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A comparative case study of the VIKOR and TOPSIS rankings similarity

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Abstract

Multi-criteria decision-methods (MCDA) has a broad field of applications in various areas, such as engineering, logistic, health management, and others. Their main objective is to rank the decision variants, from the best to the worst. It is always essential to get a reliable solution to a decision problem. However, rankings obtained with different MCDA methods are often different, and that is why an interesting research gap is related to measuring the accuracy and reliability of MCDA methods.

In this paper, we examine how much different can be rankings obtained using TOPSIS and VIKOR methods. For this purpose, we apply classical versions of TOPSIS and VIKOR methods to randomly generated decision matrices with different criteria and alternatives. Then, we compare the obtained ranking using three ranking similarity coefficients. The comparison results of conducted simulations are represented as boxplots, which contain the primary distribution of similarity of results calculated using the tested methods. The work is finished with a discussion and conclusions on the results in different classes of problems.

Keywords: Type your keywords here, separated by semicolons ;

1. Introduction

Decision making is an essential part of our lives. Every day we make decisions of all kinds, from the most straightforward decisions that do not require deep knowledge or hard thinking, to complicated decisions where mistakes can have consequences, and making the right choice requires a lot of knowledge and effort, and may even be impossible. Complicated decision-making problems require a large number of criteria [15, 26] with different levels of importance, and it is almost impossible for humans to identify the right decision. In such cases, multi-criteria decision analysis (MCDA) methods are often useful and aid the decision-making process to the optimal solution for a specific decision

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problem. However, attention should be paid to choosing the right method for the given decision problem to make the results reliable [29].

Today there are many different MCDA methods, such as TOPSIS [4], VIKOR [18], PROMETHEE [6], COPRAS [35], COMET [31, 32, 33], and other [27, 30]. New methods are being created, and old ones are being developed. It is becoming more and more difficult to choose from these methods a suitable one for the problem to obtain a reliable result [29]. MCDA methods aim to present the best alternative from the set [21]. Still, often the results obtained with the help of different methods vary greatly or generally do not meet our expectations. In addition to choosing the best alternative, these methods are most often used to rank decision variants according to their degree of preference [10, 20].

TOPSIS and VIKOR methods, based on the distance from the ideal solution, have become very popular in the MCDA field. The first one, TOPSIS, is an acronym that stands for ”Technique of Order Preference Similarity”. This method was presented in [4, 19]. The second one is also an acronym, but in Serbian: VlseKriterijumska Optimizacija I Kompromisno Resenje. It was originally introduced by Opricovic [16] and also was presented in [19]. As it was mentioned before, both methods are based on certain ”closeness to the ideal” function [17].

TOPSIS and VIKOR techniques found application in many different domains, such as logistics [2, 9], manufacturing [1, 28], environment management [11, 14], energy management [5, 13], chemical engineering [24, 25], and many other [4, 34]. However, although TOPSIS and VIKOR persecute the same objective, the rankings obtained using these methods often differ [3, 12, 17]. There are also several papers, which shows that we can obtained identical or very similar rankings using TOPSIS and VIKOR [7, 8, 17].

In this paper, we will explore how different results are obtained using TOPSIS and VIKOR methods for different decision matrices. We will randomly generate some decision matrices with different numbers of criteria and alternatives and then process them with TOPSIS and VIKOR methods. In our simulations, few classes of decision matrices will be observed. For each of the classes, we will calculate three correlation coefficients to determine how many different obtained rankings are. In the last step, we will analyze the obtained correlation coefficient with plots to discuss the distribution of similarity ranking levels in each class.

The rest of the article is structured as follows. Sections 2 and 3 contain descriptions of TOPSIS and VIKOR methods, respectively. Section 4 describes the correlation coefficients that will be used to compare results. Section 5 contains a description of how comparisons will be performed. Section 6 contains results and discussion. Finally, the work is summarised in section 7.

2. TOPSIS

The TOPSIS method is a simple MCDA technique used in many practical problems. Thanks to its simplicity of use it is widely used in solving multi-criteria problems. Below we present its algorithm [4]. We assume, that we have decision matrix with m alternatives and n criteria is represented as $X = (x_{ij})_{m \times n}$.

Step 1. Calculate the normalized decision matrix. The normalized values r_{ij} calculated according to equation (1) for profit criteria and (2) for cost criteria. We use this normalization method, because [22] shows that it performs better that classical vector normalization.

$$r_{ij} = \frac{x_{ij} - min_j(x_{ij})}{max_j(x_{ij}) - min_j(x_{ij})} \tag{1}$$

$$r_{ij} = \frac{max_j(x_{ij}) - x_{ij}}{max_j(x_{ij}) - min_j(x_{ij})} \tag{2}$$

Step 2. Calculate the weighted normalized decision matrix v_{ij} according to equation (3).

$$v_{ij} = w_i r_{ij} \tag{3}$$

Step 3. Calculate Positive Ideal Solution (PIS) and Negative Ideal Solution (NIS) vectors. PIS is defined as maximum values for each criteria (4) and NIS as minimum values (5). We don't need to split criteria into profit and cost here, because in step 1 we use normalization which turns cost criteria into profit criteria.

$$v_j^+ = \{v_1^+, v_2^+, \cdots, v_n^+\} = \{max_j(v_{ij})\} \tag{4}$$

$$v_j^- = \{v_1^-, v_2^-, \cdots, v_n^-\} = \{min_j(v_{ij})\} \tag{5}$$

Step 4. Calculate distance from PIS and NIS for each alternative. As shows equations (6) and (7).

$$D_i^+ = \sqrt{\sum_{j=1}^{n}(v_{ij} - v_j^+)^2} \tag{6}$$

$$D_i^- = \sqrt{\sum_{j=1}^{n}(v_{ij} - v_j^-)^2} \tag{7}$$

Step 5. Calculate each alternative's score according to equation (8). This value is always between 0 and 1, and the alternatives which got values closer to 1 are better.

$$C_i = \frac{D_i^-}{D_i^- + D_i^+} \tag{8}$$

3. VIKOR

The Vikor method, similarly to the TOPSIS method, is based on distance measurements. In this approach a compromise solution is sought. The description of the method will be quoted according to [16, 17]. Let's say, that we have decision matrix with m alternatives and n criteria is represented as $X = f_{ij}(A_i)_{m \times n}$.

Step 1. Determine the best f_i^* and the worth f_i^- values for each criteria functions. Use (9) for profit criteria and (10) for cost criteria.

$$f_j^* = \max_i f_{ij}, \quad f_j^- = \min_i f_{ij} \tag{9}$$

$$f_j^* = \min_i f_{ij}, \quad f_j^- = \max_i f_{ij} \tag{10}$$

Step 2. Calculate the S_i and R_i values by the equations (11) and (12).

$$S_i = \sum_{j=1}^{n} w_j \left(f_j^* - f_{ij}\right) / \left(f_j^* - f_j^-\right) \tag{11}$$

$$R_i = \max_j \left[w_j \left(f_j^* - f_{ij}\right) / \left(f_j^* - f_j^-\right)\right] \tag{12}$$

Step 3. Compute the Q_i values using equation (13).

$$Q_i = v\,(S_i - S^*) / (S^- - S^*) + (1 - v)\,(R_i - R^*) / (R^- - R^*) \tag{13}$$

where
$S^* = \min_i S_i, \quad S^* = \min_i S_i$
$R^* = \min_i R_i, \quad R^* = \max_i R_i$
and v is introduced as a weigh for the strategy "majority of criteria". We use $v = 0.5$ here.
Step 4. Rank alternatives, sorting by the values S, R, Q in ascending order. Result is three ranking lists.
Step 5. Normally, we should use S, R, Q ranking lists to propose the compromise solution or set of compromise solutions, as showed in [17] and [19]. However, in this paper would be used only Q ranking list.

4. Correlation coefficients

Correlation coefficients make it possible to compare obtained results and determine how similar they are. In this paper we compare ranking lists obtained by TOPSIS and VIKOR using Spearman rank correlation coeffictient (14), weighted Spearman correlation coefficietnt (16) and rank similarity coefficient (17).

4.1. Spearman's rank correlation coefficient

For the rank values rg_X and rg_Y defined as (14). However, if we are dealing with rankings where the values of preferences are unique and do not repeat themselves, each variant has a different position in the ranking, the formula (15) can be used.

$$r_s = \frac{cov(rg_X, rg_Y)}{\sigma_{rg_X}\sigma_{rg_Y}} \tag{14}$$

$$r_s = 1 - \frac{6 \cdot \sum_{i=1}^{N}(rg_{X_i} - rg_{Y_i})}{N(N^2 - 1} \tag{15}$$

4.2. Weighted Spearman's rank correlation coefficient

For a samples of size N, the rank values x_i and y_i is defined as (16). In this approach, the positions at the top of both rankings are more important. The weight of significance is calculated for each comparison. It is the element that determines the main difference to the Spearman's rank correlation coefficient, which examines whether the differences appeared and not where they appeared.

$$r_w = 1 - \frac{6\sum_{i=1}^{N}(x_i - y_i)^2((N - x_i + 1) + (N - y_i + 1))}{N^4 + N^3 - N^2 - N} \tag{16}$$

4.3. Rank Similarity coefficient

For a samples of size N, the rank values x_i and y_i is defined as 17 [23]. It is an asymmetric measure. The weight of a given comparison is determined based on the significance of the position in the first ranking, which is used as a reference ranking during the calculation.

$$WS = 1 - \sum_{i=1}^{N} 2^{-x_i} \frac{|x_i - y_i|}{max(|x_i - 1|, |x_i - N|)} \tag{17}$$

5. Study case

The research procedure involves carrying out simulation tests to compare results obtained by using TOPSIS and VIKOR methods. For this purpose, we proposed short algorithm, which showing clearly the next steps of the test procedure. Proposed research is presented as a pseudo-code in Algorithm 1.

Algorithm 1 Pseudocode of the algorithm

```
N ← 10000
for num_of_crit = 2 to 5 do
    weights ← generate_equal_weights()
    types ← generate_crit_types()
    for num_of_altsin[3, 5, 10, 50, 100] do
        for i = 1 to N do
            matrix ← generate_random_matrix(num_of_alts, num_of_crit)
            topsis_rank ← topsis(matrix, weights, types)
            vikor_rank ← vikor(matrix, weights, types)
            calculate_correlations(topsis_rank, vikor_rank)
        end for
    end for
end for
```

The whole procedure has four steps. For $n = 2$ to $n = 5$ as number of criteria and for $m \in \{3, 5, 10, 50, 100\}$ as number of alternatives, there should be perform followed steps:

Step 1. Generate $N = 10000$ random decision matrices with n criteria and m alternatives using uniform random distribution. We also generate equal weights for criteria and split them into profit and cost criteria following way: assuming we have n criteria, first $\lceil n/2 \rceil$ criteria are considered as profit criteria, and the other criteria are considered as a cost.

Step 2. Calculate TOPSIS and VIKOR rankings for generated decision matrix according to algorithms described in sections 2 and 3. *Note:* If TOPSIS or VIKOR returns equal ranks for all alternatives, we skip this matrix and generate a new one instead. It is because we cannot calculate Spearman's correlation coefficient (14) when the standard deviation of rank values is zero.

Step 3. Calculate ranking similarity coefficients between obtained rankings (using TOPSIS and VIKOR) according to equations (14), (16), (17).

Step 4. If both methods rank certain alternative as the best alternative, increase the counter. The procedure is repeated for all generated matrices.

The numerical example is shown better to understand the single iteration of the proposed algorithm. It will allow for a deeper understanding of the results of the comparative studies. The presented example shows computations for five criteria and five alternatives decision matrix (Table 1). The data normalization process is an initial step that is observed in most multi-criteria decision-making methods. Table 2 shows normalized decision matrix, computed using equations (1) and (2). Criteria from 1 to 3 are considered as profit and other two are considered as cost type.

Table 1: Example decision matrix

	C_1	C_2	C_3	C_4	C_5
A_1	0.55	0.72	0.6	0.54	0.42
A_2	0.65	0.44	0.89	0.96	0.38
A_3	0.79	0.53	0.57	0.93	0.07
A_4	0.09	0.02	0.83	0.78	0.87
A_5	0.98	0.8	0.46	0.78	0.12

Table 3 shows alternative rankings obtained by using TOPSIS and VIKOR methods. These rankings vary considerably, even though they were built on the same data (Table X) and using the same weighting criteria. Only the A_5 alternative came second in both rankings. All other alternatives have extremely different positions in both rankings.

Table 2: Normalized decision matrix

	C_1	C_2	C_3	C_4	C_5
A_1	0.52	0.9	0.33	1.0	0.56
A_2	0.63	0.54	1.0	0.0	0.61
A_3	0.79	0.65	0.26	0.07	1.0
A_4	0.0	0.0	0.86	0.43	0.0
A_5	1.0	1.0	0.0	0.43	0.94

Table 3: TOPSIS and VIKOR ranks

Alternative	TOPSIS ranks	VIKOR ranks
A_1	1	5
A_2	3	1
A_3	4	3
A_4	5	4
A_5	2	2

Table 4: Correlation coefficients

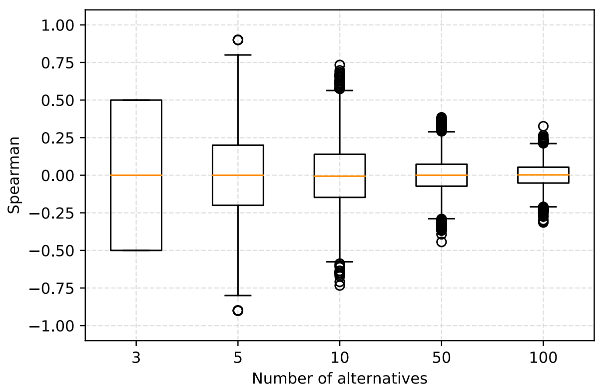
Spearman (r_s)	Weighted Spearman (r_w)	Rank Similarity coefficient (WS)
-0.1	-0.1333	0.3464

Table 4 shows ranking similarity coefficient values calculated for ranks from table 3. This values was calculated according equations (14), (16) and (17). These values confirm the observation and indicate a very low similarity of the rankings. The Spearman correlation is even negative, which indicates high variability in both ranking positions.

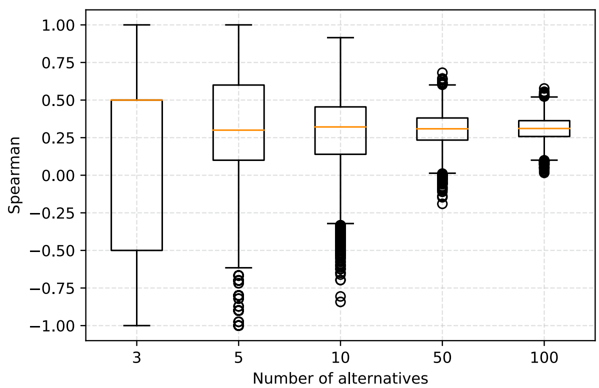
6. Results and discussion

The results of our simulations are mainly represented by using boxplots, which show how correlation coefficient values are distributed depending on the size of a decision matrix. The X-axis corresponds to a number of alternatives, and the Y-axis corresponds to a coefficient value. Each boxplot was generated based on 10000 random decision matrices.

Figures 1 and 2 show distribution of Spearman's correlation coefficient (14) values depending on the size of a decision matrix. As we can see, the average value of the correlation coefficient for cases with even number of criteria (2 or 4) is around zero, and for odd number of criteria (3 or 5) is descending in positive values from 0.25 to 0.5. It means that rankings obtained by using TOPSIS and VIKOR methods are most often uncorrelated. In the experiment

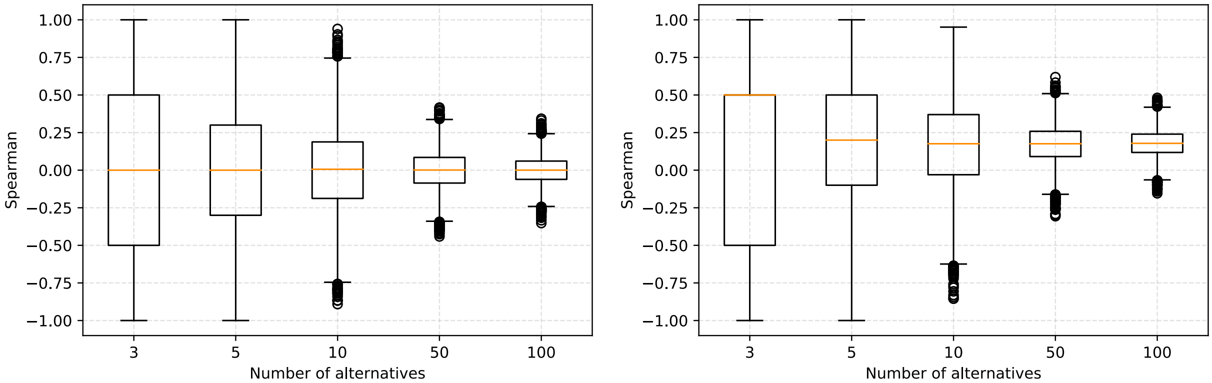


(a) For 2 criteria



(b) For 3 criteria

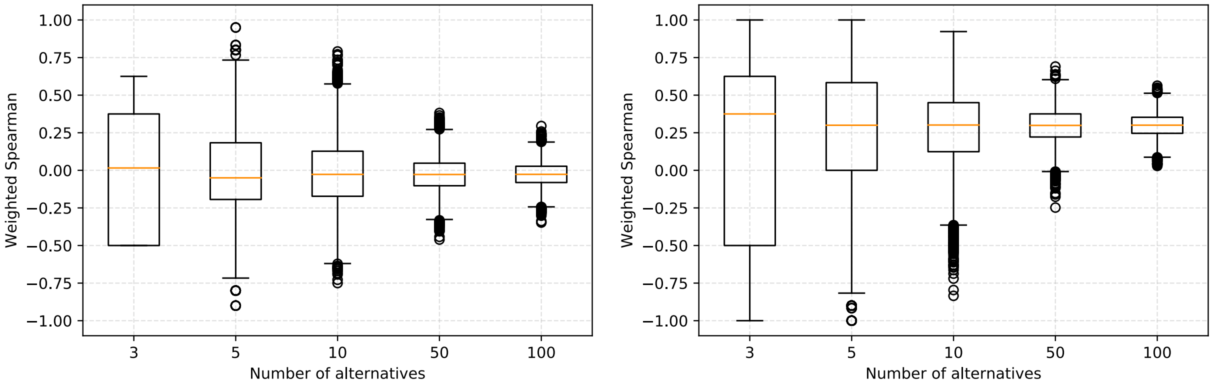
Fig. 1: Values of Spearman's correlation coefficient (for 2 and 3 criteria)



(a) For 4 criteria

(b) For 5 criteria

Fig. 2: Values of Spearman's correlation coefficient (for 4 and 5 criteria)



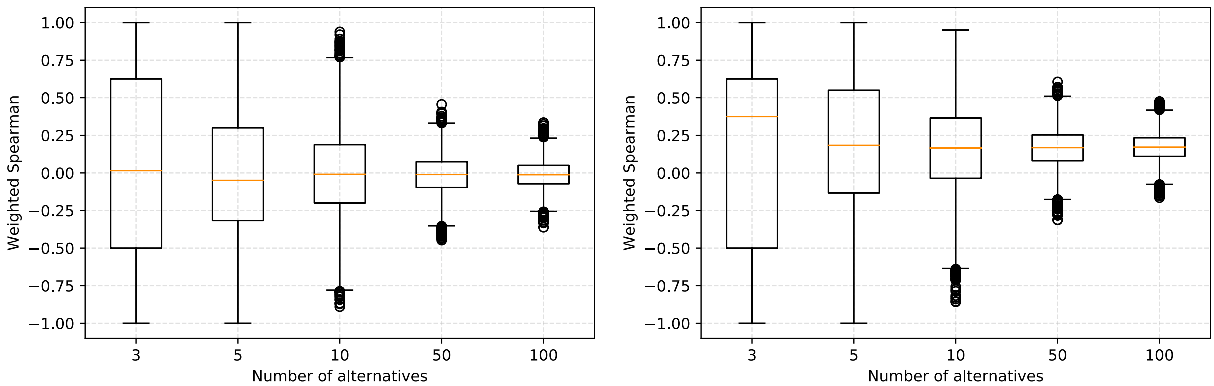
(a) For 2 criteria

(b) For 3 criteria

Fig. 3: Values of Weighted Spearman's correlation coefficient (for 2 and 3 criteria)

for the two criteria, none of the rankings received a linear correlation value, i.e., equal to one. As the number of criteria increased, this situation improved. Unfortunately, there were also answers showing a negative correlation, which means the correct ranking but in the opposite direction. The results for an odd number of criteria are much better than the results obtained for an even number. It may involve dividing the criteria into cost and profit. This fact is quite an interesting observation for preliminary results. It is particularly interesting whether this observation can be generalized for larger decision matrices (a larger number of criteria), as the number of alternatives increases, the range of obtained grades decreases, and at the same time the number of outliers increases. The results obtained are worse than those assumed before the experiment was performed. It was assumed that these values would be more shifted upwards, so the rankings' similarity will be higher. An observation that can be generalized without any doubts is the fact that the probability of obtaining similar rankings in case of using larger and larger sets of decision options is decreasing.

Figures 3 and 4 show distribution of weighted Spearman correlation coefficient (16) values. We can see that the distributions of the values are quite similar to distributions of simple Spearman's correlation coefficient. As previously, the average values are around zero for decision matrices with 2 to 4 criteria and are between 0 and 0.25 for 3 and 5 criteria. In our results most of the values are between 0.3 and 0.7, it means that we have rather low level of the corrlation between rankings. It can also be seen that the number of outliers increases when using the weighted version of the coefficient. The fact that the distributions are very similar to those obtained in the previous figures may be due

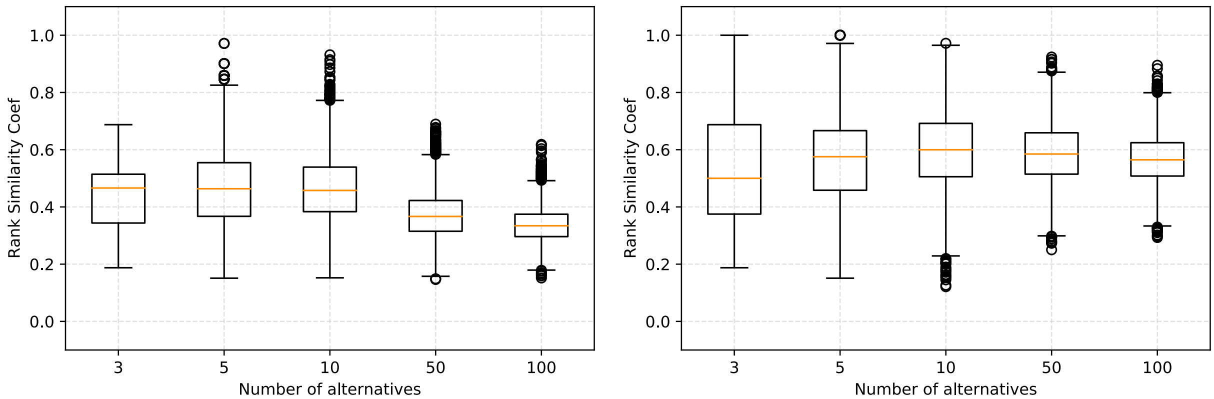


(a) For 4 criteria

(b) For 5 criteria

Fig. 4: Values of Weighted Spearman's correlation coefficient (for 4 and 5 criteria)

to a small number of similar pa rankings. Besides, it can be seen that greater asymmetry of the distribution occurs in a few sets of alternatives and a greater number of decision criteria.



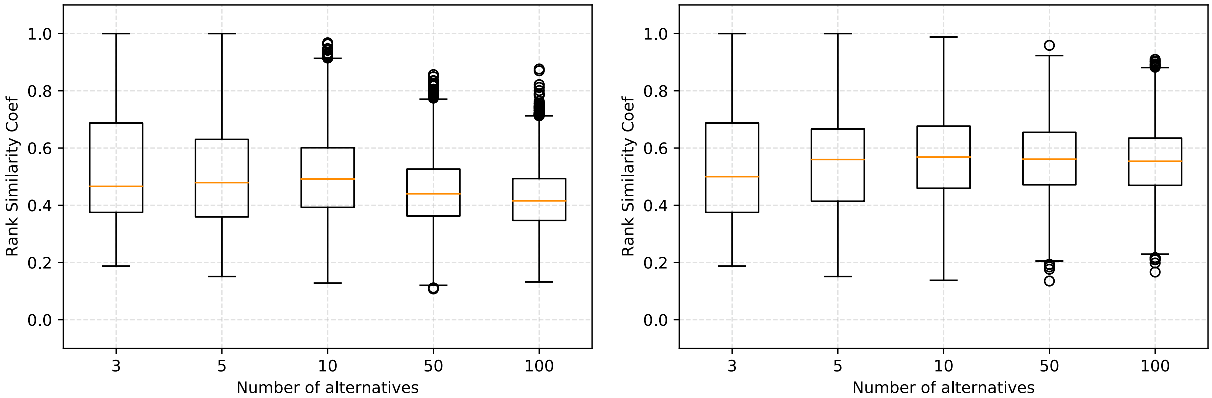
(a) For 2 criteria

(b) For 3 criteria

Fig. 5: Values of Rank Similarity coefficient (for 2 and 3 criteria)

Figures 5 and 6 show distributions of rank similarity coefficient values (17). This correlation coefficient takes values between 0 and 1. According to [23], if WS is less than 0.234 the correlation is low and for the values higher than 0.808 correlation considered as high. For the two criteria, only outliers have a high similarity to each other. A relatively small number of rankings have low similarity. However, as the number of alternatives increases, the similarity of rankings to each other decreases. The situation is slightly different in the case of the three criteria where much better results were obtained. It is related to the previous observation where it was established that for odd values due to the division of criterion types, better results were obtained. The similarity values obtained are not symmetrical when using this coefficient.

During the simulation studies, the number of cases where both methods returned the same alternative as the best decision option was also investigated. Table 5 contains a summary showing the relationship between the number of correct indications and the number of alternatives and the number of criteria. This table was created with 10000 random matrices for each combination if criteria and alternative number. The results for an odd number of criteria were better, which may be a symptom of equal distribution of weights and distribution of criteria types. The difference decreased with the increase in the number of alternatives and, in the most optimistic case, exceeded the expected value



(a) For 4 criteria

(b) For 5 criteria

Fig. 6: Values of Rank Similarity coefficient (for 4 and 5 criteria)

from the attempt to guess the best alternative. This shows that the results of the two methods are not very close to each other.

Table 5: Percent of cases when best alternatives are equal

	3 alternatives	5 alternatives	10 alternatives	50 alternatives	100 alternatives
2 criteria	18.22%	7.81%	0.60%	0.00%	0.00%
3 criteria	40.75%	23.65%	9.00%	0.00%	0.00%
4 criteria	31.99%	13.77%	3.78%	0.00%	0.00%
5 criteria	41.24%	20.89%	9.21%	0.21%	0.01%

7. Conclusion

As a result of the research, similarities were compared between the rankings obtained using the VIKOR method and the TOPSIS method. Both methods are based on measures of distance from reference objects. However, it turns out that both the task of indicating the best alternative and ranking a set of decision options have similar results only to a very limited extent. The division of the criteria into cost criteria and what to assign to particular weighting criteria plays a quite important role. In the conducted experiment, it was confirmed that the choice of the method is crucial for the obtained result, and the similarity between the obtained results can be very high. The probability of getting more similar results is when using fewer criteria and fewer alternatives. Due to obtaining interesting results, it would be necessary to expand the research in future works and focus on the similarity of other methods in terms of obtained results. Besides, it would also be necessary to develop the databases of reference models based on which it would be possible not only to compare the similarity of results but also to estimate individual methods' accuracy.

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