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An Interval-Valued Circular Intuitionistic Fuzzy MARCOS Method for Renewable Energy Source Selection

Vahideh Shahin[1,*], Moslem Alimohammadlou[1], Dragan Pamucar[2,3,4,*]

1 Department of Management, Faculty of Economics, Management and Social Sciences, Shiraz University, Shiraz, Iran
2 Department of Applied Mathematical Science, College of Science and Technology, Korea University, Sejong 30019, Republic of Korea
3 Industrial Engineering Department, Faculty of Engineering and Natural Sciences, İstinye University, İstanbul, Türkiye
4 School of Engineering and Technology, Sunway University, Selangor, Malaysia

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ABSTRACT

The global shift toward renewable energy has heightened the demand for precise decision-making frameworks that can effectively handle uncertainty in complex, multi-criteria evaluations. Traditional approaches often fall short in capturing the nonlinear hesitation and interval-based uncertainty present in real-world assessments. To address this challenge, this study introduces a novel decision-making framework that integrates interval-valued circular intuitionistic fuzzy sets (IVCIFSs) with the Measurement of Alternatives and Ranking according to COmpromise Solution (MARCOS) method. This hybrid approach effectively captures both interval-based uncertainty and nonlinear hesitation in expert judgments, making it particularly suitable for evaluating renewable energy sources (RES), where subjective assessments and conflicting criteria are common. To validate its practical utility, the framework was applied to a case study involving 10 RES alternatives across 7 criteria for a mid-sized Iranian food manufacturer. The analysis identified Economic Feasibility, Technical Viability, and Environmental Impact as critical criteria, with photovoltaic, biomass, and biodiesel emerging as the most favorable options. Comprehensive sensitivity and comparative analyses confirmed the model's robustness across varying expert perspectives and its alignment with advanced multi-criteria decision-making (MCDM) methods. This study not only advances decision-making theory through the IVCIF-MARCOS integration but also offers a practical, adaptable tool for supporting effective energy transitions in uncertain and complex environments.

1. Introduction

The progressive emergence of new technologies and analytical methodologies continues to shape the dynamic landscape of decision-making processes [1]. A central aim of these advancements is to equip decision-makers with more robust, adaptive, and reliable tools to support sound judgments under various conditions. In response, decision support systems (DSSs) have been designed to address specific decision problems by delivering structured knowledge and enhancing the quality of

* *Corresponding author.*
E-mail address: vshahin121@gmail.com; dpamucar@gmail.com

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decision outcomes [2]. Functioning as dedicated information systems or methodological platforms, these tools enable decision-makers to perform systematic analyses of potential options and consider diverse scenarios, including real-world uncertainties [3].

Within many DSSs, multi-criteria decision-making (MCDM) methods have gained widespread recognition for offering structured and replicable frameworks to deal with complex decision-making situations [4]. These methods have proven effective across numerous real-life applications, particularly in contexts where decision-makers must reconcile multiple and often conflicting criteria [5]. Recognizing that decision-making is rarely one-size-fits-all, researchers have introduced a variety of tailored MCDM techniques to match the evolving demands of specific domains and decision contexts [6]. This evolution reflects an ongoing effort to address the limitations of traditional approaches while increasing the robustness, precision, and credibility of evaluation outcomes [2].

Driven by the increasing demand for adaptable and accurate decision models, many new MCDM techniques have been introduced in recent years to refine decision evaluations [7]. MCDM frameworks have attracted considerable interest from the academic community and have been effectively applied in diverse practical settings to guide the evaluation of alternatives and criteria [8]. By enabling comprehensive assessments, MCDM supports the identification and selection of optimal alternatives from among competing options. An essential phase in this process is the ranking and comparison of alternatives based on their performance relative to evaluation criteria. During this step, a well-chosen method ensures reliable differentiation among decision options [7].

Among the available MCDM methods, the Measurement of Alternatives and Ranking according to Compromise Solution (MARCOS), developed by Stević *et al.,* [9], offers a compelling approach for prioritizing alternatives based on compromise solutions [10, 11]. This methodology operates by establishing utility functions derived from the relative distances of alternatives to ideal and anti-ideal reference points [12]. The optimal solution is identified as the alternative with the closest proximity to the ideal and the greatest distance from the anti-ideal benchmark [4].

MARCOS has been widely adopted to address decision-making problems across various fields. For example, it has been employed in evaluating health service performance of insurers [13], regional network outage losses [14], bus rapid transit systems [15], sustainable transportation alternatives [16], wind farm site selection [7], commercial bank performance [12], safety assessment of survival crafts on cargo ships [17], and evaluation of renewable energy alternatives [18].

Compared to traditional MCDM methods such as the Simple Additive Weighting (SAW), Weighted Aggregated Sum Product Assessment (WASPAS), and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), the MARCOS method demonstrates superior efficiency, clarity in formulation, and robustness across varying measurement scales while effectively addressing the issue of rank reversal [9, 19]. Its main advantages include the ability to manage multiple objectives, resistance to rank reversal, insensitivity to the number of criteria and alternatives, and a simplified computational structure that ensures consistent and reliable results [4, 12].

1.1 Motivations for the Study

The MARCOS method provides a systematic and reliable approach for ranking alternatives in MCDM problems [20]. While effective in structured environments, MARCOS—like many classical MCDM techniques—relies on crisp data and assumes deterministic inputs. This assumption does not hold in many real-world scenarios where decision-makers face uncertainty, ambiguity, and hesitancy in their evaluations [8]. Consequently, using crisp values can lead to inaccurate assessments and ultimately weaken the quality of decisions [21].

To address this limitation, scholars have extended the conventional MARCOS framework using various fuzzy set theories that aim to reflect expert hesitancy and imprecision more realistically.

These include fuzzy sets [22], intuitionistic fuzzy sets [13], Pythagorean fuzzy sets [23], picture fuzzy sets [24], q-rung orthopair fuzzy sets [25], spherical fuzzy sets [26], and Fermatean fuzzy sets [27]. While each of these approaches enhances the modeling of vagueness to some degree, they may still fall short in adequately capturing complex, qualitative judgments in problems characterized by high levels of uncertainty.

To better address this challenge, circular intuitionistic fuzzy sets (CIFSs)—which build upon intuitionistic fuzzy sets by incorporating a circular representation of membership and non-membership—offer a more flexible and intuitive structure for handling imprecision in human judgments [28]. CIFSs use the radius of a circle to reflect the degree of vagueness, thus providing richer information about the level of hesitation [29]. When further combined with interval-valued intuitionistic fuzzy sets, the resulting interval-valued circular intuitionistic fuzzy sets (IVCIFSs) enhance this expressiveness by capturing both bounded intervals and their associated uncertainty zones [30].

Despite the increasing use of CIFSs and IVCIFSs in MCDM research, a clear gap remains: the MARCOS method has not yet been integrated within the IVCIFS environment. This absence highlights a methodological shortcoming in the literature—especially given the MARCOS method's strengths in ranking and its compatibility with fuzzy structures. Therefore, this study is motivated by the need to fill this gap through the development of an IVCIF-MARCOS approach. This integration is expected to significantly improve the ability of MCDM frameworks to handle uncertainty, better reflect decision-makers' hesitancies, and produce more reliable and realistic evaluations in uncertain and multi-dimensional decision contexts.

1.2 Contributions

The main contributions of this paper are summarized as follows:

i. A thorough and systematic literature review is conducted to trace the evolution of the MARCOS method under various fuzzy environments, ranging from traditional to advanced approaches. This review highlights existing gap and provides a comprehensive understanding of current research trends, thereby contributing to the expansion of knowledge in the field.
ii. A novel integration of the MARCOS method with IVCIFS is proposed to enhance decision-making under uncertainty. This approach leverages both the inherent advantages of the conventional MARCOS method over other MCDM techniques and the superior ability of IVCIFS to handle vague, imprecise, and conflicting information. The proposed framework demonstrates strong potential for addressing complex real-world decision-making problems.
iii. An illustrative example is provided to demonstrate the proposed algorithm in a step-by-step manner, ensuring methodological clarity and supporting its replicability for future academic and practical applications.
iv. A comprehensive sensitivity and comparative analysis is performed to evaluate the stability, reliability, and practical validity of the proposed method. The comparative analysis with existing fuzzy extensions of MARCOS further reinforces the robustness and superiority of the integrated IV-CIFS–MARCOS framework.

1.3 Literature Review

1.3.1 Fuzzy sets in MCDM: traditional to advanced types

Fuzzy set theory, pioneered by Zadeh [31], revolutionized the mathematical modeling of ambiguity in human reasoning by proposing *partial membership*, where elements could belong to a set with a degree ranging continuously between 0 and 1. This pivotal concept challenged classical binary logic and became instrumental in Multi-Criteria Decision-Making (MCDM), where human subjectivity and incomplete information often lead to inherent uncertainty [7]. While traditional fuzzy sets marked significant progress, their limitations in handling complex uncertainty prompted further developments by Zadeh in 1975, including Type-2 Fuzzy Sets [32] that introduce second-order uncertainty through fuzzy membership grades, and the particularly influential Interval-Valued Fuzzy Sets [32] that utilize interval ranges rather than precise values to better accommodate real-world imprecision. Subsequent advances by Atanassov [33] led to Intuitionistic Fuzzy Sets (IFSs), integrating degrees of membership, non-membership, and hesitation, thereby offering a more comprehensive structure for modeling expert uncertainty [34]. Building upon the novelty of IFS, Yager [35] introduced Pythagorean Fuzzy Sets (PyFS), which constrained the square sum of membership and non-membership degrees to values less than or equal to one. This formulation expanded the permissible decision space beyond IFS, offering greater flexibility in capturing uncertainty [25]. To further enhance this flexibility, [36] proposed the q-Rung Orthopair Fuzzy Set (q-ROFS), which generalizes both IFS (q=1) and PyFS (q=2) by allowing the q-th power sum of membership and non-membership degrees to remain within the unit interval. This adjustment enables a more precise representation of uncertainty, offering decision-makers greater control over model granularity based on problem-specific requirements [21]. Parallel to these developments, Cuong and Kreinovich [37] introduced Picture Fuzzy Sets (PFS), which incorporate a neutral (or abstention) degree alongside membership and non-membership values. This structure captures the uncertainty arising from indecision, making it particularly suitable for group decision-making scenarios where diverse opinions need to be integrated [38]. This concept was extended by Khalil *et al.,* [39] through Interval-Valued Picture Fuzzy Sets (IV-PFS), which embedded interval-based logic into the PFS framework, enhancing the capacity to model ambiguous data, particularly in finance and other data-intensive domains. In a further step toward more geometrically grounded representations, Kutlu Gündoğdu and Kahraman [40] introduced Spherical Fuzzy Sets (SFS), which use a spherical constraint to define the relationship between membership, non-membership, and hesitation degrees. This approach provides a more balanced and cognitively aligned structure, gaining traction for its interpretability and practical alignment with real-world decision processes [8]. Advancing fuzzy set theory further, Atanassov and Kahraman [41] presented Circular Intuitionistic Fuzzy Sets (C-IFS), characterized by a circular geometry that defines the distance and relationship between membership and non -membership. This structure improves precision when modeling ambiguity in complex systems. Subsequently, Circular Pythagorean Fuzzy Sets [41] emerged, enhancing the interpretation of expert judgments and capturing hesitation more effectively [21]. The most recent development in this lineage, Interval-Valued Circular Fuzzy Sets (IV-CIFS), proposed by Otay *et al.,* [30], integrates interval-based logic with circular geometry. This innovative approach addresses extreme uncertainty by utilizing interval bounds within a circular structure, offering a highly adaptable framework for decision-making under uncertain conditions. Throughout these advancements, fuzzy MCDM methods—particularly enhanced versions of the MARCOS method—have continuously evolved to accommodate the complexity of real-world decision problems, addressing the inherent ambiguity and human subjectivity that classical binary logic cannot manage [42].

1.3.2 Evolution of the MARCOS method in fuzzy environments

To explore the evolution of the MARCOS method in conjunction with fuzzy sets in recent years, a systematic literature review (SLR) approach was employed. Accordingly, after defining the objective—namely, identifying studies that have enhanced the MARCOS method using various types of fuzzy sets—English-language articles were searched in the Scopus and Web of Science databases. As of April 6, 2025, each database returned 181 results based on the search strings listed in Table 1.

Table 1
Search strategy for MARCOS method extensions with fuzzy sets

Database	Query string	date	Results
Scopus	TITLE-ABS-KEY (("Measurement Alternatives and Ranking according to Compromise Solution" OR MARCOS) AND fuzzy) AND (LIMIT-TO (DOCTYPE , "ar")) AND (LIMIT-TO (LANGUAGE , "English"))	4/6/2025	181
Web of Science Core Collection	("Measurement Alternatives and Ranking according to Compromise Solution" OR MARCOS) AND fuzzy (Topic) and Article (Document Types) and English (Languages)	4/6/2025	181

After removing duplicates, a total of 194 articles were selected as the initial sample. To identify articles that proposed a novel version of the MARCOS method under fuzzy set environments, we adopted the PRISMA approach. Following this approach, throughh filtering the articles based on their “titles”, "abstracts and keywords," and full texts, a total of 26 articles were identified as having contributed to the development of the MARCOS method under fuzzy set frameworks. An in-depth analysis shows that the MARCOS method has evolved through systematic integration with increasingly sophisticated fuzzy set frameworks, as summarized in Table 2.

Table 2
Advances in MARCOS method extensions using fuzzy sets

Fuzzy Set	Options Prioritizing Method	Criteria Weight-Determining Method	Application	Source	Cited by
Triangular Fuzzy Numbers (TFNs)	F-MARCOS	F-PIPRECIA	Assessment of risk level at road sections	[22]	251
	F-MARCOS	Rough PIPRECIA	Assessment of sustainable production in the circular economy context	[43]	15
Fuzzy ZE-Numbers	ZE-MARCOS	ZE-BCM	Smart jewelry selection	[44]	16
Fuzzy–Rough	Fuzzy–Rough MARCOS	Fuzzy–Rough SWARA	Electric Delivery Vehicle selection	[45]	9
Interval Type-2 Fuzzy Sets (IT2FSs)	IT2F-MARCOS	IT2F-FUCOM	Facilities layout evaluation	[46]	20
	IT2F-MARCOS	-	Survival craft selection for cargo ships	[17]	0
Intuitionistic Fuzzy Sets	IF-MARCOS	IFWA operator	Private health insurance company selection	[13]	147
	IF-MARCOS	The CRITIC Method	Failure Mode and Effect Analysis	[47]	2
Interval-Valued Intuitionistic Fuzzy	IVIF-E-VIKOR, IVIF-MARCOS	IVIF-Shannon entropy	Sustainable Supplier Selection	[10]	66
	IVIF-MARCOS	MDL	Sustainable selection of carbon-based microwave absorbing materials	[48]	3
Single-Valued Neutrosophic Fuzzy (SVNF)	SVNF-MARCOS	FUCOM-F	Assessment of fuel vehicles for sustainable road transportation	[49]	165
	SVNF-MARCOS	Trapezoidal Fuzzy FUCOM	Evaluation of the crucial elements in a water treatment plant's efficiency analysis	[50]	18

Table 2
Continued

Fuzzy Set	Options Prioritizing Method	Criteria Weight-Determining Method	Application	Source	Cited by
Interval-Valued Fuzzy Neutrosophic Numbers	IVFN-MARCOS	IVFN-LOPCOW	Sustainable aviation fuel supplier selection for airlines	[51]	2
Hesitant Fuzzy	HF-MARCOS	HFWA operator	Sports supplier selection	[52]	0
Pythagorean Fuzzy	PF-MARCOS	PF-CRITIC-PIPRECIA	Sustainable circular supplier selection	[11]	14
Pythagorean Hesitant Fuzzy	PHF-MARCOS	-	Site evaluation of subsea tunnels with sightseeing function	[53]	10
	PHFS- MARCOS	-	Renewable enrgy source selection	[18]	1
Picture Fuzzy	PF-MARCOS	PF Direct Rating and PF-Tsallis–Havrda–Charvát Entropy	Risk assessment of railway infrastructure	[54]	64
	PF-MARCOS	A novel weight-determining approach	Sustainable supplier selection	[24]	21
Interval-Valued Picture Fuzzy	IVPF-MARCOS	IVPF-WA	Assessment of investment options	[21]	0
q-Rung	q-ROF-MARCOS	-	Assessment of the cache placement policy	[25]	22
q-Rung Picture Fuzzy	q-RPF-MARCOS	q-RPF-LOPCOW	Emergency logistics suppliers selection	[55]	5
Spherical Fuzzy	SF-MARCOS	SF-CRITIC	Smartphone selection	[26]	60
Disc-Spherical Fuzzy	D-SF-MARCOS	D-SF-MEREC and D-SF-SWARA	Crude oil pretreatment system selection	[20]	6
Fermatean Fuzzy	FF-MARCOS	FF-MEREC and FF-SWARA	Household waste recycling plant location selection	[27]	3
Interval-Valued Fermatean Fuzzy	IVFF-MARCOS	FWZIC	Assessment of offshore Carbon Capture Utilization and Storage (CCUS) projects	[56]	1

The initial extension of the MARCOS method to fuzzy environments was developed by Stankovic *et al.,* [22], who integrated the fuzzy MARCOS (F-MARCOS) approach with the fuzzy PIvot Pairwise Relative Criteria Importance Assessment (fuzzy PIPRECIA) method for assessing road traffic risks. This pioneering work demonstrated the method's effectiveness in handling uncertainty within ordinary fuzzy set frameworks. Stević *et al.,* [43] later combined it with Rough PIPRECIA for forestry sustainability evaluation. Further methodological advancements emerged through the fuzzy-rough MARCOS approach developed by Wang *et al.,* [45], which employed the Fuzzy-Rough Step-wise Weight Assessment Ratio Analysis (Fuzzy-Rough SWARA) method for electric vehicle selection problems. The method versatility was further demonstrated by Haseli *et al.,* [57] through the development of ZE-MARCOS, which combined fuzzy ZE-numbers with the ZE-Best Criterion Method (ZE-BCM) weighting approach for smart jewelry selection. The method capabilities expanded substantially through higher-order fuzzy extensions. Gölcük *et al.,* [46] developed the Interval Type-2 Fuzzy MARCOS (IT2F-MARCOS) approach incorporating the Interval Type-2 Fuzzy Full Consistency Method (IT2F-FUCOM), while Aydin *et al.,* [17] applied this framework for survival craft assessment in maritime safety. In intuitionistic fuzzy environments, Ecer and Pamucar [13] introduced the

Intuitionistic Fuzzy MARCOS (IF-MARCOS) method using the Intuitionistic Fuzzy Weighted Averaging (IFWA) operator for healthcare insurance evaluation, with Akkus and Testik [47] later employing the Criteria Importance Through Intercriteria Correlation (CRITIC) method for failure mode analysis applications.

The methodological progression continued with interval-valued intuitionistic fuzzy extensions, including the Interval-Valued Intuitionistic Fuzzy MARCOS (IVIF-MARCOS) with IVIF-Shannon entropy weighting developed by Salimian *et al.,* [10] for sustainable supplier selection, and the implementation using the Modified Digital Logic (MDL) approach proposed by Saeed *et al.,* [48] for material selection. Neutrosophic extensions marked another significant advancement, with the Single-Valued Neutrosophic Fuzzy MARCOS (SVNF-MARCOS) method integrated with the Fuzzy Full Consistency Method (FUCOM-F) developed by Pamucar *et al.,* [49] for sustainable transportation analysis, followed by the incorporation of trapezoidal fuzzy FUCOM for water treatment plant evaluation by Majumder [58].

Recent methodological innovations have pushed the boundaries of MARCOS applications through advanced fuzzy set integrations. These include the Interval-Valued Fuzzy Neutrosophic MARCOS (IVFN-MARCOS) with Logarithmic Percentage Change-driven Objective Weighting (LOPCOW) developed by Ecer *et al.,* [51] for aviation fuel supplier evaluation, and the Hesitant Fuzzy MARCOS (HF-MARCOS) proposed by Li *et al.,* [52] for sports supplier selection. Pythagorean fuzzy implementations encompass the Pythagorean Fuzzy MARCOS (PF-MARCOS) with PF-CRITIC-PIPRECIA weighting developed by Mishra *et al.,* [11] for circular supplier selection and the Pythagorean Hesitant Fuzzy MARCOS (PHF-MARCOS) proposed by Zeng *et al.,* [53] for subsea tunnel site evaluation. The Picture Fuzzy MARCOS (PF-MARCOS) method was first introduced by Simic *et al.,* [54] using picture fuzzy direct rating and Tsallis-Havrda-Charvát entropy weighting for railway infrastructure risk assessment. Rani *et al.,* [24] enhanced this approach by developing a novel similarity measure for the PF-MARCOS framework. Further, Shang *et al.,* [21] developed the Interval-Valued Picture Fuzzy MARCOS (IVPF-MARCOS) with the Interval-Valued Picture Fuzzy Weighted Averaging (IVPFWA) operator for financial risk management. Recent q-rung orthopair developments include q-ROF MARCOS for cache placement [25] and q-RPF-MARCOS with LOPCOW for emergency logistics [55].

The methodological evolution of MARCOS progressed with the development of the Spherical Fuzzy MARCOS (SF-MARCOS) framework by Ali [26], which incorporated CRITIC weighting for product selection. Building on this, Ahmad *et al.,* [20] proposed the Disc-Spherical Fuzzy MARCOS (D-SF MARCOS), a more refined model integrating MEREC-SWARA weighting to tackle crude oil pretreatment challenges.

The MARCOS method was further extended by Mishra *et al.,* [27] through the incorporation of Fermatean fuzzy sets, resulting in the FF-MARCOS approach, integrated with fuzzy-weighted zero-inconsistency (FWZIC) and MEREC weighting methods for waste recycling plant location problems. At the forefront of current literature, Mao *et al.,* [56] proposed the Interval-Valued Fermatean Fuzzy MARCOS (IVFF-MARCOS), which combines Fuzzy-Weighted Zero-Inconsistency (FWZIC) and MEREC methods for the evaluation of carbon capture projects.

Despite the extensive evolution of MARCOS through various fuzzy extensions, a critical methodological gap remains—the integration of IVCIFSs. While MARCOS is known for its rigorous ranking accuracy, resistance to rank reversal, and adaptability across diverse decision contexts, its reliance on precise data can limit its effectiveness in complex, uncertain environments. In contrast, IVCIFSs provide a more comprehensive representation of expert evaluations by capturing both interval-based ambiguity and nuanced hesitation, reflecting the inherent uncertainty in human judgment more accurately. To address this gap, this study proposes an IVCIF-MARCOS framework that synergizes the structured, utility-based ranking of MARCOS with the expressive uncertainty modeling of IVCIFSs. This integration aims to enhance the robustness, reliability, and adaptability of decision analysis in complex, multi-dimensional contexts, offering a more precise and context-sensitive approach to uncertainty management.

2. Methodology

2.1 Preliminaries of IVCIFSs

IVCIFS as an extension of CIFS was first introduced by Otay *et al.,* [30]. The basic definitions of IVCIFs are presented in the following.

Definition 1 [30]. Let *R* be a fixed universe, and *x* denote a generic element of $\tilde{A}_r^I$ as an IVCIFS in *R*. This IVCIFS is defined as:

$$\tilde{A}_r^I=\{<x: [\mu_A^l(x), \mu_A^u(x)], [\nu_A^l(x), \nu_A^u(x)]; r>, x \in R\} \quad (1)$$

where μ_A^l & μ_A^u represent the membership interval, and ν_A^l & ν_A^u the non-membership interval of the element $x \in R$ to the set $\tilde{A}_r^I$ subject to the condition:

$$0 \leq \mu_A^u(x)+\nu_A^u(x)\ ) \leq 1,\ r \in [0. \sqrt{2}] \quad (2)$$

where radius $r \in [0. \sqrt{2}]$ indicates the uncertainty of the membership and non-membership intervals.

Definition 2 [30]. Let $\tilde{A}_{r1}^I$ =<$[\mu_{A_1}^l(x). \mu_{A_1}^u(x)]$, $[\nu_{A_1}^l(x). \nu_{A_1}^u(x)]; r_1$> and $\tilde{A}_{r2}^I$ =<$[\mu_{A_2}^l(x). \mu_{A_2}^u(x)]$, $[\nu_{A_2}^l(x). \nu_{A_2}^u(x)]; r_2$> represent two IVCIFSs. The basic operations are defined as follows:

Addition:

$$\tilde{A}_{r1}^I \oplus \tilde{A}_{r2}^I=\{<x, [\mu_{A_1}^l(x) + \mu_{A_2}^l(x) - \mu_{A_1}^l(x) \times \mu_{A_2}^l(x). \mu_{A_1}^u(x) + \mu_{A_2}^u(x) - \mu_{A_1}^u(x) \times \mu_{A_2}^u(x)], [\nu_{A_1}^l(x) \times \nu_{A_2}^l(x). \nu_{A_1}^u(x) \times \nu_{A_2}^u(x)]; (r_1+ r_2)/2>, x \in R\} \quad (3)$$

Multiplication by a scaler:

$$\lambda.\tilde{A}_{r1}^I=\{< x,[1-(1- \mu_{A_1}^l(x))^\lambda, 1-(1- \mu_{A_1}^u(x))^\lambda], [(\nu_{A_1}^l(x))^\lambda. (\nu_{A_1}^u(x))^\lambda]; r_1>, x \in R\} \quad (4)$$

Definition 3. Let {<$[\mu_{i.1}^l. \mu_{i.1}^u]$, $[\nu_{i.1}^l. \nu_{i.1}^u]$>, <$[\mu_{i.2}^l. \mu_{i.2}^u]$, $[\nu_{i.2}^l. \nu_{i.2}^u]$>,... } be a set of IVIF pairs, and $W_i = \{w_{i,1}, ... , w_{i,k}\}$ represent the set of weights for these IVIF pairs. The weighted IVIF arithmetic mean of these pairs, denoted as $\bar{\tilde{M}}_i^I$, is defined as follows [30]:

$$\bar{\tilde{M}}_i^I=([\mu_{M_i}^l. \mu_{M_i}^u], [\nu_{M_i}^l. \nu_{M_i}^u]) =([\textstyle\sum_{j=1}^{k_i} \mu_{i.j}^l\, w_{i.j} , \sum_{j=1}^{k_i} \mu_{i.j}^u\, w_{i.j}], [\sum_{j=1}^{k_i} \nu_{i.j}^l\, w_{i.j} , \sum_{j=1}^{k_i} \nu_{i.j}^r\, w_{i.j}]) \quad (5)$$

Subject to:

$w_{i.j} \in [0, 1]$, $\sum_{j=1}^{k_i} w_{i.j}= 1$

where *ki* is the number of IVCIF pairs in the *i*-th set.

Based on the $\tilde{M}_i$ value, the weighted IVCIF arithmetic mean of these pairs can be obtained as:

$$\bar{\tilde{M}}_{ri}^I=([\mu_{M_i}^l. \mu_{M_i}^u], [\nu_{M_i}^l. \nu_{M_i}^u]; r_{M_i}) ,$$

$$r_{M_i}\text{=max}\left(\begin{array}{l}\max\limits_{1\le j\le k_i}\sqrt{\left(\mu^l_{M_i}-\mu^l_{i.j}\right)^2+\left(\nu^l_{M_i}-\nu^l_{i.j}\right)^2}\ .\ \max\limits_{1\le j\le k_i}\sqrt{\left(\mu^l_{M_i}-\mu^l_{i.j}\right)^2+\left(\nu^u_{M_i}-\nu^u_{i.j}\right)^2}\ . \\ \max\limits_{1\le j\le k_i}\sqrt{\left(\mu^u_{M_i}-\mu^u_{i.j}\right)^2+\left(\nu^l_{M_i}-\nu^l_{i.j}\right)^2}\ .\ \max\limits_{1\le j\le k_i}\sqrt{(\mu^u_{M_i}-\mu^u_{i.j})^2+(\nu^u_{M_i}-\nu^u_{i.j})^2}\end{array}\right) \quad (6)$$

2.2 The Proposed IVCIF-MARCOS Method

The MARCOS method, introduced by Stevic *et al.,* [59], evaluates alternatives based on utility functions relative to ideal and anti-ideal solutions [60]. It offers greater efficiency, clarity, and optimization compared to other MCDM methods [61]. Although applied in various fuzzy contexts, MARCOS has not yet been extended to IVCIFSs. This study addresses that gap by proposing the IVCIF-MARCOS method, which involves the following steps:

Step 1: Construct the decision matrices. Define the set of alternatives $A=\{A_1, A_2, \ldots, A_i, \ldots, A_m\}$and criteria $C = \{C1, C_2, \ldots, C_j, \ldots, C_n\}$. Gather the IVIF decision matrix from the k-th expert, using the linguistic scales provided in Table 3 [10].

$$\widetilde{D}^{I\,(k)}=\left[\tilde{d}^{I\,(k)}_{ij}\right]_{n\times m}=\begin{bmatrix}\tilde{d}^{I\,(k)}_{11} & \tilde{d}^{I\,(k)}_{12} & \cdots & \tilde{d}^{I\,(k)}_{1n}\\ \tilde{d}^{I\,(k)}_{21} & \tilde{d}^{I\,(k)}_{22} & \cdots & \tilde{d}^{I\,(k)}_{2n}\\ \vdots & \vdots & \ddots & \vdots\\ \tilde{d}^{I\,(k)}_{m1} & \tilde{d}^{I\,(k)}_{m2} & \cdots & \tilde{d}^{I\,(k)}_{nm}\end{bmatrix} \quad (7)$$

where, $\tilde{d}^{I\,(k)}_{ij}$ = <$[\mu^l_{ij}.\,\mu^u_{ij}].\,[v^l_{ij}.\,v^u_{ij}]$> denotes the evaluation of alternative i with respect to criterion j, expressed by the k-th expert in the form of IVIF numbers.

Step 2: Construct the aggregated decision matrix. Based on the linguistic terms presented in Table 3, assess each expert according to their knowledge and practical experience. Compute the weight of the k-th expert (ω_k) using the following equation [48]:

$$\omega_k=\frac{2+\left(\mu^l_k-v^l_k\right)+\left(\mu^u_k-v^u_k\right)}{\sum_{k=1}^{K}[2+\left(\mu^l_k-v^l_k\right)+\left(\mu^u_k-v^u_k\right)]},\ \sum_{k=1}^{K}\omega_k=1 \quad (8)$$

Table 3
Linguistic scale and corresponding IVIF numbers [30]

Linguistic term	IVIF values
Absolutely High (AH)	([0.8, 1], [0, 0])
Very High (VH)	([0.7, 0.9], [0, 0.1])
High (H)	([0.6, 0.8], [0, 0.2])
Medium High (MH)	([0.5, 0.7], [0.1, 0.3])
Fair (F)	([0.5, 0.5], [0.5, 0.5])
Medium Low (ML)	([0.1, 0.3], [0.5, 0.7])
Low (L)	([0, 0.2], [0.6, 0.8])
Very Low (VL)	([0, 0.1], [0.7, 0.9])
Absolutely Low (AL)	([0, 0], [0.8, 1])

Then, using Equations 5-6, construct the IVCIF aggregated decision matrix as follows [30]:

$$\tilde{A}^I_r=\left[\tilde{a}^I_{r.ij}\right]_{n\times m},\ \tilde{a}^I_{r.ij}=<[\mu^{l\,Agg}_{ij}.\mu^{u\,Agg}_{ij}].[v^{l\,Agg}_{ij}.v^{u\,Agg}_{ij}];\ r_{ij}> \quad (9)$$

Hear, $\tilde{a}_{r.ij}^{I\,Agg}$ indicates the evaluation of alternative *i* with respect to criterion *j*, expressed as an IVICIF value.

Step 3: Construct the normalized decision matrix. Apply the below normalization process to the aggregated decision matrix to obtain the normalized decision matrix $\widetilde{N}_r^I$ [8]:

$$\widetilde{N}_r^I = \left[\tilde{n}_{r.ij}^I\right]_{n\times m},\ \tilde{n}_{r.ij}^I = \begin{cases} < \left[\mu_{ij}^{l\,Agg}.\mu_{ij}^{u\,Agg}\right].\left[v_{ij}^{l\,Agg}.v_{ij}^{u\,Agg}\right];\ r_{ij} > & \text{for benefit criteria} \\ < \left[v_{ij}^{l\,Agg}.v_{ij}^{u\,Agg}\right].\left[\mu_{ij}^{l\,Agg}.\mu_{ij}^{u\,Agg}\right];\ r_{ij} > & \text{for cost criteria} \end{cases} \tag{10}$$

Step 4: Construct the weighted decision matrix. Apply Equation (4) to combine the normalized decision matrix with the criteria weights, and obtain the weighted decision matrix $\widetilde{W}_r^I$ [10]:

$$\widetilde{W}_r^I = \left[\widetilde{w}_{r.ij}^I\right]_{n\times m},\ \widetilde{w}_{r.ij}^I = < [\mu_{ij}^{l\,W}.\mu_{ij}^{u\,W}].[v_{ij}^{l\,W}.v_{ij}^{u\,W}];\ r_{ij} > \tag{11}$$

Step 5: Identify the Reference Points. Determine the IVCIF-based ideal and anti-ideal alternatives for each criterion j [62]:

$$\begin{aligned} \tilde{A}_{r.j}^{I+} &= ([\max_i \mu_{ij}^{l\,W}.\max_i \mu_{ij}^{l\,W}].[\min_i v_{ij}^{l\,W}.\min v_{ij}^{l\,W}];\ \max r_{ij}), \\ \tilde{A}_{r.j}^{I-} &= ([\min_i \mu_{ij}^{l\,W}.\min_i \mu_{ij}^{l\,W}].[\max_i v_{ij}^{l\,W}.\max v_{ij}^{l\,W}];\ \max r_{ij}) \end{aligned} \tag{12}$$

Step 6: Calculate the IVCIF weighted sums. Determine the IVCIF-based rating of each alternative by calculating its weighted sum using Equation (3), as shown below:

$$\begin{cases} \tilde{S}_{r.i}^I = < [\mu_i^{l\,S}.\ \mu_i^{u\,S}].\ [v_i^{l\,S}.\ v_i^{u\,S}];\ r_i^s > = \oplus \sum_{j=1}^n \widetilde{w}_{r.ij}^I \\ \tilde{S}_r^{I+} = < [\mu^{l\,S+}.\mu^{u\,S+}].\ [v^{l\,S+}.v^{u\,S+}];\ r^{s+} > = \oplus \sum_{j=1}^n \tilde{a}_{r.j}^{I+} \\ \tilde{S}_r^{I-} = < [\mu^{l\,S-}.\mu^{u\,S-}].\ [v^{l\,S-}.v^{u\,S-}];\ r^{s-} > = \oplus \sum_{j=1}^n \tilde{a}_{r.j}^{I-} \end{cases} \tag{13}$$

Step 7: Find the CIF weighted sums. Convert the IVCIF weighted sums into CIF values using the formula below [63]:

$$\begin{cases} \tilde{S}_{r.i} = <\mu_i^s.\ v_i^s;\ r_i^s> = <(\mu_i^{l\,S} + \mu_i^{u\,S})/2,\ (v_i^{l\,S} + v_i^{u\,S})/2;\ r_i^s> \\ \tilde{S}_r^+ = <\mu_i^{s+}.\ v_i^{s+};\ r_i^{s+}> = <(\mu_i^{l\,S+} + \mu_i^{u\,S+})/2,\ (v_i^{l\,S+} + v_i^{u\,S+})/2;\ r^{s+}> \\ \tilde{S}_r^- = <\mu_i^{s-}.\ v_i^{s-};\ r_i^{s-}> = <(\mu_i^{l\,S-} + \mu_i^{u\,S-})/2,\ (v_i^{l\,S-} + v_i^{u\,S-})/2;\ r^{s-}> \end{cases} \tag{14}$$

Step 8: Calculate the IF weighted sums. Set λ within [0,1] to reflect the decision-maker's attitude: 0 for full pessimism, 1 for full optimism, values below 0.5 for a pessimistic view, above 0.5 for optimism, and 0.5 for neutrality [64]. Next, defuzzify the CIF weighted sums of each alternative into IF values using Equation (15):

$$\begin{cases} \tilde{S}_i = <\mu_i\,.\,v_i> = <\mu_i^s + (2\lambda - 1)\times\frac{r_i^s}{\sqrt{2}}\ .\ v_i^s - (2\lambda - 1)\times\frac{r_i^s}{\sqrt{2}}> \\ \tilde{S}^+ = <\mu^+.\ v^+> = <\mu^{s+} + (2\lambda - 1)\times\frac{r^{s+}}{\sqrt{2}}\ .\ v^{s+} - (2\lambda - 1)\times\frac{r^{s+}}{\sqrt{2}}> \\ \tilde{S}^- = <\mu^-.\ v^-> = <\mu^{s-} + (2\lambda - 1)\times\frac{r^{s-}}{\sqrt{2}}\ .\ v^{s-} - (2\lambda - 1)\times\frac{r^{s-}}{\sqrt{2}}> \end{cases} \tag{15}$$

Step 9: Find the IF utility degrees of alternatives. Determine the positive $\widetilde{U}_i^+$ and negative $\widetilde{U}_i^-$ IF utility degrees of the alternatives by applying the division operation presented in Equation 16 for IF values. Let $\tilde{A}_1$(<$m_1 . n_1$>) and $\tilde{A}_2$(<$m_2 . n_2$>) represent two IF numbers, with the division operator defiened as follows [65]:

$$\tilde{A}_1 \oslash \tilde{A}_2 = \begin{cases} <\frac{m_1}{m_2}, 0> & m_1 \le m_2, n_1 \le n_2 \\ <\frac{m_1}{m_2}, \frac{n_1 - n_2}{1-n_2}> & 0 \le \frac{n_1}{n_2} \le \frac{1-m_1}{1-m_2} \le 1 \\ <\frac{1-n_1}{1-n2}, \frac{n_1-n_2}{1-n_2}> & m_1 > m_2, \frac{1-m_1}{1-m_2} < \frac{n_1}{n_2} \\ <1, 0> & m_1 \le m_2, n_1 > n_2 \end{cases} \tag{16}$$

Then, calculate the IF utility degrees using the following formulas:

$$\widetilde{U}_i^+ = \tilde{S}_i \oslash \tilde{S}_i^+, \quad \widetilde{U}_i^- = \tilde{S}_i \oslash \tilde{S}_i^- \tag{17}$$

Step 10: Determine the IF utility functions for the alternatives. Compute the positive $\tilde{f}(U_i^+)$ and negative $\tilde{f}(U_i^-)$ IF utility functions for each decision alternative using the division operator defined in Equation 16 and the addition operator given in Equation 18. Let $\tilde{A}_1$(<$m_1 . n_1$>) and $\tilde{A}_2$(<$m_2 . n_2$>) be two IF numbers, with their addition defined as follows [30]:

$$\tilde{A}_1 \oplus \tilde{A}_2 = <m_1 + m_2 - m_1 \times m_2, n_1 \times n_2)> \tag{18}$$

Determine the IF utility functions using the formulas below:

$$\tilde{f}(U_i^+) = \widetilde{U}_i^- \oslash (\widetilde{U}_i^+ \oplus \widetilde{U}_i^-), \quad \tilde{f}(U_i^-) = \widetilde{U}_i^+ \oslash (\widetilde{U}_i^+ \oplus \widetilde{U}_i^-) \tag{19}$$

Step 11: Calculate the final utility function of alternatives. Using the score function in Equation 20, derive the crisp scores of the positive and negative IF utility functions $f(U_i^+)$ and $f(U_i^-)$, along with the crisp sum of utility degrees $U_i^+ + U_i^-$. For an IF number $\tilde{A}$ (<*m, n*>), the crisp score is given by [64]:

$$S_{IFS}(\tilde{A}) = (m-n+1)/2, \; S_{IFS}(\tilde{A}) \in [0, 1] \tag{20}$$

Evaluate the final utility function $f(U_i)$ by applying the following formula [59]:

$$f(U_i) = \frac{U_i^+ + U_i^-}{1 + \frac{1-f(U_i^+)}{f(U_i^+)} + \frac{1-f(U_i^-)}{f(U_i^-)}} \tag{21}$$

Step 12: Establish the ranking of alternatives. Order the alternatives in descending sequence according to their final utility values [59].

3. Results

3.1 Illustrative example: Selection of Renewable Energy Sources

Maximizing investments in renewable energy is crucial for promoting sustainable growth in the current energy landscape. Investing in renewable sources is not only important for environmental protection but also a strategic and ethical imperative [66]. Governments and businesses have the opportunity to address urgent environmental crises while securing long-term financial benefits through renewable energy investments [18].

In this context, a medium-sized enterprise in the food manufacturing industry located in Shiraz, Iran, has recently faced increasing challenges such as volatile energy prices, frequent electricity outages, heightened environmental concerns, and growing pressure from governmental bodies and customers to comply with sustainability regulations. In response, the top manager made a strategic decision to invest in renewable energy sources (RESs) to mitigate energy-related risks, improve the company's environmental performance, and meet stakeholder expectations.

However, selecting the most suitable renewable energy option involves multiple and often conflicting criteria, making it a complex MCDM problem. To address this complexity, we apply the proposed framework to systematically evaluate the available alternatives under uncertainty, thereby supporting the organization in making an informed and robust investment decision. Criteria for RES Assessment in this case are identified as below:

Regulatory Compliance (C_1): Examines how well each investment option conforms to relevant laws and regulations. It includes an evaluation of necessary permits, eligibility for governmental incentives such as tax benefits and subsidies, and adherence to industry norms [18, 67].

Scalability (C_2): Assesses the potential to expand renewable systems to meet future energy needs without incurring significant additional costs or environmental damage [68].

Technical Viability (C_3): Assesses the maturity and availability of natural resources [67] relevant technologies, infrastructure [69], and expert workforce required for implementing and maintaining renewable energy systems [18].

Economic Feasibility (C_4): Evaluates the cost-effectiveness of renewable energy systems, including installation, maintenance, operational expenses, Return on investment and the Levelized Cost of Energy, which allows comparison across technologies over their lifecycle [70]. This criterion gauges the efficiency with which resources are leveraged to generate revenue or realize targeted outcomes [18].

Reliability (C_5): Evaluates the consistency of power generation, addressing issues such as intermittency, energy storage, and the capacity to maintain supply during peak demand [68].

Social Acceptance (C_6): Focuses on local community support, public perception, and involvement in renewable energy projects, which are critical for their success [67, 71].

Environmental Impact (C_7): Considers the environmental consequences such as emissions, land use, pollution, and effects on ecosystems, even though renewable sources generally produce fewer emissions than fossil fuels [69, 72, 73].

Based on relevant studies, the alternatives applicable to the context of our case study are identified and outlined below.

Wind Energy (A_1): Leverages wind's kinetic energy to generate electricity through turbines. Advancements in turbine blade design, materials, and aerodynamic efficiency have enhanced the feasibility and economic viability of wind power, particularly in areas with consistent wind patterns [18, 68, 73, 74].

Biomechanical Energy (A_2): Captures mechanical energy from bodily movements, such as walking, joint motion, and physical exertion. Piezoelectric and triboelectric nanogenerators convert this kinetic and thermal energy into electricity, though it remains a niche source due to its limited scale and application [75, 76].

Photovoltaic (A_3): Converts sunlight directly into electricity using semiconductor materials. Recent innovations, including multi-junction cells and perovskite-based materials, have significantly improved efficiency and reduced costs, positioning photovoltaic technology as a leading option for clean, scalable energy in regions with high solar potential [18, 68, 73, 77].

Solar Thermal Energy (A_4): Captures and stores solar thermal energy for direct heating or electricity generation. Solar collectors focus sunlight, and integration with thermal storage systems ensures a continuous and reliable energy supply [78].

Biogas (A_5): Produced through the anaerobic digestion of organic materials such as farm residues, food waste, and sewage, biogas is a versatile fuel that can be used for heating, electricity generation, or as a sustainable transport fuel [68, 79].

Biodiesel (A_6): Derived from waste oils or animal fats via transesterification, biodiesel is a renewable alternative to fossil diesel. It is commonly used in backup generators, heavy machinery, and transportation, offering a reduced carbon footprint compared to conventional fuels [80].

Algal Biofuel (A_7): Sourced from microalgae, this biofuel presents a promising renewable energy solution, especially when integrated into wastewater treatment processes. It addresses both energy generation and environmental concerns, making it a compelling option for sustainable energy [81, 82].

Biomass (A_8): Generated from the combustion or advanced processing (e.g., gasification) of organic residues, including farm and forest by-products, biomass offers a reliable and flexible energy source, complementing waste management practices in the food processing industry [18, 68, 83].

Green Hydrogen Fuel Cells (A_9): Generate electricity through the electrochemical reaction of hydrogen with oxygen, producing water as the only byproduct. Technological advancements have enhanced their efficiency and cost-effectiveness, making them a viable option for stationary power and transportation applications [84].

Geothermal Power (A_{10}): Utilizes the Earth's internal heat for both direct heating and electricity generation. Advances in geothermal drilling and enhanced systems have expanded the feasibility of geothermal power in geologically suitable areas [68, 73, 85].

To evaluate these alternatives, a panel of five experts was selected, with further details provided in Table 4.

Table 4
Profile of research experts

Expert	Educational Background	Field of Expertise	Years of Experience	Current Position
E1	M.Sc. in Food Industry Engineering	Marketing strategy, supplier management, and market analysis in the food sector	12 years	Marketing Manager at the company under study
E2	M.Sc. in Energy Systems Engineering	R&D in industrial energy management, process optimization, and sustainable technology	12 years	R&D Manager at the company under study
E3	M.Sc. in Industrial Engineering	Innovation management, sustainability, and entrepreneurship	5 years	Innovation and Entrepreneurship Manager at Iran Small Industries and Industrial Parks Organization (ISIPO)
E4	Ph.D. in Chemical Engineering	Biomass conversion, waste-to-energy systems, and environmental impact	10 years	University faculty and lead researcher at a biomass research center
E5	B.Sc. in Financial Accounting	Financial analysis, project investment, and risk assessment	8 years	Financial Manager at the company under study

The decisionmakers in this study were qualified to participate based on at least five years of relevant experience, specialized knowledge in renewable energy and/or the food sector, familiarity with local (Iranian) regulatory and environmental conditions, and active involvement in applied renewable energy or innovation projects.

3.2 Findings

The results derived from applying the proposed the IVCIF-MARCOS approach within the case study context are detailed in this section.

Step 1. The decision alternatives were designated as $A= \{A_1, A_2, …, A_{10}\}$, while the evaluation criteria for the prioritization task were represented by $C= \{C1, C_2, …, C_7\}$. The expert panel's linguistic evaluations, summarized in Table 5, were collected and then transformed into IVIF decision matrices in accordance with Equation (7).

Table 5
Initial decision matrix

	Expert	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}
	E1	MH	H	MH	F	MH	H	L	H	ML	L
	E2	H	MH	MH	Ml	MH	MH	ML	H	L	VL
C_1	E3	F	H	F	ML	H	H	ML	H	ML	VL
	E4	MH	MH	F	ML	VH	MH	L	H	L	VL
	E5	F	H	F	ML	H	MH	ML	MH	L	AL
	E1	MH	ML	ML	H	ML	L	H	L	MH	MH
	E2	H	L	L	F	F	F	H	F	F	MH
C_2	E3	H	ML	F	MH	ML	ML	MH	ML	H	F
	E4	MH	VL	L	H	F	L	MH	L	F	MH
	E5	H	L	ML	F	L	F	H	ML	MH	MH
	E1	ML	L	H	H	MH	L	ML	H	ML	F
	E2	ML	ML	H	F	MH	L	ML	H	L	ML
C_3	E3	L	L	H	MH	H	L	L	MH	L	F
	E4	ML	L	VH	F	MH	L	L	H	L	ML
	E5	L	ML	H	MH	H	ML	L	MH	ML	F
	E1	F	ML	MH	ML	L	MH	ML	H	MH	ML
	E2	MH	ML	H	ML	ML	MH	L	MH	F	ML
C_4	E3	MH	L	MH	ML	L	MH	F	MH	MH	ML
	E4	F	ML	H	L	ML	H	F	MH	H	F
	E5	F	L	H	L	L	MH	ML	H	H	L
	E1	MH	ML	H	ML	L	H	L	F	L	H
	E2	MH	L	MH	F	L	H	ML	ML	L	MH
C_5	E3	H	ML	MH	ML	ML	VH	ML	ML	ML	MH
	E4	MH	ML	H	F	L	MH	L	F	ML	H
	E5	MH	L	H	ML	VL	H	ML	F	ML	H
	E1	L	VL	H	H	H	AL	ML	H	MH	VL
	E2	ML	ML	MH	H	MH	ML	L	MH	MH	L
C_6	E3	L	VL	H	MH	F	L	L	H	H	L
	E4	ML	L	MH	H	MH	L	ML	H	MH	L
	E5	L	L	H	H	H	ML	ML	H	MH	L
	E1	L	ML	H	ML	L	F	F	H	L	MH
	E2	L	ML	H	ML	F	ML	F	H	ML	MH
C_7	E3	L	L	MH	F	L	F	MH	MH	ML	F
	E4	ML	ML	H	F	ML	ML	F	MH	L	ML
	E5	VL	ML	H	L	F	ML	MH	H	L	ML

Step 2. Using Equation (8), the weight of each expert was calculated as W_E = *{0.209, 0.229, 0.248, 0.183, 0.131}*. Following this, the IVCIF aggregated decision matrix was formed using Equation (9).

Step 3. Following Equation (10), the aggregated matrix was normalized, as shown in Table 6. Notably, the second criterion, Environmental Impact (C_2), is classified as a cost criterion, while the others are benefit criteria.

Table 6
The IVCIF normal aggregated decision matrix

$\widetilde{N}_r^I$	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}
C_1	<[0.523, 0.647], [0.229, 0.353]; 0.309>	<[0.559, 0.759], [0.041, 0.241]; 0.083>	<[0.500, 0.588], [0.325, 0.412]; 0.251>	<[0.184, 0.342], [0.500, 0.658]; 0.354>	<[0.575, 0.775], [0.044, 0.225]; 0.177>	<[0.546, 0.746], [0.054, 0.254]; 0.077>	<[0.061, 0.261], [0.539, 0.739]; 0.086>	<[0.587, 0.787], [0.013, 0.213]; 0.123>	<[0.046, 0.246], [0.554, 0.754]; 0.077>	<[0.000, 0.108], [0.692, 0.892]; 0.153>
C_2	<[0.039, 0.239], [0.561, 0.761]; 0.086>	<[0.573, 0.773], [0.046, 0.227]; 0.180>	<[0.541, 0.692], [0.158, 0.308]; 0.392>	<[0.205, 0.333], [0.539, 0.667]; 0.340>	<[0.513, 0.631], [0.252, 0.369]; 0.303>	<[0.539, 0.667], [0.205, 0.333]; 0.340>	<[0.043, 0.243], [0.557, 0.757]; 0.080>	<[0.539, 0.693], [0.152, 0.307]; 0.398>	<[0.240, 0.358], [0.525, 0.642]; 0.297>	<[0.199, 0.350], [0.500, 0.650]; 0.336>
C_3	<[0.062, 0.262], [0.538, 0.738]; 0.088>	<[0.036, 0.236], [0.564, 0.764]; 0.091>	<[0.618, 0.818], [0.000, 0.182]; 0.116>	<[0.521, 0.639], [0.244, 0.361]; 0.292>	<[0.538, 0.738], [0.062, 0.262]; 0.088>	<[0.013, 0.213], [0.587, 0.787]; 0.123>	<[0.044, 0.244], [0.556, 0.756]; 0.079>	<[0.562, 0.762], [0.038, 0.238]; 0.088>	<[0.034, 0.234], [0.566, 0.766]; 0.093>	<[0.335, 0.418], [0.500, 0.582]; 0.263>
C_4	<[0.500, 0.595], [0.309, 0.405]; 0.234>	<[0.062, 0.262], [0.538, 0.738]; 0.088>	<[0.554, 0.754], [0.046, 0.246]; 0.077>	<[0.069, 0.269], [0.531, 0.731]; 0.097>	<[0.041, 0.241], [0.559, 0.759]; 0.083>	<[0.518, 0.718], [0.082, 0.282]; 0.116>	<[0.250, 0.363], [0.523, 0.637]; 0.298>	<[0.534, 0.734], [0.066, 0.266]; 0.093>	<[0.531, 0.686], [0.160, 0.314]; 0.387>	<[0.160, 0.324], [0.513, 0.676]; 0.383>
C_5	<[0.525, 0.725], [0.075, 0.275]; 0.106>	<[0.064, 0.264], [0.536, 0.736]; 0.091>	<[0.552, 0.752], [0.048, 0.248]; 0.074>	<[0.265, 0.382], [0.500, 0.618]; 0.263>	<[0.025, 0.212], [0.588, 0.788]; 0.158>	<[0.607, 0.807], [0.018, 0.193]; 0.151>	<[0.061, 0.261], [0.539, 0.739]; 0.086>	<[0.309, 0.405], [0.500, 0.595]; 0.234>	<[0.056, 0.256], [0.544, 0.744]; 0.079>	<[0.552, 0.752], [0.048, 0.248]; 0.074>
C_6	<[0.041, 0.241], [0.559, 0.759]; 0.083>	<[0.023, 0.177], [0.623, 0.823]; 0.174>	<[0.559, 0.759], [0.041, 0.241]; 0.083>	<[0.575, 0.775], [0.025, 0.225]; 0.106>	<[0.534, 0.684], [0.165, 0.316]; 0.382>	<[0.036, 0.194], [0.606, 0.806]; 0.275>	<[0.052, 0.252], [0.548, 0.748]; 0.074>	<[0.577, 0.777], [0.023, 0.223]; 0.109>	<[0.525, 0.725], [0.075, 0.275]; 0.106>	<[0.000, 0.179], [0.621, 0.821]; 0.112>
C_7	<[0.018, 0.205], [0.595, 0.795]; 0.149>	<[0.075, 0.275], [0.525, 0.725]; 0.106>	<[0.575, 0.775], [0.025, 0.225]; 0.106>	<[0.259, 0.373], [0.513, 0.627]; 0.312>	<[0.198, 0.326], [0.546, 0.674]; 0.348>	<[0.283, 0.392], [0.500, 0.608]; 0.243>	<[0.500, 0.576], [0.348, 0.424]; 0.278>	<[0.557, 0.757], [0.043, 0.243]; 0.080>	<[0.048, 0.248], [0.552, 0.752]; 0.074>	<[0.375, 0.525], [0.325, 0.475]; 0.355>

Step 4. Equation (11) was used to obtain the weighted decision matrix by combining the normalized decision matrix with the criteria weights. The criteria weights, derived from Equation (8) based on experts' opinions, are *C = {0.081, 0.135, 0.189, 0.270, 0.054, 0.108, 0.162}*. The weighted decision matrix is shown in Table 7.

Table 7
The IVCIF weighted decision matrix

$\widetilde{W}_r^I$	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}	$\widetilde{A}_{r.j}^{I+}$	$\widetilde{A}_{r.j}^{I-}$
C_1	<[0.058, 0.081], [0.887, 0.919]; 0.309>	<[0.064, 0.109], [0.772, 0.891]; 0.083>	<[0.055, 0.069], [0.913, 0.931]; 0.251>	<[0.016, 0.033], [0.945, 0.967]; 0.354>	<[0.067, 0.114], [0.776, 0.886]; 0.177>	<[0.062, 0.105], [0.790, 0.895]; 0.077>	<[0.005, 0.024], [0.951, 0.976]; 0.086>	<[0.069, 0.118], [0.704, 0.882]; 0.123>	<[0.004, 0.023], [0.953, 0.977]; 0.077>	<[0.000, 0.009], [0.971, 0.991]; 0.153>	<[0.069, 0.118], [0.704, 0.882]; 0.354>	<[0.000, 0.009], [0.971, 0.991]; 0.354>

Table 7
Continued

C_2	<[0.005, 0.036], [0.925, 0.964]; 0.086>	<[0.109, 0.181], [0.659, 0.819]; 0.180>	<[0.100, 0.147], [0.779, 0.853]; 0.392>	<[0.030, 0.053], [0.920, 0.947]; 0.340>	<[0.093, 0.126], [0.830, 0.874]; 0.303>	<[0.099, 0.138], [0.807, 0.862]; 0.340>	<[0.006, 0.037], [0.924, 0.963]; 0.080>	<[0.099, 0.148], [0.775, 0.852]; 0.398>	<[0.036, 0.058], [0.917, 0.942]; 0.297>	<[0.030, 0.056], [0.911, 0.944]; 0.336>	<[0.109, 0.181], [0.659, 0.819]; 0.398>	<[0.005, 0.036], [0.925, 0.964]; 0.398>
C_3	<[0.012, 0.056], [0.889, 0.944]; 0.088>	<[0.007, 0.050], [0.897, 0.950]; 0.091>	<[0.167, 0.276], [0.000, 0.724]; 0.116>	<[0.130, 0.175], [0.766, 0.825]; 0.292>	<[0.136, 0.224], [0.591, 0.776]; 0.088>	<[0.002, 0.044], [0.904, 0.956]; 0.123>	<[0.008, 0.051], [0.895, 0.949]; 0.079>	<[0.145, 0.238], [0.538, 0.762]; 0.088>	<[0.007, 0.049], [0.898, 0.951]; 0.093>	<[0.074, 0.097], [0.877, 0.903]; 0.263>	<[0.167, 0.276], [0.000, 0.724]; 0.292>	<[0.002, 0.044], [0.904, 0.956]; 0.292>
C_4	<[0.171, 0.217], [0.728, 0.783]; 0.234>	<[0.017, 0.079], [0.846, 0.921]; 0.088>	<[0.196, 0.316], [0.434, 0.684]; 0.077>	<[0.019, 0.081], [0.843, 0.919]; 0.097>	<[0.011, 0.072], [0.854, 0.928]; 0.083>	<[0.179, 0.290], [0.508, 0.710]; 0.116>	<[0.075, 0.115], [0.839, 0.885]; 0.298>	<[0.186, 0.301], [0.480, 0.699]; 0.093>	<[0.185, 0.269], [0.610, 0.731]; 0.387>	<[0.046, 0.100], [0.835, 0.900]; 0.383>	<[0.196, 0.316], [0.434, 0.684]; 0.387>	<[0.011, 0.072], [0.854, 0.928]; 0.387>
C_5	<[0.039, 0.067], [0.869, 0.933]; 0.106>	<[0.004, 0.016], [0.967, 0.984]; 0.091>	<[0.043, 0.073], [0.848, 0.927]; 0.074>	<[0.016, 0.026], [0.963, 0.974]; 0.263>	<[0.001, 0.013], [0.972, 0.987]; 0.158>	<[0.049, 0.085], [0.806, 0.915]; 0.151>	<[0.003, 0.016], [0.967, 0.984]; 0.086>	<[0.020, 0.028], [0.963, 0.972]; 0.234>	<[0.003, 0.016], [0.968, 0.984]; 0.079>	<[0.043, 0.073], [0.848, 0.927]; 0.074>	<[0.049, 0.085], [0.806, 0.915]; 0.263>	<[0.001, 0.013], [0.972, 0.987]; 0.263>
C_6	<[0.005, 0.029], [0.939, 0.971]; 0.083>	<[0.002, 0.021], [0.950, 0.979]; 0.174>	<[0.085, 0.143], [0.708, 0.857]; 0.083>	<[0.088, 0.149], [0.671, 0.851]; 0.106>	<[0.079, 0.117], [0.823, 0.883]; 0.382>	<[0.004, 0.023], [0.947, 0.977]; 0.275>	<[0.006, 0.031], [0.937, 0.969]; 0.074>	<[0.089, 0.150], [0.665, 0.850]; 0.109>	<[0.077, 0.130], [0.756, 0.870]; 0.106>	<[0.000, 0.021], [0.950, 0.979]; 0.112>	<[0.089, 0.150], [0.665, 0.850]; 0.382>	<[0.000, 0.021], [0.950, 0.979]; 0.382>
C_7	<[0.003, 0.037], [0.919, 0.963]; 0.149>	<[0.013, 0.051], [0.901, 0.949]; 0.106>	<[0.130, 0.215], [0.549, 0.785]; 0.106>	<[0.048, 0.073], [0.897, 0.927]; 0.312>	<[0.035, 0.062], [0.906, 0.938]; 0.348>	<[0.053, 0.077], [0.894, 0.923]; 0.243>	<[0.106, 0.130], [0.843, 0.870]; 0.278>	<[0.124, 0.205], [0.601, 0.795]; 0.080>	<[0.008, 0.045], [0.908, 0.955]; 0.074>	<[0.073, 0.114], [0.833, 0.886]; 0.355>	<[0.130, 0.215], [0.549, 0.785]; 0.355>	<[0.003, 0.037], [0.919, 0.963]; 0.355>

Step 5. The ideal and anti-ideal alternatives for each criterion were determined using Equation (12), as presented in Table 8.

Step 6. The IVCIF weighted sum for each alternative was determined using Equation (13), with the results displayed in Table 8.

Step 7. Using Equation (14), the previously obtained IVCIF weighted sums were transformed into CIF values, as shown in Table 8.

Step 8. Equation (15) was used to defuzzify the CIF weighted sums from the previous step, with λ set at 0.7 based on experts' feedback. The obtained IF weighted sums are provided in Table 8.

Table 8
The weighted sums of decision alternatives' rates

	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}	A^+	A^-
$\tilde{S}_r^I$	<[0.268, 0.429], [0.399, 0.571]; 0.132>	<[0.201, 0.416], [0.320, 0.584]; 0.120>	<[0.565, 0.754], [0.000, 0.246]; 0.102>	<[0.305, 0.467], [0.325, 0.533]; 0.241>	<[0.358, 0.544], [0.236, 0.456]; 0.305>	<[0.379, 0.568], [0.200, 0.432]; 0.226>	<[0.196, 0.346], [0.504, 0.654]; 0.192>	<[0.543, 0.737], [0.054, 0.263]; 0.113>	<[0.291, 0.477], [0.318, 0.523]; 0.106>	<[0.240, 0.389], [0.435, 0.611]; 0.254>	<[0.581, 0.781], [0.000, 0.219]; 0.351>	<[0.023, 0.211], [0.588, 0.789]; 0.351>

Table 8
Continued

	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A+	A-
$\tilde{S}_r$	<0.349, 0.485; 0.132>	<0.309, 0.452; 0.120>	<0.660, 0.123; 0.102>	<0.386, 0.429; 0.241>	<0.451, 0.346; 0.305>	<0.474, 0.316; 0.226>	<0.271, 0.579; 0.192>	<0.640, 0.159; 0.113>	<0.384, 0.421; 0.106>	<0.314, 0.523; 0.254>	<0.681, 0.109; 0.351>	<0.117, 0.689; 0.351>
$\tilde{S}$	<0.386, 0.448>	<0.343, 0.418>	<0.689, 0.094>	<0.454, 0.361>	<0.537, 0.260>	<0.538, 0.252>	<0.325, 0.525>	<0.672, 0.127>	<0.414, 0.390>	<0.386, 0.451>	<0.780, 0.010>	<0.217, 0.589>

Step 9. The positive and negative IF utility degrees of each alternative were calculated using Equations (16) and (17).

Step 10. Equations (18) and (19) were used to obtain the corresponding IF utility functions.

Step 11. The final utility function of the alternatives were derived by applying Equations (20) and (21).

Step 12. Based on the outcomes of Steps 9 to 11, the renewable energy alternatives were prioritized. The results of all these steps are presented in Table 9.

Table 9
Utility measures and rank of decision alternatives

	$\tilde{U}_i^+$		$\tilde{U}_i^-$		$\tilde{f}(U_i^+)$		$\tilde{f}(U_i^-)$		$f(U_i)$	Rank
	μ	v	μ	v	μ	v	μ	v	*crisp*	
A1	0.495	0.442	1.000	0.000	1.000	0.000	0.558	0.442	0.5581	8
A2	0.439	0.412	1.000	0.000	1.000	0.000	0.588	0.412	0.5883	7
A3	0.882	0.085	1.000	0.000	1.000	0.000	0.915	0.085	0.9151	1
A4	0.582	0.355	1.000	0.000	1.000	0.000	0.645	0.355	0.6455	5
A5	0.689	0.252	1.000	0.000	1.000	0.000	0.748	0.252	0.7478	4
A6	0.689	0.244	1.000	0.000	1.000	0.000	0.756	0.244	0.756	3
A7	0.417	0.520	1.000	0.000	1.000	0.000	0.480	0.520	0.480	10
A8	0.861	0.118	1.000	0.000	1.000	0.000	0.882	0.118	0.882	2
A9	0.530	0.384	1.000	0.000	1.000	0.000	0.616	0.384	0.616	6
A10	0.495	0.445	1.000	0.000	1.000	0.000	0.555	0.445	0.555	9

3.3 Sensitivity analysis

To assess the robustness of the proposed approach, a sensitivity analysis was performed [69]. This involved examining the effect of varying the λ parameter, which reflects expert perspectives. Figure 1 illustrates the changes in utility rates across ten scenarios, with λ ranging from 0 to 1 in increments of 0.1.

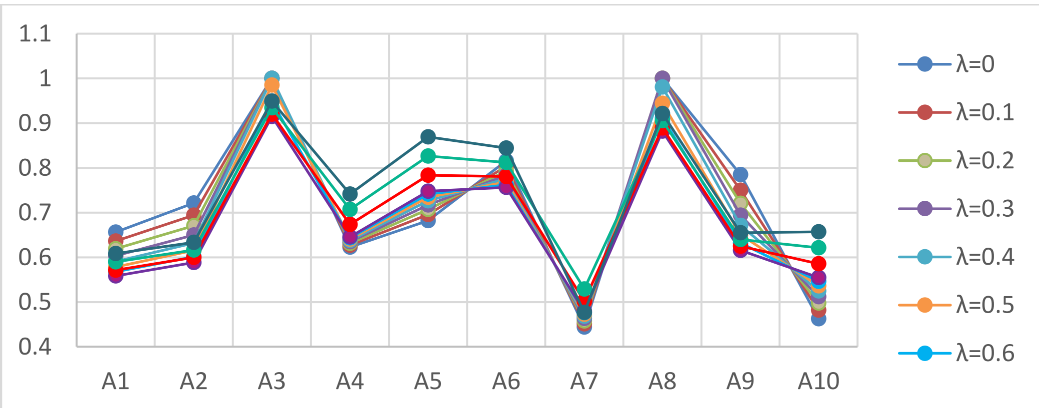

Fig. 1. Utility rate of alternatives across ten scenarios with different λ values

The results show that the utility rates and final rankings of alternatives remain largely stable across different λ values, indicating the model's robustness to varying degrees of optimism or pessimism among experts. In particular, alternatives A_3 and A_8 consistently retained top positions, while A_7 was repeatedly ranked lowest. These findings confirm that the IVCIF-MARCOS method produces stable outcomes under different attitudinal settings, with only minor shifts observed among middle-ranked alternatives, such as A_2, A_5, A_6, and A_{10}. This suggests that the method maintains its reliability even when exposed to variation in subjective inputs

3.4 Comparative analysis

To assess the performance validity and result consistency of the proposed IVCIF-MARCOS method, a comparative analysis was performed against six variations of the MARCOS framework. These included CIF-MARCOS, IF-MARCOS [86], IVIF-MARCOS [10], PyF-MARCOS [87], SF-MARCOS [88], and the original MARCOS model [9]. As shown in Figure 2, the proposed method consistently generated stable rankings that were in alignment with established models.

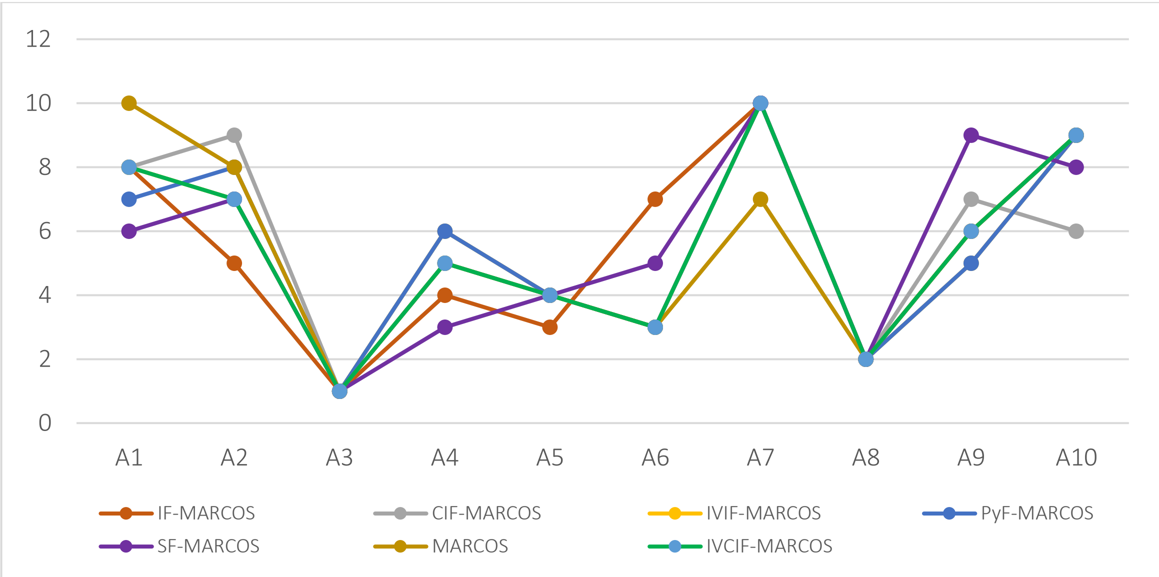

Fig. 2. Utility degrees of alternatives across various MARCOS methods

To support the validity of the comparison results, Spearman's rank correlation coefficient (SCC) was applied— an established statistical measure frequently used to assess agreement among ranking or score functions in MCDM methods [34, 89]. The SCC is computed using the following equation [90]:

$$R = 1- \frac{6\sum_{i=1}^{n} d_i^2}{n(n^2-1)} \tag{22}$$

where d_i denotes the difference in utility rate of each alternative and n the total number of alternatives. Table 10 presents the SCC values for the alternative utility rates obtained through different versions of the MARCOS method.

Table 10
SCC values for the utility rates of alternatives

	IVCIF-MARCOS	IF-MARCOS	CIF-MARCOS	IVIF-MARCOS	PyF-MARCOS	SF-MARCOS	MARCOS
IVCIF-MARCOS	1.000	0.867	0.915	0.988	0.976	0.867	0.915
IF-MARCOS		1.000	0.733	0.842	0.806	0.855	0.758
CIF-MARCOS			1.000	0.891	0.903	0.855	0.855
IVIF-MARCOS				1.000	0.988	0.794	0.903
PyF-MARCOS					1.000	0.806	0.879
SF-MARCOS						1.000	0.733
MARCOS							1.000

The results in Table 10 demonstrate that the IVCIF-MARCOS method consistently provides the most stable and reliable utility rates of alternatives, as reflected in its high SCC values. It shows strong correlations of 0.988 with IVIF-MARCOS, 0.976 with PyF-MARCOS, and 0.915 with CIF-MARCOS and MARCOS. In comparison, other methods such as IF-MARCOS and SF-MARCOS showed relatively lower correlations, indicating less consistency in the utility rates.

3.5 Discussion

The proposed IVCIF–MARCOS method offers a significant advancement in addressing RES selection under uncertainty. Sensitivity analysis confirmed the stability of utility rates across diverse expert perspectives, while strong correlations with comparable methods—such as IVIF-MARCOS, PyF-MARCOS, and CIF-MARCOS—validated its consistency. The broader literature shows that the MARCOS framework has been successfully adapted to various fuzzy environments, demonstrating the approach's robustness across different uncertainty representations. While direct comparisons with other IVCIF-based methods remain limited, this established adaptability of the MARCOS methodology provides theoretical support for our IVCIF extension. Ecer and Pamucar [13] demonstrated the consistency of IF–MARCOS with other intuitionistic fuzzy methods such as IF–COPRAS, IF–MABAC, and IF–TOPSIS, reinforcing the model's structural reliability. Pamucar *et al.,* [49] showed that the SVNF version of MARCOS outperformed D–MARCOS and IFV–MARCOS methods, confirming its effectiveness in complex scenarios. Likewise, Salimian *et al.,* [10] validated the performance of IVIF–MARCOS by comparing it with IVIF–VIKOR and IVIF–TOPSIS. Their findings supported the reliability of MARCOS when extended to IVIF domains. Simic *et al.,* [54] similarly demonstrated the reliability of PF–MARCOS through a comprehensive comparative analysis involving PF–TOPSIS, EDAS, grey relational analysis, grey projection, and cross-entropy, all of which showed high consistency with the PF–MARCOS rankings. Further evidence of consistency and robustness comes from [84], who found that the HF–MARCOS results were highly aligned with those of HF–SCORE and HF–TOPSIS. Mei *et al.,* [23] also confirmed the validity of PyF–MARCOS by demonstrating its ranking consistency with PyF–TOPSIS and PyF–WASPAS. Mishra *et al.,* [27] extended this validation to the FF environment, confirming the soundness of FF–MARCOS through comparisons with FF–TOPSIS, FF–ARAS, FF–WASPAS, and FF–CoCoSo. Similarly, Shang *et al.,* [21] found the IVPF–MARCOS method more appropriate than conventional models including ESP–COMET, SESP–SPOTIS, TOPSIS, VIKOR, WASPAS, and AHP. Ahmad *et al.,* [20] supported the robustness of the D–SF MARCOS approach via comparison with the CoCoSo method. These collective findings reinforce the credibility of integrating advanced fuzzy environments with the original MARCOS structure. In alignment with this body of work, our proposed IVCIF–MARCOS method extends this trajectory by leveraging the representational richness of IVCIFSs, offering a more expressive and reliable approach for evaluating alternatives in uncertain and complex decision contexts.

Beyond the methodological robustness established in our comparative analyses, the thematic consistency between our findings and prior renewable energy selection studies further validates the IVCIF-MARCOS approach as both theoretically sound and practically relevant for real-world decision-making. Our results identified Photovoltaic (A3), Biomass (A8), and Biodiesel (A6) as the top three RESs suitable for the context of the case study. Given the high solar insolation levels in the area, photovoltaic (PV) systems offer a practical solution, providing clean, scalable power with relatively low operational costs [18]. Similarly, Puška *et al.,* [69], using the fuzzy RAWEC method, identified this RES as the highest-rated option among six alternatives, emphasizing its strong potential in regions like Bosnia and Herzegovina, where abundant sunlight supports sustainable and cost-effective power generation. In another study, Moreno-Rocha *et al.,* [73], applying the fuzzy AHP method, highlighted photovoltaic energy as the most suitable choice among ten renewable sources for Colombia's Caribbean region, noting its tropical climate and ample solar radiation as key advantages. Additionally, Younis *et al.,* [18], using the PHFS-MARCOS method, confirmed the superiority of photovoltaic systems over wind, hydroelectric, and biomass sources. Lenarczyk *et al.,* [67], employing the AHP-Numerical Taxonomy method, observed that while distributed photovoltaic power plants ranked second, large-scale solar installations faced limitations in Poland, placing them fourth among eight alternatives due to less favorable conditions. Following PV, biomass (A8) emerged as the second most appropriate RES for the case study, particularly suited to capitalize on typical food processing waste streams, supporting steady heat and power production while aligning with circular economy principles [73]. In their analysis using the fuzzy TOPSIS method, Moreno-Rocha *et al.,* [73] identified biomass as the top-ranked option among ten alternatives in Colombia's Orinoquia region, highlighting the potential for utilizing agricultural and forestry residues. Similarly, Puška *et al.,* [69], using the fuzzy RAWEC method, ranked biomass as the third most appropriate RES among six options, citing the abundant agricultural waste available in Bosnia and Herzegovina as a key factor. Overall, this analysis indicates that while the priority ranking of RESs varies depending on regional characteristics, methodological approaches, and expert perspectives, multiple studies align with our findings, providing a consistent theoretical basis for the selected RESs in the case under study.

4. Conclusion

In the current research, the IVCIF-MARCOS method was designed to complement the original MARCOS method with the facility to handle the intrinsic uncertainty and vagueness typical of MCDM problems. To demonstrate its practical applicability, a case study on RES selection was conducted, providing a realistic context for validation. Sensitivity and comparative analyses confirmed the model's robustness, showing stable utility rates across varying expert perspectives and a strong alignment with related advanced methods. The results identified Photovoltaic (A3), Biomass (A8), and Biodiesel (A6) as the most suitable RESs for the case context. Furthermore, a comprehensive discussion was conducted to verify the consistency of these findings with previous studies, reinforcing the validity of the proposed approach for both MARCOS model development under fuzzy environments and renewable energy decision-making.

4.1 Implications

Theoretically, IVCIF-MARCOS advances MCDM by integrating IVCIFSs to better capture complex uncertainty and expert hesitation in real-world decisions. Its dual-layered fuzzification handles conflicting judgments and vague boundaries, offering superior modeling accuracy compared to traditional fuzzy approaches—particularly for sustainability-focused choices like RES selection.

Practically, the method proves valuable for strategic decision-making under uncertainty, as demonstrated in our RES case study. By effectively navigating imprecise criteria, it helps organizations balance economic and sustainability objectives. The framework is particularly relevant for energy-intensive industries transitioning to greener alternatives, providing a robust, evidence-based decision tool.

4.2 Limitations

Despite its strengths, the proposed model has certain limitations that present opportunities for further refinement. First, the model relies on IVCIF weighted averaging for criteria weighting, which, while efficent in capturing subjective judgments, may benefit from a novel method to enhance weight credibility under IVCIFS. Second, the current framework evaluates a predefined set of alternatives tailored to the specific case study, potentially limiting its flexibility in broader applications. Third, while IVCIFSs effectively capture interval-based uncertainty, even more advanced hybrid fuzzy sets, might further improve its capacity to handle complex, high-uncertainty environments. Finally, the model's validation is currently based on a single case study, which, while illustrative, restricts the generalizability of its findings.

4.3 Future research directions

To further enhance the IVCIF-MARCOS method, several key research directions can be explored. First, integrating established criteria weight-determination methods like CRITIC, SWARA, or FUCOM under the IVCIFS framework could improve the reliability of criteria weights. Second, expanding the criteria and alternative sets beyond case-specific designs would increase the model's versatility and robustness. Third, applying advanced hybrid fuzzy sets, such as Circular Q-Rung Orthopair Fuzzy Sets or Circular Pythagorean Fuzzy Sets, could further strengthen the method's capacity to handle complex uncertainty. Additionally, exploring alternative ranking techniques like COCOSO, MABAC, or MULTIMOORA under IVCIFS could provide valuable benchmarks for comparison. Finally, validating the approach across diverse sectors and geographical contexts would enhance its generalizability and practical impact.

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Conflicts of Interest

The authors declare no conflicts of interest.

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