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DOE-MARCOS: A NEW APPROACH TO MULTI-CRITERIA DECISION MAKING

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Choosing the best among the available alternatives seems to be expected in all fields. As each alternative is considered by multiple criteria, the selection of the best alternative must take into account all of those criteria. MCDMs are methods that have been widely used to solve problems of this type. However, if only a certain MCDM is applied, the ranking of alternatives must be done from the beginning as adding/removing one or more alternatives from the option list. This paper presents a probably new approach to deal with this situation. DOE method was used in combination with the MARCOS method to build a relationship between the scores of the options and the criteria. This mix is called DOE-MARCOS. Based on this, the calculation of the scores of the alternatives may be faster and less complicated than only using the MCDM. A simple example was made to evaluate the effectiveness of the proposed method when an alternative was added to the list. Two other examples were also conducted to assess the performance of the proposed method (DOE-MARCOS) in ranking cutting tools. The results of ranking options using the DOE-MARCOS are compared with other methods. Sensitivity analysis in each example under different scenarios was also carried out. Its results show that the proposed method is highly effective for multi-criteria decision making.

Keywords: MCDM, MARCOS method, DOE method, DOE-MARCOS method, Cutting tool selection

1 INTRODUCTION

Hundreds of multi-criteria decision-making (MCDM) methods are developed in order to rank alternatives and select the best [1-2]. Although each MCDM is implemented differently, most of them have the same three-step process, containing: normalizing the data, determining the weights for the criteria, and calculating the scores for each alternative [3]. Then, ranking the options is made based on these scores. However, identifying the appropriate data normalization method for combining with a certain MCDM is relatively complicated [4-6]. Moreover, in order to conclude that a data normalization method is suitable for combining with the MCDM, it must be examined using many different data normalization methods simultaneously [7, 8]. This is time-consuming and not suitable for urgent decision making. Likewise, the weight method significantly has an impact on the rank results of the alternatives. Sometimes the best solution is found to be different when dissimilar weight methods are applied [9, 10]. Thus, it can be said that determining the data normalization and weight method are considerable difficulties for decision makers.

Measurement Alternatives and Ranking according to COmpromise Solution (MARCOS), proposed in 2020, is a method that appeared fairly late compared to most other methods [11]. This method has shown that it has significant advantages over other methods such as: the rank results of the alternatives are less dependent on the weight method, as well as the data normalization method [12]. Its advantages have been strongly taken recently: to evaluate resources in transport companies [13], to select equipment in logistics operations [14], to rank financial applications [15], to rank insurance companies and health care services [16], to select the best alternative for the process of powder-mixed electrical discharge machining (PEDM) [17], to assess logistics operations by drone [18], to select sustainable suppliers [19], to evaluate power system operation solutions [20], to review e-learning site [21], to take a solution for protecting the environment within the textile industry in Nigeria [22], to determine the effectiveness of railway systems in Africa [23], etc.

However, like most other MCDMs, in the use of MARCOS method, scholars often consider ranking the available alternatives, not taking into account the case that there are alternatives arising in an implementation process. This appears to be a large gap that needs to be filled. A simple example is as follows: at the moment that the selection of one of the four options has been made, there is a recommendation of a fifth, even a sixth, or more. Then, if only a certain MCDM method is used, the calculation may be done from the beginning every time options are added. This is clearly time-consuming for the decision makers. This study proposes a solution to overcome this disadvantage. First, the DOE is used to build an experimental matrix. After performing the experiments, the calculations in the MARCOS method help to build the relationship between the scores of the options with the criteria as (1). The blend of the Design-Of-Experiments (DOE) method and MARCOS devises a new method, called DOE-MARCOS.

$$f(K_i) = f(C_1, C_2, \dots, C_n) \quad (1)$$

Where:

$f(K_i)$ is the *MARCOS* score of the alternative *i*.

C_1, C_2, …., C_n are the criteria.

Equation (1) is used not only for defining the score of the available alternatives, but also for identifying the score of the additional alternatives. This is a new feature that does not seem to be possible with all current *MCDM* methods. In the second part of this research, steps are presented so as for ranking the alternatives according to the *MARCOS* method. And some examples of applying the *DOE-MARCOS* are presented in the third section. The first example is performed to evaluate the effectiveness of the *DOE-MARCOS* as a new alternative (additional) appears. The two next examples are conducted using data from published studies. Sensitivity analysis in ranking alternatives is also tested in different scenarios. The final part of this study is the conclusions and future work.

2 MARCOS METHOD

The steps for implementation of multi-criteria decision making according to the *MARCOS* method are as follows [11]:

Step 1: Building a decision matrix.

$$X = \begin{bmatrix} x_{11} & x_{1j} & x_{1n} \\ x_{21} & \cdots & x_{2n} \\ x_{i1} & x_{ij} & \vdots \\ x_{mn} & \cdots & x_{mn} \end{bmatrix} \tag{2}$$

Where: *m* is the number of alternatives, *n* is the number of criteria, x_{ij} is the value of criterion *j* at alternative *i*, with $1 \le i \le m$; $1 \le j \le n$.

Step 2: The extended decision matrix is built by adding an ideal alternative *(AI)* and an anti-ideal alternative *(AAI)*.

$$X = \begin{matrix} AAI \\ A_1 \\ A_2 \\ \vdots \\ A_m \\ AI \end{matrix} \begin{bmatrix} x_{aa1} & \cdots & x_{aan} \\ x_{11} & \cdots & x_{1n} \\ x_{21} & \cdots & x_{2n} \\ \vdots & \vdots & \vdots \\ x_{m1} & \cdots & x_{mn} \\ x_{ai1} & \cdots & x_{ain} \end{bmatrix} \tag{3}$$

- For max criteria:

  $AAI = min(x_{ij})$; *i* = 1, 2, …, *m*; *j* = 1, 2, …, *n*

  $AI = max(x_{ij})$; *i* = 1, 2, …, *m*; *j* = 1, 2, …, *n*
- For min criteria:

  $AAI = max(x_{ij})$; *i* = 1, 2, …, *m*; *j* = 1, 2, …, *n*

  $AI = min(x_{ij})$; *i* = 1, 2, …, *m*; *j* = 1, 2, …, *n*

Step 3: Normalizing the extended decision matrix according to the equation:

- For max criteria:

$$n_{ij} = \frac{x_{ij}}{x_{AI}} \tag{4}$$

- For min criteria:

$$n_{ij} = \frac{x_{AI}}{x_{ij}} \tag{5}$$

Step 4: Defining the normalized value, taking into account the weight of the criteria according to the following equation.

$$v_{ij} = n_{ij} \cdot w_j \tag{6}$$

Where, w_j is the weight of the criterion *j*.

Step 5: The coefficients K_i^+ and K_i^- are calculated according to the equations (7) and (8).

$$K_i^- = \frac{S_i}{S_{AAI}} \tag{7}$$

$$K_i^+ = \frac{S_i}{S_{AI}} \tag{8}$$

Where:

S_i, S_{AAI} and S_{AI} are the sum of the values of v_{ij}, x_{aai} and x_{ai}, respectively, where $i = 1, 2, ..., m$.

Step 6: $f(K_i^+)$ and $f(K_i^-)$ are calculated according to the equations (9) and (10).

$$f(K_i^-) = \frac{K_i^+}{K_i^+ + K_i^i} \quad (9)$$

$$f(K_i^+) = \frac{K_i^-}{K_i^+ + K_i^i} \quad (10)$$

Step 7: Calculating the *MARCOS* score for each alternative ($f(K_i)$ according to the equation (11). Ranking is based on the rule that the option with the highest score is considered the best.

$$f(K_i) = \frac{K_i^+ + K_i^-}{1 + \frac{1 - f(K_i^+)}{f(K_i^+)} + \frac{1 - f(K_i^-)}{f(K_i^-)}} \quad (11)$$

3 EXAMPLES

3.1 Example 1

This example is made to examine the effectiveness of the *DOE-MARCOS* approach when an alternative is added in the decision-making process. The example is described as follows: There are four alternatives *A1*, *A2*, *A3*, *A4*, evaluated by three criteria *C1*, *C2*, and *C3*. Where *C1* and *C2* represent the max criterion and *C4* represents the min criterion. The values of the criteria in each alternative are selected at random, as shown in Table 1.

Table 1. Data for example 1

No.	C1	C2	C3
A1	8	10	7
A2	9	8	8
A3	5	13	6
A4	11	9	10

The multi-criteria decision-making in this case is to determine an alternative that *C1* and *C2* are maximum and *C3* is minimum simultaneously. Both two methods *DOE-MARCOS* and *MARCOS* are applied. Assuming the weights of the criteria are all equal, being 1/3.

Applying the seven steps of the *MARCOS* method (introduced in section 2), the *MARCOS* score of each alternative is calculated as shown in Table 2. This table also presents the ranking results of the alternatives using the *MARCOS* method.

The *DOE-MARCOS* method is applied as follows: The experimental matrix is built in the form of two full levels (2^k), where *k* is the number of criteria (*k=3*), including 8 experiments. When building up the experimental matrix, the minimum and maximum values of each criterion are also the minimum and maximum values of that criterion which are taken from Table 1. Two full levels is the simplest form of experimental design that still has the accuracy of the relationship between input and output parameters [24-26]. Experimental matrix is presented in Table 3. The *MARCOS* score of each experiment is calculated and summarized in this table as well.

Table 2. MARCOS scores and rank of alternatives in the example 1

No.	*f(Ki)*	Rank
A1	0.019623	2
A2	0.018205	4
A3	0.020464	1
A4	0.019112	3

Table 3. Experimental matrix and MARCOS scores of experiments

No.	C1	C2	C3	$f(K_i)$
1	11	8	6	0.021805

No.	C1	C2	C3	*f(K_i)*
2	5	13	10	0.017129
3	11	8	10	0.018470
4	5	8	6	0.017258
5	5	13	6	0.020464
6	11	13	10	0.021677
7	5	8	10	0.013923
8	11	13	6	0.025012

Minitab 16 software is used to build the relationship between $f(K_i)$ with the criteria, the result is as shown in equation (12). To evaluate the accuracy of equation (12), it is necessary to rely on the values of the parameters *R-Sq*, *R-Sq(pred)*, and *R-Sq(adj)*. The significance of these parameters has been discussed in detail in many research [24-26]. The equation is said to have high accuracy as the values of these parameters are close to 1. In this case, all three parameters mentioned are equal to 1, that means equation (12) probably has a high accuracy.

$$f(K_i) = 0.01334 + 0.00076 \cdot C_1 + 0.00064 \cdot C_2 - 8.3372 \cdot 10^{-4} \cdot C_3 \\ +7.6189 \cdot 10^{-20} \cdot C_1 \cdot C_2 - 7.0771 \cdot 10^{-20} \cdot C_1 \cdot C_3 + 2.1865 \cdot 10^{-19} \cdot C_2 \cdot C_3 \quad (12)$$

Equation (12) is used to recalculate the scores of the four alternatives, called the *DOE-MARCOS* scores, the results of which are shown in Table 4. This table also presents the rank of the alternatives using the DOE-MARCOS method.

Table 4. DOE-MARCOS scores and rank of alternatives in the example 1

No.	*f(Ki)*	Rank
A1	0.020033	2
A2	0.018676	4
A3	0.020516	1
A4	0.019165	3

The data in Tables 2 and 4 show that the rank of the alternatives are the same as using the two methods *MARCOS* and *DOE-MARCOS*. As a consequence, multi-criteria decision making by the *DOE-MARCOS* method is evaluated as equivalent to *MARCOS* method. However, this problem is not the only advantage of the *DOE-MARCOS*. The advantage of this method needs to be further clarified when one/several options are included in the list of alternatives later. Suppose an alternative *A5* is added to the list with the values of the three criteria *C1*, *C2* and *C3* to be 12, 10, and 8 respectively. Then the decision matrix is re-established as Table 5.

Table 5. Decision matrix with alternative A5

No.	C1	C2	C3
A1	8	10	7
A2	9	8	8
A3	5	13	6
A4	11	9	10
A5	12	10	8

So as to rank the five alternatives in Table 5, the seven steps of the *MARCOS* method need to be repeated. Meanwhile, there is only equation (12) needed to calculate *MARCOS* score for five options if applying *DOE-MARCOS* method. Table 6 displays the MARCOS scores, the *DOE-MARCOS* scores and the rank of the alternatives using these two methods.

Table 6. Rank of alternatives in the example 1 using MARCOS and DOE-MARCOS

No.	MARCOS		DOE-MARCOS	
	$f(K_i)$	Rank	$f(K_i)$	Rank
A1	0.019231	3	0.020033	3
A2	0.017841	5	0.018676	5

No.	MARCOS		DOE-MARCOS	
	$f(K_i)$	Rank	$f(K_i)$	Rank
A3	0.020055	2	0.020516	2
A4	0.018730	4	0.019165	4
A5	0.021327	1	0.022231	1

It can be seen that the rank of options using the *DOE-MARCOS* accords with the rank of alternatives using the *MARCOS* after the option *A5* is added. However, the implementation of the *DOE-MARCOS* method is less complicated than that of the *MARCOS* method. Hence, this example demonstrates the outstanding advantage of the *DOE-MARCOS* method over the *MARCOS* method. Two following examples are carried out in order to compare the performance of the *DOE-MARCOS* method with other methods. In the scope of this study, those examples are both conducted for the selection of cutting tool materials.

3.2 Example 2

Data on twelve types of cutting tools used in this case are given in Calıskan's study [27], as shown in Table 7. Each type of cutting tool is evaluated by seven criteria, of which only *C4* is the min criterion, while the rest is the max criteria.

Table 7. Data on cutting tools [27]

No.	*C1*	*C2*	*C3*	*C4*	*C5*	*C6*	*C7*
A1	34	380	60	0.6	30	0.089	0.272
A2	31	380	59	0.49	50	0.082	0.206
A3	20	280	49	0.45	41	0.071	0.102
A4	23	300	46	0.45	46	0.077	0.135
A5	19	270	45	0.45	46	0.7	0.094
A6	30	370	53	0.52	22	0.081	0.197
A7	19	270	43	0.51	47	0.07	0.094
A8	25	340	47	0.45	90	0.074	0.135
A9	17	280	40	0.5	67	0.061	0.063
A10	23	300	48	0.52	54	0.077	0.135
A11	20	260	46	0.43	37	0.077	0.118
A12	19	280	44	0.45	41	0.068	0.087

The best solution is determined to be *Ai* (with i = 1÷12) that simultaneously obtain the criteria *C1*, *C2*, *C3*, *C5*, *C6* and *C7* to be the maximum and *C4* is to be the minimum. Calıskan [27] does the same when applying two methods *EXPROM2* (Extended Preference Ranking Organization Method for enrichment evaluation) and *VIKOR* (Vlsekriterijumska optimizacija i KOmpromisno Resenje (in Serbian)). Specifically, the weight of the criteria from *C1* to *C7* was determined based on a combination of *AHP* (Analytic Hierarchy Process) and Entropy method, with corresponding values of 0.147, 0.128, 0.129, 0.156, 0.153, 0.157, and 0.129. His rank of alternatives is used to compare the results of this study.

The experimental matrix is built in the form of two full levels (2^k), where *k* is the number of criteria (*k=7*), including 128 experiments. A part of the experimental matrix is presented in Table 8. The *MARCOS* scores (*f(Ki)*) of the experiments are identified according to the steps of the *MARCOS* method, and the results are also included in this table.

The Minitab 16 is applied to build the relationship between *f(Ki)* with the criteria as well, then the result is as shown in equation (13). All three parameters *R-Sq, R-Sq(pred) and R-Sq(adj)* of this equation are equal to 1, which means that equation (13) has a high accuracy.

Table 8. Part of the experimental matrix in example 2

No.	C1	C2	C3	C4	C5	C6	C7	f(Ki)
1	17	380	40	0.43	90	0.7	0.272	0.00001079
2	17	260	40	0.43	22	0.7	0.063	0.00000545
3	34	260	60	0.43	22	0.061	0.272	0.00000678
4	34	260	60	0.6	22	0.7	0.063	0.00000678

No.	C1	C2	C3	C4	C5	C6	C7	f(Ki)
5	34	380	40	0.43	90	0.7	0.063	0.00001017
6	17	260	60	0.6	22	0.7	0.272	0.00000729
...	...	...	...	...	...	...	...	...
127	17	380	40	0.6	90	0.7	0.272	0.00000973
128	17	380	40	0.6	90	0.7	0.063	0.00000757

Equation (13) is used to calculate the *DOE-MARCOS* scores for the twelve alternatives, the results of which are shown in Table 9. The rank of the alternatives on the basis of the scores are summarized in this table as well.

$$\begin{gathered} f(K_i) = 1.31944\cdot10^{-7} + 4.53311\cdot10^{-8}\cdot C_1 + 3.50879\cdot10^{-9}\cdot C_2 \\ +2.23787\cdot10^{-8}\cdot C_3 - 9.71730\cdot10^{-7}\cdot C_4 + 1.71172\cdot10^{-8}\cdot C_5 \\ +2.19723\cdot10^{-6}\cdot C_6 + 4.46875\cdot10^{-6}\cdot C_7 + 4.02474\cdot10^{-11}\cdot C_1\cdot C_2 \\ +2.56891\cdot10^{-10}\cdot C_1\cdot C_3 - 3.10659\cdot10^{-8}\cdot C_1\cdot C_4 + 2.03123\cdot10^{-10}\cdot C_1\cdot C_5 \\ +2.67986\cdot10^{-8}\cdot C_1\cdot C_6 + 5.66672\cdot10^{-8}\cdot C_1\cdot C_7 + 2.00142\cdot10^{-11}\cdot C_2\cdot C_3 \\ -2.42032\cdot10^{-9}\cdot C_2\cdot C_4 + 1.58253\cdot10^{-11}\cdot C_2\cdot C_5 + 2.08786\cdot10^{-9}\cdot C_2\cdot C_6 \\ +4.41489\cdot10^{-9}\cdot C_2\cdot C_7 - 1.54484\cdot10^{-8}\cdot C_3\cdot C_4 + 1.01009\cdot10^{-10}\cdot C_3\cdot C_5 \\ +1.33264\cdot10^{-8}\cdot C_3\cdot C_6 + 2.81794\cdot10^{-8}\cdot C_3\cdot C_7 - 1.22150\cdot10^{-8}\cdot C_4\cdot C_5 \\ -1.61156\cdot10^{-6}\cdot C_4\cdot C_6 - 3.40774\cdot10^{-6}\cdot C_4\cdot C_7 + 1.05371\cdot10^{-8}\cdot C_5\cdot C_6 \\ +2.22814\cdot10^{-8}\cdot C_5\cdot C_7 + 2.93965\cdot10^{-6}\cdot C_6\cdot C_7 \end{gathered} \tag{13}$$

Table 9. Rank of alternatives in the example 2 using DOE-MARCOS

No.	*C1*	*C2*	*C3*	*C4*	*C5*	*C6*	*C7*	*f(Ki)*	*Rank*
A1	34	380	60	0.6	30	0.089	0.272	0.0000071	2
A2	31	380	59	0.49	50	0.082	0.206	0.0000075	1
A3	20	280	49	0.45	41	0.071	0.102	0.0000046	8
A4	23	300	46	0.45	46	0.077	0.135	0.0000053	7
A5	19	270	45	0.45	46	0.7	0.094	0.0000069	4
A6	30	370	53	0.52	22	0.081	0.197	0.0000059	5
A7	19	270	43	0.51	47	0.07	0.094	0.0000041	12
A8	25	340	47	0.45	90	0.074	0.135	0.0000070	3
A9	17	280	40	0.5	67	0.061	0.063	0.0000042	11
A10	23	300	48	0.52	54	0.077	0.135	0.0000053	6
A11	20	260	46	0.43	37	0.077	0.118	0.0000045	9
A12	19	280	44	0.45	41	0.068	0.087	0.0000042	10

Ranking the alternatives based on *MARCOS* is also conducted. Table 10 shows the rank of the alternatives according to the *DOE-MARCOS*, the *MARCOS*, the *EXPROM2* and *VIKOR* methods [27]. The data in Table 10 is also presented in graph form as shown in Figure 1 for the convenience of observation.

Table 10. Rank of alternatives in the example 2 using some methods

No.	*DOE-MARCOS*	*MARCOS*	*EXPROM2*	*VIKOR*
A1	2	2	2	5
A2	1	1	1	1
A3	8	8	8	6
A4	7	6	5	3
A5	4	4	10	10

No.	*DOE-MARCOS*	*MARCOS*	*EXPROM2*	*VIKOR*
A6	5	5	4	7
A7	12	12	9	9
A8	3	3	3	2
A9	11	11	12	12
A10	6	7	6	4
A11	9	9	7	8
A12	10	10	11	11

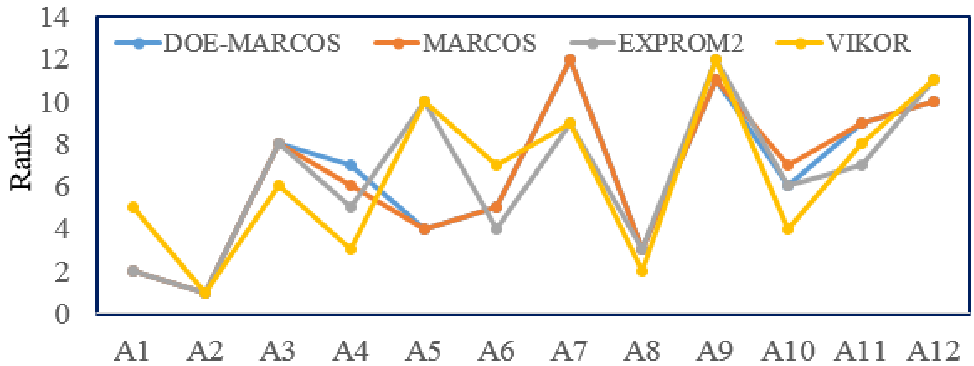

Fig 1. Rank of alternatives in the example 2 using some methods

The data in Table 10 and Figure 1 reveals:

- The difference in the rank of the alternatives using distinct methods is explained by the fact that these methods used distinctive data normalization methods [7].
- There is only a slight difference in the rank of the alternatives using the *DOE-MARCOS* and *MARCOS* method. Specifically, 10/12 options are ranked equally using these two methods, only the alternatives ranked 6 and ranked 7 are swapped with each other.
- Furthermore, all four methods indicate that *A2* is the best option. Thus, it can be affirmed that the *DOE-MARCOS* method is effective in determining the best alternative.

Evaluating an *MCDM* method based only on the best alternative it identifies is unlikely to be sufficient without sensitivity analysis [28]. Sensitivity analysis is performed with different scenarios and the most commonly used scenarios are to change the weight of the criteria or remove one/several options from the list of alternatives.

In this case, changing the weight of the criteria is applied. In addition to the set of weights used above, the different sets are determined based on five other methods, including Entropy, *EQUAL*, *ROC* (Rank Order Centroid), *RS* (Rank Sum) and *MEREC (*Method based on the Removal Effects of Criteria*)*. The two methods Entropy and *MEREC* are used due to many recommendations [29]. Besides, the other three methods seem to be easily manageable, using only one equation [30, 31]. Details of the steps of determining the weights according to this method are introduced in many documents [29 - 33]. Table 11 presents the weights of the criteria determined by different methods.

Table 11. Weights of criteria in example 2 determined by different methods

Weight method	C1	C2	C3	C4	C5	C6	C7
AHP+Entropy [22]	0.147	0.128	0.129	0.156	0.153	0.157	0.129
Entropy	0.1088	0.1243	0.2558	0.0901	0.1632	0.1628	0.0951
EQUAL	1/7	1/7	1/7	1/7	1/7	1/7	1/7
ROC	0.3704	0.2276	0.1561	0.1085	0.0728	0.0442	0.0204
RS	0.2500	0.2143	0.1786	0.1429	0.1071	0.0714	0.0357
MEREC	0.1067	0.0591	0.0663	0.0829	0.2801	0.1432	0.2616

Table 12 presents the ranks of the alternatives with different sets of weights. It can be seen that these ranks are the same as six different weighting methods are applied. That means there is not any rank reversal of the alternatives, even though implemented in all different scenarios. This is distinctive and advantageous of the *DOE-MARCOS* method over many other *MCDM* methods. This is also understandable since this advantage is discovered using the *MARCOS* method [12]. In summary, the *DOE-MARCOS* method is effective in this case.

Table 12. Rank of the alternatives in the example 2 using DOE-MARCOS with different weight methods

No.	AHP+Entropy	Entropy	EQUAL	ROC	RS	MEREC
A1	2	2	2	2	2	2
A2	1	1	1	1	1	1
A3	8	8	8	8	8	8
A4	7	7	7	7	7	7
A5	4	4	4	4	4	4
A6	5	5	5	5	5	5
A7	12	12	12	12	12	12
A8	3	3	3	3	3	3
A9	11	11	11	11	11	11
A10	6	6	6	6	6	6
A11	9	9	9	9	9	9
A12	10	10	10	10	10	10

3.3 Example 3

This example uses data on eight tool materials according to Chatterjee et al. [34], as shown in Table 13. Seven criteria are used for selecting material, six criteria from *C1* to *C6* are maximum, whereas *C7* is minimum. The task of multi-criteria decision making in this case is to determine the best out of eight alternatives that simultaneously have the criteria from *C1* to *C6* to be the highest and *C7* to be the smallest. Chatterjee et al. [34] did this work using six different variants of the VIKOR method (including: VIKOR, Comprehensive *VIKOR*, Fuzzy *VIKOR*, Regret *VIKOR*, Modified *VIKOR* and Interval *VIKOR*). The weights of the criteria from *C1* to *C7* were determined by the Entropy method, with values of 0.3552, 0.0429, 0.4356, 0.1248, 0.01661, 0.0001, and 0.0252 respectively. Their rank of alternatives is used to compare the results found in this study.

With seven criteria, a matrix of 128 experiments is established as shown in Table 14. *MARCOS* scores of the options are calculated and included in this table.

On the basis of the data in Table 14, the relationship between the scores of the options and the criteria is built as shown in equation (14). This equation has the coefficients *R-Sq, R-Sq(pred)* and *R-Sq(adj)* all equal to 1, which means the equation has a high accuracy.

Table 13. Data on cutting tools [34]

No.	C1	C2	C3	C4	C5	C6	C7
A1	3200	451	3475	756	17	4.15	18
A2	2400	690	4975	1324	98	3	60
A3	5000	850	6900	1532	13	4.5	864
A4	3000	400	3800	879	30	4	152
A5	8000	953	6700	4688	1200	8.6	1300
A6	2550	440	4600	480	200	3.1	10
A7	2800	460	1721	600	90	2.5	50
A8	1200	160	1750	620	2.2	8.2	45

Table 14. Part of the experimental matrix in example 3

No.	C1	C2	C3	C4	C5	C6	C7	$f(K_i)$
1	1200	953	1721	480	1200	8.6	1300	0.00001035
2	1200	160	6900	4688	1200	8.6	1300	0.00002816
3	8000	953	1721	480	1200	2.5	1300	0.00002368
4	1200	953	6900	4688	1200	8.6	10	0.00003084
5	8000	953	6900	4688	2.2	8.6	10	0.00004344
6	8000	160	6900	480	1200	2.5	10	0.00003764
…	…	…	…	…	…	…	…	
127	1200	953	1721	480	2.2	8.6	1300	0.00000962

128	8000	160	1721	4688	1200	2.5	10	0.00002816

$$\begin{aligned}
f(K_i) &= 1.12120 \cdot 10^{-6} + 1.96037 \cdot 10^{-9} \cdot C_1 + 1.98756 \cdot 10^{-9} \cdot C_2 \\
&+2.78736 \cdot 10^{-9} \cdot C_3 + 1.17539 \cdot 10^{-9} \cdot C_4 + 6.10776 \cdot 10^{-10} \cdot C_5 \\
&+5.13401 \cdot 10^{-10} \cdot C_6 - 8.55879 \cdot 10^{-10} \cdot C_7 + 9.38951 \cdot 10^{-28} \cdot C_1 \cdot C_2 \\
&+6.60523 \cdot 10^{-29} \cdot C_1 \cdot C_3 - 1.16594 \cdot 10^{-29} \cdot C_1 \cdot C_4 + 2.53946 \cdot 10^{-28} \cdot C_1 \cdot C_5 \\
&-4.75856 \cdot 10^{-26} \cdot C_1 \cdot C_6 - 1.75149 \cdot 10^{-28} \cdot C_1 \cdot C_7 + 5.38576 \cdot 10^{-28} \cdot C_2 \cdot C_3 \\
&+1.92366 \cdot 10^{-27} \cdot C_2 \cdot C_4 + 3.61124 \cdot 10^{-27} \cdot C_2 \cdot C_5 + 4.14838 \cdot 10^{-25} \cdot C_2 \cdot C_6 \\
&-2.55543 \cdot 10^{-27} \cdot C_2 \cdot C_7 + 1.07427 \cdot 10^{-28} \cdot C_3 \cdot C_4 + 4.69104 \cdot 10^{-28} \cdot C_3 \cdot C_5 \\
&-8.27493 \cdot 10^{-26} \cdot C_3 \cdot C_6 - 3.48845 \cdot 10^{-28} \cdot C_3 \cdot C_7 - 3.43674 \cdot 10^{-28} \cdot C_4 \cdot C_5 \\
&-3.34246 \cdot 10^{-26} \cdot C_4 \cdot C_6 - 1.19186 \cdot 10^{-29} \cdot C_4 \cdot C_7 + 3.49989 \cdot 10^{-25} \cdot C_5 \cdot C_6 \\
&-2.18360 \cdot 10^{-27} \cdot C_5 \cdot C_7 - 4.14890 \cdot 10^{-26} \cdot C_6 \cdot C_7
\end{aligned} \tag{14}$$

Equation (14) is used to calculate the *DOE-MARCOS* scores for each alternative, the results are summarized in Table 15. This table also presents the rank of the alternatives according to *DOE-MARCOS* scores. Table 16 and figure 2 show the ranks of eight alternatives using the *DOE-MARCOS* method, the *MARCOS* method and six variants of the *VIKOR* method [34].

The data in Table 16 revealed that:

- The best alternative (*A5*) and the second ranked alternative (*A3*) are the same as all eight different methods are applied.
- Seven out of eight methods identify *A8* as the worst option and *A7* as the second worst, except for the Interval *VIKOR* method.
- The four methods *DOE-MARCOS*, *MARCOS*, Comprehensive *VIKOR* and Regret *VIKOR* give the rank of the options coincide.

It can be said that *A5* is the best alternative, *A8* is the worst, and the *DOE-MARCOS* method is effective in this case.

Table 15. Rank of alternatives in the example 3 using DOE-MARCOS

No.	C1	C2	C3	C4	C5	C6	C7	*f(Ki)*	*Rank*
A1	3200	451	3475	756	17	4.15	18	0.00001886	6
A2	2400	690	4975	1324	98	3	60	0.00002263	3
A3	5000	850	6900	1532	13	4.5	864	0.00003292	2
A4	3000	400	3800	879	30	4	152	0.00001931	5
A5	8000	953	6700	4688	1200	8.6	1300	0.00004251	1
A6	2550	440	4600	480	200	3.1	10	0.00002050	4
A7	2800	460	1721	600	90	2.5	50	0.00001304	7
A8	1200	160	1750	620	2.2	8.2	45	0.00000937	8

Table 16. Rank of alternatives in the example 3 using some methods

No.	*DOE-MARCOS*	*MARCOS*	*VIKOR*	Comprehensive VIKOR	Fuzzy VIKOR	Regret VIKOR	Modified VIKOR	Interval VIKOR
A1	6	6	6	6	6	6	6	5
A2	3	3	3	3	3	5	3	4
A3	2	2	2	2	2	2	2	2
A4	5	5	4	5	4	3	5	3
A5	1	1	1	1	1	1	1	1
A6	4	4	5	4	5	4	4	6
A7	7	7	7	7	7	7	7	8
A8	8	8	8	8	8	8	8	7

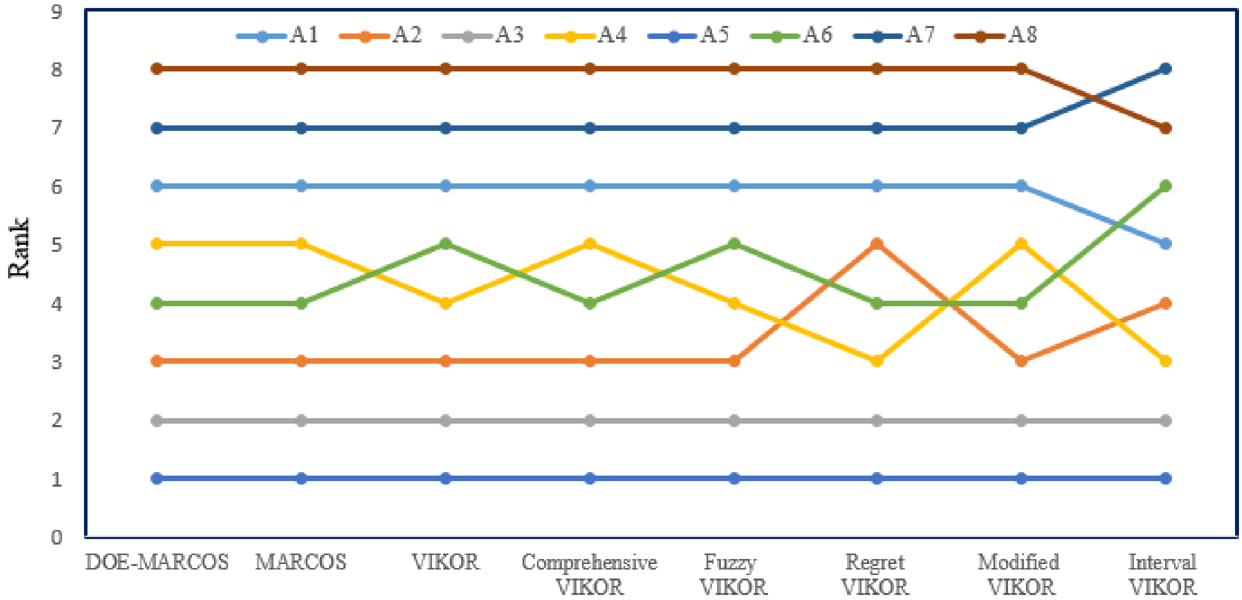

Fig. 2. Rank of alternatives in the example 3 using some methods

The sensitivity analysis is performed as the weights of the criteria are determined by different methods. Table 17 presents the weights of the criteria determined by different methods.

The ranks of eight options with different weight sets are displayed in Table 18.

Table 17. Weights of criteria in example 3 determined by different methods

Weight method	C1	C2	C3	C4	C5	C6	C7
Entropy [29]	0.3552	0.0429	0.4356	0.1248	0.0166	0.0001	0.0252
EQUAL	1/7	1/7	1/7	1/7	1/7	1/7	1/7
ROC	0.3704	0.2276	0.1561	0.1085	0.0728	0.0442	0.0204
RS	0.2500	0.2143	0.1786	0.1429	0.1071	0.0714	0.0357
MEREC	0.0881	0.1056	0.0732	0.0696	0.3068	0.0570	0.2998

Table 18. Rank of the alternatives in the example 3 using DOE-MARCOS with different weight methods

No.	Entropy	EQUAL	ROC	RS	MEREC
A1	6	6	6	6	6
A2	3	3	3	3	3
A3	2	2	2	2	2
A4	5	5	5	5	5
A5	1	1	1	1	1
A6	4	4	4	4	4
A7	7	7	7	7	7
A8	8	8	8	8	8

The data in Table 18 also show that the rank of the alternatives are the same when using the five different weight methods. The advantage of the *DOE-MARCOS* method is that there is not any rank reversal even though it is implemented in the different scenarios. In short, the *DOE-MARCOS* method is sufficient in this circumstance.

The application of the *DOE-MARCOS* method in three examples demonstrates that:

- The defined best alternative appears always similar to if using the other methods.
- In addition to the best option, the rank order of the remaining alternatives has a high similarity, compared with the use of other methods.
- There is no rank reversal even though it is considered in many different scenarios (using the different sets of weights).
- When one/several options are added to the list of alternatives, it is significantly less complicated to apply the *DOE-MARCOS* method than the *MARCOS* method.

The results obtained state that the proposed method ensures high effectiveness for ranking the alternatives.

4 CONCLUSION

For problems with multiple solutions and each of them being assessed by multiple criteria, choosing the best solution is likely complicated, but important in many cases. Some research has been done to deal with this type of situations using the different *MCDM* methods. However, the workload will considerably increase when one/several alternatives are added to the list of options if a certain *MCDM* method is only applied. This study proposes a new approach to deal with this disadvantage. The blend of the *DOE* and *MARCOS* devises a new method, called *DOE-MARCOS*. Some examples are made to examine the effectiveness of the proposed method, and some conclusions are drawn as follows:

- The best alternative determined by the method appears always similar, compared to the other methods.
- There is no rank reversal to occur when the proposed method is applied.
- When one/several alternatives are added, the use of the proposed method probably results in the economy of effort, compared to the current *MCDM* methods.
- The *DOE-MARCOS* method is not only effective for cutting tool selection in the two examples carried out in this study, but also expected to be effective for application in other fields.
- The combination of the *DOE* method with another *MCDM* method is recommended as well.
- This study attempt to consider the criteria in quantitative form. Upgrading the DOE-MARCOS method for ranking the alternatives using the criteria in qualitative form (color, shape, ect.) is needed to be done as soon as possible so as to further improve this method.

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