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An Integrated Approach for Fuzzy-Dynamic Multi-Attribute Group Decision Making With Application in Renewable Energy

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ABSTRACT This article proposes a methodology for tackling intuitionistic fuzzy-dynamic multi-attribute group decision-making (IF-DMAGDM) problems in the presence of uncertainty. The ELECTRE I approach is integrated with the VIKOR method by considering intuitionistic fuzzy environments. This work introduces a novel form of representing how informed judgements affect the performance of alternatives with respect to attributes at different times that take the form of intuitionistic fuzzy sets (IFSs). The proposal incorporates three different relative weights: the first is for the decision makers, the second is for the attributes in each range of time, and the last is for the time intervals themselves. The method is suitable for complex and conflicting scenarios, and how an expert's opinion changes over an interval of time is accurately described. An evaluation of the sustainability indicators for renewable energy systems is provided as an illustrative example. To validate the results, a sensitivity analysis and comparative analysis with existing methods are presented.

INDEX TERMS Dynamic multi-attribute group decision-making, ELECTRE, intuitionistic fuzzy sets, outranking methods, renewable energy, VIKOR.

I. INTRODUCTION

Multi-attribute group decision-making (MAGDM) has been among the most important topics in decision science from both the theoretical and practical points of view [1], [2]. Over the last few decades, it has become one of the fastest developing fields, and it has been used in various research fields such as energy, engineering, economics, management, and social sciences [3]. MAGDM analyses a discrete set of possible alternatives associated with conflicting attributes, and a group of decision makers (DMs) attempts to find the most desirable alternative(s) by considering their opinions and/or preferences [4], [5]. Most real-world cases imply uncertainty; thus, it is impossible to accurately comprehend all aspects of the problem. In this context, an illustrative example for a real-time charging vehicle is provided in [6]. A comprehensive review about the uncertainty concept is found in [7]. From the above, it is clear that DMs are susceptible to imprecise or vague information. In response to the above, fuzzy set theory (FST) was introduced in 1965 [8]. However, a significant limitation was observed later: it did not involve hesitation, which is common in real-world problems. Intuitionistic fuzzy sets (IFSs), which consider non-membership and the degree of hesitation, was introduced to address the hesitation in MAGDM problems [9]. Since the emergence of intuitionistic fuzzy MAGDM (IF-MAGDM), its application in different fields and scopes has proliferated. Some examples include supplier selection [10]–[12], human resources selection [13], deciding a manufacturing plant's location [14], information technology assessment [15], emergency plan selection [16], reliability evaluation [17], and strategic business partner selection [18].

Under a less simplistic perspective, MAGDM problems can be described as dynamic environments, which mean that informed judgements on the performance of alternatives with respect to attributes are different over time. This scenario is called dynamic MAGDM (DMAGDM) [19]–[22]. In DMAGDM problems, decision-related information about the weights and values of the attributes collected from DMs are time-dependent [19], [20]. A typical real-world DMAGDM problem is challenging, owing to the imprecisions, uncertainties, and/or incomplete information provided by DMs at different times during the assessment process in the corresponding decision analysis [3], [4], [21].

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In the DMAGDM literature, the IFS approach has garnered significant attention, although the research field remains nascent. Aggregation operators are considered fundamental for solving DMAGDM problems; a recent demonstration showed that IFS-based aggregation operators have several advantages when tackling complex and conflicting problems [19], [23]–[25]. For instance, the dynamic intuitionistic fuzzy weighted averaging (DIFWA) operator [19], the dynamic intuitionistic fuzzy weighted geometric (DIFWG) operator [23], the uncertain dynamic intuitionistic fuzzy weighted averaging (UDIFWA) operator [23], the intuitionistic fuzzy weighted geometric (IFWG) operator [19], the dynamic weighted geometric aggregation (DWGA) operator [20], and the modified dynamic intuitionistic fuzzy weighted geometric (MDIFWG) operator [25] have been applied in different scenarios and contexts. On the other hand, not many studies have addressed Intuitionistic fuzzy-dynamic MAGDM (IF-DMAGDM) problems and the methods for solving them using multi-attribute methods and aggregation operators. Xu [20] proposed a hybrid DMAGDM by utilizing the hybrid geometric aggregation (HGA) operator, the dynamic weighted geometric aggregation (DWGA) operator, and three different techniques for order performance by similarity to ideal solution (TOPSIS) methods (real-valued TOPSIS, interval-valued TOPSIS, and fuzzy-valued TOPSIS). Su *et al.* [21] integrated the TOPSIS and DIFWA methods to study IF-DMAGDM problems. Park *et al.* [26] extended the compromise ranking Vlsekriterijumska Optimizacija I Kompromisno Resenje) (VIKOR) method with two aggregation operators, DIFWG and UDIFWG, for ranking and selecting optimal alternatives in IF-DMAGDM problems. Xie *et al.* [27] proposed the IF-DMAGDM approach by applying the decision-making trial and evaluation laboratory (DEMATEL) and the DIFWA operator to analyze the selection processes.

Outranking problems are defined by a finite number of $\boldsymbol{S}$ binary relations that are observed on a matrix $\boldsymbol{X}$ of order n ($i = 1, \ldots, n$) $\times$ m ($j = 1, \ldots, m$), in which each element $S_{i,j}$ refers to the DM's preference and its related quality [28]. Considering the above, outranking problems are given on the basis of a set of pairwise comparisons of alternatives. The outranking relation provides the DMs with a recommendation by performing pairwise comparisons of alternatives according to each attribute to determine the alternatives' preferred positions [28]. Roy [29] developed the first outranking method, well known in the literature as elimination and choice translating reality (ELECTRE I). Subsequently, researchers have developed other outranking methods such as the family of ELECTRE methods (I, II, III, IV, IS), PROMETHEE, MAPPAC, PRAGMA, IDRA, and PACMAN (for additional information, refer to [30]).

Among the existing outranking methods, the ELECTRE method and its derivatives have been preferred [28]. ELECTRE I was designed to assist DMs in setting a small set of preferable alternatives by comparing them independently for each attribute, exclusive of aggregating the alternatives' performances for all attributes [29], [30]. For uncertain situations, the ELECTRE method under the IFS environment has been proposed using the concepts of outranking relations, concordances, and discordances [31]. Although ELECTRE is applied to a wide range of scenarios and problems, three limitations are documented in the literature: rank reversal, intransitivity, and complexity. The first is also known as a violation of the independence of the alternatives. Consider the case when an alternative is replaced by a worse one, keeping all others unchanged; then, the new ranking is composed of a different order of alternatives. Intransitivity refers to the fact that it is not possible to change the number of alternatives without affecting the final ranking. Finally, there is evidence that explaining and reporting ELECTRE outputs tends to be difficult. In most cases, stakeholders prefer simpler methods and clearer outcomes [32].

The VIKOR method [33] presents a compromise ranking that maximizes the group utility and minimizes the individual regret. It introduces an aggregating function that demonstrates the distance of each alternative from the ideal solution, helping DMs obtain a clear list of alternative rankings [33], [34]. The first VIKOR version employed crisp numbers to assess alternatives and determine the weight of the criteria. Therefore, it was limited to coping with vagueness and uncertainty, which are usual in real-life scenarios. To overcome these shortcomings, an extended version for fuzzy environments was proposed in [35]. More robust varieties of this method emerged, such as VIKOR with triangular fuzzy numbers [36] and VIKOR that transforms linguistic variables into trapezoidal fuzzy numbers [37]. During the last decade, VIKOR and its varieties have become increasingly popular, with applications in renewable energy planning [38], evaluating the level of Industry 4.0 development [39], public transportation [40], strategic planning [41], and healthcare management [42], among others. In contrast to other MAGDM methods, VIKOR is flexible in different scenarios and contexts. It is suitable for problems with conflicting criteria and can simultaneously consider the group utility of each alternative or the individual regret of DMs [43]. However, VIKOR has limitations when dealing with real-world circumstances. For instance, the values of alternative performance related to a group of criteria should be defined as fixed numbers, which is also an important limitation when attempting to accurately describe complex problems [44].

In our exhaustive literature review, we found that Çalıand Balaman combined ELECTRE and VIKOR under a static perspective [34]. Their methodology captures uncertain situations, including hesitancy in the evaluation process. A case study assessing contractors in the industry sector assesses its applicability [45]. In [46], a comparison of the achieved performance among both methods is provided. An analysis based on real data related to selecting the most suitable materials complements that proposal. An application for managerial engineering, which is based on a hybrid version of the intuitionistic fuzzy-ELECTRE based on the VIKOR method, is provided in [47]. Due to space limitations, we have referenced only the research relevant to our work, and a small number of studies have been omitted. Exhaustive literature reviews of fuzzy sets, theory, and methods are available in [34], [44], [45]. As far as we know, an integration of ELECTRE I and VIKOR under a dynamic IFS perspective does not exist in the literature yet. This work makes a novel contribution by considering the strengths of ELECTRE I and VIKOR and integrates them to accurately describe dynamic hesitation and uncertainty, which is appropriate for complex decision-making processes. As shown in the following sections, the proposed methodology is suitable for solving IF-DMAGDM problems. The IFS is utilized for tackling uncertainty and hesitation rather than using crisp values in the evaluation of DMAGDM problems. As an initial assumption, we consider that DMs provide imperfect or insufficient knowledge for assessing the alternatives with respect to the attributes at different times, which takes the form of IF numbers. Unlike the previously mentioned works, the relative weights of the DMs, the relative weights of the attributes in different periods of time, and the relative weights of periods are accurately aggregated to yield more accurate results. Furthermore, the weighted distance measure (based on the IF-ELECTRE approach) is applied to determine the concordance sets' weights. As shown in [48], this measure provides reliable weights. The modified dynamic intuitionistic fuzzy weighted geometric (MDIFWG) operator [25], the DWGA operator [20], the IFWG operator [24], the IFS-ELECTRE method, and the VIKOR method are assembled to dynamically describe complex problems with respect to changes in time. An evaluation of sustainability indicators for renewable energy is provided as an illustrative example.

The remainder of this article is organized as follows. The mathematical formulations, on which our proposal is based, are provided in the next section. The related algorithm is also presented in this section. An application of the methodology to illustrate its suitability in dealing with complex problems is presented in Section 3. A discussion explaining how our research relates to other studies is provided in Section 4. The last section presents the conclusions and future lines of research. The list of abbreviations adopted hereafter is given in Table 1.

TABLE 1. List of abbreviations.

Definition	Abbreviation
Decision maker	DM
Decision-making trial and evaluation laboratory	DEMATEL
Dynamic intuitionistic fuzzy	DIF
Dynamic intuitionistic fuzzy weighted averaging	DIFWA
Dynamic intuitionistic fuzzy weighted geometric	DIFWG
Dynamic MAGDM	DMAGDM
Dynamic weighted geometric aggregation	DWGA
Elimination and choice translating reality	ELECTRE
Fuzzy set theory	FST
Group Decision Making	GDM
Grey relational analysis	GRA
Hybrid geometric aggregation	HGA
Intuitionistic fuzzy MAGDM	IF-MAGDM
Intuitionistic fuzzy set	IFS
Intuitionistic fuzzy weighted geometric	IFWG
Intuitionistic fuzzy-dynamic MAGDM	IF-DMAGDM
Modified dynamic intuitionistic fuzzy weighted geometric	MDIFWG
Multi-attribute group decision-making	MAGDM
Techniques for order performance by similarity to ideal solution	TOPSIS
Uncertain dynamic intuitionistic fuzzy weighted averaging	UDIFWA
Vlsekriterijumska Optimizacija I Kompromisno Resenje	VIKOR
Weighted distance	WD

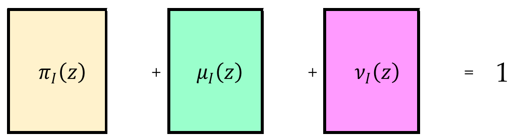

FIGURE 1. Graphical representation of membership, non-membership, and hesitancy relations.

II. MATERIALS AND METHODS

Some mathematical formulations are presented in this section, starting with the formal definitions of IFSs and ending with a proposed compromise solution and the selection of the best alternative. A general framework (algorithm) for the methodology, which comprises 12 steps, is also provided.

A. IFS

According to Zadeh [8], an FS is expressed as follows. Let Z denote a universal set. Then, an FS ($F\epsilon Z$) is characterised as

$$F = \{\langle z, \mu_F(z)\rangle / z \in Z\}$$

where $\mu_F(z) : Z \rightarrow [0, 1]$ denotes the membership degree of $z \in Z$ in subset F of Z. On the other hand, Atanassov [9] states that an IFS ($I\epsilon Z$) is characterised as

$$I = \{\langle z, \mu_I(z), \nu_I(z)\rangle / z \in Z\}$$

where $\mu_I(z) : Z \rightarrow [0, 1]$ and $\nu_I(z) : Z \rightarrow [0, 1]$ denote the membership degree and the non-membership degree of $z \in Z$ in the subsets I of Z, respectively; and $\mu_I(z)$ and $\nu_I(z)$ satisf y$0 \leq \mu_I(z) + \nu_I(z) \leq 1$. For any element $z \in Z$, $\pi_I(z)$ denotes the degree of hesitancy (i.e., indeterminacy or uncertainty) $\pi_I(z) = 1 - \mu_I(z) - \nu_I(z)$, see Figure 1.

B. IFS OPERATIONAL RULES AND DISTANCES BETWEEN THEM

Let $\alpha = (\mu_\alpha, \nu_\alpha)$ and $\beta = (\mu_\beta, \nu_\beta)$ be two intuitionistic fuzzy numbers (IFNs). According to Xu [49] and Xu and Yager [19], the operational rules of IFSs can be represented as follows:

$$\alpha \oplus \beta = (\mu_\alpha + \mu_\beta - \mu_\alpha * \mu_\beta, 1 - \nu_\alpha * \nu_\beta) \quad (1)$$

$$\lambda\alpha = \left(1-(1-\mu_\alpha)^\lambda, 1-\nu_\alpha^\lambda\right) \tag{2}$$

According to Wu and Chen [31] and Szmidt and Kacprzyk [50], the distance between two IFNs can be obtained as follows. Let α and β be two IFNs in $Z = \{z_1, z_2, \ldots, z_n\}$. Then, the normalised Euclidean distance $d(\alpha, \beta)$ between α and β is

$$d(\alpha,\beta) = \sqrt{\frac{1}{2n}\sum_{i=1}^{n}\begin{bmatrix}(\mu_\alpha(z_i)-\mu_\beta(z_i))^2\\ +(\nu_\alpha(z_i)-\nu_\beta(z_i))^2\\ +(\pi_\alpha(z_i)-\pi_\beta(z_i))^2\end{bmatrix}} \tag{3}$$

C. DMAGDM ENVIRONMENT BASED ON IFS THEORY

In an IF-DMAGDM problem, the evaluated values of all attributes are offered by the same group of DMs but are collected at different points in time, where the evaluated values are given in the form of IFNs. The underlying theoretical framework is described below. For simplicity, only five concepts are highlighted.

1) Let $T = \{t_1, t_2, \ldots, t_p\}$ be a set of p periods whose weight vector is $[\delta(t_1), \delta(t_2), \ldots, \delta(t_p)]$, where $\delta(t_l) > 0, l = 1, 2, \ldots p, \sum_{l=1}^{p}\delta(t_l) = 1$. Several methods have been proposed for deriving the weight vector of the time periods, including a combination of subjective and objective methods [51], a minimal-variability-based method [1], a geometric series-based method [19], an exponential distribution-based method 19], and a multi-target nonlinear programming model based on the time and information entropy [52].
2) Let $A = \{a_1, a_2, \ldots, a_m\}$ be a set of m feasible alternatives.
3) In addition, let $C = \{c_1, c_2, \ldots, c_n\}$ be a finite set of n attributes. During the period t_l, C is associated with a weight $[w_1(t_l), w_2(t_l), \ldots, w_j(t_l)]$ and $w_j(t_l) > 0, j = 1, 2, \ldots, n, \sum_{j=1}^{n} w_j(t_l) = 1$. Several approaches have been proposed for deriving the attribute weights: the simple multi-attribute rating technique [53], the judgement pairwise comparison method [54], the fuzzy programming method [55], the information entropy method [56], the maximal deviation-based method [57], and adjusted possibility distribution matrices [58].
4) Considering $E = \{e_1, e_2, \ldots, e_k\}$ is the same set of k DMs at each period, E is associated with a vector of weights denoted as $[\lambda_1, \lambda_2, \ldots, \lambda_q]$, where $\lambda_q > 0, q = 1, 2, \ldots k, \sum_{q=1}^{k}\lambda_q = 1$. In the GDM literature, some approaches have been proposed for determining the relative weights of DMs to ensure the credibility of the judgements of DMs and the impact of these judgements on the final decision. Researchers have used several approaches for deriving the DMs' weights, such as similarity-based approaches, index-based approaches, clustering-based approaches, and integrated approaches; many additional approaches are discussed in [59].

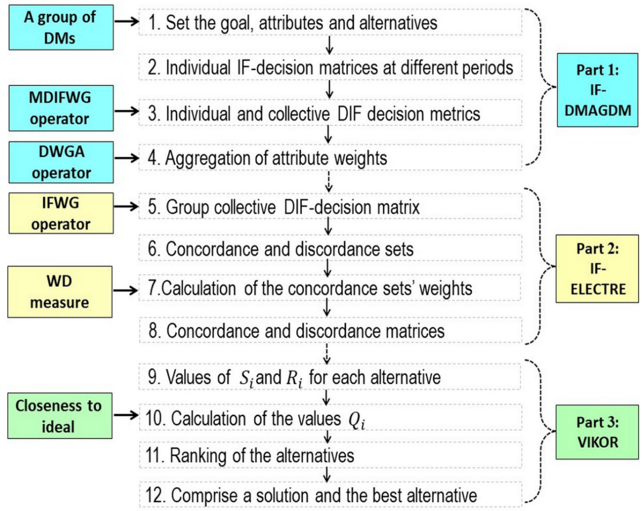

FIGURE 2. Flowchart of the proposed method.

5) The DMs $e_q(q = 1, 2, \ldots k)$ provided $r_{ij}\left(t_l^{(q)}\right)$ as the evaluation values of the alternatives $a_i \epsilon A(i = 1, 2, \ldots, m)$ with respect to the attributes $c_j \epsilon C(j = 1, 2, \ldots, n)$ at the time points $t_l(l = 1, 2, \ldots p)$. The individual IF-decision matrices at t_l are constructed as $R\left(t_l^{(q)}\right) = \left[r_{ij}\left(t_l^{(q)}\right)\right]_{m\times n}$. The value of the alternative $r_{ij}\left(t_l^{(q)}\right)$ is represented as an IF-number in the form of $\left(\mu_{r_{ij}\left(t_l^{(q)}\right)}, \nu_{r_{ij}\left(t_l^{(q)}\right)}, \pi_{r_{ij}\left(t_l^{(q)}\right)}\right)$, where $\mu_{r_{ij}\left(t_l^{(q)}\right)}$ specifies the degree of satisfaction, $\nu_{r_{ij}\left(t_l^{(q)}\right)}$ denotes the degree of dissatisfaction, and $\pi_{r_{ij}\left(t_l^{(q)}\right)}$ denotes the hesitancy degree of the alternative a_j according to attribute c_i in period t_l for DM e_q such that (for$i = 1, 2, \ldots, n$ and $j = 1, 2, \ldots, m$)

$$\begin{gathered}0 \le \mu_{r_{ij}\left(t_l^{(q)}\right)} + \nu_{r_{ij}\left(t_l^{(q)}\right)} \le 1,\\ \pi_{r_{ij}\left(t_l^{(q)}\right)} = 1 - \mu_{r_{ij}\left(t_l^{(q)}\right)} - \nu_{r_{ij}\left(t_l^{(q)}\right)}\end{gathered} \tag{4}$$

D. PROPOSED IF-DMAGDM METHODOLOGY

An extended outranking methodology focusing on efficient solutions of IF-DMAGDM problems in the presence of uncertainty is proposed in this subsection. As shown in Figure 2, our methodology comprises three sections and twelve steps. Note that the flowchart is unidirectional, and all the steps are performed only once. The remainder of this section provides a detailed explanation of these components.

1) STEP 1. FRAMING THE PROBLEM

The starting point consists of defining a finite number of alternatives. Each alternative is also associated with additional parameters, such as attributes, weights, performance, or noise. The goal of a group of DMs is to identify the best possible alternative.

2) STEP 2. CONSTRUCTING INDIVIDUAL IF-DECISION MATRICES

IF-decision matrices are based on the DMs' opinions at different periods of time. The same group of DMs assesses the alternatives according to each attribute at different periods of time using IFNs. Then, the individual IF-decision matrices are built, as shown below:

$$R\left(t_l^{(q)}\right)=\left[r_{ij}\left(t_l^{(q)}\right)\right]_{m\times n}=\begin{bmatrix} r_{11}\left(t_l^{(q)}\right) & \dots & r_{1n}\left(t_l^{(q)}\right)\\ \vdots & \vdots & \vdots\\ \vdots & \vdots & \vdots\\ r_{m1}\left(t_l^{(q)}\right) & \dots & r_{mn}\left(t_l^{(q)}\right)\end{bmatrix} \tag{5}$$

Note that DMs' assessments for different periods of time are the input in Eq. 5. There is no presence of weights in this step, but they are incorporated in next one.

3) STEP 3: DETERMINATION OF INDIVIDUAL COLLECTIVE DIF-DECISION MATRICES

The individual evaluations of each DM at different time points, represented by IF-decision matrices, are aggregated to construct an individual collective DIF-decision matrix for each DM using the MDIFWG operator [25]. The MDIFWG operator has characteristics that surmount the drawbacks of some existing aggregation operators, such as the ability to distinguish the preference order of alternatives and achieve the proper preference order of alternatives in some conditions. A more detailed explanation of the advantages of MDIFW with respect to other operators is available in [25]. Thus, the MDIFWG operator is utilized to aggregate all individual IF-decision matrices $R\left(t_l^{(q)}\right)=\left[r_{ij}\left(t_l^{(q)}\right)\right]_{m\times n}$ at period $t_l(l=1,2,..p)$ into the individual collective DIF-decision matrix $R^q=\left[r_{ij}^{(q)}\right]_{m\times n}$. Note that each DM $e_q(q=1,2,\dots k)$ and its respective weight period vectors $[\delta(t_1),\delta(t_2),\dots,\delta(t_p)]^T$ play important roles in the aggregation procedure. According to Xu and Yager [19], this situation can be represented as follows:

$$\begin{aligned} r_{ij}^{(q)} &= \left(\mu_{ij}^{(q)},\nu_{ij}^{(q)},\pi_{ij}^{(q)}\right)\\ &= MDIFWG_{\delta(t)}\left(r_{ij}\left(t_1^{(q)}\right),r_{ij}\left(t_2^{(q)}\right),..,r_{ij}\left(t_p^{(q)}\right)\right)\\ &= \delta\left(t_1\right)r_{ij}\left(t_1^{(q)}\right)\oplus\delta\left(t_2\right)r_{ij}\left(t_2^{(q)}\right)\oplus\ldots\oplus\delta\left(t_p\right)r_{ij}\left(t_p^{(q)}\right)\\ &= \left[1-\prod_{l=1}^{p}\left(1-\mu_{r_{ij}\left(t_l^{(q)}\right)}\right)^{\delta(t_l)},\prod_{l=1}^{p}\left(1-\mu_{r_{ij}\left(t_l^{(q)}\right)}\right)^{\delta(t_l)}\right.\\ &\quad -\prod_{l=1}^{p}\left(1-\mu_{r_{ij}\left(t_l^{(q)}\right)}-\nu_{r_{ij}\left(t_l^{(q)}\right)}\right)^{\delta(t_l)},\\ &\quad \left.\prod_{l=1}^{p}\left(1-\mu_{r_{ij}\left(t_l^{(q)}\right)}-\nu_{r_{ij}\left(t_l^{(q)}\right)}\right)^{\delta(t_l)}\right] \end{aligned} \tag{6}$$

The individual collective DIF-decision matrix $R^q=\left[r_{ij}^{(q)}\right]_{m\times n}$ for each DM is represented as follows:

$$\begin{aligned} R^q=\left[r_{ij}^{(q)}\right]_{m\times n} &= \begin{bmatrix} r_{11}^{(q)} & \dots & r_{1n}^{(q)}\\ \vdots & \vdots & \vdots\\ \vdots & \vdots & \vdots\\ r_{1m}^{(q)} & \dots & r_{nm}^{(q)}\end{bmatrix}\\ &= \begin{bmatrix} \left(\mu_{11}^{(q)},\nu_{11}^{(q)},\pi_{11}^{(q)}\right) & \dots & \left(\mu_{1n}^{(q)},\nu_{1n}^{(q)},\pi_{1n}^{(q)}\right)\\ \vdots & \vdots & \vdots\\ \vdots & \vdots & \vdots\\ \left(\mu_{1m}^{(q)},\nu_{1m}^{(q)},\pi_{1m}^{(q)}\right) & \dots & \left(\mu_{nm}^{(q)},\nu_{nm}^{(q)},\pi_{nm}^{(q)}\right)\end{bmatrix} \end{aligned} \tag{7}$$

4) STEP 4: AGGREGATION OF THE ATTRIBUTE WEIGHTS

The DWGA operator [20] is utilized to aggregate the attribute weights in different periods into collective attribute weights. Thus, to aggregate the weights' vector of attributes $w_j\left(t_l\right)$ in different periods t_l $(l=1,2,\dots p)$ into the collective weights of attributes $w_j\,(j=1,2,\dots n)$, the following equation is used:

$$\begin{aligned} w_j &= DWGA_{\delta(t)}\left(w_j\left(t_1\right),w_j\left(t_2\right),\dots,w_j\left(t_p\right)\right)\\ &= \prod_{l=1}^{p}\left(w_j\left(t_l\right)\right)^{\delta(t_l)} \end{aligned} \tag{8}$$

Equation 8 allows us to integrate both weights—the first related to the periods of time, and the second referring to the attribute —into a unique indicator. A synthetic weight, which accurately balances the differences across time periods and attributes, is then obtained.

5) STEP 5: CONSTRUCTION OF A GROUP COLLECTIVE DIF-DECISION MATRIX

The group collective DIF-decision matrix is constructed by utilizing the IFWG operator [24] to aggregate all individual collective DIF-decision matrices for DMs. The IFWA operator is employed to aggregate all individual collective DIF-decision matrices $R^q=\left[r_{ij}^{(q)}\right]_{m\times n}$ for each DM $e_q(q=1,2,\dots k)$ into the group collective DIF-decision matrix $R=\left[r_{ij}\right]_{m\times n}$, and the DMs' weights λ_q $(q=1,2,\dots,k)$, are significant factors in the aggregation procedure. The values are calculated as follows [24]:

$$\begin{aligned} r_{ij} &= IFWG_{\lambda}\left(r_{ij}^{(1)},r_{ij}^{(2)},\dots,r_{ij}^{(q)}\right)\\ &= \lambda_1 r_{ij}^{(1)}\oplus\lambda_2 r_{ij}^{(2)}\oplus\ldots\oplus\lambda_q r_{ij}^{(q)}\\ &= \left[\prod_{q=1}^{k}\left(\mu_{ij}^{(q)}\right)^{\lambda_q},1-\prod_{q=1}^{k}\left(1-\nu_{ij}^{(q)}\right)^{\lambda_q},\right.\\ &\quad \left.\prod_{q=1}^{k}\left(1-\nu_{ij}^{(q)}\right)^{\lambda_q}-\prod_{q=1}^{k}\left(\mu_{ij}^{(q)}\right)^{\lambda_q}\right] \end{aligned} \tag{9}$$

The group collective DIF-decision matrix $R = \left[r_{ij}\right]_{m\times n}$ is represented as follows:

$$R = \left[r_{ij}\right]_{m\times n} = \begin{bmatrix} r_{11} & \cdots & r_{1n} \\ \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots \\ r_{1m} & \cdots & r_{nm} \end{bmatrix}$$
$$= \begin{bmatrix} (\mu_{11}, \nu_{11}, \pi_{11}) & \cdots & (\mu_{n1}, \nu_{n1}, \pi_{n1}) \\ \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots \\ (\mu_{1m}, \nu_{1m}, \pi_{1m}) & \cdots & (\mu_{nm}, \nu_{nm}, \pi_{nm}) \end{bmatrix} \quad (10)$$

where r_{ij} denotes the evaluated value of alternative i with respect to attribute j. By applying Eqs. 9-10, the aggregation of the individual collective metrics (one of each DM) into a unique group collective matrix on is carried out.

6) STEP 6: DETERMINATION OF THE CONCORDANCE SETS AND DISCORDANCE SETS

The notions of the score function, accuracy function, and hesitancy degree of the IF values are used to compare different alternatives to their IF values, and then construct concordance sets and discordance sets [34], [57]. Concordance sets C_{zy} are combined for all attributes in which alternative a_z is superior to a_y, whereas discordance sets D_{zy} are combined for all attributes in which alternative a_z is not preferred to a_y. Based on the dominance relationships of alternatives a_z and a_y for all attributes $j = 1, 2, \ldots n$, the following attribute sets are defined [34], [48].

1) The strong concordance set C'_{zy} is

$$C'_{zy} = \{j \setminus \mu_{zj} \geq \mu_{yj}, \nu_{zj} < \nu_{yj} \; and \; \pi_{zj} < \pi_{yj}\} \quad (11)$$

2) The midrange concordance set C''_{zy} is

$$C''_{zy} = \{j \setminus \mu_{zj} \geq \mu_{yj}, \nu_{zj} < \nu_{yj} \; and \; \pi_{zj} \geq \pi_{yj}\} \quad (12)$$

3) The weak concordance set C'''_{zy} is

$$C'''_{zy} = \{j \setminus \mu_{zj} \geq \mu_{yj}, \nu_{zj} \geq \nu_{yj}\} \quad (13)$$

4) The strong discordance set D'_{zy} is

$$D'_{zy} = \{j \setminus \mu_{az} < \mu_{yj}, \nu_{zj} \geq \nu_{yj} \; and \; \pi_{zj} \geq \pi_{yj}\} \quad (14)$$

5) The midrange discordance set D''_{zy} is

$$D''_{zy} = \{j \setminus \mu_{zj} < \mu_{yj}, \nu_{zj} \geq \nu_{yj} \; and \; \pi_{zj} < \pi_{yj}\} \quad (15)$$

6) The weak discordance set D'''_{zy} is

$$D'''_{zy} = \{j \setminus \mu_{zj} < \mu_{yj}, \nu_{zj} < \nu_{yj}\} \quad (16)$$

7) STEP 7: CALCULATION OF THE WEIGHTS OF THE CONCORDANCE SETS

The weights for the strong, moderate, and weak concordance sets, based on the weighted distance (WD) measure, are used to obtain reliable weights, as discussed by Zhang *et al.* [48]. Çali and Balaman [34] proposed Eqs. 17–19 for computing strong, midrange, and weak WD measures, respectively. The weight of the strong concordance set ($\omega_{C'}$) is computed as follows (17), as shown at the bottom of the next page.

The weight of the midrange concordance set ($\omega_{C''}$) is computed as follows (18), as shown at the bottom of the next page.

The weak concordance set weight ($\omega_{C'''}$) is computed as follows (19), as shown at the bottom of the next page.

Based on Eqs. 17–19, $d\left(r_{zj}, r_{yj}\right)$ is interpreted as the distance between a_z and a_y. While the first refers to the evaluation value of alternative z, the second corresponds to alternative y, given the attributes $c_j, j = 1, 2, \ldots n$. Note that for each criterion c_j, there is an associated w_j.

8) STEP 8: CONSTRUCTION OF CONCORDANCE AND DISCORDANCE MATRICES

Zhang *et al.* [48] and Çali and Balaman [34] state that the concordance and discordance matrices denote superior and inferior alternatives, respectively. Similarly, the elements of the concordance matrix are interpreted as the concordance indices. In addition, the elements of the discordance matrix constitute the discordance indices. By implementing Steps 5 and 6 of our proposed algorithm (Figure 2), these matrices can be calculated. The concordance matrix is shown in Eq. 20, and the discordance matrix is shown in Eq. 22.

$$C = \begin{bmatrix} - & C_{12} & \cdots & \cdots & C_{1m} \\ C_{21} & - & C_{23} & \cdots & C_{2m} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ C_{(m-1)1} & \cdots & \cdots & - & C_{(m-1)m} \\ C_{m1} & C_{m2} & \cdots & C_{m(m-1)} & - \end{bmatrix} \quad (20)$$

In the above, C_{zy} is the concordance index between alternatives a_z and a_y, and it is calculated based on the comprehensive concordance index [46] as follows:

$$C_{zy} = w_{C'} * \sum\nolimits_{j\epsilon C'_{zy}} w_j + w_{C''} * \sum\nolimits_{j\epsilon C''_{zy}} w_j + w_{C'''} * \sum\nolimits_{j\epsilon C'''_{zy}} w_j \quad (21)$$

The discordance matrix D is modelled as follows:

$$D = \begin{bmatrix} - & D_{12} & \cdots & \cdots & D_{1m} \\ D_{21} & - & D_{23} & \cdots & D_{2m} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ D_{(m-1)1} & \cdots & \cdots & - & D_{(m-1)m} \\ D_{m1} & D_{m2} & \cdots & D_{m(m-1)} & - \end{bmatrix} \quad (22)$$

where D_{zy} is the discordance index between alternatives a_z and a_y, and it is calculated as [34], [48]

$$D_{zy} = \frac{max_{j\in D'_{zy}\cup D''_{zy}\cup D'''_{zy}}\left[w_j * d(r_{zj}, r_{zj})\right]}{max_{j\in J}\left[d(r_{zj}, r_{yj})\right]} \quad (23)$$

9) STEP 9: COMPUTING THE VALUES OF S_i AND R_i FOR EACH ALTERNATIVE

A combination of the ELECTRE and VIKOR methods has been used to form a complete ranking of alternatives [28]. Thus, the IF-pairwise comparisons for each alternative provided by creating the concordance and discordance matrices in Step 7 are integrated into the VIKOR method to obtain a complete ranking of alternatives. According to the VIKOR method, two different ranking lists S_j and R_j are proposed for each alternative i with respect to the discordance and concordance matrices using the following equations [34]:

$$S_i = 1 - C_z \tag{24}$$

where $C_z = \sum_{i \neq z}^{m} \frac{C_{zi}}{m-1}$, and $i = \{1, 2, \ldots m\}$; and

$$R_i = h_z * W \tag{25}$$

where $W = \max_j w_j$ and $h_z = \max_{ij} h_{zi}, i \neq z$, $i = \{1, 2, \ldots m\}$.

10) STEP 10: CALCULATION OF THE VALUES OF Q_i FOR EACH ALTERNATIVE

The VIKOR method uses an aggregating function Q_i for each alternative i that represents 'closeness to the ideal' as follows:

$$Q_i = \gamma * \frac{S_i - min\ S_i}{max\ S_i - min\ S_i} + (1-\gamma)(\frac{R_i - min\ R_i}{max\ R_i - min\ R_i}) \tag{26}$$

where $\gamma \epsilon [0, 1]$ is the weight of the maximal group utility, and $(1 - \gamma)$ is the weight of the minimal individual regret.

11) STEP 11. RANKING THE ALTERNATIVES

The values of S_i, R_i, and Q_i are sorted in decreasing order, and a compromise solution is proposed as the alternative a^*, which is best ranked using the minimal Q index, subject to simultaneously satisfying the following conditions.

- **Condition 1**: $Q(a^{**}) - Q(a^*) \geq \frac{1}{m-1}$, where a^{**} is the alternative that is ranked second by Q, and m is the overall number of alternatives.
- **Condition 2**: Alternative a^* is also ranked first, according to both S and R. This compromise solution is stable within the decision-making process, which could be "voting by majority rule" ($\gamma > 0.5$ is needed), "by consensus" ($\gamma \approx 0.5$ is needed), or "with veto" ($\gamma < 0.5$ is needed).

If one of the conditions is not satisfied, then a set of compromise solutions is proposed as follows.

- Alternatives a^* and a^{**} represent the compromise solutions if only condition 2 is not satisfied.
- Alternatives $a_1, a_2, \ldots, a_m$ represent the compromise solutions if condition 1 is not satisfied, where $Q(a^{**}) - Q(a^*) < \frac{1}{m-1}$.

12) STEP 12. PROPOSING A COMPROMISE SOLUTION AND THE BEST ALTERNATIVE

Considering the finite number of alternatives provided in Step 1, the study can conclude when the best alternatives are identified. To produce helpful data for improved decision-making, it is imperative to rank or cluster the investigated alternatives. While ranking refers to ordering the available alternatives according to their importance, clustering amounts to categorizing the alternatives into groups based on the similarity of their characteristics.

III. ILLUSTRATIVE APPLICATION: EVALUATION OF THE SUSTAINABILITY OF RENEWABLE ENERGY

Sustainability indicators play a strategic role in the way governments deploy economic policies, set industrial regulations, and/or introduce technological and agricultural innovations [60]. In this context, one of the major challenges is the accurate evaluation of the sustainability indicators for renewable energy [61], [62]. According to the literature, this challenge amounts to the evaluation of several alternatives by an interested energy company (for example) to select the best alternative [61], [62]. The results pertaining to assessed

$$\omega_{c'} = \frac{\sum_{z,y=1,z\neq y}^{m} \sum_{j\epsilon C'_{zy}} w_j * d(r_{zj}, r_{yj})}{\begin{array}{l}\sum_{z,y=1,z\neq y}^{m} \sum_{j\epsilon C'_{zy}} w_j * d\left(r_{zj}, r_{yj}\right) + \\ \sum_{z,y=1,z\neq y}^{m} \sum_{j\epsilon C''_{zy}} w_j * d(r_{zj}, r_{yj}) \sum_{z,y=1,z\neq y}^{m} \sum_{j\epsilon C'''_{zy}} w_j * d(r_{zj}, r_{zj})\end{array}} \tag{17}$$

$$\omega_{C''} = \frac{\sum_{z,y=1,z\neq y}^{m} \sum_{j\epsilon C''_{zy}} w_j * d(r_{zj}, r_{yj})}{\begin{array}{l}\sum_{z,y=1,z\neq y}^{m} \sum_{j\epsilon C'_{zy}} w_j * d\left(r_{zj}, r_{yj}\right) + \\ \sum_{z,y=1,z\neq y}^{m} \sum_{j\epsilon C''_{zy}} w_j * d(r_{zj}, r_{yj}) \sum_{z,y=1,z\neq y}^{m} \sum_{j\epsilon C'''_{zy}} w_j * d(r_{zj}, r_{zj})\end{array}} \tag{18}$$

$$\omega_{C'''} = \frac{\sum_{z,y=1,z\neq y}^{m} \sum_{j\epsilon C'''_{zy}} w_j * d(r_{zj}, r_{yj})}{\begin{array}{l}\sum_{z,y=1,z\neq y}^{m} \sum_{j\epsilon C'_{zy}} w_j * d\left(r_{zj}, r_{yj}\right) + \\ \sum_{z,y=1,z\neq y}^{m} \sum_{j\epsilon C''_{zy}} w_j * d(r_{zj}, r_{yj}) \sum_{z,y=1,z\neq y}^{m} \sum_{j\epsilon C'''_{zy}} w_j * d(r_{zj}, r_{zj})\end{array}} \tag{19}$$

TABLE 2. If-decision matrices for different time periods for the three DMs.

DM	Period	Alternatives	Sustainability indicators c_1	c_2	c_3	c_4	c_5
DM1	2017	a_1	(0.400,0.500,0.100)	(0.700,0.200,0.100)	(0.400,0.500,0.100)	(0.800,0.100,0.100)	(0.500,0.400,0.100)
		a_2	(0.700,0.200,0.100)	(0.800,0.100,0.100)	(0.800,0.100,0.100)	(0.800,0.100,0.100)	(0.800,0.100,0.100)
		a_3	(0.400,0.500,0.100)	(0.700,0.200,0.100)	(0.500,0.400,0.100)	(0.700,0.200,0.100)	(0.600,0.300,0.100)
		a_4	(0.800,0.100,0.100)	(0.600,0.300,0.100)	(0.700,0.200,0.100)	(0.700,0.200,0.100)	(0.700,0.200,0.100)
	2018	a_1	(0.700,0.200,0.100)	(0.500,0.400,0.100)	(0.700,0.200,0.100)	(0.700,0.200,0.100)	(0.500,0.400,0.100)
		a_2	(0.700,0.200,0.100)	(0.700,0.200,0.100)	(0.800,0.100,0.100)	(0.800,0.100,0.100)	(0.600,0.300,0.100)
		a_3	(0.700,0.200,0.100)	(0.700,0.200,0.100)	(0.600,0.300,0.100)	(0.700,0.200,0.100)	(0.800,0.100,0.100)
		a_4	(0.700,0.200,0.100)	(0.600,0.300,0.100)	(0.600,0.300,0.100)	(0.800,0.100,0.100)	(0.700,0.200,0.100)
	2019	a_1	(0.600,0.300,0.100)	(0.500,0.400,0.100)	(0.700,0.200,0.100)	(0.800,0.100,0.100)	(0.600,0.300,0.100)
		a_2	(0.400,0.500,0.100)	(0.800,0.100,0.100)	(0.700,0.200,0.100)	(0.800,0.100,0.100)	(0.800,0.100,0.100)
		a_3	(0.700,0.200,0.100)	(0.500,0.400,0.100)	(0.500,0.400,0.100)	(0.600,0.300,0.100)	(0.500,0.400,0.100)
		a_4	(0.700,0.200,0.100)	(0.500,0.400,0.100)	(0.800,0.100,0.100)	(0.600,0.300,0.100)	(0.700,0.200,0.100)
DM2	2017	a_1	(0.500,0.400,0.100)	(0.800,0.100,0.100)	(0.400,0.500,0.100)	(0.400,0.500,0.100)	(0.600,0.300,0.100)
		a_2	(0.600,0.300,0.100)	(0.600,0.300,0.100)	(0.400,0.500,0.100)	(0.600,0.300,0.100)	(0.500,0.400,0.100)
		a_3	(0.400,0.500,0.100)	(0.600,0.300,0.100)	(0.700,0.200,0.100)	(0.700,0.200,0.100)	(0.700,0.200,0.100)
		a_4	(0.700,0.200,0.100)	(0.500,0.400,0.100)	(0.600,0.300,0.100)	(0.400,0.500,0.100)	(0.500,0.400,0.100)
	2018	a_1	(0.400,0.500,0.100)	(0.500,0.400,0.100)	(0.700,0.200,0.100)	(0.400,0.500,0.100)	(0.800,0.100,0.100)
		a_2	(0.600,0.300,0.100)	(0.500,0.400,0.100)	(0.500,0.400,0.100)	(0.800,0.100,0.100)	(0.700,0.200,0.100)
		a_3	(0.600,0.300,0.100)	(0.800,0.100,0.100)	(0.600,0.300,0.100)	(0.600,0.300,0.100)	(0.500,0.400,0.100)
		a_4	(0.500,0.400,0.100)	(0.700,0.200,0.100)	(0.700,0.200,0.100)	(0.700,0.200,0.100)	(0.400,0.500,0.100)
	2019	a_1	(0.700,0.200,0.100)	(0.600,0.300,0.100)	(0.600,0.300,0.100)	(0.600,0.300,0.100)	(0.800,0.100,0.100)
		a_2	(0.800,0.100,0.100)	(0.600,0.300,0.100)	(0.500,0.400,0.100)	(0.400,0.500,0.100)	(0.800,0.100,0.100)
		a_3	(0.800,0.100,0.100)	(0.800,0.100,0.100)	(0.400,0.500,0.100)	(0.400,0.500,0.100)	(0.600,0.300,0.100)
		a_4	(0.400,0.500,0.100)	(0.500,0.400,0.100)	(0.400,0.500,0.100)	(0.600,0.300,0.100)	(0.600,0.300,0.100)
DM3	2017	a_1	(0.700,0.200,0.100)	(0.800,0.100,0.100)	(0.600,0.300,0.100)	(0.700,0.200,0.100)	(0.800,0.100,0.100)
		a_2	(0.700,0.200,0.100)	(0.800,0.100,0.100)	(0.500,0.400,0.100)	(0.600,0.300,0.100)	(0.700,0.200,0.100)
		a_3	(0.700,0.200,0.100)	(0.800,0.100,0.100)	(0.800,0.100,0.100)	(0.800,0.100,0.100)	(0.600,0.300,0.100)
		a_4	(0.800,0.100,0.100)	(0.700,0.200,0.100)	(0.600,0.300,0.100)	(0.500,0.400,0.100)	(0.600,0.300,0.100)
	2018	a_1	(0.600,0.300,0.100)	(0.600,0.300,0.100)	(0.400,0.500,0.100)	(0.500,0.400,0.100)	(0.500,0.400,0.100)
		a_2	(0.800,0.100,0.100)	(0.600,0.300,0.100)	(0.400,0.500,0.100)	(0.600,0.300,0.100)	(0.700,0.200,0.100)
		a_3	(0.800,0.100,0.100)	(0.600,0.300,0.100)	(0.800,0.100,0.100)	(0.700,0.200,0.100)	(0.500,0.400,0.100)
		a_4	(0.700,0.200,0.100)	(0.500,0.400,0.100)	(0.800,0.100,0.100)	(0.500,0.400,0.100)	(0.500,0.400,0.100)
	2019	a_1	(0.400,0.500,0.100)	(0.400,0.500,0.100)	(0.500,0.400,0.100)	(0.700,0.200,0.100)	(0.700,0.200,0.100)
		a_2	(0.500,0.400,0.100)	(0.600,0.300,0.100)	(0.600,0.300,0.100)	(0.700,0.200,0.100)	(0.600,0.300,0.100)
		a_3	(0.500,0.400,0.100)	(0.600,0.300,0.100)	(0.800,0.100,0.100)	(0.800,0.100,0.100)	(0.500,0.400,0.100)
		a_4	(0.600,0.300,0.100)	(0.600,0.300,0.100)	(0.600,0.300,0.100)	(0.500,0.400,0.100)	(0.600,0.300,0.100)

alternatives are later applied to support better-informed decision-making processes. In this section, we consider evaluating the sustainability of renewable energy. First, we set up the problem, and then conduct the study. Finally, we report our results and conduct a sensitivity analysis.

A. SETTING UP THE PROBLEM

A renewable energy company evaluates the sustainability indicators for renewable energy systems during the 2017–2019 period. The objective is to identify some of the best alternatives that will serve as a foundation for an accurate strategic system in the year 2020. According to the proposed methodology, we consider four renewable energy system alternatives (a_1, a_2, a_3, and a_4), namely, solar energy systems (a_1), wind energy systems (a_2), phosphoric acid fuel cells (a_3), and solid oxide fuel cells (a_4). Similarly, five sustainability indicators (c_1, c_2, c_3, c_4, and c_5), namely, a resource indicator (c_1), an environmental indicator (c_2), an economic indicator (c_3), a social indicator (c_4), and a technology indicator (c_5), are included. The reasons for choosing these alternative indicators over others are consistent with our literature review [62]. There is evidence that these alternative indicators are among the most critical ones for decision making in the renewable energy field [62]. The analysis also comprises three time periods.

Suppose three DMs $e_q(q = 1, 2, 3)$ (with the weight vector $\lambda_q = [0.3, 0.3, 0.4]$), who are experts in the renewable energy industry, provide the evaluation information of the four renewable energy system alternatives $a_i(i = 1, 2, 3, 4)$ using IFNs for all five sustainability indicators $c_i(i = 1, 2, 3, 4, 5)$ in the three years $t_l(l = 1, 2, 3)$ denoting a set of three periods, where t_1 represents the year 2017, t_2 denotes the year 2018, and t_3 denotes the year 2019. Thus, the individual IF-evaluation information matrices $R\left(t_l^{(q)}\right)$ are for the years 2017, 2018, and 2019. Table 2 shows the individual IF-evaluation information matrices in different periods for the

TABLE 3. Individual collective DIF-evaluation information matrices for DM1, DM2, and DM3.

DM	Alternatives	Sustainability indicators				
		c_1	c_2	c_3	c_4	c_5
DM1	a_1	(0.547,0.353, 0.100)	(0.603,0.297, 0.100)	(0.590,0.310, 0.100)	(0.783,0.117, 0.100)	(0.538,0.362, 0.100)
	a_2	(0.618,0.282, 0.100)	(0.783,0.117, 0.100)	(0.770,0.130, 0.100)	(0.800,0.100, 0.100)	(0.770,0.130, 0.100)
	a_3	(0.590,0.310, 0.100)	(0.641,0.259, 0.100)	(0.522,0.378, 0.100)	(0.668,0.232, 0.100)	(0.623,0.277, 0.100)
	a_4	(0.750,0.150, 0.100)	(0.568,0.332, 0.100)	(0.712,0.188, 0.100)	(0.694,0.206, 0.100)	(0.700,0.200, 0.100)
DM2	a_1	(0.686,0.214, 0.100)	(0.582,0.318, 0.100)	(0.457,0.443, 0.100)	(0.599,0.301, 0.100)	(0.672,0.228, 0.100)
	a_2	(0.623,0.277, 0.100)	(0.727,0.173, 0.100)	(0.595,0.305, 0.100)	(0.595,0.305, 0.100)	(0.633,0.267, 0.100)
	a_3	(0.577,0.323, 0.100)	(0.549,0.351, 0.100)	(0.565,0.335, 0.100)	(0.547,0.353, 0.100)	(0.520,0.380, 0.100)
	a_4	(0.595,0.305, 0.100)	(0.663,0.237, 0.100)	(0.531,0.369, 0.100)	(0.668,0.232, 0.100)	(0.723,0.177, 0.100)
DM3	a_1	(0.669,0.231, 0.100)	(0.707,0.193, 0.100)	(0.520,0.380, 0.100)	(0.638,0.262, 0.100)	(0.668,0.232, 0.100)
	a_2	(0.669,0.231, 0.100)	(0.707,0.193, 0.100)	(0.800,0.100, 0.100)	(0.783,0.117, 0.100)	(0.548,0.352, 0.100)
	a_3	(0.724,0.176, 0.100)	(0.633,0.267, 0.100)	(0.652,0.248, 0.100)	(0.500,0.400, 0.100)	(0.582,0.318, 0.100)
	a_4	(0.686,0.214, 0.100)	(0.582,0.318, 0.100)	(0.457,0.443, 0.100)	(0.599,0.301, 0.100)	(0.672,0.228, 0.100)

three DMs. Note that the weight vector for the three years is given by $\delta(t_l) = [0.45, 0.20, 0.35]$ and the sustainability indicator weights are $w_j(t_l)(j= 1, 2, 3, 4, 5)$. In addition, the weights of the sustainability indicators for the different years are as follows:

$$w(t_1) = [0.188, 0.295, 0.147, 0.203, 0.169],$$
$$w(t_2) = [0.23, 0.171, 0.229, 0.214, 0.158],$$

and

$$w(t_3) = [0.19, 0.139, 0.174, 0.274, 0.225].$$

We apply our proposed method using these parameters, as explained in the next subsection.

B. APPLICATION OF THE PROPOSED IF-DMAGDM METHODOLOGY

The proposed methodology is utilized for evaluating the sustainability indicators of renewable energy. Note that the application is based on the steps presented in Figure 2.

Steps 1 and *2* are carried out. The individual IF-evaluation information matrices in different periods (2017, 2018, and 2019, respectively) given by the three DMs are provided in Table 2.

Step 3. Apply the MDIFWG operator (Eq. 6) to aggregate the individual IF-evaluation information matrices $R\left(t_l^{(q)}\right)$ for the years 2017, 2018, and 2019, and determine the individual collective DIF-evaluation information matrix R^q for each DM e_q $(q = 1, 2, 3)$ by considering the weight vector for the three years $\delta(t_l) = [0.45, 0.20, 0.35]$. The results of this aggregation are shown in Table 3.

Step 4. Apply the DWGA operator (Eq. 8) to aggregate the weights of the five sustainability indicators, $w_j(t_l)(j = 1, 2, 3, 4, 5)$, for the three years $t_l(l = 1, 2, 3)$ into the collective weights of the five sustainability indicators w_j $(j = 1, 2, 3, 4, 5)$, as follows:

$$[w_1, w_2, w_3, w_4, w_5] = [0.197, 0.215, 0.173, 0.230, 0.186]$$

Step 5. Use the IFWG operator (Eq. 9) to aggregate all individual collective DIF evaluation information matrices R^q for each DM e_q $(q = 1, 2, 3)$. This aggregation is done by considering the weight vector of the three DMs $\lambda_q = [0.3, 0.3, 0.4]$ in the group collective DIF evaluation information matrix R, as presented in Table 4.

Step 6. Use the equations with dominance relationships (Eqs. 11–16) to specify the strong, midrange, and weak concordance sets and the strong, midrange, and weak discordance sets, respectively. The results are presented in Table 5.

Step 7. Use the equations based on the WD measure (Eqs. 17–19) to compute the weights of the strong, midrange, and weak concordance sets as $\omega_{c'}$, $\omega_{c''}$, and $\omega_{c'''}$ respectively. The weights are obtained as follows:

$$\omega_{c'} = 0.541, \quad \omega_{c''} = 0.459, \quad \omega_{c'''} = 0$$

Step 8. Calculate the concordance indices and discordance indices using Eqs. 21 and 23, respectively. Then, build the concordance and discordance matrices with respect to Eqs. 20 and 22, respectively. The concordance matrix C and discordance matrix D are modelled as follows:

$$C = \begin{bmatrix} - & 0.000 & 0.067 & 0.369 \\ 0.490 & - & 0.156 & 0.370 \\ 0.441 & 0.385 & - & 0.375 \\ 0.1201 & 0.130 & 0.133 & - \end{bmatrix}$$

$$D = \begin{bmatrix} - & 0.197 & 0.173 & 0.197 \\ 0.000 & - & 0.173 & 0.173 \\ 0.186 & 0.186 & - & 0.196 \\ 0.230 & 0.229 & 0.229 & - \end{bmatrix}$$

TABLE 4. The group collective DIF evaluation information matrix.

Alternatives	Sustainability indicators				
	c_1	c_2	c_3	c_4	c_5
a_1	(0.572,0.328, 0.100)	(0.653,0.247, 0.100)	(0.553,0.347, 0.100)	(0.634,0.264,0.102)	(0.663,0.237,0.101)
a_2	(0.658,0.242, 0.100)	(0.688,0.212,0.101)	(0.563,0.335,0.102)	(0.670,0.229,0.101)	(0.699,0.201,0.100)
a_3	(0.631,0.269, 0.100)	(0.692,0.207,0.100)	(0.644,0.255,0.101)	(0.688,0.212,0.101)	(0.595,0.305,0.100)
a_4	(0.683,0.216,0.101)	(0.587,0.313,0.100)	(0.641,0.259, 0.100)	(0.567,0.333,0.101)	(0.595,0.305,0.101)

TABLE 5. Concordance sets and discordance sets.

Concordance sets			Discordance sets		
Strong	Midrange	Weak	Strong	Midrange	Weak
$C'_{12}=\{\emptyset\}$	$C''_{12}=\{\emptyset\}$	$C'''_{12}=\{\emptyset\}$	$D'_{12}=\{4,5\}$	$D''_{12}=\{1,2,3\}$	$D'''_{12}=\{\emptyset\}$
$C'_{13}=\{\emptyset\}$	$C''_{13}=\{5\}$	$C'''_{13}=\{\emptyset\}$	$D'_{13}=\{2,4\}$	$D''_{13}=\{1,3\}$	$D'''_{13}=\{\emptyset\}$
$C'_{14}=\{2\}$	$C''_{14}=\{4,5\}$	$C'''_{14}=\{\emptyset\}$	$D'_{14}=\{\emptyset\}$	$D''_{14}=\{1,3\}$	$D'''_{14}=\{\emptyset\}$
$C'_{21}=\{4,5\}$	$C''_{21}=\{1,2,3\}$	$C'''_{21}=\{\emptyset\}$	$D'_{21}=\{\emptyset\}$	$D''_{21}=\{\emptyset\}$	$D'''_{21}=\{\emptyset\}$
$C'_{23}=\{1,5\}$	$C''_{23}=\{\emptyset\}$	$C'''_{23}=\{\emptyset\}$	$D'_{23}=\{2,3,4\}$	$D''_{23}=\{\emptyset\}$	$D'''_{23}=\{\emptyset\}$
$C'_{24}=\{4,5\}$	$C''_{24}=\{2\}$	$C'''_{24}=\{\emptyset\}$	$D'_{24}=\{3\}$	$D''_{24}=\{1\}$	$D'''_{24}=\{\emptyset\}$
$C'_{31}=\{2,4\}$	$C''_{31}=\{1,3\}$	$C'''_{31}=\{\emptyset\}$	$D'_{31}=\{\emptyset\}$	$D''_{31}=\{5\}$	$D'''_{31}=\{\emptyset\}$
$C'_{32}=\{2,3,4\}$	$C''_{32}=\{\emptyset\}$	$C'''_{32}=\{\emptyset\}$	$D'_{32}=\{1,5\}$	$D''_{32}=\{\emptyset\}$	$D'''_{32}=\{\emptyset\}$
$C'_{34}=\{2,4\}$	$C''_{34}=\{3\}$	$C'''_{34}=\{\emptyset\}$	$D'_{34}=\{\emptyset\}$	$D''_{34}=\{1,5\}$	$D'''_{34}=\{\emptyset\}$
$C'_{41}=\{\emptyset\}$	$C''_{41}=\{1,3\}$	$C'''_{41}=\{\emptyset\}$	$D'_{41}=\{2\}$	$D''_{41}=\{4,5\}$	$D'''_{41}=\{\emptyset\}$
$C'_{42}=\{4\}$	$C''_{42}=\{1\}$	$C'''_{42}=\{\emptyset\}$	$D'_{42}=\{4,5\}$	$D''_{42}=\{2\}$	$D'''_{42}=\{\emptyset\}$
$C'_{43}=\{\emptyset\}$	$C''_{43}=\{1,5\}$	$C'''_{43}=\{\emptyset\}$	$D'_{43}=\{2,4\}$	$D''_{43}=\{3\}$	$D'''_{43}=\{\emptyset\}$

TABLE 6. Ranking of renewable energy system alternatives according to *S*, *R*, and *Q*.

	Renewable energy system alternatives				Ranking order
	a_1	a_2	a_3	a_4	
S_i	0.855	0.662	0.560	0.872	$a_3 \geq a_2 \geq a_1 \geq a_4$
R_i	0.036	0.027	0.033	0.082	$a_2 \geq a_3 \geq a_1 \geq a_4$
Q_i	0.548	0.113	0.057	1.000	$a_3 \geq a_2 \geq a_1 \geq a_4$

Step 9. Calculate two different ranking lists S_i and R_i for each renewable energy system alternative (a_1, a_2, a_3, and a_4) according to the discordance and concordance matrices using Eqs. 24 and 25, respectively. The outcomes are shown in Table 6.

Step 10. Compute the Q_i values for each renewable energy system alternative (a_1, a_2, a_3, and a_4), capturing the 'closeness to the ideal' based on Eq. 26. In this step, the value of $\gamma = 0.5$ is considered, which means that the weight of the maximal group utility equals the weight of the minimal individual regret. The values of Q_i for each renewable energy system considering $\gamma = 0.5$ can be found in Table 6.

Step 11. Rank the renewable energy system alternatives (a_1, a_2, a_3, and a_4) by sorting the values of S_i, R_i, and Q_i in the decreasing order, as shown in Table 6. Then, the most preferred solution under condition 1, proposed by the

TABLE 7. Results of the sensitivity analysis.

	Q Values for renewable energy system alternatives				Ranking order
γ	Q_1	Q_2	Q_3	Q_4	
0.000	0.161	0.000	0.114	1.000	$a_2 \geq a_3 \geq a_1 \geq a_4$
0.100	0.238	0.167	0.144	0.245	$a_3 \geq a_2 \geq a_1 \geq a_4$
0.200	0.316	0.045	0.092	1.000	$a_2 \geq a_3 \geq a_1 \geq a_4$
0.300	0.393	0.068	0.080	1.000	$a_2 \geq a_3 \geq a_1 \geq a_4$
0.400	0.471	0.090	0.069	1.000	$a_3 \geq a_2 \geq a_1 \geq a_4$
0.500	0.548	0.113	0.057	1.000	$a_3 \geq a_2 \geq a_1 \geq a_4$
0.600	0.626	0.136	0.046	1.000	$a_3 \geq a_2 \geq a_1 \geq a_4$
0.700	0.703	0.158	0.034	1.000	$a_3 \geq a_2 \geq a_1 \geq a_4$
0.800	0.781	0.181	0.023	1.000	$a_3 \geq a_2 \geq a_1 \geq a_4$
0.900	0.858	0.203	0.011	1.000	$a_3 \geq a_2 \geq a_1 \geq a_4$
1.000	0.936	0.226	0.000	1.000	$a_3 \geq a_2 \geq a_1 \geq a_4$

examination, is as follows:

$$Q_2 - Q_3 \geq \frac{1}{4-1} \xrightarrow{yields} 0.113 - 0.057 \geq \frac{1}{4-1}$$

where a_3 is listed as the first position and a_2 is listed as the second position of the ranking lists for Q_i. Consequently, condition 1 is satisfied.

Step 12. Propose a compromise solution and identify the best alternative for evaluating the sustainability indicators of renewable energy. From step 11, it can be noticed that a_3 is in the first position with respect to just the ranking list S_i. Thus, condition 2 is not satisfied. Therefore, phosphoric acid fuel cells (a_3) and wind energy systems (a_2) are the compromise solutions. The ranking order for all considered alternatives is $a_3 \geq a_2 \geq a_1 \geq a_4$ when $\gamma = 0.5$. It means that if the DMs assign equal importance weights to the maximal group utility ($\gamma = 0.5$) and the weight of the minimal individual regret (1-$\gamma = 0.5$), which is the consensus case, the final ranking order would be $a_3 \geq a_2 \geq a_1 \geq a_4$.

C. SENSITIVITY ANALYSIS

A sensitivity analysis was conducted by varying the weights of the maximal group utility (γ) and of the minimal individual regret ($1-\gamma$). Different values of γ were assigned according to the 11 different scenarios of the DMs to reveal in what way the ranking order of the alternatives varied. Table 7 illustrates the results of the sensitivity analysis. The following conclusions can be drawn from these results.

1) For $\gamma = \{0, 0.2, 0.3\}$, the ranking order of all the alternatives is $a_2 \geq a_3 \geq a_1 \geq a_4$, and $\{a_2, a_3\}$ are the compromise solutions.
2) For $\gamma = \{0.1, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1\}$, the ranking order of all the alternatives is $a_3 \geq a_2 \geq a_1 \geq a_4$, and $\{a_3, a_2\}$ are the compromise solutions.

It can be observed that $\{a_3, a_2\}$ are the compromise solutions under all considered scenarios. In other words, the compromise solutions remain unchanged in terms of the weights of the maximal group utility (γ) and minimal individual regret ($1-\gamma$). However, the first and second positions of the ranking order were different, and the ranking of the other positions remained the same. Consequently, the output was affected by changing the weight values of the maximal group utility and minimal individual regret. This change means that DMs should pay more attention to assigning the weights of the maximal group utility (γ) and minimal individual regret ($1-\gamma$).

A visual representation of the sensitivity analysis results is shown in Figure 3. The group utility Υ on the horizontal axis was considered in the 01 range, and the alternatives are shown on the vertical axis. Note that Q_1 is the most sensitive alternative for a range of different utility values. For instance, if $\Upsilon = 0$, we have $Q_1 = 0.160$. In addition, when Υ attains the highest possible value ($\Upsilon = 0.160$), we have $Q_1 = 0.930$; thus, the alternative Q_1 is the most sensitive to changes in Υ. The opposite case is given by an alternative Q_3. Note that $Q_3 = 0.110$ when $\Upsilon = 0$, and Q_3 decreases to 0 (zero) when $\Upsilon = 1$. Thus, Q_3 is the less sensitive alternative.

To conclude, a sensitivity analysis was conducted to determine how utility (Υ) affects the four studied alternatives. This analysis is useful to understand how alternatives change when different values of Υ are given. As mentioned, Q_1, referring to solar energy systems, is the most sensitive one. On the other hand, Q_4 (solid oxide fuel cells) is the least sensitive.

D. COMPARISON ANALYSIS

To further demonstrate the feasibility and validity of the proposed outranking methodology, a comparison with the existing approaches under an IF-DMAGDM environment was carried out. Thus, the comparative analysis was conducted based on the different approaches proposed by Su *et al.* [21] and Yin *el al.* [22]. The results corresponding to comparison analysis are represented in Table 8.

TABLE 8. Comparative analysis.

	Renewable energy system alternatives				Ranking order
	a_1	a_2	a_3	a_4	
Su and Chen [21]	0.489	0.582	0.595	0.357	$a_3 \geq a_2 \geq a_1 \geq a_4$
Yin *el al*. [22]	0.290	0.445	0.421	0.279	$a_2 \geq a_3 \geq a_1 \geq a_4$
Our proposed outranking methodology	0.548	0.113	0.057	1.000	$a_3 \geq a_2 \geq a_1 \geq a_4$

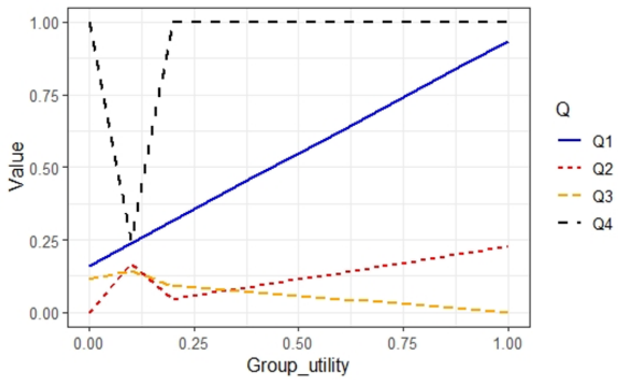

FIGURE 3. Sensitivity analysis of alternatives for different values of utility Υ.

With respect to this analysis, it is obvious that the result of the existing approaches is consistent with the compromise solutions obtained from proposed methodology. A discussion that contrasts the advantages and disadvantages of the compared methods is provided in the next section.

IV. DISCUSSION

In this work, an extended outranking methodology focusing on efficient solutions to intuitionistic fuzzy-dynamic MAGDM (IF-DMAGDM) is proposed. It integrates the ELECTRE I and VIKOR methods under the IFS theory. The method is suitable for analyzing problems in which DMs' judgements take the form of IFSs with uncertainty across different periods of time. The outranking relations among alternatives and judgements are shaped by the IF-ELECTRE, and the concordance sets' weights are accurately determined. The limitations in ELECTRE I, as previously mentioned, are overcome by including the VIKOR method. First, the MDIFWG operator, which considers the vectors of weights at different periods of time, is applied to calculate the individual and collective DIF-decision matrices. Later, the DWGA operator helps in aggregating the attributes' weights in the corresponding periods of time. This aggregation allows us to obtain a synthetic weight that accurately balances the differences across time periods and alternatives. The IFWG method is utilized to obtain the group collective DIF-decision matrix. In this way, individual collective matrices are aggregated into a unique DIF-matrix that summarizes the preferences for all investigated alternatives. The obtained output comprises as many matrices as the number of investigated indicators. Taking this as the starting point, the group collective DIF-decision matrix, the concordance matrices, and the discordance matrices are calculated. Based on the WD measure, three levels of concordance weights are obtained: strong, moderate, and weak. At this point, the VIKOR method is applied to obtain the closest one to the ideal solution, propose a compromise solution, and identify the best alternative. Finally, an application related to the selection of renewable energies is provided to illustrate the suitability of this methodology.

A significant number of studies in the literature focus on intuitionistic fuzzy decision problems. A search for these words in the Web of Science and filtering them by title yielded 63 articles. Note that 52% of these articles were published during the last four years [63]. Among them, one of the first studies investigated group decision-making problems in which the DMs give their information in the form of interval-value intuitionistic fuzzy decision matrices [64]. A paper published in 2011 investigated IF-DMAGDM. To obtain the individual ranking of alternatives, intuitionistic fuzzy TOPSIS was employed. This paper introduced the IF-DMAGDM concept [21]. Later, another study focused on DIF-MADDM problems. It combined the dynamic intuitionistic fuzzy power geometric weighted average (DIF-PGWA) operator and a prediction model based on intuitionistic fuzzy values (IFVs) and GM (1,1) [22]. No outranking methods were used. An application related to the recruitment of employees was provided as an illustrative example [22]. In 2018, one of the first papers that integrated ELECTRE and VIKOR under an IFS perspective was published. It was primarily focused on integrating the mentioned methods with grey relational analysis (GRA). The study is limited because only the IFWG operator is applied for aggregating DM preferences [45]. Another work proposes a methodology for solving outranking problems based on the integration of ELECTRE and VIKOR under uncertainty. Although it applies pairwise comparisons and outranking relations to obtain concordance and discordance matrices, the dynamic relations given by different periods of time were not investigated [34].

As far as we know, none of the outranking methods available in the literature integrate ELECTRE and VIKOR under uncertainty and dynamic perspectives. The advantages of this integration have been previously discussed [34], [44], [45]. Some of them are accurately proposing a compromise solution, identifying the best alternative, providing a complete ranking of alternatives, offering different ranking orders based on different DM strategies, describing uncertainty, and incorporating it into the problem. By considering these characteristics and using them in a dynamic environment that contemplates different periods of time, our work makes an original contribution.

V. CONCLUSION AND FUTURE WORK

With the emergence of data science, which is characterized by the massive accumulation of data, several DMAGDM methodologies have gained importance. This gain has occurred mainly because of their capability to accurately exploit available data, especially when data are partially missing, there are different structures, or there are different periods of time. From this perspective, an extended outranking methodology focusing on DMAGDM problems under uncertainty was proposed. We believe that this method is helpful in assisting groups and DMs to provide their evaluation judgements for decision problems in the form of IFSs in different periods of time. Unlike the existing methodologies for solving DMAGDM problems, our algorithm provides a complete ranking list by using a combination of the IF-ELECTRE and VIKOR methods. In addition, this algorithm (IF-DMAGDM) is capable of incorporating the relative weights of the DMs, the relative weights of attributes in different periods of time, and the relative weights of periods, which are vital for any DMAGDM problem.

However, the present approach has some limitations, which necessitate additional research. All the relative weights considered in this approach (for DMs, attributes, and periods) were captured as exact numerical values. However, these relative weights can be derived in a fuzzy environment and can then be formed as FSs or IFSs. In addition, the IFS concept was primarily used in the present work. In the forthcoming works, other types of fuzzy forms, such as linguistic IFSs, interval-valued IFSs, and picture FSs, will be considered to improve the proposed method. Considering that this method is conceived to tackle real-world scenarios, it is designed to be easy to understand and easy to replicate. This design sets it apart from other available methods [22], [34], [44], [45], [60]. Although an application for a renewable energy indicator ranking was provided, future work will seek to apply it to investigate problems in areas such finance, artificial intelligence, and the spread of infections.

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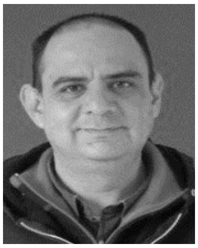

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