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TOWARDS RELIABLE DECISION-MAKING IN THE GREEN URBAN TRANSPORT DOMAIN

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Abstract. *Operational research is a scientific discipline related to the decision theory that allows determining solutions for specific problems related to, for example, widely understood transport. Increasingly popular in this field are issues related to the domain of the green urban transport. In order to support the decision-making process in this area, methods of multi-criteria decision analysis (MCDA) are used more and more often. However, if we solve a specific problem using different MCDA methods, we get different rankings, as each method has a different methodological basis. Therefore, the challenge is how to make a reliable decision. This paper presents a numerical example from the green urban transport domain, which is solved by six different MCDA methods that return a complete ranking. We measure the similarity of these rankings using coefficients r_w and WS, and then we propose a simple way of determining a compromise solution. The obtained compromise ranking is guaranteed to be the best match to the selected MCDA methods' rankings, which is proved in the paper. Finally, possible directions for further development work are identified.*

Key Words: *MCDA, Transport Selection, Green Urban Transport, Operational Research*

1. INTRODUCTION

Decision-making problems appear in every aspect of our lives. Many factors are involved in making a choice, which makes it much more difficult [1]. Sometimes decision-making is influenced by emotions, making the choices made biased. However, making a choice should always maximize benefits and minimize possible losses. To support decision-making and to remain objective in the process, many methods have been

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developed to support the decision-maker [2, 3]. The models based on these methods are designed to indicate which of the considered alternatives are better than the others. Nevertheless, a more critical aspect is whether getting even different rankings can contribute to a more reliable solution.

There are often used methods belonging to the multi-criteria decision analysis (MCDA) methods in support systems, which work on the basis of evaluating a set of alternatives and giving them preference values thus assessing their quality concerning other options [4]. The group of MCDA methods is constantly extended by newly created methods, making it difficult to choose a method to solve the selected task [5, 6]. Moreover, another difficulty may be determining whether choosing a different method to solve the same problem may give different results [1]. It makes it worthwhile to lean into answering the question if the choice of MCDA method matters.

MCDA methods can be divided into three main groups, the American school of methods, the European school of methods and rule-based methods [7, 8]. Each group is based on slightly different assumptions about how the problem should be solved, but in general, each attempts to obtain a ranking that evaluates the alternatives under consideration. The effectiveness of MCDA methods has been tested many times, and they have been used to solve problems of selecting industrial locations [9, 10], material suppliers [11, 12], in sports [13, 14] or medicine [15]. These methods are willingly used by experts, making them increasingly applicable to a wide range of problems. Moreover, a particular decision problem can often be solved using more than one method but then we get different rankings. It is related to assumptions used in the algorithms, which can be exemplary based on the distance from the best or the best and the worst element. Therefore, these solutions are not incorrect from the methodological point of view. However, it should be considered how to decide on the basis of such rankings in order to make the decision as reliable as possible.

However, in the cases where MCDA methods guarantee different results within one problem, it is worthwhile to determine the extent to which the obtained results are similar [16]. For this purpose, correlation coefficients can be used to assess the similarity of the analyzed rankings through numerical values. These coefficients include Spearman's weighted correlation coefficient and *WS* similarity coefficient [8, 17]. Firstly, it is an opportunity to determine how strongly different results were returned by the methods used. Secondly, it can be used to establish a compromise ranking. For this purpose, measures need to be defined to determine whether a given ranking is a better compromise.

In this paper, we propose a new approach to determine the compromise ranking based on the similarity rankings. The proposed approach is extremely simple and is intended to compromise ranking based on the rankings obtained from various MCDA methods. We present our methodology by using a theoretical multi-criteria problem in the form of the selection of the electric bus. For this purpose, we have selected six MCDA methods that give a full ranking as a result. The obtained results from TOPSIS, VIKOR, PROMETHEE II, COPRAS, COMET, and SPOTIS methods are then compared using the similarity coefficients to check how the rankings correspond to each other. On this basis, we define two measures indicating which of the resulting rankings the best compromise ranking is. Then, we determine the compromise ranking whose result is the closest to all the rankings considered. This results in a final compromise ranking that indicates the most reliable solutions in the absence of knowledge of the reference solution.

The rest of the paper is organized as follows. In Sections 2.1-2.6, the preliminaries of selected MCDA methods are presented. The ranking similarity coefficients are presented in Section 2.7. Section 3 includes an empirical study case, in which the comparison of six given methods application, namely TOPSIS, VIKOR, PROMETHEE II, COPRAS, COMET, and SPOTIS, is made. Section 4 describes the proposed approach to obtain compromise ranking and a short discussion, and finally, the conclusions from the research are drawn in Section 5.

2. Preliminaries

Multi-Criteria Decision Analysis (MCDA) methods solve a multi-criteria problem in various areas [13, 14, 18]. With an extended trend in using these methods to solve problems, more extensions and new techniques are being developed [19, 20]. In this section, we recall the algorithms of the MCDA methods (Sections 2.1-2.6) and the used similarity coefficients (Sections 2.7 and 2.8). It is necessary because there are many versions of these algorithms in the literature [21, 22, and 23].

2.1. The TOPSIS method

The Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) method was developed in 1992 [24]. Chen and Hwang proposed an approach to examining the set of alternatives based on the calculation of the distance to the ideal solution. To evaluate the alternatives' preferences, the Positive Ideal Solution (PIS) and Negative Ideal Solution (NIS) are used [25, 26]. The method application requires an expert to define a weights vector, which describes the relevance of criteria [27]. The first step is to normalize the decision matrix in order to obtain the correct final result. Next, a weighted normalized decision matrix should be calculated using the following Eq. (1).

$$v_{ij} = w_i \cdot r_{ij},\ j = 1,\ldots,J; i = 1,\ldots,n \tag{1}$$

where w_i is the value of the *i-th* weighting, r_{ij} is the normalized attribute for the *j-th* alternative against the *i-th* criterion, v_{ij} is the weighted normalized attribute for the *j-th* alternative against the *i-th* criterion, n is the number of criteria, and J is the number of alternatives. Positive (A^*) and negative (A^-) ideal solutions for a defined decision-making problem should also be identified as Eq. (2):

$$\begin{aligned} A^* &= \{v_1^*,\ldots,v_n^*\} = \{(\max_j v_{ij} \mid i \in I^P), (\min_j v_{ij} \mid i \in I^C)\} \\ A^- &= \{v_1^-,\ldots,v_n^-\} = \{(\min_j v_{ij} \mid i \in I^P), (\max_j v_{ij} \mid i \in I^C)\} \end{aligned} \tag{2}$$

where I^C stands for cost type criteria and I^P for profit type.

Negative and positive distance from an ideal solution should be calculated using the n-dimensional Euclidean distance. To apply such calculations, the formula presented below should be used Eq. (3):

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

The last step is to calculate the relative closeness to the ideal solution by Eq. (4):

$$C_j^* = \frac{D_j^-}{(D_j^* + D_j^-)},\ j = 1,\ldots,J \quad (4)$$

2.2. The VIKOR method

The VIKOR (*VIseKriterijumska Optimizacija I Kompromisno Resenje*) method was developed by Opricovic in 1998 [28]. The final preferences for alternatives are calculated using expert knowledge and the closeness of the solution to the ideal solution [29, 30]. The input data does not need to be normalized as in the TOPSIS method [31]. Each of the criteria is initially defined as a cost or profit type of criteria by Eq. (5). The cost type shows that we want it to achieve the lowest possible values, while the profit type should achieve the highest possible values.

$$f_i^* = max_j\, f_{ij},\ f_i^- = min_j\, f_{ij}\ \ if\ \ the\ i-th\ criteria\ is\ a\ \ profi\ type;$$
$$f_i^* = min_j\, f_{ij},\ f_i^- = max_j\, f_{ij}\ \ if\ \ the\ i-th\ criteria\ is\ a\ cost\ type \quad (5)$$

$$w_j \cdot \frac{f_j^* - f_{ij}}{f_j^* - f_i^-} \quad (6)$$

For each of the criteria, the best f_i^* and the worst f_i^- values are defined. Then, using the formula presented in Eq. (6), preference values for each criterion are calculated, taking into account the weights for criteria defined at the beginning. On this basis, the closeness to the ideal solution is calculated, considered in three different rankings calculated from Eq. (7), Eq. (8) and Eq. (9) for *S*, *R*, and *Q*, respectively.

$$S_i = \sum_{j=1}^{N} w_j \cdot \frac{f_j^* - f_{ij}}{f_j^* - f_i^-} \quad (7)$$

$$R_i = max_j \left[w_j \cdot \frac{f_j^* - f_{ij}}{f_j^* - f_i^-} \right] \quad (8)$$

$$Q_i = v \cdot \frac{S_i - S^*}{S^- - S^*} + (1 - v) \cdot \frac{R_i - R^*}{R^- - R^*} \quad (9)$$

2.3. The PROMETHEE II method

The Preference Ranking Organization METHod for Enrichment of Evaluations (PROMETHEE) is a family of MCDA methods developed by Brans [32, 33]. It uses input data similar to other methods, but it optionally requires choosing preference function and some other variables. In this paper, we use the PROMETHEE II method because the output of this method is a full ranking of the alternatives. It is the approach where a complete ranking of the actions is based on the multicriteria net flow. It includes preferences and indifferences (preorder) [34]. According to [32, 35], PROMETHEE II is designed to solve the following multicriteria problems:

$$max\{\ g_1(a), g_2(a), \ldots g_n(a) \mid a \in A\ \} \tag{10}$$

where A is a finite set of alternatives and $g_i(\cdot)$ is a set of evaluation criteria either to be maximized or minimized. In other words, $g_i(a_j)$ is a value of criteria i for alternative a_j. With this values and weights we can define evaluation table.

Table 1 Evaluation table

a	$g_1(\cdot)$	$g_2(\cdot)$	$\ldots$	$g_n(\cdot)$
	w_1	w_2	$\ldots$	w_n
a_1	$g_1(a_1)$	$g_2(a_1)$	$\ldots$	$g_n(a_1)$
a_1	$g_1(a_2)$	$g_2(a_2)$	$\ldots$	$g_n(a_2)$
$\ldots$	$\ldots$	$\ldots$	$\ldots$	$\ldots$
a_m	$g_1(a_m)$	$g_2(a_m)$	$\ldots$	$g_n(a_m)$

Step 1. After defining the problem as described above, calculate preference function values. It defined as Eq. (11) for profit criteria.

$$P(a,b) = F[d(a,b)], \forall a,b \in A \tag{11}$$

where *d(a,b)* is the difference between two actions (pairwise comparison):

$$d(a,b) = g(a) - g(b) \tag{12}$$

and the value of preference function P is always between 0 and 1 and it is calculated for each criterion.

Step 2. Calculate aggregated preference indices by Eq. (13).

$$\begin{cases} \pi(a,b) = \sum_{j=1}^{n} P_j(a,b) w_j \\ \pi(b,a) = \sum_{j=1}^{n} P_j(b,a) w_j \end{cases} \tag{13}$$

where a and b are alternatives and $\pi(a,b)$ shows how much alternative a is preferred to b over all of the criteria. There are some properties Eq. (14) which must be true for all alternatives set A.

$$\begin{cases} \pi(a,a) = 0 \\ 0 \le \pi(a,b) \le 1 \\ 0 \le \pi(b,a) \le 1 \\ 0 \le \pi(a,b) + \pi(b,a) \le 1 \end{cases} \tag{14}$$

Step 3. Next, calculate positive Eq. (15) and negative Eq. (16) outranking flows.

$$\phi^{+}(a) = \frac{1}{m-1}\sum_{x \in A}\pi(a,x) \tag{15}$$

$$\phi^{-}(a) = \frac{1}{m-1}\sum_{x \in A}\pi(x,a) \tag{16}$$

Step 4. In this paper, we use only PROMETHEE II, which results in a complete ranking of alternatives. Ranking is based on the net flow Φ Eq. (17).

$$\Phi(a) = \Phi^{+}(a) - \Phi^{-}(a) \tag{17}$$

A larger value of $\Phi(a)$ means a higher position in the ranking.

2.4. The COPRAS method

The COmplex PRoportional ASsessment (COPRAS), introduced by Zavadskas [36, 37] assumes a direct and proportional relationship of the importance of the investigated variants on a system of criteria adequately describing the decision variants as well as on values and weights of the criteria [38].

This method ranks alternatives based on their relative importance (weight). Final ranking is creating using the positive and negative ideal solutions [37, 39]. Assuming that we have decision matrix with m alternatives and n criteria is represented as $X = f_{ij}(A_i)_{m \times n}$, COPRAS method is defined in the following five steps.:

Step 1. Calculate normalized decision matrix using Eq. (18).

$$r_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \tag{18}$$

Step 2. Calculate difficult normalized decision matrix, which represents multiplication of the normalized decision matrix elements with the appropriate weight coefficients using Eq. (19).

$$v_{ij} = r_{ij} \cdot w_j \tag{19}$$

Step 3. Determine the sums of difficult normalized values which were calculated previously. Eq. (20) should be used for profit criteria and Eq. (21) for cost criteria.

$$S_{+i} = \sum_{j=1}^{k} v_{ij} \tag{20}$$

$$S_{-i} = \sum_{j=k+1}^{n} v_{ij} \tag{21}$$

Step 4. Calculate the relative significance of alternatives using Eq. (22).

$$Q_i = S_{+i} + \frac{S_{-min} \cdot \sum_{i=1}^{m} S_{-i}}{S_{-i} \cdot \sum_{i=1}^{m} \left(\frac{S_{-min}}{S_{-i}} \right)} \tag{22}$$

Step 5 Final ranking is performed according U_i values Eq. (23).

$$U_i = \frac{Q_i}{Q_i^{max}} \cdot 100\% \tag{23}$$

where Q_i^{max} stands for maximum value of the utility function. Better alternatives have higher U_i value, e.g. the best alternative has $U_i = 100$.

2.5. The COMET method

The Characteristic Objects Method (COMET) belongs to the rule-based MCDA methods [41]. The final preferences for the alternatives are calculated on the rule base, which is obtained by defining the Characteristic Objects and pairwise comparison made by expert [42]. Moreover, it is worth noticing that COMET is the first method to be completely free of the rank reversal phenomenon [42, 43]. The formal notation of this method can be shortly recalled in the following five steps [44, 45, 46, 47].

Step 1. Define the Space of the Problem – the expert determines the dimensionality of the problem by selecting number r of criteria, $C_1, C_2, ..., C_r$. Then, the set of fuzzy numbers for each criterion C_i is selected Eq. (24):

$$C_{n_r} = \{C_{r1}, C_{r2}, ..., C_{rn_r}\} \tag{24}$$

where n_r is a number of the fuzzy numbers for criterion r.

Step 2. Generate Characteristic Objects – The characteristic objects (CO) are obtained by using the Cartesian Product of fuzzy numbers cores for each criterion as follows Eq. (25):

$$CO = C(C_1) \times C(C_2) \times \ldots \times C(C_r) \tag{25}$$

Step 3. Rank the Characteristic Objects – the expert determines the Matrix of Expert Judgment (MEJ). It is a result of pairwise comparison of the COs by the problem expert. The MEJ matrix contains results of comparing characteristic objects by the expert, where α_{ij} is the result of comparing CO_i and CO_j by the expert. Function f_{exp} denotes the mental function of the expert. It depends solely on the knowledge of the expert and can be presented as Eq. (26). Afterwards, the vertical vector of the Summed Judgments (SJ) is obtained as follows Eq. (27).

$$\alpha_{ij} = \begin{cases} 0.0, & f_{\exp}(CO_i) < f_{\exp}(CO_j) \\ 0.5, & f_{\exp}(CO_i) = f_{\exp}(CO_j) \\ 1.0, & f_{\exp}(CO_i) > f_{\exp}(CO_j) \end{cases} \tag{26}$$

$$SJ_i = \sum_{j=1}^{t} \alpha_{ij} \tag{27}$$

Finally, the values of preference are approximated for each characteristic object. As a result, vertical vector *P* is obtained, where *i-th* row contains the approximate value of preference for CO_i.

Step 4. The Rule Base – each characteristic object and value of preference is converted to a fuzzy rule as follows Eq. (28):

$$IF\ C(C_{1i})\ AND\ C(C_{2i})AND \ldots THEN\ P_i \tag{28}$$

In this way, the complete fuzzy rule base is obtained.

Step 5 Inference and Final Ranking – each alternative is presented as a set of crisp numbers (e.g., $Ai = \{a_{1i}, a_{2i}, ..., a_{ri}\}$). This set corresponds to criteria $C_1, C_2, ..., C_r$. Mamdani's fuzzy inference method is used to compute preference of *i-th* alternative. The rule base guarantees that the obtained results are unequivocal.

2.6. The SPOTIS method

The Stable Preference Ordering Towards Ideal Solution (SPOTIS) method is a recently developed method [48]. Similarly to the COMET method, it is declared fully resistant to the rank reversal phenomenon. This method's main assumption is to define the data boundaries, which are used to determine Ideal Solution Point (ISP). Based on it, further calculations to obtain the final preferences for alternatives are being made [49].

The definition of the data boundaries requires to select maximum S_j^{max} and minimum S_j^{min} bound for each criterion C_j. Ideal Solution Point S_j^* is defined as $S_j^* = S_j^{max}$ for profit and as $S_j^* = S_j^{min}$ for cost type of criterion. More necessary transformations during the method application are presented below.

Step 1. Calculation of the normalized distances to Ideal Solution Point Eq. (29).

$$d_{ij}(A_i, S_j^*) = \frac{\left|S_{ij} - S_j^*\right|}{\left|S_j^{max} - S_j^{min}\right|} \tag{29}$$

Step 2. Calculation of weighted normalized distances $d(A_i, S^*) \in [0,1]$, according to Eq. (30).

$$d(A_i, S^*) = \sum_{j=1}^{N} w_j d_{ij}(A_i, S_j^*) \tag{30}$$

Step 3. Final ranking should be determined based on $d(A_i, S^*)$ values. Smaller values $d(A_i, S^*)$ which are preferences of alternatives result in better position in general ranking.

2.7. The ranking similarity coefficients

The idea of using the rankings similarity coefficients is not new and has been the subject of many works [50, 51]. Particularly interesting are works related to the weighted rank measure of correlation r_w [52, 53]. Recently, a new coefficient is proposed by Sałabun [8]. It is an asymmetric measure, where the weight of a given comparison is determined based on the significance of the position in the reference ranking. These coefficients can be presented as Eq. (31) and Eq. (32) respectively:

$$r_w = 1 - \frac{6 \cdot \sum_{i=1}^{n} (R_{xi} - R_{yi})^2 ((n - R_{xi} + 1) + (n - R_{yi} + 1))}{n \cdot (n^3 + n^2 - n - 1)} \tag{31}$$

$$WS = 1 - \sum_{i=1}^{n} \left(2^{-R_{xi}} \frac{| R_{xi} - R_{yi} |}{\max\{| 1 - R_{xi} |, | N - R_{xi} |\}} \right) \tag{32}$$

where r_w is a value of the weighted rank measure of correlation, *WS* is a value of similarity coefficient, *n* is a length of ranking, R_{xi} and R_{yi} mean the place in the ranking for *i-th* element in, respectively, ranking *x* and ranking *y*.

3. Numerical Example in Green Urban Transport Domain

The problem of electric bus selection is presented as an exemplary problem from the green urban transport domain. This problem considers seven criteria and nine alternatives, where the choice of criteria was taken by the most critical elements of importance in assessing electric buses' quality [54, 55, 56]. We assume that a reference ranking is not available, and our task is to find the best compromise solution.

The defined criteria are presented in Table 2, where the criterion name, its type and the unit in which the values will be given are shown. On the other hand, the decision matrix for the selected nine alternatives, which is used to calculate the final preference values in each of the MCDA methods used, is included in Table 3. Each alternative contains the name of the electric bus model and the manufacturer's values for the criteria considered. Six vehicle manufacturers were selected, and one of the selected models was presented in four different alternatives.

Table 2 Considered criteria C_i to electric bus selection

C_i	Name	Type	Units
C_1	Battery capacity	Profit	kWh
C_2	Engine power	Profit	kW
C_3	Range	Profit	Km
C_4	Price	Cost	Thousands PLN
C_5	All places	Profit	Unit
C_6	Seating places	Profit	Unit
C_7	Places for disabled	Profit	Unit

Six MCDA methods were selected to solve the problem of selecting the optimal electric bus to compare the results and check whether the obtained results would be significantly different from each other. TOPSIS method with minmax normalization, VIKOR method without using normalization, PROMETHEE II method with usual type preference function, COPRAS method in standard configuration, COMET method with object evaluation by TOPSIS method and SPOTIS method in the standard configuration were used in the research.

Table 3 Decision matrix with set of alternatives A_i

A_i	Name	C_1	C_2	C_3	C_4	C_5	C_6	C_7
A_1	Ursus City Smile 18M	230	120	150	2051.74	83	24	1
A_2	Solaris Urbino 12 Electric	210	160	150	2212.86	85	32	1
A_3	Byd K9	324	180	250	2101.78	80	25	1
A_4	Volvo 7900E	250	200	200	2550.00	83	30	1
A_5	Proterra Catalyst FC	94	190	109	2020.00	80	40	0
A_6	Proterra Catalyst XR	220	190	264	2465.00	80	40	0
A_7	Proterra Catalyst E2	440	190	491	2885.00	80	40	0
A_8	Proterra Catalyst E2 Max	660	190	685	3370.00	80	40	0
A_9	New Flyer Xcelsior CHARGE 40's	300	159	210	3293.75	83	40	2

The obtained preference values using the mentioned methods are shown in Table 4. When TOPSIS, PROMETHEE II, COPRAS and COMET methods are used, a higher preference value means a better-evaluated alternative. On the other hand, when preferences obtained from applying the VIKOR and SPOTIS methods are analyzed, a smaller value indicates a better choice. To facilitate the interpretation of the results, the obtained rankings in the form of positional rankings are included in Table 5. A histogram shows the positional rankings' visualization for the different methods and alternatives in Fig. 1.

Table 4 Obtained preferences of alternatives for selected MCDA methods

A_i	TOPSIS	VIKOR	PROM. II	COPRAS	COMET	SPOTIS
A_1	0.3939	1.0000	-0.1786	0.7446	0.2908	0.6589
A_2	0.5139	0.5813	-0.0714	0.7831	0.5722	0.4810
A_3	0.4399	0.9144	0.0179	0.8580	0.3897	0.5853
A_4	0.5018	0.2783	0.1250	0.8191	0.5320	0.4977
A_5	0.4535	0.9360	-0.1786	0.5988	0.4141	0.5893
A_6	0.4584	0.8167	-0.0357	0.6863	0.4278	0.5661
A_7	0.5008	0.6577	0.1071	0.8487	0.5304	0.4987
A_8	0.5277	0.5000	0.1071	1.0000	0.5988	0.4464
A_9	0.5178	0.0443	0.1071	0.9983	0.5848	0.4738

Table 5 Positional rankings of obtained results from application of MCDA methods

A_i	TOPSIS	VIKOR	PROM. II	COPRAS	COMET	SPOTIS
A_1	9	9	9	7	9	9
A_2	3	4	7	6	3	3
A_3	8	7	5	3	8	7
A_4	4	2	1	5	4	4
A_5	7	8	8	9	7	8
A_6	6	6	6	8	6	6
A_7	5	5	4	4	5	5
A_8	1	3	3	1	1	1
A_9	2	1	2	2	2	2

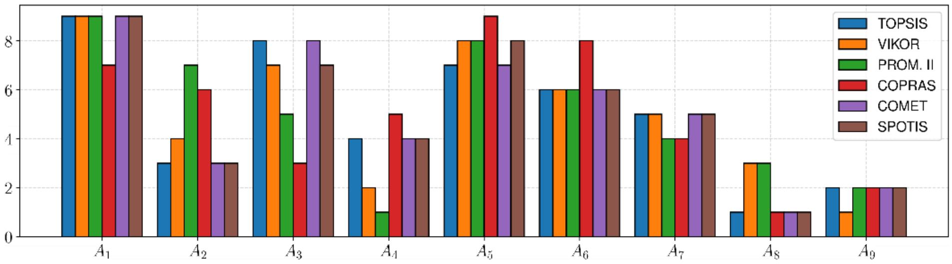

Fig. 1 Visualization of the positional rankings comparison of used MCDA methods

It is worth noting that for the results obtained for the PROMETHEE II method, the preference values for the alternatives A_7, A_8 and A_9 were the same, as they were for the pair of alternatives A_1 and A_5. Differences in preference values were very small, which may be caused by errors in the numerical representation of floating-point numbers. The results obtained with the PROMETHEE method with ties is presented in Table 6, where the preference values and the positional ranking for the set of alternatives from the decision matrix are listed.

Table 6 Obtained preferences for PROMETHEE I and II application

A_i	ϕ^-	ϕ^+	ϕ	PROM. II
A_1	0.5357	0.3571	-0.1786	8.5
A_2	0.5000	0.4286	-0.0714	7
A_3	0.4286	0.4464	0.0179	5
A_4	0.3929	0.5179	0.1250	1
A_5	0.4643	0.2857	-0.1786	8.5
A_6	0.3929	0.3571	-0.0357	6
A_7	0.3214	0.4286	0.1071	3
A_8	0.3214	0.4286	0.1071	3
A_9	0.3929	0.5000	0.1071	3

When the preference values are rounded to four significant decimal places, the obtained ranking correlation values may change. The rankings' obtained similarity values when taking into account the rounding of the preference values are presented in Table 7. A visualization of the newly obtained correlation relationships between the obtained rankings is shown in Fig. 2, where the correlation values were represented by histograms for the analyzed alternatives and methods.

Table 7 Correlation between PROMETHEE with ties and other methods

Method	r_w	*WS*
TOPSIS	0.5869	0.6991
VIKOR	0.7971	0.7832
PROM. II	1.0000	1.0000
COPRAS	0.6619	0.7476
COMET	0.5869	0.6991

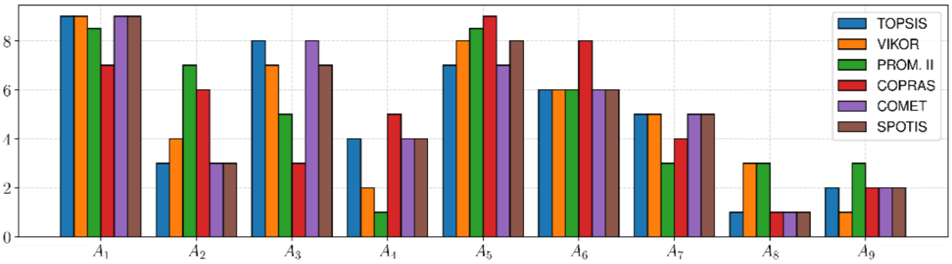

Fig. 2 Alternate comparison of obtained rankings from MCDA methods

Analyzing the obtained values for the preference values derived from the application of the selected six MCDA methods, it can be observed that the PROMETHEE II method guaranteed equal preference values for the alternatives A_7 - A_9 and for the alternatives A_1 and A_5. It is worth noting that the raw preference values obtained by the MCDA methods included in Table 4 are challenging to compare, due to the variety of values obtained. On the other hand, when analyzing the obtained positional rankings shown in Table 5, which are more representative, it can be observed that some of the alternatives have different orders depending on the method used. Alternative A_8 can be considered the optimal choice, having been best ranked by four of the six methods. On the other hand, the second place in the rankings analyzed was most often obtained by alternative A_9, which was ranked in this position five times.

When the preference values obtained for the PROMETHEE method were considered and rounded to four decimal places, it is worth noting that the rankings' similarity values differed from those when no rounding was considered. The correlation values presented in Table 7 showed that only when comparing the rounded preference values with those obtained from the VIKOR method, the correlation increased slightly. In contrast, the correlation decreased for the other rankings. It shows that, in addition to the methods used to solve a given multi-criteria problem, the results are also affected by inaccuracies and numerical errors arising from the execution of operations and machine representation of floating-point numbers.

4. The Proposed Approach

The next phase of our research is to determine the similarity of the rankings obtained. For this purpose, it was decided to use the weighted Spearman correlation coefficient and the *WS* similarity coefficient. Both determinants are based on the obtained ranking values from the multi-criteria decision-making methods used. Table 8 shows the calculated correlations between the obtained rankings using the weighted Spearman correlation coefficient. Using this determinant of similarity guarantees obtaining values of the interval [-1.0, 1.0], where a value of -1.0 means a complete lack of similarity, while 1.0 means their equality. When examining the correlation of the ranking with itself, it will give a value of 1.0 in each case. In turn, the similarity results obtained using the similarity coefficient *WS* are included in Table 9. The values obtained using this determinant guarantee the similarity defined on the interval (0.0, 1.0], where the value 0.0 means no similarity of rankings, while the value 1.0 means the identical rankings. The similarity obtained is highly influenced by changes noted on the first positions among the analyzed orders.

The most correlated rankings were obtained by the TOPSIS, COMET and SPOTIS methods. The reason may be that these methods use the concept of reference objects. Despite using the same concept by the VIKOR method, the obtained rankings correlations differed significantly from those mentioned above. The divergence between TOPSIS, COPRAS, PROMETHEE II and VIKOR rankings is a frequent phenomenon appearing in the performance studies of MCDA methods. Meanwhile, using the *WS* similarity coefficient for the correlation study, it was noted that the most correlated rankings were obtained using TOPSIS, COMET and SPOTIS methods, which shows that both coefficients equally indicate the most similar rankings. The lowest similarity of rankings was noted for the PROMETHEE II method concerning the other rankings.

Table 8 Rankings correlation for Spearman weighted correlation coefficient r_w

r_w	TOPSIS	VIKOR	PROM. II	COPRAS	COMET	SPOTIS
TOPSIS	1.0000	0.8667	0.6350	0.6650	1.0000	0.9917
VIKOR	0.8667	1.0000	0.8683	0.6233	0.8667	0.8750
PROM. II	0.6350	0.8683	1.0000	0.6783	0.6350	0.6650
COPRAS	0.6650	0.6233	0.6783	1.0000	0.6650	0.7300
COMET	1.0000	0.8667	0.6350	0.6650	1.0000	0.9917
SPOTIS	0.9917	0.8750	0.6650	0.7300	0.9917	1.0000

Table 9 Rankings correlation for *WS* similarity coefficient

WS	TOPSIS	VIKOR	PROM. II	COPRAS	COMET	SPOTIS
TOPSIS	1.0000	0.7916	0.7434	0.9051	1.0000	0.9981
VIKOR	0.8100	1.0000	0.8539	0.7434	0.8100	0.8119
PROM. II	0.7291	0.8698	1.0000	0.6841	0.7291	0.7375
COPRAS	0.8619	0.7098	0.7950	1.0000	0.8619	0.8830
COMET	1.0000	0.7916	0.7434	0.9051	1.0000	0.9981
SPOTIS	0.9981	0.7935	0.7438	0.9047	0.9981	1.0000

The proposed approach is to combine the usual voting approach and the similarity coefficients of the rankings. Each of the methods used takes a vote, where each alternative is given a number of points corresponding to a place in the ranking. A new ranking is then established where the highest-ranked alternative is the one that has received the least number of points. Of course, the compromise solution may vary due to the number of methods and the methods chosen. Table 10 shows the seven rankings that have been created based on the proposed approach, i.e., Rank 1 using all six methods, Rank 2 using five methods without TOPSIS, Rank 3 using five methods without VIKOR, Rank 4 using five methods without PROMETHEE II, Rank 5 using five methods without COPRAS, Rank 6 using five methods without COMET, and Rank 7 using five methods without SPOTIS.

Table 10 Position values for candidate compromise rankings

A_i	Rank 1	Rank 2	Rank 3	Rank 4	Rank 5	Rank 6	Rank 7
A_1	9	9	9	9	9	9	9
A_2	4	4.5	4	3.5	4	4.5	4.5
A_3	6.5	6	6	7	7	6	6
A_4	3	3	3	3.5	3	3	3
A_5	8	8	8	8	8	8	8
A_6	6.5	7	7	6	6	7	7
A_7	5	4.5	5	5	5	4.5	4.5
A_8	1	1.5	1	1	1.5	1.5	1.5
A_9	2	1.5	2	2	1.5	1.5	1.5

In order to obtain a compromise ranking, the measure of its fit must first be defined. When the reference value is not known, one should select a ranking that best fits the selected MCDA methods' rankings. Thus, we use two matching measures, i.e., the minimum similarity value and the average similarity value. In Table 8, the best compromise ranking from among the rankings determined by the MCDA methods is the ranking obtained with the SPOTIS method, which has the highest minimum and average similarity value of the rankings, which amount to 0.665 and 0.876, respectively. On the other hand, the worst compromise ranking would be the ranking obtained using the COPRAS method. It has the lowest minimum and average value of ranking similarity, which are 0.623 and 0.727, respectively. An interesting situation is when comparing using the *WS* coefficient, where three times we obtain the same average value for the TOPSIS, COMET and SPOTIS methods. However, taking into account the highest minimum value, the ranking determined by the SPOTIS method is again the best (0.0004 higher than TOPSIS and COMET).

Tables 11 and 12 show the similarity between the candidate compromise rankings and those obtained using the MCDA methods. Thus Rank 1 has an average r_w of 0.900 and a minimum similarity value of 0.7842. This means a much higher match than was obtained from each ranking obtained using the MCDA methods tested. The best fit was obtained for five methods when TOPSI, COMET or SPOTIS were eliminated (Rank 2, 6 and 7, respectively). This is logical because in these three cases, precisely the same ranking was obtained. The matching looks different for the *WS* measure. Different compromise ranks are determined using the average value of similarity of rankings and others in the minimum level criterion. In the first case, the best result is obtained for Rank 4 because here the average value of matching is 0.9065, but the minimum value is only 0.7682.

Table 11 Values of similarity coefficient r_w for candidate compromise rankings

r_w	TOPSIS	VIKOR	PROM. II	COPRAS	COMET	SPOTIS
Rank 1	0.9623	0.9171	0.7992	0.7842	0.9623	0.9754
Rank 2	0.9265	0.9385	0.8542	0.8302	0.9265	0.9448
Rank 3	0.9483	0.9083	0.8033	0.8150	0.9483	0.9667
Rank 4	0.9862	0.9027	0.7331	0.7454	0.9862	0.9946
Rank 5	0.9629	0.9548	0.8108	0.7412	0.9629	0.9712
Rank 6	0.9265	0.9385	0.8542	0.8302	0.9265	0.9448
Rank 7	0.9265	0.9385	0.8542	0.8302	0.9265	0.9448

Table 12 Values of similarity coefficient *WS* for candidate compromise rankings

WS	TOPSIS	VIKOR	PROM. II	COPRAS	COMET	SPOTIS
Rank 1	0.9621	0.8164	0.7840	0.9144	0.9621	0.9647
Rank 2	0.9043	0.8706	0.8302	0.8798	0.9043	0.9080
Rank 3	0.9586	0.8140	0.7836	0.9138	0.9586	0.9622
Rank 4	0.9821	0.8071	0.7682	0.9154	0.9821	0.9839
Rank 5	0.9177	0.8849	0.8161	0.8659	0.9177	0.9195
Rank 6	0.9043	0.8706	0.8302	0.8798	0.9043	0.9080
Rank 7	0.9043	0.8706	0.8302	0.8798	0.9043	0.9080

The compromise solution, in this case, should be selected as the order indicated by Rank 2, 6 or 7 (these rankings are identical), as this guarantees maximum matching for all the rankings examined. Finally, we also show how strongly similar solutions have been obtained using all methods or combinations of the five elements. Tables 13 and 14 show the similarity values of the rankings among themselves. As we can see, the rankings are very similar to each other, so the choice of methods is not a big problem in determining the compromise ranking, but the research presented in this paper should be extended and continued to generalize the observations of this paper.

Table 13 Correlation matrix for rw values for candidate compromise rankings

r_w	Rank 1	Rank 2	Rank 3	Rank 4	Rank 5	Rank 6	Rank 7
Rank 1	1.0000	0.9854	0.9971	0.9917	0.9900	0.9854	0.9854
Rank 2	0.9854	1.0000	0.9883	0.9662	0.9838	1.0000	1.0000
Rank 3	0.9971	0.9883	1.0000	0.9829	0.9812	0.9883	0.9883
Rank 4	0.9917	0.9662	0.9829	1.0000	0.9875	0.9662	0.9662
Rank 5	0.9900	0.9838	0.9812	0.9875	1.0000	0.9838	0.9838
Rank 6	0.9854	1.0000	0.9883	0.9662	0.9838	1.0000	1.0000
Rank 7	0.9854	1.0000	0.9883	0.9662	0.9838	1.0000	1.0000

Table 14 Correlation matrix for *WS* values for candidate compromise rankings

WS	Rank 1	Rank 2	Rank 3	Rank 4	Rank 5	Rank 6	Rank 7
Rank 1	1.0000	0.9387	0.9980	0.9813	0.9489	0.9387	0.9387
Rank 2	0.9408	1.0000	0.9430	0.9233	0.9858	1.0000	1.0000
Rank 3	0.9978	0.9407	1.0000	0.9789	0.9465	0.9407	0.9407
Rank 4	0.9817	0.9185	0.9795	1.0000	0.9348	0.9185	0.9185
Rank 5	0.9506	0.9854	0.9484	0.9362	1.0000	0.9854	0.9854
Rank 6	0.9408	1.0000	0.9430	0.9233	0.9858	1.0000	1.0000
Rank 7	0.9408	1.0000	0.9430	0.9233	0.9858	1.0000	1.0000

5. Conclusions

The presented study shows a simple way of building a compromise ranking, which is quite helpful when the obtained ranking results are not unambiguous. Additionally, two criteria were given for the selection of the best compromise ranking. It allows obtaining a solution, which is maximally compatible with all methods involved in determining this solution. The presented example for the selection of electric buses has shown that this solution is effective, and the proposed compromise solutions are better than any of the obtained solutions. Due to the fact that each method has a different methodological background, no solution can be discriminated against. Thanks to this approach, we obtain a solution that is a true compromise based on the available data.

For further research directions, it is worth considering more MCDA methods to receive more benchmarkable results. The algorithm for selecting a compromise solution should also be refined. Research should also be expanded to develop criteria for selecting the best compromise solution.

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