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A Novel CRITIC-RS-VIKOR Group Method with Intuitionistic Fuzzy Information for Renewable Energy Sources Assessment

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Abstract
This study aims to propose a new group multi-attribute decision-analysis (MADA) model to prioritize the renewable energy sources (RESs) from sustainability perspectives. The selection of RESs can be considered as a MADA problem due to considering the numerous conflicting sustainability indicators/factors. In this regard, we propose an integrated decision-making framework with the "criteria importance through inter-criteria correlation (CRITIC)", the "rank sum (RS)" and the "Vlse Kriterijumska Optimizacija Kompromisno Resenje (VIKOR)" approaches with intuitionistic fuzzy information called the "IF-CRITIC-RS-VIKOR" model. In the developed model, the CRITIC is applied to derive the objective weights, while the RS model is used to compute the subjective weights of the considered sustainability indicators. Further, an incorporated weight-determining formula is presented by combining the CRITIC and RS models under intuitionistic fuzzy environment. Moreover, the VIKOR method is employed to rank the candidate RESs by means of several sustainability indicators. In this line, new intuitionistic fuzzy distance measures are proposed to calculate the "group utility (GU)" and "individual regret (IR)" degrees of candidate RESs. Based on the obtained results, the most significant factors for RESs assessment are impact on ecosystem, technology cost and efficiency, respectively. The assessment outcomes show that the wind energy can serve as an effective RES followed by the solar energy, biomass energy and small hydel energy. Furthermore, comparative study and sensitivity analysis are discussed to show the utility and reasonability of the proposed method.

Keywords Intuitionistic fuzzy sets · Group decision making · Renewable energy source · Distance measure · CRITIC · VIKOR

Abbreviations

AHP	Analytic hierarchy process
AI	Absolutely important

Extended author information available on the last page of the article

AI	Absolutely insignificant
AIF-DM	Aggregated intuitionistic fuzzy decision matrix
AS	Absolutely significant
AU	Absolutely unimportant
CC	Closeness coefficient
CoCoSo	Combined compromise solution
COPRAS	Complex proportional assessment
CRITIC	Criteria importance through inter-criteria correlation
CS	Compromise score
DEMATEL	Decision-making trial and evaluation laboratory
DME	Decision-maker
DNMA	Double normalization-based multi-aggregation
EDAS	Evaluation based on distance from average solution
GHG	Green house gas
GLDS	Gain loss dominance score
GRA	Grey relational analysis
GU	Group utility
FST	Fuzzy set theory
HD	Hesitancy degree
I	Important
IN	Insignificant
IF	Intuitionistic fuzzy
IFI	Intuitionistic fuzzy information
IF-AIS	IF-anti ideal solution
IF-IS	IF-ideal solution
IFN	Intuitionistic fuzzy number
IFS	Intuitionistic fuzzy set
IFWA	IF-weighted averaging
IFWG	IF-weighted geometric
IR	Individual regret
LDM	Linguistic decision matrix
LRs	Linguistic ratings
M	Medium
MADA	Multi-attribute decision-analysis
MEREC	Method based on removal effects of criteria
MD	Membership degree
MI	Much insignificant
MS	Much significant
MULTIMOORA	Multi-objective optimization on the basis of ratio analysis plus full multiplicative form
NMD	Non-membership degree
OCRA	Operational competitiveness rating
O&M	Operation and maintenance
PFS	Pythagorean fuzzy set
QI	Quite insignificant
QS	Quite significant

RESs	Renewable energy sources
RS	Rank sum
S	Significant
SWARA	Step-wise weight assessment ratio analysis
TFNs	Triangular fuzzy numbers
TOPSIS	Technique for order of preference by similarity to ideal solution
U	Unimportant
VI	Very important
VI	Very insignificant
VS	Very significant
VU	Very unimportant
VIKOR	VlseKriterijumska optimizacija I kompromisno resenje
WASPAS	Weighted aggregated sum product assessment

1 Introduction

In reality, we are commonly handled with choosing the suitable option using several conflicting factors. Such problems can be treated by multi-attribute decision analysis (MADA) models, which utilize a hierarchical procedure to assess the presented options. In some circumstances, a set of decision makers (DMEs) evaluates the options, for recovering decision analysis, in what are recognized as MADA problems. Recently, MADA models have been broadly studied (Pamucar et al. 2022; Mishra and Rani 2018; Pandey et al. 2023; Gupta et al. 2023). MADA models permit the DMEs to assess the options and factors of problem reasonably. The data provided by the DMEs are generally qualitative (imprecise and subjective judgments in nature). Thus, to tackle this complex data, scholars have provided different methods to deal vague information in an accurate mathematical procedure (Zadeh 1965; Atanassov 1986; Yager 2014). Fuzzy sets (FSs) doctrine is a renowned model amongst scholars for dealing uncertain decision analysis problems. Various generalizations of FSs (Mehlawat et al. 2020; Mishra et al. 2022b, 2023b; Deveci et al. 2023) have been developed. Amongst these, the theory of IFS is more powerful as compared to FS as it deals with membership, non-membership, and hesitant degrees. For instance, suppose electors may be divided into three groups of those who vote for, who vote against and who abstain. If we take $\langle o_1,\ 0.5,\ 0.4\rangle$ as an element of IFS S of voting, we can interpret that "the vote for the applicant is 0.5 in favor to 0.4 against with 0.1 nonparticipations". Such characteristics offer a considerable advantage over the FSs theory as they can better reflect the ambiguity of decision-making, particularly when eliciting judgment.

In MADA, the aggregation procedure of evaluation ratings is the most sensitive part. When aggregating the information, we need weights for the DMEs and the factors, which may be known, partially known, or fully unknown. If the weights are ''partially known or fully unknown'', well-defined models are needed to compute them. Weighting estimation models based on entropy, similarity, and possibility techniques (Mishra and Rani 2018; Gupta et al. 2023; Rani et al. 2019; Hezam et al. 2022; Narang et al. 2023) are preferred. The decision analysis procedure can be abridged as: factors selecting-preference collection-alternatives ranking, specifically a decision group invites several DMEs from diverse disciplines to assess available options over considered factors and further the optimal option is recognized with the combined evaluations. In reality, DMEs are difficult to deliver precise crisp ratings for the assessment of option over the diverse factors, which awaken several researchers to consider a weight on uncertain MADA models. This work attempts to address the following problems: (1) How to assess the complex and uncertain ratings considering individual behaviors? (2) How to convert and combine various personalized ratings from diverse DMEs? (3) How to determine the weights of different factors in view of multiple ratings and DMEs opinions? (4) How to achieve the reliable prioritization outcomes of options over the multiple DMEs, multiple factors, multiple dimensions and multiple preference situations?

1.1 Literature Review

To get a wider application of the set theory, Zadeh (1965) initiated the notion of fuzzy set (FS) that has extensively been used in practice to treat the vagueness of human decision choices. In this theory, each element of a FS has degree of membership which is a real number between zero and one. However, in actual fact, it may not always be true that the degree of non-membership of an element in a FS is equal to one minus the membership degree because there may be some hesitation degree. To overcome the limitation of FS, Atanassov (1986) introduced the concept of intuitionistic fuzzy set (IFS), which is characterized by the degrees of membership, non-membership and hesitation. In IFS, the degree of hesitation is defined as one minus the sum of membership and non-membership degrees. The theory of IFS is more powerful as compared to FS as it deals with membership, non-membership, and hesitant degrees. For instance, suppose electors may be divided into three groups of those who vote for, who vote against and who abstain. If we take $\langle o_1,\ 0.5,\ 0.4\rangle$ as an element of IFS S of voting, we can interpret that "the vote for the applicant is 0.5 in favor to 0.4 against with 0.1 nonparticipations". Such characteristics offer a considerable advantage over the FS theory as they can better reflect the ambiguity of decision-making, particularly when eliciting judgment.

Information measures including similarity and distance measures are fundamental tools in the theory of FS as well as IFS. Dengfeng and Chuntian (2002) firstly presented the definition of similarity measure for IFSs. Further, they introduced several intuitionistic fuzzy similarity measures with their applications in pattern recognitions. Later, Mitchell (2003) investigated the counter-intuitive cases of Dengfeng and Chuntian's measures (Dengfeng and Chuntian 2002). In addition, Mitchell (2003) suggested an improved similarity measure and its application to pattern recognition. Liang and Shi (2003) presented some counter-intuitive examples to show the limitations of existing intuitionistic fuzzy similarity measures. Furthermore, they introduced several similarity measures for IFSs and presented the relationships between them. Vlachos and Sergiadis (2007) analyzed the drawbacks of existing information measures including distance, similarity, dissimilarity and correction of IFSs. Further, they presented discrimination information, cross-entropy and De Luca-Termini nonprobabilistic entropy under IFS context. Hung and Yang (2008a, b) reviewed existing similarity measures and then proposed new intuitionistic similarity measures with their enviable properties. Duan and Li (2021) gave the IF-similarity measures based on implication operator and the consequent logical metric spaces. They presented the application of IF-similarity measures in pattern recognition problem.

A distance measure is an important tool for determining the degree of distance between two objects. In the context of IFS, Burillo and Bustince (1996) firstly gave the definition of distance measure and further developed the Hamming, Euclidean, normalized Hamming and normalized Euclidean distance measures for IFSs. However, the distance measures proposed by Burillo and Bustince (1996) consider only membership and non-membership degrees. Szmidt and Kacprzyk (2000) presented the geometrical interpretation of intuitionistic fuzzy distance measure and introduced some distance measures by considering all three parameters, i.e., membership, non-membership and hesitation degrees. Wang and Xin (2005) firstly analyzed the drawback of Szmidt and Kacprzyk's distance measures (Szmidt and Kacprzyk 2000) and then presented a new definition of intuitionistic fuzzy distance measure. In addition, they proposed many distance measures for IFSs with their applications. Xu and Chen (2008a, b) presented a comprehensive survey on existing distance and similarity measures for IFSs. Moreover, they developed some intuitionistic fuzzy distance and similarity measures using continuous universe of discourse. Zhang and Yu (2013) pointed out that the prior studies on intuitionistic fuzzy and interval-valued fuzzy distance and similarity measures are mainly based on particular points. To conquer this issue, they introduced new distance measures for IFSs and interval-valued fuzzy sets. Apart from these studies, Hao et al. (2021) introduced a context-based IF-distance measure, which includes the domination and competition relations of the options. Further, they illustrated the usefulness of the presented information measures and their applicability in marine energy transportation route selection problem. Garg and Rani (2022) introduced some IF-distance measures and their properties. Further, they studied several illustrations related to pattern recognition and clustering assessment. Pandey et al. (2023) gave a feature selection model using IF-entropy. In this regard, they proposed new entropy for IFS and compared with some of the previously developed entropy measures. Mishra et al. (2023a) discussed a MADA framework for assessing and ranking the sustainable urban transportation (SUT) options under IFSs and developed IF-distance measures and their properties to obtain the criteria weight. Hezam et al. (2023a) developed the IF-GLDS approach using the developed IF-entropy to deal with the sustainable supplier selection in iron and steel industry in India. Hezam et al. (2023b) presented integrated IF-GLDS model with Yager weighted aggregation (IFYWA) operators and proposed weight-determining IF-SPC procedure for prioritizing the zero-carbon measures for sustainable urban transportation.

During the process of multi-attribute decision analysis (MADA), one of the most challenging issues for decision makers (DMs) is the assessment of criteria importance degrees. Lots of procedures have been suggested by different scholars for the computation of the criteria weights (Mishra and Rani 2018; Ali et al. 2023; Tešić et al. 2023; Khan et al. 2023; Narang et al. 2023). In a general classification, criteria weights are determined with two different approaches: objective and subjective. The criteria importance through intercriteria correlation (CRITIC) (Diakoulaki et al. 1995) method has pioneered for the purpose of deriving objective weights of criteria. This method incorporates both the contrast intensity of each criterion and conflict between criteria. The contrast intensity of criteria is considered by the standard deviation, and conflict between them is measured by the correlation coefficient. The method ensures that a criterion with a higher contrast intensity or standard deviation is assigned with a higher weight. Moreover, a conflict between criteria represents a type of relationship that can be present between decision criteria. The CRITIC method considers such conflicting relationships by utilizing the Pearson correlation coefficient, which ranges between -1 and 1. When the coefficient is zero, it implies that the two attributes Q_j and Q_n are independent of each other. Meanwhile, a negative coefficient indicates that both attributes move in an opposite direction. To be precise, as the coefficient approaches -1, the conflict between the two attributes becomes stronger. On the other hand, a positive coefficient indicates a parallel direction between both attributes. It means that two attributes with a high positive coefficient share too much redundant information. Thus, the CRITIC method ensures that an attribute with a higher degree of conflict or a lower degree of redundancy, is assigned with a higher weight. In the literature, the CRITIC method has been utilized for various purposes (Abdel-Basset and Mohamed 2020; Haktanır and Kahraman 2022; Liu et al. 2022; Pamucar et al. 2022). Mishra et al. (2022a) introduced a generalized score function-based Fermatean fuzzy CRITIC-EDAS model to solve sustainable third-party reverse logistics provider selection problem. Mishra et al. (2023a, b) presented a score function –based criteria importance through intercriteria correlation (CRITIC) method and the gained and lost dominance score (GLDS) method with Fermatean fuzzy information to deal with decision analysis problem.

For subjective weights of criteria, Stillwell et al. (1981) pioneered an effective RS model, which can successfully help the DEs in the ranking of criteria importance degrees. Narayanamoorthy et al. (2020) proposed a collective weighting procedure with CRITIC and RS models for assessing the significant indicators in bio-medical waste disposal methods. Based on the proposed weight-determining model, they suggested a hybrid hesitant fuzzy-information based approach for assessing the bio-medical waste disposal technologies. Recently, Hezam et al. (2022) discussed an IF-information based RS model with the purpose of evaluating the sustainability criteria in the assessment of AFVs. Thus far, there is no study regarding an incorporated IF- information based CRITIC-RS weight determining model for the assessment of RESs with multiple sustainability indicators. Hezam et al. (2023c) gave an integrated model under IFSs, the standard deviation (SD), the rank-sum (RS) and the measurement of alternatives and ranking using the compromise solution (MARCOS) approach for solving hospital sites selection (HSS) problem.

Opricovic (1998) introduced the idea of VIKOR technique for handing the MADA problems with conflicting and non-commensurable attributes. In this technique, the solution is obtained with the integration of maximum group utility (GU) and minimum individual regret (IR) of the opponent in the form of a compromise solution which directs the DMs to the final decision. An interval-valued fuzzy extension of VIKOR method has presented by Vahdani et al. (2010). They applied their method to evaluate and prioritize the practical maintenance strategies under interval-valued fuzzy environment. Devi (2011) proposed an intuitionistic fuzzy VIKOR method for robot selection. Park et al. (2011) introduced a novel extension of VIKOR method using interval-valued intuitionistic fuzzy information. With the use of dynamic intuitionistic fuzzy weighted geometric (DIFWG) and uncertain DIFWG operators, Park et al. (2013) introduced a novel VIKOR method from dynamic intuitionistic fuzzy perspectives. Gul et al. (2016) presented an extensive review on VIKOR method and its applications in several fields. Rani et al. (2019) put forward a generalized VIKOR model for assessing the RESs under Pythagorean fuzzy environment. They presented their model with the combination of Pythagorean fuzzy entropy and divergence measures. Suh et al. (2019) discussed a fuzzy VIKOR approach and then applied in mobile service quality selection problem. Yücenur and Şenol (2021) studied a sequential SWARA and fuzzy VIKOR approaches for construction of a lean production system by choosing the most suitable lean technique. Hosseini et al. (2021) gave an incorporated decision support system with the integration of DEMATEL and fuzzy VIKOR models, and utilized to rank the practical action plans for ecotourism centers. In a study, Mousavi et al. (2021) introduced a decision-analysis tool that allows the R&D executives to efficiently scrutinize the riskiness on fuzzy information and evaluate the related risk factors. Jing et al. (2021) studied a hybridized MADA model with the combination of information entropy, Dempster-Shafer evidence theory and VIKOR models from IFSs perspective. They further implemented their model on an illustrative study of a new tree climbing and trimming machine to validate its effectiveness. Mishra et al. (2022b) discussed a MADA approach based on Fermatean hesitant fuzzy sets (FHFSs) and the modified VIKOR method to handle the decision analysis problems.

1.2 Need of the Paper

Although present studies succeeded in dealing the renewable energy sources (RESs) selection issue, there are three crucial challenges remaining to be addressed.

- In the literature (Khan et al. 2020; Mishra et al. 2019; Gitinavard and Shirazi 2018; Gupta et al. 2023), the weights of the attributes are generally considered to be known as objective type. As decision analysis in an uncertain environment is a sensitive process in terms of the attributes' weights, a single value may change the results. Thus, there is a need for a method that calculates the weights of the attributes using the DEs' assessments of the alternatives as subjective type also.
- The methods (Khan et al. 2020; Mishra et al. 2019; Gitinavard and Shirazi 2018) developed for the specific uncertain settings are not flexible enough for implement in various uncertain settings without significant changes. Uncertainty is a concern that cannot be treated in a single specific setting. There is a need for a model that can be implemented in diverse uncertain settings without many changes.
- The MADA models under uncertain setting have been validated to be effective for RESs selection. However, complex decision analysis in realistic prob-

lems should permit diverse DMEs to explicate individual views with different linguistic assessments and even different kinds of depictions, which may be neglected in extant models. To precisely explore the realistic decision analysis, it is essential to propose an MADA model involving multiple DMEs, multiple sustainability dimensions, multiple factors and multiple preferences.

1.3 Contribution of the Study

Since the concept of FS has proposed (Zadeh 1965), many innovative concepts of higher order FS have been introduced. Among them, the concept of IFS has been found to be highly efficient in managing the vagueness. To take the flexibility and effectiveness of IFS theory, the current study establishes a hybridized decision-analysis tool to solve the MADA problem from the intuitionistic fuzzy information (IFI) perspective. For this purpose, an integrated weight model is proposed with the integration of the IF-CRITIC and IF-RS models. The IF-CRITIC and IF-RS tools are presented to determine the objective and subjective weighting values of the criteria, respectively. Further, an extension of IF-VIKOR approach is presented with new distance measure and combined weight-determining model, and named as IF-CRITIC-RS-VIKOR. The proposed VIKOR method is utilized to assess the multi-criteria RESs from intuitionistic fuzzy perspective. The key contributions of the proposed study are as follows:

- Two new intuitionistic fuzzy distance measures are proposed to quantify the distance between IFSs.
- An integrated weighting procedure by utilizing the IF-CRITIC and IF-RS models is presented to compute the weight values of considered factors.
- New intuitionistic fuzzy distance measures to calculate the "group utility (GU)" and "individual regret (IR)" degrees of candidate RESs.
- A hybrid IF-VIKOR method is proposed based on new distance measure and a combined weighting procedure for the aim of ranking the RESs.
- Comparative study and sensitivity investigation are performed to validate the obtained results by IF-CRITIC-RS-VIKOR method.

1.4 Organization of the Study

The rest part of the study is arranged in the following way: in Sect. 1, we discuss some existing studies related to this paper. In Sect. 2, we present the preliminaries and developed IF-distance measures. In Sect. 3, we introduce a hybridized approach for RESs assessment under IFS context. In Sect. 4, the developed IF-CRITIC-RS-VIKOR approach is applied to a case study of RESs assessment problem. Section 5 discusses the findings and results of comparative and sensitivity analyses. Section 6 confers the conclusions and further scopes for future researches.

2 Proposed Intuitionistic Fuzzy Distance Measure

This section proposes new distance measures for IFSs. For this purpose, we firstly present some basic concepts related to IFSs.

2.1 Preliminaries

Atanassov (1986) gave the idea of IFS, which is mathematically presented as.

Definition 2.1. An IFS K on $Y = \{y_1,\ y_2,\ ...,\ y_n\}$ is defined as.

$$K = \{\langle y_j,\ \mu_K(y_j),\ \nu_K(y_j)\rangle\ :\ y_j \in Y\}, \tag{1}$$

where $\mu_K : Y \to [0,\ 1]$ and $\nu_K : Y \to [0,\ 1]$ represent the membership and non-membership degrees, respectively, of y_j to K in Y, with the condition

$$0 \le \mu_K(y_j) \le 1, \quad 0 \le \nu_K(y_j) \le 1 \quad \text{and} \quad 0 \le \mu_K(y_j) + \nu_K(y_j) \le 1, \quad \forall\ y_j \in Y. \tag{2}$$

The hesitation degree of an object $y_j \in Y$ to K is given by

$$\pi_K(y_j) = 1 - \mu_K(y_j) - \nu_K(y_j) \quad \text{and} \quad 0 \le \pi_K(y_j) \le 1,\ \ \forall y_j \in Y.$$

For convenience, Xu (2007) characterized the IFN $\varsigma = (\mu_\varsigma,\ \nu_\varsigma)$, which satisfies $\mu_\varsigma,\ \nu_\varsigma \in [0,\ 1]$ and $0 \le \mu_\varsigma + \nu_\varsigma \le 1$.

Definition 2.2 (Xu 2007). The score and accuracy values of an IFN $\varsigma_j = (\mu_j,\ \nu_j)$ is defined by

$$S(\varsigma_j) = (\mu_j - \nu_j) \tag{3}$$

$$A(\varsigma_j) = (\mu_j + \nu_j), \tag{4}$$

respectively. Here, $S(\varsigma_j) \in [-1, 1]$ and $A(\varsigma_j) \in [0, 1]$.

As $S(\varsigma_j) \in [-1, 1]$, then Xu et al. (2015) discussed a modified score function for IFN, which as.

Definition 2.3 (Xu et al. 2015). Consider $\varsigma_j = (\mu_j,\ \nu_j)$ be an IFN. Then,

$$S^*(\varsigma_k) = \frac{1}{2}(S(\varsigma_j) + 1) \tag{5}$$

is defined as normalized score function for IFN ς_j. Here, $S^*(\varsigma_j) \in [0, 1]$.

Definition 2.4 (Xu 2007) Let $\varsigma_j = (\mu_j,\ \nu_j)$, $j = 1, 2, ... n$ be the collection of IFNs. Then the intuitionistic fuzzy weighted averaging (IFWA) and the intuitionistic fuzzy weighted geometric (IFWG) operators are presented as

$$IFWA_w(\varsigma_1, \varsigma_2, ..., \varsigma_n) = \overset{n}{\underset{j=1}{\oplus}} \psi_j \varsigma_j = \left[1 - \prod_{j=1}^{n} \left(1 - \mu_j\right)^{\psi_j}, \prod_{j=1}^{n} \nu_j^{\psi_j} \right], \tag{6}$$

$$IFWG_w(\varsigma_1, \varsigma_2, ..., \varsigma_n) = \overset{n}{\underset{j=1}{\otimes}} \varsigma_j^{\psi_j} = \left[\prod_{k=1}^{n} \mu_j^{\psi_j}, 1 - \prod_{j=1}^{n} \left(1 - \nu_j\right)^{\psi_j} \right]. \tag{7}$$

In Eqs. (6) and (7), $\psi = \left(\psi_1, \psi_2, ..., \psi_n\right)^T$ denotes the weight values of ς_j, $j = 1, 2, ..., n$, with $\sum_{j=1}^{n} \psi_j = 1$ and $\psi_j \in [0, 1]$.

Definition 2.5 (Xu and Chen 2008a, b). An IF-distance measure is a real-valued function $d : IFSs(Y) \times IFSs(Y) \to [0, 1]$, which fulfils the following axioms:

(r_1). $0 \leq d(K, L) \leq 1$, $\forall K, L \in IFSs(Y)$,
(r_2). $d(K, L) = 0 \Leftrightarrow K = L$, $\forall K, L \in IFSs(Y)$,
(r_3). $d(K, K^c) = 1 \Leftrightarrow K = K^c$, $\forall K \in IFS(Y)$, where K^c represents the complement of K.
(r_4). $d(K, L) = d(L, K)$, $\forall K, L \in IFSs(Y)$,
(r_5). If $K \subseteq L \subseteq M$, then $d(K, M) \geq d(K, L)$ and $d(K, M) \geq d(L, M)$, $\forall K, L, M \in IFSs(Y)$.

2.2 Distance Measures for IFSs

As the exponential function has an advantage over the polynomial, trigonometric and logarithmic functions. Inspired by Hung and Yang (2008a, b), this study combines the exponential function and Hamming distance to propose new distance measures for IFSs.

Let $K, L \in IFSs(Y)$. Then a new generalized intuitionistic fuzzy distance measure is given as follows:

$$d_1(K, L) = \frac{1 - \exp\left[-\frac{1}{2} \left(\sum_{j=1}^{n} \left(\left| \mu_K(y_j) - \mu_L(y_j) \right|^{\alpha} + \left| \nu_K(y_j) - \nu_L(y_j) \right|^{\alpha} \right) \right)^{1/\alpha} \right]}{1 - \exp(-n)}, \quad \alpha > 0, \quad \alpha \neq 1. \tag{8}$$

Lemma 2.1 *If* $\phi(\lambda) = \frac{1 - \exp(-\lambda)}{1 - \exp(-n)}$, *then*

$$\min_{\lambda \in [0, n]} \phi(\lambda) = \phi(0) = 0 \quad \text{and} \quad \max_{\lambda \in [0, n]} \phi(\lambda) = \phi(n) = 1.$$

Proof Since $\phi'(\lambda) = \frac{\exp(-\lambda)}{1 - \exp(-n)} < 0$, $\forall \lambda \in [0, n]$, thus, $\phi(\lambda)$ is increasing in $[0, n]$. □

Theorem 2.1 *The measure* $d_1(K, L)$, *defined by Eq.* (8), *is a valid distance measure for IFSs.*

Proof In the following, we prove the requirements of Definition 2.5:

(r_1). Let $\lambda = \frac{1}{2}\left(\sum_{j=1}^{n}\left(\left|\mu_K(y_j) - \mu_L(y_j)\right|^{\alpha} + \left|\nu_K(y_j) - \nu_L(y_j)\right|^{\alpha}\right)\right)^{1/\alpha}$.

Since $\lambda \in [0, n]$, therefore, $d_1(K, L) = \phi(\lambda)$. Hence, using Lemma 2.1, we have $0 \le d_1(K, L) \le 1$.

(r_2). Let $K = L$. This implies that $\mu_K(y_j) = \mu_L(y_j)$, $\nu_K(y_j) = \nu_L(y_j)$, $\forall y_j \in Y$. Thus, from Eq. (8), we have $d_1(K, L) = 0$.

Suppose $d_1(K, L) = 0$. Then Eq. (8) becomes

$$\frac{1 - \exp\left[-\frac{1}{2}\left(\sum_{j=1}^{n}\left(\left|\mu_K(y_j) - \mu_L(y_j)\right|^{\alpha} + \left|\nu_K(y_j) - \nu_L(y_j)\right|^{\alpha}\right)\right)^{1/\alpha}\right]}{1 - \exp(-n)} = 0,\ \alpha > 0,\ \alpha \neq 1, \forall y_j \in Y.$$

It implies that

$$\sum_{j=1}^{n}\left(\left|\mu_K(y_j) - \mu_L(y_j)\right|^{\alpha} + \left|\nu_K(y_j) - \nu_L(y_j)\right|^{\alpha}\right) = 0,\ \forall y_j \in Y.$$

Thus, $K = L$.

(r_3)-(r_4). These properties are obvious. Hence, we omitted the proofs.

(r_5). Let $K \subseteq L \subseteq M$. Then, $\mu_K(y_j) \le \mu_L(y_j) \le \mu_M(y_j)$ and $\nu_M(y_j) \le \nu_L(y_j) \le \nu_K(y_j)$, $\forall y_j \in Y$.

Consider

$$\lambda_1 = \frac{1}{2}\left(\sum_{j=1}^{n}\left(\left|\mu_K(y_j) - \mu_L(y_j)\right|^{\alpha} + \left|\nu_K(y_j) - \nu_L(y_j)\right|^{\alpha}\right)\right)^{1/\alpha}$$
$$\le \lambda_2 = \frac{1}{2}\left(\sum_{j=1}^{n}\left(\left|\mu_K(y_j) - \mu_M(y_j)\right|^{\alpha} + \left|\nu_K(y_j) - \nu_M(y_j)\right|^{\alpha}\right)\right)^{1/\alpha}, \quad \forall y_j \in Y.$$

In accordance with Lemma 2.1, we get $d_1(K, L) = \phi(\lambda_1) \le \phi(\lambda_2) = d_1(K, M)$. Similarly, we can express that $d_1(L, M) \le d_1(K, M)$. Hence, the measure $d_1(K, L)$ is a valid distance measure for IFSs.

Here, we propose one more distance measure to quantify the degree of distance between IFSs.

Consider $K = (k_{ij})$ and $L = (l_{ij})$, $i = 1, 2, ..., m$, $j = 1, 2, ..., n$ be two matrices such that $s_{ik} = \left\langle \mu_{ij}^{k}, \nu_{ij}^{k} \right\rangle$ and $l_{ij} = \left\langle \mu_{ij}^{l}, \nu_{ij}^{l} \right\rangle$ are IFNs. Now, the intuitionistic fuzzy distance measure between K and L is given by

$$d_2(K, L) = \frac{1 - \exp\left[-\frac{1}{2}\left(\sum_{i=1}^{m}\sum_{j=1}^{n}\left(\left|\mu_{ij}^{k} - \mu_{ij}^{l}\right|^{\alpha} + \left|\nu_{ij}^{k} - \nu_{ij}^{l}\right|^{\alpha}\right)\right)^{1/\alpha}\right]}{1 - \exp(-mn)}, \quad i = 1, 2, ..., m. \tag{9}$$

□

Theorem 2.2 *The measure $d_2(K, L)$, defined by Eq. (9), is a valid distance measure for IFSs.*

Proof Proof is similar as Theorem 2.1. Thus, we have omitted the proof. □

3 Proposed IF-CRITIC-RS-VIKOR Method for Solving MADA Problems

This section introduces an extended MADA framework, named as IF-CRITIC-RS-VIKOR. In this framework, the objective weights of attributes are determined by the IF-CRITIC model and the subjective weights of attributes are derived by the IF-RS process. Moreover, the new IF-distance measure-based VIKOR approach is introduced to assess and prioritize the alternatives over considered criteria. The steps of IF-CRITIC-RS-VIKOR model are displayed as follows:

Step 1: Create the linguistic decision matrix (LDM).

Firstly, consider the sets of alternatives/options and criteria, which are $G = \{g_1, g_2, ..., g_p\}$ and $H = \{h_1, h_2, ..., h_q\}$, respectively. Form a group of DMEs $D = \{d_1, d_2, ..., d_l\}$ to elect the best candidate(s) among a set of options. Let $T = \left(\xi_{ij}^{(m)}\right)_{p\times q}$ be the LDM presented by DMEs, wherein $\xi_{ij}^{(m)}$ denotes the linguistic performance value of a candidate g_i by means of a criterion h_j provided by mth DME.

Step 2: Find the crisp weight of DMEs.

In order to process the group decision analysis, it is very significant to derive the weight of DMEs. In this sense, firstly we present the significance values of DMEs in the form of linguistic ratings (LRs) and their consequent IFNs as per discussion with experts. If $d_m = (t_m, f_m)$ be the significance value of mth DME, then the weight of the mth DME is given by

$$\lambda_m = \frac{1}{2}\left(\frac{t_m(2 - t_m - f_m)}{\sum_{m=1}^{l}\left[t_m(2 - t_m - f_m)\right]} + \frac{l - r_m + 1}{\sum_{k=1}^{l}(l - r_m + 1)}\right), \quad m = 1, 2, ..., l, \tag{10}$$

where $\lambda_m \geq 0$ and $\sum\limits_{m=1}^{l} \lambda_m = 1$.

Step 3: Make the aggregated IF-decision matrix (AIF-DM).

For this purpose, the IFWA (or IFWG) operator is used to find the AIF-DM $Z = (z_{ij})_{p\times q} = (t_{ij}, f_{ij})$, where

$$z_{ij} = (t_{ij}, f_{ij}) = IFWA_\lambda\left(\xi_{ij}^{(1)}, \xi_{ij}^{(2)}, ..., \xi_{ij}^{(l)}\right) \text{ or } IFWG_\lambda\left(\xi_{ij}^{(1)}, \xi_{ij}^{(2)}, ..., \xi_{ij}^{(l)}\right). \tag{11}$$

Step 4: Integrated IF-CRITIC-RS model for deriving the criteria weights.

In the following, the criteria significance degrees are computed by the combination of objective weights by IF-CRITIC approach and subjective weights by IF-RS model.

Case I: Objective weights by IF-CRITIC model.

The IF-CRITIC model includes the following phases:

Step 4a: Create the score matrix $\Theta = \left(\wp_{ij}\right)_{p\times q}$, $i = 1, 2, ..., p$, $j = 1, 2, ..., q$, wherein

$$\wp_{ij} = 0.5\left(\left(t_{ij} - f_{ij}\right) + 1\right), \quad i = 1, 2, ..., p, \quad j = 1, 2, ..., q, \tag{12}$$

Step 4b: Form the standard matrix $\tilde{\Theta} = \left(\tilde{\wp}_{ij}\right)_{p\times q}$, wherein

$$\tilde{\wp}_{ij} = \begin{cases} \dfrac{\wp_{ij} - \wp_j^-}{\wp_j^+ - \wp_j^-}, & j \in h_b \\ \dfrac{\wp_j^+ - \wp_{ij}}{\wp_j^+ - \wp_j^-}, & j \in h_n \end{cases} \tag{13}$$

wherein $\wp_j^+ = \max\limits_i \wp_{ij}$ and $\wp_j^- = \min\limits_i \wp_{ij}$.

Step 4c: Calculate the criteria standard deviations by using

$$\sigma_j = \sqrt{\frac{\sum\limits_{i=1}^{p} \left(\tilde{\wp}_{ij} - \overline{\wp}_j\right)^2}{p}}, \quad \text{wherein} \quad \overline{\wp}_j = \sum\nolimits_{i=1}^{p} \tilde{\wp}_{ij}/p. \tag{14}$$

Step 4d: Evaluate the correlation coefficients between the criteria pairs:

$$c_{jk} = \frac{\sum\limits_{i=1}^{p} \left(\tilde{\wp}_{ij} - \overline{\wp}_j\right)\left(\tilde{\wp}_{ik} - \overline{\wp}_k\right)}{\sqrt{\sum\limits_{i=1}^{p} \left(\tilde{\wp}_{ij} - \overline{\wp}_j\right)^2 \sum\limits_{i=1}^{p} \left(\tilde{\wp}_{ik} - \overline{\wp}_k\right)^2}}. \tag{15}$$

Step 4e: Find the amount of information of criteria by using

$$I_j = \sigma_j \sum_{k=1}^{q} \left(1 - c_{jk}\right), \quad j = 1, 2, ..., q. \tag{16}$$

Step 4f: Estimate the objective weight of *j*th criterion

$$w_j^o = \frac{I_j}{\sum_{j=1}^{q} I_j}, \quad j = 1, 2, ..., q. \tag{17}$$

Case II: Criteria weights by subjective weighting model.

For this purpose, we utilize the IF-RS model. The formula of IF-RS method is presented as

$$w_j^s = \frac{q - r_j + 1}{\sum_{j=1}^{q} \left(q - r_j + 1\right)}, \quad j = 1, 2, ..., q. \tag{18}$$

where r_j represents the rank of each criterion, $j = 1, 2, \ldots, q$.

Case III: Combined weights of criteria.

In the following, we combine the IF-CRITIC and IF-RS models to take the advantages of objective and subjective weight-determining approaches. The formula for combined weight of *j*th criteria is discussed as

$$w_j = \tau w_j^o + (1 - \tau) w_j^s, \quad j = 1, 2, ..., q, \tag{19}$$

wherein $\tau \in [0, 1]$ be the coefficient of decision strategy.

Step 5: Form the best and worst values.

Here, the IF-IS ϕ_j^+ and the IF-AIS ϕ_j^- are defined as the best and worst values, where

$$\phi_j^+ = \begin{cases} \max\limits_i t_{ij}, & \text{for } \textit{benefit criterion } h_b \\ \min\limits_i f_{ij}, & \text{for } \textit{cost criterion } h_n \end{cases} \quad \textit{for } j = 1, 2, ..., q, \tag{20}$$

$$\phi_j^- = \begin{cases} \min\limits_i t_{ij}, & \text{for } \textit{benefit criterion } h_b \\ \max\limits_i f_{ij}, & \text{for } \textit{cost criterion } h_n \end{cases} \quad \textit{for } j = 1, 2, ..., q. \tag{21}$$

Step 6: Estimate the GU, IR and compromise score (CS).

In accordance with proposed IF-distance measure and AIF-DM, we compute the GU $\left(x_i\right)$ and the IR $\left(y_i\right)$ over each option g_i and are given by

$$x_i = L_{1,i} = \sum_{j=1}^{q} w_j \frac{d_\beta\left(\phi_j^+, z_{ij}\right)}{d_\beta\left(\phi_j^+, \phi_j^-\right)}, \quad \beta = 1, 2, \tag{22}$$

$$y_i = L_{\infty,i} = \max_{1 \le j \le q} \left(w_j \frac{d_\beta\left(\phi_j^+, z_{ij}\right)}{d_\beta\left(\phi_j^+, \phi_j^-\right)} \right), \tag{23}$$

where $d_\beta\left(\phi_j^+, z_{ij}\right), \beta = 1, 2$ is defined in Eq. (8) [or Eq. (9)].

The CS (e_i) for each option is computed as

$$e_i = \tau \frac{\left(x_i - x^+\right)}{\left(x^- - x^+\right)} + (1 - \tau) \frac{\left(y_i - y^+\right)}{\left(y^- - y^+\right)}, \tag{24}$$

where $x^{+} = \min_i x_i$, $x^{-} = \max_i x_i$, $y^{+} = \min_i y_i$, $y^{-} = \max_i y_i$ and $\tau \in [0, 1]$ is the coefficient of decision mechanism.

Step 7: Prioritize the options.

Corresponding to the values of GU, IR and CS, determine the ranking order of the given options.

Step 8: Determination of the compromise solution.

Consider the candidate g_i as a CS in accordance with e_1 (the least among e_i values) if

(P_1): The option g_i has an acceptable advantage, i.e., $e_2 - e_1 \geq \frac{1}{(p-1)}$, wherein p determines the number of alternatives.

(P_2): The alternative g_i is stable in the MADA process; i.e., it is also best rated by x_i or y_i.

If anyone of the conditions is not hold, then a group of CSs is presented, which consists of.

Alternatives g_1 and g_2 if only the condition (P_2) is not hold.

Alternatives $g_1, g_2, g_3, \ldots, g_k$ if (P_1) is not satisfied and g_k is evaluated by $e_k - e_1 < \frac{1}{(p-1)}$.

4 Case Study: Assessment of Renewable Energy Source (RESs) Selection

Energy is one of the major inputs for the economic growth of any country. Due to technological advancements and human needs, the global energy demand grows much faster than the increase in energy supply. Together with the energy consumption, environmental pollution and the GHG emissions from human activities are also increasing speedily. As an elucidation to this global issue, a shift to renewable and clean energy sources is arising globally. Fossil fuels supply about 80% of current global primary energy demand. The RESs are becoming more and more crucial because it has the potential to offer the ready supply of power without utilizing natural resources, mitigate climate change, reduce the environmental footprint of the energy and assure the requirement of clean and sustainable development (Alberizzi et al. 2020; Ulewicz et al. 2021).

Energy services have an intense effect on health, food and water security, education, productivity and communication services. Accessibility to sustainable energy service is essential to ensure an improved quality of life, better health, poverty reduction, social and economic growth. In the recent period, many investigators have paid their interest on the prioritization of most appropriate energy source for given sectors. The optimization of energy source selection against several indicators could help the policymakers to make a decision regarding the energy consumption, supply, and production (Gupta et al. 2023; Mishra et al. 2019). In this respect, the MADA approaches have been considered as one of the most appropriate ways to deal with the realistic problems (Gao et al. 2021; Ali et al. 2020).

Clean and affordable energy plays an imperative role in achieving the sustainable development goals and its accessibility remains a challenge in most of the developing countries. Selection of most suitable RES alternative would not only enhance the economic growth of the nation but also reduce the negative impacts of climate change and ecological burdens. In the process of MADA with multiple experts, each decision-making expert (DME) expresses the qualitative or quantitative measure or both to assess the given set of alternatives under different criteria. On the other hand, due to the ambiguity and subjectivity of DMEs' judgments in the assessment of RES selection, it is impossible to provide the accurate performance values of the candidates by means of multiple sustainability indicators/factors/criteria.

In this study, we discuss a case study of RESs assessment in Tamil Nadu, India, which illustrates the application of introduced IF-CRITIC-RS-VIKOR methodology. Tamil Nadu is a state in southern India. This state is bordered by Kerala to the west, Andhra Pradesh to the north, Karnataka to the northwest, the Bay of Bengal to the east and the Indian Ocean to the south. This state is blessed with various natural resources and the Government has set up an agency, namely "Tamil Nadu Energy Development Agency (TEDA)" in 1985 (Elavarasan et al. 2020), to mitigate the climate change and meet the demand of energy in a sustainable manner. Figure 1 displays the overall installed capacity through different RESs in Tamil Nadu (MNRE Report 2022).

Based on comprehensive analysis, 4 RESs are chosen as the potential candidates, shown in Fig. 1. Further, a team of 4 DMEs is formed to assess the given candidate RESs over a set of sustainable indicators. In view of the literature survey and

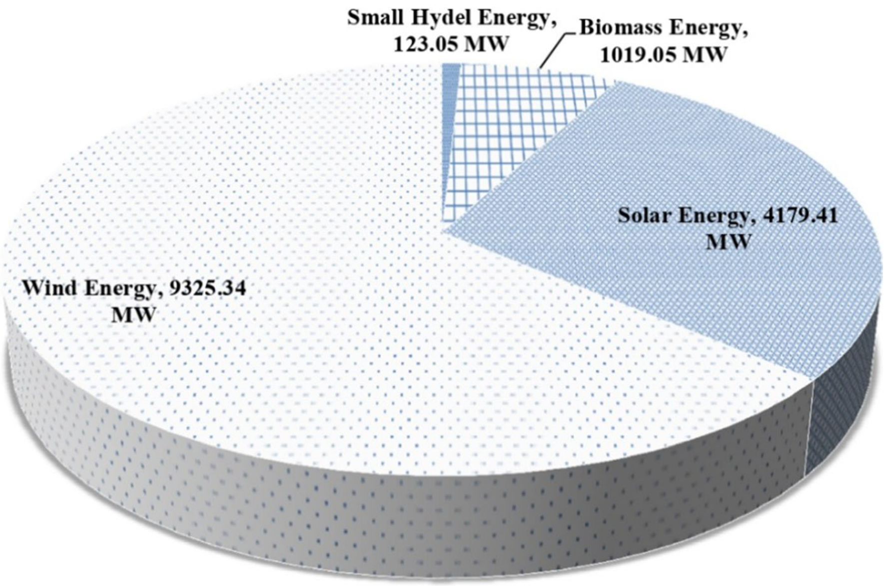

Fig. 1 The overall installed capacity of RESs in Tamil Nadu as on 31st January 2022 (MNRE report)

discussion with DMEs, a set of 13 criteria are chosen by taking the technological, economic, environmental and social dimensions into consideration (see Table 1).

Nowadays, the energy consumption appears a never-ending increasing tendency. The sustainable development goals are the blueprint to accomplish a better and more sustainable future for all. In order to meet future energy challenges, it is required to assess and select the RESs from various sustainability perspectives. According to the relevant literatures and discussions, we consider four different pillars of sustainability, which are economic, environmental, social and technological, which are needed to be considered in the processes of evaluating RESs (Kaya and Kahraman 2010; Zhao et al. 2022; Alkan and Albayrak 2020). The details of the four aspects are interpreted as follows:

4.1 Social Factors

In this study, we have considered three indicators of social factors, which are as follows:

Public acceptance (h_1) (Lee and Chang 2018; Abdul et al. 2021; Rani et al. 2020; Cui et al. 2020): public acceptance is of utmost importance for the successful execution of RES project (Lee and Chang 2018). People will approve this project as long as it is 'Not-in-My-Backyard' (Cui et al. 2020). But when it is 'in my backyard', their attitude may be different. Local residents may resist the construction of the RES projects because of the unknown effects on health and ecosystem.

Job creation (h_2) (Malkawi et al. 2017; Ahmad et al. 2017; Abdul et al. 2021): the implementation of renewable energy projects employs a number of employees from manufacture to operation (Wu et al. 2018; Abdul et al. 2021). Hence, job creation is created as an important factor in RESs assessment.

Social benefits (h_3) (Wang et al. 2009; Hezam et al. 2022): social benefits are directly related to the people' life (Wang et al. 2009). It denotes the social

Table 1 Index system for the RES evaluation

Dimensions	Criteria	Types
Social (*S*)	Public acceptability (h_1)	Beneficial
	Job creation (h_2)	Beneficial
	Social benefits (h_3)	Beneficial
Environmental (*En*)	Impact on land (h_4)	Beneficial
	Greenhouse gas emissions (h_5)	Non-beneficial
	Impact on ecosystem (h_6)	Beneficial
Economic (*Ec*)	Operational life (h_7)	Beneficial
	Operation and maintenance cost (h_8)	Non-beneficial
	Investment cost (h_9)	Non-beneficial
	Technology cost (h_{10})	Non-beneficial
Technological (*T*)	Reliability (h_{11})	Beneficial
	Maturity (h_{12})	Beneficial
	Efficiency (h_{13})	Beneficial

development accompanied by commencing a RES project in the region (Wu et al. 2018).

4.2 Environmental Aspects

Environmental aspects (*En*) involve impact on land (h_4), greenhouse gas emission (h_5) and impact on ecosystem (h_6).

Land use (h_6) (Wang et al. 2009; Abdul et al. 2021): the establishment of RES projects will require land use planning to meet the sustainable development goals. The acquisition of the land is a major challenge for the companies operating in the RES projects.

Greenhouse gas emission (h_5) (Wang et al. 2009; Kaya and Kahraman 2010; Alkan and Albayrak 2020; Abdul et al. 2021; Rani et al. 2020): greenhouse gases may cause various environmental problems such as negative effects of climate change, which is an important factor to monitor the effect of RES because the less greenhouse gas emission is a main difference between RES and traditional fossil fuel (Rani et al. 2020).

Impact on ecosystem (h_4) (Al Garni et al. 2016; Wu et al. 2018; Abdul et al. 2021): creation of new RES projects may negatively affect the ecosystem services. Measurement of eco-friendly is required to keep the ecological balance and biodiversity (Amer and Daim 2011).

4.3 Economic Aspects

Economic aspects (*Ec*) include 4 sub-criteria which are presented as follows:

Operational life (h_7) (Wang et al. 2009; Kaya and Kahraman 2010; Al Garni et al. 2016; Alkan and Albayrak 2020; Abdul et al. 2021): long operational life is more preferable for RES projects (Wang et al. 2009). Thus, it is considered as a significant factor for RESs assessment.

Operation and maintenance (O&M) cost (h_8) (Wang et al. 2009; Amer and Daim 2011; Wu et al. 2018; Lee and Chang 2018): O&M cost consists of two parts operation cost and maintenance cost. Operation cost includes the overall expenses of wages, material purchase, and the necessary products and services for operations (Wang et al. 2009). Maintenance cost means the budget used to keep normal operation of equipment and prolong the life of RES project (Wu et al. 2018).

Investment cost (h_9) (Wang et al. 2009; Kaya and Kahraman 2010; Wu et al. 2018; Lee and Chang 2018): investment cost includes the equipment cost, installation cost, cost etc. (Wu et al. 2018). Thus, the decision makers must consider the investment cost in the evaluation of RESs (Lee and Chang 2018).

Technology cost (h_{10}) (Shen et al. 2010; Abdul et al. 2021): technology cost is a main criterion when assessing RESs, which involves industrial equipment cost, technical development cost and others (Abdul et al. 2021).

4.4 Technological Aspects

Technological aspects (*T*) involve the following criteria in the assessment of RESs:

Reliability (h_{11}) (Kaya and Kahraman 2010; Amer and Daim 2011; Troldborg et al. 2014; Al Garni et al. 2016; Wu et al. 2018): the reliability of a RES project is extremely critical for the DMEs. It considers the capability of the RES projects precisely operated as planned (Wu et al. 2018).

Maturity (h_{12}) (Amer and Daim 2011; Troldborg et al. 2014; Wu et al. 2018; Lee and Chang 2018; Abdul et al. 2021): the maturity is an important criterion when assessing the RES project.

It is a determinant about how broadly the RES technology will spread.

Efficiency (h_{13}) (Amer and Daim 2011; Kaya and Kahraman 2010; Lee and Chang 2018; Abdul et al. 2021): this criterion determines the useful energy output. RES with high efficiency enhances the power generation capacity with reduced energy consumption.

There is no doubt that a comprehensive and reasonable system is beneficial to the evaluation. Hence, an evaluation index system is provided in Table 1.

4.5 Implementation of the Proposed Approach

The systematic process for choosing the most appropriate RES candidate is presented as follows:

Steps 1–3: Tables 2 and 3 show the LRs and their corresponding IFNs for the significance values of the DMEs and criteria (Rani et al. 2021; Mishra et al. 2021). Table 4 presents the computed weights of DMEs by means of Table 2 and Eq. (9). Table 5 represents the linguistic decision opinion of each DME for each RES g_i over the considered criteria. From Table 5 and Eq. (10), the AIF-DM is formed and discussed in Table 6.

Step 4: By utilizing Table 4 and Eqs. (11)–(16), we find the objective weights of criteria. The overall computational steps of CRITIC method for objective weights are presented in Table 7.

From Eq. (17), the subjective weighting values by IF-RS model are determined and mentioned in Table 8.

Table 2 LRs and their corresponding IFNs for DMEs' weights

LRs	IFNs
Absolutely important (AI)	(0.90, 0.10)
Very important (VI)	(0.80, 0.15)
Important (I)	(0.70, 0.25)
Medium (M)	(0.60, 0.35)
Unimportant (U)	(0.40, 0.55)
Very unimportant (VU)	(0.20, 0.75)
Absolutely unimportant (AU)	(0.10, 0.90)

Table 3 LRs and their corresponding IFNs for the importance of criteria

LRs	IFNs
Absolutely significant (AS)	(0.95, 0.05)
Very significant (VS)	(0.85, 0.10)
Much significant (MS)	(0.80, 0.15)
Significant (S)	(0.70, 0.20)
Quite significant (QS)	(0.60, 0.30)
Medium (M)	(0.50, 0.40)
Quite insignificant (QI)	(0.40, 0.50)
Insignificant (IN)	(0.30,0.60)
Much insignificant (MI)	(0.20, 0.70)
Very insignificant (VI)	(0.10, 0.80)
Absolutely insignificant (AI)	(0.05, 0.95)

Table 4 DMEs' weights for RESs assessment

DMEs	LRs	IFNs	Score value	Rank	Weight
d_1	VI	(0.80, 0.15)	0.8400	2	0.2853
d_2	I	(0.70, 0.25)	0.7350	3	0.2184
d_3	M	(0.60, 0.35)	0.6300	4	0.1514
d_4	AI	(0.90, 0.10)	0.9000	1	0.3449

Table 5 LDM created by the opinions of DMEs

Criteria	g_1	g_2	g_3	g_4
h_1	(QS,S,M,QS)	(MS,S,MS,M)	(QI,QS,M,QS)	(MS,QI,M,QS)
h_2	(VS,S,M,QS)	(QS,S,MS,M)	(QI,QS,M,MS)	(S,QI,M,S)
h_3	(M,S,QS,MS)	(VS,S,S,M)	(QS,S,M,S)	(QS,S,M,QS)
h_4	(M,MS,QS,S)	(QS,S,S,QS)	(QS,QS,M,S)	(S,QI,MS,MS)
h_5	(I,MI,MI,QI)	(I,QI,MI,I)	(M,QI,M,I)	(QI,QI,M,I)
h_6	(M,QI,MS,M)	(I,QI,M,S)	(S,MS,M,QS)	(M,QS,M,S)
h_7	(QS,I,M,VS)	(M,I,QI,QS)	(QS,M,MS,S)	(VS,S,M,QS)
h_8	(MI,I,M,I)	(M,MI,I,QI)	(M,QS,QI,I)	(MI,QI,MI,QI)
h_9	(I,MI,I,MI)	(MI,QI,MI,M)	(M,I,M,QI)	(QI,I,M,M)
h_{10}	(I,MI,M,I)	(MI,I,I,QI)	(QS,M,QI,M)	(MI,I,QI,I)
h_{11}	(QS,M,MI,QI)	(M,QI,QS,S)	(S,M,S,VS)	(QS,QI,M,MS)
h_{12}	(AS,QI,M,QS)	(MS,QS,M,QS)	(MS,M,QS,QI)	(QI,QS,MS,S)
h_{13}	(MS,S,MS,M)	(M,MS,MS,QS)	(QS,QI,M,)	(QS,MS,MS,S)

To find the final weights of criteria, we combine the IF-CRITIC and IF-RS model by means of Eq. (18). Thus, the final criteria weights' set is given as ($\tau = 0.5$).

w=(0.0678, 0.0582, 0.0856, 0.0797, 0.0424, 0.1334, 0.0639, 0.0859, 0.0591, 0.1018, 0.0633, 0.0668, 0.0922).

Table 6 AIF-DM for RESs evaluation

Criteria	g_1	g_2	g_3	g_4
h_1	(0.611, 0.287)	(0.700, 0.224)	(0.536, 0.363)	(0.629, 0.287)
h_2	(0.706, 0.210)	(0.694, 0.215)	(0.634, 0.285)	(0.623, 0.271)
h_3	(0.685, 0.235)	(0.706, 0.208)	(0.648, 0.249)	(0.611, 0.287)
h_4	(0.668, 0.243)	(0.640, 0.258)	(0.625, 0.272)	(0.715, 0.212)
h_5	(0.303, 0.596)	(0.309, 0.590)	(0.416, 0.483)	(0.384, 0.515)
h_6	(0.547, 0.362)	(0.520, 0.371)	(0.672, 0.240)	(0.601, 0.296)
h_7	(0.667, 0.250)	(0.488, 0.409)	(0.658, 0.250)	(0.706, 0.210)
h_8	(0.309, 0.590)	(0.379, 0.519)	(0.426, 0.470)	(0.320, 0.579)
h_9	(0.245, 0.654)	(0.361, 0.536)	(0.427, 0.472)	(0.433, 0.466)
h_{10}	(0.315, 0.584)	(0.310, 0.589)	(0.518, 0.381)	(0.290, 0.610)
h_{11}	(0.464, 0.433)	(0.578, 0.317)	(0.736, 0.183)	(0.644, 0.276)
h_{12}	(0.750, 0.210)	(0.660, 0.257)	(0.604, 0.313)	(0.563, 0.345)
h_{13}	(0.700, 0.224)	(0.715, 0.207)	(0.548, 0.350)	(0.689, 0.224)

Table 7 The standard IF-matrix and objective weight values for RESs using IF-CRITIC tool

Criteria	g_1	g_2	g_3	g_4	σ_j	r_j	w_j
h_1	0.500	1.000	0.000	0.556	0.354	3.313	0.0587
h_2	1.000	0.879	0.000	0.018	0.467	4.092	0.0725
h_3	0.724	1.000	0.428	0.000	0.371	4.082	0.0723
h_4	0.480	0.195	0.000	1.000	0.376	4.036	0.0715
h_5	1.000	0.943	0.000	0.278	0.428	3.544	0.0628
h_6	0.129	0.000	1.000	0.551	0.392	7.617	0.1349
h_7	0.810	0.000	0.787	1.000	0.384	5.355	0.0948
h_8	1.000	0.404	0.000	0.910	0.404	3.493	0.0619
h_9	1.000	0.378	0.033	0.000	0.402	3.570	0.0632
h_{10}	0.887	0.908	0.000	1.000	0.406	3.425	0.0607
h_{11}	0.000	0.443	1.000	0.647	0.362	6.524	0.1156
h_{12}	1.000	0.575	0.226	0.000	0.378	3.818	0.0676
h_{13}	0.898	1.000	0.000	0.860	0.401	3.589	0.0636

Figure 2 shows the objective, subjective and combined weights of attributes for RESs assessment. The parameter Impact on ecosystem (h_6) with weight value 0.1334 has come out to be the most important parameter of RESs selection. Technology cost (h_{10}) with weight value 0.1018 is the second most important factor in the evaluation of RESs. Efficiency (h_{13}) with significance value 0.0922, is the third most important indicator in RESs assessment.

Step 5: By employing Eqs. (19) and (20), the IF-IS and IFA-IS of the RES options are computed as

Table 8 Results by IF-RS model

Criteria	d_1	d_2	d_3	d_4	Aggregated IFNs	Crisp values	Rank of factors	w_j^s
h_1	M	M	QI	QS	(0.524, 0.375)	0.5747	7	0.0769
h_2	QS	M	QI	I	(0.458, 0.438)	0.5100	10	0.0440
h_3	M	S	I	M	(0.529, 0.366)	0.5819	5	0.0989
h_4	S	I	QI	M	(0.522, 0.371)	0.5754	6	0.0879
h_5	I	QS	I	QI	(0.413, 0.484)	0.4642	12	0.0220
h_6	M	S	QS	M	(0.568, 0.329)	0.6192	2	0.1319
h_7	QI	M	S	I	(0.453, 0.441)	0.5055	11	0.0330
h_8	QS	M	I	QS	(0.543, 0.355)	0.5940	4	0.1099
h_9	M	QI	QS	QI	(0.464, 0.434)	0.5150	9	0.0549
h_{10}	S	QI	M	QS	(0.584, 0.312)	0.6357	1	0.1429
h_{11}	I	MI	QS	QI	(0.372, 0.525)	0.4237	13	0.0110
h_{12}	QI	QS	QS	M	(0.515, 0.383)	0.5659	8	0.0659
h_{13}	S	QI	I	QS	(0.562, 0.332)	0.6150	3	0.1209

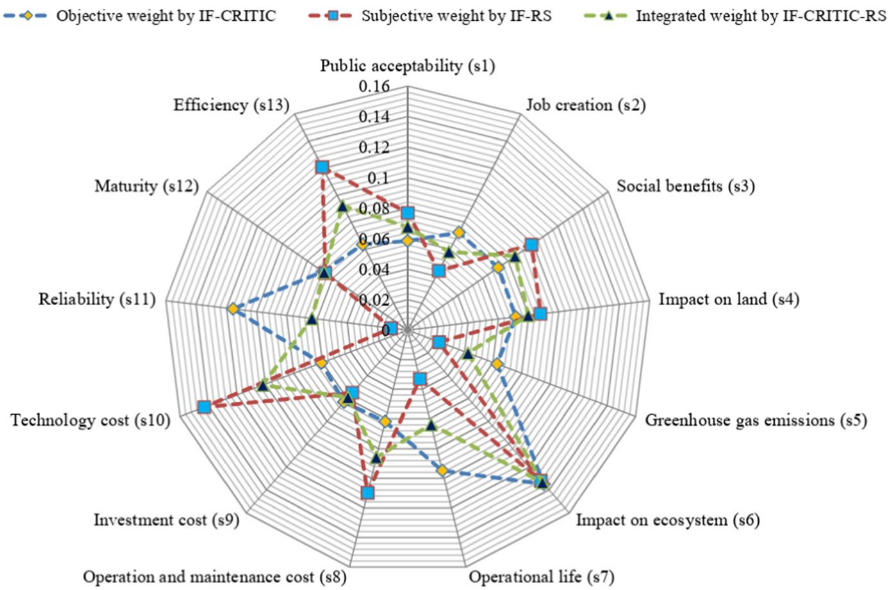

Fig. 2 Weight of considered attributes for RESs selection using IF-CRITIC-RS method

ϕ_j^+ ={(0.700, 0.224), (0.706, 0.210), (0.706, 0.208), (0.715, 0.212), (0.303, 0.596), (0.672, 0.240), (0.706, 0.210), (0.309, 0.590), (0.245, 0.654), (0.290, 0.610), (0.736, 0.183), (0.750, 0.210), (0.715, 0.207)}.

ϕ_j^- ={(0.536, 0.363), (0.634, 0.285), (0.611, 0.287), (0.625, 0.272), (0.416, 0.483), (0.520, 0.371), (0.488, 0.409), (0.426, 0.470), (0.433, 0.466), (0.518, 0.381), (0.464, 0.433), (0.563, 0.345), (0.548, 0.350)}.

Steps 6–8: Using Eqs. (21) and (23), the values of x_i, y_i and e_i are derived and shown in Table 9. In accordance with these obtained values, the prioritization of RESs is determined (see Table 9). Minimum value of e_i determines the best RES g_1, i.e., wind energy is the optimal choice.

5 Comparison and Sensitivity Discussions

This section firstly discusses the comparison between proposed and existing methods. Further, sensitivity analysis is presented to illustrate the robustness of the obtained results.

5.1 Comparative Study

This section is presented to compare the results obtained by the proposed IF-CRITIC-RS-VIKOR and some of the existing methods. For this purpose, we have considered the methods, which are Khan et al. (2020) method, Gupta et al. (2023) method, Mishra et al. (2019) method, Gitinavard and Shirazi (2018), and Mishra (2016) method.

In the literature, by comparison to MADA models with IFNs, various studies exist with intuitionistic fuzzy settings. It is challenging to obtain which solution is ''the best'' in decision-analysis, since each problem has its own set of factors and is dependent on the information available. The field's innovation is focused on the criteria weights, DMEs' weights, and the evaluation information of RES options over different criteria. Here, to certify the developed model, a comparative discussion with the extant related models is presented in Table 10. On the basis of comparative study with COPRAS and TOPSIS models, the advantages of the present method are given as below (see Fig. 3):

(a) The present method computes the criteria weights using combined IF-CRITIC-RS method, which achieves the significance of both the objective and subjective weight-determining models, whereas IF-COPRAS and IF-TOPSIS methods consider only objective weight of criteria by using divergence measure and similarity measure, respectively.

Table 9 The values of x_i, y_i and e_i for the evaluation of RESs

RESs	x_i	y_i	e_i
g_1	0.320	0.118	0.067
g_2	0.441	0.134	0.384
g_3	0.703	0.102	0.934
g_4	0.441	0.085	0.284
Ranking order	$u_1 \succ u_2 \approx u_4 \succ u_3$	$r_4 \succ r_3 \succ r_1 \succ r_2$	$e_1 \succ e_4 \succ e_2 \succ e_3$

(b) The compromise measure based ranking in IF-VIKOR method can not only guarantee the excellent performance of chosen RES candidate, but also avoid the bad performance over each sustainability indicator. Thus, the IF-CRITIC-RS-VIKOR can offer a more precise result in comparison with IF-COPRAS and IF-TOPSIS models.

(c) In comparison with other models, the wind energy is obtained as the most appropriate RES alternative by all methods. But the results obtained by IF-CRITIC-RS-VIKOR are more authentic because it uses both linear and vector normalization processes for aggregation, while IF-COPRAS and IF-TOPSIS models utilize the vector and linear normalization procedures, respectively. Thus, the IF-CRITIC-RS-VIKOR is more general and more valuable for realistic MCDM problems under uncertain environment.

5.2 Sensitivity Investigation

This section presents the sensitivity investigation over to varying values of the criteria weights and the parameter τ. By this process, we analyze the significance of objective and subjective weights for preferred evaluation criteria and the parameter τ in the developed IF-CRITIC-RS-VIKOR method. The analyses are performed by making two cases:

Case I: In the case, firstly the objective weight of attributes is derived by the IF-CRITIC model and subjective weights are estimated with the IF-RS in the place of combined weights. Instead of combined weights, we present the ranking with the objective weighting and subjective weighting of attributes. Figure 4 shows the obtained results by means of varying values ofτ. For $\tau=0.0$ to $\tau=0.2$, the ranking order of RES is $g_4 \succ g_3 \succ g_1 \succ g_2$, for $\tau=0.3$ to $\tau=0.4$, we obtain $g_4 \succ g_1 \succ g_3 \succ g_2$, for $\tau=0.5$ to $\tau=0.9$, we have $g_1 \succ g_4 \succ g_2 \succ g_3$ and for $\tau=1.0$, the prioritization order of RESs is $g_1 \succ g_4 \approx g_2 \succ g_3$. Thus, the option g_4 has secured the first position for $\tau=0.0$ to $\tau=0.4$, while $g_1$has obtained as best choice for $\tau=0.5$ to $\tau=1.0$. This shows that the adequate stability and flexibility of the proposed IF-CRITIC-RS-VIKOR method.

Case II: In the process of MADA, the integration of objective weighting and subjective weighting provides the precise and better weight of attribute. Here, the criteria weights are computed by considering objective weights rather than incorporated weights, i.e., the ranking results have been produced by varying the objective weights in place of IF-CRITIC-RS weight and are given in Table 11 and Fig. 5. Utilizing IF-CRITIC-based procedure, the CSs and the performance values of candidate RESs are $g_1=0.074$, $g_2=0.516$, $g_3=0.901$ and $g_4=0.373$, and the preferences of candidate RESs is given in the following form $g_1 \succ g_4 \succ g_2 \succ g_3$. Applying the IF-RS method, the CSs and the performance values of RESs are $g_1=0.040$, $g_2=0.286$, $g_3=1.000$ and$g_4=0.235$, and the preference ordering of RESs is given in the following form $g_1 \succ g_4 \succ g_2 \succ g_3$. As a consequence, we can say that by employing the different values of parameter will advance the stability of the IF-CRITIC-RS-VIKOR methodology.

Table 10 Parameters to compare the developed model with diverse extant tools

Aspects	Khan et al. (2020) method	Gupta et al. (2023) method	Mishra et al. (2019) method	Gitinavard and Shirazi (2018) method	Mishra (2016) method	Proposed approach
Method	VIKOR	VIKOR	Ranking method	COPRAS	TOPSIS	VIKOR
Environment	Generalized intuitionistic fuzzy soft sets (GIFSSs)	Trapezoidal intuitionistic fuzzy linguistic numbers (TrIFLNs)	IFS	IFS	IFS	IFS
Aggregation process	Not applicable	Einstein arithmetic	Arithmetic	Arithmetic,	Not applicable	Arithmetic
Criteria weights	Only objective weight using score function-based tool	Objective weight using entropy-based method	Objective weight using advantage and disadvantage scores-based method	Computed using IFWAO	Objective weight using information measures	Integrated weight using IF-CRITIC-RS model
MCDM procedure	Single	Group	Group	Group	Single	Group
DMs' weights	Not considered	Evaluated	Computed	Evaluated	Not considered	Evaluated
Normalization type	Linear	Linear	Linear	Not applicable	Vector	Linear
Ranking order	$g_3 \succ g_1 \succ g_2 \succ g_4$	$g_1 \succ g_4 \succ g_2 \succ g_3$	$g_1 \succ g_3 \succ g_4 \succ g_2$	$g_1 \succ g_4 \succ g_2 \succ g_3$	$g_1 \succ g_4 \succ g_2 \succ g_3$	$g_1 \succ g_4 \succ g_2 \succ g_3$
Optimal option	g_3	g_1	g_1	g_1	g_1	g_1

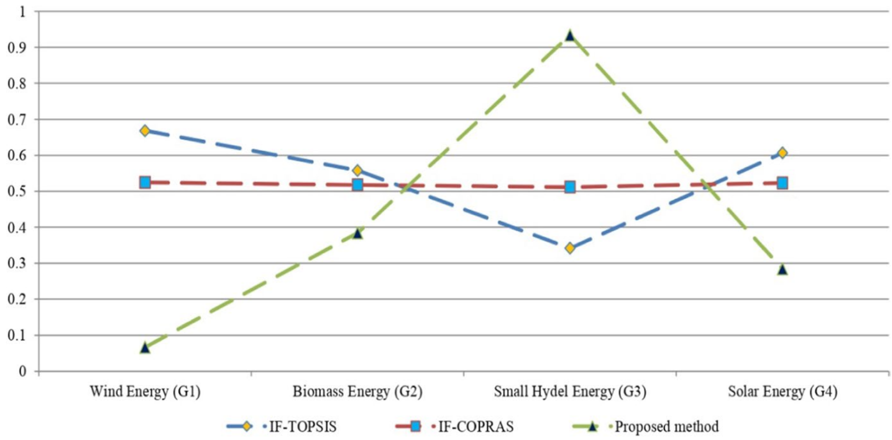

Fig. 3 Prioritization ordering of RESs using diverse methods

6 Conclusions

Excess of sustainability indicators, presence of quantitative and qualitative variables, involvement of subjective ideas and uncertainty make it necessary to use MADA methods for the assessment of RESs. Thus, the purpose of this work is to develop a new MADA model by combining the IF-CRITIC-RS and the IF-VIKOR approaches for assessing the multi-attribute RESs from intuitionistic fuzzy perspective. This model offers a better RESs assessment method to improve the ability of consumers, policymakers, politicians and authorities in making an effective decision. The developed methodology has utilized to assess the RESs in Tamil Nadu, India, considering multiple economic, social, environmental and technological indicators. Based on obtained results, the alternative g_1 (wind energy) has considered as the most optimum RES candidate, while g_3 (Small Hydel Energy) has been obtained as the least attractive alternative. Comparative and sensitivity studies have performed to see the stability and robustness of the obtained outcomes. The findings of the study conclude that the present VIKOR model is suitable for handling the RESs assessment problems under uncertainty and modeling the optimism level of multiple DMEs. In future, the presented IF-CRITIC-VIKOR model can be properly applied to other problems, like electric bus selection, roadmap for renewable energy production based on present and future sustainability assessment, plastic waste disposal technology assessment, and others. In addition, we will implement some other models like as DNMA, MULTIMOORA, and simple weighted sum product (WISP), the gained lost dominance score (GLDS) to review and assess the RESs progress, challenges, and policies of leading states in India with a global perspective.

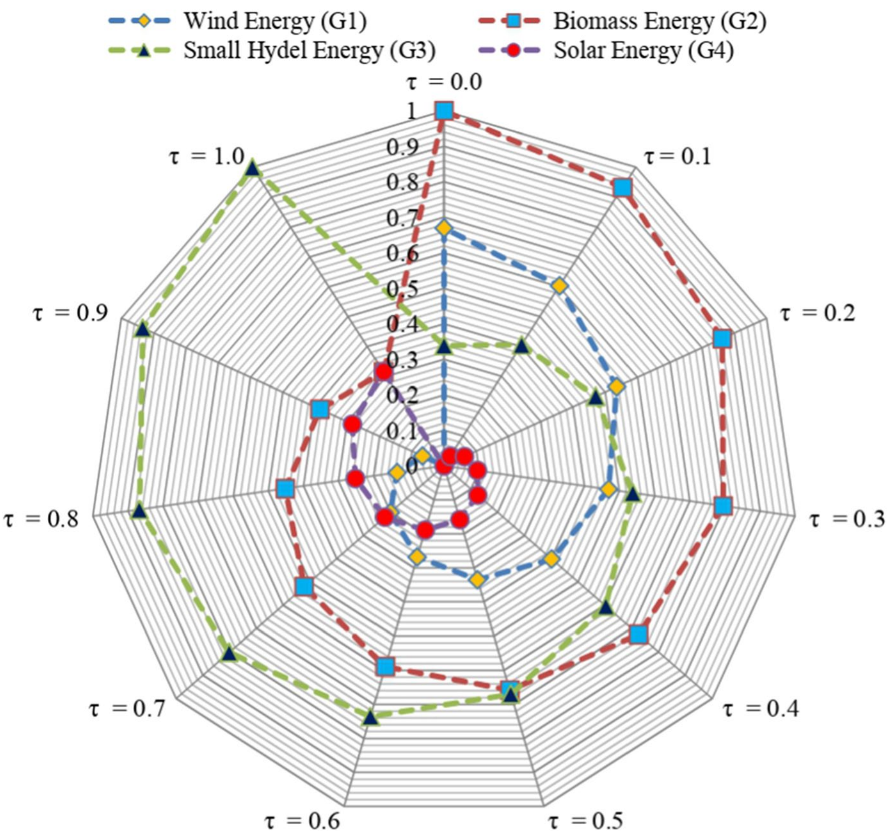

Fig. 4 Obtained ranking results by means of variation in parameter τ

Table 11 The CSs of RESs over different weighting procedures

Weight-determining method	The CSs of RESs options				Ordering
	g_1	g_2	g_3	g_4	
IF-CRITIC method	0.074	0.516	0.901	0.373	$g_1 \succ g_4 \succ g_2 \succ g_3$
IF-RS method	0.040	0.286	1.000	0.235	$g_1 \succ g_4 \succ g_2 \succ g_3$
Integrated method	0.067	0.384	0.934	0.284	$g_1 \succ g_4 \succ g_2 \succ g_3$

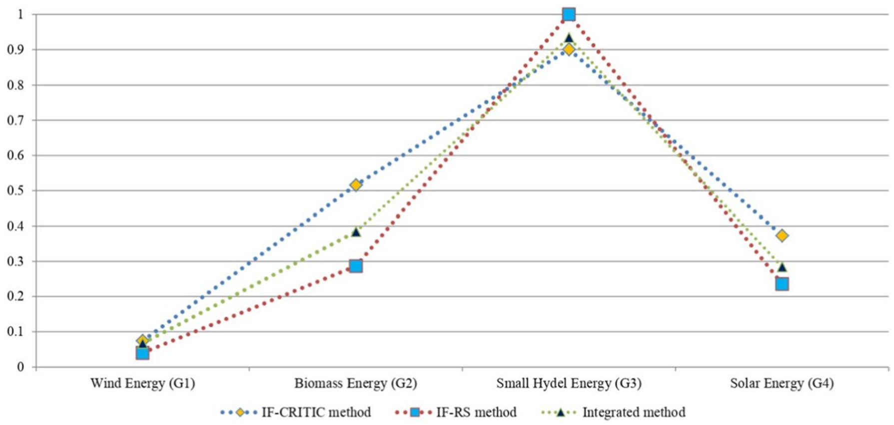

Fig. 5 Results obtained by different weighting methods

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Declarations

Conflict of Interest The authors declare no conflict of interest.

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