The Iterative Compromise Ranking Analysis (ICRA) - The New Approach to Make Reliable Decisions

Bartosz Paradowski[1], Bartłomiej Kizielewicz[1,2], Andrii Shekhovtsov[1,2], and Wojciech Sałabun[1,2](✉)

[1] Research Team on Intelligent Decision Support Systems, Department of Artificial Intelligence and Applied Mathematics, Faculty of Computer Science and Information Technology, West Pomeranian University of Technology, Szczecin, Poland
{bartosz-paradowski,bartlomiej-kizielewicz,jakub-wieckowski, wojciech.salabun}@zut.edu.pl

[2] National Institute of Telecommunications, Szachowa 1, 04-894 Warsaw, Poland

Abstract. In the field of multi-criteria decision-making, compromise is often sought because it is highly desirable for decision-making. However, over the years, many methods have been developed for decision-making, between which discrepancies in the final rankings are often present. For this reason, it is worth noting the possibility of a compromise between different multi-criteria decision-making methods. One such solution is the Iterative Compromise Ranking Analysis (ICRA), which, by means of an iterative evaluation of the preferences of alternatives, leads to a compromise between the methods under consideration. This work presents an example of a solution to a theoretical decision problem, for which five methods were used: TOPSIS, VIKOR, MARCOS, MABAC and EDAS. In addition, an empirical analysis of the compromise solution was carried out to check the effect of parameters on the number of iterations needed to reach a compromise and the differences between the rankings proposed by the methods and the compromise ranking. The work showed that this is an interesting tool that can find its use in the field of multi-criteria decision-making as well as can be used to analyze the behaviour of multi-criteria decision-making methods.

Keywords: Compromise · ICRA · MCDA

1 Introduction

A number of new approaches to solving multi-criteria problems have emerged over recent years. For this reason, there have been many works attempting to compare methods of multi-criteria decision-making in different fields [8] as well as attempts to empirically compare methods among themselves [3] or to present approaches to how to benchmark them. In addition, due to the number of methods available Wątróbski et al. presented a generalised framework of selection of

E. Ziemba et al. (Eds.): FedCSIS-AIST 2022/ISM 2022, LNBIP 471, pp. 151–170, 2023.
https://doi.org/10.1007/978-3-031-29570-6_8

multi-criteria decision-making method as the sole selection of a method becomes a problem in itself [28]. However, choosing one method is not necessarily the only way out, in cases where the decision maker believes that several methods can guarantee an adequate result, a compromise approach can be used.

Compromise in decision-making is a desirable phenomenon that manifests itself in this field in many forms. Virtually every method seeks to compromise through the principle of linear programming, however, some methods e.g. VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) [1], The Measurement Alternatives and Ranking according to COmpromise Solution (MARCOS) [25] and A Combined Compromise Solution (CoCoSo) [30] methods extend it even further. Moreover, the compromise might be sought through objective criteria weighting [20] as it provides a direct impact on criteria significance in the considered problem.

Another popular approach is the ranked voting system, which is used to establish a compromise ranking based on reference rankings. Many voting approaches were used in multi-criteria decision-making in specific practical problems such as the Borda rule and the Copeland rule for performance assessment of battery electric vehicles [7], the Copeland rule for E-commerce recommender system [2]. Moreover, Lamboray presented a comparison between available voting system [15].

However, these methods mainly focus on rankings in which it is difficult to observe slight differences between the obtained preferences of decision options. For the purpose of providing a better-suited way of obtaining a compromise, the Iterative Compromise Ranking Analysis (ICRA) was proposed by Kizielewicz et al. [13]. This new approach use evaluations of the decision alternatives obtained by the selected methods by creating a new decision matrix consisting of mentioned preference values, where the types of attributes for the newly formed matrix depend on the ranking method and iteratively seeking the compromise.

In this study, five multi-criteria decision-making methods were selected to perform the ICRA, namely the TOPSIS, the VIKOR, the MARCOS, the MABAC, and the EDAS methods. This approach makes it possible to obtain a consensus between different rankings that presents some discrepancies by means of an iterative evaluation using the multi-criteria decision-making methods considered. An example of the use of this approach to solve a specific theoretical multi-criteria problem is presented and a quantitative analysis of the influence of the factors of the course of obtaining a consensus on the number of iterations and the final consensus ranking obtained is carried out.

The rest of the article is structured as follows. Section 2 presents a literature review of different approaches to compromise in multi-criteria decision-making. In Sect. 3, preliminaries are presented that include the newly proposed method and selected methods of multi-criteria decision-making. In Sect. 4, a study case is presented in which the performance of the algorithm on five methods is presented and quantitative analysis is carried out with a discussion of the acquired results. Finally, in Sect. 5 the conclusions were drawn and a summary is presented.

2 Literature Review

Compromise is one aspect of multi-criteria decision-making that should be highly desirable. It allows the use of one of the available options which will be close to the majority, but at the same time will take into account the minority. Most multi-criteria decision-making use linear programming to provide for the aspect of compromise among considered alternatives, which often might not be enough, thus some methods tried to present a different approach. Several methods have emerged in multi-criteria decision-making that base their core principles on compromise and assess the set of considered alternatives.

The most well-known and regarded classic method is the VIKOR method presented by Serafim Opricovic [6]. This method in its assumptions proposes two rankings, which can then be aggregated using the compromise value given by the expert. This method has been used in many works, demonstrating its usefulness in various fields. In addition, the method has seen many developments, e.g. for group decision-making [10], an approach that operates in a fuzzy environment [9] and uses interval numbers [22]. Since the VIKOR method was presented, few methods have directly addressed compromise, two solutions being the relatively new, namely the combined compromise solution (COCOSO) method and the Measurement of alternatives and ranking according to the COmpromise solution (MARCOS) method. The COCOSO method was proposed by Yazdani et al. in work presented in 2018 [30], where the new method combines the weighted product method (WPM) and the weighted sum method (WSM) to provide a new equation which results in balanced compromise of those two scores in accordance to the best and the worst alternative. The MARCOS method, on the other hand, was first introduced by Željko Stević et al. in 2020 [25]. This method presented the utility functions which provided the compromise of the considered alternatives in relation to the ideal and anti-ideal solution. They presented the usage of this function in the example of sustainable supplier selection in healthcare industries.

Another approach to incorporating comparison in multi-criteria decision-making methods is to use objective criteria weighting methods. These methods do not directly address the use of comparison, but by checking the correlation between the criteria considered they provide some degree of compromise value of the importance of a criterion. Such approaches, although rarely considered, can be helpful in the case of a problem in determining the relevance of criteria. Such methods allow for a better resolution of the conflict characterizing a given decision situation. One of the best-known and also oldest methods is CRiteria Importance Through Intercriteria Correlation (CRITIC) presented by Diakoulaki et al. in 1995 [5]. This method determines the importance of a criterion through the calculation of intercriteria correlation. In 2021 Krishnan et al. presented an extension of the CRITIC method where a new distance correlation coefficient was incorporated [14]. Aggregated method of Integrated Determination of Objective CRIteria Weights (IDOCRIW) was presented by Zavadskas and Podvezko in 2016 [31] which used the assumptions of the criterion impact loss (CILOS) approach and entropy and was further extended by them into a fuzzy environment in 2020 [21]. One of the latest methods is MEthod based on the Removal Effects of Criteria (MEREC) presented by Keshavarz-Ghorabaee et al. in 2021 [11]. This method provides a new perspective on objective weighting methods as the criterion's removal effect on the performance of alternatives is presented and incorporated into the algorithm.

More relevant, from the point of view of this work, are solutions that make compromises between rankings obtained using multiple multi-criteria decision-making methods. For this purpose, the Borda count methodology was applied. Its usage in multi-criteria decision-making is prominent in many fields, for example, Roozbahani et al. presented a framework that incorporated Borda count for the final ranking calculation in Ground Water Management Based problem [23], on the other hand, Serrai et al. presented its usage for compromise ranking for a problem of web service selection [24]. This methodology was further used by Wu et al. to extend MULTIMOORA decision-making method to improve robustness in the alternatives assessment [29]. Another well-known and highly used method is the Copeland method, which execution was presented for example by Özdagoglu et al. in the case study of motorcycle selection [18] or by Lestari et al. in the performance comparison of Copeland and Borda methods in a recommender system [16]. Even though those two are most prominent in research where aggregation of rankings is considered, there are many different approaches to provide a compromise solution. There are such approaches as Kemeny's rule and Condorcet's rule which were used by Muravyov et al. [17].

In this work, we present the iterative approach to obtain a compromise solution of rankings provided by several multi-criteria decision-making methods. This approach let the decision-maker choose more than one desirable method and acquire one final ranking. Such an approach may be highly desirable in scenarios where selecting a specific method might not be considered easy.

3 Research Methodology

3.1 TOPSIS Method

Technique of Order Preference Similarity (TOPSIS) is based on the ideal solution approach for solving multi-criteria decision problems [4]. The approach evaluates decision alternatives for the distance between a positive ideal solution and a negative ideal solution. Its basic version can be presented in the following steps:

Step 1. Construct the decision matrix and determine the weight of criteria and type of it (1). Criteria can be either: profit (more is better) or cost (less is better).

$$F = \begin{bmatrix} f_{11} & f_{12} & \cdots & f_{1n} \\ f_{21} & f_{22} & \cdots & f_{2n} \\ \vdots & \vdots & \dots & \vdots \\ f_{m1} & f_{m2} & \cdots & f_{mn} \end{bmatrix}, \tag{1}$$

where f_m denotes alternative m.

Step 2. Calculate the normalized decision matrix. This step allows the attributes to be converted to a single scale for easier comparison.

Step 3. Determine the weighted normalized decision matrix. The weighted normalized value is calculated in the following way (2):

$$F^w = \begin{bmatrix} r_{11} \cdot w_1 & r_{12} \cdot w_2 & \cdots & r_{1n} \cdot w_n \\ r_{21} \cdot w_1 & r_{22} \cdot w_2 & \cdots & r_{2n} \cdot w_n \\ \vdots & \vdots & \cdots & \vdots \\ r_{m1} \cdot w_1 & r_{m2} \cdot w_2 & \cdots & r_{mn} \cdot w_n \end{bmatrix} = \begin{bmatrix} v_{11} & v_{12} & \cdots & v_{1n} \\ v_{21} & v_{22} & \cdots & v_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ v_{m1} & v_{m2} & \cdots & v_{mn} \end{bmatrix}, \quad (2)$$

where r_m - normalized alternative m, w - weight corresponding to criteria.

Step 4. Calculate positive and negative ideal solution. Calculate the separation measures, using the n-dimensional Euclidean distance. The separation of each alternative from the positive ideal solution is given as (3):

$$D_j^* = \sqrt{\sum_{i=1}^{n} (v_{ij} - v_i^*)^2}, \quad j = 1, \ldots, J, \quad (3)$$

where $v_{ij} = r_{ij} \cdot w_j$, v_i^* - positive ideal solution.

Similarly, the separation from the negative ideal solution is given as (4):

$$D_j^- = \sqrt{\sum_{i=1}^{n} \left(v_{ij} - v_i^-\right)^2}, \quad j = 1, \ldots, J, \quad (4)$$

where $v_{ij} = r_{ij} \cdot w_j$, v_i^- - negative ideal solution.

Step 5. Calculate the relative closeness to the ideal solution. The relative closeness of the alternative a_j is defined as follows (5):

$$C_j^* = \frac{D_j^-}{\left(D_j^* + D_j^-\right)}, \quad j = 1, \ldots, J \quad (5)$$

Step 6. Rank the preference order.

3.2 VIKOR Method

VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) is a method based on the compromise approach, which evaluates alternatives with conflicting types of criteria [1]. The compromise solution in this method is considered to be the solution that is closest to the ideal. On the other hand, compromise is achieved through mutual concessions. This method can be presented in the following steps:

Step 1. Determine the best and the worst values of all criteria - determine best and worst values in given problem for the profit type criteria (6) and cost type criteria (7).

$$f_j^* = \max_i f_{ij},\ f_j^- = \min_i f_{ij},\ i = 1, 2, \cdots, m,\ j = 1, 2, \cdots, n \tag{6}$$

$$f_j^* = \min_i f_{ij},\ f_j^- = \max_i f_{ij},\ i = 1, 2, \cdots, m,\ j = 1, 2, \cdots, n \tag{7}$$

Step 2. Compute S_i (8) and R_i values (9) - w_j is weight vector which describe the relevance of a given criterion.

$$S_i = \sum_{i=1}^{n} w_j \frac{(f_j^* - f_{ij})}{(f_j^* - f_j^-)},\ i = 1, 2, \cdots, m,\ j = 1, 2, \cdots, n \tag{8}$$

$$R_i = \max_j \left[w_j \frac{(f_j^* - f_{ij})}{(f_j^* - f_j^-)} \right],\ i = 1, 2, \cdots, m,\ j = 1, 2, \cdots, n \tag{9}$$

Step 3. Compute the values of Q_i by Eq. (10) - v is introduced as a weight for the strategy of the majority of criteria, whereas 1 - v is the weight of the individual regret. These strategies could be compromised by $v = 0.5$.

$$Q_i = v \frac{(S_i - S^*)}{(S^- - S^*)} + (1 - v) \frac{(R_i - R^*)}{(R^- - R^*)},\ i = 1, 2, \cdots, m \tag{10}$$

Step 4. Rank the alternatives - the VIKOR method provides three rankings named S, R and Q. Each of them should be ranked in ascending order. The measures of S and R are integrated into Q for a compromise solution, the base for an agreement established by mutual concessions. It is up to the decision-maker to choose a preferred solution.

3.3 MARCOS Method

The Measurement Alternatives and Ranking according to COmpromise Solution (MARCOS) method provided a new approach to solving decision problems by considering an anti-ideal and an ideal solution a the initial steps of problem-solving. It was first proposed by Željko Stević et al. in 2020 [25] where they introduced the method by solving the problem of sustainable supplier selection in healthcare industries. Moreover, they proposed a new way to determine utility functions and their further aggregation, while maintaining stability in the problems requiring a large set of alternatives and criteria.

Step 1. The initial step requires to define set of n criteria and m alternatives to create decision matrix.

Step 2. Next, the extended initial matrix X should be formed by defining ideal (AI) and anti-ideal(AAI) solution.

$$X = \begin{matrix} AII \\ A_1 \\ A_2 \\ \dots \\ A_m \\ AI \end{matrix} \begin{bmatrix} x_{aa1} & x_{aa2} & \dots & x_{aan} \\ x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \dots & \dots & \dots & \dots \\ x_{m1} & x_{22} & \cdots & x_{mn} \\ x_{ai1} & x_{ai2} & \cdots & x_{ain} \end{bmatrix} \tag{11}$$

The anti-ideal solution (AAI) which is the worst alternative is defined by Eq. (12), whereas the ideal solution (AI) is the best alternative in the problem at hand defined by Eq. (13).

$$AAI = \min_i x_{ij} \quad \text{if } j \in B \text{ and } \max_i x_{ij} \quad \text{if } j \in C \tag{12}$$

$$AI = \max_i x_{ij} \quad \text{if } j \in B \text{ and } \min_i x_{ij} \quad \text{if } j \in C \tag{13}$$

where B is a benefit group of criteria and C is a group of cost criteria.

Step 3. After defining anti-ideal and ideal solutions, the extended initial matrix X needs to be normalized, by applying Eqs. (14) and (15) creating normalized matrix N.

$$n_{ij} = \frac{x_{ai}}{x_{ij}} \quad \text{if } j \in C \tag{14}$$

$$n_{ij} = \frac{x_{ij}}{x_{ai}} \quad \text{if } j \in B \tag{15}$$

Step 4. The weight for each criterion needs to be defined to present its importance in accordance with others. The weighted matrix V needs to be calculated by multiplying the normalized matrix N with the weight vector through Eq. (16).

$$v_{ij} = n_{ij} \times w_j \tag{16}$$

Step 5. Next, the utility degree K of alternatives in relation to the anti-ideal and ideal solutions needs to be calculated by using Eqs. (17) and (18).

$$K_i^- = \frac{\sum_{i=1}^n v_{ij}}{\sum_{i=1}^n v_{aai}} \tag{17}$$

$$K_i^+ = \frac{\sum_{i=1}^n v_{ij}}{\sum_{i=1}^n v_{ai}} \tag{18}$$

Step 6. The utility function f of alternatives, which is the compromise of the observed alternative in relation to the ideal and anti-ideal solution, needs to be determined. Its done using Eq. (19).

$$f\left(K_i\right)=\frac{K_i^{+}+K_i^{-}}{1+\frac{1-f\left(K_i^{+}\right)}{f\left(K_i^{+}\right)}+\frac{1-f\left(K_i^{-}\right)}{f\left(K_i^{-}\right)}} \tag{19}$$

where $f\left(K_i^{-}\right)$ represents the utility function in relation to the anti-ideal solution and $f\left(K_i^{+}\right)$ represents the utility function in relation to the ideal solution.

Utility functions in relation to the ideal and anti-ideal solution are determined by applying Eqs. (20) and (21).

$$f\left(K_i^{-}\right)=\frac{K_i^{+}}{K_i^{+}+K_i^{-}} \tag{20}$$

$$f\left(K_i^{+}\right)=\frac{K_i^{-}}{K_i^{+}+K_i^{-}} \tag{21}$$

Step 7. Finally, rank alternatives accordingly to the values of the utility functions. The higher the value the better an alternative is.

3.4 MABAC Method

The Multi-Attributive Border Approximation Area Comparison (MABAC) is a multi-criteria decision-making method introduced by Pamučar and Ćirović in 2015 [19] on the problem of selection of transport and handling resources in logistics centres. This method's approach was to determine the distance measures between each possible alternative and the boundary approximation area (BAA). Moreover, this method has seen many developments such as extensions into hesitant fuzzy linguistic [26] or q-rung orthopair fuzzy environments [27]. Its original version can be presented in the following steps:

Step 1. Define a decision matrix of dimension $n \times m$, where n is the number of alternatives, and m is the number of criteria (22).

$$x_{ij}=\begin{bmatrix} x_{11} & x_{12} & \dots & x_{1m} \\ x_{21} & x_{22} & \dots & x_{2m} \\ \dots & \dots & \dots & \dots \\ x_{n1} & x_{n2} & \dots & x_{nm} \end{bmatrix} \tag{22}$$

Step 2. Normalization of the decision matrix, where for criteria of type profit use Eq. (23) and for criteria of type cost use Eq. (24).

$$n_{ij}=\frac{x_{ij}-\min x_i}{\max x_i-\min x_i} \tag{23}$$

$$n_{ij}=\frac{x_{ij}-\max x_i}{\min x_i-\max x_i} \tag{24}$$

Step 3. Create a weighted matrix based on the values from the normalized matrix according to the formula (25).

$$v_{ij} = w_i \cdot (n_{ij} + 1) \tag{25}$$

Step 4. Boundary approximation area (G) matrix determination. The Boundary Approximation Area (BAA) for all criteria can be determined using the formula (26).

$$g_i = \left(\prod_{j=1}^{m} v_{ij} \right)^{1/m} \tag{26}$$

Step 5. Distance calculation of alternatives from the boundary approximation area for matrix elements (Q) by Eq. (27).

$$Q = \begin{bmatrix} v_{11} - g_1 & v_{12} - g_2 & \dots & v_{1n} - g_n \\ v_{21} - g_1 & v_{22} - g_2 & \dots & v_{2n} - g_n \\ \dots & \dots & \dots & \dots \\ v_{m1} - g_1 & v_{m2} - g_2 & \dots & v_{mn} - g_n \end{bmatrix} = \begin{bmatrix} q_{11} & q_{12} & \dots & q_{1n} \\ q_{21} & q_{22} & & q_{2n} \\ \dots & \dots & \dots & \dots \\ q_{m1} & q_{m2} & \dots & q_{mn} \end{bmatrix} \tag{27}$$

The membership of a given alternative A_i to the approximation area (G, G^+ or G^-) is established by (28).

$$A_i \in \begin{cases} G^+ \text{ if } & q_{ij} > 0 \\ G \quad \text{ if } & q_{ij} = 0 \\ G^- \text{ if } & q_{ij} < 0 \end{cases} \tag{28}$$

Step 6. Ranking the alternatives according to the sum of the distances of the alternatives from the areas of approximation of the borders (29).

$$S_i = \sum_{j=1}^{n} q_{ij}, \quad j = 1, 2, \dots, n, \quad i = 1, 2, \dots, m \tag{29}$$

3.5 EDAS Method

The Evaluation based on Distance from Average Solution (EDAS) method was proposed by Keshavarz et al. in 2015 [12] and its main aim was to design a method which would be useful when conflicting criteria are present. This method utilizes two different measures, the positive distance from average (PDA), and the negative distance from average (NDA) which can show the difference between each alternative and the average solution. The higher the PDA values are or the lower the NDA values are, the better is the alternative in comparison to the average solution. This method can be executed by following steps:

Step 1. Define a decision matrix of dimension $n \times m$, where n is the number of alternatives, and m is the number of criteria (30).

$$X_{ij} = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1\,m} \\ x_{21} & x_{22} & \dots & x_{2\,m} \\ \dots & \dots & \dots & \dots \\ x_{n1} & x_{n2} & \dots & x_{nm} \end{bmatrix} \tag{30}$$

Step 2. Calculate the average solution for each criterion according to the formula (31).

$$AV_j = \frac{\sum_{i=1}^{n} X_{ij}}{n} \tag{31}$$

Step 3. Calculating the positive distance from the mean solution and the negative distance from the mean solution for the alternatives. When the criterion is of profit type, the negative distance and the positive distance are calculated using Eqs. (32) and (33), while when the criterion is of cost type, the distances are calculated using formulas (34) and (35).

$$NDA_{ij} = \frac{\max\left(0, (AV_j - X_{ij})\right)}{AV_j} \tag{32}$$

$$PDA_{ij} = \frac{\max\left(0, (X_{ij} - AV_j)\right)}{AV_j} \tag{33}$$

$$NDA_{ij} = \frac{\max\left(0, (X_{ij} - AV_j)\right)}{AV_j} \tag{34}$$

$$PDA_{ij} = \frac{\max\left(0, (AV_j - X_{ij})\right)}{AV_j} \tag{35}$$

Step 4. Calculate the weighted sums of PDA and NDA for each decision variant using Eqs. (36) and (37).

$$\mathrm{A}SP_i = \sum_{j=1}^{m} w_j PDA_{ij} \tag{36}$$

$$SN_i = \sum_{j=1}^{m} w_j NDA_{ij} \tag{37}$$

Step 5. Normalize the weighted sums of negative and positive distances using Eqs. (38) and (39).

$$NSN_i = 1 - \frac{SN_i}{\max_i (SN_i)} \tag{38}$$

$$NSP_i = \frac{SP_i}{\max_i (SP_i)} \tag{39}$$

Step 6. Calculate the evaluation score (AS) for each alternative using the formula (40). A higher point value determines a higher ranking alternative.

$$AS_i = \frac{1}{2} (NSP_i + NSN_i) \tag{40}$$

3.6 Weighted Spearman's Correlation Coefficient

Correlation coefficients are used to represent the similarity of compared rankings in a quantifiable way. The weighted Spearman's correlation coefficient is one of the most commonly used coefficients. It was designed to consider the most relevant alternatives which are the ones that were rated the best. This coefficient is presented in Eq. (41).

$$r_w = 1 - \frac{6 \cdot \sum_{i=1}^{n} (x_i - y_i)^2 ((N - x_i + 1) + (N - y_i + 1))}{n \cdot (n^3 + n^2 - n - 1)} \tag{41}$$

4 Research Findings and Discussion

The Iterative Compromise Ranking Approach (ICRA) main aim is to provide a way of compromising rankings obtained through different multi-criteria decision-making methods. A need arose as many methods are proposed which provided a new way of evaluating the alternatives. However, this creates a problem in which the best decision-making method must be picked for the final evaluation of alternatives, which might not be an easy case in some situations, thus such a compromise approach might be better suited. To carry out this approach, the following steps are required:

Step 1. Evaluate formed decision matrix by n MCDM methods

Step 2. Create a decision matrix based on the preference value calculated by MCDM methods. Criteria types are determined based on the method's ranking type.

Step 3. Return to step 1 until rankings provided by all selected methods are the same. For the purpose of comparison correlation coefficient usage is preferred and in this work, the weighted Spearman's correlation coefficient was used.
The study of the solution was carried out by demonstrating the use of ICRA on a randomly generated example, and by analyzing the influence of factors on the course of the solution by generating one hundred random decision matrices, and then changing the research factor, whose influence was shown on boxen plots.

4.1 Theoretical Example

In the first approach, a decision matrix with ten alternatives and eight criteria was generated. The types of criteria were set as follows: C_1 - Cost, C_2 - Cost, C_3 - Profit, C_4 - Cost, C_5 - Profit, C_6 - Profit, C_7 - Cost, C_8 - Cost. The matrix was randomly generated, where the values fell within the normal distribution $[0, 1]$. For the use of multi-criteria decision-making methods, the weights were divided evenly, i.e. each criterion had the same significance. The matrix is shown in Table 1.

The Spearman weighted correlation values of ranking i with ranking $i-1$ are shown in Table 2. From the values shown, we can see that the TOPSIS method stabilised the fastest, followed by the MABAC method, the EDAS method and

Table 1. Generated theoretical problem decision matrix.

A_i	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	0.695342	0.537567	0.817879	0.590484	0.669001	0.06372	0.224616	0.936154
A_2	0.191504	0.485942	0.041557	0.288029	0.011213	0.981233	0.312331	0.222928
A_3	0.30724	0.320894	0.453718	0.573191	0.711328	0.314716	0.365802	0.893979
A_4	0.947824	0.307941	0.537124	0.961897	0.089169	0.698669	0.976673	0.465632
A_5	0.121483	0.376043	0.571574	0.292358	0.728113	0.739274	0.958435	0.836585
A_6	0.741406	0.482223	0.844639	0.254446	0.509148	0.429902	0.490728	0.308689
A_7	0.170687	0.433029	0.030963	0.932767	0.7613	0.930262	0.54715	0.038406
A_8	0.734518	0.738879	0.572844	0.649799	0.812476	0.85712	0.832846	0.181159
A_9	0.729182	0.103717	0.92813	0.532178	0.442577	0.298785	0.293263	0.050323
A_10	0.82726	0.327959	0.759711	0.407212	0.848137	0.578501	0.307067	0.854799
$Type$	$Cost$	$Cost$	$Profit$	$Cost$	$Profit$	$Profit$	$Cost$	$Profit$

Table 2. Spearman's weighted coefficient r_w values for subsequent iterations.

Iteration	Methods				
	TOPSIS	VIKOR	MARCOS	MABAC	EDAS
i = 2	1.0	0.906336	0.850137	0.987878	0.990082
i = 3	1.0	0.960330	0.940495	1.0	0.966942
i = 4	1.0	0.987878	1.0	1.0	1.0
i = 5	1.0	1.0	1.0	1.0	1.0

the MARCOS method, and finally the VIKOR method, where in the case of the VIKOR method five iterations were needed to obtain the final compromise. It is interesting case that the TOPSIS method ranking in this case did not require any modification.

The rankings obtained in each iteration for each method are shown in Fig. 1. As can be seen, the TOPSIS method showed no changes, MABAC and EDAS have slightly visible changes, but the largest changes in rankings are seen for the MARCOS and VIKOR methods. For the MABAC method, the most significant changes are the positions of the sixth and ninth alternatives, where they have swapped positions, but this is not a change at the podium of the ranking so it is not that significant. In the case of the EDAS method, the situation is similar, except that there are more changes, namely for the second, sixth and ninth alternatives, but these are also not significant changes as these alternatives are more or less in the middle of the ranking. In the case of the MARCOS and VIKOR methods, changes are evident not only in the middle of the ranking but also in the podium, which means that the initial ranking differs quite significantly compared to the compromise ranking.

In Fig. 2 the preferences in consecutive iterations are presented for each of the considered methods. Even though, the ranking for the TOPSIS method did not change the preferences changed significantly, more precisely the range and

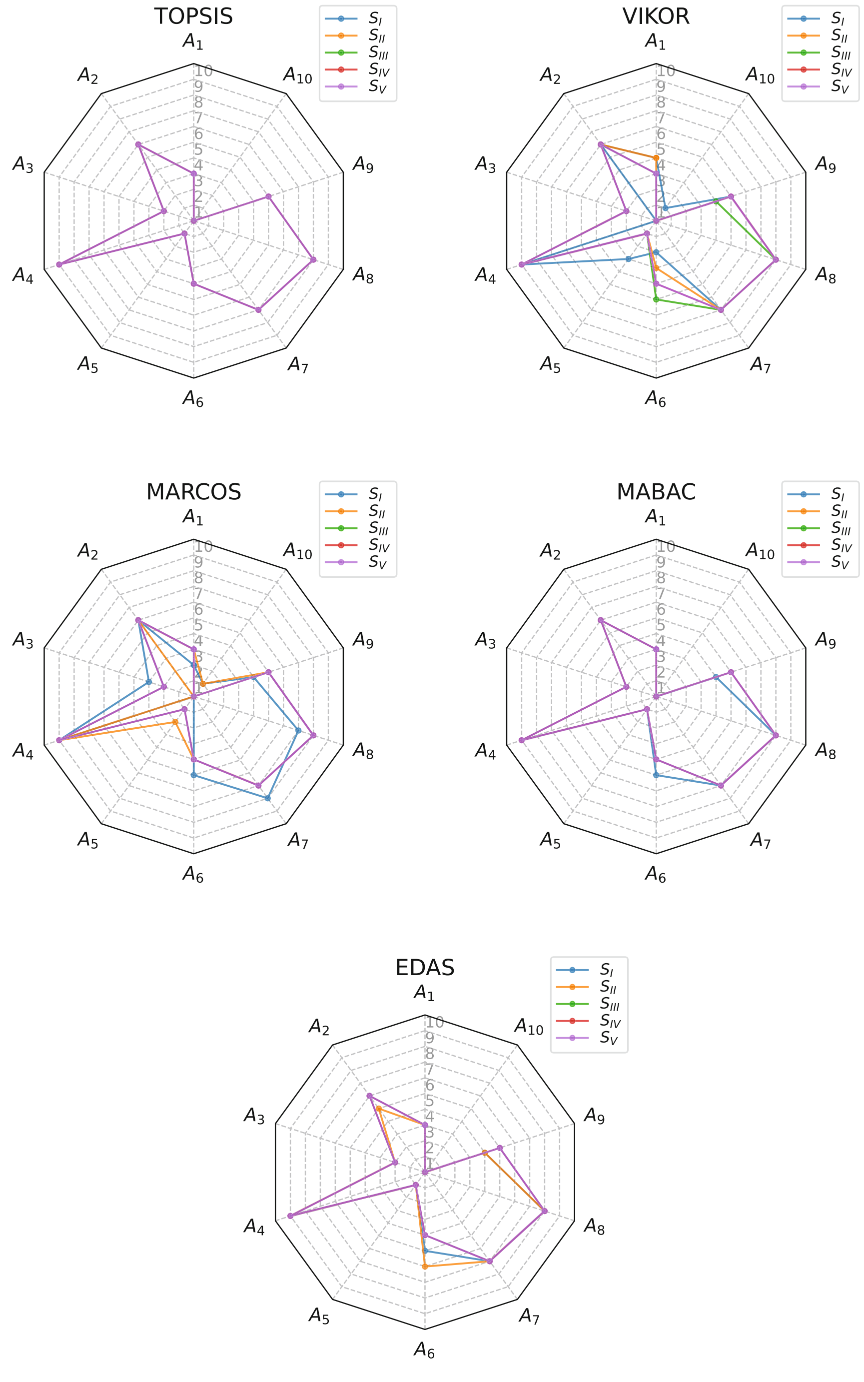

Fig. 1. Obtained rankings for TOPSIS, VIKOR, MARCOS, MABAC, and EDAS methods in subsequent iterations.

standard deviation of values have changed. In the first iteration, the standard deviation of preference values was around 0.0885, whereas in the last iteration the values presented a standard deviation of around 0.2987. Moreover, the range of the values extended from $[0.3658, 0.6679]$ to $[0, 1]$, making the spread 0.7 higher than in the first iteration. A similar high change in the standard deviation of values can be seen in the MARCOS method where it changed from 0.0917 to 0.3372 and the spread increased by around 0.8. In the case of the MABAC method, the changes are less visible as the standard deviation in the first iteration was around 0.1189 and 0.2988 in the last iteration. The spread of the values increased by around 0.595. However, the least change occurred in the VIKOR and the EDAS methods. It is interesting as the highest change in the actual ranking was presented by the VIKOR method. In the case of the VIKOR method the standard deviation changed from 0.2888 to 0.3 and the spread of values increased by around 0.065. The MABAC method presented a similar small change as in the standard deviation it was a difference of around 0.038, namely from 0.2473 to 0.2853 and the spread of values increased by around 0.13. This shows that an iterative approach to compromise ranking stretches the range of values of preferences and provides more distinctive evaluation of alternatives as the standard deviation and spread is higher.

4.2 Analysis of the Compromise Approach

The second approach consisted of generating one hundred decision matrices to draw quantitative conclusions from the compromise ranking approach under consideration. The research was conducted on the same five multi-criteria decision-making methods used in the theoretical example. First, the effect of the number of alternatives in the decision problem on the number of iterations needed to obtain a compromise was tested. Each matrix size was generated one hundred times, where the matrix size was n alternatives by six criteria, and the values were generated from the normal distribution $[0, 1]$.

Initially, the matrices were generated with the number of alternatives in the range $[10, 100]$ with a step of 10, which should represent most small problems. The results obtained are shown in the Fig. 3. It can be seen that for small problems i.e. those that contain ten alternatives, the average number of iterations remains at 4. The number of iterations increases gradually as the number of iterations increases, slowing down with a larger number of alternatives, whereas with 100 alternatives, an average of 9 iterations were needed to reach a compromise.

The second case that was considered was problems consisting of a much larger number of alternatives. The sizes that were checked are in the range of $[100, 1000]$ with a step of 100. The results for this case are shown in Fig. 4. As can be seen in the boxen plots shown, the values slowly increased until, with a matrix containing 700 alternatives, it grew rapidly, but at higher values, it already increased slightly. This behaviour may show that the number of iterations needed can increase sharply in huge decision problems at specific sizes and then stay within a single value. In the case of 1000 alternatives, the compromise was obtained after 22 iterations on average, which, looking at the size of the

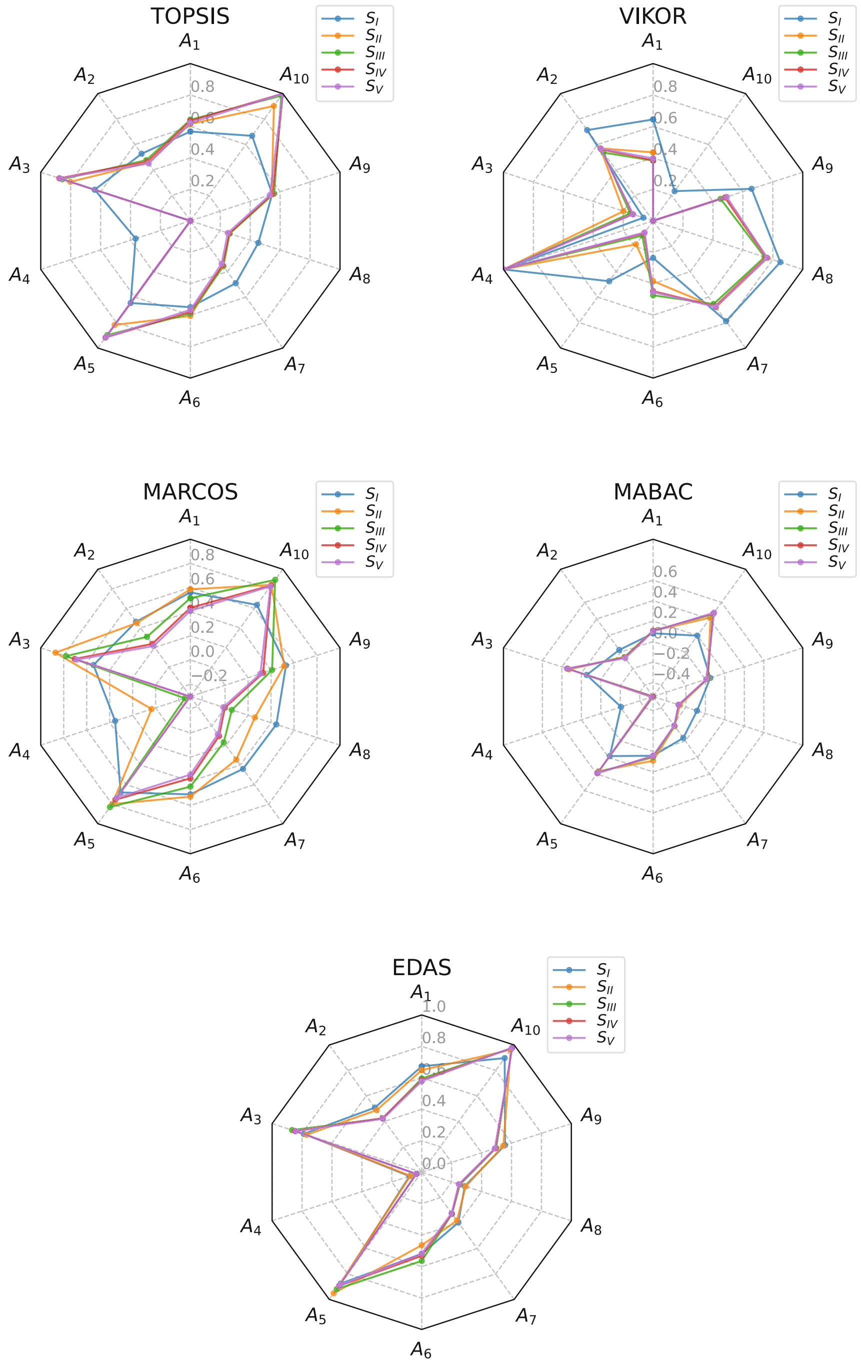

Fig. 2. Obtained preference for TOPSIS, VIKOR, MARCOS, MABAC, and EDAS methods in subsequent iterations.

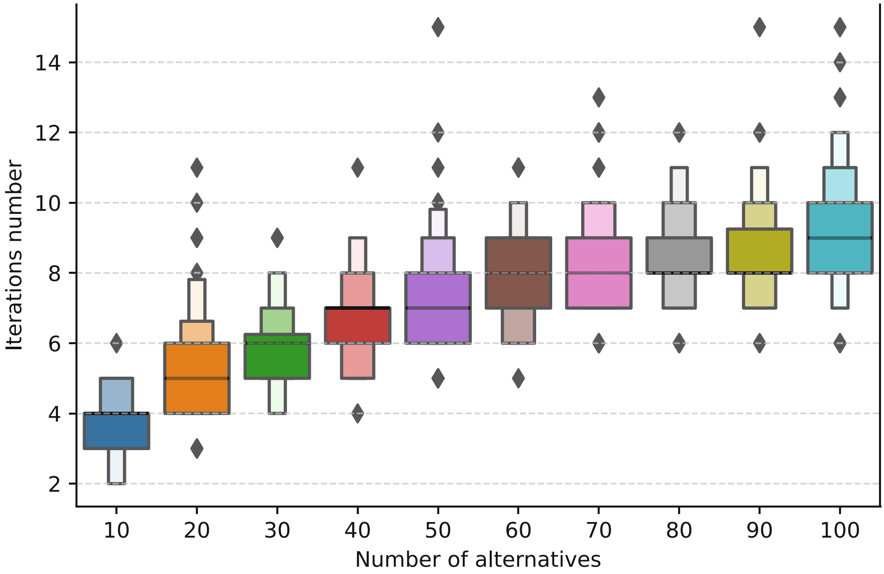

Fig. 3. Influence of number of alternatives on the number of iterations in small decision problems.

problem, does not seem to be a large value, because as the number of alternatives in a decision problem increases, the difficulty of decision-making increases significantly.

For each method considered, it was checked how the ranking proposed in the first step by methods changes in relation to the compromise ranking obtained. A hundred matrices were generated with values from the normal distribution $[0, 1]$ with the size of ten alternatives and six criteria. The values were visualized in Fig. 5. The TOPSIS method in this chart proposed rankings closest to the compromise rankings, followed by the MABAC method, MARCOS, EDAS, and finally VIKOR. In the case of the VIKOR method, there were the greatest discrepancies in the compromise rankings relative to the initial rankings. It can be said in this case that all methods except VIKOR proposed similar rankings. In such cases, the compromise approach can prove to be a good solution, as it takes into account how the majority opined, given the rating, which differed significantly.

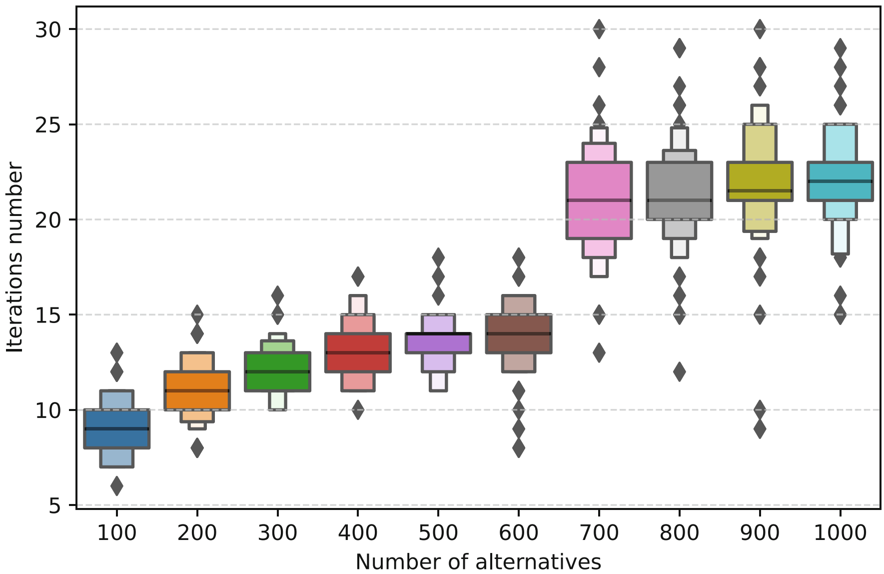

Fig. 4. Influence of number of alternatives on the number of iterations in big decision problems.

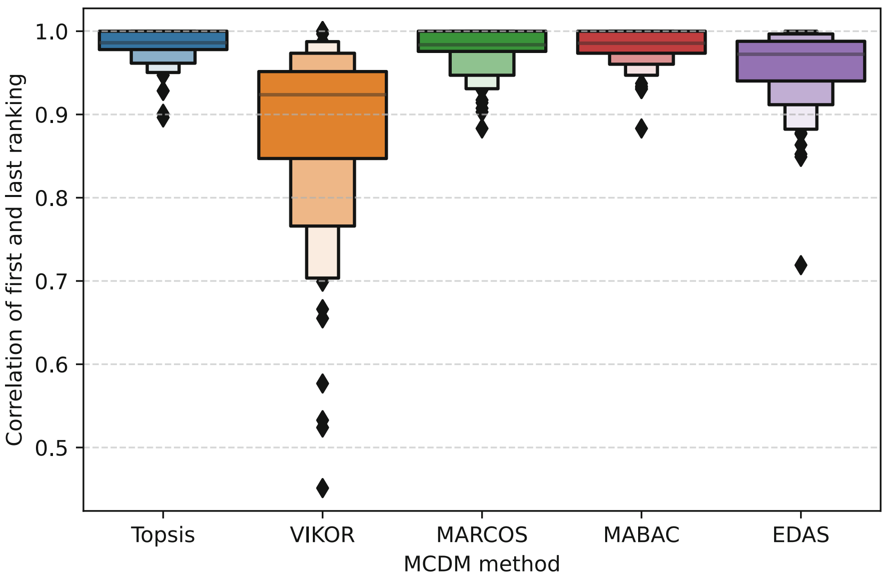

Fig. 5. Correlation between first ranking provided by a method and compromise ranking.

5 Conclusion

The ever-evolving field of multi-criteria decision-making requires the search for non-standard solutions to produce a result that could be considered appropriate by the decision-maker. One of the important problems is obtaining a compromise between different decision-making methods. While these are interesting tools for determining the set of best solutions to the problem under consideration, discrepancies in final rankings often arise between the results from different methods. To determine a single final ranking from different multi-criteria decision-making methods, we can use an iterative approach to obtain a compromise ranking.

In this study, the use of this approach to solve the theoretical problem using TOPSIS, VIKOR, MARCOS, MABAC, and EDAS methods is presented. The use of the ranking similarity coefficient to obtain the final result guarantees its stability and reliability. The study showed that this is a method that can easily be used to obtain a compromise ranking, which will allow aggregation of results from multiple methods using a larger value space for preference evaluation, as well as an increased standard deviation of preference values. An additional quantitative study showed how the method behaves according to the different number of alternatives and the similarity of the initial rankings to the compromise ranking for a particular method. This shows the feasibility of using this method to compare multi-criteria decision-making methods as well as the simplicity and fast execution of using this approach.

In future studies, it would be worthwhile to test the broader applicability of this approach for comparing multi-criteria decision-making methods. In addition, it would be important to see how the number and specific set of methods affect the resulting solution, and to what extent this affects the number of iterations needed to reach a compromise. Moreover, it would be good practice to conduct multiple analyses of real-world problems.

References

1. Abdul, D., Wenqi, J., Tanveer, A.: Prioritization of renewable energy source for electricity generation through AHP-VIKOR integrated methodology. Renew. Energy **184**, 1018–1032 (2022). https://doi.org/10.1016/j.renene.2021.10.082
2. Bączkiewicz, A., Kizielewicz, B., Shekhovtsov, A., Wątróbski, J., Sałabun, W.: Methodical aspects of MCDM based e-commerce recommender system. J. Theor. Appl. Electron. Commer. Res. **16**(6), 2192–2229 (2021). https://doi.org/10.3390/jtaer16060122
3. Ceballos, B., Lamata, M.T., Pelta, D.A.: A comparative analysis of multi-criteria decision-making methods. Progr. Artif. Intell. **5**(4), 315–322 (2016). https://doi.org/10.1007/s13748-016-0093-1
4. Chodha, V., Dubey, R., Kumar, R., Singh, S., Kaur, S.: Selection of industrial arc welding robot with topsis and entropy MCDM techniques. Mater. Today Proc. **50**, 709–715 (2022). https://doi.org/10.1016/j.matpr.2021.04.487
5. Diakoulaki, D., Mavrotas, G., Papayannakis, L.: Determining objective weights in multiple criteria problems: the critic method. Comput. Oper. Res. **22**(7), 763–770 (1995). https://doi.org/10.1016/0305-0548(94)00059-H

6. Duckstein, L., Opricovic, S.: Multiobjective optimization in river basin development. Water Resour. Res. **16**(1), 14–20 (1980). https://doi.org/10.1029/WR016i001p00014
7. Ecer, F.: A consolidated MCDM framework for performance assessment of battery electric vehicles based on ranking strategies. Renew. Sustain. Energy Rev. **143**, 110916 (2021). https://doi.org/10.1016/j.rser.2021.110916
8. Ghaleb, A.M., Kaid, H., Alsamhan, A., Mian, S.H., Hidri, L.: Assessment and comparison of various MCDM approaches in the selection of manufacturing process. Adv. Mater. Sci. Eng. **2020**, 1–16 (2020). https://doi.org/10.1155/2020/4039253
9. Gul, M., Celik, E., Aydin, N., Gumus, A.T., Guneri, A.F.: A state of the art literature review of VIKOR and its fuzzy extensions on applications. Appl. Soft Comput. **46**, 60–89 (2016). https://doi.org/10.1016/j.asoc.2016.04.040
10. Ju, Y., Wang, A.: Extension of VIKOR method for multi-criteria group decision making problem with linguistic information. Appl. Math. Model. **37**(5), 3112–3125 (2013). https://doi.org/10.1016/j.apm.2012.07.035
11. Keshavarz-Ghorabaee, M., Amiri, M., Zavadskas, E.K., Turskis, Z., Antucheviciene, J.: Determination of objective weights using a new method based on the removal effects of criteria (MEREC). Symmetry **13**(4), 525 (2021). https://doi.org/10.3390/sym13040525
12. Keshavarz Ghorabaee, M., Zavadskas, E.K., Olfat, L., Turskis, Z.: Multi-criteria inventory classification using a new method of evaluation based on distance from average solution (EDAS). Informatica **26**(3), 435–451 (2015)
13. Kizielewicz, B., Shekhovtsov, A., Sałabun, W.: A novel iterative approach to determining compromise rankings. In: 2022 17th Conference on Computer Science and Intelligence Systems (FedCSIS), pp. 783–787. IEEE (2022). https://doi.org/10.15439/2022F255
14. Krishnan, A.R., Kasim, M.M., Hamid, R., Ghazali, M.F.: A modified critic method to estimate the objective weights of decision criteria. Symmetry **13**(6), 973 (2021). https://doi.org/10.3390/sym13060973
15. Lamboray, C.: A comparison between the prudent order and the ranking obtained with Borda's, Copeland's, slater's and Kemeny's rules. Math. Soc. Sci. **54**(1), 1–16 (2007). https://doi.org/10.1016/j.mathsocsci.2007.04.004
16. Lestari, S., Adji, T.B., Permanasari, A.E.: Performance comparison of rank aggregation using Borda and Copeland in recommender system. In: 2018 International Workshop on Big Data and Information Security (IWBIS), pp. 69–74. IEEE (2018). https://doi.org/10.1109/IWBIS.2018.8471722
17. Muravyov, S.V., Emelyanova, E.Y.: Kemeny rule for preference aggregation: reducing all exact solutions to a single one. Measurement **182**, 109403 (2021). https://doi.org/10.1016/j.measurement.2021.109403
18. Özdağoğlu, A., Keleş, M.K., Altınata, A., Ulutaş, A.: Combining different MCDM methods with the Copeland method: an investigation on motorcycle selection. J. Process. Manag. New Technol. **9**(3–4), 13–27 (2021). https://doi.org/10.5937/jpmnt9-34120
19. Pamučar, D., Ćirović, G.: The selection of transport and handling resources in logistics centers using multi-attributive border approximation area comparison (MABAC). Expert Syst. Appl. **42**(6), 3016–3028 (2015). https://doi.org/10.1016/j.eswa.2014.11.057
20. Paradowski, B., Shekhovtsov, A., Bączkiewicz, A., Kizielewicz, B., Sałabun, W.: Similarity analysis of methods for objective determination of weights in multi-criteria decision support systems. Symmetry **13**(10), 1874 (2021). https://doi.org/10.3390/sym13101874

21. Podvezko, V., Zavadskas, E.K., Podviezko, A.: An extension of the new objective weight assessment methods CILOS and IDOCRIW to fuzzy MCDM. Econ. Comput. Econ. Cybern. Stud. Res. **54**(2) (2020). https://doi.org/10.24818/18423264/54.2.20.04
22. Qin, J., Liu, X., Pedrycz, W.: An extended VIKOR method based on prospect theory for multiple attribute decision making under interval type-2 fuzzy environment. Knowl.-Based Syst. **86**, 116–130 (2015). https://doi.org/10.1016/j.knosys.2015.05.025
23. Roozbahani, A., Ebrahimi, E., Banihabib, M.E.: A framework for ground water management based on Bayesian network and MCDM techniques. Water Resour. Manag. **32**(15), 4985–5005 (2018). https://doi.org/10.1007/s11269-018-2118-y
24. Serrai, W., Abdelli, A., Mokdad, L., Hammal, Y.: Towards an efficient and a more accurate web service selection using MCDM methods. J. Comput. Sci. **22**, 253–267 (2017). https://doi.org/10.1016/j.jocs.2017.05.024
25. Stević, Ž, Pamučar, D., Puška, A., Chatterjee, P.: Sustainable supplier selection in healthcare industries using a new MCDM method: measurement of alternatives and ranking according to compromise solution (MARCOS). Comput. Industr. Eng. **140**, 106231 (2020). https://doi.org/10.1016/j.cie.2019.106231
26. Sun, R., Hu, J., Zhou, J., Chen, X.: A hesitant fuzzy linguistic projection-based MABAC method for patients' prioritization. Int. J. Fuzzy Syst. **20**(7), 2144–2160 (2017). https://doi.org/10.1007/s40815-017-0345-7
27. Wang, J., Wei, G., Wei, C., Wei, Y.: MABAC method for multiple attribute group decision making under q-rung orthopair fuzzy environment. Defence Technol. **16**(1), 208–216 (2020). https://doi.org/10.1016/j.dt.2019.06.019
28. Wątróbski, J., Jankowski, J., Ziemba, P., Karczmarczyk, A., Zioło, M.: Generalised framework for multi-criteria method selection. Omega **86**, 107–124 (2019). https://doi.org/10.1016/j.omega.2018.07.004
29. Wu, X., Liao, H., Xu, Z., Hafezalkotob, A., Herrera, F.: Probabilistic linguistic multimoora: a multicriteria decision making method based on the probabilistic linguistic expectation function and the improved Borda rule. IEEE Trans. Fuzzy Syst. **26**(6), 3688–3702 (2018). https://doi.org/10.1109/TFUZZ.2018.2843330
30. Yazdani, M., Zarate, P., Zavadskas, E.K., Turskis, Z.: A combined compromise solution (COCOSO) method for multi-criteria decision-making problems. Manag. Decis. **57**(9), 2501–2519 (2018). https://doi.org/10.1108/MD-05-2017-0458
31. Zavadskas, E.K., Podvezko, V.: Integrated determination of objective criteria weights in MCDM. Int. J. Inf. Technol. Decis. Making **15**(02), 267–283 (2016). https://doi.org/10.1142/S0219622016500036