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A NOVEL APPROACH FOR CRITERIA WEIGHTING TO ENHANCE RANKING STABILITY OF ALTERNATIVES FOR INDUSTRIAL EQUIPMENT AND MATERIAL SELECTION

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Abstract:
Ranking industrial equipment and materials constitutes a significant and intricate task due to the necessity of considering multiple, sometimes conflicting, criteria. Consequently, this ranking process is regarded as a multi-criteria decision-making (MCDM) problem. Within MCDM problems, the determination of criteria weights holds paramount importance. These weights significantly influence the ranking stability of alternatives when evaluated using various MCDM methodologies. Each weighting method, whether it is subjective or objective, has specific advantages and limitations. This study was conducted to propose a new method for determining criteria weights, named the MEREC-ROC method. The weighting calculation process for the criteria using the MEREC-ROC method is carried out in two stages. First, the objective weights of the criteria are calculated using the MEREC method to determine the priority order of the criteria. This priority order is then utilized to calculate the subjective criteria weights using the ROC method. To compare the MEREC-ROC method with the MEREC method, four different case studies related to the ranking of industrial equipment and materials were performed. The results show that using the MEREC-ROC method to determine criteria weights ensures higher stability in the ranking of alternatives when different MCDM methods are applied, compared to using the MEREC method alone. The sensitivity analysis conducted for all four cases further demonstrates the superiority of the MEREC-ROC method over the MEREC method. The limitations of this research and directions for future studies are also discussed in the final section of this paper.

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1. INTRODUCTION

Ranking industrial equipment and materials is a critical task for selecting the best products for the manufacturing process [1]. This practice plays a significant role in ensuring a safe production environment while simultaneously improving productivity and reducing costs [2]. However, this ranking process is inherently complex. The complexity arises from the fact that each type of equipment and material possesses a multitude of characteristic parameters, spanning technical aspects (capacity, durability, performance), economic considerations (investment cost, operational expenses, lifespan), and operational capabilities (flexibility, reliability, compatibility). Notably, these parameters often exhibit trade-offs across different alternatives. For instance, high-performance equipment may come with a substantial initial investment, or a durable material might lack flexibility in its applications [3].

Ranking alternatives, where each is characterized by multiple, often conflicting criteria, is a complex task known as an MCDM process [4-6]. The application of MCDM methods, which helps decision-makers rank alternatives and identify the best option, has been widely adopted across numerous fields [7,8]. The potency and utility of

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MCDM are further underscored by the conclusion that it can address virtually any decision-making problem [9,10].

Nevertheless, the substantial number of available MCDM methods renders the selection of an appropriate method a challenging decision in itself [11]. Furthermore, due to the inherent algorithmic differences among MCDM methods, the ranking result of alternatives could be changed remarkably when submitted to different MCDM methods [11]. Research has also concluded that no single method is universally optimal for achieving desired outcomes across all problem contexts [12]. For this reason, to ensure the accuracy of the final decision, it is necessary to use a combination of several MCDM methods for each specific case [13]. However, even when multiple MCDM methods are applied simultaneously, the order of alternatives can still vary significantly [14,15]. Therefore, creating stability in the ranking of alternatives across different methods is crucial. One of the main factors causing changes in the ranking of alternatives is the weighting method used for the criteria [16-18]. The selection of a specific method for defining criteria weights has itself become a complex decision within MCDM practice [19]. This motivates the search for criteria weighting methods that ensure stable alternative rankings if various MCDM approaches are applied to evaluate the alternatives. Section 2 provides a concise literature review of criteria weighting methods. The proposed novel method to calculate the criteria weighting is detailed in Section 3. Several illustrative examples assessing the performance of the proposed method are presented in Section 4, and Section 5 undertakes a sensitivity analysis to re-evaluate the effectiveness of this approach.

2. LITERATURE REVIEW

As highlighted in the introduction, the weights associated with criteria have a considerable effect on the order of alternatives when evaluated using MCDM methods. Fundamentally, three primary categories of methods exist for determining criteria weights: objective weighting methods, subjective weighting methods, and hybrid methods that integrate two or more weighting approaches [20,21]. When employing objective weighting methods, the weight values of criteria are solely derived from the raw numerical data within the decision matrix, disregarding the role of the decision-maker. This can sometimes lead to suboptimal or unexpected ranking outcomes [22]. In other words, objective weighting methods inherently lack any input from the decision-maker [23]. In certain instances, the weights of criteria calculated through objective methods can exhibit opposing trends. For example, one report revealed that a criterion with a high weight when calculated using the LOPCOW method might have a low weight when determined by the entropy method [24]. Furthermore, another report indicated that the application of objective weighting methods such as entropy, CRITIC, and SD (standard deviation) might be inappropriate in some MCDM problems [25]. A recent study has also shown that the entropy objective weighting method is unsuitable because a highly significant criterion can be assigned a very low weight when calculated using this approach [26]. Furthermore, the effectiveness of objective weighting methods varies significantly in MCDM problems. For example, recently, a study assessed the three objective weighting methods, including Entropy, SPC, and MEREC. The results showed their performance ranked from highest to lowest as Entropy, MEREC, and SPC [27]. Moreover, it is crucial to emphasize the significant role of the decision-maker in MCDM problems; thus, the failure of objective weighting methods to consider their input is widely acknowledged as a major limitation [28,29].

Conversely, when using subjective weighting methods to determine criteria weights, the process is generally more straightforward and computationally less demanding compared to objective methods [30]. However, with subjective methods, the weight values of criteria are contingent upon the decision-maker's subjective opinions, knowledge, and experience, and can sometimes be influenced by their psychological state or biases towards specific criteria [31]. Furthermore, subjective weighting methods also reveal certain limitations. For example, the AHP method does not entirely overcome the uncertainty associated with providing criteria weights through pairwise comparisons [32]. Additionally, a report concluded that two fundamental limitations of subjective weighting methods are the inconsistent judgments of human users, which increase the level of ambiguity, and the large number of comparisons required, which complicates the model's application [33].

To address the shortcomings of both objective and subjective weighting method categories, as mentioned above, research proposing hybrid weighting methods that combine several approaches has been undertaken. Integrated methods that incorporate both subjective weight and objective ones can not only avoid the issue of objective weights emphasizing factual data and overlooking subordinate criteria attributes, leading to unreasonable weight results, but also circumvent the problem of overly subjective expert opinions, thereby yielding more effective weights [34]. A few examples of studies within this domain are summarized below.

The Delphi method was employed to identify criteria significantly influencing the development of the digital economy in certain regions of China, followed by the objective anti-entropy weight (AEW) method to calculate initial criteria weights, and finally, the best-worst method (BWM) was used to determine the final criteria weights [34]. In [35], the subjective weighting of criteria using the AHP method can mitigate subjectivity or the level of understanding of the evaluators if combined with the Data Envelopment Analysis (DEA) method. In [36], an incorporation of the subjective AHP weighting method and the objective entropy weighting method was implemented. In [37], when weighting sustainable electricity development alternatives in Turkey, it was observed that while objective weighting methods such as entropy, SD, and CRITIC provided relatively large variations in weights, subjective methods like AHP and BWM yielded more similar influences of the criteria. Nevertheless, when using multiple MCDM techniques to organize the alternatives, employing the BWM method for determining criteria influence resulted in the most stable ranking of alternatives. Several studies also used the normalized product weighting method of subjective weight and objective one to calculate the criteria weights [38,39].

Evidently, the integration of subjective and objective methods for weighting has attracted particular attention from numerous scientists, a few of whose studies have just been listed. This research does not aim to provide an in-depth analysis of the combined weighting methods found in published literature. Instead, the main purpose of this report is to propose a novel method to specify the criteria weights.

ROC is a subjective weighting method that has been assessed to have an accuracy of up to 96% when choosing the greatest alternative [40]. The essence of the ROC method is in minimizing the errors related to partial weights by recognizing the centroid of potential weights while preserving the order of the purposes [41]. Many recently published studies are also utilizing this approach for determining criteria weights, an idea appears to ensure the accuracy [42]. However, when applying the ROC method in particular, as well as the general subjective weighting ones, the users still need to set up the priority ranking of the parameters. This will be further clarified when the order of steps to use the ROC method is outlined in the following section of this report. Clearly, the weights of the criteria depend heavily on the decision-maker's subjectivity [43], and this problem enhances the challenge when the number of criteria is increased [44,45]. So, an idea emerged to ensure the accuracy of the criteria's importance when using the ROC weighting method. Originating from this idea, the motivation of this study is to assess the criteria weights preliminarily to obtain their priority ranking. After that, the weighting ROC method is used to find the final criteria weights. To calculate these preliminary weights, this study employs the MEREC method, which is an objective weighting method. The reason for using MEREC in this research is that it is a recommended method and has been utilized in many recent studies [46]. A recent research also revealed that MEREC is the most frequently used method [47]. Drawing upon the notable characteristics of the objective MEREC weighting method and the subjective ROC weighting method, this research proposes a novel approach for determining criteria weights that combines the MEREC and ROC methods, termed the MEREC-ROC method.

3. PROPOSED MEREC-ROC METHOD

The proposed MEREC-ROC method is based on a combination of the MEREC and ROC methods. Therefore, it is first necessary to introduce the procedure for calculating the criteria weights using each of these individual methods.

The process of using the MEREC method to calculate criteria weights is carried out in the following sequence [46,47].

Step 1: The decision matrix comprising *m* alternatives and *n* criteria was constructed, as shown in Eq. (1), where x_{ij} denotes the value of criterion *j* for alternative *i*:

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \cdots & x_{ij} & \cdots & \cdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \quad (1)$$

Step 2: Normalized values are calculated according to Eq. (2) for criteria where "larger is better" and Eq. (3) for criteria where "smaller is better":

$$n_{ij} = \frac{min x_{ij}}{x_{ij}} \quad (2)$$

$$n_{ij} = \frac{x_{ij}}{max\, x_{ij}} \quad (3)$$

Step 3: The overall performance of the alternatives was computed using Eq. (4):

$$S_i = Ln\left[1 + \left(\frac{1}{n}\sum_j^n \left|ln\left(n_{ij}\right)\right|\right)\right] \quad (4)$$

Step 4: The performance of the alternatives was calculated when each criterion j was removed, using Eq. (5):

$$S'_{ij} = Ln\left[1 + \left(\frac{1}{n}\sum_{k,k\neq j}^n \left|ln\left(n_{ij}\right)\right|\right)\right] \quad (5)$$

Step 5: The absolute deviations were calculated using Eq. (6):

$$E_j = \sum_i^m \left|S'_{ij} - S_i\right| \quad (6)$$

Step 6: The weights of the criteria were determined using Eq. (7).

$$w_j = \frac{E_j}{\sum_k^n E_k} \quad (7)$$

It is necessary to follow the sequence below for using the subjective weighting method ROC to determine criteria weights [40,41]:

Step 1: Ranking the criteria in the order of descending priority – the most important criterion was assigned as rank 1, and the least important one was assigned as rank *n.*

Step 2: The weights of the criteria were calculated using Eq. (8), where k_j represented the rank of criterion *j*.

$$w_j = \frac{1}{n}\sum_{k=i}^{n}\frac{1}{k} \quad (8)$$

The MEREC-ROC method presents a smooth integration between the individual MEREC and ROC methods. The flowchart illustrating the sequential process for calculating criteria weights using the MEREC-ROC method is depicted in Fig. 1.

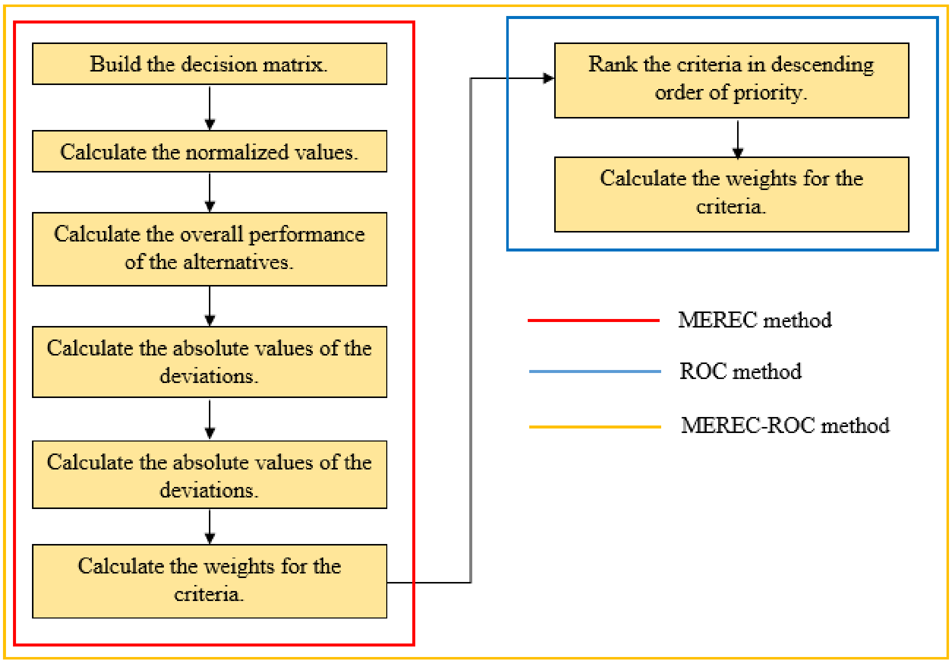

Fig. 1. Flowchart of the MEREC-ROC method

4. EVALUATION OF THE PROPOSED METHOD

To determine the advantages of the MEREC-ROC method, this section undertakes a comparative analysis against the MEREC method in the case of using it to rank several products within the industrial equipment and materials domain. To ensure objectivity when comparing two methods, MEREC-ROC and MEREC, four case studies of distinct ones were conducted, varying in the number of ranked alternatives, the amount of considered criteria, and their application to different subjects. The benchmark for comparing these two methods is the average Spearman's rank correlation coefficient obtained when employing various MCDM techniques to arrange the alternatives [48,49]. This coefficient is calculated using Eq. (9), where D_i stands for the change in the order of alternative *i* arranged by other MCDM methods [48,49].

$$S = 1 - \frac{6\sum_{i=1}^m D_i^2}{m(m^2-1)} \quad (9)$$

For ranking the priorities in each case, this research utilizes five distinct MCDM methods: SAW, TOPSIS, ROV, PIV, and RAM. The rationale for selecting these five methods is briefly summarized as follows. SAW is included due to its status as one of the earliest and most widely adopted MCDM techniques, often considered as an initial technique to develop subsequent ones [50]. TOPSIS and ROV are employed due to their established prominence and extensive application across diverse fields [51]. PIV is selected because of its benefit in reducing the reversal of the ranking, which was recognized [52]. RAM is included as a relatively new (emerging in September 2023) and straightforward method with the ability to balance between beneficial and non-beneficial criteria [53].

4.1. Case 1: Ranking of Cutting Fluids

The first case study was done with four types of cutting fluids, which have characteristics summarized in Table 1, to compare the MEREC-ROC weighting method and MEREC. These four alternatives are denoted as CF1, CF2, CF3, and CF4, respectively. Each cutting fluid is characterized by three beneficial criteria (Type B criteria), namely C2, C3, and C4, and one non-beneficial criterion (Type C criterion), which is C1 [54].

Applying Eqs. (1) through (7), the result is shown in Table 2. They were the criteria weights calculated by the MEREC method. From the MEREC-derived criteria weights, the primacy ranking of the criteria was determined, as shown in the four horizontal lines of Table 2. Utilizing this ranking of criteria, Eq. (8) was used to achieve the weights of the criteria by the ROC method, as condensed in the last row of this table. Because the criteria weights calculated by the ROC method are established from the criteria ranking obtained by applying the MEREC method, these ROC-derived weights represent the criteria weights obtained by the MEREC-ROC method.

Table 1. Characteristics of cutting fluids [54]

Type	C1	C2	C3	C4
	density	viscosity index	viscosity at 100 °C	viscosity at 40 °C
	C	B	B	C
CF1	0.883	95	9	71.73
CF2	0.953	82	8.67	75.82
CF3	0.9058	390	4.9	12.67
CF4	0.8316	166	2.67	8.04

Table 2. Criteria weights in case 1

Weight method	C1	C2	C3	C4
MEREC	0.0272	0.2607	0.2599	0.4523
	Rank			
	4	2	3	1
MEREC-ROC	0.0625	0.2708	0.1458	0.5208

The upper half of Table 3 summarizes the rankings of the CF alternatives obtained using the five MCDM methods (SAW, TOPSIS, ROV, PIV, and RAM) when the criteria weights were determined by the MEREC method. The lower half of Table 3 presents the Spearman's rank correlation coefficients between the different MCDM methods. The last row of Table 3 displays the average Spearman's rank correlation coefficient across the MCDM methods.

Similarly, the upper half of Table 4 summarizes the rankings of the CF alternatives obtained using the five MCDM methods when the criteria weights were determined by the MEREC-ROC method. The lower half of Table 4 presents the Spearman's rank correlation coefficients between the different MCDM methods. The last row of Table 4 displays the average Spearman's rank correlation coefficient across the MCDM methods.

It can be seen from the data in Tables 3 and 4 that, in this particular case, the Spearman's rank correlation coefficient of each pair of MCDM methods remains identical whenever using the MEREC or MEREC-ROC methods. Specifically, the correlation between SAW and TOPSIS is 1, between SAW and PIV is 1, between SAW and ROV is 0.8, between SAW and RAM is 1, between TOPSIS and PIV is 1, between TOPSIS and ROV is 0.8, between TOPSIS and RAM is 1, between PIV and ROV is 0.8, between PIV and RAM is 1, and between ROV and RAM is also 0.8. Consequently, the average Spearman's rank correlation coefficient over the methods is 0.9200 for both the MEREC-ROC and MEREC methods in defining criteria weights. Thus, in this particular case, it can be concluded that the MEREC-ROC and MEREC methods exhibit equivalent performance in ensuring the ranking stability of the cutting fluids when evaluated by various MCDM techniques. However, it would be premature to draw definitive conclusions about the comparison between MEREC-ROC and MEREC based on a single example. Instead, further case studies relating to the ranking of different subjects need to be conducted.

Table 3. Alternative rankings and Spearman's rank correlation coefficients between MCDM methods with MEREC weights (Case 1)

Type	SAW	TOPSIS	PIV	ROV	RAM
	Rank				
CF1	2	2	2	1	2
CF2	1	1	1	2	1
CF3	3	3	3	3	3
CF4	4	4	4	4	4
Spearman coefficient					
SAW	-	1	1	0.8	1
TOPSIS		-	1	0.8	1
PIV			-	0.8	1
ROV				-	0.8
RAM					-
Average: 0.9200					

Table 4. Alternative rankings and Spearman's rank correlation coefficients of each pair of MCDM approaches using MEREC-ROC weights (Case 1)

Type	SAW	TOPSIS	PIV	ROV	RAM
	Rank				
CF1	2	2	2	1	2
CF2	1	1	1	2	1
CF3	3	3	3	3	3
CF4	4	4	4	4	4
Spearman coefficient					
SAW	-	1	1	0.8	1
TOPSIS		-	1	0.8	1
PIV			-	0.8	1
ROV				-	0.8
RAM					-
Average: 0.9200					

4.2. Case 2: Ranking of Robots

In this case study, the MEREC-ROC and MEREC methods in the ranking of seven types of robots were used to compare. Table 5 compiles the information regarding these seven robots to be ranked, denoted as RB1 to RB7, respectively. Every alternative is specified by four beneficial criteria (Type B criteria), namely C1, C2, C4, and C5, and one non-beneficial criterion (Type C criterion), which is C3 [55].

Table 5. Characteristics of robots [55]

Type	C1	C2	C3	C4	C5
	Load capacity	Maximum tip speed	Repeatability	Memory capacity	Manipulator reach
	B	B	C	B	B
RB1	60	0.4	2540	500	990
RB2	6.35	0.15	1016	3000	1041
RB3	6.8	0.1	1727.2	1500	1676
RB4	10	0.2	1000	2000	965
RB5	2.5	0.1	560	500	915
RB6	4.5	0.08	1016	350	508
RB7	3	0.1	1778	1000	920

Following a similar procedure to Case 1, the criteria weights were calculated using the MEREC method, which subsequently allowed for the determination of the priority ranking among the criteria. From this ranking, the criteria weights were also calculated using the MEREC-ROC method. Table 6 presents all these results.

Table 6. Criteria weights in case 2

Weight method	C1	C2	C3	C4	C5
MEREC	0.2568	0.1254	0.2037	0.2570	0.1570
	Rank				
	2	5	3	1	4
MEREC-ROC	0.2567	0.0400	0.1567	0.4567	0.0900

Tables 7 and 8 present the rankings of the RBs when evaluated by the MCDM methods under two scenarios: first, with the weights of criteria defined by the MEREC method, and second, with those of criteria defined by the MEREC-ROC method. Each table also lists the Spearman's rank correlation coefficients of each pair of methods.

The data in Tables 7 and 8 indicate that for Table 7, the lowest Spearman's rank correlation coefficient is 0.8214, observed between PIV and ROV, and also between ROV and RAM. In contrast, for Table 10, the lowest Spearman's rank correlation coefficient is 0.8571, found between SAW and RAM, and between ROV and RAM. From this perspective as well, the MEREC-ROC method appears to offer an advantage over the MEREC method. Notably, the average Spearman's rank correlation coefficient among the MCDM methods in Table 8 is 0.9321, which is greater than the 0.9214 observed in Table 9. Therefore, it can be asserted that in this case, employing the MEREC-ROC weighting calculation for determining the weights of criteria is more beneficial in comparison to using only the MEREC method.

Table 7. Alternative rankings and Spearman's rank correlation coefficients between MCDM methods with MEREC weights (Case 2)

Type	SAW	TOPSIS	PIV	ROV	RAM
	Rank				
RB1	1	1	1	3	1
RB2	2	2	2	1	2
RB3	4	4	4	5	4
RB4	3	3	3	2	3
RB5	5	5	5	4	5
RB6	6	6	7	6	7
RB7	7	7	6	7	6
Spearman coefficient					
SAW	-	1	0.9643	0.8571	0.9643
TOPSIS		-	0.9643	0.8571	0.9643
PIV			-	0.8214	1
ROV				-	0.8214
RAM					-
Average: 0.9214					

Table 8. Alternative rankings and Spearman's rank correlation coefficients of each pair of MCDM approaches using MEREC-ROC weights (Case 2)

Type	SAW	TOPSIS	PIV	ROV	RAM
	Rank				
RB1	3	2	3	3	1
RB2	1	1	1	1	2
RB3	4	4	4	4	4
RB4	2	3	2	2	3
RB5	5	6	6	5	6
RB6	7	7	7	7	7
RB7	6	5	5	6	5
Spearman coefficient					
SAW	-	0.9286	0.9643	1	0.8571
TOPSIS		-	0.9643	0.9286	0.9643
PIV			-	0.9643	0.8929
ROV				-	0.8571
RAM					-
Average: 0.9321					

While Case 1 demonstrated comparable effectiveness between the MEREC-ROC and MEREC methods, Case 2 expresses an outstanding effectiveness of the MEREC-ROC method over the MEREC method. To arrive at a more robust conclusion regarding the comparative performance of both above methods, another case studies of the ranking of different subjects are warranted.

4.3. Case 3: Ranking of Wood Planers

The third case study for comparing MEREC-ROC and MEREC methods involves determining the criteria weights in the case of ranking different types of wood planers. Table 9 compiles the information regarding six types of wood planers, denoted as WP1 to WP6, respectively. Each planer is characterized by three beneficial criteria (Type B criteria), C1 to C3, and three non-beneficial criteria (Type C criteria), C4 to C6 [56].

Table 9. Characteristics of wood planers [56]

Type	C1	C2	C3	C4	C5	C6
	planing width	maximum planing depth	maximum no-load speed	total machine length	weight	price
	B	B	B	C	C	C
WP1	82	2	16000	285	3	1.586
WP2	82	2.6	16500	300	2.8	1.529
WP3	82	1.8	16000	290	2.5	1.39
WP4	102	1	17000	280	2.7	2.43
WP5	82	2	11500	280	2.7	1.135
WP6	82	3	18000	390	4.6	2.218

Following a similar procedure to Case 1, the criteria weights were calculated using the MEREC method, which subsequently allowed for the determination of the priority ranking among the criteria. From this ranking, the criteria weights were also calculated using the MEREC-ROC method. All these results are presented in Table 10.

Tables 11 and 12 present the rankings of the WPs when evaluated by the MCDM methods under two scenarios: first, with the weights of criteria which are defined by the MEREC method, and second, with the weights of criteria which are defined by MEREC-ROC one. Each table also lists the Spearman's rank correlation coefficients between the methods.

Table 10. Criteria Weights in Case 3

Weight method	C1	C2	C3	C4	C5	C6
MEREC	0.0185	0.3267	0.1494	0.1203	0.2060	0.1791
	Rank					
	6	1	4	5	2	3
MEREC-ROC	0.0278	0.4083	0.1028	0.0611	0.2417	0.1583

Table 11. Alternative rankings and Spearman's rank correlation coefficients between MCDM methods with MEREC weights (Case 3)

Alt.	SAW	TOPSIS	PIV	ROV	RAM
	Rank				
WP1	5	5	5	4	5
WP2	1	2	1	1	1
WP3	4	4	3	2	4
WP4	6	6	6	6	6
WP5	2	3	2	3	3
WP6	3	1	4	5	2
Spearman coefficient					
SAW	-	0.8286	0.9429	0.7143	0.9429
TOPSIS		-	0.6571	0.3714	0.9429
PIV			-	0.8857	0.8286
ROV				-	0.6000
RAM					-
Average: 0.7333					

Table 12. Alternative rankings and Spearman's rank correlation coefficients of each pair of MCDM approaches using MEREC-ROC weights (Case 3)

Alt.	SAW	TOPSIS	PIV	ROV	RAM
	Rank				
WP1	5	5	5	4	5
WP2	1	2	1	1	1
WP3	4	4	3	2	4
WP4	6	6	6	6	6
WP5	2	3	2	3	3
WP6	3	1	4	5	2
Spearman coefficient					
SAW	-	0.8286	0.9429	0.7143	0.9429
TOPSIS		-	0.6571	0.3714	0.9429
PIV			-	0.8857	0.8286
ROV				-	0.6000
RAM					-
Average: 0.7333					

It was observed that when both the MEREC and MEREC-ROC methods were used to calculate criteria weights, the average Spearman's rank correlation coefficient among the MCDM methods was 0.7333. This result indicates that in this specific case, the MEREC-ROC method is equivalent to the MEREC method. Therefore, while Case 1 and Case 3 showed that MEREC-ROC and MEREC are equally effective, Case 2 demonstrated that MEREC-ROC has an advantage over MEREC. This provides preliminary evidence suggesting that employing the MEREC-ROC method for determining criteria weights offers advantages over the MEREC method. Nevertheless, to enhance the generalizability of this conclusion, one more illustrative example warrants investigation.

4.4. Case 4: Ranking of Gear Manufacturing Materials

Table 13 presents the compiled information for eight types of gear manufacturing materials, symbolized as MG1 to MG8, respectively. Each alternative is specified by six beneficial criteria (Type B criteria, C1 to C6) and one non-beneficial criterion (Type C criterion, C7) [57].

Following a similar procedure to Case 1, the criteria weights, alternative rankings, and Spearman's rank correlation coefficients between the methods were calculated, as summarized in Tables 14-16.

Table 13. Characteristics of gear manufacturing materials [57]

Materials	C1	C2	C3	C4	C5	C6	C7
	tensile strength	elongation	hardness	melting point	stiffness	impact toughness	cost
	B	B	B	B	B	B	C
MG1	780	18	55	635	229	880	22000
MG2	880	15	50	735	225	390	30000
MG3	930	13	45	785	269	590	31000
MG4	980	15	45	785	217	600	22000
MG5	980	12	45	835	250	950	24000
MG6	1080	12	50	930	220	960	22000
MG7	885	12	40	685	195	970	21000
MG8	750	12	45	400	179	940	20000

Table 14. Criteria weights in case 4

Weight method	C1	C2	C3	C4	C5	C6	C7
MEREC	0.1576	0.1700	0.1624	0.1089	0.1533	0.1021	0.1456
	Rank						
	3	1	2	6	4	7	5
MEREC-ROC	0.1561	0.3704	0.2276	0.0442	0.1085	0.0204	0.0728

Table 15. Alternative rankings and Spearman's rank correlation coefficients between MCDM methods with MEREC weights (Case 4)

Type	SAW	TOPSIS	PIV	ROV	RAM
	Rank				
MG1	2	1	2	1	2
MG2	7	7	7	6	7
MG3	6	6	6	5	5
MG4	4	4	4	4	4
MG5	3	3	3	3	3
MG6	1	2	1	2	1
MG7	5	5	5	7	6
MG8	8	8	8	8	8
Spearman coefficient					
SAW	-	0.9762	1	0.9048	0.9762
TOPSIS		-	0.9762	0.9286	0.9524
PIV			-	0.9048	0.9762
ROV				-	0.9524
RAM					-
Average: 0.9548					

Table 16. Alternative rankings and Spearman's rank correlation coefficients of each pair of MCDM approaches using MEREC-ROC weights (Case 4)

Type	SAW	TOPSIS	PIV	ROV	RAM
	Rank				
MG1	1	1	1	1	1
MG2	4	3	4	3	3
MG3	6	5	6	6	6
MG4	2	2	2	2	2
MG5	5	6	5	5	5
MG6	3	4	3	4	4
MG7	7	7	7	7	7
MG8	8	8	8	8	8
Spearman coefficient					
SAW	-	0.9524	1	0.9762	0.9762
TOPSIS		-	0.9524	0.9762	0.9762
PIV			-	0.9762	0.9762
ROV				-	1
RAM					-
Average: 0.9762					

It is also observed that when using the MEREC method for weighting criteria, the lowest Spearman's rank correlation coefficient is 0.9048, found between SAW and ROV, and between PIV and ROV. Conversely, when the MEREC-ROC method is employed for criteria weighting (Table 16), the lowest Spearman's rank correlation coefficient is 0.9524, observed between SAW and TOPSIS, and between TOPSIS and PIV. Thus, from this perspective, the MEREC-ROC method exhibits an advantage over the MEREC method. Notably, the average Spearman's rank correlation coefficient among the methods is 0.9762 if the MEREC-ROC method was used to calculate the weights, which is also significantly higher than the 0.9548 obtained with the MEREC method. This result firmly establishes that, in this case as well, the MEREC-ROC method outperforms the MEREC method.

To facilitate a review of the four conducted case studies, their fundamental information has been aggregated in Table 17.

Table 17. Basic information of the conducted case studies

Case	The number of alternatives	Total number of criteria	The number of beneficial criteria	The number of non-beneficial criteria	The application domain	Average Spearman's rank correlation coefficient	
						MEREC weight	MEREC-ROC weight
1	4	4	3	1	cutting fluid	0.9200	0.9200
2	7	5	4	1	Robot	0.9214	0.9321
3	6	6	3	3	Wood Planer	0.7333	0.7333
4	8	7	6	1	Gear Manufacturing Material	0.9548	0.9762

From four above case studies, it can be seen that although many factors (such as the number of ranked alternatives, to total number of criteria, the number of Type B and Type C criteria, the field of application) were different between the cases, but the cases 2 and 4 showed consistently more effective of the MEREC-ROC method than the MEREC method at ensuring the stability of alternative rankings when evaluated by different MCDM methods, while the cases 1 and 3 showed the equally effective of the both methods. Therefore, it can be concluded that, overall, using the MEREC-ROC method to calculate criteria weights provides a greater advantage compared to the MEREC method.

Although the overall analysis indicates that employing the calculated weighting of the MEREC-ROC method for criteria weighting ensures higher ranking stability of alternatives when applying the various MCDM methods to rank compared to the use of the MEREC method alone, a sensitivity analysis is necessary for a comprehensive evaluation of the differentiation between MEREC-ROC and MEREC. The subsequent section will perform a sensitivity analysis for each of the four conducted case studies.

5. SENSITIVITY ANALYSIS

Sensitivity analysis can be performed in several ways, such as by changing the weights of the criteria, altering the number of alternatives to be ranked, adjusting the number of criteria used to evaluate each alternative, or modifying the data normalization method [58,59]. In this study, for each case, the sensitivity analysis was conducted by removing a specific alternative from the list of those to be ranked [60]. To do the comparison objectively of two methods, MEREC-ROC and MEREC, in each case, an alternative was also selected randomly to remove. In this study, for Case 1, the last alternative (CF4) was removed from the four ones; for Case 2, alternative 4 (RB4) was removed from the seven ones; for Case 3, alternative 3 (WP3) was removed from the six ones; and for Case 4, the first one (MG1) was removed among the eight alternatives.

Arranging the order of the remaining alternatives and the calculation of Spearman's rank correlation coefficients in every case were performed analogously to the procedures described in Section 4. Tables 18-21 summarize the Spearman's rank correlation coefficient data for each scenario.

Table 18. Spearman's rank correlation coefficients for case 1 after removing CF4

Method	MEREC				MEREC-ROC			
	TOPSIS	PIV	ROV	RAM	TOPSIS	PIV	ROV	RAM
SAW	1	1	0.5	1	1	1	0.5	1
TOPSIS		1	0.5	1		1	0.5	1
PIV			0.5	1			0.5	1
ROV				0.5				0.5
Average	0.8				0.8			

Table 19. Spearman's rank correlation coefficients for case 2 after removing RB4

Method	MEREC				MEREC-ROC			
	TOPSIS	PIV	ROV	RAM	TOPSIS	PIV	ROV	RAM
SAW	1	0.9429	0.8857	0.9429	0.9643	1	0.9429	0.9429
TOPSIS		0.9429	0.8857	0.9429		0.9429	1	0.8286
PIV			0.8286	1			0.9429	0.9429
ROV				0.8286				0.8286
Average	0.9200				0.9336			

Table 20. Spearman's rank correlation coefficients for case 3 after removing WP3

Method	MEREC				MEREC-ROC			
	TOPSIS	PIV	ROV	RAM	TOPSIS	PIV	ROV	RAM
SAW	0.7000	0.9000	0.7000	0.9000	0.7000	1.0000	0.9000	0.9000
TOPSIS		0.4000	0.3000	0.9000		0.7000	0.4000	0.9000
PIV			0.9000	0.7000			0.9000	0.9000
ROV				0.6000				0.7000
Average	0.6500				0.7667			

Table 21. Spearman's rank correlation coefficients for case 4 after removing MG1

Method	MEREC				MEREC-ROC			
	TOPSIS	PIV	ROV	RAM	TOPSIS	PIV	ROV	RAM
SAW	0.9286	0.9643	0.8571	1	0.9643	1	0.9286	1
TOPSIS		0.9643	0.7143	0.9286		0.9643	0.8929	0.9643
PIV			0.8214	0.9643			0.9286	1
ROV				0.8571				0.9286
Average	0.9000				0.9571			

Observing the data in Tables 17-21 reveals that for Case 1, for Case 1, even with the removal of CF4, the MEREC-ROC and MEREC methods continue to exhibit similar performance, consistent with the findings before the removal (refer back to Section 4.1). For the three other cases, employing MEREC-ROC for the criteria weights also yields a higher average Spearman's rank correlation coefficient compared to using MEREC for criteria weighting. This confirms the excellent effectiveness of MEREC-ROC in comparison to MEREC in these three cases.

Based on the collective results obtained, a robust conclusion can be drawn: the ranking stability of alternatives when evaluated by different MCDM methods is enhanced when the MEREC-ROC method is used for criteria weighting compared to using the MEREC method alone.

This study introduces a new method called MEREC-ROC, which leverages the strengths of two component methods: the objective weighting of the MEREC method and the subjective weighting of the ROC method. This represents an innovative discovery for creating a hybrid weighting method that combines both objective and subjective factors. The goal is to ensure high stability in the ranking of alternatives when they are evaluated using various MCDM methods.

6. CONCLUSION

Calculating the weights for the criteria is a crucial task in solving MCDM problems. Using an objective method to determine these weights can diminish the role of experts in the decision-making process, sometimes leading to undesirable outcomes. Conversely, relying on subjective methods for weighting can easily introduce errors stemming from a decision maker's personal experience or their bias towards a particular criterion. This study combines the MEREC objective weighting method with the ROC subjective weighting method to form a hybrid approach called the MEREC-ROC weighting method. From a series of evaluations, including a case-by-case sensitivity analysis, it can be verified that the ranking of alternatives by different MCDM methods will be more stable if using the MEREC-ROC method to calculate criteria weights instead of using the MEREC method alone.

The hybrid MEREC-ROC weighting method proposed in this study represents a judicious fusion of MEREC and ROC, yielding a valuable technique that contributes to the existing repertoire of weighting ones to contribute to solve MCDM issues.

In this investigation, the efficacy of MEREC-ROC has been demonstrated to be superior to that of MEREC. However, the achieved results are confined to specific case studies involving the ranking of industrial equipment and materials. The advantages of MEREC-ROC over MEREC are anticipated to extend to other domains as well. Nevertheless, this expectation warrants empirical validation in subsequent research endeavors.

This study has primarily compared the effectiveness of MEREC-ROC against MEREC in scenarios where the elements within the decision matrix are concrete numerical values. Future research should extend this comparison to situations where the decision matrix incorporates fuzzy sets and rough analysis.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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