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Stock selection using a hybrid MCDM approach

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Abstract. The problem of selecting the right stocks to invest in is of immense interest for investors on both emerging and developed capital markets. Moreover, an investor should take into account all available data regarding stocks on the particular market. This includes fundamental and stock market indicators. The decision making process includes several stocks to invest in and more than one criterion. Therefore, the task of selecting the stocks to invest in can be viewed as a multiple criteria decision making (MCDM) problem. Using several MCDM methods often leads to divergent rankings. The goal of this paper is to resolve these possible divergent results obtained from different MCDM methods using a hybrid MCDM approach based on Spearman's rank correlation coefficient. Five MCDM methods are selected: COPRAS, linear assignment, PROMETHEE, SAW and TOPSIS. The weights for all criteria are obtained by using the AHP method. Data for this study includes information on stock returns and traded volumes from March 2012 to March 2014 for 19 stocks on the Croatian capital market. It also includes the most important fundamental and stock market indicators for selected stocks. Rankings using five selected MCDM methods in the stock selection problem yield divergent results. However, after applying the proposed approach the final hybrid rankings are obtained. The results show that the worse stocks to invest in happen to be the same when the industry is taken into consideration or when not. However, when the industry is taken into account, the best stocks to invest in are slightly different, because some industries are more profitable than the others.

Key words: MCDM approach, Spearman's rank coefficient, stock selection

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1. Introduction

The problem of choosing the optimal set of stocks to invest in is of huge importance for all investors on capital markets, especially on emerging capital markets as the Croatian capital market. Analysing securities is as important for small, individual investors as for big, institutional investors. When selecting the stocks, it is important to analyse securities thoroughly, which includes capital

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market and financial indicators. They measure the risk of a particular share, its liquidity, volatility, its systematic risk, i.e., risk in comparison to the market as a whole. Moreover, financial statements and financial indicators can be different for financial and non-financial companies, i.e., financial indicators should also take into consideration the industry the company belongs to. Only after a detailed analysis of all information gathered, the investor can engage in trading stocks in order to minimise investment risks.

Since the decision making process includes several stocks to invest in and more than one criterion, the task of selecting the stocks to invest in can be viewed as a multiple criteria decision making (MCDM) problem. MCDM refers to making decisions in the presence of multiple, usually conflicting, criteria. All MCDM problems share the following common characteristics. Those are multiple objectives/attributes, conflict among criteria and incommensurable units. The researcher - analyst should model his or her preferences in order to choose the best compromise solution of the given multicriteria problem. In the MCDM problem, the decision maker plays an important role, i.e., he or she cannot be replaced by any method, no matter how good the method is. No method itself can determine the best solution to a particular situation. At best, the decision maker can use the method to strengthen the basis the decisions are made on and to improve the quality of the decision-making process.

Many MCDM methods have been developed and widely used in empirical research. However, these methods often rank the alternatives using a different approach and while the rankings of the alternatives provided by different methods may sometimes be in agreement, they often lead to divergent results. Opricovic and Tzeng [10] illustrated a comparative analysis of TOPSIS and COPRAS with a numerical example showing their similarity and some differences. Xidonas et al. [13] present a multiple criteria methodology for supporting decisions that concern the selection of equities based on financial analysis. The ELECTRE Tri outranking classification method is employed for selecting the attractive equities through the evaluation of the overall corporate performance of the corresponding firms. The crucial importance issue of the industry/sectoral accounting particularities was taken into account. Finally, the validity of the proposed methodology is tested through the application on the Athens Stock Exchange. Hamzaçebi and Pekkaya [5] use grey relational analysis (GRA) for ordering some financial firms' stocks, which are in the Financial Sector Index of the Istanbul Stock Exchange. Besides, because of the importance of criteria weights in decision making, three different approaches – heuristic, AHP, and learning via sample – were experimented to find best values of criteria weights in the GRA process. Baležentis et al. [2] offer a novel procedure for integrated assessment and comparison of Lithuanian economic sectors based on financial ratios and fuzzy MCDM methods. The application of the three MCDM methods (VIKOR, TOPSIS and ARAS) was successful, yielding somewhere excellent and somewhere low correlation between rankings. Kou et al. [9] proposed an approach to resolve disagreements among MCDM methods (TOPSIS, ELECTRE, GRA, VIKOR, PROMETHEE) based on Spearman's rank correlation coefficient, using 17 classification algorithms and 10 performance criteria over 11 public-domain binary classification datasets in the experimental study. Kassaee et al. [8] proposed a hybrid MCDM technique to determine the structural relationships and the interrelationships among all evaluation's dimensions based on the Analytic Network Process (ANP) method determining appropriate weightings to each sub-criterion. Then the TOPSIS is used to rank all competing alternatives in terms of their overall performances. Babić and Perić [1] solved the problem of multiproduct vendor selection with volume discounts as fuzzy multi-objective programming, using an integration of AHP, Weighted sum model (WSM) and fuzzy multi-objective mixed-integer programming to define the optimum quantities among the selected suppliers. Kabak and Dağdeviren [7] proposed an integrated approach, which employs ANP and PROMETHEE together, to assess the sustainability of students' preferences for university selection. The ANP is used to analyse the structure of the university selection problem and to determine weights of the criteria, and the PROMETHEE method is used to obtain the final ranking.

Most of the research combine several methods to find the final ranking, since the results show divergent results. The best way to reach the optimal solution is by combining these methods. Therefore, the goal of this paper is to resolve these possible divergent rankings of the alternatives obtained by five MCDM methods using a hybrid MCDM approach based on Spearman's rank correlation coefficient [9]. Five MCDM methods are selected, which include COPRAS, linear assignment, PROMETHEE, SAW and TOPSIS method. The weights for all criteria are obtained by using the AHP method. Data for this study is obtained from the REUTERS database and it includes information on stock returns and traded volumes in the period from March 2012 to March 2014, averaged over the sample period for 19 stocks which are constituents of stock indices on the Croatian capital market. It also includes the most important fundamental and stock market indicators for selected stocks in that period.

The rest of the paper is organized as follows. In the second part, the research methodology is explained in detail, including the explanation of different MCDM methods and Spearman's rank correlation coefficient. In the third part of the paper, the data and results are presented and discussed. Finally, the last part of the paper summarizes the main findings of the research.

2. Research methodology

2.1. MCDM methods

2.1.1. The Analytic Hierarchy Process (AHP)

The Analytic Hierarchy Process (AHP) is one of the most outstanding multi-criteria decision making approaches. The AHP method (see [11]) has a great importance in problem structuring and decision making. Its application allows interactive creation of the problem hierarchy that serves as preparation for the decision making scenario. The next step is a pair-wise comparison of hierarchy elements (goals, criteria and alternatives) and eventually all mutual comparisons are synthesized and weight coefficients for each element are determined. The sum of weight elements on each hierarchy level is equal to 1 and allows the decision maker to rank all hierarchy elements in terms of importance.

2.1.2. Complex proportional assessment method (COPRAS)

COPRAS method (see [6]) assumes direct and proportional dependences of the priority and utility degree of available alternatives under the presence of mutually conflicting criteria. It takes into account the performance of alternatives with respect to different criteria and the corresponding criteria weights. The method determines a solution with the ratio to the ideal solution and the ratio to the anti-ideal solution and has some similarity with the TOPSIS method. The degree of utility is determined by comparing the analysed alternatives with the best one. The procedural steps of the COPRAS method are:

Step 1: Develop the decision matrix $X = \left[x_{ij}\right]_{mxn}$, where x_{ij} is the performance of the i^{th} alternative on the j^{th} criterion, m is the number of alternatives, and n is the number of criteria.

Step 2: Normalise the decision matrix to obtain dimensionless values so that all of them can be compared, and determine the weighted normalised decision matrix D (where w_j is the weight of the j^{th} criterion) using the following equations:

$$R = \left[r_{ij}\right] = x_{ij} \Big/ \sum_{i=1}^{m} x_{ij}\,, \quad D = \left[y_{ij}\right] = r_{ij} \cdot w_j\,. \tag{1}$$

Step 3: The sums of weighted normalised values are calculated for both beneficial and non-beneficial attributes. These sums are calculated using the following equations:

$$S_{+i} = \sum_{j=1}^{n} y_{+ij}\ ,\quad S_{-i} = \sum_{j=1}^{n} y_{-ij}\ , \tag{2}$$

where y_{+ij} and y_{-ij} are the weighted normalised values for the beneficial and non-beneficial attributes, respectively. The greater the value of S_{+i}, the better the alternative, and the lower the value of S_{-i}, the better the alternative.

Step 4: Determine the relative preferences or priorities of the alternatives. The priorities of the alternatives are calculated on the basis of Q_i. The greater the value of Q_i, the higher the priority of the alternative. The relative preference value (priority), Q_i of the i^{th} alternative can be obtained as below:

$$Q_i = S_{+i} + \frac{S_{-\min} \cdot \sum_{i=1}^{m} S_{-i}}{S_{-i} \cdot \sum_{i=1}^{m} \left(S_{-\min} / S_{-i} \right)} \tag{3}$$

Step 5: Calculate the quantitative utility (U_i) for the i^{th} alternative. The degree of an alternative's utility is directly associated with its relative preference value (Q_i) and determined by comparing the priorities of all alternatives with the most efficient one and can be denoted as follows:

$$U_i = \left[Q_i / Q_{\max} \right] \times 100\%\ , \tag{4}$$

where $Q_{\max}$ is the maximum relative preference value.

2.1.3. Linear assignment method

Bernardo and Blin (see [6]) developed the linear assignment method based on a set of attributewise rankings and a set of attribute weights. The linear assignment method implies that we have a decision matrix and a set of criterion weights. In the first step, matrix π is defined, a square (m, m) matrix, whose elements π_{ik} represent the frequency (or number) that alternative A_i is ranked the k^{th} attributewise ranking. If the weights are not the same, then matrix π is calculated by summing the weights belonging to criteria by which alternative A_i is assigned k^{th} rank. The element of matrix π, π_{ik}, measures the contribution of A_i to the overall ranking, if A_i is assigned to the k^{th} overall rank. In other words, π_{ik} indicates the concordance with a hypothesis that in the final rank alternative A_i is assigned the k^{th} overall rank. The larger π_{ik} implies the better concordance with that hypothesis. The problem is to find A_i for each k (k = 1,..., n) which maximizes $\sum_{k=1}^{m} \pi_{ik}$. This is an m! comparison problem and it can be easily solved by the Hungarian method.

2.1.4. Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE)

PROMETHEE method is designed by J.P. Brans, Ph. Vincke and B. Mareschal (see [3]) and it compares and ranks alternatives which are simultaneously evaluated on the number of quantitative and qualitative criteria (attributes). The PROMETHEE method is one of the so-called "outranking" methods which consist of a compromise between too poor dominance relations and the excessive ones generated by utility functions. Let us consider the following multicriteria problem:

$$\text{Max } \{f_1(a), f_2(a), \ldots.., f_n(a) \mid a \in A \}, \tag{5}$$

where A is a finite set of possible actions (alternatives), i.e., $A = \{ A_1, A_2, \ldots, A_m \}$, and f_j are n criteria which have to be maximized. Every criterion is the function from set A to R, or in any other ordered set. When two actions a and b (A_k and A_l) are compared with respect to a particular criterion the result of the comparison has to be expressed in terms of preferences. We therefore define a preference function P:

$$P: A \text{ X } A \rightarrow [\, 0, 1 \,], \tag{6}$$

giving the intensity of preference of the action a over the action b. From six types of preference functions, the analyst and the decision maker choose one for each criterion depending on their knowledge about the intensity and the course of preferences.

The next task is to determine the relative importance (ponders, weights) w_j for every criterion f_j ($j = 1, 2, \ldots, n$). Let us suppose that the decision maker has specified a preference function P_j and a weight w_j for each criterion f_j ($j = 1, \ldots, n$) of multicriteria problem (5). The multicriteria preference index Π is then defined as the weighted average of preference functions P_j:

$$\Pi(a,b) = \frac{\sum_{j=1}^{n} w_j P_j(a,b)}{\sum_{j=1}^{n} w_j} \tag{7}$$

Preference index $\Pi(a, b)$ represents the intensity of preference of the decision maker of action a over action b, when considering all criteria simultaneously. For each alternative a, let us define the leaving or positive flow $\Phi^+(a)$ and the entering or negative flow $\Phi^-(a)$:

$$\Phi^{+}(a)=\frac{1}{m-1}\sum_{x\in A}\Pi(a,x),\ \Phi^{-}(a)=\frac{1}{m-1}\sum_{x\in A}\Pi(x,a) \tag{8}$$

The positive flow provides a measure of the outranking character of *a*. The positive outranking flow expresses how an alternative *a* is outranking all the others. It is its power, its outranking character. The higher $\Phi^{+}(a)$, the better the alternative. The negative flow provides a measure of the outranked character of *a*. It is its weakness, its outranked character. The lower the $\Phi^{-}(a)$, the better the alternative. That is the PROMETHEE I partial relation. It provides to the decision maker a graph in which some actions are comparable, some others are not. This information can be used fruitfully in concrete applications for making decisions.

Suppose a total preorder (complete ranking without incomparabilities) has been requested by the decision maker. Then for each action $a\in A$ we can consider the net outranking flow as the balance between the "power" and the "weakness" for each alternative:

$$\Phi(a) = \Phi^{+}(a) - \Phi^{-}(a)\ . \tag{9}$$

The higher the net flow $\Phi(a)$, the better the alternative. This is the PROMETHEE II complete relation. All the actions of *A* are now completely ranked, but the resulting information can be more disputable because more information gets lost by considering the difference (9).

2.1.5. Simple Additive Weighting (SAW)

The main characteristics of this method can be found in Triantaphyllou [12] or Hwang and Yoon [6]. SAW is probably the best known and very widely used method of multi attribute decision making (MADM). To each of the criteria (attribute) in this method, the importance weight is assigned, obtained either directly from the decision maker or from some of the methods for the importance of weight assessment.

After that, the weights of each criterion, become the coefficients of variables from the decision matrix in a way that a total score for each alternative is obtained simply by multiplying the scale rating for each attribute value by the importance weight assigned to the attribute. Summing these products over all attributes, the final rating of each alternative is obtained. After the total scores are computed for each alternative, the alternative with the highest score (the highest weighted average) is the one prescribed by the decision maker.

Mathematically, a simple additive weighting method can be stated as follows: Suppose we have a set of importance weights to the attributes, $W = \{ w_1, w_2,\dots, w_n \}$.
Then the most preferred alternative, A^*, is selected such that:

$$A^* = \{ A_i \mid \max_i \left(\sum_{j=1}^{n} w_j x_{ij} \Big/ \sum_{j=1}^{n} w_j \right) \}, \tag{10}$$

where x_{ij} is the outcome of the i^{th} alternative about the j^{th} attribute with a numerically comparable scale. Hence, if the attributes are not set in the same units of measure, then its transformation is required.

2.1.6. Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)

Yoon and Hwang (see [6]) developed the TOPSIS method based upon the concept that the chosen alternative should have the shortest distance from the ideal solution and the farthest distance from the negative-ideal solution. TOPSIS considers the distances to both the ideal and the negative-ideal solutions simultaneously by taking relative closeness to the ideal solution and in that way the final alternatives ranking is obtained.

Let us have the decision matrix $D = \left[x_{ij} \right]_{mxn}$, where x_{ij} is the performance of the i^{th} alternative on the j^{th} criterion, m is the number of alternatives, and n is the number of criteria. The TOPSIS method is presented as a series of successive steps:
Step 1. Determine the ideal and the negative-ideal solution
Define the ideal alternative as the one containing the best values by each attribute, i.e.,

$$A^+ = \{ (\max x_{ij} \mid j \in J), (\min x_{ij} \mid j \in J'), \ i = 1, 2,\dots, m \} = \{ x_1^+, x_2^+,\dots, x_n^+ \},$$

where J is a set of benefit attributes indices, and J' is a set of cost attributes indices.
On the other hand, a negative-ideal alternative is

$$A^- = \{ (\min x_{ij} \mid j \in J), (\max x_{ij} \mid j \in J'), \ i = 1, 2,\dots, m \} = \{ x_1^-, x_2^-,\dots, x_n^- \}$$

Then it is certain that the two created alternatives indicate the most preferable alternative (ideal solution) and the least preferable alternative (negative-ideal solution). It is also obvious that these alternatives inside the offered set of alternatives will not exist. Namely, if A^+ existed, the problem would be solved, i.e., the perfect solution would exist.

Step 2. Transformation of attributes
The TOPSIS method requires the transformation of the attributes in order to have nondimensional values, which allow for a comparison between attributes. One way of transformation is vector normalization, which divides every column of the decision matrix (vector X_j) by the norm of that vector. Column vectors in the decision matrix then become:

$$\overline{X_j} = \frac{X_j}{\| X_j \|} = \frac{X_j}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}, \quad j = 1, 2, \ldots, n \tag{11}$$

Step 3. Calculation of the distance
Suppose the set of weights is given by the decision maker: $W = \{ w_1, w_2, \ldots, w_n \}$. We can define the distance of any alternative A_i from A^+ and A^- as a weighted Euclidean distance as:

$$S_{i+} = \sqrt{\sum_{j=1}^{n} \left[\frac{w_j (x_{ij} - x_j^+)}{\| X_j \|} \right]^2}, \quad S_{i-} = \sqrt{\sum_{j=1}^{n} \left[\frac{w_j (x_{ij} - x_j^-)}{\| X_j \|} \right]^2} \tag{12}$$

Step 4. Calculating relative closeness to the ideal solution
Relative closeness of alternative A_i with respect to ideal solution A^+ is defined as:

$$RC_i = \frac{S_{i-}}{S_{i+} + S_{i-}} \tag{13}$$

Obviously, $RC_i = 1$ if $A_i = A^+$ and $RC_i = 0$ if $A_i = A^-$. An alternative is closer to the ideal solution (and therefore better) as RC_i approaches to 1.

2.1.7. Spearman's rank correlation coefficient

Spearman's rank correlation coefficient measures the similarity between two sets of rankings. The idea of this paper is to calculate Spearman's rank correlation coefficient based on rankings of the five MCDM methods. A larger absolute value of Spearman's rank correlation coefficient indicates a good agreement between the MCDM method and other MCDM methods. Afterwards, this approach proposes to assign a weight to each MCDM method according to the similarities between the ranking it generated and the rankings obtained by other MCDM methods in order to find the final hybrid ranking of the alternatives (see [5]).
Spearman's rank correlation coefficient between the k^{th} and the i^{th} MCDM method is calculated as follows:

$$\rho_{ki} = 1 - \frac{6\sum_{i=1}^{n} d_i^2}{n^3 - n}, \tag{14}$$

where n is the number of alternatives and d_i is the difference between the ranks of two MCDM methods. Based on the value of ρ_{ki}, the average similarities between the k^{th} MCDM method and other MCDM methods can be calculated as

$$\rho_k = \frac{1}{q-1} \sum_{i=1, i \neq k}^{q} \rho_{ki}, \; k = 1, 2, \ldots, q, \tag{15}$$

where q is the number of MCDM methods. The larger the ρ_k value, the more important the MCDM method. Normalized ρ_k values can then be used as weights for MCDM methods to obtain the final hybrid ranking of the alternatives. The most preferred alternative, A^*, is selected such that:

$$A^* = \left\{ A_i \mid \max_i \left(\sum_{k=1}^{q} \rho_k r_{ik} \Big/ \sum_{k=1}^{q} \rho_k \right) \right\}, \tag{16}$$

where r_{ik} is the outcome of the i^{th} alternative about the k^{th} MCDM method.

3. Empirical results

3.1. Data

In this paper, nineteen most traded shares from the Zagreb stock exchange have been singled out, in the period from March 2012 to March 2014. For each security from the sample the closing price at the end of each day and traded volumes are downloaded from the REUTERS database. Data consists of around 500 daily observations. Moreover, in March 2014 other indicators are also obtained from the REUTERS database, including beta, earnings per share (EPS), price-to-book ratio (P/B), price-to-sales ratio (P/S), return on equity (ROE) and return on asset (ROA).

Firstly, the daily returns for each security are calculated, which are used for the calculation of daily mean return and daily standard deviation. Average daily traded volume is calculated from the daily volumes. Mean return is the average earning in the observed period, standard deviation measures the risk of a particular share, traded volume its liquidity and beta is a measure of volatility, or systematic risk, in comparison to the market as a whole. Those criteria are industry independent and represent the stock market indicators. Secondly, it is well known that both financial statements and financial indicators can be different for financial and non-financial companies. Therefore, only the indicators that can be calculated both for financial and non-financial companies are used in this paper. Financial indicators used in this paper are ROA, ROE, EPS, P/S and P/B ratio. It should be noted that the selected companies belong to different industries, i.e., dairy products, heavy electrical equipment, diversified chemicals, chocolate and confectionery, food processing, telecommunications, deep sea fright, hotels, motels and cruise lines, commercial banks, manufacturer of plastic components for automotive industry, cigarettes and cigarette manufacturing, construction and engineering, fishing and farming, industrial conglomerate and marine port services.

The initial data for this study is given in Table 1. It includes 19 stocks, i.e., alternatives (A1 to A19) and 9 indicators, i.e., criteria (C1 to C9).

		Mean (%)	St.dev. (%)	Volume	Beta	EPS	ROE	P/B	P/S	ROA
	STOCK	C1	C2	C3	C4	C5	C6	C7	C8	C9
A1	BLJE.ZA	-0.0049	4.10	3481.20	1.17	-12.45	-9.15	0.32	0.20	-2.65
A2	DLKV.ZA	-0.0085	6.55	3994.70	1.27	-138.01	-83.99	0.36	0.06	-15.75
A3	PTKM.ZA	-0.3706	2.77	1471.76	1.69	-55.38	-27.56	0.76	0.15	-9.87
A4	KRAS.ZA	-0.0880	1.40	229.80	0.54	0.80	0.17	0.82	0.49	0.15
A5	ATGR.ZA	-0.0174	1.58	300.98	0.67	58.46	12.83	1.59	0.51	3.89
A6	HT.ZA	-0.0001	1.93	11863.43	0.31	17.60	13.34	1.29	1.93	11.11
A7	PODR.ZA	0.0053	1.41	972.13	1.27	12.70	4.09	0.95	0.42	1.93
A8	ATPL.ZA	-0.0596	2.91	688.13	1.16	-3.10	-0.29	0.40	1.08	-0.11
A9	DOMF.ZA	0.0125	1.61	3059.58	1.43	14.54	3.59	0.84	1.26	2.16
A10	ZBB.ZA	-0.1705	2.11	4005.34	1.08	2.16	3.91	0.47	1.60	0.63
A11	ADPL.ZA	0.0080	1.08	2681.43	0.78	13.69	7.98	0.69	0.62	4.45
A12	ADGR_p.ZA	-0.0440	0.97	1792.23	1.03	23.26	5.07	0.59	0.93	4.26
A13	INGR.ZA	0.0030	3.48	37260.06	1.50	-9.38	-36.85	0.15	0.27	-8.40
A14	VPIK.ZA	-0.1477	2.05	910.77	1.76	6.96	1.90	0.26	0.32	0.81
A15	DDJH.ZA	-0.0183	3.98	2638.39	1.30	-10.77	-2.27	0.89	0.16	-0.90
A16	LUKA.ZA	-0.1312	2.32	684.90	1.98	0.77	1.28	1.15	3.13	0.92
A17	ERNT.ZA	-0.0055	1.36	287.49	0.63	101.23	15.71	2.65	1.05	10.75
A18	KONL.ZA	-0.0834	1.35	667.88	1.05	56.89	8.49	0.93	0.70	5.08
A19	ULPL.ZA	-0.0222	1.98	239.24	1.33	-157.23	-20.42	0.31	0.50	-4.24
		max	min	max	min	max	max	min	min	max

Table 1: *Initial data*

Since some of the criteria have negative values, for the purpose of calculation those criteria are translated, i.e., for each criterion with negative values in the Table 1 minimum is calculated and it is subtracted from each value in a particular column. For the criteria with all positive values, nothing is done. Therefore, no information is lost.†

Considering the fact that there are 19 different stocks belonging to different industries that all have their similarities and differences, for the purpose of the analysis the translated data is also given with respect to the industry the company belongs to, i.e., the indicators from the financial statements are calculated relative to the industry average. Based on the particular criterion, the value above 1 indicates that the particular company is better than the industry average, and the value below 1 shows the opposite.‡

3.2. Results

The weights for further calculations are obtained using the AHP method in Expert choice and it is based on the experts' opinion. Weights for each criterion are given in Table 2. Based on the decision matrix (Scenario 1) and weights from Table 2, the rankings for five MCDM methods are calculated in Excel and Decision Lab and presented in Table 3. It can be concluded that the best stocks to invest in are A6, A11 and A17 which have the lowest rank in all MCDM methods. The worse stocks to invest in are A2, A3 and A19, i.e., they all have the highest rank in all MCDM methods. However, five different MCDM methods show divergent results.

	C1	C2	C3	C4	C5	C6	C7	C8	C9
W_j	0.223	0.107	0.050	0.020	0.076	0.299	0.043	0.025	0.157

Table 2: *Weights for each criterion obtained by the AHP method*

Based on the decision matrix (Scenario 2) and weights from Table 2, the rankings for all MCDM methods are calculated and presented in Table 4. This part of analysis considers the importance of the industry. It can be concluded that the best stocks to invest in are A11, A15 and A18 which have the lowest rank in all MCDM methods. The worse stocks to invest in are A2, A3 and A19,

†Decision matrix (Scenario 1) is excluded due to a lack of space. It is available from the authors upon request.

‡Decision matrix (Scenario 2) is excluded due to a lack of space. It is available from the authors upon request.

i.e., they all have the highest rank in all MCDM methods. However, five different MCDM methods still show divergent results.

	SAW		TOPSIS		LINEAR ASSIGNMENT	COPRAS		PROMETHEE	
	SCORE	RANK	R_{ci}	RANK	RANK	U_i	RANK	ϕ	RANK
A1	0.62	12	0.61	15	15	73.05	15	-0.0679	15
A2	0.29	19	0.34	19	19	32.67	19	-0.5154	19
A3	0.30	18	0.40	18	17	40.00	18	-0.4967	18
A4	0.65	9	0.65	9	12	79.50	10	0.0285	10
A5	0.76	4	0.70	5	3	86.45	6	0.1904	4
A6	0.81	2	0.77	1	2	100.00	1	0.2904	1
A7	0.73	6	0.69	8	7	85.94	7	0.1155	8
A8	0.63	11	0.64	10	13	73.56	14	-0.0022	12
A9	0.72	7	0.70	6	9	85.20	9	0.1346	7
A10	0.60	14	0.63	12	8	73.78	12	0.0663	9
A11	0.78	3	0.72	2	5	95.55	2	0.2111	3
A12	0.76	5	0.70	4	6	90.49	5	0.1643	6
A13	0.58	16	0.60	16	18	94.97	3	-0.2525	16
A14	0.62	13	0.63	11	10	75.90	11	0.0200	11
A15	0.63	10	0.62	13	14	73.74	13	-0.0163	13
A16	0.59	15	0.61	14	11	66.95	16	-0.0446	14
A17	0.83	1	0.71	3	1	91.07	4	0.2694	2
A18	0.72	8	0.69	7	4	85.94	8	0.1685	5
A19	0.54	17	0.57	17	16	65.84	17	-0.2633	17

Table 3: *Results for the rankings using five selected MCDM methods*

The worse stocks to invest in happen to be the same when the industry is taken into consideration or not (Table 3 and Table 4, respectively). However, when the industry is taken into consideration, the best stocks to invest in are slightly different. This can be explained by the fact that when taking industry into account these companies: ADPL.ZA, DDJH.ZA and KONL.ZA are definitely good stocks to invest in, and they are at the top of the heap compared to their industry. In comparison with that, HT.ZA and ERNT.ZA belong practically to the same industry, they are the best stocks to invest in and their industry is already at the top of the heap, but beat each other in several criteria when the industry is taken into consideration. Moreover, ADPL.ZA is among the best stocks when considering both scenarios and all available data, meaning that it is probably the right choice to invest in.

	SAW		TOPSIS		LINEAR ASSIGNMENT	COPRAS		PROMETHEE	
	SCORE	RANK	R_{ci}	RANK	RANK	U_i	RANK	ϕ	RANK
A1	0.53	12	0.49	16	16	63.75	15	-0.0472	15
A2	0.31	18	0.27	19	19	29.69	19	-0.5021	19
A3	0.28	19	0.38	18	15	40.93	18	-0.2801	18
A4	0.58	10	0.57	4	4	70.98	10	0.0419	7
A5	0.59	8	0.57	6	6	70.06	12	0.0173	10
A6	0.60	4	0.56	7	14	80.20	4	0.0716	4
A7	0.58	9	0.55	10	13	70.33	11	0.0043	11
A8	0.58	11	0.57	5	5	71.69	9	0.0500	5
A9	0.59	7	0.55	9	12	73.68	7	0.0429	6
A10	0.47	17	0.50	14	10	63.36	16	-0.0031	12
A11	0.76	2	0.71	2	2	93.06	2	0.3090	2
A12	0.60	6	0.54	11	11	74.02	6	0.0355	8
A13	0.51	15	0.48	17	18	85.61	3	-0.1183	16
A14	0.52	14	0.52	13	8	64.70	14	-0.0319	14
A15	0.61	3	0.61	3	3	75.45	5	0.0973	3
A16	0.52	13	0.54	12	7	65.16	13	-0.0223	13
A17	0.60	5	0.55	8	9	73.23	8	0.0274	9
A18	0.80	1	0.76	1	1	100.00	1	0.4434	1
A19	0.49	16	0.49	15	17	60.25	17	-0.1356	17

Table 4: *Results for the rankings using five selected MCDM methods with respect to industry*

Considering that five MCDM methods show divergent results of rankings in both scenarios, Spearman's rank correlation coefficients are calculated. Table 5 gives an overview of Spearman's rank correlation coefficients between rankings of the five MCDM methods. It was the starting point for calculation of the weights and normalized weights given in Table 6.

	SAW	TOPSIS	LINEAR ASSIGNMENT	COPRAS	PROMETHEE
SAW	1	**0.9632**	**0.8842**	**0.8018**	**0.9421**
TOPSIS	**0.9632**	1	**0.9193**	**0.8211**	**0.9772**
LINEAR ASSIGNMENT	**0.8842**	**0.9193**	1	**0.7193**	**0.9684**
COPRAS	**0.8018**	**0.8211**	**0.7193**	1	**0.8158**
PROMETHEE	**0.9421**	**0.9772**	**0.9684**	**0.8158**	1

Table 5: *Spearman's rank correlation coefficients*

	SAW	TOPSIS	LINEAR ASSIGNMENT	COPRAS	PROMETHEE
WEIGHTS	0.8978	0.9202	0.8728	0.7895	0.9259
NORMALIZED WEIGHTS	0.2038	0.2088	0.1981	0.1792	0.2101

Table 6: *Weights and normalized weights*

It can be seen that the PROMETHEE method was given the highest weight, indicating a good agreement between this method and other MCDM methods and COPRAS the lowest weight, indicating a lower but still good agreement between this method and other MCDM methods.

	SAW	TOPSIS	LINEAR ASSIGNMENT	COPRAS	PROMETHEE
SAW	1	**0.8614**	**0.6298**	**0.8298**	**0.9018**
TOPSIS	**0.8614**	1	**0.8702**	**0.7035**	**0.9421**
LINEAR ASSIGNMENT	**0.6298**	**0.8702**	1	**0.4825**	**0.7684**
COPRAS	**0.8298**	**0.7035**	**0.4825**	1	**0.8035**
PROMETHEE	**0.9018**	**0.9421**	**0.7684**	**0.8035**	1

Table 7: *Spearman's rank correlation coefficients with respect to industry*

	SAW	TOPSIS	LINEAR ASSIGNMENT	COPRAS	PROMETHEE
WEIGHTS	0.8057	0.8443	0.6877	0.7048	0.8539
NORMALIZED WEIGHTS	0.2068	0.2167	0.1765	0.1809	0.2192

Table 8: *Weights and normalized weights with respect to industry*

Table 7 gives an overview of Spearman's rank correlation coefficients between rankings of the five MCDM methods in the second scenario, i.e., relative to the industry average. It was the starting point for calculation of the weights and normalized weights in Table 8. It can be seen that the PROMETHEE method was given the highest weight, indicating a good agreement between this method and other MCDM methods and linear assignment the lowest weight, indicating a lower but still good agreement between this method and other MCDM methods.

Finally, divergent rankings are corrected, eliminated and presented in Table 9 for both scenarios. Based on rankings from all five MCDM methods from Table 3 and their weights from Table 6, the final rankings are calculated and presented in the first two columns.

In scenario 1, A6, A17 and A11 are the best three ranked stocks to invest in and that A2, A3 and A19 are the worse three ranked stocks. This confirms the findings from Table 3, but it gives the final hybrid ranking of the stocks. Moreover, based on rankings from all five MCDM methods from Table 4 and their weights from Table 8, the final rankings are calculated and presented in the last two columns for data with respect to the industry average. It can be seen that A18, A11 and A15 are the best three ranked stocks to invest in when taking into account the industry average and that A2, A3 and A19 are the worse three ranked stocks. This confirms the findings from Table 4, but it gives the final hybrid ranking of the stocks. It can also be concluded from Table 9 that the worse stocks to invest in happen to be the same when the industry is taken into consideration or not. However, when the industry is taken into consideration, the best stocks to invest in are slightly different. This can be explained by the fact that when considering industry, DDJH.ZA and KONL.ZA are definitely good stocks to invest in, and they are much better than their industry. In comparison with that, HT.ZA and ERNT.ZA belong practically to the same industry, they are the best stocks to invest in and their industry is already at the top of the heap, but they conflict each other in several criteria when the industry is taken into consideration. Moreover, ADPL.ZA is among the best stocks when considering both scenarios and all available data, meaning that it is probably the right choice to invest in.

		SCENARIO 1		SCENARIO 2	
	STOCK	SCORE	RANK	SCORE	RANK
A1	BLJE.ZA	14.39	16	14.77	16
A2	DLKV.ZA	19.00	19	18.79	19
A3	PTKM.ZA	17.80	18	17.68	18
A4	KRAS.ZA	9.98	9	6.98	6
A5	ATGR.ZA	4.37	4	8.38	9
A6	HT.ZA	1.40	1	6.42	4
A7	PODR.ZA	7.22	7	10.72	11
A8	ATPL.ZA	11.93	12	6.96	5
A9	DOMF.ZA	7.55	8	8.10	8
A10	ZBB.ZA	10.98	10	13.84	14
A11	ADPL.ZA	3.01	3	2.00	2
A12	ADGR_p.ZA	5.20	5	8.40	10
A13	INGR.ZA	14.07	15	14.01	15
A14	VPIK.ZA	11.21	11	12.72	13
A15	DDJH.ZA	12.59	13	3.36	3
A16	LUKA.ZA	13.97	14	11.72	12
A17	ERNT.ZA	2.17	2	7.78	7
A18	KONL.ZA	6.37	6	1.00	1
A19	ULPL.ZA	16.80	17	16.36	17

Table 9: *Final hybrid ranking*

4. Conclusion

The problem of stock selection using a hybrid MCDM approach is addressed in this paper. Namely, choosing the optimal set of stocks to invest in is of huge importance for both individual and institutional investors. All in all, when selecting the stocks, it is important to analyse securities thoroughly, including capital market and financial indicators. Since the decision making process includes several stocks to invest in and more than one criterion, the task of selecting the stocks to invest in can be viewed as a multiple criteria decision making (MCDM) problem. Many MCDM methods have been developed and widely used in empirical research. However, these methods often rank the alternatives using a different approach which can sometimes lead to divergent results. Therefore, the goal of this paper is to resolve these possible divergent rankings of the alternatives obtained from five MCDM methods using a hybrid MCDM approach based on Spearman's rank correlation coefficient.

Firstly, the rankings are calculated based on MCDM methods, which include COPRAS, linear assignment, PROMETHEE, SAW and TOPSIS method. The weights for all criteria are obtained using the AHP method. Secondly, since these methods show divergent results, based on Spearman's rank correlation coefficient between rankings of one MCDM method and all another MCDM methods, the weights and normalized weights are calculated. These weights are then used to find the final hybrid ranking of the stocks.
This hybrid approach is somewhat new in the MCDM context and in the field of stock selection. Moreover, this process is empirically tested with and without taking into consideration the industry of the particular stock. This implies the theoretical and empirical contribution is achieved through this paper.

Further research may include creation of a new and improved hybrid method for merging different MCDM methods into one to obtain the final rankings in this or/and in the other fields of application.

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