**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 (S3) 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 cellulolic 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 Kersuliene 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. Karabaševic 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. Ghorabaee 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, Ghorabaee 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 $U = \{u_1, u_2, \ldots, u_n\}$ is given by

$$R = \{(u_i, \mu_R(u_i), \nu_R(u_i)) : u_i \in U\},$$

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

$$0 \leq \mu_R(u_i) \leq 1, 0 \leq \nu_R(u_i) \leq 1 \text{ and } 0 \leq \mu_R(u_i) + \nu_R(u_i) \leq 1, \forall u_i \in U.$$
For an IFS in $U$, we define the hesitancy degree of $u_i \in U$ to $R$ as follows:

$$\pi_R(u_i) = 1 - \mu_R(u_i) - \nu_R(u_i)$$

and $0 \leq \pi_R(u_i) \leq 1, \ \forall u_i \in U$. \hfill (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 $0 \leq \mu_\xi + \nu_\xi \leq 1$ \cite{56}.

**Definition 2** \cite{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

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

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

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

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

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

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

where $w = (w_1, w_2, \ldots, w_n)^T$ is a weight vector of $\xi_j$, \ $j = 1(1)n$, 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 Kersuliene et al. \cite{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:

**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 \( S = \{S_1, S_2, \ldots, S_m\} \) under the criterion set \( L = \{L_1, L_2, \ldots, L_n\} \). Consider a committee of \( \ell \) decision experts (DEs) \( E = \{E_1, E_2, \ldots, E_\ell\} \), 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 \( \ell \) DEs with weight vector \( \omega = (\omega_1, \omega_2, \ldots, \omega_\ell)^T \). 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]:

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

**Step 3:** Create the aggregated IF decision matrix (AIF-DM).
To compute the AIF-DM, we facilitate the IFWAO [56], then we obtain \( R = (\eta_{kj})_{\ell \times n} \), where

\[
\eta_{kj} = \text{IFWA} \left( \eta_{kj}^{(1)}, \eta_{kj}^{(2)}, \ldots, \eta_{kj}^{(\ell)} \right) = \left\{ 1 - \prod_{k=1}^{\ell} (1 - \mu_k)^{\omega_k}, \prod_{k=1}^{\ell} (\nu_k)^{\omega_k} \right\}. \tag{9}
\]

**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

\[
k_j = \begin{cases} 
1, & j = 1 \\
s_j + 1, & j > 1, 
\end{cases}
\tag{10}
\]

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

\[
p_j = \begin{cases} 
1, & j = 1 \\
\frac{k_{j-1}}{k_j}, & j > 1. 
\end{cases}
\tag{11}
\]

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

\[
w_j = \frac{p_j}{\sum_{j=1}^{\ell} p_j}. \tag{12}
\]

**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 \( \alpha_i \) (benefit-type) and minimizing \( \beta_i \) (cost-type); i.e., the optimum results are maximization and minimization, respectively. In these conditions, \( \alpha_i \) and \( \beta_i \) are calculated as follows.

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

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

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

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

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 $\gamma_i$ of the option is calculated as follows:

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

(15)

Here, $S^*(\alpha_i)$ is the score value of $\alpha_i$ and $S^*(\beta_i)$ is the score value of $\beta_i$.

Equation (8) can also be demonstrated, as follows:

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

(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.

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

(17)

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

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

(18)

where $\gamma_i$ and $\gamma_{\text{max}}$ 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   | $S_2$   |
|                   | 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       | Qualitative    |         |
| Social           | Effects on food security ($L_9$)                    | Benefit       | Quantitative   | $S_5$   |
|                   | Job creation ($L_{10}$)                            | Benefit       | Qualitative    | $S_6$   |
|                   | 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       | E1   | E2   | E3   |     |     |     |
| 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 ($\omega_k$)  | 0.3530 | 0.2352 | 0.4118 |     |     |     |

| Table 5. IF ratings are given by DMs for bioenergy production technology selection. |
|------------------------|------|------|------|------|------|------|
| DMs                   | $E_1$ | $E_2$ | $E_3$ |     |     |     |
| $L_1$                  | (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, 0.15) | (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) |

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 $\alpha_i, S^*(\alpha_i), \beta_i, S^*(\beta_i), \gamma_i$ 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.

| Criteria | $S_1$ | $S_2$ | $S_3$ | $S_4$ | $S_5$ | $S_6$ |
|----------|-------|-------|-------|-------|-------|-------|
| $L_1$    | 0.793 | 0.769 | 0.697 | 0.409 | 0.369 | 0.356 |
| $L_2$    | 0.518 | 0.632 | 0.673 | 0.740 | 0.654 | 0.664 |
| $L_3$    | 0.240 | 0.720 | 0.757 | 0.742 | 0.723 | 0.699 |
| $L_4$    | 0.538 | 0.570 | 0.537 | 0.571 | 0.611 | 0.622 |
| $L_5$    | 0.482 | 0.583 | 0.557 | 0.761 | 0.690 | 0.626 |
| $L_6$    | 0.485 | 0.491 | 0.679 | 0.703 | 0.720 | 0.695 |
| $L_7$    | 0.351 | 0.594 | 0.647 | 0.712 | 0.668 | 0.734 |
| $L_8$    | 0.257 | 0.714 | 0.746 | 0.735 | 0.726 | 0.683 |
| $L_9$    | 0.549 | 0.565 | 0.544 | 0.565 | 0.619 | 0.618 |
| $L_{10}$ | 0.526 | 0.583 | 0.554 | 0.736 | 0.708 | 0.640 |
| $L_{11}$ | 0.519 | 0.474 | 0.665 | 0.703 | 0.700 | 0.690 |

**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 $S^*(\xi_{kj})$ |
|----------|-------|-------|-------|-----------------|-----------------|
| $L_1$    | 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 ($\eta_j$) | Criteria Weight ($w_j$) |
|----------|--------------|-----------------------------------------------|-------------------|-------------------|-----------------|
| $L_5$    | 0.838        |                                               | 1.000             | 1.000             | 0.1112          |
| $L_1$    | 0.827        | 0.111                                         | 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 | $\alpha_i$ | $S^*(\alpha_i)$ | $\beta_i$ | $S^*(\beta_i)$ | $\lambda_i$ | $\eta_i$ |
|------|-------------|-----------------|-----------|----------------|-------------|--------|
| $S_1$| (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

$$Q_i^{(1)} = \sum_{j=1}^{n} w_j \bar{\eta}_{ij}.$$  

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

$$Q_i^{(2)} = \prod_{j=1}^{n} w_j \bar{\eta}_{ij}.$$  

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

$$Q_i = \delta Q_i^{(1)} + (1 - \delta) Q_i^{(2)},$$

where $\delta$ denotes the coefficient of decision mechanism that estimates the precision of WASPAS according to the initial criteria exactness and $\delta \in [0, 1]$ (when $\delta = 0$ and $\delta = 1$, 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 |
|------|-----|-----|--------|---------|
|      | $Q_i^{(1)}$ | $S'(Q_i^{(1)})$ | $Q_i^{(2)}$ | $S'(Q_i^{(2)})$ | $S'(Q_i(\delta))$ |
| $S_1$ | (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.
Author Contributions: A.R.M., P.R., K.P., A.M., J.S., D.S. and M.A. conceived and worked together to achieve this work. A.R.M., P.R. and K.P. developed the method and worked on computational and comparative discussion, A.M. worked on literature review and introduction, J.S. and D.S. worked on case study and conclusion and M.A. worked on introduction. Finally, all the authors have read and approved the final manuscript. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Conflicts of Interest: All the authors declare that there is no conflict of interest.

References

1. Yue, D.; You, F.; Snyder, S.W. Biomass-to-bioenergy and biofuel supply chain optimization: Overview, key issues and challenges. Comput. Chem. Eng. 2014, 66, 36–56. [CrossRef]

2. Sharma, B.; Ingalls, R.G.; Jones, C.L.; Khanchi, A. Biomass supply chain design and analysis: Basis, overview, modeling, challenges, and analysis. Renew. Sust. Energ. Rev. 2013, 24, 608–627. [CrossRef]

3. Khishtandar, S.; Zandieh, M.; Dorri, B. A multi criteria decision making framework for sustainability assessment of bioenergy production technologies with hesitant fuzzy linguistic term sets: The case of Iran. Renew. Sust. Energ. Rev. 2017, 77, 1130–1145. [CrossRef]

4. Voivontas, D.; Assimacopoulos, D.; Koukios, E.G. Assessment of biomass potential for power production: A GIS based method. Biomass Bioenergy 2001, 20, 101–112. [CrossRef]

5. Nixon, J.D.; Dey, P.K.; Ghosh, S.K.; Davies, P.A. Evaluation of options for energy recovery from municipal Solid waste in India using the hierarchical analytical network process. Energy 2013, 59, 215–223. [CrossRef]

6. De Meyer, A.; Cattrysse, D.; Rasinmäki, J.; Orshoven, J.V. Methods to optimize the design and management of biomass-for-bioenergy supply chains: A review. Renew. Sust. Energ. Rev. 2014, 31, 657–670. [CrossRef]

7. Buchholz, T.; Rametsteiner, E.; Volk, T.A.; Luzadis, A. Multi criteria analysis for bioenergy systems assessments. Energy Policy 2009, 37, 484–495. [CrossRef]

8. Zadeh, L.A. Fuzzy sets. Inf. Sci. 1965, 8, 338–353. [CrossRef]

9. Doukas, H.C.; Andreas, B.M.; Psarras, J.E. Multi-criteria decision aid for the formulation of sustainable technological energy priorities using linguistic variables. Eur. J. Oper. Res. 2007, 182, 844–855. [CrossRef]

10. Kahraman, C.; Kaya, I.; Cebi, S. A comparative analysis for multiattribute selection among renewable energy alternatives using fuzzy axiomatic design and fuzzy analytic hierarchy process. Energy 2009, 34, 1603–1616. [CrossRef]

11. Ren, J.; Fedele, A.; Mason, M.; Manzardo, A.; Scipioni, A. Fuzzy multi-actor multi-criteria decision making for sustainability assessment of biomass-based technologies for hydrogen production. Int. J. Hydrog. Energy 2013, 38, 9111–9120. [CrossRef]

12. Şengül, Ü.; Eren, M.; Shiraz, S.E.; Gezder, V.; Şengül, A.B. Fuzzy TOPSIS method for ranking renewable energy supply systems in Turkey. Renew. Energy 2015, 75, 617–625. [CrossRef]

13. Zadeh, L.A. The concept of a linguistic variable and its application to approximate reasoning-I. Inf. Sci. 1975, 8, 199–249. [CrossRef]

14. Atanassov, K.T. Intuitionistic fuzzy sets. Fuzzy Sets Syst. 1986, 20, 87–96. [CrossRef]

15. Gau, W.L.; Buehrer, D.J. Vague sets. IEEE Trans. Syst. Man Cybern. Syst. 1993, 23, 610–614. [CrossRef]

16. Torra, V. Hesitant fuzzy sets. Int. J. Intell. Syst. 2010, 25, 529–539. [CrossRef]

17. Yager, R.R. Pythagorean fuzzy subsets. In Proceedings of the 2013 Joint IFSA World Congress and NAFIPS Annual Meeting (IFSA/NAFIPS), Edmonton, AB, Canada, 24–28 June 2013; pp. 57–61.

18. Mishra, A.R.; Jain, D.; Hooda, D.S. Exponential Intuitionistic Fuzzy Information Measure with Assessment of Service Quality. Int. J. Fuzzy Syst. 2017, 19, 788–798. [CrossRef]

19. Ansari, M.D.; Mishra, A.R.; Ansari, F.T. New Divergence and Entropy Measures for Intuitionistic Fuzzy Sets on Edge Detection. Int. J. Fuzzy Syst. 2018, 20, 474–487. [CrossRef]

20. Çalı, S.; Balaman, Ş.Y. A novel outranking based multi criteria group decision making methodology integrating ELECTRE and VIKOR under intuitionistic fuzzy environment. Expert Syst. Appl. 2019, 119, 36–50. [CrossRef]

21. Mishra, A.R.; Rani, P. Shapley Divergence Measures with VIKOR Method for Multi-Attribute Decision Making Problems. Neural. Comput. Appl. 2019, 31, 1299–1316. [CrossRef]
22. Liu, P.; Gao, H. Some intuitionistic fuzzy power Bonferroni mean operators in the framework of Dempster–Shafer theory and their application to multicriteria decision making. *Appl. Soft Comput.* 2019. [CrossRef]

23. Mishra, A.R.; Kumari, R.; Sharma, D.K. Intuitionistic Fuzzy Divergence Measure-Based Multi-Criteria Decision-Making Method. *Neural. Comput. Appl.* 2019, 31, 2279–2294. [CrossRef]

24. Mishra, A.R.; Chandel, A.; Motwani, D. Extended MABAC method based on divergence measures for multi-criteria assessment of programming language with interval-valued intuitionistic fuzzy sets. *Granul. Comput.* 2020, 5, 97–117. [CrossRef]

25. Mishra, A.R.; Sisodia, G.; Pardasani, K.R.; Sharma, K. Multicriteria IT personnel selection on intuitionistic fuzzy information measures and ARAS methodology. *Iran. J. Fuzzy Syst.* 2020. [CrossRef]

26. Liu, J.; Liu, P.; Liu, S.F.; Zhou, X.Z.; Zhang, T. A study of decision process in MCDM problems with large number of criteria. *Int. Trans. Oper. Res.* 2015, 22, 237–264. [CrossRef]

27. Diakoulaki, D.; Mavrotas, G.; Papayannakis, I. Determining objective weights in multiple criteria problems: The CRITIC method. *Comput. Oper. Res.* 1995, 22, 763–770. [CrossRef]

28. Mishra, A.R. Intuitionistic Fuzzy Information with Application in Rating of Township Development. *Iran. J. Fuzzy Syst.* 2016, 13, 49–70.

29. Mishra, A.R.; Rani, P. Interval-valued intuitionistic fuzzy WASPAS method: Application in reservoir flood control management policy. *Group Decis. Negot.* 2018, 27, 1047–1078. [CrossRef]

30. Mishra, A.R.; Singh, R.K.; Motwani, D. Intuitionistic fuzzy divergence measure based ELECTRE method for performance of cellular mobile telephone service providers. *Neural. Comput. Appl.* 2018. [CrossRef]

31. Rani, P.; Mishra, A.R.; Razaei, G.; Liao, H.; Mardani, A. Extended Pythagorean Fuzzy TOPSIS Method Based on Similarity Measure for Sustainable Recycling Partner Selection. *Int. J. Fuzzy Syst.* 2019. [CrossRef]

32. Kersuliene, V.; Zavadskas, E.; Turskis, Z. Selection of rational dispute resolution method by applying new step-wise weight assessment ratio analysis (SWARA). *J. Bus. Econ. Manag.* 2010, 11, 243–258. [CrossRef]

33. Karabasevic, D.; Paunkovic, J.; Stanujkic, D. Ranking of companies according to the indicators of corporate social responsibility based on SWARA and ARAS methods. *Serb. J. Manag.* 2016, 11, 43–53. [CrossRef]

34. Isik, A.T.; Adal, E.A. A new integrated decision making approach based on SWARA and OCRA methods for the hotel selection problem. *Int. J. Adv. Oper. Manag.* 2016, 8, 140–151.

35. Mavi, R.K.; Goh, M.; Zarbakhshnia, N. Sustainable third-party reverse logistic provider selection with fuzzy SWARA and fuzzy MOORA in plastic industry. *Int. J. Adv. Manuf. Technol.* 2017, 91, 2401–2418. [CrossRef]

36. Stanujkic, D.; Karabasevic, D.; Zavadskas, E. A new approach for selecting alternatives based on the adapted weighted sum and the SWARA methods: A case of personnel selection. *Econ. Comput. Econ. Cybern. Stud. Res.* 2017, 51, 39–56.

37. Karabasevic, D.; Stanujkic, D.; Urosevic, S.; Popovic, G.; Maksimovic, M. An approach to criteria weights determination by integrating the Delphi and the adapted SWARA methods. *Manag. J. Theory Pract. Manag.* 2017, 22, 15–25. [CrossRef]

38. Stanujkic, D.; Zavadskas, E.K.; Karabasevic, D.; Turskis, Z.; Kersuliene, V. New group decision-making ARCAS approach based on the integration of the SWARA and the ARAS methods adapted for negotiations. *J. Bus. Econ. Manag.* 2017, 18, 599–618. [CrossRef]

39. Urosevic, S.; Karabasevic, D.; Stanujkic, D.; Maksimovic, M. An approach to personnel selection in the tourism industry based on the SWARA and the WASPAS methods. *Econ. Comput. Econ. Cybern. Stud. Res.* 2017, 51, 75–88.

40. Ghorabaei, M.K.; Amiri, M.; Zavadskas, E.K.; Antucheviciene, J. A new hybrid fuzzy MCDM approach for evaluation of construction equipment with sustainability considerations. *Arch. Civ. Mech. Eng.* 2017, 18, 32–49. [CrossRef]

41. Mardani, A.; Nilashi, M.; Zakuan, N.; Loganathan, N.; Soheilirad, S.; Saman, M.Z.M.; Ibrahim, O. A systematic review and meta-analysis of SWARA and WASPAS methods: Theory and applications with recent fuzzy developments. *Appl. Soft Comput.* 2017, 57, 265–292. [CrossRef]

42. Dahooee, J.H.; Abadi, E.B.J.; Vanaki, A.S.; Firoozfar, H.R. Competency-based IT personnel selection using a hybrid SWARA and ARAS-G methodology. *Hum. Factors Ergon. Manuf. Serv. Ind.* 2018, 28, 5–16. [CrossRef]

43. Zavadskas, E.; Kaklauska, A.; Sarka, V. The new method of multicriteria complex proportional assessment of projects. *Technol. Econ. Dev. Econ.* 1994, 1, 131–139.
44. Nancy, G.H. Algorithms for possibility linguistic single-valued neutrosophic decision-making based on COPRAS and aggregation operators with new information measures. *Measurement* 2019, 138, 278–290. [CrossRef]

45. Roy, J.; Sharma, H.K.; Kar, S.; Zavadskas, E.K.; Saparauskas, J. An extended COPRAS model for multi-criteria decision-making problems and its application in web-based hotel evaluation and selection. *Econ. Res. Ekon. Istraživanja* 2019, 32, 219–253. [CrossRef]

46. Kouchaksaraei, R.H.; Zolfani, S.H.; Golabchi, M. Glasshouse locating based on SWARA-COPRAS approach. *Int. J. Strateg. Prop. Manag.* 2015, 19, 111–122. [CrossRef]

47. Liou, J.J.; Tamosaitiene, J.; Zavadskas, E.K.; Tzeng, G. New hybrid COPRAS-G MADM Model for improving and selecting suppliers in green supply chain management. *Int. J. Prod. Res.* 2016, 54, 114–134. [CrossRef]

48. Mulliner, E.; Malys, N.; Maliene, V. Comparative analysis of MCDM methods for the assessment of sustainable housing affordability. *Omega* 2016, 59, 146–156. [CrossRef]

49. Ghorabaee, M.K.; Amiri, M.; Sadaghiani, J.S.; Goodarzi, G.H. Multiple criteria group decision-making for supplier selection based on COPRAS method with interval type-2 fuzzy sets. *Int. J. Adv. Manuf. Technol.* 2014, 75, 1115–1130. [CrossRef]

50. Bekar, E.T.; Cakmakci, M.; Kahraman, C. Fuzzy COPRAS method for performance measurement in total productive maintenance: A comparative analysis. *J. Bus. Econ. Manag.* 2016, 17, 663–684. [CrossRef]

51. Zheng, Y.H.; Xu, Z.S.; He, Y.; Liao, H.C. Severity assessment of chronic obstructive pulmonary disease based on hesitant fuzzy linguistic COPRAS method. *Appl. Soft Comput.* 2018, 69, 60–71. [CrossRef]

52. Mishra, A.R.; Rani, P.; Pardasani, K.R. Multiple-criteria decision-making for service quality selection based on Shapley COPRAS method under hesitant fuzzy sets. *Granul. Comput.* 2019, 4, 435–449. [CrossRef]

53. Mishra, A.R.; Rani, P.; Mardani, A.; Pardasani, K.R.; Govindan, K.; Alrasedi, M. Healthcare evaluation in hazardous waste recycling using novel interval-valued intuitionistic fuzzy information based on complex proportional assessment method. *Comput. Ind. Eng.* 2020. [CrossRef]

54. Kumari, R.; Mishra, A.R. Multi-Criteria COPRAS Method Based on Parametric Measures for Intuitionistic Fuzzy Sets: Application of Green Supplier Selection. *Iran. J. Sci. Technol. Trans. Electr. Eng.* 2020. [CrossRef]

55. Boran, F.E.; Genç, S.; Kurt, M.; Akay, D. A multi-criteria intuitionistic fuzzy group decision making for supplier selection with TOPSIS method. *Expert Syst. Appl.* 2009, 36, 11363–11368. [CrossRef]

56. Xu, Z. Methods for aggregating interval-valued intuitionistic fuzzy information and their application to decision making. *Control Decis.* 2007, 22, 215.

57. Xu, G.L.; Wan, S.P.; Xie, X.L. A Selection Method Based on MAGDM with Interval-Valued Intuitionistic Fuzzy Sets. *Math. Probl. Eng.* 2015, 791204, 1–13. [CrossRef]

58. Mishra, A.R.; Singh, R.K.; Motwani, D. Multi-criteria assessment of cellular mobile telephone service providers using intuitionistic fuzzy WASPAS method with similarity measures. *Granul. Comput.* 2019, 4, 511–529. [CrossRef]