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# A CONTRIBUTION TO THE SELECTION OF ADEQUATE MCDM TECHNIQUE: STATISTICAL COMPARISON OF THE SELECTION RESULTS OF MATERIAL HANDLING EQUIPMENT

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***Abstract***

*Selecting an appropriate MCDM technique determines the quality of the recommended decision and can save computation time without sacrificing quality in the final rank of alternatives. In addition, according to the standard MCDM methods, the most common issues are in topics of standardizing criteria and obtaining criteria weights, the possibility to work with massive data (a large number of criteria and alternatives) as well as the ranking and selecting the most desirable alternative. The purpose of this paper was to give a systematic review of the literature on MCDM techniques and make adequate support for decision-making in the selection procedure in the domain of logistics systems. Kendall's tau-b and Spearman's rho test has been selected to evaluate the similarity of the final ranks produced by different decision-ranking techniques. The results can guide in the formation of a comprehensive tool for solving a wide range of real and practical engineering problems.*

***Keywords****: decision-making, material handling, criteria, Kendall's tau-b, Spearman's rho*

## 1INTRODUCTION

The material handling process incorporates a wide range of equipment and systems that support logistics and make the logistics system work.

The determination of the proper material handling system is important for reduced costs, increased profits and efficiency of the labor force. It is observed that there are about 50 different types of material handling equipment (MHE) and they are characterized by about 30 different attributes [1]. For that reason, MCDM methods are the most common approach applied for the selection of MHE. Decision-makers, in great number of such real problems, must meet one or more goals as well as the numerous conflict criteria. Selecting an appropriate MCDM technique determines the quality of the recommended decision and saves computation time without sacrificing quality in the final rank of alternatives. Also, different decision-ranking methods may rank specific alternatives in different orders, and different decision-ranking methods have different levels of computational intensity.
This paper reviews the literature on MCDM techniques and the most common issues present in topics of standardizing criteria, obtaining criteria weights, the possibility to work with massive data (a large number of criteria and alternatives) as well as the final ranking and selecting the most desirable alternative. The results of this study statistically compare the performances of commonly used MCDM techniques and newly developed approach. The statistical significances of the differences between the obtained ranks are calculated using Spearman's rho and Kendall's tau-b test. This research provides efforts to create an effective decision-making process through emphasizes the importance of comparing different techniques, but there is no recommendation as to whether one technique is better than another.

### 1.1. Survey of related works

In the available literature do not many existing works that evaluating and comparing the performance of MCDM methods. Studies [2] and [3] give a systematic reviews of comparing the MCDM techniques. This reviews categorized and evaluated popular MCDM methods (SAW (Simple Additive Weighting**)**, ELECTRE (ELimination Et Choix Traduisant la REalité), TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution), AHP (Analytic Hierarchy Process), VIKOR (Vlse Kriterijumska Optimizacija Kompromisno Resenje) and PROMETHEE (The Preference Ranking Organization *METHod*for Enrichment of Evaluations)) in the fields of transportation and logistics, manufacturing, economy, energy and education. A significant part of multi-criteria methods belongs to outranking methods because of their adaptability to real problems [4]. In the existing literature [5, 6], there are numerous examples where the PROMETHEE methods and their modifications are used in the selection of final decisions in solving various multicriteria tasks.
When evaluating a decision-making problem, it is necessary to take into account a large number of criteria/sub-criteria and determine their relative weights. Therefore, in order to make an accurate and flexible decision, some studies developed solutions for considering the interaction among criteria in the MCDM problems [7,8,9]. Criterion reduction is a useful method to extract useful knowledge from large amounts of information [10,11]. Authors give an effective decision process method which is proposed to address the challenge in the MCDM problem because of a large number of criteria.

This methods are based on the criteria reduction, tolerance relation, and prospect theory. On the other side, authors [12] identify plausible interpretations of criteria weights and their roles in different MCDM models. The true meaning of criteria weights is important for MCDM models and many different approaches were proposed for assessing criteria weights [13,14,15].

The multidimensionality mentioned above and a large number of different criteria present in such problems indicate that there are many different approaches and models for formulating and solving them. The most commonly used approach for this purpose is the application of an analytically hierarchical procedure - AHP [16,17]. For the purpose of procuring new equipment, the AHP technique is used for determining the relative weights of the criteria and the ranking of alternatives is performed using the higher-order PROMETHEE method [18]. These are works in the field of so-called combined or hybrid methods (based on the combined application of different decision-making methods ELECTRE, TOPSIS etc.) that address the choice of equipment that satisfies the decision maker [19, 20]. In recent years, problems related to group decision-making, decision-makers subjectivity, and the use of qualitative expressions for alternative values by individual criteria have been shown by numerous extended methods based on generalized fuzzy numbers, in the case of equipment selection [21, 22, 23] or equipment features [24, 25, 26]. Combining the methods for determining the relative importance of criteria and alternatives ranking methods, the optimal decision is made about certain multicriteria problems regardless of the nature of parameters describing it. Further review of the literature shows that part of the research in this area also focuses on the development of expert systems to support the decision on the selection of adequate equipment [27, 28].

In this paper, we selected and analyzed a few common ranking methods – SAW, TOPSIS, PROMETHEE and VIKOR and developed MODIPROM approach [29] and statistically investigated their similarities, differences, and performances in producing final ranks in the selection of appropriate material handling the equipment. Further analysis of the ranking effects obtained by different MCDM techniques determines the influences of a number of criteria, alternatives, final ranking methods on results similarities and also shows opportunities newly developed approach.

## 2 MCDM METHODS – THE BASIC CONCEPTS

### 2.1. Simple Additive Weighting (SAW) method

The basic concept of the SAW method is to search for the weighted sums obtained from the performance ratings of each alternative on all criteria. SAW method requires a process of normalizing the decision matrix to a scale that can be compared with all ratings of existing alternatives. For benefit and cost attributes, normalized performance alternatives are determined using the Eq. (1) and Eq. (2):

$$r_{ij} = \frac{x_{ij}}{x_j^{\max}} \tag{1}$$

$$r_{ij} = 1 - \frac{x_{ij}}{x_j^{\max}} \tag{2}$$

where are: $x_{ij}$ - the current value (performance/rating) of the *i-th* alternative with respect to the *j-th* criterion and $x_j^{max}$- the maximum value (maximum performance) of all alternatives with respect to the $C_j$ criterion. After that, the best alternative is determined by applying Eq. (3):

$$A^* = \max_i \sum_{i=1}^{m} r_{ij}\omega_j \tag{3}$$

where $\omega_{ij}$ is theweights of all criteria.

### 2.2. Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS)

The principle of TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) is the chosen alternative must have the closest distance from the ideal ideal solution and furthest from the ideal ideal solution from a geometric point of view using the Euclidean distance to determine the relative proximity of an alternative with the optimal solution. According to TOPSIS, we computing the elements of the normalised decision matrix $\left(r_{ji}\right)$:

$$r_{ji} = \frac{x_{ji}}{\sqrt{\sum_{j=1}^{N} x_{ji}^2}},\ j = 1, 2, ..., N; i = 1, 2, ..., k \tag{4}$$

where $x_{ji}$ is value of alternative *j* with respect to attribute *i*. The weighted normalized decision matrix can be calculated by multiplying each row of the normalised decision matrix with its associated attribute weight, because all attributes do not have same importance:

$$v_{ji} = \omega_i r_{ji},\ j = 1, 2, ..., N; i = 1, 2, ..., k \tag{5}$$

where $\omega_i$ is weight of *i* –th attribute.
After the weighting procedure step, positive-ideal solution $A^*$ and negative-ideal solution $A^-$ must be defined. Determination of the positive-ideal solution can be made by taking the largest elements for each benefit attribute, and the smallest element for each cost attribute. The negative-ideal solution is the opposite formation of the positive solution.

$$A^* = \left\{v_1^*, v_2^*, ..., v_i^*, ..., v_k^*\right\}$$
$$v_i^* = \left\{\max_j v_{ji}^*, i \in J_1; \min_j v_{ji}^*, i \in J_2\right\} \tag{6}$$
$$A^- = \left\{v_1^-, v_2^-, ..., v_i^-, ..., v_k^-\right\}$$

$$v_i^- = \left\{\max_j v_{ji}^-, i \in J_1; \min_j v_{ji}^-, i \in J_2\right\} \tag{7}$$

$J_1$ is the set of benefit attribute and $J_2$ is the set of cost attributes.

Finally, distance between alternatives can be measured by the Euclidean distance. Separation of each alternative from the positive-ideal and negativ-ideal solution is given by:

$$S_j^* = \sqrt{\sum_{i=1}^{k}\left(v_{ji} - v_i^*\right)^2},\ j = 1, 2, ..., N \tag{8}$$

$$S_j^- = \sqrt{\sum_{i=1}^{k}\left(v_{ji} - v_i^-\right)^2},\ j = 1, 2, ..., N \tag{9}$$

Relative closeness of $A_j$ with respect to $A^*$ is defined as

$$C_j^* = \frac{S_j^-}{S_j^* + S_j^-}, 0 < C_j^* < 1; j = 1, 2, ..., N \tag{10}$$

where $C^*_j$ is close to 1, the alternative is regarded as ideal, or when it is close to 0 the alternative is regarded as non-ideal.

### 2.3. Preference Ranking Organization Method for Enrichment of Evaluations (PROMETHEE)

Promethee is one method of determining the order or priority in MCDM. The task of optimization is to enable selection of the best variant (best solution) from a series of variants, i.e. in its mathematical form optimization is reduced to maximization of the criterion function $Max\{f_1(x),..., f_n(x)\}$ in the given set $x \in A\{a_1,...,a_m\}$. The values $f_{ij}$ are known for each criterion $f_j$ for each possible alternative $A_i$

$$f_{ij} = f_j(a_{ij})\ \forall(i,j);\ i = 1,2,\ldots,m;\ j = 1,2,\ldots,n \tag{11}$$

The procedure of ranking the $m$ number of alternatives $A=\{a_1,...,a_i,...a_m\}$ covers generalization of the concept of the $n$ number of criteria $f=\{f_1,...,f_k,...f_n\}$, establishing ranking relations and a comparative analysis of results. Let $f_j(a)$ be the value of the criterion $f_j$ for the alternative $a$. After the creation of the initial matrix, one preference value $P_j(a,b)$ is assigned to each criterion which makes the basis for comparison of two alternatives, and it expresses the intensity of preference of the alternative $a$ in relation to the alternative $b$. On the basis of preference functions, which are infinite, the type of generalized criterion function whose value is between $0$ and $1$ is chosen and, in a general case, that value is:

$$P_j(a,b) = \begin{cases} 0, \text{if } f(a) \le f(b) \\ P_j\left[f(a) - f(b)\right] = P_j\left[d(a,b)\right] \end{cases} \tag{12}$$

Six types of generalized criterion functions for expressing preferences of the decision maker regarding concrete criteria for the problem is the main characteristic of this family of methods. Each criterion is assigned a certain weight $\omega_j, j = 1, \ldots, k$ as a measure of relative importance of the criterion, so that $\sum_{j=1}^{k}\omega_j = 1,\ 0 < \omega_j < 1$.

The multicriteria preference index is determined in accordance with the expression:

$$\Pi(a,b) = \sum_{j=1}^{k}\omega_j\, p_i(a,b) \tag{13}$$

The index represents the measure of preference of the alternative $a$ in relation to the alternative $b$ and the closer it is to one, the preference is bigger. It takes into account all criteria at the same time. The positive, negative and net outranking flows of action are now defined for each alternative. The net outranking flow of the alternative $a$ represents the difference:

$$\Phi(a) = \Phi^+(a) - \Phi^-(a) \tag{14}$$

where the negative outranking flow ($\Phi^-(a)$) and the positive outranking flow ($\Phi^+(a)$) are respectively:

$$\Phi^-(a) = \sum_{\forall b \in A}\Pi(b,a) \tag{15}$$

$$\Phi^+(a) = \sum_{\forall b \in A}\Pi(a,b) \tag{16}$$

In accordance with PROMETHEE I, it is established that the higher the output flow, the more other alternatives are dominated by the alternative $a$, and the lower the input flow, the smaller number of other alternatives dominate over $a$. In other words:

- if ($\Phi^-(a) \ge \Phi^+(b)$ and $\Phi^+(a) \le \Phi^+(b)$, it is said that $a$ prefers $b$.

The equality $\Phi^-$ and $\Phi^+$ point to indifference during comparison of two alternatives. The alternatives $a$ and $b$ are incomparable if:

- $\Phi^-(a) > \Phi^-(b)$ and $\Phi^+(a) > \Phi^+(b)$ or
  $\Phi^-(a) < \Phi^-(b)$ and $\Phi^+(a) < \Phi^+(b)$

In PROMETHEE II, the net outranking flow indicates the priority of each alternative in relation to the others and gives the complete ranking of alternatives. Thus, the value of difference between flows is used for ranking all alternatives in such a way that a better alternative corresponds to a higher value:

- if $\Phi(a) > \Phi(b)$, it is said that $a$ prefers $b$
- if $\Phi(a) = \Phi(b)$, it is said that $a$ is indifferent in relation to $b$

The PROMETHEE III method performs ranking by assigning each alternative $a$ the interval $[x_a, y_a]$ on the basis of which the complete ranking for each pair of alternatives $(a,b)$ is determined using the following definitions:

- if $x_a > x_b$, it is said that $a$ prefers $b$ (has a higher rank),
- if $x_a \le y_b$ $i$ $x_b \le y_a$, it is said that $a$ is indifferent in relation to $b$, where are:

$$x_a = \Phi(a) - \alpha\sigma_a$$

$$y_a = \underline{\Phi}(a) + \alpha\sigma_a$$

$$\underline{\Phi}(a) = \frac{1}{m}\sum_{b \in A}(\Pi(a,b) - \Pi(b,a)) = \frac{1}{m}\Phi(a)$$

$$\sigma_a = \sqrt{\frac{1}{m}\sum_{b \in A}(\Pi(a,b) - \Pi(b,a) - \underline{\Phi}(a))^2}$$

$$\alpha > 0$$

### 2.4. The MODIPROM method (MODIfied PROmethee Method)

The developed MODIPROM method (MODIfied PROmethee Method)[29] is based on the improvement of a group of methods for multicriteria ranking, as follows:

- change of the existing generalized criteria and introduction of the new ones,
- procedure of selection of generalized criteria within one criterion function,
- analysis of effects of change of weight coefficients, and
- transformation of the mean values of the outranking flow for the purpose of solving complex criterion functions.

Changes of generalized criteria refer to retaining generalized criteria I (Usual criterion), II (U-shape criterion), IV(Level criterion) and VI (Gaussian criterion). Criterion III (V-shape criterion) and V (V-shape with indifference criterion) are replaced with the linear criterion whose parameters are calculated through linear regression. The square and cube criteria whose parameters are calculated by regression analysis are introduced. The influence of experience and subjective evaluation of the decision maker in the selection of generalized criteria is reduced to minimum, in other words, the selection performed on the basis of the methods of the least squares so that the generalized criterion is chosen in which the sum of squares of deviations of experimental points from the theoretical curve of the generalized criterion is least.

### 2.5. VIKOR method (Vlse Kriterijumska Optimizacija Kompromisno Resenje)

This method focuses on ranking and selecting from a set of alternatives and determines compromise solution for a problem with conflicting criteria. The VIKOR method determines the best $f_j^*$ and the worst $f_j^-$ values of all criterion functions *j=1, 2,...,n* (if the *j-th* function represent a benefit: $f_j^* = \max_j f_{ij}$, $f_j^- = \min_j f_{ij}$). In the next step, the values $S_i$and $R_i$ are computed by Eq.(17):

$$S_i = \sum_{j=1}^{n} \omega_j (f_j^* - f_{ij}) / (f_j^* - f_j^-)$$
$$R_i = \max_j \omega_j (f_j^* - f_{ij}) / (f_j^* - f_{ij}) \qquad (17)$$

where $w_j$ are the weights of criteria. The values $Q_i$, *i=1,2,...,m* are computed by relation:

$$Q_i = \nu(S_i - S^*)/(S^- - S^*) + (1-\nu)/(R_i - R^*)/(R^- - R^*) \quad (18)$$

where are:

$$S^* = \min_i S_i,\ S^- = \max_i S_i,$$
$$R^* = \min_i R_i,\ R^- = \max_i R_i.$$

and $\nu$is weight of the strategy of the majority of criteria.
Sorrting by the values *S*, *R* and *Q* in decreasing order is obtained a final ranking of the alternatives. Proposing as a compomise solution the alternative *A'*, which is ranked the best by the measure *Q* (minimum) if the following two condition are satisfied:

- Acceptable advantage: $Q(A'') - Q(A') \geq DQ$, where $A''$ is the alternative with second position in the ranking list by *Q*: *DQ=1/(m-1)*, *m* is the number of alternatives.
- Acceptable stability in decision making*:*Alternative *A'* must also be the best ranked by *S* or/and *R*. This compromise solution is stable within a decision making process (which could be: when ν>0.5 is needed-*voting by majority rule;* ν≈0.5- *by concesus*; ν<0.5 – *with veto*).

If one of the condition is not satisfied, than a set of compromise solution is proposed:

- Alternatives *A'* and *A''* if only condition C2 is not satisifed or
- Alternatives *A', A'',..., A*$^{(M)}$ if condition C1 is not satisfied, *A*$^{(M)}$ is defined by the relation $Q(A^{(M)}) - Q(A') < DQ$ for the maximum M (the positions of these alternatives are *in closeness*)

The obtained compromise solution could be accepted by the decision makers because it provides a maximum "*group utility*" (represented by min *S*) of the "*majority*", and a minimum of the "*individual regret*" (represented by min *R*) of the "*opponent*". The compromise solutions could be the basis for negotiations, involving the decision maker's preference by criteria weights.

## 3 STATISTICAL COMPARISON OF RANKING METHODS

Kendall's tau-b and Spearman's rho test were selected to analyze the produced ranks through different decision-ranking methods in terms of their pairwise correlations. These two non-parametric tests are used to measure the ordinal association between the two measured quantities (the final ranks compare among the methods) and to test for associations in hypothesis testing. The null hypothesis ($H_0$) is that there is no association between the variables under study or that there is no correlation. To prove something using statistics, you should assume the opposite, that there is no correlation between your data sets. The p (or probability) value obtained from the calculation is a measure of how likely or probable it is that any observed correlation is due to chance. P-values range between 0 (0%) and 1 (100%). A p-value close to 1 suggests no correlation other than due to chance and that your null hypothesis assumption is correct. If your p-value is close to 0, the observed correlation is unlikely to be due to chance and there is a very high probability that the null hypothesis is wrong. In this case, you must accept the alternative ($H_1$) hypothesis that there is a correlation between your data sets.

### 3.1. Kendall's tau-b test

Kendall's tau-b test coefficients indicate the concordant and discordant association between the ranks of two compared groups of ranks. Kendall's tau-b coefficient is calculated using Eq. (19) as follows [2]:

$$\tau_B = \frac{n_C - n_D}{\sqrt{(n_0 - n_1)(n_0 - n_2)}} \qquad (19)$$

where are:

$n_0 = n(n-1)/2$, $n_1 = \sum_i t_i (t_i - 1)/2$, $n_2 = \sum_j u_j (u_j - 1)/2$, and$n_C$ is the number of concordant pairs; $n_D$ is the number of discordant pairs; $t_i$ is the number of tied values in the *i-th* group of ties for the first quantity and $u_j$ is the number of tied values in the *j-th* group of ties for the second quantity. This formulation yields $\tau_B$ between −1 and + 1. The value

of −1 stands for 100% negative association, and the value of + 1 stands for 100% positive associations.
The value of zero stands for the absence of any association. The main advantages of using Kendall’s tau-b test are as follows:

- The distribution of Kendall’s tau-b has better statistical properties.
- The interpretation of Kendall’s tau-b in terms of the probabilities of observing the agreeable (concordant) and non-agreeable (discordant) pairs is very direct.
- In most of the situations, the interpretations of Kendall’s tau-b and Spearman’s rank correlation coefficient are very similar and thus invariably lead to the same inferences.

### 3.2. Spearman’s rho test

Spearman’s rank correlation test, which is a special form of correlation test, is used when the actual values of paired data are substituted with the ranks, which the values occupy in the respective samples [2]. Spearman’s rho usually has larger values than Kendall’s tau and calculations are based on deviations and much more sensitive to error and discrepancies in data.
The Spearman's rank correlation coefficient value (Eq.(20)) is a statistical measure of the strength of a link or relationship between two sets of data.

$$r_s = 1 - \left[ \frac{6 \cdot \sum_{j=1}^{K} (d_j)^2}{K(K^2 - 1)} \right] \tag{20}$$

The answer will always be between 1.0 (a perfect positive correlation) and -1.0 (a perfect negative correlation). An $r_s$ of 0 indicates no association between ranks (Fig.1).

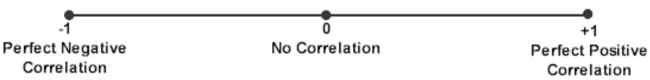


**Fig.1** *The association between ranks*

We can describe the strength of the correlation using the following guide for the value of $r_s$ (Table 1).

**Table 1** The strength of a correlation

| The strength of a correlation | |
|---|---|
| **Value of coefficient $r_s$ (positive or negative)** | **Meaning** |
| 0.00 to 0.19 | A very weak correlation |
| 0.20 to 0.39 | A weak correlation |
| 0.40 to 0.69 | A moderate correlation |
| 0.70 to 0.89 | A strong correlation |
| 0.90 to 1.00 | A very strong correlation |

A guide to interpreting a p-value is shown on Fig.2. So you must accept the alternative hypothesis (that there is a strong positive correlation between your data sets) and reject the null hypothesis that there is no correlation. This correlation does not imply causation. One variable may not cause the other.

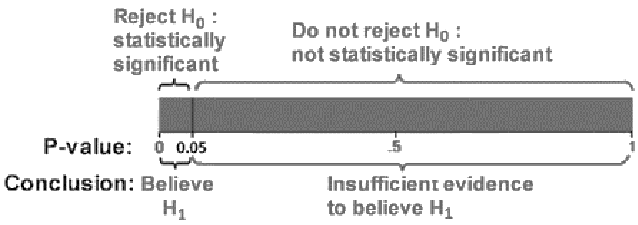


**Fig.2** *A guide to interpreting a p-value*

## 4 NUMERICAL EXAMPLE AND ANALYSIS

In this section, the numerical example of purchasing a forklift for the one warehouse facility is analyzed. It is an MCDM problem and for ranking a set of forklift alternatives that satisfy in advance required parameters, the initial set of 9 characteristics was observed (Table 2).

**Table 2** *A initial set of selection criteria and alternatives*

| Model | Capacity (kg) | Max. lift height (mm) | Travel speed with the load (km/h) | Lift speed with the load (m/s) | Turning radius (mm) | Level of noise (dB) | Engine power (kW) | Wheel-base (mm) | Total width (mm) |
|---|---|---|---|---|---|---|---|---|---|
| **7FBEST15** | 1500 | 3310 | 12 | 0.3 | 1450 | 62.4 | 7.5 | 1200 | 990 |
| **2ET2500** | 1300 | 3000 | 16 | 0.48 | 1440 | 66 | 11.5 | 1249 | 1060 |
| **2ETC3000** | 1600 | 3000 | 16 | 0.49 | 1548 | 66 | 11.5 | 1357 | 1060 |
| **J30XNT** | 1361 | 3032 | 15.7 | 0.39 | 1481 | 69 | 4.8 | 1290 | 1050 |
| **J35XNT** | 1588 | 3032 | 15.7 | 0.36 | 1577 | 69 | 4.8 | 1386 | 1050 |
| **TX30N** | 1350 | 3300 | 14.5 | 0.34 | 1525 | 61 | 10.7 | 1300 | 1105 |
| **TX35N** | 1600 | 3300 | 14.5 | 0.31 | 1525 | 61 | 10.7 | 1300 | 1105 |
| **ERP15VC** | 1500 | 3320 | 12 | 0.3 | 1452 | 59 | 6 | 1222 | 996 |
| **ERP15VT** | 1500 | 3320 | 16 | 0.43 | 1476 | 65 | 12 | 1290 | 1050 |
| **ERP16VT** | 1600 | 3320 | 16 | 0.43 | 1476 | 65 | 12 | 1290 | 1050 |

In order to analyze and to compare the results of ranking are developed the program tools in the environment of Microsoft Excel. The fourth decision matrices were developed (with 5 alternatives and 5 criteria (5A-5C); 7 alternatives and 7 criteria (7A-7C); 10 alternatives and 9 criteria (10A-9C) and 5 alternatives and 7 criteria (5A-7C) in order to investigate the role of changing of criteria number.

The fourth standard MCDM methods and recently developed approach were applied to each decision matrix. The final, sorted ranks were statistically analyzed by Kendall’s tau-b and Spearman's rho test using a specific macro written in Excel.

### 4.1. Numerical results and discussion

Table 3 gives a statistical results of the Spearman’s rho and Kendall’s tau-b test for decision matrix with 10 alternatives and 9 criteria. The results obtained for α-level = 0.05 shows similarity of performances between two statistical test. The Sig (2-tailed) p-value tells us if correlation was significant at a chosen alpha level. If p-value is small, then the correlation is significant.For the purpose of investigating the correlation strength between ranks obtained with analyzed methods, Kendall’s tau-b correlation coefficients have been selected as supplementary data sets for further evaluation.

Fig. 3-7 shows the statistical results of the correlation significance percentages among different ranking methods applied on decion matrices with 5 alternatives and 5 criteria; 7 alternatives and 7 criteria; 10 alternatives and 9 criteria.

**Table 3** Correlation coefficient obtained by different ranking methods for decision matrix with 10 alternatives and 9 criteria

| | SAW | TOPSIS | PROMETHEE | MODIPROM | VIKOR |
|---|---|---|---|---|---|
| **Sperman's rho test** | | | | | |
| SAW | 1.000 | 0.050 | -0.15 | -0.016 | 0.116 |
| TOPSIS | 0.050 | 1.000 | -0.116 | -0.050 | 0.450 |
| PROMETHEE | -0.150 | -0.116 | 1.000 | 0.666 | 0.050 |
| MODIPROM | -0.016 | -0.050 | 0.666 | 1.000 | -0.016 |
| VIKOR | 0.116 | 0.450 | 0.050 | -0.016 | 1.000 |
| **Kendall's tau-b test** | | | | | |
| SAW | 1.000 | 0.055 | -0.111 | 0.000 | 0.055 |
| TOPSIS | 0.055 | 1.000 | -0.055 | -0.055 | 0.333 |
| PROMETHEE | -0.111 | -0.055 | 1.000 | 0.444 | -0.055 |
| MODIPROM | 0.000 | -0.055 | 0.444 | 1.000 | 0.055 |
| VIKOR | 0.055 | 0.333 | -0.055 | 0.055 | 1.000 |

The results show that SAW had the highest significant correlation percentages with the TOPSIS; MODIPROM had the highest significant correlation percentages with PROMETHEE; PROMETHEE had the highest significant correlation percentages with MODIPROM and partially with VIKOR. SAW and TOPSIS had the lowest significant correlation percentages with VIKOR.

Fig. 8-12 ilustrated the comparasion of results of ranking methods applied on decision matrix with an equal number of alternatives as the number of criteria increased (5 alternatives and 5 criteria and 5 alternatives and 7 criteria). The statistically significant correlation percentage is mostly constant for SAW but in the case of VIKOR methods increases. It is evident that in all cases the results of the ranking obtainedwith new approach MODIROM are statistically similar to theresults obtained by other traditional approaches.For a better analysis of the influence of changing the number of criteria, it is necessary to applied MCDM methods on decision matrices different sizes.

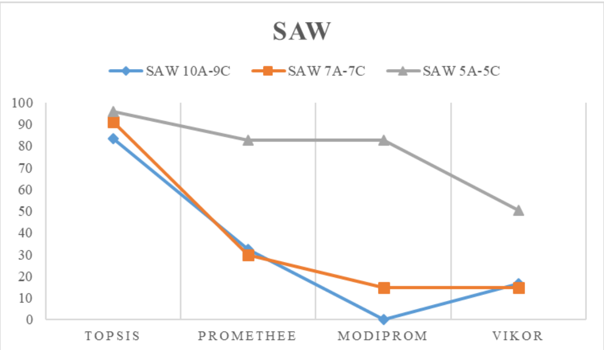


**Fig.3** *Multiple comparasion of statistical results of SAW versus different methods*

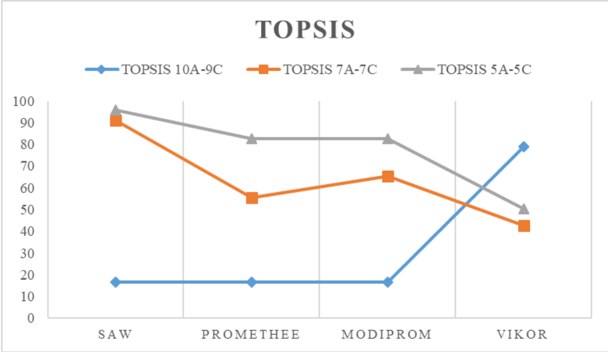


**Fig.4** *Multiple comparasion of statistical results of TOPSIS versus different methods*

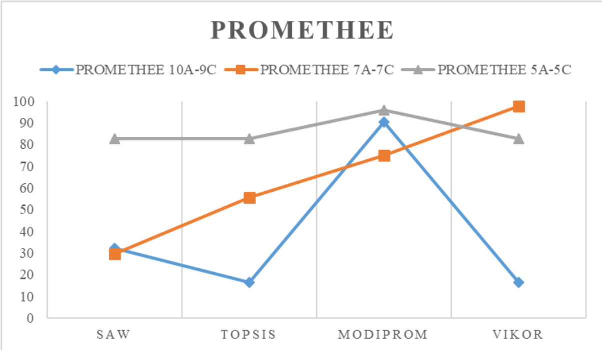


**Fig.5** *Multiple comparasion of statistical results of PROMETHEE versus different methods*

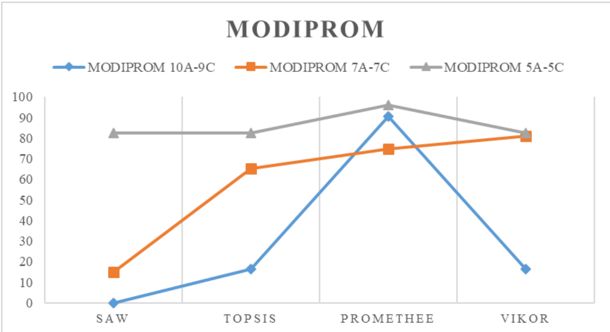


**Fig.6** *Multiple comparasion of statistical results of MODIPROM versus different methods*

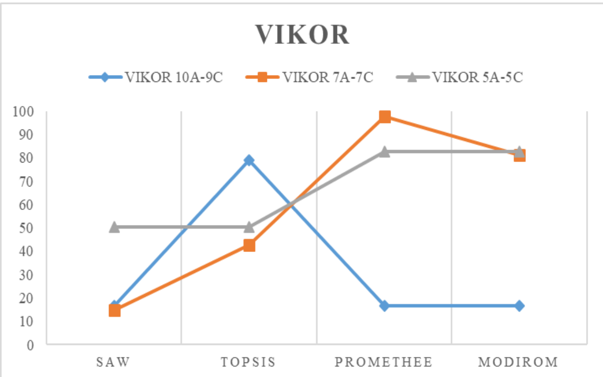


**Fig.7** *Multiple comparasion of statistical results of VIKOR versus different methods*

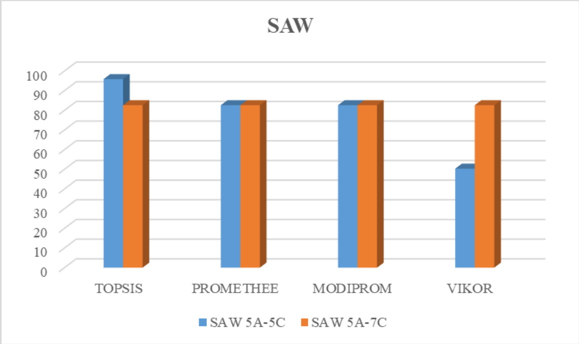


**Fig.8** *Comparasion of statistical results of SAW versus different methods applied on decision matrices with 5A-5C and 5A-7C*

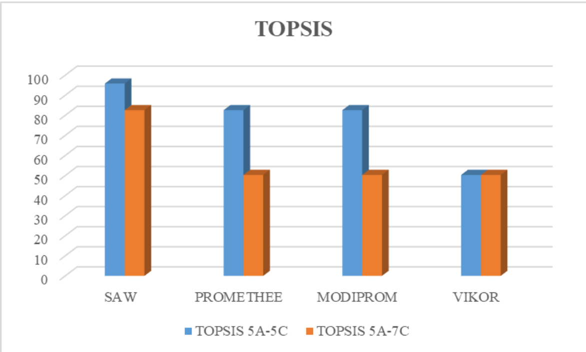


**Fig.9** *Comparasion of statistical results of TOPSIS versus different methods applied on decision matrices with 5A-5C and 5A-7C*

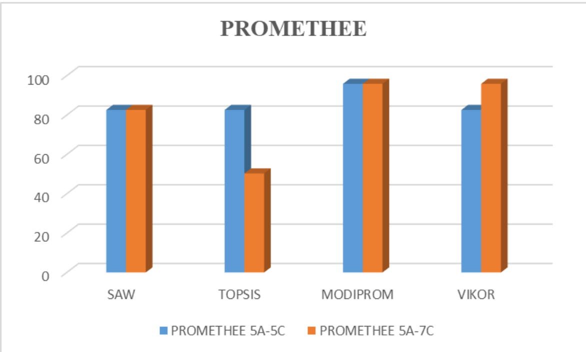


**Fig.10** *Comparasion of statistical results of PROMETHEE versus different methods applied on decision matrices with 5A-5C and 5A-7C*

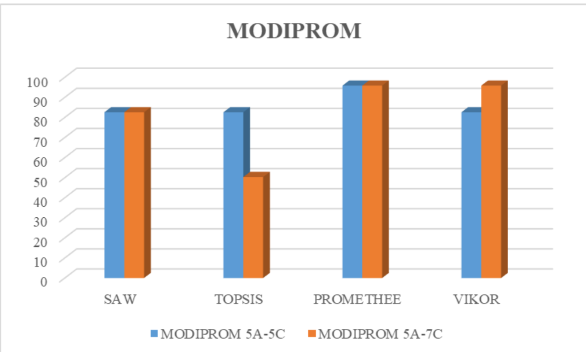


**Fig.11** *Comparasion of statistical results of MODIPROM versus different methods applied on decision matrices with 5A-5C and 5A-7C*

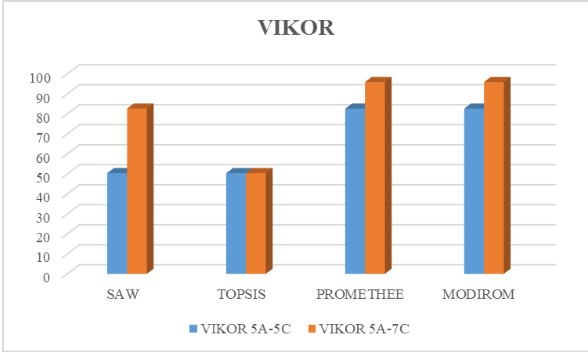


**Fig.12** *Comparasion of statistical results of VIKOR versus different methods applied on decision matrices with 5A-5C and 5A-7C*

## 6 CONCLUSION

Statistical analysis of the different decision matrices indicates that SAW and TOPSIS as well as PROMETHEE and MODIPROM have similar performances and produced almost identical performances. Also, the graphical presentation of the results indicates that by increasing the size of the decision matrix the p-value or percentage of significant correlation among the ranks of pairwise decreases. On the other side, with increasing the number of criteria for the same number of alternatives statistical significant correlation percentage is mostly constant for SAW, PROMETHEE and MODIPROM, but a decreases for TOPSIS. This research provides efforts to create an effective decision-making process and emphasizes the importance of comparing different techniques, but there is no recommendation as to whether one technique is better than another. Also, the results of this study statistically compares the performances of commonly used and classic MCDM techniques and proposed a new approach. The results can guide in the formation of a comprehensive tool for solving a wide range of real and practical engineering problems. Definition of new cases i.e. comparasions of results obtained under fuzzy enviroment (in most real situation criteria are not deterministic) or obtained by new hybrid models are direction for further analysis. Also, it is recommended to investigate the magnitude of the correlation coefficients among the ranks by different techniques applied on the same decison matrix with changing of relative weights of criteria and their number.

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## REFERENCES

1. Khandekar, A.V., Chakraborty, S., 2014, *Material Handling Equipment Selection using Fuzzy Axiomatic Design Principles*, 5th International & 26th All India Manufacturing Technology, Design and Research Conference (AIMTDR 2014), IIT Guwahati, Assam, India, pp. 21-1-21-7.

2. Sabzi H.Y., King J.P., Gard C.C., Abudu S., 2016, *Statistical and analytical comparasion of multi-criteria decision-making techniques under fuzzy environment*, Operations Research Perspectives, 3(19), pp. 92-117.
3. Zanakis, S., Solomon, A., Wishart, N., Dublish, S., 1998, *Multi-attribute decision-making: a simulation comparison of select methods*, Eur J 1998.
4. Behzadian, M., Kaemzadeh, R. B., Albadvi, A., Aghdasi, M., 2009, *PROMETHEE: A comprehensive literature review on methodologies and applications*, European Journal of Operations Research 200: 198–215, doi: 10.1016/j.ejor.2009.01.021
5. Dias, L., Costal, J. P., Clímaco, J. N., 1998, *A parallel implementation of the PROMETHEE method*, European Journal of Operations Research, 104: 521–531.
6. Goumas, M., Lygerrou, V., 2000, *An extension of the PROMETHEE method for decision making in fuzzy environment: Ranking of alternative energy exploitation projects*, European Journal of Operations Research, 123: 606–613.
7. Zdzistaw, P. Skowron, A., 2007, *Rough sets: some extensions*. Inf Sci. 177(1):28–40.
8. Cancer, V., 2010, *Considering Interactions among Multiple Criteria for the Server Selection*. JIOS, 34 (1):55-65.
9. Moaven, S., Ahmadi, H., Habibi, J., Kamandi, A., 2008, *A Fuzzy Model for Solving Architecture Styles Selection Multi-Criteria Problem*. In Proceedings of the Second UKSIM European Symposium on Computer Modelling and Simulation. IEEE Computer Society, pp.388-393.
10. Liu, J., Zhao, H.K., Bin, Li Z., Liu, SF., 2017, *Decision process in MCDM with large number of criteria and heterogeneous risk preferences*, Operations research Perspectives, 4:106-112.
11. Zhang, W.X., Qiu, GF, 2005, *Uncertain decision making based on rough sets*, Beijing, Tsinghua University Press (in Chinese).
12. Choo, Eng U., Schoner, B., Wedley, C.W.,1999, *Interpretation of criteria weights in multicriteria decision making*. Computer & Industrial Engineering, 37:527-541.
13. Bagherikahvarin, M., De Smet Y., 2017, *Determining new possible weight values in PROMETHEE: a procedure based on data envelopment analysis*, Journal of the Operational Research Society, 68(5): 484-495
14. Saaty, T.L., 1977, *A scaling method for priorities in hierarchical structures*. Journal of mathematical psychology, 15(3): 234-281.
15. Torfi, F., Farahani, R.Z., Rezapour, S., 2010, *Fuzzy AHP to determine the relative weights of evaluation criteria and Fuzzy TOPSIS to rank the alternatives*, Applied Soft Computing, 10(2): 520-528.
16. Chakraborty. S., Banik, D., 2006, *Design of material handling equipment selection model using analytic hierarchy process*, Intelligent Journal of Advanced Manufacturing Technologies,28, 1237-1245.
17. Zahedi, F., 1986: *The analytic hierarchy process: A survey of the method and its applications*, Interfaces, 16(4), pp. 96-108.
18. Dagdeviren, M., 2008, *Decision Making in equipment selection: an integrated approach with AHP and PROMETHEE*, Journal of Intelligent Manufacturing, 19, pp. 397-406.
19. Chang, C.-W., 2012, *Collaborative decision making algorithm for selection of optimal wire saw in photovoltaic wafer manufacture*, Journal of Intelligent Manufacturing, 23(2012), pp. 533-539.
20. Stam, A., Kuula, M., 1991, *Selecting a flexible manufacturing system using multiple criteria analysis*, International Journal of Production Research, 29, pp. 803-820.
21. Kulak, O., 2005, *A decision support system for fuzzy multi-atribute selection of material handling equipments*, Expert Systems with Applications 29(2005), pp.310-319.
22. Tuzkaya, G., Gulsun, B., Kahraman, C. Ozgen, D., 2010, *An integrated fuzzy multi-criteria decision making methodology for material handling equipment selection problem and an application*, Expert Systems witjh Applications 37 (2010), pp.2853-2863.
23. Wang, T. Y., Shaaw, Ch. F., Chen, Y. L., 2000, *Machine selection in flexible manufacturing cell: A fuzzy multiple attribute decision-making approach*, International Journal of Production Research, 38, pp. 2079-2097.
24. Ayang, Z., Ozdemir, R. G., 2006, *A fuzzy AHP approach to evaluating machine tools alternatives*, Journal of Intelligent Manufacturing,17,pp. 179-190.
25. Rai, R., Kameshwaran, S., Tiwari, M.K., 2002, *Machine tool selection and operation allocation in FMS: solving a fuzzy goal programming model using a genetic algorithm*, International Journal of Production Research, 40, pp. 641-645.
26. Yurdakul, M., Tansel, I. Y., 2009, *Analysis of the benefit generated by using fuzzy numbers in a TOPSIS model developed for machine tool selection problems*, Journal of Material Processing Technology, 209, pp. 310-317.
27. Fisher, E.L., Farber, J. B., Kay, M. G., 1998, *MATEHS: An expert system for material handling equipment selection*, Engineering Costs and Production Economics, 14, pp.297- 310.
28. Fonseca, D. J., Uppal, G., Greene, T. J., 2004, *A knowledge-based system for conveyor equipment selection, Expert Systems with Applications*, 26, pp. 615-623.
29. Marković G., Gašić M., Kolarević M., Savković M., Marinković Z., 2013, *Application of the MODIPROM method to the final solution of logistics centre location*, Transport 28(4), pp. 341-351.


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