emamat 2019). In the past decades, many MCDM methods have been proposed, and the most popular methods are the analytic hierarchy process (AHP) (Saaty 1977, 1986, 1990), analytic network process (Saaty 1996), technique for order of preference by similarity to ideal solution (TOPSIS) (Hwang and Yoon 1981), VIseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) (Opricovic and Tzeng 2004), ELimination and Choice Expressing REality (ELECTRE) (Roy 1968, 1991), and Preference Ranking Organization METHod for Enrichment Evaluation (PROMETHEE) (Brans and Vincke 1985).

Roy (1968) established the foundations of the MCDM outranking approach by developing the ELECTRE method. Since then, the outranking approach has been widely used by researchers. The outranking relation is a binary relation for representing the DM's preferences and is used to examine the strength of the preference of alternatives over each other. Outranking methods generally operate in two steps: developing outranking relations for all the alternatives and exploiting the outranking relations for choosing, sorting, or ranking alternatives (Xidonas et al. 2012). ELECTRE and PROMETHEE families are the main methods covered under the label of the outranking approach (Figueira et al. 2005). ELECTRE and PROMETHEE methods can deal with lack of information and some vagueness. However, the main advantage of PROMETHEE methods is that they are easy to use (Velasquez and Hester 2013).

The performance values of alternatives being affected by imprecision and inaccurate determination are not uncommon. Different solutions exist for modeling these phenomena, including probability distribution, confidence intervals, and fuzzy numbers. However, the concept of pseudo criterion and its two thresholds (indifference and preference thresholds), known in the outranking approach, allow these phenomena to be considered (Roy et al. 1986; Takeda 2001).

Roy (1981) identified four types of decision problems: choice, sorting, ranking, and description problems (Ishizaka and Nemery 2013). Among these problems, the sorting problems aim to assign alternatives to predefined homogenous groups by considering different criteria. Sorting problems have numerous applications, for instance, medicine (Belacel 2000; Belacel and Boulassel 2004), human resources (Gomes and Santos 2008; Pereira and Mota 2016), sustainability analysis (Silva et al. 2014a), location analysis (Silva et al. 2014b), finance and economics (Verheyden and De Moor 2014; Doumpos et al. 2016), risk (Shen et al. 2016; Certa et al. 2017), supply chain management (Govindan and Jepsen 2016; Silva and Sobral 2017), project management (Micale et al. 2019b; de Araújo et al. 2021), and warehouse management (Micale et al. 2019b). For solving multi-criteria sorting problems, ELECTRE-TRI (Yu 1992) extends the ELECTRE family, and FlowSort (Nemery and Lamboray 2008) is an extension of the PROMETHEE family. ELECTRE-TRI is the most frequently used sorting method based on the outranking approach (Doumpos and Zopounidis 2002).

In real-life decision-making, DMs consider multiple criteria (Kou et al. 2021), and as a popular approach in decision-making, the use of MCDM is increasing. However, the development of numerous MCDM methods has been faced with several criticisms. The main question is, "Do we have a greater need for developing new methods or for evaluating the accuracy of existing methods?".

Roy and Bouyssou (1993) believed that, although the diversity of MCDM methods is a strong point, such diversity can also be a weakness. Deciding whether a certain method makes more sense than the other in a specific problem situation is challenging (Ishizaka and Nemery 2013). Doumpos and Zopounidis (2002) stated that, despite the significant theoretical developments of MCDM classification methodologies, studies on the efficiency of these methodologies are still sparse.

Capital market investment is a growing stream in the economic literature (Gupta et al. 2019). In this study, two multi-criteria sorting methods, ELECTRE-TRI and FlowSort, have been applied to form the stock portfolio. These methods are well adapted to the nature of the stock portfolio selection (SPS) problem, as they consider conflicting and multiple criteria in the analysis. Classic portfolio models could not consider more than two criteria. However, presently, many investors prefer to consider additional criteria. In addition, the formation of a stock portfolio is a sorting problem, so multi-criteria sorting methods are very suitable for this type of problem. Multi-criteria sorting methods assign alternatives to classes by comparing alternatives with reference profiles. The stock portfolio can be formed easily using this process. ELECTRE and PROMETHEE families of methods are very popular in MCDM and have been applied successfully in several studies. ELECTRE-TRI and FlowSort are sorting methods belonging to ELECTRE and PROMETHEE families, respectively.

One of the advantages of multi-criteria sorting methods over clustering methods is that, in multi-criteria sorting methods, the order of groups is clear. Thus, the first group always contains the best alternatives, while the last group always contains the worst. Multi-criteria sorting methods are adapted to the nature of the SPS problem as the first group can be a stock portfolio. In clustering methods, the priority between groups is unspecified. Therefore, after clustering, determining the order of groups is challenging.

The present study aimed to implement ELECTRE-TRI and FlowSort in SPS to understand how these methods perform in SPS problems. As SPS is an attractive field of finance and obtaining real returns in finance is possible, the results can be analyzed accordingly. SPS is an important decision process for investors to select stocks from a large pool of stocks (Hargreaves 2013). Compared with PROMETHEE methods, ELECTRE methods have been used more in SPS problems, and in some studies, the ELECTRE-TRI method has been applied. For instance, Hurson and Zopounidis (1997) applied ELECTRE-TRI and MINORA methods in an SPS problem, and Xidonas et al. (2009a) applied ELECTRE-TRI, ELECTRE III, and a nonlinear model in the SPS problem. These studies were conducted in Athens Stock Exchange. Hurson and Ricci-Xella (1998) and Hurson and Ricci-Xella (2002) applied ELECTRE-TRI and MINORA to the French stock market for SPS. Mehregan et al. (2018) applied UTADIS in SPS, and after a post optimality stage, stocks were classified into two groups. Mehregan et al. (2019) applied ELECTRE-TRI in SPS and considered four approaches in their study. In the present study, research results obtained by Mehregan et al. (2019) and 15 approaches for FlowSort were taken into account. Finally, 19 approaches were considered to classify stocks. The best–worst method (BWM) was applied to identify the criteria weights as it is compatible with the problem of this study and the number of comparisons is suitable (2n-3). The current study is performed on the Tehran Stock Exchange (TES). Established in 1967, it is the largest stock exchange in Iran with a market capitalization of 226 billion dollars.

This study presents an application of two known multi-criteria sorting methods to an SPS problem. The present study applies the FlowSort in an SPS context for the first time. This study is the first to use a hybrid approach using BWM and FlowSort in a real problem. To the best of the authors' knowledge, a comprehensive sensitivity analysis on all method parameters, as conducted in this study, has not occurred in other studies. This research also analyzes the results obtained by the ELECTRE-TRI and the FlowSort simultaneously.

Section "Background of SPS" introduces Markowitz's theory and the expanded framework. Section "Background for comparison of MCDM methods" presents a background for a comparison of MCDM methods. Section "Theoretical foundation" presents an overview of applied methods. Section "Research methodology" presents the methodology and study framework. Section "Results and discussion" presents the results and discussion. Section "Managerial implications" presents the managerial implications, and Section "Conclusion" concludes the study.

Background of SPS

SPS has been one of the most critical decision-making areas in modern finance since the 1950s (Mansour et al. 2019). SPS aims at assessing a combination of securities from a wide range of available alternatives. The modern portfolio theory (MPT) proposed by Markowitz (1952) transformed the field of finance. Markowitz received a nobel prize for his pioneering theoretical contributions to economics after proposing the MPT. The proposed model has two important aspects. First, any investor's preference is to maximize return. Second, having a diversified portfolio of unrelated securities can decrease risk. Markowitz proposed the model in the form of a mathematical program (Eq. (1)) (Aouni et al. 2018).

$$\begin{aligned}
&\text{Min}\left\{\sum_{i=1}^{m}\sum_{j=1}^{m} x_i\sigma_{ij}x_j\right\}\\
&s.t.\\
&\sum_{i=1}^{m} E(r_i)x_i = \rho\\
&\sum_{i=1}^{m} x_i = 1\\
&x_i \geq 0, i = 1, \ldots, m
\end{aligned} \tag{1}$$

In this model, r_i is the random variable for the return to be realized on a security i over a future period. $E(r_i)$ is the expected rate of return on stock i; ρ is the desired expected return for the portfolio; σ_{ij} is the covariance of r_i with r_j; x_i is the proportion of capital invested in stock i, and m is the number of assets. According to the proposed model, investors must make a trade-off between maximizing return and minimizing risk (Rahiminezhad Galankashi et al. 2020). In addition to the Markowitz model, Sharpe (1963) and Perold (1984) also proposed index models. They introduced the concept of factors affecting stock prices for enabling investors to reduce the amount of computation. Later, Sharpe (1964) and Lintner (1965) proposed the capital asset pricing model, and Ross (1976) developed the arbitrage pricing theory. More recent studies suggested considering additional decision criteria for SPS (Mansour et al. 2019). Ehrgott et al. (2004) extended the model of Markowitz mean–variance, considering five objectives related to return and risk. A utility function of DM was defined for each objective. Huang (2008) developed a new model by giving a new definition of SPS risk and applying a hybrid intelligent algorithm to solve the model.

Remarkably, after years, MPT has remained largely intact. Although this framework has endured many criticisms, one criticism has perhaps been the most persistent. The basic model is not able to consider additional criteria. In MPT, two criteria include the expected value of the portfolio's return random variable (Return) and the random variable (Risk) variance, considered the main inputs. However, investors may have additional concerns (Steuer et al. 2008). As investors face different options, aspects that influence their attitudes should be considered (Atta Mills et al. 2020). Most studies on SPS focused on return and risk as to the main decision-making criteria. However, several other important criteria have been ignored (Sundar et al. 2016; Rahiminezhad Galankashi et al. 2020). Lee and Lerro (1973) attested to a growing need for including criteria beyond mean and variance. Since 1973, many criterion ideas have been introduced in the multi-criteria portfolio selection (Aouni et al. 2018). Many multi-criteria methods have been applied in SPS (Bouri et al. 2002; Dominiak 1997; Gupta et al. 2013; Jerry Ho et al. 2011; Kazemi et al. 2014; Tiryaki and Ahlatcioglu 2005; Touni et al. 2019). In this expanded framework, multi-criteria sorting methods have been applied for constructing a list of securities (Dimitras and Sagka 2012; Hurson and Zopounidis 1997; Mehregan et al. 2018; Xidonas et al. 2009b; Xidonas and Psarras 2010). As an unsupervised learning algorithm, cluster analysis (CA) is another developed approach for SPS. CA is a multivariate statistical method for categorizing stocks into homogeneous categories (Mansour et al. 2019). The current study intends to recommend stocks using multi-criteria sorting methods.

Background for comparison of MCDM methods

In previous studies, researchers attempted to compare MCDM methods. For instance, Parkan and Wu (2000) compared three procedures: OCRA, AHP, and DEA. The comparison was performed based on the size of the problem, computational ease, flexibility, and adaptability. Then, Thor et al. (2013) compared four MCDM methods (i.e., AHP, ELECTRE, SAW, and TOPSIS) from the perspective of maintenance alternative selection. Comparisons were based on consistency, problem structure, concept, core process, and the accuracy of final results. The results showed that TOPSIS exhibits the highest potential in maintenance decision analysis. For an equipment selection problem, Hodgett (2016) evaluated three MCDM methods (i.e., AHP, MARE, and ELECTRE). The results revealed that MARE is the most effective method for accurately representing the DM's preferences and comprehending the present uncertainty. To assess sustainable housing affordability, Mulliner et al. (2016) compared MCDM methods (WPM, WSM, revised AHP, AHP, TOPSIS, and COPRAS). In this study, 20 evaluation criteria and 10 alternatives were considered. Researchers concluded that ideally and where possible, more than one method should be applied to the same problem to provide a more comprehensive decision basis. Asgharizadeh et al. (2019) clustered 17 MCDM methods in two clusters using the fuzzy c-means method. This clustering was based on seven variables (i.e., simplicity in learning and developing, speed, complexity of calculations, the number of inputs, the quality of the underlying logic, the quality of ranking, and the growth rate in large problems). Ameri et al. (2018) compared four MCDM methods: SAW, TOPSIS, VIKOR, and compound factor (CF). They prioritized sub-watersheds using the percentage and intensity of changes. The results indicated that VIKOR has a higher performance than TOPSIS, SAW, and CF. Vakilipour et al. (2021) evaluated the quality of life at different spatial levels using SAW, TOPSIS, VIKOR, and ELECTRE methods. They computed

Table 1 Summary of relevant studies on MCDM methods

References	Applied methods	Basis of analysis
Parkan and Wu (2000)	OCRA, AHP, and DEA	Size of the problem, computational ease, flexibility, and adaptability
Thor et al. (2013)	AHP, ELECTRE, SAW, and TOPSIS	Consistency, problem structure, concept, core process, and the accuracy of final results
Hodgett (2016)	AHP, MARE, and ELECTRE	Final results
Mulliner et al. (2016)	WPM, WSM, revised AHP, AHP, TOPSIS, and COPRAS	Final results
Asgharizadeh et al. (2019)	SAW, ELECTRE, TOPSIS, ORESTE, PROMETHEE I, EVAMIX, MAUT, REGIME, MAPPAC, TACTIC, VIKOR, ARGUS, COPRAS, SMART, PACMAN, MOORA, and ARAS	Simplicity in learning and developing, speed, complexity of calculations, the number of inputs, the quality of the underlying logic, the quality of ranking, and the rate of growth in large problems
Ameri et al. (2018)	SAW, TOPSIS, VIKOR, and compound factor (CF)	Percentages of change
Vakilipour et al. (2021)	SAW, TOPSIS, VIKOR, and ELECTRE	Correlation and stability

the correlation and the stability of the methods to compare the methods. Table 1 presents a summary of relevant studies on MCDM methods.

Theoretical foundation

BWM

The problem of deriving priorities from pairwise comparisons is the core of MCDM problems (Zhang et al. 2021). The BWM (Rezaei 2015) is an MCDM method that applies two vectors of pairwise comparisons to define the weights of criteria. The BWM is similar to the AHP, and both are based on pairwise comparisons. The AHP is a widely used method in MCDM, and its root dates back to 1972 (Yu et al. 2021). BWM requires fewer pairwise comparisons than AHP, which is the main advantage of BWM. In BWM, DM determines the best and worst criteria and compares the best criterion over all the other criteria and then all the other criteria to the worst criterion. This structure helps the DM to have a clear understanding of evaluation and leads to more reliable comparisons. BWM is the most data- and time-efficient model, which can check the consistency of comparisons (Rezaei 2020). The steps of BWM are as follows:

Step 1. Determine a set of decision criteria $\{g_1, \ldots, g_j, \ldots, g_n\}$. The recommended number of criteria should not exceed nine. In general, the DM cannot process information to make comparisons for many criteria (La Fata et al. 2021).

Step 2. Determine the best (e.g., most desirable, most important) and the worst (e.g., least desirable, least important) criteria.

Step 3. Determine the preference of the best criterion over all the other criteria using a number between 1 and 9. The best-to-other vector can be shown as $A_B = (a_{B1}, \ldots, a_{Bj}, \ldots, a_{Bn})$ where a_{Bj} indicates the preference of criterion $_B$ over criterion j ($j = 1, \ldots, n$).

Step 4. Determine the preference of all criteria over the worst criterion using a number between 1 and 9. The others-to-worst vector can be shown as $A_W=(a_{1W}, \ldots, a_{jW}, \ldots, a_{nW})^T$, where a_{jW} indicates the preference of criterion j over the worst criterion W.

Step 5. Find the optimal weights $\left(w_1^*, \ldots, w_j^*, \ldots, w_n^*\right)$ and ε^* using Eq. (2).

$$
\begin{aligned}
&\min \varepsilon \\
&s.t. \\
&\left|\frac{w_B}{w_j} - a_{Bj}\right| \leq \varepsilon, \quad \textit{for all } j \\
&\left|\frac{w_j}{w_W} - a_{jW}\right| \leq \varepsilon, \quad \textit{for all } j \\
&\sum_j w_j = 1 \\
&w_j \geq 0, \quad \textit{for all } j
\end{aligned}
\tag{2}
$$

Pairwise comparisons come from the DM's subjective judgments, where inconsistencies exist naturally (Wang et al. 2021). BWM can calculate the consistency between pairwise comparisons. After solving the above model, the reliability of the weights can be checked using a consistency ratio (*CR*). Considering the consistency index (*CI*) (Table 2), the *CR* is calculated as in Eq. (3).

$$
CR = \frac{\varepsilon^*}{CI} \tag{3}
$$

Multi-criteria Sorting Methods

In the current study, the multi-criteria sorting approach creates a stock portfolio. The multi-criteria sorting approach is well adapted to the nature of the SPS problem as conflicting multi-criteria in this approach can be considered. In multi-criteria sorting methods, the order of groups is always specified. That is, the first group always contains the best alternatives. In the SPS problem, we attempt to find the best stocks and form a stock portfolio accordingly. Thus, the multi-criteria sorting approach can provide an appropriate structure for solving SPS problems. In this section, the steps of ELECTRE-TRI and FlowSort are explained. Those methods are also known as ordinal sorting methods.

ELECTRE-TRI

ELECTRE-TRI is an MCDM method belonging to ELECTRE family methods and one of the most well-known ordinal sorting methods. This method involves assessing each alternative on several quantitative and/or qualitative criteria (Micale et al. 2019a). ELECTRE-TRI assigns alternatives to predefined ordered groups by comparing the alternatives with the profiles defining the limits of the groups (or categories). *F*

Table 2 Consistency Index

a_{BW}	1	2	3	4	5	6	7	8	9
CI (*max* ε)	0.00	0.44	1.00	1.63	2.30	3.00	3.73	4.47	5.23

denotes the set of indices of the criteria g_1, ..., g_j, ..., g_n ($F = \{1, 2, \ldots, n\}$), and B is the set of indices of the profiles defining $p+1$ groups ($B = \{1, 2, \ldots, p\}$). b_h is the upper profile of group C_h and the lower profile of group C_{h+1}, $h = 1,2, \ldots, p$. The categories to which the actions must be assigned are completely ordered such that the limiting profiles b_h must fulfill the dominance-base separability condition (Fernández et al. 2017). ELECTRE-TRI uses outranking relations to validate or invalidate assertation aSb_h (and b_hSa), which means that "a is at least as good as b_h." Indifference, preference, and veto thresholds (i.e., $q_j(b_h)$, $p_j(b_h)$, and $v_j(b_h)$) constitute the intra-criteria preferential information.

The indifference threshold is the biggest difference between the performance of the alternatives and profiles on the criterion; thus, the DM considers them indifferent. The preference threshold is the greatest difference between the performance of the alternatives and profiles such that one is preferable to the other on the considered criterion (Ishizaka and Nemery 2013). The veto threshold indicates situations when the performance difference between the alternatives and profiles on a specific criterion requires the DM to negate any outranking relationship indicated by other criteria (Nowak 2004). The steps of ELECTRE-TRI are below.

Step 1. Compute partial concordance indices ($c_j(a,b_h)\ \forall j \in$ F). The concordance index measures the strength of the hypothesis that alternative a is at least as good as profile b_h (Mary and Suganya 2016). The partial concordance index can be calculated for each criterion by Eq. (4).

$$c_j(a, b_h) = \begin{cases} 0 & \textit{if} \quad g_j(b_h) - g_j(a) \geq p_j(b_h) \\ 1 & \textit{if} \quad g_j(b_h) - g_j(a) \leq q_j(b_h) \\ \frac{p_j(b_h) + g_j(a) - g_j(b_h)}{p_j(b_h) - q_j(b_h)} & \textit{otherwise} \end{cases} \tag{4}$$

Step 2. Compute the comprehensive concordance index ($c(a,b_h)$).

After calculating the partial concordance index for all criteria, the comprehensive concordance index can be calculated using Eq. (5).

$$c(a, b_h) = \frac{\sum_{j \in F} w_j . c_j(a, b_h)}{\sum_{j \in F} w_j} \tag{5}$$

Step 3. Compute discordance indices ($d_j(a,b_h)\ \forall j \in$ F).

The discordance index specifies the strength of evidence against the hypothesis that alternative a is at least as good as profile b_h (Mary and Suganya 2016). The discordance index can be calculated using Eq. (6).

$$d_j(a, b_h) = \begin{cases} 0 & \textit{if} \quad g_j(b_h) - g_j(a) \leq p_j(b_h) \\ 1 & \textit{if} \quad g_j(b_h) - g_j(a) > v_j(b_h) \\ \frac{g_j(b_h) - g_j(a) - p_j(b_h)}{v_j(b_h) - p_j(b_h)} & \textit{otherwise} \end{cases} \tag{6}$$

Step 4. Compute the credibility index of the outranking relation ($\sigma(a,b_h)$).

The degree of credibility ($\sigma(a,b_h) \in [0,1]$) is an index that shows the credibility of assertation aSb_h (and b_hSa) in ELECTRE-TRI. Assertation aSb_h (and b_hSa) is valid if $\sigma(a,b_h) \geq \lambda$ ($\sigma(b_h,a) \geq \lambda$). λ is a cutting level such that $\lambda \in [0.5,1]$. $\sigma(a,b_h)$ can be obtained by Eq. (7) ($\sigma(b_h,a)$ can be computed analogously):

$$\sigma(a,b_h) = \begin{cases} c(a,b_h) \cdot \prod_{j \in \overline{F}} \frac{1-d_j(a,b_h)}{1-c(a,b_h)} \end{cases} \quad (7)$$

where

$$\overline{F} = \{j \in F : d_j(a,b_h) > c(a,b_h)\} \quad (8)$$

The preference situation between a and b_h can be determined by the value of $\sigma(a,b_h)$, $\sigma(b_h,a)$ and λ:

$$\sigma(a,b_h) \geq \lambda \, and \, \sigma(b_h,a) \geq \lambda \Rightarrow aSb_h \, and \, b_hSa \Rightarrow aIb_h(a \text{ is indifferent to } b_h).$$

$$\sigma(a,b_h) \geq \lambda \, and \, \sigma(b_h,a) < \lambda \Rightarrow aSb_h \, and \, not \, b_hSa \Rightarrow a \succ b_h(a \, is \text{ preferred to } b_h).$$

$$\sigma(a,b_h) < \lambda \, and \, \sigma(b_h,a) \geq \lambda \Rightarrow not \, aSb_h \, and \, b_hSa \Rightarrow b_h \succ a(b_h \, is \text{ preferred to } a).$$

$$\sigma(a,b_h) < \lambda \, and \, \sigma(b_h,a) < \lambda \Rightarrow not \, aSb_h \, and \, not \, b_hSa \Rightarrow b_hRa(a \, is \text{ incomparable to } b_h).$$

Increasing the value of λ makes it difficult for an alternative to outrank a profile and vice versa. Correlatively, the number of incomparability relations has increased (Micale et al. 2019b).

Step 5. Assign alternatives to categories.

Two assignment procedures exist:

Pessimistic procedure: Compare a successively to b_t, for $t=p$, p-1, …, 1; b_h being the first profile such that aSb_h; assign a to category $C_{h+1.}$

Optimistic procedure: Compare a successively to b_t, for $t=1$, 2, …, p; b_h being the first profile such that $b_h \succ a$; assign a to category $C_{h.}$

The pessimistic approach can be applied in situations requiring caution or with limited resources. The optimistic approach can be applied to encourage alternatives that have attractive or exceptional qualities (Ramezanian 2019). Notably, if an alternative is incomparable to one or more profiles, a divergence exists in the outcomes obtained by the two approaches. In this situation, the pessimistic approach assigns the alternative to a group lower than the optimistic approach (Mendas et al. 2020).

Unlike clustering methods, in multi-criteria sorting methods, the order of groups is always specified. The first group always contains the best alternatives, whereas the last group always contains the worst ones. Therefore, in multi-criteria sorting methods, no further step is needed for ranking groups. Additional details on ELECTRE-TRI can be found in Mousseau et al. (2001) and Rogers et al. (2013).

FlowSort

FlowSort (Nemery and Lamboray 2008) is an extension of the PROMETHEE method for assigning alternatives to predefined ordered categories (C_1, C_2, …, C_p). FlowSort needs input data, including criteria weights, alternatives' performance, reference profiles, and thresholds. In this method, categories are definable by two limiting profiles or one central profile. In this study, two limiting profiles are considered for defining categories.

That is, a category is defined by the upper and lower profiles and $b_1 \succ b_2 \succ \ldots \succ b_{p+1}$ because the categories are completely ordered. The steps of FlowSort are as follows:

Step 1. Compute the preference degree.

R_i denotes the set of reference profiles and is an alternative to be classified as $\{b_1, \ldots, b_{p+1}\} \cup \{a_i\}$, $i = 1, \ldots, m$. b_1 is the best, whereas b_{p+1} is the worst profile. The preference degree $p_j(x,y)$ ($\forall j \in \{1, \ldots, n\}$) can be computed for any pair of $(x,y) \in R_i$. $p_j(x,y)$ calculates the preference strength of x over y in criterion j by considering the deviation between x and y and the DM preferences. The amount of deviation between x and y can be calculated using Eq. (9).

$$d_j(x, y) = g_j(x) - g_j(y) \tag{9}$$

The preference degree for benefit criteria can be obtained by Eq. (10), and that for cost criteria can be obtained by Eq. (11). The value of $P_j(x,y)$ ranges from 0 to 1.

$$P_j(x, y) = F_j\left[d_j(x, y)\right] \tag{10}$$

$$P_j(x, y) = F_j\left[-d_j(x, y)\right] \tag{11}$$

DM should select the desired function shape. "Appendix 1" shows five types of preference functions.

Step 2. Compute the global preference degree.

The global preference degree of each pair of alternatives can be computed as in Eq. (12):

$$\pi(x, y) = \sum_{j=1}^{n} p_j(x, y).w_j \tag{12}$$

Step 3. Compute the leaving (positive), entering (negative), and net flows.

Leaving, entering, and net flows for the set of R_i can be computed as in Eqs. (13)–(15) ($x \in R_i$).

$$\Phi^{+}_{R_i}(x) = \frac{1}{|R_i| - 1} \sum_{y \in R_i} \pi(x, y) \tag{13}$$

$$\Phi^{-}_{R_i}(x) = \frac{1}{|R_i| - 1} \sum_{y \in R_i} \pi(y, x) \tag{14}$$

$$\Phi_{R_i}(x) = \Phi^{+}_{R_i}(x) - \Phi^{-}_{R_i}(x) \tag{15}$$

where $|R_i|$ is the number of elements belonging to set R_i.

Step 4. Assign alternatives to categories.

Finally, the assignment of alternative a to category C_h can be performed based on net flows as in Eq. (16).

$$C_\Phi(a_i) = C_h \quad \text{if} \quad \Phi_{R_i}(b_h) \geq \Phi_{R_i}(a_i) > \Phi_{R_i}(b_{h+1}) \tag{16}$$

Similar assignment rules are based on $\Phi^{+}_{R_i}(a_i)$ and $\Phi^{-}_{R_i}(a_i)$ to obtain $C^{+}(a_i)$ and $C^{-}(a_i)$ (Eqs. (17)–(18)).

$$C_{\Phi^+}(a_i) = C_h \quad \text{if} \quad \Phi^{+}_{R_i}(b_h) \geq \Phi^{+}_{R_i}(a_i) > \Phi^{+}_{R_i}(b_{h+1}) \tag{17}$$

$$C_{\Phi^-}(a_i) = C_h \quad \text{if} \quad \Phi^{-}_{R_i}(b_h) < \Phi^{-}_{R_i}(a_i) \leq \Phi^{-}_{R_i}(b_{h+1}) \tag{18}$$

Additional details on FlowSort can be found in Nemery and Lamboray (2008), Janssen and Nemery (2013), and Campos et al. (2015).

CA

K-means clustering

The K-means clustering is a popular algorithm, which was described by MacQueen (1967). In this algorithm, the number of clusters k should be determined before clustering. K-means allocates the alternative to the nearest cluster. An error function exits, which should be calculated after each iteration. This process will be stopped when the error function or the membership of the clusters does not change. Two following main steps can describe K-means.

Step 1. The K-means randomly allocates the alternatives into k clusters.

Step 2. The distance between each alternative and cluster should be calculated. Alternatives should be allocated to the nearest cluster. This step is the iteration phase.

The error function can be computed as in Eq. (19).

$$\text{Error function} = \sum_{i=1}^{k} \sum_{x \in C_i} d(x, \mu(C_i)) \tag{19}$$

where $\mu(C_i)$ is the center of cluster i. k is the number of clusters, and x is an alternative that belongs to cluster i. $d(x, \mu(C_i))$ denotes the distance between x and $\mu(C_i)$. The Euclidean distance can be considered for calculating the distance (Gan et al. 2007).

Cluster validation

Cluster validation is a process of evaluating how well a partition fits the structure underlying the data. Generally, the number of clusters is determined by running the clustering algorithm several times with different numbers of clusters. The partitions that best fit the data should be selected (Arbelaitz et al. 2013).

Silhouette coefficient The silhouette coefficient (SC) (Kaufman and Rousseeuw 2009) is a useful measure for indicating the amount of the clustering structure for a clustering method. This coefficient can be used to determine the optimum number of groups. The silhouette value for ith alternative (s_i) can be calculated by Eq. (20).

$$s_i = \frac{b_i - a_i}{\max(a_i, b_i)} \tag{20}$$

where a_i denotes the average distance between ith and other alternatives in the same cluster. b_i is the minimum average distance between ith and alternatives in a different cluster, which is minimized over clusters. $\bar{s}(k)$ is the average of s_i for all alternatives and regarded as the average silhouette width. The SC can be computed by Eq. (21).

$$SC = \max_k \bar{s}(k) \tag{21}$$

"Appendix 2" shows the proposed interpretation for SC. The silhouette test evaluates the SC of clustering results iteratively with different cluster numbers. The silhouette test is easy because the principle is to select the optimal number of clusters based on the highest score (Li et al. 2021).

Davies–Bouldin index The Davies–Bouldin index (Davies and Bouldin 1979) is defined by Eq. (22).

$$\mathrm{DB} = \frac{1}{k}\sum_{i=1}^{k} \max_{i \neq j} \left\{ D_{i,j} \right\} \tag{22}$$

In the above equation, $D_{i,j}$ is the within-to-between cluster distance ratio for the ith and jth clusters. $D_{i,j}$ can be computed as in Eq. (23).

$$D_{i,j} = \frac{\left(\overline{d}_i + \overline{d}_j\right)}{d_{i,j}} \tag{23}$$

where $\overline{d}_i$ and $\overline{d}_j$ denote the average distance between each alternative in the ith cluster and the center of the ith cluster and between each alternative in the jth cluster and the center of the jth cluster, respectively. $d_{i,j}$ denotes the Euclidean distance between the center of the ith and jth clusters. The optimal clustering has the smallest Davies–Bouldin index value.

The difference between multi-criteria sorting and clustering methods is that the former use predefined ordered groups, whereas the latter identify similarities between alternatives. Unlike clustering methods, in multi-criteria sorting methods, the ranking of groups is always specified. Multi-criteria sorting methods seem to have stronger and more diverse theoretical foundations, such as preference modeling, with different features than clustering methods.

Research methodology

This section presents a step-by-step research methodology. Figure 1 depicts the research framework. In this study, we followed the steps proposed by Mehregan et al. (2019) to provide a fair comparison of the results for different parameters of the methods.

Step 1. The first step is collecting previous studies and extracting the most frequent factors through the literature review. In this step, the frequency of indicators from 63 articles was considered a basis for the initial selection of indicators. Then, the indicators that were used in more than 15 articles were identified. There were nine widely used indicators. Twelve financial experts, including four stock portfolio managers, four investment company managers, and four finance professors, checked the factors. Each expert then filled out a five-point Likert scale questionnaire including nine factors

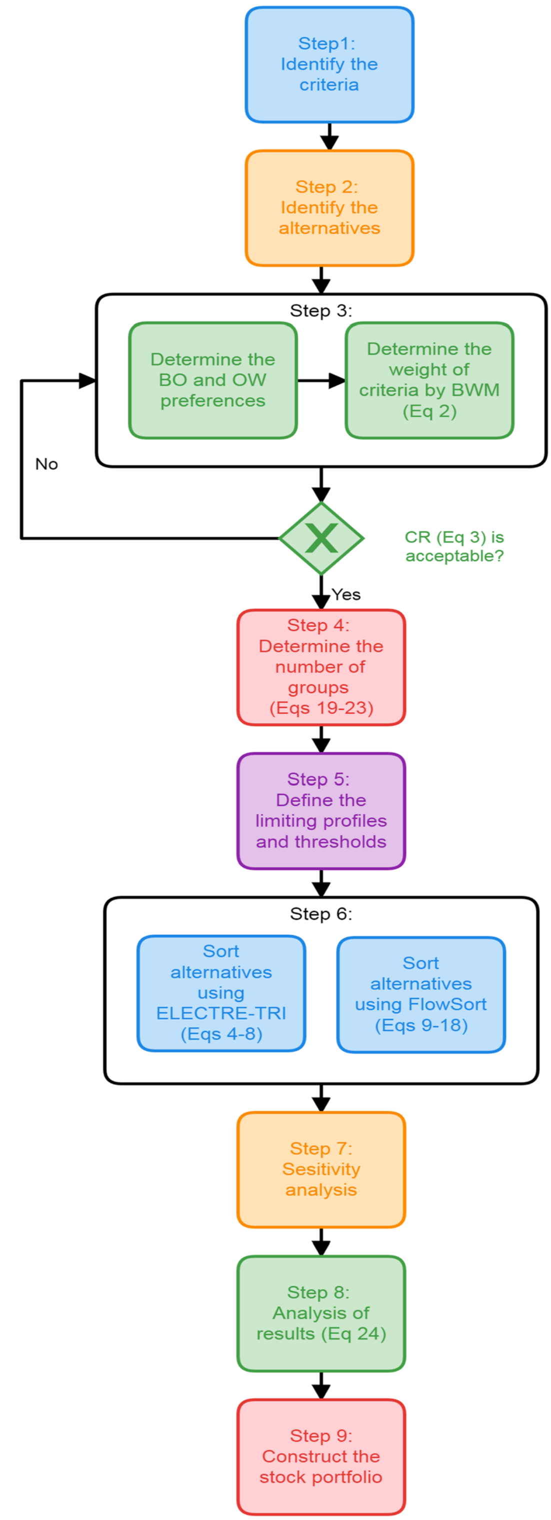


Fig. 1 Flow diagram of the research methodology

during a session that lasted an average of one hour. The experts were asked to indicate any significant factors not included in the questionnaire. According to the average scores of each factor, eight factors were chosen. The investor confirmed the process of determining factors and the obtained factors for SPS. The identified indicators are briefly explained as follows:

Return: An investment's yield is often expressed as a percentage of the amount invested (Rezaeian and Akbari 2015).

Earnings per share (EPS): EPS indicates the amount of money a company can make from each stock share (Amin and Hajjami 2021).

Price/earnings ratio (P/E): The main concept behind the P/E is the market's willingness to pay for the firm's earnings (Yalcin et al. 2012).

Beta (systematic risk): The dependency of a stock's return on the market is measured by beta (Abdelaziz et al. 2007).

Return on assets (ROA): The percentage of a company's ability to generate a return from its assets (Amin and Hajjami 2021).

Return on equity (ROE): The percentage of profit earned on common stockholders' investment in the companies (Yalcin et al. 2012).

Price to book value (P/BV): The P/BV estimates the stock's market value to its book value per share (Kadim et al. 2020).

Net profit margin: The net profit margin is a percentage that indicates how much of a company's revenues are kept as net income (Rist and Pizzica 2015).

Step 2. Fifty companies were selected according to the list of 50 most active companies published by the Securities and Exchange Organization per season. Companies that had the most repetitions in this list during the 12 seasons were selected.

Step 3. The weight of factors was obtained through BWM.

Step 4. The final number of groups was obtained by researching three aspects, namely, clustering quality measures (SC and Davies–Bouldin index), previous studies, and investor preference. Clustering techniques group alternatives by similarity. Although applying clustering techniques provides a very different result without ordering the groups, this step was done as an exploratory analysis to differentiate some alternatives. Clustering quality measures represent how well each alternative has been classified, and they were used to determine the number of groups.

Step 5. The researcher and investor agreement defined profiles and parameters for ELECTRE-TRI and FlowSort. The analyst should explain the meaning of parameters to DM to obtain the proper values (Brito et al. 2010). Therefore, the concept of these parameters and limiting profiles was explained to the investor. The investor was then asked to determine the values of parameters and limiting profiles. In determining the values of the parameters and profiles, the researcher provided feedback to the investor. In some cases, the values were modified with the acceptance of the investor.

Step 6. ELECTRE-TRI and FlowSort were applied to sort stocks. In the present study, 15 approaches for FlowSort and four approaches for ELECTRE-TRI were considered. In other words, at the end of the study, we had 19 assessments over different approaches.

Step 7. A comprehensive sensitivity analysis was performed based on factor weights, first profile, preference thresholds, indifference thresholds, and cutting level. Considering this sensitivity analysis can decrease the effect of different definitions of parameters' values by different DMs.

Step 8. The results were analyzed by considering the real return in the next period (year). Analysis was performed based on the value from Eq. (24). A larger value of F shows a better result.

$$F = \frac{\sum_{i=1}^{m} x_i.y_i}{m} \cdot 100 \tag{24}$$

where x_i and y_i can be calculated using Eqs. (25) and (26), and n is the number of stocks in the portfolio.

$$x_i = \begin{cases} 1 & \text{If stock ith is in portfolio} \\ 0 & \text{Otherwise} \end{cases} \tag{25}$$

$$y_i = \begin{cases} 1 & \text{If return of stock ith is more than average return of all stocks} \\ 0 & \text{Otherwise} \end{cases} \tag{26}$$

Step 9. The stock portfolio was constructed based on the best result.

This research performed computations by ELECTRE-TRI 2.0a software for ELECTRE-TRI, Smart-PickerPro 4.3 for FlowSort, LINGO 11.0 for BWM, and MATLAB 2016 for K-means clustering. This research was conducted in the National Investment Company of Iran, and stocks were selected from the TSE market. Table 3 shows the average historical data of stocks from 2011 to 2014, which were obtained from Rahavard Novin software. Rahavard Novin is a software that collects financial data of stocks from TSE. Table 4 shows which industry group the stock belongs to.

Results and discussion

As ELECTRE-TRI and FlowSort need the weight of criteria, the BWM was employed to determine the weight of eight criteria. Table 5 presents the result of the BWM.

SC and Davies–Bouldin indices were computed by MATLAB 2016 using the K-means clustering method to detect the optimal number of groups. The best value for the SC was 0.675 for the three groups. Similarly, the best value for the Davies–Bouldin index was 0.37 for the three groups.

A review of similar studies also indicated that, in many cases, researchers considered three groups for classifying stocks. For example, Hurson and Zopounidis (1997), Zopounidis et al. (1999), Hurson and Ricci-Xella (2002), Doumpos and Zopounidis (2002), Xidonas and Psarras (2010), and Zitouni (2014) considered three groups for classification in their studies. In addition, the investor expressed that the number of groups should be three in this study. Three groups were considered based on the above validation criteria, previous studies, and investor preferences. Multi-criteria sorting methods classify alternatives into predefined groups, and these groups are in order. The first group

Table 3 Decision matrix

Code	Alternative	Return	Beta	Net Profit Margin	ROA	ROE	EPS	P/E	P/BV
A1	Azarab	86.692	1.146	10.327	4.94	22.855	402	7.169	2.183
A2	Mobile Telecommunication Company of Iran	23.666	0.322	31.513	21.389	29.745	9331.333	6.701	1.905
A3	Electric Khodro Shargh	24.695	1.794	2.418	2.644	9.642	127.333	16.885	1.007
A4	Iran Transfo	24.145	1.489	30.193	6.101	21.223	469.667	11.951	1.742
A5	Iran Khodro	0.279	1.42	− 1.236	− 0.081	− 39.005	− 58.333	100	3.051
A6	Iran Yasa	103.495	1.379	12.536	14.722	59.18	2603.667	7.738	2.981
A7	Bama	35.747	1.005	52.491	34.533	44.535	1565.333	7.145	3.172
A8	Behceram	121.102	1.103	2.073	0.758	− 28.316	58.667	69.733	20.786
A9	Pars Khodro	31.643	1.146	− 10.159	− 6.553	− 47.223	− 505.333	250	0.828
A10	Kharg Petrochemical Company	67.379	1.276	72.002	61.141	85.927	7527.333	4.853	4.228
A11	Shazand Petrochemical Company	204.761	1.302	17.371	24.637	59.911	3313.333	8.091	3.121
A12	Shiraz Petrochemical Company	97.489	0.593	45.938	14.533	45.104	1171.667	8.333	3.108
A13	Fanavaran Petrochemical Company	100.181	1.391	64.639	43.411	68.788	4802.333	6.142	4.075
A14	Techinco	46.36	0.939	14.166	11.607	26.443	743.667	14.388	1.911
A15	Behshahr Industrial Development Corp	46.993	1.159	96.066	14.912	19.765	374	9.979	1.765
A16	Chadormalu Industrial Company	54.133	1.186	62.478	41.887	56.698	1506.667	5.569	3.994
A17	North Drilling	82.361	1.023	28.614	14.808	34.276	664	11.682	2.669
A18	Informatics Services Corporation	61.004	0.471	144.01	29.242	50.169	3060.333	9.156	7.513
A19	Jaber Ebne Hayyan Pharmacy	49.54	1.967	29.94	18.873	36.125	1005	10.14	2.547
A20	RAZAK Pharmaceutical Company	115.57	0.964	31.935	23.115	60.48	2673.667	8.684	3.436
A21	Rayan Saipa	− 9.145	1.141	37.453	4.916	25.06	628.333	2.726	1.694
A22	Zamyad	− 4.476	1.953	− 1.696	− 1.009	− 4.421	− 46	130	0.773
A23	Saipa	− 2.406	0.955	− 9.333	− 2.995	− 36.529	− 209.667	200	2.246
A24	Saipa Azin	36.293	1.944	− 0.547	− 0.863	− 10.613	− 72	105	1.771
A25	Tehran Cement	62.824	0.749	39.808	7.556	27.533	653.333	8.608	1.929
A26	Khazar Cement	129.896	1.148	17.002	11.337	29.042	569.333	11.715	1.78
A27	Shahroud Cement	78.941	1.499	29.087	17.412	36.373	755	8.886	1.81
A28	Gharb Cement	148.506	0.617	32.868	24.777	45.046	1088.333	7.491	2.203
A29	Shahid Ghandi Corporation Complex	11.437	0.95	3.559	2.428	11.377	188	10.856	1.306
A30	Kermanshah Petrochemical Industries Company	105.115	0.1	64.46	27.252	58.391	1484	6.147	3.021
A31	Iran Refractories Company	263.307	2.563	24.245	25.116	57.525	2080.667	9.479	2.521

Table 3 (continued)

Code	Alternative	Return	Beta	Net Profit Margin	ROA	ROE	EPS	P/E	P/BV
A32	Faravari Mavad Madani Iran	− 1.221	0.739	21.956	26.824	38.109	831.333	5.797	2.823
A33	Khouzestan Steel Company	139.535	0.739	26.339	31.301	62.479	3465.667	2.71	4.585
A34	Mobarakeh Steel Company	50.781	1.223	27.082	16.003	34.194	669.667	6.455	1.936
A35	Khorasan Steel Company	75.047	0.463	28.002	24.719	36.402	737.667	13.066	4.583
A36	Calcimine	32.199	1.017	49.163	32.073	41.901	1034.333	4.15	2.015
A37	Piazar Agro industry	67.954	0.913	12.533	12.901	23.099	404	9.757	2.814
A38	Chemi Darou	50.416	3.421	19.395	13.415	31.608	621.667	13.388	2.398
A39	Bahman Group	12.917	0.881	43.592	10.996	19.705	503.667	4.888	0.843
A40	MAPNA Group	67.118	1.652	26.533	3.878	14.733	545.333	15.937	1.758
A41	Golgohar Mining and Industrial Company	79.686	1.124	61.344	36.966	54.492	1554.667	6.645	3.617
A42	Sahand Rubber Industries Company	171.557	1.419	49.806	25.332	38.578	1207.667	7.635	1.895
A43	Telecommunication Company of Iran	9.669	0.762	103.157	13.723	18.348	436.667	7.754	2.494
A44	Shahid Bahonar Copper Industries Company	62.877	1.628	2.492	3.057	16.364	247.333	13.35	1.267
A45	Bafgh Mining	150.822	0.788	37.259	31.046	36.09	2201.667	12.932	4.325
A46	Iran Zinc Mines Development	23.018	0.87	101.85	23.686	27.024	570	4.323	1.715
A47	National Iranian Lead & Zinc Company	1.738	1.107	9.433	9.698	15.379	160	13.85	1.649
A48	National Iranian Copper Industry Company	18.465	0.64	42.077	25.043	37.398	879.667	3.623	1.415
A49	Mehr Cam Pars	31.448	1.6	− 2.41	− 2.643	− 16.397	− 114.333	180	1.554
A50	Behran Oil Company	90.647	1.31	20.255	20.052	68.113	3219.333	13.216	5.363

contains the best alternatives, whereas the last group contains the worst ones. There are three groups of stocks in this study. The first group includes the best stocks, the third group includes the worst stocks, and the second group includes the mid-level stocks. As the best stocks are in the first group, this group can be considered a stock portfolio. The second group can be added to the stock portfolio if the number of stocks in the first group is less than a minimum. In this study, the minimum number of stocks in the stock portfolio was considered five stocks, but in all cases, the number of stocks in the stock portfolio was more than five. Therefore, adding the stocks of the second group to the stock portfolio is not necessary. The researcher and investor agreement determined the limiting profiles and parameters in ELECTRE-TRI and FlowSort (Table 6).

Table 4 Stock industry groups

Alternative	Industry
A1	Fabricated metal products
A2	Telecommunications
A3, A5, A9, A22, A23, A24, A39, A49	Automobile and parts
A4, A29	Electrical equipment
A6, A42	Rubber & plastic products
A7, A16, A41, A45, A46	Extraction of metal ores
A8	Tile and ceramic
A10, A11, A12, A13, A30	Chemical products
A14, A40	Engineering
A15, A37	Food & beverage products
A17	Oil and gas extraction (except exploration)
A18	Computer
A19, A20, A38	Manufacture of pharmaceuticals
A21	Financial intermediation
A25, A26, A27, A28	Cement, lime & plaster
A31	Non-metallic mineral products
A32, A33, A34, A35, A36, A47, A48	Base metals
A43	Communication equipment
A44	Non-ferrous precious metals
A50	Oil products

The classification results after solving the problem are presented in "Appendix 3". Based on Table 17, a total of 19 approaches were available, with four approaches for ELECTRE-TRI. These approaches include pessimistic assignment considering the veto threshold, pessimistic assignment without considering the veto threshold, optimistic assignment considering the veto threshold, and optimistic assignment without considering the veto threshold. The FlowSort method considered five well-known preference functions. These preference functions include usual, U-shape, V-shape, V-shape with indifference, and the level. For each preference function, three types of assignments were used. The assignment procedure used in this research is based on the leaving flow (Φ^{+}), entering flow (Φ^{-}), and net flow (Φ). As the first group includes the best stocks, this group is considered a stock portfolio. Table 7 shows the stock portfolio created by each approach.

Several studies have examined ranking methods and validated their results (Pamucar et al. 2017; Mukhametzyanov and Pamucar 2018; Biswas et al. 2019; Pamučar et al. 2021). Correlation coefficients of the ranking results obtained using the proposed and previous methods are often calculated. According to the obtained correlation coefficient, the validity of the proposed model is examined. As the correlation coefficient increases, the proposed method's validity also increases. A few studies have validated the results of multi-criteria classification methods. The validation method in the present study is inferred from the validation method used by Xidonas et al. (2009b). In the present study, the validation formula is defined by Eq. (24). Table 8 shows the

Table 5 Weight of criteria

Criteria	Weight
Return	0.207
Beta	0.207
Net profit margin	0.098
ROA	0.041
ROE	0.065
EPS	0.144
P/E	0.14
P/BV	0.098

Table 6 Parameters of ELECTRE-TRI and FlowSort

Parameters	Return	Beta	Net Profit Margin	ROA	ROE	EPS	P/E	P/BV
Indifference threshold	5	0.05	3	3	3	50	0.5	0.4
Preference threshold	15	0.15	8	6	8	300	1.5	1.2
Veto threshold	180	0.8	80	50	50	1000	4	4
Profile 1	50	0.6	25	20	30	400	5.5	4
Profile 2	20	0.9	10	10	15	50	8	6

values of F for primary results. Notably, the effectiveness index (F) is obtained by real return in the next period (2015) (Table 9). The F index indicates the percentage of stocks with more than the average return (Eq. (24)). The return criterion in Tables 3 and 8 refers to the average real return in 2011–2014 and in 2015, respectively. In this study, the return criterion in Table 9 has been used to evaluate the classification results.

As shown in Table 8, the FlowSort presents the best initial result when considering the V-shape preference function and the leaving flow assignment. ELECTRE-TRI presents the best initial result when pessimistic assignment procedure without veto threshold is considered.

The sensitivity analysis aims to overcome the effect of the probable inappropriate amount of parameters and profiles. Therefore, a comprehensive sensitivity analysis was performed on the best results. The sensitivity analysis was conducted on the weight of criteria, first limiting profile, preference thresholds, indifference thresholds, and cutting level. As any change in sensitivity analysis changes the stock portfolio, F's value will also change. Therefore, in all cases, the value of F is calculated.

Influence of changing criteria weights on the results obtained by ELECTRE-TRI

Sorting results mostly depend on the weight of the criteria (Pamucar et al. 2017). According to Table 10, 18 scenarios for changing the criteria weight are considered. Scenario one is the weights obtained in this study. In scenarios two to nine, the weights of

Table 7 Stock portfolio made by each approach

ELECTRE-TRI				FLOWSORT														
Pessimistic		Optimistic		Usual			U-shape			V-shape			V-shape with indifference			Level		
with veto	without veto	with veto	without veto	Φ+	Φ-	Φ	Φ+	Φ-	Φ	Φ+	Φ-	Φ	Φ+	Φ-	Φ	Φ+	Φ-	Φ
A12 A16 A28 A30 A33 A48	A10 A12 A13 A16 A18 A28 A30 A33 A35 A48	A1, A2, A6, A7, A10, A11, A12, A13, A15, A16, A17, A18, A19, A20, A21, A25, A26, A27, A28, A30, A31, A32, A33, A35 A36, A37, A40, A41, A42, A43, A44, A45, A46, A48, A50	A1, A2, A6, A7, A10, A11, A12, A13, A16, A17, A18, A19, A20, A21, A25, A26, A27, A28, A30, A31, A32, A33, A35, A36, A37, A40, A41, A42, A44, A45, A46, A48, A50	A2 A10 A12 A16 A18 A28 A30 A33 A34 A35 A41 A42 A46	A2 A10 A12 A16 A18 A28 A30 A33 A34 A35 A41 A42 A46	A2 A10 A12 A16 A18 A28 A30 A33 A34 A35 A41 A42 A46	A10 A12 A13 A18 A28 A30 A33 A35 A41 A45 A48	A2 A10 A12 A13 A18 A25 A28 A30 A33 A35 A41 A42 A45 A46 A48	A2 A10 A12 A13 A18 A28 A30 A33 A35 A41 A42 A45 A48	A2 A10 A12 A13 A18 A28 A30 A33 A35 A41 A48	A2 A10 A12 A13 A18 A20 A25 A28 A30 A33 A35 A41 A42 A45 A48	A2 A10 A12 A13 A18 A28 A30 A33 A35 A41 A42 A48	A10 A12 A13 A18 A28 A30 A33 A35 A41 A48	A2 A10 A12 A13 A18 A20 A25 A28 A30 A33 A35 A36 A41 A42 A45 A48	A2 A10 A12 A13 A18 A28 A30 A33 A35 A41 A42 A45 A48	A10 A12 A13 A18 A28 A30 A33 A35 A41 A48	A2 A10 A12 A13 A18 A20 A25 A28 A30 A33 A35 A41 A42 A45 A48	A2 A10 A12 A13 A18 A28 A30 A33 A35 A41 A42 A48

Table 8 Values of *F* based on different approaches of ELECTRE-TRI and FlowSort

Sorting method		Approach	Value of *F*
ELECTRE-TRI	Pessimistic	With veto threshold	16.7
		Without veto threshold	**40.0**
	Optimistic	With veto threshold	34.3
		Without veto threshold	36.4
FLOWSORT	Usual	Φ+	30.8
		Φ-	30.8
		Φ	30.8
	U-shape	Φ+	40.0
		Φ-	33.3
		Φ	38.5
	V-shape	Φ+	**45.5**
		Φ-	40.0
		Φ	41.7
	V-shape with indifference	Φ+	40.0
		Φ-	37.5
		Φ	38.5
	Level	Φ+	40.0
		Φ-	40.0
		Φ	41.7

Best values are in bold

the first to eighth criteria are set to zero, respectively. The criterion weight is divided equally among the other criteria. In these scenarios, we have examined the effect of eliminating each of these criteria on the final classification. In scenario 10, the weights of all criteria are considered the same. In scenarios 11 to 18, the weight of criteria one to eight is considered higher than the initial value, respectively. The results of changing criteria weights showed that if the weight of the ROA or P/E had increased to 0.35, a better stock portfolio would have been obtained.

Influence of changing criteria weights on the results obtained by FlowSort

Similar to ELECTRE-TRI, the same scenarios are considered for FlowSort. According to Table 10, eliminating ROA or ROE does not change the stock portfolio. If the weight of the P/BV increases to 0.35, then the worst results are obtained. According to Table 10, changes in the weight of criteria have not improved the stock portfolio. The change in the weight of the P/BV shows that the worst value of *F* is related to the scenario, in which the weight of the P/BV increased. In this case, the value of *F* has reached 0.1875, which is the lowest value in the total sensitivity analysis performed in this study. From another aspect, the results of changing the weight of P/BV in ELECTRE-TRI also show that eliminating P/BV did not worsen the value of *F*. Increasing the weight of P/BV in ELECTRE-TRI has also made the value of *F* worse. Therefore, according to the results obtained by two methods, less weight could have been assigned to P/BV.

Table 9 Real return in the next period

Alternative	Return	Alternative	Return
A1	6.18	A26	− 26.43
A2	12.90	A27	− 26.08
A3	− 0.62	A28	− 30.42
A4	51.90	A29	− 26.26
A5	20.25	A30	− 1.22
A6	− 1.28	A31	− 38.90
A7	− 11.30	A32	− 29.61
A8	− 65.73	A33	− 37.62
A9	47.11	A34	− 28.77
A10	14.38	A35	− 16.11
A11	− 33.31	A36	− 21.02
A12	− 29.42	A37	27.78
A13	5.52	A38	− 4.59
A14	23.65	A39	0.45
A15	− 12.33	A40	− 17.40
A16	− 32.60	A41	− 28.20
A17	− 33.29	A42	− 38.96
A18	22.59	A43	− 11.08
A19	− 3.06	A44	− 22.41
A20	37.39	A45	− 47.01
A21	52.38	A46	− 21.39
A22	14.73	A47	− 50.50
A23	37.69	A48	− 22.52
A24	33.32	A49	9.14
A25	− 39.56	A50	7.38
Average return			− 7.69

Influence of changing the profile on the results obtained by ELECTRE-TRI

In this study, stock portfolio formation is based on the alternatives available in the first class; therefore, we examine the effect of change in the first limiting profile. By increasing the first limiting profile values, the number of alternatives in the first class usually decreases. On the contrary, decreasing the values of the first limiting profile usually increases the number of alternatives in the first class. The first row of Table 11 shows the initial values of the first limiting profile, in which different degrees of changes in the first limiting profile are considered. Due to their cost nature, the changes on the beta, P/E, and P/BV criteria have been done in contrast to the other criteria. According to Table 11, the only scenario that has improved the stock portfolio is when the first limiting profile values increase by 10%.

Influence of changing the profile on the results obtained by FlowSort

According to Table 11, by increasing the values of the first profile to 5% or 10%, the value of F decreases slightly. However, with a large increase in first limiting profile values, the worst results are obtained. From another aspect, by reducing the values of the first limiting profile, the same results are obtained in all cases. The value of F decreases by approximately 0.1, which means that a worse stock portfolio is obtained.

Table 10 Sensitivity analysis on the weight of criteria

No	Return	Beta	Net Profit Margin	ROA	ROE	EPS	P/E	P/BV	ELECTRE-TRI F Value	FlowSort F Value
1	0.207	0.207	0.098	0.041	0.065	0.144	0.14	0.098	0.4	0.4545
2	0	0.237	0.128	0.071	0.095	0.174	0.17	0.128	0.25	0.3333
3	0.237	0	0.128	0.071	0.095	0.174	0.17	0.128	0.227	0.25
4	0.221	0.221	0	0.055	0.079	0.158	0.154	0.122	0.3333	0.375
5	0.213	0.213	0.104	0	0.071	0.15	0.146	0.104	0.4	0.4545
6	0.216	0.216	0.107	0.05	0	0.153	0.149	0.107	0.3333	0.4545
7	0.228	0.228	0.119	0.062	0.086	0	0.161	0.119	0.25	0.375
8	0.227	0.227	0.118	0.061	0.085	0.164	0	0.118	0.368	0.3
9	0.221	0.221	0.112	0.055	0.079	0.158	0.154	0	0.4	0.3333
10	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.3182	0.2631
11	0.35	0.187	0.078	0.021	0.045	0.124	0.12	0.078	0.4	0.3571
12	0.187	0.35	0.078	0.021	0.045	0.124	0.12	0.078	0.3333	0.4286
13	0.171	0.171	0.35	0.005	0.029	0.108	0.104	0.062	0.385	0.3529
14	0.163	0.163	0.054	0.35	0.021	0.1	0.096	0.054	0.4545	0.3333
15	0.173	0.173	0.064	0.007	0.3	0.11	0.106	0.064	0.3846	0.2222
16	0.178	0.178	0.069	0.012	0.036	0.35	0.111	0.069	0.3333	0.3
17	0.177	0.177	0.068	0.011	0.035	0.114	0.35	0.068	0.5	0.4
18	0.171	0.171	0.062	0.005	0.029	0.108	0.104	0.35	0.3333	0.1875

Table 11 Sensitivity analysis on profile r_1

Profile	Return	Beta	Net Profit Margin	ROA	ROE	EPS	P/E	P/BV	ELECTRE-TRI F Value	FlowSort F Value
r1	50	0.6	25	20	30	400	5.5	4	0.4	0.4545
r1 + 5%	52.5	0.57	26.25	21	31.5	420	5.225	3.8	0.375	0.4
r1 + 10%	55	0.54	27.5	22	33	440	4.95	3.6	0.4285	0.4285
r1 + 15%	57.5	0.51	28.75	23	34.5	460	4.675	3.4	0.3928	0.2
r1 + 20%	60	0.48	30	24	36	480	4.4	3.2	0.3928	0.25
r1-5%	47.5	0.63	23.75	19	28.5	380	5.775	4.2	0.3636	0.3571
r1-10%	45	0.66	22.5	18	27	360	6.05	4.4	0.3846	0.3571
r1-15%	42.5	0.69	21.25	17	25.5	340	6.325	4.6	0.3125	0.3571
r1-20%	40	0.72	20	16	24	320	6.6	4.8	0.2941	0.3571

Influence of changing preference threshold on the results obtained by ELECTRE-TRI

In general, the preference threshold value should always be greater than the indifference threshold value. Therefore, in all scenarios, the minimum value considered for the preference threshold is greater than the initial value of the indifference threshold. Table 12 shows the sensitivity analysis result. The initial value of the preference threshold is the italics value. In the sensitivity analysis, values more and less than the initial value are considered. As shown in Table 12, increasing the preference threshold value in return to 100 and decreasing the preference threshold value in P/BV have improved the results. Table 12 also shows that the change in the preference threshold did not cause much change in the final results.

Table 12 Sensitivity analysis on preference threshold

No	Criteria	Preference threshold									
1	**Return**	0	7	*15*	25	40	50	75	100	150	
	ELECTRE-TRI F value	–	0.4	0.4	0.4	0.455	0.455	0.417	0.417	0.385	
	FlowSort F value	0.4166	0.4166	0.4545	0.4545	0.3846	0.3571	0.3571	0.3846	0.3571	
2	**Beta**	0	0.05	0.1	*0.15*	0.3	0.4	0.45	0.5	0.7	1
	ELECTRE-TRI F value	–	0.4	0.4	0.4	0.4	0.417	0.333	0.308	0.357	0.312
	FlowSort F value	0.4545	0.4545	0.4166	0.4545	0.4545	0.3571	0.3571	0.375	0.3125	0.2777
3	**Net Profit Margin**	0	4	*8*	12	18	25	50	100		
	ELECTRE-TRI F value	–	0.4	0.4	0.4	0.4	0.4	0.4	0.4		
	FlowSort F value	0.4545	0.4545	0.4545	0.4545	0.3846	0.3846	0.3636	0.4		
4	**ROA**	0	4	*6*	10	15	30	50			
	ELECTRE-TRI F value	–	0.4	0.4	0.4	0.4	0.4	0.4			
	FlowSort F value	0.4545	0.4545	0.4545	0.4545	0.4545	0.4545	0.4545			
5	**ROE**	0	4	6	*8*	12	18	25	50	100	
	ELECTRE-TRI F value	–	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	
	FlowSort F value	0.4	0.4545	0.4545	0.4545	0.4545	0.4	0.4166	0.4545	0.4545	
6	**EPS**	0	100	150	*300*	500	800	1000	2000	5000	
	ELECTRE-TRI F value	–	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	
	FlowSort F value	0.4545	0.4545	0.4545	0.4545	0.3571	0.3571	0.3571	0.3846	0.5555	
7	**P/E**	0	0.5	0.8	*1.5*	2	2.5	3	4		
	ELECTRE-TRI F value	–	0.333	0.333	0.4	0.4	0.379	0.384	0.384		
	FlowSort F value	0.3636	0.3636	0.333	0.4545	0.4545	0.4545	0.4166	0.3846		
8	**P/BV**	0	0.5	0.6	0.8	*1.2*	1.5	2			
	ELECTRE-TRI F value	–	0.444	0.444	0.4	0.4	0.4	0.4			
	FlowSort F value	0.3636	0.4545	0.4545	0.4545	0.4545	0.4545	0.4545			

Influence of changing preference threshold on the results obtained by FlowSort

Given that the best initial result in FlowSort was obtained using the V-shape preference function, we do not consider the indifference threshold parameter in this case. Therefore, we do not have a low threshold limit, and the minimum value of the preference threshold can be zero. Thus, more scenarios are considered in comparison with the sensitivity analysis performed on the preference threshold in ELECTRE-TRI. The changes in the preference threshold value on the EPS criterion indicate that increasing

Table 13 Sensitivity analysis on the indifference threshold in ELECTRE-TRI

No	Criteria	Indifference threshold						
1	Return	0	1	3	*5*	8	12	
	F value	0.4	0.4	0.4	0.4	0.4	0.4	
2	Beta	0	0.02	*0.05*	0.08	0.1	0.15	
	F value	0.393	0.4	0.4	0.4	0.4	0.3	
3	Net Profit Margin	0	1.5	*3*	5	8		
	F value	0.4	0.4	0.4	0.4	0.4		
4	ROA	0	2	*3*	4	5		
	F value	0.4	0.4	0.4	0.4	0.4		
5	ROE	0	1	*3*	5	8		
	F value	0.4	0.4	0.4	0.4	0.4		
6	EPS	0	*50*	100	300			
	F value	0.4	0.4	0.4	0.4			
7	P/E	0	0.25	*0.5*	0.75	1	1.25	1.5
	F value	0.333	0.333	0.4	0.4	0.363	0.385	0.385
8	P/BV	0	0.2	*0.4*	0.8	1.2		
	F value	0.4	0.4	0.4	0.4	0.4		

Table 14 Sensitivity analysis on cutting level (λ) in ELECTRE-TRI

Cutting level (λ)	0.6	0.625	0.65	0.675	0.7	0.725	*0.75*	0.775	0.8
F value	0.318	0.368	0.368	0.384	0.333	0.4	0.4	0.25	0.2

the preference threshold value in most cases has resulted in worse results. However, by increasing the preference threshold to 5000, the best performance for the stock portfolio is achieved (Table 12).

Influence of changing indifference threshold on the results obtained by ELECTRE-TRI

The indifference threshold allows considering the imprecise nature of the data into the model. Table 13 presents the sensitivity analysis result. The initial value of the indifference threshold is the italics value. In the sensitivity analysis, values more and less than the initial value are considered. In ELECTRE-TRI, in addition to the indifference threshold, the preference threshold is also defined, and the value of the indifference threshold should not be greater than the preference threshold. Thus, this limitation is considered in the sensitivity analysis. The maximum possible values for the indifference threshold are considered in this sensitivity analysis. As shown in Table 13, the change in the indifference threshold has not caused much change to the stock portfolios.

Influence of changing the cutting level on the results obtained by ELECTRE-TRI

The cutting level is a parameter used in the ELECTRE-TRI method. As shown in Table 14, increasing or decreasing the cutting level did not improve the results. Therefore, the initial value of 0.75 is a good value. Notable, in many studies, the cutting level value is 0.75. Determining the cutting level value properly in the ELECTRE-TRI is very important because determining an inappropriate value for the cutting level can significantly worsen the result.

In this section, sensitivity analysis on the best results obtained by ELECTRE-TRI and FlowSort was presented. The sensitivity analysis was conducted on the weight of criteria, first limiting profile, preference thresholds, indifference thresholds, and cutting level. According to the sensitivity analysis, the best value of F for the FlowSort and ELECTRE-TRI is 55.5 and 50, respectively. FlowSort provided a stock portfolio of 55.5%, with a stock return higher than the average return of all stocks. The stock portfolio constructed by FlowSort includes the Mobile Telecommunication Company of Iran (A2), Kharg Petrochemical Company (A10), Shiraz Petrochemical Company (A12), Fanavaran Petrochemical Company (A13), Informatics Services Corporation (A18), Gharb Cement (A28), Kermanshah Petrochemical Industries Company (A30), Khouzestan Steel Company (A33), and Khorasan Steel Company (A35) considering sensitivity analysis.

Nemery and Lamboray (2008) stated that working with veto thresholds in ELECTRE-TRI further increases the difference between optimistic and pessimistic assignments. As shown in Table 8, the difference between optimistic and pessimistic assignments in ELECTRE-TRI was 0.176. This study confirmed that using the veto threshold increases the difference between two types of assignments. Doumpos and Zopounidis (2002) mentioned that introducing the veto threshold facilitates the development of non-compensatory models. In these models, an alternative's significantly low performance in an evaluation criterion is not compensated by the alternative's performance on the remaining criteria. As shown in Table 8, the worst F value is obtained when the pessimistic approach with the veto threshold was applied in ELECTRE-TRI. A comparison of optimistic approaches also shows that the F value is worse when we apply the veto threshold in ELECTRE-TRI.

Managerial implications

SPS is an important decision process for investment managers to select stocks from a large pool of stocks. The presented framework in this study can be applied in investment companies to help managers construct a stock portfolio. Applying this framework can help investment managers increase their profitability by using a rational approach and choosing the right stocks in the stock portfolio.

In classic models, two criteria, including the return and risk, were considered. In the real world, investors may have additional concerns (Steuer et al. 2008). Multi-criteria sorting methods can consider multiple conflicting criteria for solving the SPS problems. This study presented an application of two known multi-criteria sorting methods to a real financial problem. The advantage of these methods is that investment managers can easily enter their preferences into these techniques. Among the applied methods in this research, FlowSort allows the use of different preference functions. In addition, FlowSort is more suitable for investment managers who want to be more involved in the modeling and problem-solving process. This study applies the FlowSort in an SPS context for the first time. According to the results of this study, using V-shape or level preference function and using net flow may probably be a better choice for investment managers who intend to apply FlowSort.

Notably, the framework presented in this study is only for stock selection, so this framework is not applicable for determining asset allocation. To allocate assets, multi-objective or goal programming models can be applied. Another point is that the criteria used to select stocks may not be the same as those required for asset allocation. Therefore, the criteria required for asset allocation are identifiable from the literature and through a survey of experts.

Conclusion

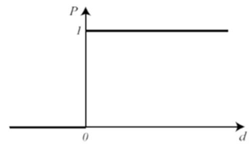
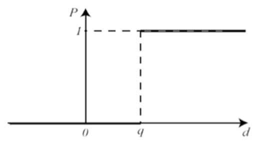
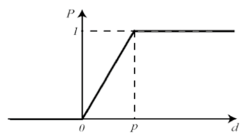
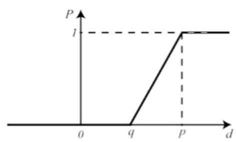
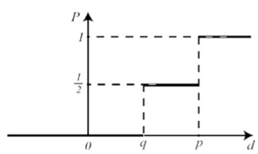
This study aimed to examine ELECTRE-TRI and FlowSort for SPS, and the analysis was performed based on the real return in the new period. In ELECTRE-TRI, if the results from the pessimistic approach are very different from the optimistic approach, then several incompatibilities exist between an alternative and the profiles of the categories. The results obtained from the ELECTRE-TRI show a situation of incomparability in several cases (A17, A19, A21, A26, A31, A35, A40, A44, and A50). According to the optimistic or pessimistic approach, nine alternatives are allocated to the best (first) or worse (third) class but not to the intermediate (second) class. In all these cases, evidence to support the assignments is not enough. Thus, more information might be needed to properly assign these alternatives, such as including other decision criteria or providing precise evaluations. The result also shows that using the veto threshold for ELECTRE-TRI does not produce a good result for that SPS problem. The reason may be the nature of the SPS problem and its compatibility with non-compensatory models. We suggest that other researchers refrain from using veto thresholds in this kind of problem. The results obtained by FlowSort show that this method can create a better portfolio when V-shape or level preference function is applied. This research used three types of outranking flow, namely, leaving, entering, and net flow, for FlowSort. In the FlowSort, no high difference exists between leaving and entering flow results for all alternatives. This study showed that when the FlowSort uses the net flow assignment approach, regardless of the type of preference function, a very high similarity is visible between the stock portfolios obtained. Therefore, we can conclude that using the net flow approach helps to achieve more reliable results. One of the limitations of the research is the lack of stock market stability. The results showed that stocks performed poorly in the three years but had a very good return in the next period, such as stocks in the automobile and parts industry group. A longer period for real return can increase the evaluation's accuracy. This study also highlighted the importance of correctly defining the parameter values. In recent studies, researchers proposed some approaches for eliciting thresholds and profiles from examples. These approaches can be compared in future studies.

Appendix 1

See Table 15

.

Table 15 Common preference functions (Greco et al. 2016)

Type	Graph	Function	Parameter
Usual		$P(d) = \begin{cases} 0 & d \le 0 \\ 1 & d > 0 \end{cases}$	-
U-shape		$P(d) = \begin{cases} 0 & d \le q \\ 1 & d > q \end{cases}$	q
V-shape		$P(d) = \begin{cases} 0 & d \le 0 \\ \frac{d}{p} & 0 \le d \le p \\ 1 & d > p \end{cases}$	p
V-shape with indifference		$P(d) = \begin{cases} 0 & d \le q \\ \frac{d-q}{p-q} & q < d \le p \\ 1 & d > p \end{cases}$	q, p
Level		$P(d) = \begin{cases} 0 & d \le q \\ \frac{1}{2} & q < d \le p \\ 1 & d > p \end{cases}$	q, p

Appendix 2

See Table 16.

Table 16 Subjective interpretation of the Silhouette coefficient (Kaufman and Rousseeuw 2009)

Silhouette coefficient	Proposed interpretation
0.71–1.00	A strong structure has been found
0.51–0.70	A reasonable structure has been found
0.26–50	The structure is weak and could be artificial
0.25	No substantial structure has been found

Appendix 3

See Table 17.

Table 17 Primary results of classification

Stock	ELECTRE-TRI				FLOWSORT														
	Pessimistic		Optimistic		Usual			U-shape			V-shape			V-shape with indifference			Level		
	with veto	without veto	with veto	without veto	Φ+	Φ-	Φ	Φ+	Φ-	Φ	Φ+	Φ-	Φ	Φ+	Φ-	Φ	Φ+	Φ-	Φ
A1	2	2	1	1	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
A2	2	2	1	1	1	1	1	2	1	1	1	1	1	2	1	1	2	1	1
A3	3	3	2	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
A4	3	3	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
A5	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
A6	2	2	1	1	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
A7	2	2	1	1	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
A8	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
A9	3	3	2	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
A10	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
A11	2	2	1	1	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
A12	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
A13	2	1	1	1	2	2	2	1	1	1	1	1	1	1	1	1	1	1	1
A14	3	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
A15	3	3	1	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
A16	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2	2	2	2	2
A17	3	3	1	1	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
A18	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
A19	3	3	1	1	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
A20	2	2	1	1	2	2	2	2	2	2	2	1	2	2	1	2	2	1	2
A21	3	3	1	1	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
A22	3	3	2	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
A23	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
A24	3	3	2	2	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
A25	2	2	1	1	2	2	2	2	1	2	2	1	2	2	1	2	2	1	2

Table 17 (continued)

Stock	ELECTRE-TRI				FLOWSORT														
	Pessimistic		Optimistic		Usual			U-shape			V-shape			V-shape with indifference			Level		
	with veto	without veto	with veto	without veto	Φ+	Φ-	Φ	Φ+	Φ-	Φ	Φ+	Φ-	Φ	Φ+	Φ-	Φ	Φ+	Φ-	Φ
A26	3	3	1	1	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
A27	3	3	1	1	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
A28	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
A29	3	3	2	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
A30	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
A31	3	3	1	1	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
A32	2	2	1	1	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
A33	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
A34	2	2	2	2	1	1	1	2	2	2	2	2	2	2	2	2	2	2	2
A35	3	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
A36	2	2	1	1	2	2	2	2	2	2	2	2	2	2	1	2	2	2	2
A37	2	2	1	1	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
A38	3	3	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
A39	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
A40	3	3	1	1	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
A41	2	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
A42	2	2	1	1	1	1	1	2	1	1	2	1	1	2	1	1	2	1	1
A43	2	2	1	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
A44	3	3	1	1	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
A45	3	2	1	1	2	2	2	1	1	1	2	1	2	2	1	1	2	1	2
A46	2	2	1	1	1	1	1	2	1	2	2	2	2	2	2	2	2	2	2
A47	3	3	2	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
A48	1	1	1	1	2	2	2	1	1	1	1	1	1	1	1	1	1	1	1
A49	3	3	2	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
A50	3	3	1	1	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2

Abbreviations
EPS: Earnings Per Share; P/E: Price/Earnings ratio;; ROA: Return on Assets; ROE: Return on Equity; P/BV: Price to Book Value; SPS: Stock Portfolio Selection; MPT: Modern Portfolio Theory; DM: Decision-Maker; MCDM: Multi-Criteria Decision-Making; BWM: Best–Worst Method; AHP: Analytic Hierarchy Process; ANP: Analytic Network Process; TOPSIS: Technique for Order of Preference by Similarity to Ideal Solution; VIKOR: VIseKriterijumska Optizacija I Kompromisno Resenje; ELECTRE: ELimination and Choice Expressing Reality; PROMETHEE: Preference Ranking Organization METHod for Enrichment Evaluation; CF: Compound Factor; CA: Cluster Analysis; SC: Silhouette Coefficient.

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Authors' contributions
All authors participated in the development of the research. MSMME was the main contributor in the writing of the manuscript and data analysis. CMMM participated in the critical revision of the manuscript. MRM participated in the development of the conceptual idea and supervised the research. MRSM supervised the research and helped in data collection. PN reviewed the theoretical framework and empirical analysis of the research paper. All authors read and approved the final manuscript.

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Competing interests
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