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A NOVEL INTUITIONISTIC FUZZY DISTANCE MEASURE-SWARA-COPRAS METHOD FOR MULTI-CRITERIA FOOD WASTE TREATMENT TECHNOLOGY SELECTION

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Abstract: As an extension of fuzzy set, intuitionistic fuzzy set (IFS) considers the degrees of non-membership and hesitancy along with the degree of membership, therefore, the knowledge and semantic representation of IFS become more significant, resourceful and appropriate. However, with the presence of multiple sustainability indicators and uncertain information, the selection of appropriate food waste treatment technology (FWTT) can be considered as a multi-criteria decision-making (MCDM) problem. Thus, this study aims to introduce a decision support system for assessing the FWTT alternative under uncertain environment. For this purpose, a new intuitionistic fuzzy information-based MCDM methodology is proposed by combining intuitionistic fuzzy distance measure, stepwise weight assessment ratio analysis (SWARA) and the complex proportional assessment (COPRAS) methods. The combination of distance measure-based procedure and SWARA method is used to take the benefits of both the objective and subjective weights of criteria during FWTTs evaluation. Next, the hybridized COPRAS methodology is presented to assess and rank the considered FWTTs from sustainability perspective under intuitionistic fuzzy environment. Further, the present method is implemented on a case study of FWTT selection problem within the context of IFS, which shows its feasibility and effectiveness. This method not only reflects the subjective perspective of decision expert but also captures the objective evaluation of the actual performance measures of each FWTT candidate. Sensitivity and comparative analyses show a high degree of robustness and uniformity in the obtained results. Obtained outcomes point out that the present COPRAS model can effectively choose the suitable FWTT candidate and have the potential to offer practical reference for the policymakers.

Key words: *Intuitionistic fuzzy sets, Food waste, Distance measure, SWARA, COPRAS, Multi-criteria decision-analysis.*

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1. Introduction

"Food waste (FW)" is a primary component of "municipal solid waste (MSW)". The proper management of FWs is a global challenge for the environmentalists, scientists, consumers and activists (Morelli et al., 2020). Poorly managed FW causes severe unfavorable consequences like as contamination of natural resources, greenhouse gas emission, environmental pollution, global warming etc (Slorach et al., 2019). "Food waste treatment (FWT)" can produce several positive outcomes including renewable energy production, reduced methane and other greenhouse gas emissions, air quality improvement, reduced reliance on landfills and fossil fuels, job creation, economic growth and sustainable infrastructure investments. In a study, El-Mashad & Zhang (2010) added the FW into daily manure to extensively increase the biogas yield. Lal & Mohapatra (2020) employed kitchen waste as the source for biogas creation, followed by its consumption in dual-fuel compression ignition engine.

Due to increased amount of food wastes, many different "food waste treatment technologies (FWTTs)" have been emerged in the market (Pham et al., 2015; Giwa et al., 2019). As an important part of sustainable waste management system, the FWTT provides a number of benefits such as maximizing energy recovery, fertilizer production and improved soil health, resulting in economic and environmental benefits (Shewa et al., 2020; Ren & Toniolo, 2020). With the variable composition, high moisture content and low calorific value in FW, a suitable technology is required for the treatment of FWs (Rani et al., 2021, 2022a). The management and treatment of FW are affected by various indicators such as treatment cost, electricity consumption, water consumption, energy production yield, social acceptability, job creation, air/water pollution etc (Garcia-Garcia et al., 2017). In the assessment and selection of suitable FWTTs, several aspects of sustainability including economic, environmental, social and technological are involved (Sakcharoen et al., 2021), therefore, it can be considered as "multi-criteria decision-making" problem (Chadderton et al., 2017; Omar et al., 2021).

During the process of MCDM, the data available for an alternative by means of several attributes may be qualitative linguistic values or imprecise or incomplete in nature. To handle the imprecise and unclear data, Zadeh (1965) gave the notion of "fuzzy set (FS)" and applied to several decision-making applications by considering various perspectives. In FS, the element has only degree of membership but it may not always be sure that the non-membership grade of an element in a FS is just equal to 1 minus the membership grade. In addition, hesitation may have great impact on the final decision and should be considered in decision-making processes but FS ignores the hesitancy. To handle these situations, Atanassov (1986) gave the theory of "intuitionistic fuzzy set (IFS)" to get over certain limitations of FS. It is portrayed by the "membership function (MF)", "non-membership function (NF)" and "hesitancy function (HF)", wherein the values of MF, NF and HF are real numbers between zero and one. In FS, only the MF of an element is considered, whereas in IFS, the MF, the NF and the HF are considered with the sum of MF and NF is less than or equal to 1. The flexibility of IFSs in handling uncertain information is the main motive that we propose IFS-based MCDM approach in this work.

To the best of authors' information, there is no study regarding the assessment and prioritization of multi-criteria sustainable FWTT alternatives from intuitionistic fuzzy information perspective. As a consequence, this work proposes an innovative MCDM technique for assessing the sustainable FWTTs under uncertain environment. The developed framework uses IFS theory to consider the uncertainty of information offered by the "decision experts (DEs)" in the evaluation process.

In the process of MCDM, the criteria weights determination and ranking of alternatives are two important aspects for DEs. For this purpose, in this study, an integrated criteria weight-determining model is presented based on the combination of distance measure-based process for objective weights and the "step-wise weight assessment ratio analysis (SWARA)" (Kersuliene et al., 2010) method for subjecting weights of criteria under IFS context. The SWARA is one of the significant weighting models being used to rank the considered criteria by means of DEs' opinions. In addition, the classical "complex proportional assessment (COPRAS)" (Zavadskas et al., 1994) approach is presented to rank the options within "intuitionistic fuzzy (IF)" context. The proposed COPRAS approach utilizes a stepwise ordering and assessing process of the options concerning the utility degree based on intuitionistic fuzzy information. Inspired by the advantages of SWARA and COPRAS methods, we propose a hybridized method based on distance measure, SWARA and COPRAS method with "intuitionistic fuzzy numbers (IFNs)", and to apply for evaluating FWTTs with uncertainty. Till now, no one has developed a hybrid approach which combines the distance measure, the SWARA and the COPRAS methods with IFSs to evaluate the FWTTs from different aspects of sustainability.

The key contributions of the developed work are given by

- A new extension of COPRAS model is proposed for solving intuitionistic fuzzy MCDM problems with completely anonymous experts and criteria weights.
- A new weighting formula is presented to determine the DEs' weights from intuitionistic fuzzy perspective.
- To compute the criteria weights, a combined weighting process is suggested based on the combination of objective weighting model by distance measure-based formula and subjective weighting model by SWARA model under intuitionistic fuzzy environment. For this purpose, new distance measures are developed for IFSs.
- To exemplify the expediency of the present method, a case study of FWTTs selection is discussed under IF environment.

The rest part of this study is prepared as: Section 2 discusses the existing literatures. Section 3 firstly presents the basic definitions and then proposes new intuitionistic fuzzy distance measures. Section 3 introduces a hybrid COPRAS method for solving MCDM problems within IFS context. Section 5 executes the COPRAS methodology on a case study of FWTTs evaluation problem. This section further discusses the comparative study and sensitivity analysis over diverse parameter values. Section 6 concludes the work and confers the further research scopes.

2. Literature Review

In this part of the study, we present the comprehensive literature related to the current work.

2.1. Intuitionistic Fuzzy Sets (IFSs)

Due to the subjectivity of human mind and increasing complications of realistic applications, the “decision experts (DEs)” are unable to provide the exact numerical values for assessment information. FS theory (Zadeh, 1965) has widely been used to address the vagueness in decision preferences. The notion of FSs has presented its own measures of qualitative information, which finds relevance in diverse areas including pattern recognition (Shahmoradi & Shouraki, 2022; Zhou et al., 2022), image processing (Chen et al., 2022; Maneckshaw & Mahapatra, 2022), disease diagnosis (Arzi et al., 2019; Bahani et al., 2021), decision-making (Cakar and Çavuş, 2021; Narang et al., 2022), science (Szalai et al., 2022a,b) and engineering (Tyagi et al., 2021; Pamucar et al., 2022).

To manage the uncertainty and vagueness of realistic applications, Atanassov (1986) created the doctrine of IFS, which is an advance version of FS. In practical application, the use of IFS can depict the fuzziness and nonspecificity of problems by considering both the MF and NF. Therefore, IFSs are considered to be one of the most permissible theories than classical FS theory to handle the uncertainties and impreciseness in the data. Past studies have witnessed the usefulness of IFS in pattern recognition (Ashraf et al., 2019; Gohain et al., 2022), image segmentation (Arora and Tushir, 2020; Oskouei et al., 2021), clustering (Feng et al., 2018; Wei et al., 2021) etc. Apart of these studies, Zhang et al. (2020) presented an innovative infrared and visible image fusion technique through IFS. Duan and Li (2021) proposed some degrees of similarity for IFSs by means of implication operator and the corresponding metric spaces. Further, Hao et al. (2021) put forward the context-free intuitionistic fuzzy distance and similarity measures with their relevance in marine energy shipping route decision-making. Du (2021) presented the division and subtraction operational laws for IFSs based on the optimization method. In accordance with these operations, they studied the derivative and continuity operations of intuitionistic fuzzy functions. Further, Alkan and Kahraman (2022) introduced a hybrid decision support system by combining IF-CRITIC and IF-DEVADA approaches with application in waste disposal location selection. Using pseudo probability transformation, Xie et al. (2022) measures the information quality of intuitionistic fuzzy values, and derived its induced order for ranking the intuitionistic fuzzy alternatives.

2.2. SWARA Method

As the criteria weights are very important in making a decision, therefore, several weighting models have been developed in the literature (Saaty, 1980; Saaty, 2005; Kersuliene et al., 2010; Rezaei, 2015; Haseli et al., 2020; Keshavarz-Ghorabaee et al., 2021; Aytekin, 2022; Đukić, 2022). The SWARA model introduced by Kersuliene et al. (2010) is an expert opinion-oriented criteria weight-determining method. As the DEs’ preferences have a vital role in the process of MCDM, consequently, the SWARA tool is often preferred in applications that need subjective evaluations. Its key benefit is to derive the criteria weights suitably according to the criteria that each DE has created independently or mutually. As compared to "analytic hierarchy process (AHP)" (Saaty, 1980), this method does not require a large number of pair wise comparisons, has lower computational intricacy and high reliability. The use of AHP will develop the models by means of the criteria and priorities; on the other hand, the SWARA acquire the models in accordance with the situation, priorities, and weights. As compared to "best worst method (BWM)" (Haseli et al., 2021), the SWARA method does not require to compute linear objective functions, has minor computational intricacy and easy to understand (Kersuliene et al., 2010). In comparison with "MEthod based on the Removal Effects of Criteria (MEREC)" method (Keshavarz-Ghorabaee et al., 2021; Ulutaş et al., 2022), the SWARA model considers the subjective evaluations based on experts' opinions. As compared to "base-criterion method (BCM)" (Haseli et al., 2020; Haseli & Sheikh, 2022), the SWARA model does not require to choose a criterion as base criterion directly. In this method, the DEs rank the criteria in order of importance, from the most significant to the least significant, and then derive the final weights of the criteria.

Since its appearance, several ranking methods are combined with SWARA model for diverse purposes. For instance, Mardani et al. (2020) investigated the digital health interventions by using a hybrid model incorporating the hesitant fuzzy SWARA and "weighted aggregated sum product assessment (WASPAS)" method. Rani et al. (2020) incorporated the SWARA model with "VlseKriterijumska Optimizacija Kompromisno Resenje (VIKOR)" technique for assessing the solar panels from Pythagorean fuzzy information perspectives. He et al. (2021) incorporated the Pythagorean fuzzy SWARA and "multi-objective optimization by ratio analysis plus the full multiplicative form (MULTIMOORA)" methods and applied to community based tourism. Ayyildiz (2022) prioritized the indicators of sustainable development goal-7 by means of a collective Fermatean fuzzy SWARA-based decision support system. In the literature, several combinations of SWARA method have been discussed (Yücenur & Şenol, 2021; Alipour et al., 2021; Rahmati et al., 2022; Vojinović et al., 2022).

2.3. COPRAS Method

MCDM process is an important part of decision science in which the DE can choose an optimal candidate among a set of options by means of multiple criteria. Literature consists of various MCDM methods developed to solve complex decision-making problems that may occur daily. In 1994, Zavadskas et al. (1994) originated the notion of COPRAS approach, which is a compensatory approach. It is used to estimate the maximizing and minimizing indexes of criteria individually (Narang et al., 2021).This method describes the ratio to ideal solution and ratio to worst solution simultaneously. Recently, Alipour et al. (2021) ranked the fuel cell and hydrogen components suppliers based on integrated SWARA-COPRAS method. Rani et al. (2022b) gave a hybrid COPRAS technique with the integration of CRITIC and score function under interval-valued Fermatean fuzzy environment. Masoomi et al. (2022) evaluated a set of strategic suppliers by using an incorporated fuzzy BWM-WASPAS-COPRAS method from sustainability perspective. Kusakci et al. (2022) established a hybridized interval type-2 fuzzy AHP-COPRAS methodology and applied for assessing the metropolitan cities from sustainable viewpoints. Several extensions of COPRAS approach have been reported in the literature (Narang et al., 2021; Lu et al., 2021; Saraji & Streimikiene, 2022).

2.4. Methods for FWTTs Assessment

Because of the uncertain nature of the FWTT decision process concerning several sustainability indicators and their irregularity, the notion of FS and its extensions have widely been used in practice. For instance, Büyük & Temur (2022) introduced a new “spherical fuzzy analytic hierarchy process (SF-AHP)” for evaluating the FWTTs candidates with multiple sustainability indicators. Further, Rani et al. (2021) assessed and prioritized the multiple criteria FWTTs options based on single-valued neutrosophic-CRITIC-MULTIMOORA technique. Fan et al. (2022) accomplished the cost analysis and ecological impacts of FWTTs by considering life cycle assessment and life cycle cost techniques. Rani et al. (2022a) designed a hybrid Fermatean fuzzy information-based MCDM approach based on the “method based on the removal effects of criteria (MEREC)” and the “additive ratio assessment (ARAS)” approaches, and utilized it to a FWTT selection problem. Recently, few more authors have concentrated their focus on food waste treatment and management (Garcia-Garcia et al., 2017; Omar et al., 2021; Genc & Ekici, 2022).

Nonetheless, there is no work in the existing body of the literature about the introduced MCDM approach for FWTTs evaluation. So, for the first time, the current study captures the mutual benefits of the SWARA and the COPRAS methods with IFSs, and develops a novel intuitionistic fuzzy information-based MCDM methodology for evaluating and ranking the FWTT candidates from sustainability perspective. The reason of using of SWARA method is that it is easy-to-use and has not been utilized to determine the criteria weights in the process of FWTTs assessment. On the other hand, the motive of using intuitionistic fuzzy COPRAS approach is that it offers a consensual common solution to DEs in order to select the most suitable FWTT from various aspects of sustainability. In other words, we can say that this is first study which incorporates the SWARA and COPRAS methods with IFSs for assessing and prioritizing the FWTT alternatives.

3. Distance Measures for IFSs

Here, a distance measure is introduced to quantify the distance between IFSs. In this respect, we firstly present the fundamental ideas related to IFS.

3.1. Preliminaries

To conquer the drawbacks of FS theory, Atanassov (1986) developed the concept of IFS for the better depiction on uncertainty. In IFS, an element is characterized by the MF and NF with their sum is less than 1.

Definition 3.1 (Atanassov, 1986). An IFS F on a finite discourse $\Theta = \{e_1, e_2, ..., e_t\}$ is mathematically presented as

$$F = \left\{ \left\langle e_i,\ \mu_F(e_i),\ \nu_F(e_i) \right\rangle : e_i \in \Theta \right\}, \quad (1)$$

where $\mu_F : \Theta \to [0, 1]$ and $\nu_F : \Theta \to [0, 1]$ represent the MF and NF, respectively, of e_i to F in Θ, with the conditions

$$\begin{gathered} 0 \le \mu_F\left(e_i\right) \le 1,\ 0 \le \nu_F\left(e_i\right) \le 1, \\ 0 \le \mu_F\left(e_i\right) + \nu_F\left(e_i\right) \le 1,\ \forall\, e_i \in \Theta. \end{gathered} \tag{2}$$

The degree of hesitancy/indeterminacy of an element $e_i \in \Theta$ to F is defined by

$$\pi_F\left(e_i\right) = 1 - \mu_F\left(e_i\right) - \nu_F\left(e_i\right),\ \ 0 \le \pi_F\left(e_i\right) \le 1,\ \forall\, e_i \in \Theta. \tag{3}$$

For simplicity, Xu (2007) defined the term $\left(\mu_F(e_i), \nu_F(e_i)\right)$ as an "intuitionistic fuzzy number (IFN)" and indicated by $\zeta = \left(\mu_\zeta, \nu_\zeta\right)$, where $\mu_\zeta, \nu_\zeta \in [0,1]$ and $0 \le \mu_\zeta + \nu_\zeta \le 1.$

Definition 3.2 (Xu et al., 2015). Suppose $\zeta_i = \left(\mu_i, \nu_i\right)$ be an IFN. Then, the score and accuracy functions are defined as

$$\mathbb{S}^*\left(\zeta_i\right) = \frac{1}{2}\left(\mathbb{S}\left(\zeta_i\right) + 1\right);\ \mathbb{S}^*\left(\zeta_i\right) \in [0,1], \tag{4}$$

$$\hbar^\circ\left(\zeta_i\right) = \frac{1}{2}\left(\mu_i + \nu_i\right);\ \hbar^\circ\left(\zeta_i\right) \in [0,\ 1]. \tag{5}$$

Definition 3.3 (Xu, 2007). Let $\zeta_i = \left(\mu_i, \nu_i\right),\ i = 1(1)t$ be the IFNs. The "intuitionistic fuzzy weighted averaging (IFWA)" and "intuitionistic fuzzy weighted geometric (IFWG)" operators are presented as

$$IFWA_w\left(\zeta_1, \zeta_2, \ldots, \zeta_t\right) = \mathop{\oplus}_{i=1}^{t} w_i\, \zeta_i = \left[1 - \prod_{i=1}^{t}\left(1 - \mu_i\right)^{w_i}, \prod_{i=1}^{t} \nu_i^{\,w_i}\right], \tag{6}$$

$$IFWG_w\left(\zeta_1, \zeta_2, \ldots, \zeta_t\right) = \mathop{\otimes}_{i=1}^{t} w_i\, \zeta_i = \left[\prod_{i=1}^{t} \mu_i^{\,w_i},\ 1 - \prod_{i=1}^{t}\left(1 - \nu_i\right)^{w_i}\right], \tag{7}$$

wherein $w = \left(w_1, w_2, \ldots, w_t\right)^T$ is a weight vector of $\zeta_i,\ i = 1(1)t,$ with $\sum_{i=1}^{t} w_j = 1$ and $w_i \in [0,\ 1].$

Definition 3.4 (Xu and Chen, 2008). An intuitionistic fuzzy distance measure $d : IFSs(\Theta) \times IFSs(\Theta) \to [0,\ 1]$ is a real-valued function which fulfils

(C1). $0 \le d\left(F, G\right) \le 1,$

(C2). $d\left(F,G\right)=0 \Leftrightarrow F=G,$

(C3). $d\left(F,G\right)=1 \Leftrightarrow F=F^{c},$

(C4). $d\left(F,G\right)=d\left(G,F\right),$

(C5). If $F\subseteq G\subseteq H,$ then $d\left(F,H\right)\geq d\left(F,G\right)$ and $d\left(F,H\right)\geq d\left(G,H\right),$ for all $F,G,H\in IFSs(\Theta).$

3.2. New Intuitionistic Fuzzy Distance Measures

The main goal of this section is to propose new distance measures for IFSs and then, employ to derive the criteria weights in next section.

For $F=\left(\mu_F,\nu_F\right), G=\left(\mu_G,\nu_G\right)\in IFSs\left(\Theta\right),$ we develop a new distance measure for computing the difference between two IFSs, given as

$$d_1\left(F,G\right)=\frac{1-\exp\left[-\frac{1}{2}\left(\sum_{i=1}^{t}\left(\left|\mu_F(e_i)-\mu_G(e_i)\right|^{\alpha}+\left|\nu_F(e_i)-\nu_G(e_i)\right|^{\alpha}+\left|\pi_F(e_i)-\pi_G(e_i)\right|^{\alpha}\right)\right)^{1/\alpha}\right]}{1-\exp\left(-\left(t\right)^{1/\alpha}\right)} \quad (8)$$

where $\alpha>0,\ \alpha\neq 1.$

Lemma 3.1. If $h\left(\lambda\right)=1-\dfrac{1-\exp\left(-\lambda\right)}{1-\exp\left(-\left(t\right)^{1/\alpha}\right)},$ then

$$\min_{\lambda\in[0,t]} h\left(\lambda\right)=h\left(0\right)=0 \text{ and } \max_{\lambda\in[0,t]} h\left(\lambda\right)=h\left(t\right)=1.$$

Proof. Since $h'(\lambda)=\dfrac{\exp(-\lambda)}{1-\exp(-1)}<0,\ \forall\,\lambda\in[0,\,t],$ therefore, $h\left(\lambda\right)$ is increasing in $\left[0,t\right].$

Theorem 3.1. The function $d_1\left(F,G\right),$ defined by Eq. (8), is a suitable distance measure for IFSs.

Proof. In this regard, $d_1\left(F,G\right)$ must satisfy the requirements (C1)-(C5) of Definition 3.4.

(C1). Let $F,G\in IFSs(\Theta)$ and

$$\lambda=\frac{1}{2}\left(\sum_{i=1}^{t}\left(\left|\mu_F(e_i)-\mu_G(e_i)\right|^{\alpha}+\left|\nu_F(e_i)-\nu_G(e_i)\right|^{\alpha}+\left|\pi_F(e_i)-\pi_G(e_i)\right|^{\alpha}\right)\right)^{1/\alpha}.$$

Since $\lambda \in [0,t]$, therefore, $d_1(F,G) = h(\lambda)$. Hence, using Lemma 3.1, we have $0 \le d_1(F,G) \le 1$.

(C2). Suppose $F = G$, then $\mu_F(e_i) = \mu_G(e_i)$, $\nu_F(e_i) = \nu_F(e_i)$, $\forall\, e_i \in \Theta$. Then, it is evident from Eq. (8) that $d_1(F,G) = 0$.

Let $d_1(F,G) = 0$. From Eq. (8), we obtain

$$\frac{1 - \exp\left[-\frac{1}{2}\left(\sum_{i=1}^{t}\left(\left|\mu_F(e_i) - \mu_G(e_i)\right|^\alpha + \left|\nu_F(e_i) - \nu_G(e_i)\right|^\alpha + \left|\pi_F(e_i) - \pi_G(e_i)\right|^\alpha\right)\right)^{1/\alpha}\right]}{1 - \exp\left(-(t)^{1/\alpha}\right)} = 0,$$

It implies that

$$\sum_{i=1}^{t}\left(\left|\mu_F(e_i) - \mu_G(e_i)\right|^\alpha + \left|\nu_F(e_i) - \nu_G(e_i)\right|^\alpha + \left|\pi_F(e_i) - \pi_G(e_i)\right|^\alpha\right) = 0, \forall\, e_i \in \Theta.$$

Hence $F = G$.

(C3). It is clear from the definition that $d_1(F,G) = 1 \Leftrightarrow F = F^c$.

(C4). Clearly, $d_1(F,G) = d_1(G,F)$.

(C5). Given that $F \subseteq G \subseteq H$, then $\mu_F(e_i) \le \mu_G(e_i) \le \mu_H(e_i)$ and $\nu_F(e_i) \ge \nu_G(e_i) \ge \nu_H(e_i), \forall\, e_i \in \Theta$.

Now,

$$\lambda_1 = \frac{1}{2}\left(\sum_{i=1}^{t}\left(\left|\mu_F(e_i) - \mu_G(e_i)\right|^\alpha + \left|\nu_F(e_i) - \nu_G(e_i)\right|^\alpha + \left|\pi_F(e_i) - \pi_G(e_i)\right|^\alpha\right)\right)^{1/\alpha}$$

$$\le \lambda_2 = \frac{1}{2}\left(\sum_{i=1}^{t}\left(\left|\mu_F(e_i) - \mu_H(e_i)\right|^\alpha + \left|\nu_F(e_i) - \nu_H(e_i)\right|^\alpha + \left|\pi_F(e_i) - \pi_H(e_i)\right|^\alpha\right)\right)^{1/\alpha}.$$

According to Lemma 3.1, we obtain $d_1(F,G) = h(\lambda_1) \le h(\lambda_2) = d_1(F,H)$. In the same way, we can show that $d_1(G,H) \le d_1(F,H)$. Hence, measure $d_1(F,G)$ is a suitable IF-distance measure.

Next, a new distance measure between two matrices is introduced within IFS context.

Let $F=\left(f_{ij}\right)$ and $G=\left(g_{ij}\right)$, $i=1(1)\,s,\ j=1(1)t$ be two matrices, where $f_{ij}=\left\langle \mu_{ij}^{f},\nu_{ij}^{f}\right\rangle$ and $g_{ij}=\left\langle \mu_{ij}^{g},\nu_{ij}^{g}\right\rangle$ are IFNs. Thus, the distance measure between F and G is proposed as

$$d_2\left(F,G\right)=\frac{1-\exp\left[-\dfrac{1}{2st}\left(\sum_{i=1}^{s}\left(\left|\mu_{ij}^{f}(e_i)-\mu_{ij}^{g}(e_i)\right|^{\alpha}+\left|\nu_{ij}^{f}(e_i)-\nu_{ij}^{g}(e_i)\right|^{\alpha}+\left|\pi_{ij}^{f}(e_i)-\pi_{ij}^{g}(e_i)\right|^{\alpha}\right)\right)^{1/\alpha}\right]}{1-\exp\left(-1\right)}, \tag{9}$$

where $\alpha>0$, $\alpha\neq 1$.

Theorem 3.2. The measure $d_2\left(F,G\right)$, given in Eq. (9), is a suitable distance measure for IFSs.

Proof: Proof is same as Theorem 3.1. Therefore, we have omitted the proof.

4. Proposed IF-Distance Measure-SWARA-COPRAS Method

In this portion, we propose a hybrid decision support system, named as IF-distance measure-SWARA-COPRAS. In this system, the distance measure-based formula is employed to obtain the objective weight of criteria and the SWARA tool is utilized to estimate the subjective weight of criteria. Thus, an integrated weighting process is presented by combining objective and subjective weights of the criteria with IFNs. In addition, the COPRAS model is extended with IFNs to rank the alternatives over considered criteria, and thus, the final ranking result has high reliability. The procedure of IF-distance measure-SWARA-COPRAS methodology is presented as follows (Figure 1):

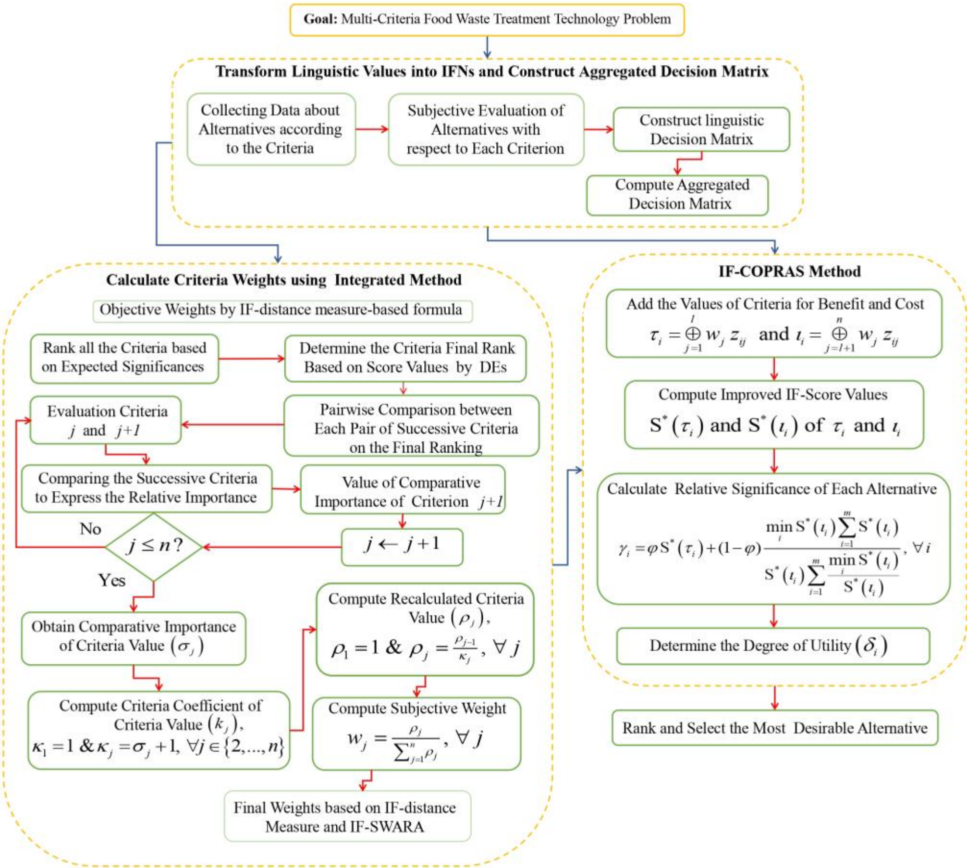

Figure 1. Graphical representation of proposed method

Step 1: Build an "intuitionistic fuzzy-decision matrix (IF-DM)".

In MCDM process, we have to select an optimal candidate among a set of options $V = \{V_1, V_2, ..., V_m\}$ over a criterion set $Q = \{Q_1, Q_2, ..., Q_n\}$. For this purpose, a team of DEs $C = \{C_1, C_2, ..., C_l\}$ is formed to make a suitable decision. Based on DEs' opinions for each alternative concerning a set of criteria, we create a "linguistic decision-matrix (LDM)" $T = \left(\alpha_{ij}^{(k)}\right)_{m\times n}$, wherein $\alpha_{ij}^{(k)}$ indicates the linguistic performance rating of an option V_i over a criterion Q_j provided by k^{th} DE and further, transformed into IF-DM by using linguistic rating table.

Step 2: Acquire the weights of DEs.

To compute the DEs' weights, the formula is as follows:

$$\lambda_k = \frac{1}{2}\left(\frac{\mu_k\left(2-\mu_k-\nu_k\right)}{\sum_{k=1}^{l}\left[\mu_k\left(2-\mu_k-\nu_k\right)\right]} + \frac{l-r_k+1}{\sum_{k=1}^{l}\left(l-r_k+1\right)} \right), \tag{10}$$

where $\lambda_k \geq 0$ and $\sum_{k=1}^{l}\lambda_k = 1.$

Step 3: Construct the "aggregated intuitionistic fuzzy decision matrix (AIF-DM)".

To combine the individual decision opinion of each DE, we use IFWA (or IFWG) operator and then the "aggregated intuitionistic fuzzy decision matrix (AIF-DM)" is $Z = \left(z_{ij}\right)_{m\times n} = \left(\mu_{ij}, \nu_{ij}\right)$, where

$$z_{ij} = \left(\mu_{ij}, \nu_{ij}\right) = IFWA_{\lambda_k}\left(\alpha_{ij}^{(1)}, \alpha_{ij}^{(2)}, \ldots, \alpha_{ij}^{(l)}\right) \tag{11a}$$

$$\text{or } z_{ij} = \left(\mu_{ij}, \nu_{ij}\right) = IFWG_{\lambda_k}\left(\alpha_{ij}^{(1)}, \alpha_{ij}^{(2)}, \ldots, \alpha_{ij}^{(l)}\right). \tag{11b}$$

Step 4: Determine the criteria weights by an incorporated weighting model.

In the following, we compute the criteria weights by combining two weighting procedures:

Case I: Intuitionistic fuzzy distance measure-based objective weighting formula.

This method unites the degree of discrimination among the different criteria. The expression of distance measure-based criteria weight-determining procedure is given as

$$w_j^o = \frac{\frac{1}{m-1}\sum_{i=1}^{m}\sum_{k=1}^{m} d_1\left(z_{ij}, z_{kj}\right)}{\sum_{j=1}^{n}\left(\frac{1}{m-1}\sum_{i=1}^{m}\sum_{k=1}^{m} d_1\left(z_{ij}, z_{kj}\right)\right)}, \quad j = 1(1)n. \tag{12}$$

Case II: Subjective weights by "intuitionistic fuzzy SWARA (IF-SWARA)"model.

To find the subjective weights, we utilize the IF-SWARA model based on intuitionistic fuzzy information. The procedural steps are given as

Step 4a: Estimate the score degrees $\mathbb{S}^*\left(z_{kj}\right)$ by Eq. (4).

Step 4b: Prioritize the criteria as per the DEs' preferences from the most to the least important criteria.

Step 4c: Establish the relative importance levels. From the second criterion, the relative importance levels are assessed as: the relative importance of criterion (*j*) in relation to the preceding criterion (*j* – 1). This ratio is called as "comparative significance of the mean value" and denoted by σ_j.

Step 4d: Evaluate the "comparative coefficient (CC)" with the use of Eq. (13).

$$\kappa_j = \begin{cases} 1, & j = 1, \\ \sigma_j + 1, & j > 1. \end{cases} \tag{13}$$

Step 4e: Estimate the initial weight of each criterion.

$$\rho_j = \begin{cases} 1, & j = 1 \\ \dfrac{\rho_{j-1}}{\kappa_j}, & j > 1. \end{cases} \tag{14}$$

Step 4f: Determine the final weight of each criterion.

$$w_j^s = \frac{\rho_j}{\sum_{j=1}^{n} \rho_j}. \tag{15}$$

Case III: Integrated weights using IF-distance measure and IF-SWARA method

Here, the DEs want to utilize the advantages of both the subjective and objective weights of criteria. Thus, the combined weight of the j^{th} criterion is given as

$$w_j = \vartheta w_j^o + (1 - \vartheta) w_j^s, \tag{16}$$

wherein $\vartheta \in [0,1]$ is the precision objective factor of decision strategy.

Step 5: Add the criteria values with benefit and cost types of criteria.

Here, each option is expressed with its sum of maximizing criterion τ_i and minimizing criterion ι_i. To get the numerical values of τ_i and ι_i, Eq. (17) and Eq. (18) are presented.

$$\tau_i = \bigoplus_{j=1}^{l} w_j \, z_{ij}, \quad \forall\, i. \tag{17}$$

$$\iota_i = \bigoplus_{j=l+1}^{n} w_j z_{ij}, \quad \forall\, i. \tag{18}$$

Here, *l* and *n* refer to the beneficial and total number of criteria, respectively.

Step 6: Determine the “relative degree (RD)”.

Based on Eq. (17), the RD of each alternative is assessed.

$$\gamma_i = \varphi \mathbb{S}^*\left(\tau_i\right) + \left(1-\varphi\right) \frac{\min\limits_i \mathbb{S}^*\left(\iota_i\right) \sum\limits_{i=1}^{m} \mathbb{S}^*\left(\iota_i\right)}{\mathbb{S}^*\left(\iota_i\right) \sum\limits_{i=1}^{m} \dfrac{\min\limits_i \mathbb{S}^*\left(\iota_i\right)}{\mathbb{S}^*\left(\iota_i\right)}}, \forall i. \tag{19}$$

Here, $\mathbb{S}^*\left(\tau_i\right)$ and $\mathbb{S}^*\left(\iota_i\right)$ are the score values of τ_i and ι_i, respectively, and $\varphi \in \left[0,1\right]$ denotes the strategy value of DE.

Step 7: Derive the “utility degree (UD)”.

To evaluate the UD of each option, Eq. (20) is applied.

$$\delta_i = \frac{\gamma_i}{E^*} \times 100\%, \ \forall i. \tag{20}$$

Here, $E^* = \max\limits_i \gamma_i$, $i = 1, 2, \ldots, m$.

5. Case Study: FWTTs Assessment

FW needs different treatment methods from common “municipal solid waste (MSW)” because it has the feature of high moisture, salinity, organic and oil substance. Copious researchers (Giwa et al., 2019; Ren and Toniolo, 2020; Shewa et al., 2020; Rani et al., 2021, 2022a) have focused their attention on FW management and treatment from ecological perspective. In general, the selection of appropriate FWTT option is a complicated MCDM process due to existence of diverse quantitative and qualitative criteria, and uncertainty (Rani et al., 2021, 2022a). Thus, there is a need to develop a suitable model to treat the FWTTs assessment under uncertain environment.

In order to assess the FWTT candidates according to several criteria, a team of four DEs is formed who have 15+ years of experience in the area of sustainable development. Out of 04 DEs, 01 is from municipality, who is master’s degree holder, 02 are environmentalists, who are doctorate degree holder and 01 is from engineering department, who is master’s degree holder. After establishing the decision-making team, we have prepared an online survey with the purpose of determining the sustainability indicators’ importance in the process of FWTTs evaluation. The indicators that have an effect on the FWTTs assessment were assembled and then discussed with the panel of four DEs. Based on the literatures and conversations with specialists, 13 sustainability indicators/factors/criteria are preferred for the given case study of FWTTs selection, which aims to promise the sustainability perspective (see Table 1). In the meantime, open interviews assisted to decide four FWTTs as the most appropriate where the study was conducted. In this study, considered alternatives are as follows: Anaerobic Digestion (V_1), Composting (V_2), Landfill (V_3) and Incineration (V_4).

Table 1. Details of chosen indicators for FWTTs evaluation

Dimension	Criteria	Description	Type
Economic (L_1)	Investment cost (Q_1)	Considers the set up cost of treatment technologies & their rescue assessment	Cost
	Operation cost (Q_2)	Considers the operation costs of assessed treatment technologies	Cost
	Collection and transportation cost (Q_3)	Considers each cost made for FW collection and their transportation	Cost
	Energy production yield (Q_4)	Considers the energy production from methane and CO_2 rich biogas	Benefit
Social (L_2)	Social acceptability (Q_5)	The quality of FWTT should be accepted socially	Benefit
	Benefit to society (Q_6)	Provides benefits to the local residents	Benefit
	Compatibility (Q_7)	Capability of FWTT to use in small scale	Benefit
	Health and safety (Q_8)	Determines the health and safety of employees and local residents	Benefit
Environmental (L_3)	Energy consumption(Q_9)	Shows the amount of energy consumed by each FWTT option	Cost
	Environmental risks(Q_{10})	Considers the pollution, spread of diseases through the execution of FWTT option	Cost
	Soil and Water pollution (Q_{11})	Pollution and contamination of groundwater resources produced by landfilling	Cost
Technological (L_4)	Technology maturity (Q_{12})	Tends to how suitable the current technology is chosen treatment alternative	Benefit
	Capacity (Q_{13})	Considers the capability and infrastructural capacity of FWTT option	Benefit

In the present part of the study, we implement the hybrid COPRAS methodology on the selection of suitable FWTT candidate from a set of options, which establishes the applicability and usefulness of the proposed methodology. Now, the procedural steps of introduced COPRAS method on the present case study are discussed as follows:

Steps 1-3: Tables 2-3 (Mishra et al.2019) present the linguistic ratings and their corresponding IFNs to express the significance values of DEs and the considered criteria for FWTTs assessment. By utilizing Table 2 and Eq. (10), the significance values of DEs are derived and shown in Table 4. Table 5 shows the “linguistic decision matrix (LDM)” provided by four DEs for each alternative V_i concerning the considered sustainability indicators. According to Eq. (11) and Table 5, the AIF-DM is constructed in Table 6.

Table 2. DEs’ ratings for FWTTs assessment

LVs	IFNs
Absolutely important (AI)	(0.90, 0.10)
Very important (VI)	(0.80, 0.15)
Important (F)	(0.70, 0.25)
Fair (F)	(0.60, 0.35)
Unimportant (U)	(0.50, 0.45)
Very unimportant (VU)	(0.40, 0.55)
Absolutely unimportant (AU)	(0.20, 0.70)

Table 3. Linguistic performances of given FWTTs and criteria

LVs	IFNs
Absolutely significant (AS)	(0.95, 0.05)
Very very significant (VVS)	(0.85, 0.10)
Very significant (VS)	(0.80, 0.15)
Significant (S)	(0.70, 0.20)
Moderately significant (MS)	(0.60, 0.30)
Moderate (A)	(0.50, 0.40)
Moderately insignificant (MI)	(0.40, 0.50)
Insignificant (I)	(0.30,0.60)
Very insignificant (VI)	(0.20, 0.70)
Very very insignificant (VVI)	(0.10, 0.80)
Extremely insignificant (EI)	(0.05, 0.95)

Table 4. DEs’ weights

DEs	C_1	C_2	C_3	C_4
Ratings	VI	I	I	AI
r_k	2	3.5	3.5	1
Weight	0.2808	0.1895	0.1895	0.3402

Table 5. Linguistic decision matrix for FWTTs assessment

Criteria	V_1	V_2	V_3	V_4
Q_1	(MI,I,VI,MI)	(I,MI,VI,I)	(M,MI,M,I)	(MI,MI,M,I)
Q_2	(I,I,M,I)	(I,MI,VI,MI)	(MI,M,MI,M)	(I,MI,MI,I)
Q_3	(MI,I,I,VI)	(I,M,VI,I)	(M,MI,M,MI)	(MI,VI,M,M)
Q_4	(M,S,MS,AS)	(S,MS,S,MS)	(S,MS,M,S)	(S,MI,VS,VS)
Q_5	(MS,S,M,MS)	(VVS,S,VS,M)	(MI,MS,M,MS)	(VS,MI,M,MS)
Q_6	(M,MI,VS,M)	(MI,MI,M,S)	(AS,VS,M,MS)	(M,MS,M,S)
Q_7	(MS,I,M,VVS)	(M,I,MI,MS)	(MS,M,VS,S)	(VS,S,M,MS)
Q_8	(VVS,S,M,MS)	(MS,S,VS,S)	(MI,MS,M,VS)	(S,MS,M,S)
Q_9	(M,I,MI,MS)	(S,I,MI,M)	(MI,I,M,MS)	(MI,L,M,MI)
Q_{10}	(VI,I,M,MI)	(M,VI,I,MI)	(M,MS,VI,I)	(VI,MI,VI,MI)
Q_{11}	(MI, M,VI,MI)	(M,MI,MS,S)	(S,M,S,VVS)	(MS,MI,M,VS)
Q_{12}	(S,MI,M,MS)	(V,AS,M,MS)	(VVS,M,MS,MI)	(MI,MS,VS,S)
Q_{13}	(VS,S,VS,M)	(S,AS,VS,MS)	(MS,MI,M,MS)	(MS,VS,MS,S)

Table 6. Aggregated decision matrix for FWTTs assessment

Criteria	V_1	V_2	V_3	V_4
Q_1	(0.348, 0.552, 0.101)	(0.303, 0.597, 0.100)	(0.420, 0.479, 0.101)	(0.389, 0.510, 0.101)
Q_2	(0.343, 0.556, 0.101)	(0.338, 0.561, 0.101)	(0.455, 0.444, 0.101)	(0.340, 0.560, 0.100)
Q_3	(0.298, 0.601, 0.101)	(0.326, 0.572, 0.101)	(0.449, 0.450, 0.101)	(0.425, 0.474, 0.102)
Q_4	(0.801, 0.164, 0.035)	(0.651, 0.248, 0.101)	(0.651, 0.246, 0.103)	(0.724, 0.204, 0.072)
Q_5	(0.605, 0.293, 0.102)	(0.728, 0.197, 0.075)	(0.532, 0.366, 0.102)	(0.629, 0.287, 0.084)
Q_6	(0.565, 0.347, 0.089)	(0.542, 0.351, 0.107)	(0.796, 0.168, 0.036)	(0.597, 0.299, 0.104)
Q_7	(0.668, 0.249, 0.084)	(0.489, 0.409, 0.103)	(0.668, 0.242, 0.090)	(0.675, 0.241, 0.084)
Q_8	(0.700, 0.216, 0.085)	(0.699, 0.212, 0.089)	(0.618, 0.301, 0.081)	(0.651, 0.246, 0.103)
Q_9	(0.489, 0.409, 0.103)	(0.522, 0.371, 0.107)	(0.480, 0.417, 0.103)	(0.403, 0.496, 0.101)
Q_{10}	(0.353, 0.545, 0.102)	(0.380, 0.518, 0.102)	(0.413, 0.483, 0.104)	(0.313, 0.586, 0.101)
Q_{11}	(0.388, 0.511, 0.101)	(0.583, 0.312, 0.105)	(0.739, 0.180, 0.081)	(0.644, 0.276, 0.080)
Q_{12}	(0.584, 0.311, 0.104)	(0.768, 0.186, 0.046)	(0.636, 0.277, 0.087)	(0.644, 0.265, 0.092)
Q_{13}	(0.705, 0.221, 0.074)	(0.782, 0.167, 0.051)	(0.549, 0.349, 0.102)	(0.682, 0.229, 0.089)

Step 4: With the use of Eq. (12), we have calculated the objective weight of each criteria by utilizing the proposed distance measure (8) (or (9)). The resultant values are given as follows (see Figure 2):

$w_j^o = (0.0024,\ 0.0023,\ 0.0039,\ 0.1980,\ 0.0855,\ 0.1934,\ 0.0542,\ 0.0597,\ 0.0166,\ 0.0074,\ 0.0807,\ 0.1534,\ 0.1426).$

Based on the IF-SWARA model given by Steps 4a-4f, we have derived the subjective weights of criteria in Table 8. The resultant values are presented as follows (see Figure 2):

$w_j^s = (0.0857,\ 0.0746,\ 0.0775,\ 0.0784,\ 0.0681,\ 0.0856,\ 0.0741,\ 0.0793,\ 0.0738,\ 0.0806,\ 0.0695,\ 0.0717,\ 0.0811).$

Table 7. Score values of criteria for FWTTs given by DEs

Criteria	C_1	C_2	C_3	C_4	Aggregated IFNs	Score values
Q_1	S	MS	M	MS	(0.615, 0.283, 0.102)	0.6662
Q_2	MS	M	M	I	(0.473, 0.424, 0.103)	0.5249
Q_3	MS	M	MI	M	(0.514, 0.385, 0.101)	0.5645
Q_4	S	I	MI	M	(0.522, 0.371, 0.107)	0.5756
Q_5	MI	MI	I	MI	(0.382, 0.518, 0.100)	0.4323
Q_6	MS	S	S	M	(0.613, 0.284, 0.103)	0.6647
Q_7	MI	M	S	I	(0.464, 0.429, 0.107)	0.5178
Q_8	MS	M	I	MS	(0.536, 0.361, 0.103)	0.5874
Q_9	MI	M	MS	MI	(0.463, 0.435, 0.102)	0.5141
Q_{10}	S	M	MI	MS	(0.552, 0.343, 0.105)	0.6041
Q_{11}	I	I	MS	MI	(0.403, 0.495, 0.103)	0.4540
Q_{12}	MI	M	MS	I	(0.434, 0.463, 0.103)	0.4857
Q_{13}	S	MI	I	MS	(0.557, 0.336, 0.107)	0.6103

Table 8. Criteria weights using SWARA model

Indicators	Score values	Comparative significance of criteria	CC	Initial weight	Final weight
Q_1	0.6662	-	1.000	1.0000	0.0857
Q_6	0.6647	0.0015	1.0015	0.9985	0.0856
Q_{13}	0.6103	0.0544	1.0544	0.9470	0.0811
Q_{10}	0.6041	0.0062	1.0062	0.9412	0.0806
Q_8	0.5874	0.0167	1.0167	0.9257	0.0793
Q_4	0.5756	0.0118	1.0118	0.9149	0.0784
Q_3	0.5645	0.0111	1.0111	0.9049	0.0775
Q_2	0.5249	0.0396	1.0396	0.8704	0.0746
Q_7	0.5178	0.0071	1.0071	0.8643	0.0741
Q_9	0.5141	0.0037	1.0037	0.8611	0.0738
Q_{12}	0.4857	0.0284	1.0284	0.8373	0.0717
Q_{11}	0.4540	0.0317	1.0317	0.8116	0.0695
Q_5	0.4323	0.0217	1.0217	0.7944	0.0681

Next, we have combined the IF-distance measure-based weighting procedure for objective weights and IF-SWARA for subjective weights by using Eq. (16). Thus, the integrated weight is depicted in Figure 2 and presented as

w_j= (0.0440, 0.0439, 0.0425, 0.1393, 0.0824, 0.1359, 0.0658, 0.0672, 0.0454, 0.0406, 0.0762, 0.1115, 0.1053).

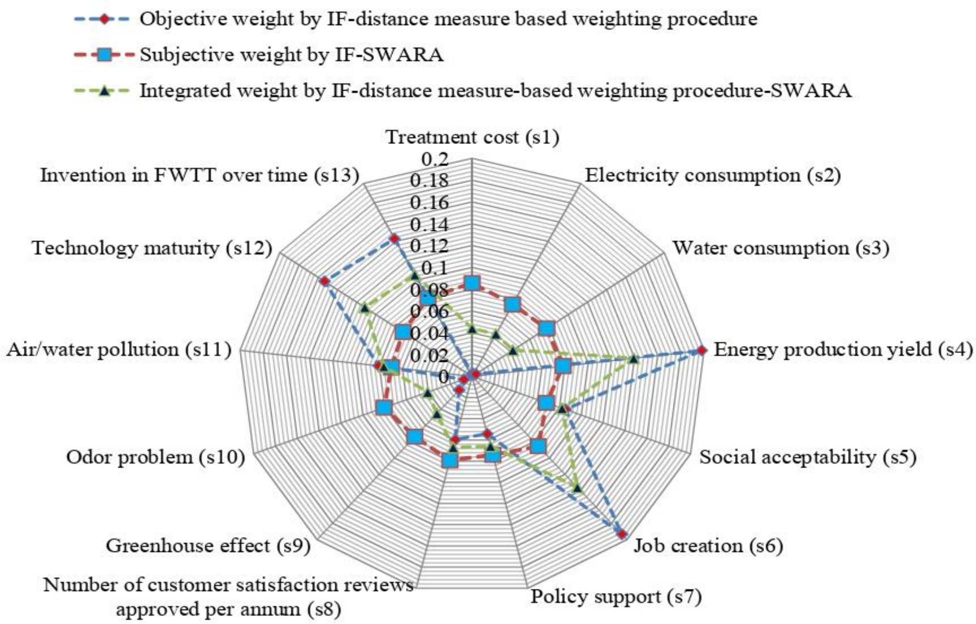

Figure 2. Criteria weights for FWTTs assessment using proposed weight-determining model

Steps 5-7: Through Eqs (17)-(20), the values of $\tau_i, \iota_i, \mathbb{S}^*(\tau_i), \mathbb{S}^*(\iota_i), \gamma_i$ and δ_i are derived and shown in Table 9. On the basis of obtained results, the ranking of the FWTTs is $V_1 \succ V_4 \succ V_2 \succ V_3$ and thus, FWTTs (V_1) is the most desirable alternative.

Table 9. Outcomes of IF-distance measure-SWARA-COPRAS method

FWTTs	τ_i	$\mathbb{S}^*(\tau_i)$	ι_i	$\mathbb{S}^*(\iota_i)$	γ_i	δ_i
V_1	(0.548, 0.375, 0.077)	0.587	(0.129, 0.827, 0.044)	0.151	0.4084	100.00
V_2	(0.554, 0.364, 0.081)	0.595	(0.157, 0.793, 0.051)	0.182	0.3930	96.21
V_3	(0.532, 0.387, 0.081)	0.572	(0.205, 0.739, 0.055)	0.233	0.3608	88.33
V_4	(0.585, 0.376, 0.039)	0.605	(0.165, 0.788, 0.047)	0.189	0.3944	96.56

5.1. Sensitivity Analysis

In this part, we have analyzed the significance of subjective and objective weights for considered criteria in the proposed weight finding technique. In addition, we have changed the values of parameter to show the performance of UDs. For this purpose, we have following cases:

Case I: Different values of $\vartheta \in [0,1]$ are taken for analysis. This investigation is presented to examine the variation of IF-distance measure-SWARA-COPRAS method. Based on the Table 10 and Figure 3, the preference ranking is $V_1 \succ V_2 \succ V_4 \succ V_3$ when ϑ = 0.0 to 0.4, while ranking order is $V_1 \succ V_4 \succ V_2 \succ V_3$ when ϑ = 0.5 to 0.7, ranking order is $V_4 \succ V_1 \succ V_2 \succ V_3$ when ϑ = 0.8 to 0.9 and ranking order is $V_4 \succ V_2 \succ V_1 \succ V_3$ when ϑ = 1.0. As a consequence, the evaluation of FWTTs is depend on and sensitive to the parameter ϑ.

Table 10. The UD of option with diverse parameter values

ϑ	V_1	V_2	V_3	V_4	Ranking order
ϑ = 0.0	0.2303	0.1910	0.1493	0.1840	$V_1 \succ V_2 \succ V_4 \succ V_3$
ϑ = 0.1	0.2659	0.2314	0.1916	0.2261	$V_1 \succ V_2 \succ V_4 \succ V_3$
ϑ = 0.2	0.3015	0.2718	0.2339	0.2682	$V_1 \succ V_2 \succ V_4 \succ V_3$
ϑ = 0.3	0.3372	0.3122	0.2762	0.3103	$V_1 \succ V_2 \succ V_4 \succ V_3$
ϑ = 0.4	0.3728	0.3526	0.3185	0.3523	$V_1 \succ V_2 \succ V_4 \succ V_3$
ϑ = 0.5	0.4084	0.3930	0.3608	0.3944	$V_1 \succ V_2 \succ V_4 \succ V_3$
ϑ = 0.6	0.4441	0.4333	0.4031	0.4365	$V_1 \succ V_4 \succ V_2 \succ V_3$
ϑ = 0.7	0.4797	0.4737	0.4454	0.4785	$V_1 \succ V_4 \succ V_2 \succ V_3$
ϑ = 0.8	0.5153	0.5141	0.4877	0.5206	$V_4 \succ V_1 \succ V_2 \succ V_3$
ϑ = 0.9	0.5510	0.5545	0.5300	0.5627	$V_4 \succ V_1 \succ V_2 \succ V_3$
ϑ = 1.0	0.5866	0.5949	0.5723	0.6047	$V_4 \succ V_2 \succ V_1 \succ V_3$

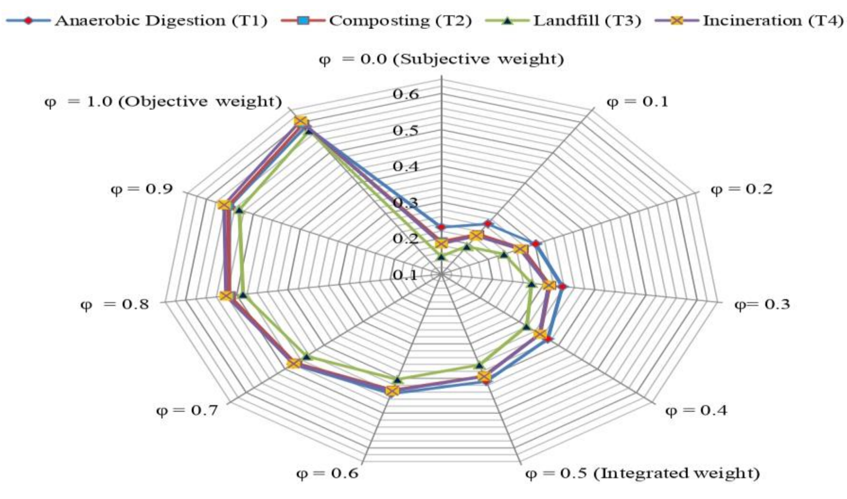

Figure 3.The UDs over diverse values of (ϑ)

Case II: In this case, the ranking results have been made by changing the objective weights instead of IF-distance measure-based weighting procedure-SWARA and given in Table 11 and Figure 4. Using IF-distance measure-based weighting procedure, the performance values of FWTTs are given as follows: V_1 = 0.4088, V_2 = 0.3884, V_3 = 0.3654 and V_4 = 0.3908 and the ranking order of FWTTs is $V_1 \succ V_4 \succ V_2 \succ V_3$. Applying the IF-SWARA method, the performance values of FWTTs are given as follows: V_1 = 0.3947, V_2 = 0.3805, V_3 =0.3412 and V_4 = 0.3807 and the ranking order of FWTTs is given as $V_1 \succ V_4 \succ V_2 \succ V_3$. Thus, it is found that by using the several parameter values has improved the stability of the IF-distance measure-SWARA-COPRAS method.

Table 11. Subordinate UD of FWTTs over diverse weighting models

Weight-determining procedure	Subordinate UDs of FWTT candidates				Ordering
	V_1	V_2	V_3	V_4	
IF-Distance measure-based weighting procedure	0.4088	0.3884	0.3654	0.3908	$V_1 \succ V_4 \succ V_2 \succ V_3$
IF-SWARA method	0.3947	0.3805	0.3412	0.3807	$V_1 \succ V_4 \succ V_2 \succ V_3$
Integrated method	0.4084	0.3930	0.3608	0.3944	$V_1 \succ V_4 \succ V_2 \succ V_3$

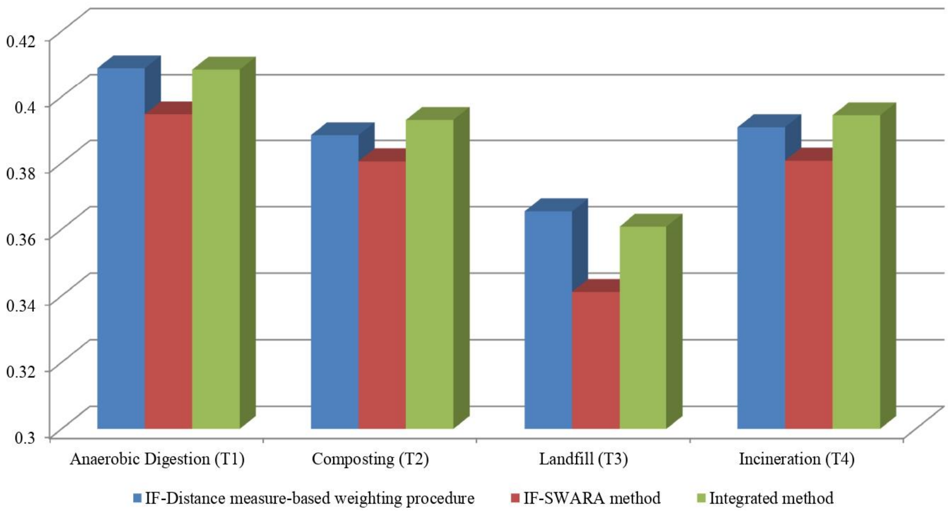

Figure 4. Results of sensitivity analysis by different weighting models for FWTTs assessment

5.2. Comparative Study

This section presents the comparison between the IF-distance measure-SWARA-COPRAS method and some other previous methods. For this purpose, we have taken the IF-WASPAS (Mishra et al., 2019) and IF-TOPSIS method (Mishra, 2016), and executed to handle the given case study.

5.2.1. IF-TOPSIS (Mishra, 2016)

From Table 6, "intuitionistic fuzzy ideal solution (IF-IS)" and "intuitionistic fuzzy anti-ideal solution (IF-AIS)" are computed, where $j = 1, 2, \ldots, 13$. Now, the whole computational results of IF-TOPSIS (Mishra, 2016) are presented in Table 12.

ϕ_j^+ = {(0.303, 0.597, 0.100), (0.338, 0.561, 0.101), (0.298, 0.601, 0.101), (0.801, 0.164, 0.035), (0.728, 0.197, 0.075), (0.796, 0.168, 0.036), (0.675, 0.241, 0.084), (0.699, 0.212, 0.089), (0.403, 0.496, 0.101), (0.313, 0.586, 0.101), (0.388, 0.511, 0.101), (0.768, 0.186, 0.046), (0.782, 0.167, 0.051)}

ϕ_j^- = {(0.420, 0.479, 0.101), (0.455, 0.444, 0.101), (0.449, 0.450, 0.101), (0.651, 0.248, 0.101), (0.532, 0.366, 0.102), (0.542, 0.351, 0.107), (0.489, 0.409, 0.103), (0.618, 0.301, 0.081), (0.522, 0.371, 0.107), (0.413, 0.483, 0.104), (0.739, 0.180, 0.081), (0.584, 0.311, 0.104), (0.549, 0.349, 0.102)}.

Thus, from Table 12, V_1 is the best FWTT alternative and ranking order of FWTT options is $V_1 \succ V_2 \succ V_4 \succ V_3$.

Table 12. Ranking orders of IF- TOPSIS method for FWTTs

FWTTs	Degree of similarity between FWTT options and IF-IS	Degree of similarity between FWTT options and IF-AIS	Relative closeness coefficient	Ranking
V_1	0.132	0.182	0.5799	1
V_2	0.146	0.162	0.5249	2
V_3	0.221	0.090	0.2883	4
V_4	0.171	0.151	0.4680	3

5.2.2. IF-WASPAS (Mishra et al., 2019)

Using IF-WASPAS, we determine the measures of "weighted sum model (WSM)", "weighted product model (WPM)" and "weighted aggregated sum product assessment (WASPAS)" in the context of IFNs. Table 13 presents the whole computational outcomes of the IF-WASPAS model. Therefore, the ranking of FWTT choice is $V_1 \succ V_4 \succ V_2 \succ V_3$ and the alternative V_1 is best FWTT alternative for given case study.

Table 13. Computational outcomes of the IF-WASPAS method

Options	Measure of "weighted sum model (WSM)"	Measure of "weighted product model (WPM)"	Score function of WSM	Score function of WPM	Measure of WASPAS	Ranking Order
V_1	(0.638, 0.280, 0.082)	(0.614, 0.297, 0.089)	0.679	0.659	0.6687	1
V_2	(0.632, 0.282, 0.086)	(0.590, 0.316, 0.094)	0.675	0.637	0.6560	3
V_3	(0.596, 0.285, 0.119)	(0.601, 0.366, 0.033)	0.655	0.618	0.6365	4
V_4	(0.614, 0.275, 0.111)	(0.624, 0.321, 0.054)	0.669	0.651	0.6604	2

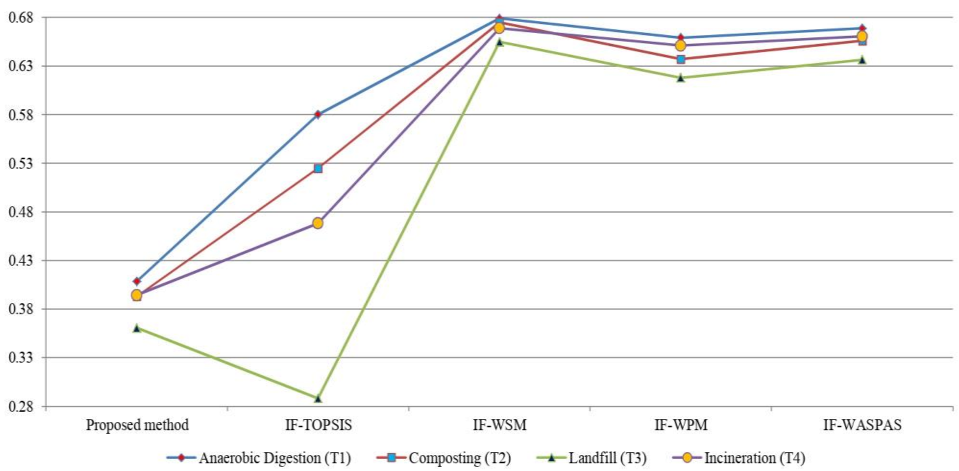

Figure 5. Ranking order of FWTTs option with different methods

Based on the comparisons between the present and existing methodologies, the advantages of the present COPRAS model are listed in the following points:

- This study computes the DEs' weights under IF environment, while the previous methods consider the assumed DEs' weights. This means that the proposed methodology can offer more exact results for MCDM problems from uncertainty perspective.
- The present COPRAS method derives the objective and subjective weights of criteria using IF-distance measure and IF-SWARA model, respectively. Therefore, it provides the more accurate outcomes under intuitionistic fuzzy environment. While the IF-WASPAS uses only objective weights of criteria by utilizing degree of similarity and IF-COPRAS considers the direct weight of each criterion.

- In the developed method, benefit and cost types of criteria are utilized. In COPRAS, both types of criteria with complex proportion contains more precise information as compared to only dealing with the cost or benefit criteria. Thus, the present approach increases the readability of initial data and the accurateness of obtained outcomes.
- The developed framework has higher operability than the IF-TOPSIS method in case of large numbers of criteria or alternatives. For the proposed framework, the IF-IS and IF-AIS are not required as IF-TOPSIS. In COPRAS, the results are computed with managing the real data, which reveals that the proposed COPRAS model can tackle more complicated and practical decision-making applications.

6. Conclusions

In this part of the study, we present the comprehensive literature related to the current work.

FWTT offers a promising solution for handling the speedily generated food waste. To meet the sustainable food waste management goals, it is required to select the suitable FWTT alternative. Here, we presented a hybrid decision support system for evaluating and prioritizing the FWTTs from uncertainty perspective. In this regard, we have incorporated the COPRAS approach with distance measure and the SWARA model within the environment of IFSs. To calculate the criteria's weights, we have integrated the objective weights of criteria by intuitionistic fuzzy distance measure-based procedure and the subjective weights of criteria by IF-SWARA model. For objective weights, new distance measures have been proposed for IFSs.

Next, a case study for FWTTs assessment has been presented to show the practicability of the hybrid COPRAS methodology. The evaluation index framework for FWTT selection is developed, which contains four aspects of sustainability, namely economic, social, environmental and technological. These four dimensions respectively consist of four, four, three and two sub-criteria and the weights of all sub-criteria are computed by an integrated weighting model. The calculation result shows that the alternative 'Anaerobic Digestion (V_1)' should be chosen as the most suitable alternative for given case study. Further, sensitivity and comparative analyses have been discussed to confirm the results acquired by proposed hybrid model. The key benefits of the presented framework are the ease of calculation in intuitionistic fuzzy background and utilizing a model for deriving more reasonable weights of indicators.

The method proposed in this paper has some limitations, which are

- This method ignores the objective weights of criteria.
- The present MCDM approach does not consider the interrelationships among the criteria.
- This study has given equal importance to each of the dimension but in fact, this is not true for a real case study.
- In this method, we consider only benefit and cost types of criteria and

ignore the target-based criteria.

In future, it would be exciting to improve the limitations of the present study by proposing some new methods such as "weighted sum-product (WISP)", "double normalization-based multiple aggregation (DNMA)", "gained lost dominance score (GLDS)" etc. In addition, this study can be extended to "q-rung orthopair fuzzy rough sets (q-ROFRSs)", "Pythagorean fuzzy soft sets (PFSSs)", "interval-valued q-rung orthopair fuzzy rough sets (IVq-ROFRSs)", and can be executed for kitchen waste treatment technologies assessment, plastic waste recycling technology selection, green energy projects assessment and vertical farming technology evaluation.

References

Alipour, M., Hafezi, R., Rani, P., Hafezi, M., & Mardani, A. (2021). A new Pythagorean fuzzy-based decision-making method through entropy measure for fuel cell and hydrogen components supplier selection. Energy, 234, 121208, https://doi.org/10.1016/j.energy.2021.121208.

Alkan, N., & Kahraman, C. (2022). An intuitionistic fuzzy multi-distance based evaluation for aggregated dynamic decision analysis (IF-DEVADA): Its application to waste disposal location selection. Engineering Applications of Artificial Intelligence, 111, 104809, https://doi.org/10.1016/j.engappai.2022.104809.

Arji, G., Ahmadi, H., Nilashi, M., Rashid, T. A., Ahmed, O. H., Aljojo, N., & Zainol, A. (2019). Fuzzy logic approach for infectious disease diagnosis: A methodical evaluation, literature and classification. Biocybernetics and Biomedical Engineering, 39(4), 937-955.

Arora, J., & Tushir, M. (2020). An Enhanced Spatial Intuitionistic Fuzzy C-means Clustering for Image Segmentation. Procedia Computer Science, 167, 646-655.

Ashraf, Z., Khan, M. S., & Lohani, Q. M. D. (2019). New bounded variation based similarity measures between Atanassov intuitionistic fuzzy sets for clustering and pattern recognition. Applied Soft Computing, 85, 105529, https://doi.org/10.1016/j.asoc.2019.105529.

Atanassov, K. T. (1986). Intuitionistic fuzzy sets. Fuzzy sets and Systems, 20(1), 87-96.

Aytekin, A. (2022). Determining criteria weights for vehicle tracking system selection using PIPRECIA-S. Journal of Process Management and New Technologies, 10(1-2), 115-124.

Ayyildiz, E. (2022). Fermatean fuzzy step-wise Weight Assessment Ratio Analysis (SWARA) and its application to prioritizing indicators to achieve sustainable development goal-7. Renewable Energy, 193, 136-148.

Bahani, K., Moujabbir, M., & Ramdania, M. (2021). An accurate fuzzy rule-based classification systems for heart disease diagnosis. Scientific African, 14, e01019, https://doi.org/10.1016/j.sciaf.2021.e01019.

Büyük, B. M., & Temur, G. T. (2022). Food waste treatment option selection through spherical fuzzy AHP. Journal of Intelligent and Fuzzy Systems, 42(1), 97-107, DOI: 10.3233/JIFS-219178.

Cakar, T., & Çavuş, B. (2021). Supplier selection process in dairy industry using fuzzy TOPSIS method. Operational Research in Engineering Sciences: Theory and Applications, 4(1), 82-98. https://doi.org/10.31181/oresta2040182c.

Chadderton, C., Foran, C. M., Rodriguez, G., Gilbert, D., Cosper, S. D., & Linkov, I. (2017). Decision support for selection of food waste technologies at military installations. Journal of Cleaner Production, 141, 267-277.

Chen, C., Liu, B., Song, F., Jiang, J., Li, Z., Song, C., Li, J., Jin, G., & Wu, J. (2022). An adaptive fuzzy logic control of green tea fixation process based on image processing technology. Biosystems Engineering, 215, 1-20.

Du, W. S. (2021). Subtraction and division operations on intuitionistic fuzzy sets derived from the Hamming distance. Information Sciences, 571, 206–224. doi:10.1016/j.ins.2021.04.068.

Duan, J., & Li, X. (2021). Similarity of intuitionistic fuzzy sets and its applications. International Journal of Approximate Reasoning, 137, 166–180. doi:10.1016/j.ijar.2021.07.009.

Đukić, T. (2022). Ranking factors that affect satisfaction and motivation of employees using the PIPRECIA method. Journal of Process Management and New Technologies, 10 (1-2), 102-114.

El-Mashad, H. M., & Zhang, R. (2010). Biogas production from co-digestion of dairy manure and food waste. Bioresour Technology, 101(11), 4021-4028.

Fan, Z., Dong, H., Geng, Y., & Fujii, M. (2022). Life cycle cost–benefit efficiency of food waste treatment technologies in China. Environment, Development and Sustainability, https://doi.org/10.1007/s10668-022-02251-4.

Feng, Z., Hanqiang, L., Jiulun, F., Wen, C. C., Rong, L., & Na, L. (2018). Intuitionistic fuzzy set approach to multi-objective evolutionary clustering with multiple spatial information for image segmentation. Neurocomputing, 312, 296-309.

Garcia-Garcia, G., Woolley, E., Rahimifard, S., Colwill, J., White, R., & Needham, L. (2017). A methodology for sustainable management of food waste. Waste and Biomass Valorization, 8, 2209-2227.

Genc, T. O., & Ekici, A. (2022). A new lens to the understanding and reduction of household food waste: A fuzzy cognitive map approach. Sustainable Production and Consumption, 33, 389-411.

Giwa, A. S., Xu, H., Chang, F., Wu, J., Li, Y., Ali, N., Ding, S., & Wang, K. (2019). Effect of biochar on reactor performance and methane generation during the anaerobic digestion of food waste treatment at long-run operations. Journal of Environmental Chemical Engineering, 7(4), 103067, https://doi.org/10.1016/j.jece.2019.103067.

Gohain, B., Chutia, R., & Dutta, P. (2022). Distance measure on intuitionistic fuzzy sets and its application in decision-making, pattern recognition, and clustering problems. International Journal of Intelligent Systems, 37(3), 2458-2501.

Hao, Z., Xu, Z., Zhao, H., & Zhang, R. (2021). The context-based distance measure for intuitionistic fuzzy set with application in marine energy transportation route decision making. Applied Soft Computing, 101, 107044, doi:10.1016/j.asoc.2020.107044.

Haseli, G., & Sheikh, R. (2022). Base Criterion Method (BCM). Multiple Criteria Decision Making. Springer, Singapore, 17-38.

Haseli, G., Sheikh, R., & Sana, S. S. (2020). Base-criterion on multi-criteria decision-making method and its applications. International Journal of Management Science and Engineering Management, 15(2), 79-88. DOI: 10.1080/17509653.2019.1633964.

Haseli, G., Sheikh, R., Wang, J., Tomaskova, H., & Tirkolaee, E. B. (2021). A novel approach for group decision making based on the best–worst method (G-BWM): Application to supply chain management. Mathematics, 9(16), 01-20. https://doi.org/10.3390/math9161881.

He, J., Huang, Z., Mishra, A. R., & Alrasheedi, M. (2021). Developing a new framework for conceptualizing the emerging sustainable community-based tourism using an extended interval-valued Pythagorean fuzzy SWARA-MULTIMOORA. Technological Forecasting and Social Change, 171, 120955. doi:10.1016/j.techfore.2021.120955.

Kersuliene, V., Zavadskas, E. K., & Turskis, Z. (2010). Selection of rational dispute resolution method by applying new step-wise weight assessment ratio analysis (SWARA). Journal of Business Economics and Management, 11, 243–258.

Keshavarz-Ghorabaee, M., Amiri, M., Zavadskas, E. K., Turskis, Z., & Antucheviciene, J. (2021). Determination of Objective Weights Using a New Method Based on the Removal Effects of Criteria (MEREC). Symmetry, 13(4), 525; https://doi.org/10.3390/sym13040525.

Kusakci, S., Yilmaz, M. K., Kusakci, A. O., Sowe, S., & Nantembelele, F. A. (2022). Towards sustainable cities: A sustainability assessment study for metropolitan cities in Turkey via a hybridized IT2F-AHP and COPRAS approach. Sustainable Cities and Society, 78, 103655, https://doi.org/10.1016/j.scs.2021.103655.

Lal, S., Mohapatra, & S. K. (2020). A feasibility study to utilize kitchen waste for power generation in urban areas using CI engine. Energy Sources, Part A: Recovery, Utilization, and Environmental Effects, 42(15), 1914-1922.

Lu, J., Zhang, S., Wu, J., & Wei, Y. (2021). COPRAS method for multiple attribute group decision making under picture fuzzy environment and their application to green supplier selection. Technological and Economic Development of Economy, 27(2), 369-385. https://doi.org/10.3846/tede.2021.14211.

Maneckshaw, B., & Mahapatra, G. S. (2022). Novel fuzzy matrix swap algorithm for fuzzy directed graph on image processing. Expert Systems with Applications, 193, 116291, https://doi.org/10.1016/j.eswa.2021.116291.

Mardani, A., Saraji, M. K., Mishra, A. R., & Rani, P. (2020). A novel extended approach under hesitant fuzzy sets to design a framework for assessing the key challenges of digital health interventions adoption during the COVID-19 outbreak. Applied Soft Computing Journal 96, 106613; https://doi.org/10.1016/j.asoc.2020.106613.

Masoomi, B., Sahebi, I. G., Fathi, M., Yıldırım, F., Ghorbani, S. (2022). Strategic supplier selection for renewable energy supply chain under green capabilities (fuzzy BWM-WASPAS-COPRAS approach). Energy Strategy Reviews, 40, 100815, https://doi.org/10.1016/j.esr.2022.100815.

Mishra, A. R. (2016). Intuitionistic Fuzzy Information Measures with Application in Rating of Township Development. Iranian Journal of Fuzzy Systems, 13(3), 49-70.

Mishra, A. R., Singh, R. K., & Motwani, D. (2019). Multi-criteria assessment of cellular mobile telephone service providers using intuitionistic fuzzy WASPAS method with similarity measures. Granular Computing, 4, 511-529, doi:10.1007/s41066-018-0114-5.

Morelli, B., Cashman, S., Ma, X., Turgeon, J., Arden, S., & Garland, J. (2020). Environmental and cost benefits of co-digesting food waste at wastewater treatment facilities. Water Science and Technology, 82(2), 227–241.

Narang, M., Joshi, M. C., Bisht, K., & Pal, A. (2022). Stock portfolio selection using a new decision-making approach based on the integration of fuzzy CoCoSo with Heronian mean operator. Decision Making: Applications in Management and Engineering, 5(1), 90-112. https://doi.org/10.31181/dmame0310022022n.

Narang, M., Joshi, M. C., & Pal, A. K. (2021). A hybrid fuzzy COPRAS-base-criterion method for multi-criteria decision making. Soft Computing, 25(13), 8391–8399. doi:10.1007/s00500-021-05762-w.

Omar, M. F., Shukor, J. A., Kassim, M. M., & Hussin, K. C. (2021). Decision model using hierarchical fuzzy TOPSIS: Towards improving decision making in food waste management. Journal of Language and Linguistic Studies, 17(3), 1639-1650.

Oskouei, A. G., Hashemzadeh, M., Asheghi, B., & Balafar, M. A. (2021). CGFFCM: Cluster-weight and Group-local Feature-weight learning in Fuzzy C-Means clustering algorithm for color image segmentation. Applied Soft Computing, 113, 108005, https://doi.org/10.1016/j.asoc.2021.108005.

Pamučar, D., Bozanic, D., Puška, A., & Marinković, D. (2022). Application of neuro-fuzzy system for predicting the success of a company in public procurement. Decision Making: Applications in Management and Engineering, 5(1), 135-153. https://doi.org/10.31181/dmame0304042022p.

Pham, T. P. T., Kaushik, R., Parshetti, G. K., Mahmood, R., & Balasubramanian, R. (2015). Food waste-to-energy conversion technologies: current status and future directions. Waste Management, 38, 399-408.

Rahmati, S., Mahdavi, M. H., Ghoushchi, S. J., Tomaskova, H., & Haseli, G. (2022). Assessment and prioritize risk factors of financial measurement of management control system for production companies using a hybrid Z-SWARA and Z-WASPAS with FMEA method: A meta-analysis. Mathematics, 10, 01-27. https://doi.org/10.3390/ math10020253.

Rani, P., Mishra, A. R., Deveci, M., & Antucheviciene, J. (2022b). New complex proportional assessment approach using Einstein aggregation operators and improved score function for interval-valued Fermatean fuzzy sets. Computers & Industrial Engineering, 169, 108165, https://doi.org/10.1016/j.cie.2022.108165.

Rani, P., Mishra, A. R., Krishankumar, R., Ravichandran, K. S., & Kar, S. (2021). Multi-criteria food waste treatment method selection using single-valued neutrosophic-CRITIC-MULTIMOORA framework. Applied Soft Computing, 111, 107657, https://doi.org/10.1016/j.asoc.2021.107657.

Rani, P., Mishra, A. R., Mardani, A., Cavallaro, F., Štreimikienė, D., & Khan, S. A. R. (2020). Pythagorean fuzzy SWARA–VIKOR framework for performance evaluation of solar panel selection. Sustainability, 12(10), 4278; https://doi.org/10.3390/su12104278.

Rani, P., Mishra, A. R., Saha, A., Hezam, I. M., and Pamucar, D. (2022a). Fermatean Fuzzy Heronian Mean Operators and MEREC-Based Additive Ratio Assessment Method: An Application to Food Waste Treatment Technology Selection. International Journal of Intelligent Systems 37(3), 2612–2647; DOI: 10.1002/int.22787.

Ren, J., & Toniolo, S. (2020). Life cycle sustainability prioritization of alternative technologies for food waste to energy: a multi-actor multi-criteria decision making approach. In Waste-to-Energy: Multi-Criteria Decision Analysis for Sustainability Assessment and Ranking, Elsevier, 345-380. https://doi.org/10.1016/B978-0-12-816394-8.00012-4.

Rezaei, J. (2015). Best-worst multi-criteria decision-making method. Omega, 53, 49–57.

Saaty, T. L. (2005). Theory and applications of the analytic network process: decision making with benefits, opportunities, costs, and risks. RWS Publications, Pittsburgh.

Saaty, T.L. (1980). The Analytical Hierarchy Process; McGraw-Hill: New York, NY, USA.

Sakcharoen, T., Ratanatamskul, C., & Chandrachai, A. (2021). Factors affecting technology selection, techno-economic and environmental sustainability assessment of a novel zero-waste system for food waste and wastewater management. Journal of Cleaner Production, 314, 128103, https://doi.org/10.1016/j.jclepro.2021.128103.

Saraji, M. K., & Streimikiene, D. (2022). Evaluating the circular supply chain adoption in manufacturing sectors: A picture fuzzy approach. Technology in Society, 70, 102050, https://doi.org/10.1016/j.techsoc.2022.102050.

Shahmoradi, S., & Shouraki, S. B. (2018). Evaluation of a novel fuzzy sequential pattern recognition tool (fuzzy elastic matching machine) and its applications in speech and handwriting recognition. Applied Soft Computing, 62, 315-327.

Shewa, W. A., Hussain, A., Chandra, R., Lee, J., Saha, S., & Lee, H. S. (2020). Valorization of food waste and economical treatment: effect of inoculation methods. Journal of Cleaner Production, 261, 121170, https://doi.org/10.1016/j.jclepro.2020.121170.

Slorach, P. C., Jeswani, H. K., Cuéllar-Franca, R., & Azapagic, A. (2019). Environmental and economic implications of recovering resources from food waste in a circular economy. Science of The Total Environment, 693, 133516; https://doi.org/10.1016/j.scitotenv.2019.07.322.

Szalai, S., Eller, B., Juhász, E., Movahedi, M. R., Németh, A., Harrach, D., Baranyai, G., & Fischer, S. (2022b). Investigation of deformations of ballasted railway track during collapse using the Digital Image Correlation Method (DICM). Reports in Mechanical Engineering, 3(1), 258-282. https://doi.org/10.31181/rme20016032022s.

Szalai, S., Szürke, S. K., Harangozó, D., & Fischer, S. (2022a). Investigation of deformations of a lithium polymer cell using the Digital Image Correlation Method (DICM). Reports in Mechanical Engineering, 3(1), 206-224. https://doi.org/10.31181/rme20008022022s.

Tyagi, M., Panchal, D., Kumar, D., & Walia, R. S. (2021). Modeling and Analysis of Lean Manufacturing Strategies Using ISM-Fuzzy MICMAC Approach. Operational Research in Engineering Sciences: Theory and Applications, 4(1), 38-66. https://doi.org/10.31181/oresta2040123t.

Ulutaş, A., Stanujkic, D., Karabasevic, D., Popovic, G., & Novaković, S. (2022). Pallet Truck Selection with MEREC and WISP-S methods. Strategic Management, DOI: 10.5937/StraMan2200013U.

Vojinović, N., Stević, Z., & Tanackov, I. (2020). A novel IMF SWARA-FDWGA-PESTEL analysis for assessment of healthcare system. Operational Research in Engineering Sciences: Theory and Applications, 5(1), 139-151.

Wei, D., Wang, Z., Si, L., Tan, C., Lu, X. (2021). An image segmentation method based on a modified local-information weighted intuitionistic fuzzy C-means clustering and gold-panning algorithm. Engineering Applications of Artificial Intelligence, 101, 104209, https://doi.org/10.1016/j.engappai.2021.104209.

Xie, D., Xiao, F., & Pedrycz, W. (2022). Information quality for intuitionistic fuzzy values with its application in decision making. Engineering Applications of Artificial Intelligence, 109, 104568, https://doi.org/10.1016/j.engappai.2021.104568.

Xu, G. L., Wan, S. P., & Xie, X. L. (2015). A Selection Method Based on MAGDM with Interval-Valued Intuitionistic Fuzzy Sets. Mathematical Problems in Engineering, 2015, Article ID 791204, 01-13, doi: 10.1155/2015/791204.

Xu, Z. S. (2007). Intuitionistic fuzzy aggregation operators. IEEE Transactions on Fuzzy Systems, 15(6), 1179–1187.

Xu, Z. S., & Chen, J. (2008). An overview of distance and similarity measures of intuitionistic fuzzy sets. International Journal of Uncertainty Fuzziness and Knowledge-Based Systems, 16(4), 529-555.

Yücenur, G. N., & Şenol, K. (2021). Sequential SWARA and fuzzy VIKOR methods in elimination of waste and creation of lean construction processes. Journal of Building Engineering, 44, 103196, https://doi.org/10.1016/j.jobe.2021.103196.

Zadeh, L. A. (1965). Fuzzy sets. Information and Control, 8, 338–353.

Zavadskas, E. K., Kaklauskas, A., & Sarka, V. (1994). The new method of multicriteria complex proportional assessment of projects. Technological and Economic Development of Economy, 1(3), 131–139.

Zhang, K., Huang, Y., Yuan, X., & Zhao, C. (2019). Infrared and Visible Image Fusion Based on Intuitionistic Fuzzy Sets. Infrared Physics & Technology, 105, 103124, doi:10.1016/j.infrared.2019.103124.

Zhou, R., Jin, J., Cui, Y., Ning, S., Bai, X., Zhang, L., Zhou, Y., Wu, C., & Tong, F. (2022). Agricultural drought vulnerability assessment and diagnosis based on entropy fuzzy pattern recognition and subtraction set pair potential. Alexandria Engineering Journal, 61(1), 51-63.