Received 10 December 2023, accepted 27 December 2023, date of publication 3 January 2024, date of current version 12 January 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3349472

RESEARCH ARTICLE

Opinion Weight Criteria Method (OWCM): A New Method for Weighting Criteria With Zero Inconsistency

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ABSTRACT Determining criteria weights is a frequent issue in multi-criteria decision-making (MCDM) techniques. The weight given to various criteria can have a significant impact on a decision's outcome. As a result, researchers developed numerous methods for determining the criteria's weights. Weighting methods can be objective, subjective, or integrated. In this study, the ''Opinion Weight Criteria Method'' (OWCM) has been proposed as a new weighting method to specify the criteria weights by integrating the concepts of objective and subjective weighing. OWCM is keen to extract the weight based on the decision-maker preferences with zero inconsistency. Some computational analyses were presented to confirm the efficiency of the OWCM. First, an example of the OWCM's procedure for calculating the weights for each criterion is provided. Second, the validity of the new method is provided. Finally, the evaluation and validation are presented to show the power of the new method. The management implications of the OWCM method highlight its capacity to improve decision-making by eliminating inconsistencies, aligning with decision-maker preferences, and fostering transparency. The conducted analyses demonstrate that the OWCM is efficient in determining the criteria weights.

INDEX TERMS Weight, opinion weight criteria method, OWCM, multi-criteria decision-making.

I. INTRODUCTION

MCDM, an interdisciplinary area, has gained substantial attention in recent years. This field of study is especially applicable in circumstances when a certain range of options must be thoroughly evaluated based on many criteria [1], [2]. The primary objective of MCDM approaches is to offer a systematic framework for decision-makers to make logical, comprehensible, and defensible choices [3], [4]. MCDM challenges are frequently encountered in many businesses and decision-making scenarios. The intricacy occurs when decision-makers must navigate among a plethora of possibilities, each assessed against a set of criteria. These criteria might include many aspects, such as cost, efficiency, sustainability, and other pertinent elements, depending on the specific circumstances of the choice [1], [2]. A commonly used approach to express MCDM problems is by using a decision matrix. The matrix represents the decision space by organizing the options and criteria in a systematic manner. Every option is evaluated based on each criterion, leading to a full assessment of the performance of each alternative across the defined criteria as follows:

$$DM = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} \mathrm{C1} & \mathrm{C2} & \ldots & \mathrm{Cn} \end{array} \\ \begin{bmatrix} x_{11} & x_{12} & \ldots & x_{1n} \\ x_{21} & x_{22} & \ldots & x_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & \ldots & x_{mn} \end{bmatrix} \end{array}$$

where $A_1 \ldots Am$ are the potential alternatives to prioritized by decision-makers; C1…Cn are the criteria by which each alternative is evaluated; x_{ij} is the evaluation of Ai concerning C_j [3], [5]. The decision matrix is an effective instrument that enables decision-makers to methodically arrange and

The associate editor coordinating the review of this manuscript and approving it for publication was Francisco J. Garcia-Penalvo.

evaluate intricate choice scenarios. MCDM approaches provide a systematic review process by organizing options and criteria in an organized manner, allowing for both quantitative and qualitative analysis. The utilization of a matrix-based representation not only improves the lucidity of the decision issue, but also establishes the groundwork for the application of diverse MCDM strategies. In general, if a weight wj ($w_j \geq 0; \sum w_j = 1$) is assigned to criterion j, then can use the additive weighted value function to obtain S_i [5], [6] as shown in equation 1, where the majority of the MCDM methods are built upon:

$$S_i = \sum_{j=1}^{n} w_j x_{ij} \tag{1}$$

According to Eq.1, the most important value which has been the impetus of several MCDM methods is how the weight of the criteria or the vector $w = (w_1, w_2, \ldots..w_n)$ is obtained [7], [8].

Several MCDM methods can extract the weight for evaluation criteria by converting the decision-makers preferences into crisp values. These values can be considered as a weight for the evaluation criteria. The most popular methods are AHP (Analytic Hierarchy Process) [9], ANP (Analytic Network Process) [10], and BWM (Best Worst Method) [7]. The main concept of AHP and ANP is deriving the weight of evaluation criteria depending on a pairwise comparison between the set of evaluation criteria [9], [10], [11]. Pairwise comparison was introduced by Thurstone [12]. Pairwise comparison is a way to extract the weight for the evaluation criteria [13], [14], [15]. On the other hand, in academic literature, several researchers have used the BWM technique to find the weight [16], [17], [18], [19], [20]. The main concept of BWM is based on assessments of the ideal criterion to other criteria and the worst criterion to further criteria [7]. It uses a Likert scale to compare and determine preferences for the chosen criterion over the others. Additionally, it selects the worst criterion and performs a reference comparison to ascertain the preferences for the remaining criteria based on the worst criterion. AHP, ANP, and BWM suffered significant challenges (i.e., the inconsistency ratio) [21], [22], [23], [24]. The inconsistency ratio is generated by comparing the evaluation criteria [25]. This number may gradually increase once the amount of criteria increases. As a result, pairwise comparisons introduce a particular amount of inconsistency [21], [22], [23], [24], [26]. Therefore, the BWM developer strives to minimize comparisons through reference comparisons [7]. Figure 1 shows the variances of comparisons between the AHP and BWM.

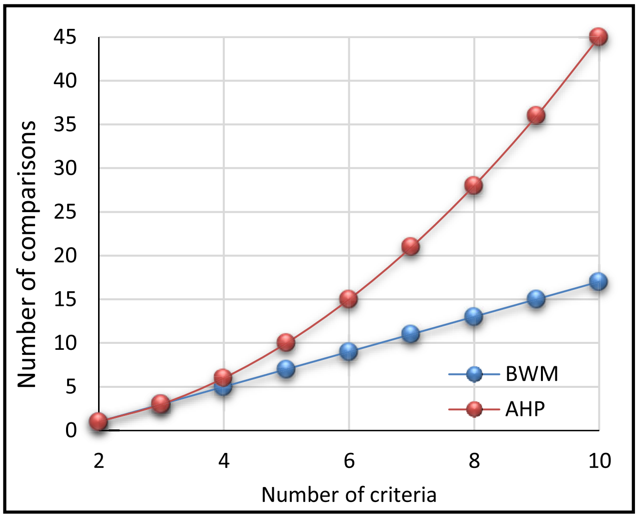

FIGURE 1. The difference in the number of comparisons between AHP and BWM.

According to Figure 1, applying ten evaluation criteria results in 45 comparisons in AHP and 17 in BWM. As a result, the inconsistency among AHP, ANP, and BWM decreases. However, BWM still suffered from inconsistency as a result of the decision-maker comparison.

FUCOM is considered one of the most important methods recently discovered by the research team, as it addressed some of the problems that AHP and BWM suffered from; however, it suffers from the nature of the dissimilar comparisons. For example, the first criteria refer to color, and the second criterion refers to sound. It is incorrect to compare the sound with color, so the FUCOM method suffers from this issue (unnatural comparison). Basically, comparing two unrelated criteria is not an inherent process and is challenging to do. Thus, the concept of an optimal solution and opinion matrix is used to address the identified obstacles. Our approach yields rational determinations since it relies on the judgment of the DM (the specialist). On the other hand, comparing two distinct quantities is not a natural procedure and requires some effort on the part of the decision-maker [27]. This proposal is motivated by the urgent requirement for creative and modern techniques for weighting criteria in MCDM. Thus, using one of these methods to evaluate any decision-making problem is considered impractical due to these disadvantages. Also, researchers have instead employed mathematical methods to extract weight for the evaluation criteria, such as the entropy method [28], [29], [30] and the Preference Selection Index (PSI) [31], [32], [33]. The mathematical approaches for determining the weight of a criterion are based on applying Mathematical equations on a decision matrix. As a result, the derived weight did not reflect the decision-maker's perspective. In light of these concerns, an intelligent solution is required. Therefore, this study presents an original method constructed on the integration of the philosophy of the fuzzy decision by opinion score method (FDOSM) to extract the evaluation criteria weights [27]. By combining the decision-maker preferences and the mathematical technique to extract the weights for the evaluation criteria, the weight reflected the decision-maker's favorites and made it easier to apply the mathematical equations. The study's contributions may be summarized as follows:

1- Propose a novel approach for determining the weight of assessment criteria by integrating decision-maker preferences with mathematical methods. The procedure is

referred to as the Opinion Weight Criteria procedure (OWCM).
2- OWMC can address the inconsistency problem.
3- The OWMC was applied to the numerical example, and it achieved a correct weight for the evaluation criteria.
4- Combine the OWMC with TOPSIS method to extract the final rank for the numerical example.
5- Several ways are applied in this paper to ensure the validation of OWMC.

II. THE PHILOSOPHY OF FDOSM

This section discusses the FDOSM philosophy. FDOSM is the abbreviation for a new method in MCDM that was developed in 2020 [27]. FDOSM comprises three blocks: data input, data transformation, and data processing.

The input unit is like other MCDM techniques with m set of alternatives and n set of criteria, as shown below.

$$DM = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C1 & C2 & \ldots & Cn \end{array} \\ \begin{bmatrix} x_{11} & x_{12} & \ldots & x_{1n} \\ \ldots & \ldots & \ldots & \ldots \\ \vdots & \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & \ldots & x_{mn} \end{bmatrix} \end{array}$$

After the decision matrix is constructed, FDOSM utilizes the transformation unit to determine the optimal solution, considering three unique parameter options: the minimum, maximum, and critical values (notably, the lowest, highest, and crucial values). The minimum value is used in combination with the cost criterion, where the lowest value is considered the ideal decision, while higher values indicate better results. The "critical value" pertains to the evaluation of value in many settings, particularly when the ideal answer is outside the boundaries of minimal or maximum values. This is represented by situations such as the assessment of blood pressure. By always retaining the same perspective, it is possible to ascertain the optimal answer for the immeasurable worth. Consequently, the optimal resolution is as follows:

$$A^* = \left\{ \left(\left(\max_i v_{ij} \mid j \in J \right) . \left(\min_i v_{ij} \mid j \in J \right) \right.\right.$$
$$\left.\left. . \left(Op_{ij} \in I.J \right) \mid i = 1 \ldots n \right) \right\} \tag{2}$$

Let max represent the optimal value based on benefit criteria, min represent the optimal solution based on cost criteria, and Opij represents the crucial value that lies between max and min.

In the next phase, decision-makers are given with evaluating whether the significant variances between the ideal solution and the alternatives heavily impact the decision-maker's perspective. The reference comparisons use an implicit allocation of weights, using five factors to assess linguistic words that span from "Huge difference" to "No difference." The decision-maker identifies the optimal solution by using Equation 3. The step of selecting the optimal solution entails a thorough comparison between the ideal solution and the alternatives that are now accessible.

$$Op_{Lang} = \left\{ \left(\left(\tilde{v}_{ij} \otimes v_{ij} \mid j \in J \right) . \mid i = 1.2.3. \ldots .m \right) \right\} \tag{3}$$

where ⊗ a reference comparison between the optimal option and the alternatives is specified. As seen in Figure 2.

Where * NO_D: No Difference / S_D: Slight Difference / DI: Difference / B_D: Big Difference / H_D: Huge Difference.

The linguistic term opinion matrix shown in the following is the end result of this process.

$$Op_{Lang} = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C1 & C2 & \ldots & Cn \end{array} \\ \begin{bmatrix} Op_{11} & Op_{12} & \ldots & Op_{1n} \\ \ldots & \ldots & \ldots & \ldots \\ \vdots & \vdots & \vdots & \vdots \\ Op_{m1} & Op_{m2} & \ldots & Op_{mn} \end{bmatrix} \end{array}$$

When Op_{mn} is the value of the alternative after transfer into an opinion linguistic term.

The opinion matrix is constructed by comparing the philosophical principles linked to the ideal value with other values in the same criteria. The inconsistency in OWCM is zero because it is developed depending on the philosophy of FDOSM. FDOSM solved the problem of inconsistency by developing the opinion matrix and comparing the values in the same criterion, not between the set of criteria itself [27].

Therefore, from the opinion matrix, the weight of each criterion will be extracted. The next section presents the Opinion Weight Criteria Method (OWCM).

III. OPINION WEIGHT CRITERIA METHOD (OWCM)

This section briefly discusses OWCM. The evaluation criteria's weight is determined by performing the steps listed below:

Step 1: Using the five Likert scale, convert the linguistic terms into crisp numbers via Table 1.

Step 2: Normalize the crisp decision matrix to standardize it. After discussing the advantages and disadvantages of the opinion matrix in a previous section [27], the normalizing method involves using the following equation:

$$\mathrm{R_{ij}} = \frac{x_{ij}}{x_j^{max}} \tag{4}$$

Step 3: Calculate the average score of the standardised decision matrix.

$$\mathrm{N} = \frac{1}{\mathrm{N}} \sum_{\mathrm{i}=1}^{\mathrm{m}} \mathrm{R_{ij}} \tag{5}$$

Step 4: Determines the degree of preference variation and its corresponding value. According to this equation, the value of each attribute's preference variation (Øj) is calculated:

$$\text{Øj} = \sum_{i=1}^{m} \left[R_{ij} - N \right]^2$$

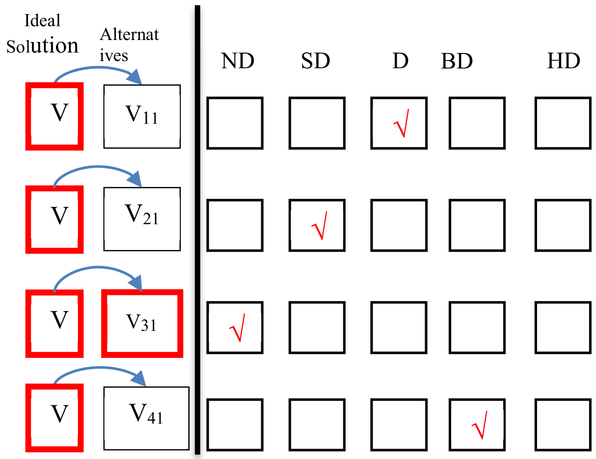

FIGURE 2. Scale used to transfer data.

$$\mathrm{j} = \textit{the value of each criterion} \tag{6}$$

Step 5: Formulate the following equation in order to calculate the deviation in preference values:

$$\Omega_{\mathrm{j}} = 1 - \emptyset j$$
$$\mathrm{j} = \textit{the value of each criterion} \tag{7}$$

Step 6: Identify the criteria weight by using the following equation:

$$w_j = \frac{\boldsymbol{\Omega}_j}{\sum_{j=1}^{n} \boldsymbol{\Omega}_j} \tag{8}$$

The total of weights for the criteria should be = 1.

In the following section, we present a numerical example to explain how to apply OWCM.

IV. NUMERICAL EXAMPLE

Machine learning methods, as described in reference [35], have become essential tools in the field of artificial intelligence for classifying and handling COVID-19. These algorithms utilize patterns and insights obtained from extensive datasets to aid in activities such as identifying problems at an early stage, predicting the severity of conditions, and categorizing patients based on their characteristics. The use of machine learning in healthcare, particularly during a worldwide epidemic, highlights the pressing need and importance of employing sophisticated technology to improve decision-making procedures. A decision matrix is created to accurately assess the efficacy of machine learning algorithms in the classification of COVID-19 [35]. This matrix functions as a complete instrument for evaluating and contrasting eight alternative machine-learning methodologies. The choice of these approaches is crucial, given the variety in their methodology and applications. The decision matrix is constructed based on nine evaluation criteria, each of which plays a crucial part in assessing the effectiveness of the machine learning algorithms. The decision matrix seeks to offer a comprehensive viewpoint on the merits and drawbacks of any machine learning technique by considering numerous factors. The details of this decision matrix are shown in Table 2.

TABLE 1. The linguistic terms.

Linguistic terms	Crisp value
NO_D	1
S_D	2
DI	3
B_D	4
H_D	5

For each criterion, the decision-maker compared the ideal solution's value versus that of each of the alternatives in that criterion as a reference point for comparison, according to Eqs. 2 and 3. The decision-maker employed a five-point Likert scale, see Table 1. The outcome of this stage is an opinion matrix for decision-makers based on the FDOSM philosophy. The opinion matrix for the first decision-maker is shown in Table 3.

The opinion matrix pertaining to the three experts is displayed in Table 3. This matrix represents the many perspectives and preferences of the decision-makers, offering significant insights into the process of making decisions based on multiple criteria. The NO D refers to the optimal choice, and HD to the worst choice.

The decision-opinion maker's matrix is expressed in crisp value based on step 1. Table 4 displayed the crisp decision matrix based on decision-maker preferences.

Table 4 serves as a vital process, reflecting the experts' choices in a crisp matrix. This depiction provides a lucid and succinct summary of the available decisions made by decision-makers, offering crucial insights to guide their choices. Every individual cell inside the crisp choice matrix represents the assessed performance of an option in relation to specified criteria, serving as the basis for a thorough study. In the second phase, Equation 4 was utilized in order to standardize the crisp decision matrix. The normalization step is crucial as it converts the values of the matrix into a standardized scale that ranges from 0 to 1. The advantages of this normalization procedure are numerous, as it offers decision-makers a uniform and comparable foundation for assessing options based on various criteria.

Table 5 offers the normalized matrix. The normalization enhances efficiency and effectiveness in conducting comparative analysis, allowing decision-makers to accurately detect patterns, trends, and ideal options.

In Step 3, the mean is calculated for each criterion value according to Eq. 5. Therefore, the means of criteria are Train time = 0.575, Test time = 0.75, AUC = 0.525, CA = 0.6, F1 = 0.725, Precision = 0.6, Recall = 0.725, LogLoss = 0.6, and Specificity = 0.625. Then, apply step 4 by using Eq. 6 to calculate the value of preference variation. The values of each criterion as follow: Train time = 0.435, Test time = 0.46, AUC = 0.715, CA = 0.48, F1 = 0.635, Precision = 0.48, Recall = 0.635, LogLoss = 0.64, and Specificity =

TABLE 2. Decision matrix.

Alternatives	Train time	Test time	AUC	CA	F1	Precision	Recall	LogLoss	Specificity
Neural Network	170.281	2.859	0.996348842	0.970532319	0.970536119	0.970634585	0.970532319	0.120653235	0.983664273
SVM	53.793	4.024	0.996283375	0.967680608	0.967633013	0.967913827	0.967680608	0.09635078	0.981727867
Logistic Regression	7.353	1.59	0.994346638	0.958174905	0.958217865	0.958408258	0.958174905	0.233274449	0.976842133
kNN	4.412	5.274	0.98892582	0.937262357	0.937270789	0.938977386	0.937262357	0.339680905	0.964713178
Random Forest	18.635	1.546	0.990371553	0.933460076	0.93361603	0.933882482	0.933460076	0.227589409	0.964689334
Naive Bayes	5.554	1.504	0.966154159	0.900190114	0.900165988	0.900320941	0.900190114	3.150001339	0.947118754
Tree	15.561	0.021	0.916583241	0.891634981	0.891641318	0.891688177	0.891634981	2.123195663	0.943975329
AdaBoost	11.153	1.347	0.901379175	0.868821293	0.869036521	0.869435613	0.868821293	4.530752037	0.933064247

0.435. in step 5, we achieved the deviation of preference value using Eq. 7, and the value of each criterion as follows: Train time = 0.565, Test time = 0.54, AUC = 0.285, CA = 0.52, F1 = 0.365, Precision = 0.52, Recall = 0.365, LogLoss = 0.36, and Specificity = 0.565. Ultimately, step 6 is carried out to determine the weight given to each criteria, as specified by Equation 8. The definitive weights for each criterion are outlined in Table 6.

Train time and Specificity have the highest weights (0.1383109 each). These criteria are considered the most important in the decision-making process, indicating that they carry the highest significance or priority when evaluating alternatives.

F1 (F1 Score) and LogLoss (Logarithmic Loss) have the lowest weights (0.0893513 and 0.0881273, respectively). These criteria are considered less important compared to the others and may have a lower influence on the final decision. Based on Table 6, the fact that there is a total weight = 1 for all criteria indicates that the OWCM successfully determined the appropriate weight to assign to each criterion by considering the preferences of the person making the decision.

V. COMBINE OWCM WITH TOPSIS

This section provides the final ranking of the machine learning algorithms using TOPSIS, based on the weights collected by OWCM for each criterion in the case mentioned above. The TOPSIS technique is widely used in MCDM to rank alternative options [36]. The primary notion of TOPSIS is to calculate the distance between alternatives, the ideal solution, and the negative solution. The optimal option is both the closest to the ideal and the furthest from the negative answer [37], [38], [39]. The stages of TOPSIS may be succinctly described as:

Step 1: Identify the decision matrix.

Step 2: Construct the normalized decision matrix: Attribute comparisons can be performed on non-dimensional attributes rather than the original multi-dimensional ones. One method divides each criterion's outcome by the norm of the criterion's whole result vector. The r_{ij} element of the normalized decision matrix is normalized using the vector normalization technique.:

$$r_{ij} = \boldsymbol{x_{ij}} \Bigg/ \sqrt{\sum_{i=1}^{m} \boldsymbol{x_{ij}^2}} \tag{9}$$

As a result, the vector unit length of each attribute is the same.

Step 3: Constructing the weighted and normalized decision matrix involves utilizing a set of weights $w = w_1, w_2, w_3, \cdots, w_j, \cdots, w_{n,}$ with the constrain $\sum_{j=1}^{m} w_j = 1$ To achieve this, the decision matrix provided by the expert is normalized, and each column of the normalized decision matrix (R) is multiplied by its corresponding weight wj The resulting matrix from this operation is denoted as. This procedure creates a new matrix V, and it represents the weighted and normalized decision matrix.

$$\mathrm{V} = \begin{bmatrix} v_{11} & v_{12} & \cdots & v_{1n} \\ \vdots & \vdots & \vdots & \vdots \\ v_{m1} & v_{m2} & \cdots & v_{mn} \end{bmatrix} = \begin{bmatrix} w_1 r_{11} & w_2 r_{12} & \cdots & w_n r_{1n} \\ \vdots & \vdots & \vdots & \vdots \\ w_1 r_{m1} & w_2 r_{m2} & \cdots & w_n r_{mn} \end{bmatrix}$$

Step 4: Detecting the ideal and anti-ideal solutions

TABLE 3. The opinion matrix for first decision-maker.

Alternatives	Train-time	Test-time	AUC	CA	F1	Precision	Recall	LogLoss	Specificity
Neural Network	H_D	B_D	NO_D	NO_D	NO_D	NO_D	NO_D	S_D	NO_D
SVM	B_D	H_D	NO_D	S_D	S_D	S_D	S_D	NO_D	S_D
Logistic Regression	S_D	B_D	S_D	S_D	DI	S_D	DI	S_D	DI
kNN	NO_D	H_D	S_D	DI	B_D	DI	B_D	DI	DI
Random Forest	DI	B_D	S_D	DI	B_D	DI	B_D	S_D	DI
Naive Bayes	S_D	B_D	DI	B_D	H_D	B_D	H_D	H_D	B_D
Tree	DI	NO_D	H_D	B_D	H_D	B_D	H_D	B_D	B_D
AdaBoost	DI	DI	H_D	H_D	H_D	H_D	H_D	H_D	H_D

TABLE 4. The crisp decision matrix.

Alternatives	Train time	Test time	AUC	CA	F1	Precision	Recall	LogLoss	Specificity
Neural Network	1	4	1	1	1	1	1	2	1
SVM	4	5	1	2	2	2	2	1	2
Logistic Regression	2	4	2	2	3	2	3	2	3
KNN	1	5	2	3	4	3	4	3	3
Random Forest	3	4	2	3	4	3	4	2	3
Naive Bayes	2	4	3	4	5	4	5	5	4
Tree	3	1	5	4	5	4	5	4	4
AdaBoost	3	3	5	5	5	5	5	5	5

TABLE 5. The normalization decision matrix.

Alternatives	Train time	Test time	AUC	CA	F1	Precision	Recall	LogLoss	Specificity
Neural_Network	1	0.8	0.2	0.2	0.2	0.2	0.2	0.4	0.2
SVM	0.8	1	0.2	0.4	0.4	0.4	0.4	0.2	0.4
Logistic Regression	0.4	0.8	0.4	0.4	0.6	0.4	0.6	0.4	0.6
kNN	0.2	1	0.4	0.6	0.8	0.6	0.8	0.6	0.6
Random Forest	0.6	0.8	0.4	0.6	0.8	0.6	0.8	0.4	0.6
Naive Bayes	0.4	0.8	0.6	0.8	1	0.8	1	1	0.8
Tree	0.6	0.2	1	0.8	1	0.8	1	0.8	0.8
AdaBoost	0.6	0.6	1	1	1	1	1	1	1

A* (the ideal) and A- (the anti-ideal) are the two artificial alternatives in this process:

$$A^{*}=\left\{\left(\left(\max_{i}.v_{ij}\,|\,j\in J\right),\left(\min_{i}.v_{ij}\,|\,j\in J^{-}\right)|\, i=1,2,\ldots,m\right)\right\}=\left\{v_1^{*},v_2^{*},\ldots,v_j^{*},\cdots v_n^{*}\right\} \tag{10}$$

$$A^{-}=\left\{\left(\left(\min_{i}.v_{ij}\,|\,j\in J\right),\left(\max_{i}.v_{ij}\,|\,j\in J^{-}\right)|\, i=1,2,\ldots,m\right)\right\}=\left\{v_1^{-},v_2^{-},\ldots,v_j^{-},\cdots v_n^{-}\right\} \tag{11}$$

where, $J=\{j=1,2,\ldots,n|j \text{ to benefit criteria}\}$

$J^{-}=\{j=1,2,\ldots,n|j \text{ to cost criteria}\}$

The A* and A- are indicated by the two newly constructed alternatives, A* and A-, respectively.

Step 5: Use the Euclidean distance to obtain the difference measurement.

The n-dimensional Euclidean Distance formula could be used to estimate the distance between options. The following formula can be used to determine the distance between each alternative and the ideal one, as follows:

$$S_{i^*}=\sqrt{\sum_{j=1}^{n}\left(v_{ij}-v_j^{*}\right)^2},\quad i=(1,2,\cdots m) \tag{12}$$

As with the anti-ideal one, the separation is determined by

$$S_{i^-}=\sqrt{\sum_{j=1}^{n}\left(v_{ij}-v_j^{-}\right)^2},\quad i=(1,2,\cdots m) \tag{13}$$

Step 6: Calculate closeness to the ideal solution

In the process, the closeness of A_i to the ideal solution A* is defined as:

$$C_{i^*}=S_{i^-}\big/\left(S_{i^*}+S_{i^-}\right),\ 0<C_{i^*}<1,\quad i=(1,2,\cdots m) \tag{14}$$

TABLE 6. The final weight for each criterion extracted by OWCM.

Criteria	Weight
Train time	0.1383109
Test time	0.1321909
AUC	0.0697674
CA	0.127295
F1	0.0893513
Precision	0.127295
Recall	0.0893513
LogLoss	0.0881273
Specificity	0.1383109
Total	1

It is clear that $C_{i^*} = 1$ if and only if $(A_i = A^*)$, similarly, $C_{i^*} = 0$ if and only if $(A_i = A^-)$ An alternative Ai is closer to A* as Ci* approaches to 1.

Step 7: Alternatives can now be rated in decreasing order of C*

According to step 2, the normalization process for the decision matrix is done using Eq. 9. The normalized decision matrix is reported in Table 7.

In step 3, the weighted normalized decision matrix, depending on the weight of each criterion, was extracted by using OWCM. The weighted normalized decision matrix is reported in Table 8.

Equation 10 and Equation 11 are used in Step 4 to ascertain the positive and negative ideal solutions for each criterion. The cost criteria in our case study include Train time, Test time, and log loss, whereas the benefit criteria comprise AUC, CA, F1, Precision, Recall, and Specificity. Proceeding to Step 5, the measurement of distance is conducted, and S* (positive ideal solution) and S- (negative ideal solution) are obtained using Equation 12 and Equation 13, respectively. Equation 14 is used to compute the proximity to the ideal solution, which ultimately determines the final scores for the alternatives. It is important to mention that the highest score indicates the most superior option. The final outcomes of the TOPSIS technique are shown in Table 9.

According to Table 9, the best alternative is Logistic Regression with a score (0.851721), and the worst alternative is Neural Network with a score (0.364321). In the next section, we present three ways to ensure the OWCM is the accurate weighted method.

VI. OWCM EVALUATION

This section will present the systematic rank way for the final result to make sure the rank of TOPSIS was provided weight by the OWCM is a systematic rank. Sensitivity analysis is also present to show the power of OWCM. Finally, a comparison analysis between OWMC and three well-known methods in MCDM for extracting criteria weighting (i.e., AHP, FUCOM, and BWM) will be explained.

A. SYSTEMATIC RANK

In MCDM, many researchers recommended using objective validation to ensure the final result is valid [2], [40], [41], [42]. The objective validation technique involves dividing the benchmarking machine learning algorithms into separate, equally sized groups. The quantity of machine learning techniques inside each category and the quantity of categories have no impact on the objective validation result. In order to verify the outcomes of benchmarking machine learning algorithms, it is necessary to carry out many procedures as shown below: (1) The machine learning techniques are ranked based on their TOPSIS final result. (2) After ranking, the machine learning methods are divided into two equal groups. (3) The mean (x ‾) for each group in GDM result is then determined using Equation 15.

$$.\bar{x} = \frac{1}{n}\sum\nolimits_{i=1}^{n} x_i \tag{15}$$

Each group's mean is used as the basis for the comparison process. The comparison method is based on the average of the results in each of the groups. There are two groups compared in this study: one with the lowest mean and one with the highest mean. We need the second group's average outcome to be larger than or equal to the first group's average outcome. If the evaluation findings are in line with the assumption, the conclusions are correct. Objective validation findings for comparing machine learning approaches are shown in Table 10.

The mean score of the first group is 0.275106545, which is less than the mean score of the second group, which is 0.349896534. This demonstrates the validity of benchmarking machine learning algorithms by using the weight of each criterion collected by OWCM. The OWCM provides weight for each criterion depending on the decision-maker's opinion with zero inconsistency. In the next section, the second type of evaluation (i.e. Sensitivity Analysis) is presented.

B. SENSITIVITY ANALYSIS

Here, the proposed OWCM method is tested for its sensitivity to shifting weights of the various evaluation criteria. Consequently, Sensitivity analysis predicts the impact on the ranking results of machine learning systems when modifying the weights of criteria. Firstly, it is crucial to choose the primary criteria for the aim of assessing sensitivity. The train schedule was the primary factor taken into account for all the criteria mentioned in Table 11 of this study. The experiment included varying the weights assigned to various criteria to see the impact of these weight changes on the products. The virtual change of each criterion compared to the most significant one (Train time) is calculated with a value of 0.1.

$$w_n : (1 - w_{z1}) = w_n^* : \left(1 - w_{z1}^*\right) \tag{16}$$

where, W_n is the advanced significant influence, and W_n^* represents the original weight values computed using OWCM.

The neural networks ranked eighth in each of the fourth, fifth, sixth, seventh, eighth, and ninth scenarios, and at the

TABLE 7. The normalized decision matrix.

Alternatives	Train time	Test time	AUC	CA	F1	Precision	Recall	LogLoss	Specificity
Neural Network	0.9415	0.3655	0.3634	0.3693	0.3693	0.3692	0.3693	0.0203	0.3615
SVM	0.2974	0.5145	0.3633	0.3682	0.3682	0.3681	0.3682	0.0162	0.3608
Logistic Regression	0.0407	0.2033	0.3626	0.3646	0.3646	0.3645	0.3646	0.0393	0.3590
kNN	0.0244	0.6743	0.3607	0.3566	0.3566	0.3571	0.3566	0.0573	0.3545
Random Forest	0.1030	0.1977	0.3612	0.3552	0.3552	0.3552	0.3552	0.0384	0.3545
Naive Bayes	0.0307	0.1923	0.3523	0.3425	0.3425	0.3424	0.3425	0.5309	0.3480
Tree	0.0860	0.0027	0.3343	0.3393	0.3393	0.3391	0.3393	0.3578	0.3469
AdaBoost	0.0617	0.1722	0.3287	0.3306	0.3307	0.3307	0.3306	0.7636	0.3429

TABLE 8. The weighted normalized decision matrix.

Alternatives	Train time	Test time	AUC	CA	F1	Precision	Recall	LogLoss	Specificity
Neural Network	0.1302	0.0483	0.0254	0.0470	0.0330	0.0470	0.0330	0.0018	0.0500
SVM	0.0411	0.0680	0.0253	0.0469	0.0329	0.0469	0.0329	0.0014	0.0499
Logistic Regression	0.0056	0.0269	0.0253	0.0464	0.0326	0.0464	0.0326	0.0035	0.0496
kNN	0.0034	0.0891	0.0252	0.0454	0.0319	0.0455	0.0319	0.0050	0.0490
Random Forest	0.0143	0.0261	0.0252	0.0452	0.0317	0.0452	0.0317	0.0034	0.0490
Naive Bayes	0.0042	0.0254	0.0246	0.0436	0.0306	0.0436	0.0306	0.0468	0.0481
Tree	0.0119	0.0004	0.0233	0.0432	0.0303	0.0432	0.0303	0.0315	0.0480
AdaBoost	0.0085	0.0228	0.0229	0.0421	0.0295	0.0421	0.0295	0.0673	0.0474

seventh rank for the tenth and third scenarios, while in the first and second scenarios, it was in fourth place. In terms of SVM, it ranked sixth in all scenarios except for the seventh and eighth scenarios, where it was in seventh place. In addition, Logistic Regression remained first in 8 scenarios but dropped to the second rank in the first and second scenarios. Moreover, KNN maintained the sixth rank in the eighth and ninth scenarios and decreased to the seventh rank in four scenarios (fourth, fifth, sixth, and seventh), while KNN was in the last rank in the remaining scenarios. Random Forest was raised to the first rank from scenario 1 and scenario 2 and maintained the second rank in all other 8 scenarios. Regarding Naive Bayes, it also dropped to fifth place in the first and second scenarios and continued in all the remaining scenarios in its fourth rank. Furthermore, Tree was in the third rank in all scenarios. Finally, AdaBoost continued in fifth place in all scenarios except for the first and second scenarios, dropping to seventh rank. Broadly, no significant changes were detected; around four to five situations consistently aligned with a certain alternative, such as Naive Bayes, Logistic Regression, and AdaBoost. Only two of the 10 possibilities changed, with the others remaining consistent. Notably, the Decision Tree's performance remained consistent across all cases. Figure 3 depicts the sensitivity analysis for ranking options in these 10 situations.

The Spearman Correlation Coefficient (SCC) was used to measure the level of correlation between the final results of different scenarios [43], [44]. The approach of Spearman's rank correlation coefficient (SCC) is highly effective in quantifying the degree of correlation among a group of variables [45]. By utilizing Equation 17, we can obtain it.

$$r_s = 1 - \frac{6\sum_i d_i^2}{n^3 - n} \tag{17}$$

where ("di") shows a contrast between the rank of ("ith") alternative in the suggested operator and the other operator, and ("n") represents the quantity pair values. The Spearman rank correlation coefficient values are presented in Table 12.

According to Table 12, the SCC value is 0.9761 in four out of ten scenarios (i.e. scenarios 4, 5, 6, 7). The other two scenarios had SCC values of 0.6667 for scenario 1 and scenario 2. On the other hand, for scenario 3 and scenario 10, the SSC value was 0.9285. Finally, in scenarios 8 and 9, the SSC value was 1. Correlation analysis results for the ranking of the machine learning methods are shown in

As a summary for this section, the results of the Spearman correlation coefficient presented a high correlation for all scenarios. That means OWCM is an advanced and robust method for weighting. In the next section, we present the third type of evaluation.

C. COMPARISON ANALYSIS

Traditional MCDM methods, such as AHP, FUCOM, and BWM, are widely used due to their efficacy and

TABLE 9. The final result of TOPSIS method.

Alternatives	Score	Rank
Neural Network	0.364321	8
SVM	0.593536	7
Logistic Regression	0.851721	1
KNN	0.614057	6
Random Forest	0.838689	2
Naive Bayes	0.73216	4
Tree	0.825803	3
AdaBoost	0.663292	5

TABLE 10. The objective validation results.

Group	Machine Learning Methods	Mean
1st Group	Logistic Regression	0.275106545
	Random Forest	
	Tree	
	Naive Bayes	
2nd Group	AdaBoost	0.349896534
	KNN	
	SVM	
	Neural Network	

adaptability [46], [47]. Although these approaches provide systematic frameworks for making decisions, it is essential to acknowledge their inherent constraints. AHP is dependent on the evaluation of pairwise comparisons, a process that can be both time-consuming and subjective [48], [50]. FUCOM, while accepting interdependencies, may become complicated as the decision network expands. BWM demonstrates proficiency in managing qualitative data but may have difficulties in prioritizing many criteria. Hence, despite their extensive utilization, decision-makers must be aware of the limitations inherent in these conventional techniques and should explore supplementary or substitute ways as necessary. Table 13 explains many key concepts: the number of judgments to be utilized, the challenge of comparing objects of various natures (such as sound and scent), the procedure of ranking, and the issue of inconsistency when a decision maker provides conflicting answers. When comparing OWCM, AHP, FUCOM, and BWM, it is important to keep in mind that AHP and BWM have a limited number of comparisons, making it a difficult task for experts to complete.

AHP and BWM rankings depend on the weights of the decision criteria in addition to the expert's comparison of alternatives. OWCM differs from other approaches by adding subjective weights implicitly into the opinion matrix, therefore closely correlating with the decision-maker's

TABLE 11. The final rank for each scenario.

tools	Neural	SVM	Logistic	KNN	Random	Naive	Tree	AdaBoost
original	8	7	1	6	2	4	3	5
S 1	4	6	2	8	1	5	3	7
S 2	4	6	2	8	1	5	3	7
S3	7	6	1	8	2	4	3	5
S 4	8	6	1	7	2	4	3	5
S 5	8	6	1	7	2	4	3	5
S 6	8	6	1	7	2	4	3	5
S 7	8	6	1	7	2	4	3	5
S 8	8	7	1	6	2	4	3	5
S 9	8	7	1	6	2	4	3	5
S 10	7	6	1	8	2	4	3	5

TABLE 12. The result of the spearman correlation coefficient.

	correlation
original	1
S 1	0.6667
S 2	0.6667
S3	0.9285
S 4	0.9761
S 5	0.9761
S 6	0.9761
S 7	0.9761
S 8	1
S 9	1
S 10	0.9285

TABLE 13. The comparison between OWCM, AHP, BWM, and ANP methods.

NO	Comparison issue	OWCM	AHP	BWM	FUCOM
1	Number of comparisons	The same number of alternatives	[n (n -1)/2]	2n−3	The same number of criteria
2	Nature of comparisons	Solved	Not solved	Not solved	Not solved
3	Process of weight	Easy	Complex	Complicated	Complicated
4	Inconsistency problem	Solved	Not solved	Not solved	Solved
5	Feedback from experts	Explanation requires less time.	It takes more time	Explaining takes time.	It takes more time.

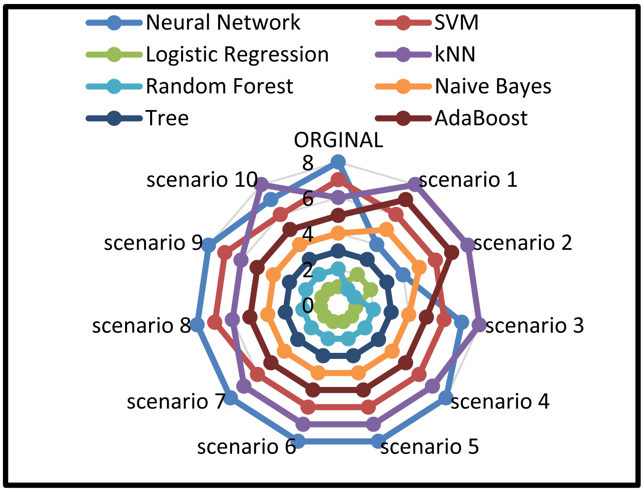

FIGURE 3. The sensitivity analysis ranking scenarios.

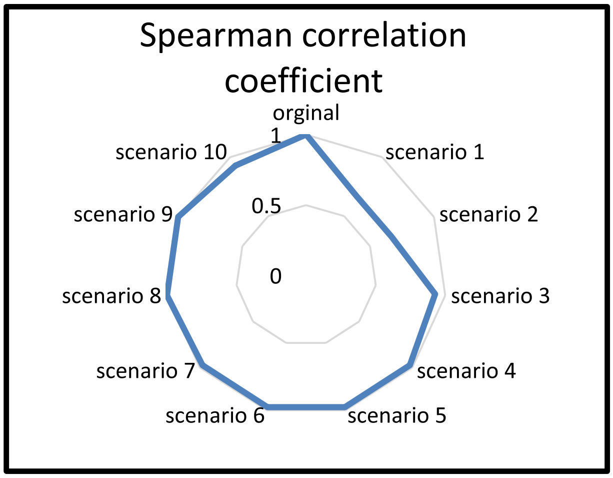

FIGURE 4. Correlation of ranks among 10 scenarios.

perspective. This technique has shown a clear and rational connection between its components. OWCM outperforms AHP FUCOM, and BWM when it comes to criterion weighting. Finally, we can conclude and confirm that the OWCM is powerful and robust as well as it provides reliable results for weighting criteria.

VII. MANAGERIAL IMPLICATIONS

The managerial implications of a method which integrates subjective and objective factors during the weighing process may seriously affect decision-making processes within the decision. By including subjective factors, decision-makers are able to clearly articulate their preferences and values. This alignment guarantees that the ultimate choice accurately represents the distinct goals of the decision-maker, resulting in a more tailored and pertinent conclusion for the final decision. The OWCM methodology tackles the issue of inconsistency seen in conventional methodologies. OWCM use an opinion matrix to compare values inside the same criterion rather than across several criteria sets. This approach helps to reduce inconsistencies and enhances the reliability and strength of the decision-making framework. The approach effectively determines the weights for each criterion by taking into account the preferences of the decision-maker. Precision is essential to ensure that the relative significance of criteria is accurately represented in the decision-making process, resulting in more knowledgeable and purposeful decisions. Integrating subjective preferences can improve the clarity of decision-making. By clearly acknowledging and integrating the viewpoints of decision-makers, the decision-making process becomes more transparent and comprehensible to stakeholders, hence promoting trust and approval of the ultimate choice. The capacity of OWCM to integrate subjective and objective factors into a cohesive framework allows for adaptable decision-making. This is especially advantageous in scenarios where a combination of quantitative and qualitative aspects needs to be taken into account, enabling a more thorough examination. By including subjective components, decision bias can be reduced since decision-makers are able to deliberately evaluate factors according to their significance. This mitigates the potential influence of unconscious biases on the choice outcome, hence fostering fairness and objectivity process. Active participation and engagement are promoted by the engagement of decision-makers in expressing their preferences and ideas. By adopting a collaborative approach, the decision-making process becomes more inclusive, ensuring that the final choice is in line with the organization's larger aims and values. Implementing the OWCM may require providing training to decision-makers to proficiently utilize the methodology and clearly express their preferences. Managers must provide resources towards the education of their teams in order to facilitate a seamless transition to this methodology, therefore improving the organization's collective decision-making prowess.

VIII. CONCLUSION

MCDM techniques are widely used to solve difficult real-world problems in the disciplines of operations research and expert systems. There are two sorts of approaches: weighing techniques and ranking methods. In turn, weighting systems might be objective, subjective, or integrated. The OWCM is a unique approach for establishing weights for assessment criteria described in this work. This approach combines subjective and objective parts of the weighing process, deriving weights depending on the decision maker's preferences. The main advantages of OWCM were that it solved the inconsistency problem by developing the opinion matrix and comparing the values in the same criterion, not between the set of criteria. In addition, OWCM extracted the weight of each criterion accurately because this weight depends on decision-maker preferences. Three ways were applied in this paper to make sure the OWCM weight is valid. We can conclude and confirm that OWCM is powerful and robust as well as that the OWCM model provided credible and reliable results for weighting criteria. The management implications of the OWCM method highlight its capacity to improve decision-making by eliminating inconsistencies, aligning with decision-maker preferences, and fostering transparency. However, its implementation necessitates a deliberate strategy, encompassing training, communication, and stakeholder involvement, in order to fully exploit the advantages of this integrated subjective-objective weighing process. We recommend that the researchers use OWCM in any decision-making problem to extract the evaluation criteria weights. Finally, as a future work, we recommend using OWCM to extract weight for criteria and integrate it with any MCDM mathematical methods like VIKOR. Also, it can extend OWCM into a fuzzy environment.

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