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Novel Multi-Criteria Intuitionistic Fuzzy SWARA–COPRAS Approach for Sustainability Evaluation of the Bioenergy Production Process

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Abstract: Bioenergy is a kind of renewable energy that can potentially contribute to a broad spectrum of economic, environmental, and societal objectives and aid sustainable development. The assessment, management, and monitoring of the diverse bioenergy production technology alternatives are complex in nature and deliver different benefits due to the lack of precise and comprehensive data. Selection of an optimal bioenergy production technology (BPT) alternative is considered a complex multi-criteria decision-making (MCDM) problem that involves many incompatible tangible and intangible as well as qualitative and quantitative criteria. The procedure of defining and evaluating the weights of the criteria is an important concern for decision experts because the assessment and the final selection of the BPT alternative are carried out on the basis of the defined set of criteria. Intuitionistic fuzzy sets (IFSs) have received considerable attention due to their ability to handle the imprecision and vagueness that can arise in real-life situations. Thus, this study presents an integrated approach, based on stepwise weight assessment ratio analysis (SWARA) and complex proportional assessment (COPRAS) approaches, for the selection of BPT alternatives. In the integrated framework, criteria weights are determined by the SWARA procedure, and the ranking of BPT alternatives is decided by the COPRAS method using IFSs. The criteria weights evaluated by this approach involve the imprecision of experts' opinions, which makes them more comprehensible. To express the efficiency and applicability of the integrated framework, a BPT selection problem is presented using IFSs. In addition, this study involved sensitivity analysis with respect to various sets of criteria weights to reveal the strength of the developed approach. The sensitivity analysis outcomes indicate that the agricultural and municipal waste of biogas (S_3) consistently secures the highest rank, despite how the criteria weights vary. Finally, a comparative study is discussed to analyze the validity of the obtained result. The findings of this study confirm that the proposed framework is more useful than and consistent with previously developed methods using the IFSs environment.

Keywords: intuitionistic fuzzy sets; SWARA; COPRAS; MCDM; biomass; bioenergy

1. Introduction

Finding suitable sources of bioenergy production is one of the major concerns for developing countries, as fossil-fuel-based energy resources are limited and negatively affect the environment. Biomass, as a renewable energy resource, is easier to produce, collect, accumulate, consume, and restore speedily without depleting natural resources than fossil fuels [1]. There is a broad array of biomass resources in many forms of material that can be transferred using a variety of technologies to different forms of bioenergy, including power, heat, biofuels, or a combination thereof [2]. Biomass is generally categorized in two ways: terrestrial biomass, which includes starch-based, sugar-based, oil-based, and cellulosic biomass feedstocks, and aquatic biomass, which includes cyanobacteria, microalgae, and macroalgae [1]. An increasing concentration of aquatic biomass has been observed in the world. The aquatic surface area of Earth is several times larger than the land, and much of the dry land is being exploited for terrestrial biomass expansion. Moreover, high productivity has been observed in aquatic weeds in comparison to terrestrial plants [3].

Biomass can be utilized for direct heating both in domestic and industrial applications, for production of fuels in gaseous or liquid form and for the production of steam for electricity generation. Direct heating is the oldest and the most extensive application, but biofuels and electricity production are becoming more popular among energy policymakers [4]. Diverse biofuels can be derived from biomass for the transport sector, and examples include ethanol, biodiesel, and advanced hydrocarbon biofuels. Several conversion technologies have been developed to produce bioenergy from different forms of biomass. It can be seen that there are many conversion pathways from various types of biomass to intermediates and final biofuel products [1]. As there is a diversity of biomass, bioenergy, and conversion technologies, a need arises for a healthier perspective on how various bioenergy production technologies (BPTs) can encourage sustainable development. An evaluation of efficient biomass-for-bioenergy conversion technologies that concerns sustainability problems is of strategic importance and can play a significant role in the design of the biomass supply network [5,6].

Sustainability is an intrinsically imprecise and multifaceted idea, and the possible significance of sustainable development is not easy to describe or estimate. Collecting precise data on the sustainability of diverse BPTs is a difficult assignment [3]. In addition, bioenergy production technologies have an intricate nature, and data that are both accurate and quantitative are not always available or are expensive to obtain [7]. The concept of fuzzy sets (FSs), introduced by Zadeh [8], has been extensively applied to address ambiguities that arise in day-to-day problems. Various authors have utilized the concepts of linguistic variables (LVs) and FSs in order to cope with uncertainties that arise in ranking alternative energy exploitation projects [3,9–12].

The concept of FSs has successfully been utilized in multi-criteria decision-making (MCDM) problems because human judgments are usually not precise when choosing an alternative concerning multiple criteria with different levels of significance. In the last few decades, several generalizations of FSs have been developed, such as interval-valued fuzzy sets (IVFSs) [13], IFSs [14], vague sets (VSs) [15], hesitant fuzzy sets (HFSs) [16], and Pythagorean fuzzy sets (PFSs) [17]. Atanassov [14] pioneered the notion of IFSs as an improvement of FSs, depicted by the membership function (MF) and non-membership function (NMF). This technique satisfies the requirement that the sum of the MF and NMF is less than or equal to 1. Compared to FSs, IFSs have been extensively implemented by many researchers in different areas, such as decision making and image processing. In recent times, several approaches have been introduced to solve the MCDM problems within the IFSs context. For instance, Mishra et al. [18] studied an entropy-measure-based approach to evaluate the service quality of vehicle insurance companies. Ansari et al. [19] pioneered entropy and divergence measures for IFSs and further employed these approaches to propose a significant technique for edge detection.

Çal et al. [20] introduced an innovative group decision-making framework based on elimination and choice. Translating Reality (ELECTRE) aims to handle outranking problems efficiently using the IFS concept. Mishra et al. [21] proposed the use of a Shapley weighted divergence measures-based model, *Vlse Kriterijumska Optimizacija I Kompromisno Resenje* in Serbian (VIKOR), to choose a cloud service provider using IFSs. Liu et al. [22] developed Bonferroni mean operators for IFSs based on Dempster-Shafer theory. Mishra et al. [23] created a novel Jensen–Shannon divergence measures-based decision-making model to solve the energy source selection problem for IFSs. Mishra et al. [24] extended a multi-attributive border approximation area comparison (MABAC) approach with new entropy and divergence measures to solve programming language selection problems with Interval-Valued Intuitionistic Fuzzy Sets (IVIFSs). Mishra et al. [25] developed an integrated intuitionistic fuzzy additive ratio assessment (IF-ARAS) approach with divergence measures to choose the best candidates in IT personnel selection.

The criteria weights are vital factors in the MCDM procedure. The criteria weights are of two types: objective and subjective weights [26]. The objective weights are evaluated from the information in decision matrices, while the subjective weights are computed based on the information given by decision experts (DEs) [27]. For evaluating objective criteria weights, various authors have developed the different types of entropy and divergence measures [28–31]. For determining subjective criteria weights, the Stepwise Weight Assessment Ratio Analysis (SWARA) approach is an efficient and relatively new process which was proposed by Kersulienė et al. [32]. This approach has minor computational complexity in comparison with other weight determination techniques. Recently, the SWARA method has widely been utilized by various authors in various real-world MCDM problems. Karabasevic et al. [33] proposed a structure for the evaluation of personnel based on ARAS and SWARA approaches within an FSs context. Isik et al. [34] proposed a SWARA and operational competitiveness ratings analysis (OCRA) technique-based hybrid approach, and then applied it to rank hotels. Mavi et al. [35] discussed a combined method concerning SWARA and MULTIMOORA on FSs and applied it to determine third-party reverse logistics provider. Stanujkic et al. [36] studied a hybrid method based on the ARAS and SWARA approaches, named as Additive Ratio Compromise Assessment (ARCAS), which permits the experts concerned in a negotiation procedure to articulate their preferences. Karabašević et al. [37] proposed an expert-based combined method based on the SWARA and Delphi techniques. Stanujkic et al. [38] introduced an improved SWARA approach, wherein the more suitable option is chosen based on negotiation, for the personnel selection problem. Urosevic et al. [39] studied the SWARA and Weighted Aggregated Sum Product Assessment (WASPAS)-based MCDM method, and, further, implemented it for personnel selection in the tourism sector. Ghorabae et al. [40] discussed a fuzzy hybrid approach based on the SWARA, Criteria Importance Through Intercriteria Correlation (CRITIC) method and Evaluation Based on Distance from Average Solution (EDAS) techniques to handle the MCDM problems, and then applied it to assess construction equipment in view of sustainability dimensions. Mardani et al. [41] discussed a thorough review of the SWARA and WASPAS approaches and their applications in diverse fuzzy environments. Dahooie et al. [42] used a combined structure-based on SWARA approach to find the criteria's weights and a grey ARAS (ARAS-G) technique to assess and select the best information technology (IT) expert.

Numerous MCDM approaches have previously been developed and augmented by earlier researchers for the solution of complex selection problems arising in our daily life. Each selection problem basically consists of the following major elements: (a) alternatives, (b) criteria, (c) relative importance (weight) of each criterion, and (d) measures of performance of options over the considered criteria. The objective of the MCDM approach is to choose the optimum choice from a set of feasible choices based on various conflicting criteria. Corresponding to compromise programming, a new approach named Complex Proportional Assessment (COPRAS), pioneered by Zavadskas et al. [43], is a reasonable and efficient framework for information processing. The key features of the COPRAS framework are as follows: it provides a valuable and appropriate way to handle the MCDM problems [44,45]; COPRAS uses complex proportional assessment, which

offers more precise information compared to diverse procedures for evaluating the benefit or cost criteria finally, it delineates the ratios of the ideal and the worst solutions at the same time. According to these benefits, various authors have extended the COPRAS approach into various disciplines in recent years [46–48]. Owing to the increasing complexity and uncertainty of MCDM problems, the classical COPRAS approach has been extended under different uncertain environments. For instance, Ghorabae et al. [49] discussed the COPRAS method for supplier selection on interval type-2 fuzzy sets. Bekar et al. [50] proposed the COPRAS approach with grey numbers to assess the MCDM procedure. Recently, Zheng et al. [51] extended the hesitant fuzzy linguistic COPRAS approach to evaluate medical disease. Mishra et al. [52] developed the COPRAS method to solve MCDM problems under HFSs. Mishra et al. [53] extended the COPRAS based on information measures to evaluate the hazardous waste recycling facility evaluation problem within an IVIFS context. Kumari et al. [54] presented the COPRAS approach associated with parametric information measures for IFSs to solve the green supplier selection problem.

In recent years, IFSs have proved to be one of the most valuable ways to tackle the uncertainty and imprecision occurring in various real-life concerns. In view of this, several authors have paid attention to the development of many theories and applications related to IFSs. Consequently, the proposed work focuses on the IFS environment. Recently, there has been increasing concern about the production and conversion of bioenergy from biomass, so, in this study, the BTP selection problem is discussed from a sustainability perspective. To address this concern, an integrated IF-SWARA-COPRAS framework is developed that can successfully tackle the inherent uncertainty and hesitancy in decision-makers' opinions. The contributions of the study are as follows:

- An integrated IF-SWARA-COPRAS framework is introduced.
- We evaluate the decision-makers weights under the intuitionistic fuzzy environment based on Boran et al.'s [55] formula.
- The IFS-based SWARA approach is applied to evaluate the criteria weights.
- To show the applicability of the proposed IF-SWARA-COPRAS model, an empirical case study of the bioenergy production technology selection problem is presented within the context of IFSs.
- A comparative and sensitivity study is studied to prove the validity and stability of the developed framework.

The remaining paper is structured as follows. Section 2 describes the fundamental concepts related to IFSs. Section 3 proposes a new intuitionistic fuzzy-SWARA-COPRAS (IF-SWARA-COPRAS) method with IFSs. Section 4 implements the proposed framework in a case study of bioenergy production technology selection, which shows the applicability and strength of the developed framework. To reveal the stability and feasibility of the developed framework, Section 5 shows the comparative and sensitivity analyses and concludes the work in Section 6.

2. Preliminaries

Here, some primary notions of IFSs and their operations are given.

Definition 1 [14]. An IFS, R , in a discourse set $U = \{u_1, u_2, \dots, u_n\}$ is given by

$$R = \{\langle u_i, \mu_R(u_i), \nu_R(u_i) \rangle : u_i \in U\}, \quad (1)$$

where $\mu_R : U \rightarrow [0, 1]$ and $\nu_R : U \rightarrow [0, 1]$ are the MF and NMF of u_i to R in U , respectively, under the condition

$$0 \leq \mu_R(u_i) \leq 1, 0 \leq \nu_R(u_i) \leq 1 \text{ and } 0 \leq \mu_R(u_i) + \nu_R(u_i) \leq 1, \forall u_i \in U. \quad (2)$$

For an IFS R in U , we define the hesitancy degree of $u_i \in U$ to R as follows:

$$\pi_R(u_i) = 1 - \mu_R(u_i) - \nu_R(u_i) \text{ and } 0 \leq \pi_R(u_i) \leq 1, \quad \forall u_i \in U. \quad (3)$$

For simplicity, the intuitionistic fuzzy number (IFN) is described by $\xi = (\mu_\xi, \nu_\xi)$, which holds for $\mu_\xi, \nu_\xi \in [0, 1]$ and $0 \leq \mu_\xi + \nu_\xi \leq 1$ [56].

Definition 2 [56]. Consider $\xi_j = (\mu_j, \nu_j)$, and $j = 1(1)n$, being the IFNs. Then, the score function and the accuracy function are defined by

$$S(\xi_j) = (\mu_j - \nu_j), \quad h(\xi_j) = (\mu_j + \nu_j). \quad (4)$$

Here, $S(\xi_j) \in [-1, 1]$ and $h(\xi_j) \in [0, 1]$. Then, Xu et al. [57] improve the score function as follows.

Definition 3 [57]. Let $\xi_j = (\mu_j, \nu_j)$ be an IFN. Then, the normalized score function and the uncertainty function are given by

$$S^*(\xi_j) = \frac{1}{2}(S(\xi_j) + 1), \quad h(\xi_j) = \frac{1}{2}(\mu_j + \nu_j). \quad (5)$$

Obviously, $S^*(\xi_j) \in [0, 1]$ and $h(\xi_j) \in [0, 1]$.

Let $\xi_1 = (\mu_1, \nu_1)$ and $\xi_2 = (\mu_2, \nu_2)$ be two IFNs. Then, a process to compare any two IFNs is defined in terms of normalized score function, and the uncertainty function as follows:

if $S^*(\xi_1) > S^*(\xi_2)$, then $\xi_1 > \xi_2$,

if $S^*(\xi_1) = S^*(\xi_2)$, then

if $h(\xi_1) > h(\xi_2)$, then $\xi_1 < \xi_2$;

if $h(\xi_1) = h(\xi_2)$, then $\xi_1 = \xi_2$.

Definition 4 [56]. Let $\xi_j = (\mu_j, \nu_j)$, and $j = 1(1)n$, be IFNs. Then, the Intuitionistic Fuzzy Weighted Average (IFWA) and the Intuitionistic Fuzzy Weighted Geometric (IFWG) operators are given by

$$IFWA_w(\xi_1, \xi_2, \dots, \xi_n) = \bigoplus_{j=1}^n w_j \xi_j = \left[1 - \prod_{j=1}^n (1 - \mu_j)^{w_j}, \prod_{j=1}^n \nu_j^{w_j} \right], \quad (6)$$

$$IFWG_w(\xi_1, \xi_2, \dots, \xi_n) = \bigotimes_{j=1}^n w_j \xi_j = \left[\prod_{j=1}^n \mu_j^{w_j}, 1 - \prod_{j=1}^n (1 - \nu_j)^{w_j} \right], \quad (7)$$

where $w = (w_1, w_2, \dots, w_n)^T$ is a weight vector of ξ_j , $j = 1(1)n$, with $\sum_{j=1}^n w_j = 1$, $w_j \in [0, 1]$.

3. Proposed IF-SWARA-COPRAS Method

In the current section, an integrated method with the SWARA and the COPRAS approaches is developed under IFSs. The SWARA method, proposed by Kersulienė et al. [32], is an efficient approach to calculate the subjective weights of the criteria. The subjective weights of the criteria are generally evaluated based on the judgment of the DEs during the MCDM process. The main advantage of the SWARA method is its ability to estimate the accuracy of the criteria regarding the weights assigned by the DEs. Additionally, a compromise approach named the COPRAS method is beneficial, as it is very easy and comprehensible; it considers the ratios of the best solution and worst solution simultaneously, and the results can be obtained in less time. Thus, we introduce an integrated IF-SWARA-COPRAS framework to estimate the subjective criteria weights and evaluate the preference order of alternatives,

respectively. The working procedure of the IF-SWARA-COPRAS framework is discussed (see Figure 1) as follows:

Figure 1. The implementation procedure of the proposed IF-SWARA-COPRAS method.

Step 1: Originate the alternatives and the criteria.

In the MCDM procedure, the objective is to select the optimal alternative from among the set of m alternatives $S = \{S_1, S_2, \dots, S_m\}$ under the criterion set $L = \{L_1, L_2, \dots, L_n\}$. Consider a committee of ℓ decision experts (DEs) $E = \{E_1, E_2, \dots, E_\ell\}$, which has been formed to achieve the best alternative(s). Let $Z = (z_{ij}^{(k)})$, $i = 1(1)m$, $j = 1(1)n$ be the linguistic decision matrix given by the DEs, where $z_{ij}^{(k)}$ represents the assessment value of an option S_i over criteria L_j in the form of linguistic values for k th the expert.

Step 2: Evaluation of DEs' weights.

There are ℓ DEs with weight vector $\omega = (\omega_1, \omega_2, \dots, \omega_\ell)^T$. The DEs' weights are considered as linguistic values and expressed in IFNs. Let $E_k = (\mu_k, \nu_k, \pi_k)$ be an IFN for evaluation of the k th expert weight. Then, the importance value of the k th DE is given by [55]:

$$\omega_k = \frac{\left(\mu_k + \pi_k \left(\frac{\mu_k}{\mu_k + \nu_k}\right)\right)}{\sum_{k=1}^{\ell} \left(\mu_k + \pi_k \left(\frac{\mu_k}{\mu_k + \nu_k}\right)\right)}, \quad k = 1(1)\ell. \quad (8)$$

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

To compute the AIF-DM, we facilitate the IFWAO [56], then we obtain $\mathbb{R} = (\eta_{kj})_{\ell \times n}$, where

$$\eta_{kj} = IFWAO(\eta_{kj}^{(1)}, \eta_{kj}^{(2)}, \dots, \eta_{kj}^{(\ell)}) = \left(1 - \prod_{k=1}^{\ell} (1 - \mu_k)^{\omega_k}, \prod_{k=1}^{\ell} (v_k)^{\omega_k} \right). \quad (9)$$

Step 4: SWARA method for evaluating the criteria weights.

The SWARA procedure starts to rank the criteria and compares pairwise direct upper to lower-ranking criteria. Next, a comparative coefficient is evaluated, and the weight is decided and measured for handling MCDM problems. Estimation of criteria weights using SWARA is done using the following steps:

Step 4.1: Calculate the crisp values. Score values $S^*(\eta_{kj})$ of IFNs obtained by Equation (5), are calculated by Definition 3.

Step 4.2: Preference order of the criteria. The criteria are arranged according to the DE's preference from the most to the least important criterion.

Step 4.3: Evaluate the comparative significance of the score value. The comparative significance is evaluated from the criteria that are preferred in second place, and successive comparative significance is evaluated by differencing criterion j and criterion $j - 1$.

Step 4.4: Compute the comparative coefficient. The coefficient k_j is given by

$$k_j = \begin{cases} 1, & j = 1 \\ s_j + 1, & j > 1, \end{cases} \quad (10)$$

where s_j is the comparative significance of score value [32].

Step 4.5: Estimate the weight. The recalculated weight, p_j , is defined by

$$p_j = \begin{cases} 1, & j = 1 \\ \frac{k_{j-1}}{k_j}, & j > 1. \end{cases} \quad (11)$$

Step 4.6: Calculate the criteria weights. The criteria weights are calculated as follows:

$$w_j = \frac{p_j}{\sum_{j=1}^n p_j}. \quad (12)$$

Step 5: Aggregate the criterion values for benefit-type and cost-type.

In the developed framework, each alternative is described with its sum of maximizing α_i (benefit-type) and minimizing β_i (cost-type); i.e., the optimum results are maximization and minimization, respectively. In these conditions, α_i and β_i are calculated as follows.

Let $\Delta = \{1, 2, \dots, l\}$ be benefit-type criteria. Then, we calculate the maximum index value in terms of IFNs for each option, is given by

$$\alpha_i = \bigoplus_{j=1}^{\ell} w_j \eta_{ij}, \quad i = 1(1)m, \quad (13)$$

Let $\nabla = \{l + 1, l + 2, \dots, n\}$ be cost-type criteria. Then, we evaluate index value in terms of IFNs for each option, defined by

$$\beta_i = \bigoplus_{j=l+1}^n w_j \eta_{ij}, \quad i = 1(1)m. \quad (14)$$

where l and n are the number of benefit types and the total number of criteria, respectively.

Step 6: Evaluate the degree of relative weight.

The degree of the relative weight γ_i of the option is calculated as follows:

$$\gamma_i = S^*(\alpha_i) + \frac{\min_i S^*(\beta_i) \sum_{i=1}^p S^*(\beta_i)}{S^*(\beta_i) \sum_{i=1}^p \frac{\min_i S^*(\beta_i)}{S^*(\beta_i)}}, i = 1(1)m. \quad (15)$$

Here, $S^*(\alpha_i)$ is the score value of α_i and $S^*(\beta_i)$ is the score value of β_i . Equation (8) can also be demonstrated, as follows:

$$\gamma_i = S^*(\alpha_i) + \frac{\sum_{i=1}^p S^*(\beta_i)}{S^*(\beta_i) \sum_{i=1}^p \frac{1}{S^*(\beta_i)}}, i = 1(1)m. \quad (16)$$

Step 7: Compute the priority order.

Based on the degree of relative weight, the preference order of options is computed. The option with a higher degree of relative weight has the first rank and is the best option.

$$S^* = \max_i \gamma_i, i = 1(1)m. \quad (17)$$

The utility degree is computed by evaluating the options with the best option, and utility degree l_i is defined by

$$l_i = \frac{\gamma_i}{\gamma_{\max}} \times 100\%, i = 1(1)m. \quad (18)$$

where γ_i and $\gamma_{\max}$ are the relative significance of options computed by (16).

Step 9: End.

4. Case Study: Sustainability Evaluation of Bioenergy Alternatives

In the current section, the proposed IF-SWARA-COPRAS framework is used to compute the optimal alternative from the set of bioenergy production technology (BPTs) alternatives, which demonstrates the applicability and feasibility of the developed framework.

In these years, numerous conversion pathways have been proposed to transform biomass into bioenergy. Yue et al. [1] mentioned key conversion pathways from terrestrial and aquatic biomass to middle product and final biofuel product. Several procedures are mature and have been introduced: for instance, biofuels from oil crops, and starch- and sugar-based feedstock. Other processes, for example, algae to biofuels, are relatively novel, and are still in the initial phase. An analysis of BPT studies in Iran [3] has been conducted to assess available BPTs and decide the best alternative. However, in this study, to collect the data, the following procedure was conducted in different stages. In the first step, to evaluate the criteria, six BPTs from The Energy and Resources Institute (TERI) of India were identified. In the second step, a survey study using interviews and literature review was conducted to identify the main important criteria for assessment of BPTs. According to the results of the survey, four main dimensions, including environmental, social, economic and technological, were identified with 11 related criteria. For this process, six bioenergy production technologies (BPTs), including oil crops to biodiesel (s1), forest residues to ethanol (s2), agricultural and municipal wastes to biogas (s3), wet biomass to biodiesel forest (s4), residues to biodiesel (s5) and wet biomass to biogas (s6) were considered under eleven criteria belonging to four dimensions: environmental, economic, technical and social.

In the following step, a self-administered questionnaire based on four dimensions and 11 criteria was developed concerning cost type and benefit type to send to experts in the field. In the next step, to evaluate BPTs, each expert, based on her/his expertise, gave their opinion related to bioenergy

production technologies. The questionnaires were designed based on linguistic terms and are presented in Tables 1 and 2. In the following steps, we prepared a list of experts who met the criteria. These selected experts had worked in universities and governmental organizations related to bioenergy production technologies. In the next step, two rounds of Delphi surveys were performed from September 2019 to February 2020 by sending questionnaires to experts to collect data on the topic to reach consensus or gain understanding. After each round of the Delphi survey, an electronic reminder was sent after one or two weeks to non-responders after the first invitation. The second round was performed anonymously by email reminder.

Table 1. LTs and their equivalent IFNs for alternative and criteria weight.

LTs	Rating	IFNs
Extremely low (EL)	Extremely poor (EP)	(0.10, 0.80, 0.10)
Very low (VL)	Very poor (VP)	(0.20, 0.70, 0.10)
Low (L)	Poor (P)	(0.30, 0.60, 0.10)
Medium low (ML)	Medium poor (MP)	(0.40, 0.50, 0.10)
Medium (M)	Fair (F)	(0.55, 0.40, 0.05)
Medium high (MH)	Medium good (MG)	(0.65, 0.30, 0.05)
High (H)	Good (G)	(0.75, 0.20, 0.05)
Very high (VH)	Very good (VG)	(0.90, 0.05, 0.05)
Extremely high (EH)	Extremely good (EG)	(1.00, 0.00, 0.00)

Table 2. Linguistic terms (LTs) for rating decision makers' (DEs) significance degree.

Ratings	IFNs
Extremely significant (ES)	(1.00, 0.00, 0.00)
Very very significant (VVS)	(0.90, 0.05, 0.05)
Very significant (VS)	(0.70, 0.20, 0.10)
Significant (S)	(0.60, 0.30, 0.10)
Less significant (LS)	(0.40, 0.50, 0.10)
Very less significant (VLS)	(0.30, 0.60, 0.10)
Extremely less significant (EL)	(0.10, 0.80, 0.10)

Finally, after these rounds of data collection, we had collected the required data from three decision experts. As a result, based on the expert's opinions, all the selected criteria for the assessment of bioenergy production technologies were considered in the analysis process. Based on the multiplicity of criteria that were taken during the prelude survey, 11 criteria were evaluated and are given in Table 3.

Table 3. Criteria evaluation for bioenergy production technology (BPT)s selection problem.

Dimensions	Criteria	Criteria Type	Classification	Options
Environmental	Contribution to climate change (L_1)	Benefit	Qualitative	S_1
	Biological diversity loss (L_2)	Cost	Quantitative	
	Water use (L_3)	Benefit	Qualitative	
	Air and water and land pollution (L_4)	Cost	Quantitative	
Economic	Microeconomic sustainability (L_5)	Benefit	Qualitative	S_3
	Macroeconomic sustainability (L_6)	Benefit	Qualitative	
Technological	Technology maturity (L_7)	Benefit	Qualitative	S_4
	Continuity and predictability of performance (L_8)	Benefit	Quantitative	
Social	Effects on food security (L_9)	Benefit	Quantitative	S_5
	Job creation (L_{10})	Benefit	Qualitative	
	Contribution to regional development (L_{11})	Benefit	Qualitative	

Next, linguistic terms (LTs) were described in a qualitative way, and these terms are more appropriate for handling the imprecise practical decision-making problems. As a result, various authors developed different linguistic scales. The LTs for preference rating of decision makers (DEs) and performance values of the alternatives and criteria are now depicted in Table 2; Table 3.

The weights of DEs were calculated from Table 2 and Equation (8) and are given in Table 4. Table 5 describes the IFNs given by the DEs for the selection and evaluation of BPTs alternatives. Based on DEs' judgments and using Equation (9) and Table 2, the aggregated IF decision matrix is created and depicted in Table 6.

Table 4. DEs' weight evaluation for bioenergy production technology selection.

Decision Expert	E ₁	E ₂	E ₃
Linguistic variables	S	LS	VS
IFNs	(0.60, 0.30, 0.10)	(0.40, 0.50, 0.10)	(0.70, 0.20, 0.10)
Weights (ω_k)	0.3530	0.2352	0.4118

Table 5. IF ratings are given by DMs for bioenergy production technology selection.

DMs		S ₁	S ₂	S ₃	S ₄	S ₅	S ₆
L ₁	E ₁	(0.80, 0.10, 0.10)	(0.75, 0.20, 0.10)	(0.78, 0.12, 0.10)	(0.35, 0.50, 0.15)	(0.38, 0.50, 0.12)	(0.45, 0.40, 0.15)
	E ₂	(0.72, 0.20, 0.08)	(0.87, 0.08, 0.05)	(0.70, 0.15, 0.15)	(0.50, 0.40, 0.10)	(0.35, 0.35, 0.30)	(0.80, 0.15, 0.05)
	E ₃	(0.82, 0.10, 0.08)	(0.70, 0.20, 0.10)	(0.60, 0.30, 0.10)	(0.40, 0.55, 0.05)	(0.37, 0.35, 0.28)	(0.59, 0.35, 0.06)
L ₂	E ₁	(0.55, 0.35, 0.10)	(0.70, 0.25, 0.05)	(0.68, 0.22, 0.10)	(0.63, 0.32, 0.05)	(0.54, 0.35, 0.11)	(0.75, 0.15, 0.10)
	E ₂	(0.50, 0.30, 0.20)	(0.65, 0.30, 0.05)	(0.70, 0.25, 0.05)	(0.60, 0.35, 0.05)	(0.50, 0.25, 0.25)	(0.75, 0.18, 0.07)
	E ₃	(0.50, 0.45, 0.05)	(0.55, 0.35, 0.10)	(0.65, 0.25, 0.10)	(0.85, 0.10, 0.05)	(0.78, 0.15, 0.07)	(0.75, 0.20, 0.05)
L ₃	E ₁	(0.20, 0.75, 0.05)	(0.70, 0.22, 0.08)	(0.75, 0.20, 0.05)	(0.85, 0.10, 0.05)	(0.65, 0.25, 0.10)	(0.55, 0.40, 0.05)
	E ₂	(0.28, 0.67, 0.05)	(0.80, 0.10, 0.10)	(0.78, 0.12, 0.10)	(0.60, 0.25, 0.15)	(0.87, 0.05, 0.08)	(0.90, 0.05, 0.05)
	E ₃	(0.25, 0.70, 0.05)	(0.68, 0.22, 0.10)	(0.75, 0.15, 0.10)	(0.68, 0.25, 0.07)	(0.65, 0.23, 0.12)	(0.60, 0.34, 0.06)
L ₄	E ₁	(0.55, 0.35, 0.10)	(0.55, 0.40, 0.05)	(0.52, 0.43, 0.05)	(0.73, 0.18, 0.09)	(0.66, 0.28, 0.06)	(0.63, 0.25, 0.12)
	E ₂	(0.58, 0.34, 0.08)	(0.50, 0.34, 0.16)	(0.52, 0.42, 0.06)	(0.52, 0.40, 0.08)	(0.48, 0.40, 0.12)	(0.53, 0.29, 0.18)
	E ₃	(0.50, 0.45, 0.05)	(0.62, 0.33, 0.05)	(0.56, 0.35, 0.09)	(0.40, 0.45, 0.15)	(0.63, 0.30, 0.07)	(0.66, 0.25, 0.09)
L ₅	E ₁	(0.38, 0.42, 0.20)	(0.55, 0.40, 0.05)	(0.52, 0.35, 0.13)	(0.60, 0.35, 0.05)	(0.55, 0.30, 0.15)	(0.63, 0.25, 0.12)
	E ₂	(0.35, 0.45, 0.20)	(0.60, 0.25, 0.15)	(0.55, 0.25, 0.20)	(0.82, 0.10, 0.08)	(0.70, 0.18, 0.12)	(0.55, 0.28, 0.17)
	E ₃	(0.61, 0.30, 0.09)	(0.60, 0.28, 0.12)	(0.59, 0.27, 0.14)	(0.82, 0.12, 0.06)	(0.77, 0.15, 0.08)	(0.66, 0.30, 0.04)
L ₆	E ₁	(0.49, 0.40, 0.11)	(0.53, 0.35, 0.12)	(0.74, 0.20, 0.06)	(0.68, 0.17, 0.15)	(0.72, 0.22, 0.06)	(0.68, 0.25, 0.07)
	E ₂	(0.45, 0.35, 0.20)	(0.50, 0.34, 0.16)	(0.70, 0.22, 0.08)	(0.80, 0.15, 0.05)	(0.70, 0.24, 0.06)	(0.60, 0.27, 0.13)
	E ₃	(0.50, 0.44, 0.06)	(0.45, 0.38, 0.17)	(0.60, 0.24, 0.16)	(0.65, 0.23, 0.12)	(0.73, 0.22, 0.05)	(0.75, 0.18, 0.07)
L ₇	E ₁	(0.58, 0.35, 0.07)	(0.65, 0.25, 0.10)	(0.64, 0.22, 0.14)	(0.60, 0.32, 0.08)	(0.58, 0.35, 0.07)	(0.74, 0.15, 0.11)
	E ₂	(0.54, 0.30, 0.16)	(0.62, 0.30, 0.08)	(0.70, 0.22, 0.08)	(0.60, 0.32, 0.08)	(0.52, 0.25, 0.23)	(0.75, 0.16, 0.09)
	E ₃	(0.53, 0.42, 0.05)	(0.52, 0.35, 0.13)	(0.62, 0.25, 0.13)	(0.82, 0.10, 0.08)	(0.78, 0.15, 0.07)	(0.72, 0.20, 0.08)
L ₈	E ₁	(0.22, 0.73, 0.05)	(0.72, 0.22, 0.06)	(0.75, 0.20, 0.05)	(0.82, 0.10, 0.08)	(0.65, 0.20, 0.15)	(0.54, 0.40, 0.06)
	E ₂	(0.27, 0.67, 0.06)	(0.77, 0.10, 0.13)	(0.76, 0.14, 0.10)	(0.64, 0.20, 0.16)	(0.86, 0.06, 0.08)	(0.88, 0.07, 0.05)
	E ₃	(0.28, 0.65, 0.07)	(0.67, 0.22, 0.11)	(0.74, 0.15, 0.11)	(0.69, 0.25, 0.06)	(0.68, 0.23, 0.09)	(0.60, 0.34, 0.06)
L ₉	E ₁	(0.57, 0.35, 0.08)	(0.55, 0.40, 0.05)	(0.50, 0.43, 0.05)	(0.71, 0.18, 0.11)	(0.67, 0.28, 0.05)	(0.64, 0.25, 0.11)
	E ₂	(0.58, 0.32, 0.10)	(0.52, 0.34, 0.14)	(0.54, 0.42, 0.04)	(0.50, 0.38, 0.12)	(0.48, 0.40, 0.12)	(0.46, 0.32, 0.22)
	E ₃	(0.51, 0.42, 0.07)	(0.60, 0.33, 0.07)	(0.58, 0.35, 0.07)	(0.43, 0.45, 0.12)	(0.64, 0.28, 0.08)	(0.67, 0.25, 0.08)
L ₁₀	E ₁	(0.40, 0.42, 0.18)	(0.55, 0.40, 0.05)	(0.51, 0.35, 0.14)	(0.60, 0.35, 0.05)	(0.55, 0.32, 0.13)	(0.62, 0.25, 0.13)
	E ₂	(0.37, 0.45, 0.18)	(0.60, 0.24, 0.16)	(0.55, 0.28, 0.17)	(0.81, 0.10, 0.09)	(0.73, 0.15, 0.12)	(0.59, 0.24, 0.17)
	E ₃	(0.67, 0.26, 0.07)	(0.60, 0.28, 0.12)	(0.59, 0.27, 0.14)	(0.78, 0.12, 0.10)	(0.79, 0.15, 0.06)	(0.68, 0.26, 0.06)
L ₁₁	E ₁	(0.57, 0.30, 0.13)	(0.51, 0.35, 0.14)	(0.73, 0.18, 0.09)	(0.68, 0.19, 0.13)	(0.77, 0.20, 0.03)	(0.67, 0.25, 0.08)
	E ₂	(0.47, 0.35, 0.18)	(0.46, 0.34, 0.20)	(0.69, 0.22, 0.09)	(0.80, 0.16, 0.06)	(0.64, 0.24, 0.12)	(0.64, 0.27, 0.09)
	E ₃	(0.50, 0.42, 0.08)	(0.45, 0.39, 0.16)	(0.58, 0.26, 0.16)	(0.65, 0.22, 0.13)	(0.66, 0.22, 0.12)	(0.73, 0.18, 0.09)

In the SWARA approach, the role of the DEs plays an important part in the process of evaluation of criteria weights. Each expert decides the significance of each criterion. Then, the DE provides the ranking of all the criteria according to their own implicit understanding and experiences (see Table 7). In Table 8, the most important criterion is presented as rank one and the least important criterion is presented as the last one. Then the final criteria weights are evaluated based on Table 8 as follows:

$$w_j = (0.1100, 0.0901, 0.1010, 0.0881, 0.1112, 0.0988, 0.0649, 0.0859, 0.0698, 0.1027, 0.0775)$$

Using (13)–(18), the values of α_i , $\mathbb{S}^*(\alpha_i)$, β_i , $\mathbb{S}^*(\beta_i)$, γ_i and l_i of S_i ($i = 1(1)6$) are estimated with respect to the criteria L_j ($j = 1(1)11$), given in Table 9.

Table 6. Aggregated decision matrix for bioenergy production technology selection.

	S_1	S_2	S_3	S_4	S_5	S_6
L_1	(0.793, 0.118, 0.090)	(0.769, 0.161, 0.070)	(0.697, 0.184, 0.118)	(0.409, 0.493, 0.098)	(0.369, 0.397, 0.234)	(0.616, 0.301, 0.084)
L_2	(0.518, 0.374, 0.107)	(0.632, 0.300, 0.068)	(0.673, 0.239, 0.088)	(0.740, 0.202, 0.057)	(0.654, 0.228, 0.118)	(0.750, 0.176, 0.074)
L_3	(0.240, 0.710, 0.050)	(0.720, 0.183, 0.097)	(0.757, 0.158, 0.085)	(0.742, 0.181, 0.077)	(0.723, 0.165, 0.112)	(0.699, 0.229, 0.072)
L_4	(0.538, 0.386, 0.077)	(0.570, 0.356, 0.075)	(0.537, 0.393, 0.070)	(0.571, 0.317, 0.113)	(0.611, 0.313, 0.076)	(0.622, 0.259, 0.119)
L_5	(0.482, 0.372, 0.146)	(0.583, 0.309, 0.108)	(0.557, 0.291, 0.152)	(0.761, 0.168, 0.071)	(0.690, 0.200, 0.110)	(0.626, 0.277, 0.097)
L_6	(0.485, 0.403, 0.112)	(0.491, 0.360, 0.149)	(0.679, 0.220, 0.101)	(0.703, 0.187, 0.110)	(0.720, 0.225, 0.056)	(0.695, 0.222, 0.082)
L_7	(0.551, 0.364, 0.086)	(0.594, 0.300, 0.107)	(0.647, 0.232, 0.121)	(0.712, 0.198, 0.090)	(0.668, 0.228, 0.104)	(0.734, 0.171, 0.094)
L_8	(0.257, 0.679, 0.064)	(0.714, 0.183, 0.103)	(0.748, 0.163, 0.088)	(0.735, 0.172, 0.093)	(0.728, 0.160, 0.112)	(0.683, 0.248, 0.068)
L_9	(0.549, 0.369, 0.082)	(0.565, 0.356, 0.080)	(0.544, 0.393, 0.063)	(0.565, 0.313, 0.122)	(0.619, 0.305, 0.076)	(0.618, 0.265, 0.117)
L_{10}	(0.526, 0.350, 0.124)	(0.583, 0.306, 0.111)	(0.554, 0.298, 0.148)	(0.738, 0.168, 0.095)	(0.708, 0.196, 0.096)	(0.640, 0.252, 0.109)
L_{11}	(0.519, 0.357, 0.123)	(0.474, 0.363, 0.162)	(0.665, 0.220, 0.115)	(0.703, 0.194, 0.103)	(0.700, 0.217, 0.083)	(0.690, 0.222, 0.088)

Table 7. Criteria weights in terms of linguistic terms for bioenergy production technology selection.

Criteria	E_1	E_2	E_3	Aggregated IFNs	Crisp Values $\mathbb{S}^*(\tilde{\xi}_{kj})$
L_1	G	VG	G	(0.798, 0.144, 0.057)	0.827
L_2	F	F	MG	(0.594, 0.355, 0.050)	0.619
L_3	G	G	MG	(0.713, 0.236, 0.051)	0.738
L_4	F	MP	MG	(0.566, 0.374, 0.060)	0.596
L_5	MG	G	VG	(0.807, 0.130, 0.063)	0.838
L_6	G	MG	MG	(0.689, 0.260, 0.051)	0.715
L_7	VP	P	VP	(0.225, 0.675, 0.100)	0.275
L_8	MG	F	MP	(0.536, 0.396, 0.067)	0.570
L_9	MP	P	VP	(0.300, 0.599, 0.101)	0.350
L_{10}	G	MG	G	(0.729, 0.220, 0.051)	0.755
L_{11}	F	MP	P	(0.422, 0.498, 0.079)	0.462

Table 8. Results obtained by the SWARA method for bioenergy production technology selection.

Criteria	Crisp Values	Comparative Significance of Criteria Value (s_j)	Coefficient (k_j)	Recalculated Weight (p_j)	Criteria Weight (w_j)
L_5	0.838	—	1.000	1.000	0.1112
L_1	0.827	0.011	1.011	0.989	0.1100
L_{10}	0.755	0.072	1.072	0.923	0.1027
L_3	0.738	0.017	1.017	0.908	0.1010
L_6	0.715	0.023	1.023	0.888	0.0988
L_2	0.619	0.096	1.096	0.810	0.0901
L_4	0.596	0.023	1.023	0.792	0.0881
L_8	0.570	0.026	1.026	0.772	0.0859
L_{11}	0.462	0.108	1.108	0.697	0.0775
L_9	0.350	0.112	1.112	0.627	0.0698
L_7	0.275	0.075	1.075	0.583	0.0649

Table 9. The overall results of the IF-SWARA-COPRAS framework for BPTs selection.

BPTs	α_i	$\mathbb{S}^*(\alpha_i)$	β_i	$\mathbb{S}^*(\beta_i)$	λ_i	η_i
S_1	(0.455, 0.438, 0.107)	0.508	(0.125, 0.842, 0.033)	0.142	0.7326	88.23%
S_2	(0.558, 0.333, 0.109)	0.613	(0.152, 0.819, 0.029)	0.166	0.8051	96.96%
S_3	(0.587, 0.296, 0.116)	0.646	(0.155, 0.810, 0.035)	0.173	0.8303	100.00%
S_4	(0.616, 0.283, 0.100)	0.667	(0.178, 0.783, 0.040)	0.198	0.8281	99.73%
S_5	(0.596, 0.292, 0.112)	0.652	(0.164, 0.790, 0.046)	0.187	0.8225	99.06%
S_6	(0.594, 0.314, 0.092)	0.640	(0.190, 0.759, 0.051)	0.215	0.7883	94.94%

From Table 9, the preference order of the bioenergy production technologies is $S_3 > S_4 > S_5 > S_2 > S_6 > S_1$ and, thus, S_3 is the best alternative.

5. Comparison and Sensitivity Analysis

Here, a comparison is discussed between the outcomes obtained from the proposed IF-SWARA-COPRAS framework with already existing approaches. To show the efficiency and display the advantages of the IF-SWARA-COPRAS method, the IF-WASPAS method [58] is implemented to handle the same decision-making problem.

5.1. IF-WASPAS Method

Steps 1–4: Same as the previous framework.

Step 5: Determine the measures of Weighted Sum Model (WSM) $Q_i^{(1)}$ for each option, given by

$$Q_i^{(1)} = \bigoplus_{j=1}^n w_j \tilde{\eta}_{ij}. \quad (19)$$

Step 6: Determine the measures of Weighted Product Model (WPM) $Q_i^{(2)}$ for each option, given by

$$Q_i^{(2)} = \bigotimes_{j=1}^n w_j \tilde{\eta}_{ij}. \quad (20)$$

Step 7: Estimate the WASPAS measure of each option, given by

$$Q_i = \vartheta Q_i^{(1)} + (1 - \vartheta) Q_i^{(2)}, \quad (21)$$

where ϑ denotes the coefficient of decision mechanism that estimates the precision of WASPAS according to the initial criteria exactness and $\vartheta \in [0, 1]$ (when $\vartheta = 0$ and $\vartheta = 1$, then WASPAS is converted to the WSM and WPM, correspondingly).

Step 8: Rank the options, based on the crisp score values of Q_i .

Step 9: End.

Now, the overall computational procedure of IF-WASPAS method is presented in Table 10.

Table 10. The outcomes of IF- WASPAS approach for BPTs selection.

BPTs	WSM		WPM		WASPAS	Ranking
	$Q_i^{(1)}$	$S^*(Q_i^{(1)})$	$Q_i^{(2)}$	$S^*(Q_i^{(2)})$	$S^*(Q_i(\vartheta))$	
S_1	(0.499, 0.391, 0.110)	0.554	(0.445, 0.458, 0.110)	0.494	0.506, 0.524, 0.542	6
S_2	(0.589, 0.304, 0.107)	0.642	(0.545, 0.351, 0.104)	0.597	0.606, 0.619, 0.633	5
S_3	(0.615, 0.271, 0.115)	0.673	(0.565, 0.326, 0.109)	0.620	0.630, 0.647, 0.662	1
S_4	(0.637, 0.262, 0.101)	0.687	(0.557, 0.346, 0.098)	0.606	0.622, 0.646, 0.671	2
S_5	(0.618, 0.269, 0.113)	0.675	(0.548, 0.330, 0.122)	0.609	0.622, 0.642, 0.662	3
S_6	(0.611, 0.294, 0.095)	0.659	(0.541, 0.359, 0.100)	0.591	0.605, 0.625, 0.645	4

From Tables 9 and 10, the preference order of the BPTs obtained by the developed IF-SWARA-COPRAS approach shows great conformity with IF-WASPAS approach. Therefore, the alternative S_3 is the most appropriate bioenergy production technology for the present case study.

5.2. Sensitivity Analysis

Four different weighting approaches have been considered to reveal different sets of DEs' preferences, and sensitivity of options ranking to criteria's weights is examined. The different frameworks are:

Holistic framework: identical significance weights to all criteria;

Environmental–social framework: dominance of environmental criteria;

Technocratic–economic framework: strong prominence of economic costs and technical concerns;

Social framework: preference toward events connecting the social benefits.

Production of biogas, electricity and heat and from agricultural and municipal wastes to biogas (S_3) is the best BPTs in two frameworks; the proposed IF-SWARA-COPRAS framework and Holistic framework of criteria weighting and wet biomass to biodiesel (S_4) is the best BPT in two frameworks: the technocratic–economic framework and the social framework (see Table 11). Production of gasoline, biodiesel and jet fuels from oil crops is assessed as the worst BPT in most frameworks.

Table 11. Relative significance of BPTs on these frameworks.

Frameworks	S_1	S_2	S_3	S_4	S_5	S_6
IF-SWARA-COPRAS Approach	0.7326	0.8051	0.8303	0.8281	0.8225	0.7883
Holistic approach	0.7299	0.8000	0.8292	0.8290	0.8255	0.7925
Environmental-social approach	0.4336	0.4731	0.4593	0.3601	0.3765	0.3723
Technocratic-economic approach	0.226	0.323	0.369	0.420	0.398	0.373
Social approach	0.200	0.209	0.232	0.288	0.279	0.264

6. Conclusions

Recently, the selection of the most appropriate bioenergy production technology (BPT) has been a significant concern in sustainable management. Owing to the occurrence of multiple conflicting criteria, the BPT selection problem is a complicated MCDM problem. To handle this problem, an integrated framework has been introduced based on the SWARA and the COPRAS approaches within an IFS context. In the proposed approach, the criteria weights have been computed by the SWARA method, which has not only determined the subjective weights within an IFS context but also modeled the uncertainty associated with the DES' opinions and preferences. To show the applicability and feasibility of the developed framework, a case study of BPT selection has been presented which confirms its effectiveness and usefulness. In this case study, an evaluation index process for BPT options was developed, which includes four dimensions: environment, economic, technical and social criteria. These criteria consist of four, two, two and three sub-criteria, respectively, which are widely considered according to the literature, research reports and experts' knowledge in various disciplines. Further, sensitivity analysis has been discussed to determine the impact of various dimensions of criteria weights, which also proves the feasibility and stability of the developed framework. Comparative analysis has been presented to prove the strength of the outcomes obtained by the developed approach. The main advantages of the proposed approach are the simplicity of computation under the IFS environment and using a procedure to find the more realistic weights of criteria, which enhances the stability of the developed method. The proposed approach can be used for any problems that have the common structure of MCDM problems and use intuitionistic fuzzy information. The investigations of the outcomes verify that the proposed method has a high efficiency with compare to the existing ones. The outcomes demonstrate that the BPT option S_3 (Agricultural and municipal wastes to biogas) finds the maximum utility degree and should be chosen as the best BPT option.

In future, we will expand our research by integrating objective and subjective criteria weight information. We will also extend the proposed approach to Pythagorean fuzzy sets, hesitant fuzzy sets, picture fuzzy sets, q-rung orthopair fuzzy sets, Pythagorean fuzzy soft sets, interval-valued Pythagorean fuzzy sets, neutrosophic sets and interval-valued picture fuzzy sets environments, and it can be applied to green supplier selection, public environmental assessment, renewable energy source selection and healthcare waste recycling facility selection.

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