



# A Healthcare Assessment for Recycling Hazardous Waste by a New Intuitionistic Fuzzy Decision Method Based On an Assembled Proportionate Evaluation Approach

S. Salimian, S.M. Mousavi \*

*Department of Industrial Engineering, Shahed University, Tehran, Iran.*

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## Abstract

An assessment of hazardous waste recycling (HWR) facility choice can be introduced as a complex multi-criteria decision-making (MCDM) problem that contains many alternative solutions with incompatible tangible and intangible indexes. This paper proposes a new decision method based on the MCDM approach under an intuitionistic fuzzy (IF) environment. Intuitionistic fuzzy set (IFS) is a well-organized theory to demonstrate information in the form of membership degrees not only in qualitative concepts but also in quantitative characters when this theory utilizes linguistic terms. The IFS theory represents the degrees of membership and non-membership that aids to specify the problem in real-world conditions. The proposed approach is separated from association operators of IFSs; Furthermore, a few modifications in the common complex proportional evaluation method and a procedure for obtaining indexes of weights are introduced. This paper is constructed based on the entropy method to compute weights of criteria, the similarity measure to obtain the decision-makers (DMs)' weights under IF conditions. Afterward, a new ranking method is introduced based on a new similarity ideal solution method. The major advantage of the suggested new ranking approach is to achieve the best alternatives compared to DMs' decisions as well as the effects of evaluation values. Hence, the proposed model is a more generalized and proper demonstration to take the real-life fuzziness than the previous studies carefully. Recently, increasing challenges for environmental subjects needs the assessment of HWR facility selection concerning various indexes; so, the feasible problem is given based on a real case study of HWR facility selection, which proves the validity and feasibility of the proposed method. Eventually, a comparative analysis is presented to verify the performance of the proposed method by comparing it with IF-CODAS approach and computing different degree measures. Moreover, sensitivity analysis is introduced to validate and assess the performance of the new extended decision approach.

## Keywords:

Healthcare Waste Recycling Management;  
Hazardous Waste Management;  
Intuitionistic Fuzzy Sets;  
Multi-Criteria Decision-Making Approach;  
Ranking Method

## Introduction

Nowadays, 40% of the industrial wastes, such as food, healthcare, and mining, is categorized as hazardous, which should be well treated to exclude from rising minus effects on the health of people and the environmental condition [1]. In healthcare industries, hazards avoidance is essential, and a healthy environment is necessary to deliver safety consequences. For this

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\* Corresponding author: (S.M. Mousavi)  
Email: mousavi.sme@gmail.com

reason, the risk evaluation for many organizations is a significant role that is attempted to prospect the approaches for the reduction or avoidance of hazards and risks, which may increase within their positions [2].

The health and safety situations evaluation of the risky facilities for waste recycling in the workplace is an assembled multi-criteria decision making (MCDM) problem, which involves several qualitative and quantitative inconsistent criteria [3-6]. The cost and benefit as a general model of personal and social decision resolution recognize, extent, and aggregate them to rank and select the optimal alternatives. The topic of cost-benefit analysis under vagueness conditions is usually used to diagnose environmental safety and health assessment [7,8]. Furthermore, the cost-benefit ratio as an economic indicator, like the cost of failure with uncertainty condition, is engaged to contrast different existing decision alternatives. Also, risk cost-benefit approaches' constraints are currently practical to appraise the safety and health environment status.

Furthermore, intuitionistic fuzzy sets (IFSs) have an essential role in the theory of fuzzy sets (FSs) to measure information under uncertainty status [9,10]. Burillo and Bustince [11] generated the idea of IF-entropy and IVIF-entropy as one of these measures. Szmidt and Kacprzyk [12] pioneered IF-entropy with their geometrical commentary. After that, different researchers would analyze the issue of entropy in FSs and IFSs [13,14]. Huang and Yang [15] generated the fuzzy entropy method under the IF environment. Afterward, Ye [16] proposed two different effective measures to calculate the entropy method under IF conditions. Chen and Li [17] introduced the entropy method to obtain the objective weight with IF requirements. Joshi and Kumar [18] introduced a parametric entropy approach under IF conditions with multiple criteria. Wei et al. [19] proposed the exponential entropy approach with interval value IF (IVIF) requirements. Also, Song et al. [20] introduced the divergence-based IF entropy method in the decision-making process. Rahimi et al. [21] proposed the entropy method under IF conditions to select a suitable supplier.

Hatami-Marbini et al. [22] introduced a fuzzy group decision-making approach based on the ELECTRE method to keep the safety and health of hazardous waste recycling facilities. Büyüközkan et al. [23] applied a fuzzy group decision-making approach in the selection process of hazardous waste carriers with IF AHP and IF VIKOR methods. Kumar and Dixit [24] proposed a hybrid MCDM method to evaluate the recycling partner in the waste management industry based on green requirements. Danesh et al. [25] introduced a decision-making model to select the appropriate site for hazardous waste disposal facilities. Also, Zhang et al. [26] proposed the MCDM method to appraise a household waste processing plant with Pythagorean fuzzy conditions. Karagöz et al. [27] applied a new MCDM method to select the suitable place of waste recycling facilities under the interval fuzzy type-2 ARAS approach. Furthermore, Sisay et al. [28] generated the MCDM-AHP model to select the landfill location facilities with GIS requirements in Gondar town. In addition, Mishra et al. [29] used the IF condition to evaluate the new technology to manage the waste of the healthcare industry. Yazdani et al. [30] proposed a rough-based MCDM method to evaluate the healthcare waste disposal location. Afterward, the case study was introduced to validate the performance of the proposed approach. Garg [31] proposed the grey theory and DEMATEL methodology to generate the e-waste mitigation strategy. Puška et al. [32] evaluated incinerators of healthcare waste by utilizing an MCDM approach. Mishra [33] assessed a location selection of disposal healthcare waste with an MCDM approach based on the WASPAS approach under the Fermatean fuzzy set. Manupati et al. [34] proposed a selection method in the COVID-19 pandemic situation to evaluate the best technique in a healthcare waste disposal problem. Torkayesh et al. [35] proposed the stratified best-worst MCDM method to assess and choose sustainable waste disposal technology. Mi et al. [36] introduced a combination MCDM model to assess healthcare waste management technologies with soft likelihood function and D-numbers.

Through the literature, fuzzy ranking approaches are generally classified into two diverse categories. The first class is based on defuzzification. Different approaches to defuzzification have been proposed. In the first class, fuzzy numbers are often defuzzified into crisp numbers in the related works. The ranking is then accomplished based on these crisp numbers. Though it is easy to obtain, the principal difficulty of this kind is that defuzzification tends to lose some data. Thus, it is incapable of understanding the feeling of uncertainty. The other type is based on the fuzzy preference relation. The advantage of this kind is that uncertainties of fuzzy numbers are kept within the ranking procedure [37].

The literature review denotes that MCDM methods with computing DMs' weights under the uncertain situation with IFSs have significantly fewer considerations. It needs mathematical tools to aid the DMs in making the best decision. The previous related works have less attention to computing weights of the DMs and less use of the IFSs to cope with uncertain conditions. The IFS has main advantages that are related to considering the membership and non-membership functions concurrently. These lead to dealing with uncertain states in real-world problems. Consequently, this paper proposes a new MCDM approach under IF requirements that uses objective information in real-life situations to compute criteria' weights and DMs' weights with an entropy method and similarity measure approach, respectively. Also, this data is used to obtain the ranking of the alternatives with a new assessing method, which is made based on ideal and anti-ideal separation matrixes. In other words, the introduced approach is based on concepts of ideal and anti-ideal points to solve decision-making problems with multi-opinions and multi-criteria in IF environments. In this model, the alternatives' rating values under the selected criteria with DMs opinions, the weights of criteria and the weight of DMs are linguistic variables expressed as IF membership and non-membership degrees.

The main innovations of this paper are provided below:

- Introducing a new MCDM framework to handle the assessment of hazardous waste of the healthcare industry under the IF environment.
- Presenting a new modified MCDM method that computes the DMs' weights and criteria' weights by applying the currently existing methods, and proposing a new ranking approach by considering the ideal and anti-ideal separation matrixes to assess the main alternatives of the problem under IF conditions to mirror the uncertainty of real-world applications better.
- Applying an entropy approach under IF requirement.
- Applying the similarity measure method to compute the weight of each DM under an IF condition.
- Proposing a new alternative ranking method that is presented based on ideal and anti-ideal separation matrixes. Also, this method is similar to procedures of the ideal solution approach.

The paper is structured as follows: [Section 2](#) proposes a new method. [Section 3](#) introduces a real-case study and, [Section 4](#) determines the conclusion and future suggestions.

## Proposed approach

In this section, the proposed method is introduced based on weighting and ranking procedures. Hence, an entropy method is extended to compute the weights of criteria under the IF environment. Furthermore, the weight of each DM is obtained based on the current methodology with an IF requirement. In addition, the new modified MCDM approach is proposed to rank the alternatives concerning conflict criteria under the IF environment. The proposed approach is applied based on two previous studies (i.e., [38] and [39]) to compute the weight of criteria with the entropy method and the weight of the DMs by obtaining the similarity measure. These methods are applied from the literature. Furthermore, a new ranking method is

introduced to obtain the ranking of alternatives in the HWR problem. The main advantages of the proposed approach are related to computing simultaneously weights of the DMs and weights of the criteria to determine the impacts of DMs' opinions and the criteria' weights on the final ranking results, respectively. Moreover, a new ranking method is presented to compute the collective index for the alternatives under IF conditions. The IFS is used to deal with an uncertain situation that has more merit to handle vagueness with the membership and non-membership functions' values.

**Step 1.** The team of experts is made, and their opinions are collected to build the decision matrix. Judgments of the experts on qualitative criteria are converted to their equivalent IFs, introduced in Table 1. The decision matrix  $D_p$  of the  $p$ th DM is constructed by using the following.

$$D_p = (\tilde{T}_{ij}^p)_{r \times s} = \begin{pmatrix} \tilde{T}_{11}^p & \cdots & \tilde{T}_{1s}^p \\ \vdots & \ddots & \vdots \\ \tilde{T}_{r1}^p & \cdots & \tilde{T}_{rs}^p \end{pmatrix}_{r \times s} \quad (1)$$

**Step 2.** The normalized value of decision-making matrix is obtained from Eq. 2 for benefit criteria and Eq. 3 for cost attributes [40].

$$\hat{\mu}_{ij}^p = \frac{T_{ij}^p - \min_j T_{ij}^p}{\max_j T_{ij}^p - \min_j T_{ij}^p} \quad (2)$$

$$v_{ij}^p = \frac{\max_j T_{ij}^p - T_{ij}^p}{\max_j T_{ij}^p - \min_j T_{ij}^p} \quad (3)$$

$$\tilde{U}_{ij}^p = (\mu_{ij}^p, v_{ij}^p) = (\hat{\mu}_{ij}^p, 1 - \hat{v}_{ij}^p) \quad (4)$$

**Step 3.** Computing the criteria' weights with entropy method [38].

**Step 3.1.** Entropy measure is computed using Eq. 5.

$$Y_j = \frac{1}{r} \sum_{i=1}^r \sum_{p=1}^P \left\{ \cos \frac{\pi[1 + \mu_{ij}^p - v_{ij}^p]}{4} - \cos \frac{\pi[1 - \mu_{ij}^p + v_{ij}^p]}{4} - 1 \right\} \frac{1}{\sqrt{2} - 1} \quad (5)$$

where,  $0 \leq Y_j \leq 1$  and  $j = 1, 2, \dots, s$ .

**Step 3.2.** The final weights of criteria are obtained from Eq. 6.

$$W_j = \frac{1 - Y_j^k}{s - \sum_{j=1}^s Y_j^k} \quad (6)$$

where  $\sum_{j=1}^s W_j = 1$  and  $0 \leq W_j \leq 1$ .

**Step 4.** Obtaining the weights of the DMs [39].

**Step 4.1.** The  $p$ th DM normalized decision-making matrix is constructed based on Step 2.

**Step 4.2.** The ideal decision-making matrix is obtained by Eqs. 7-9.

$$\mu_{ij}^* = 1 - \prod_{p=1}^P (1 - \mu_{ij}^p)^{\frac{1}{p}} \quad \forall i, j \quad (7)$$

$$v_{ij}^* = \prod_{p=1}^P (v_{ij}^p)^{\frac{1}{p}} \quad \forall i, j \quad (8)$$

$$U_{ij}^* = (\mu_{ij}^*, v_{ij}^*) \quad \forall i, j \quad (9)$$

**Step 4.3.** The similarity measure ( $S_m$ ) is computed based on Eq. 10.

$$S_m(U_p, U^*) = \frac{\sum_{i=1}^r \sum_{j=1}^s d(\tilde{U}_{ij}^p, \tilde{U}_{ij}^{*c})}{\sum_{i=1}^r \sum_{j=1}^s (d(\tilde{U}_{ij}^p, \tilde{U}_{ij}^*) + d(\tilde{U}_{ij}^p, \tilde{U}_{ij}^{*c}))} \quad (10)$$

where  $\tilde{U}_{ij}^{*c}$  and  $d(\tilde{U}_{ij}^p, \tilde{U}_{ij}^{*c})$  are obtained based on Eqs. 11 and 12, respectively.

$$\tilde{U}_{ij}^{*c} = (v_{ij}^*, \mu_{ij}^*) \quad (11)$$

$$d(\tilde{U}_{ij}^p, \tilde{U}_{ij}^{*c}) = \frac{1}{2rs} \sum_{i=1}^s \sum_{j=1}^r (|\mu_{ij}^p - \mu_{ij}^*| + |v_{ij}^p - v_{ij}^*|) \quad (12)$$

**Step 4.4.** Weights of the DMs are computed by Eq. 13.

$$\omega_p = \frac{S_m(U_p, U^*)}{\sum_{p=1}^P S_m(U_p, U^*)} \quad \forall p \quad (13)$$

**Step 5.** The new modified ranking method is proposed based on similarity to the ideal solution.

**Step 5.1.** The aggregated normalized decision-matrix is constructed based on Step 4.2 with Eqs. 7-9.

**Step 5.2.** The positive ideal solution and negative ideal solution are computed by Eqs. 14-17.

$$A^{*\mu} = \left\{ \left( \max_i \mu_{ij}^* \mid j \in J \right), \left( \min_i \mu_{ij}^* \mid j \in \bar{J} \right) \mid i = 1, \dots, s \right\} \quad (14)$$

$$A^{*v} = \left\{ \left( \min_i v_{ij}^* \mid j \in J \right), \left( \max_i v_{ij}^* \mid j \in \bar{J} \right) \mid i = 1, \dots, s \right\} \quad (15)$$

$$A^{-\mu} = \left\{ \left( \min_i \mu_{ij}^- \mid j \in J \right), \left( \max_i \mu_{ij}^- \mid j \in \bar{J} \right) \mid i = 1, \dots, s \right\} \quad (16)$$

$$A^{-v} = \left\{ \left( \max_i v_{ij}^- \mid j \in J \right), \left( \min_i v_{ij}^- \mid j \in \bar{J} \right) \mid i = 1, \dots, s \right\} \quad (17)$$

where,  $J$  is related to the benefit attribute and  $\bar{J}$  is relevant to the cost attribute.

**Step 5.3.** The ideal and anti-ideal separation matrixes ( $\Delta^*, \Delta^-$ ) are described with Eqs. 18-21, respectively.

Euclidean distance is computed according to Definition A3 (See Appendix A).

$$\Delta^{*\mu} = [\Delta_{ij}^{*\mu}] = \begin{pmatrix} \Delta(\tilde{A}_{11}^\mu, \tilde{A}_1^{*\mu}) & \dots & \Delta(\tilde{A}_{1s}^\mu, \tilde{A}_s^{*\mu}) \\ \vdots & \ddots & \vdots \\ \Delta(\tilde{A}_{r1}^\mu, \tilde{A}_1^{*\mu}) & \dots & \Delta(\tilde{A}_{rs}^\mu, \tilde{A}_s^{*\mu}) \end{pmatrix}_{r \times s} \quad (18)$$

$$\Delta^{*v} = [\Delta_{ij}^{*v}] = \begin{pmatrix} \Delta(\tilde{A}_{11}^v, \tilde{A}_1^{*v}) & \dots & \Delta(\tilde{A}_{1s}^v, \tilde{A}_s^{*v}) \\ \vdots & \ddots & \vdots \\ \Delta(\tilde{A}_{r1}^v, \tilde{A}_1^{*v}) & \dots & \Delta(\tilde{A}_{rs}^v, \tilde{A}_s^{*v}) \end{pmatrix}_{r \times s} \quad (19)$$

$$\Delta^{-\mu} = [\Delta_{ij}^{-\mu}] = \begin{pmatrix} \Delta(\tilde{A}_{11}^\mu, \tilde{A}_1^{-\mu}) & \dots & \Delta(\tilde{A}_{1s}^\mu, \tilde{A}_s^{-\mu}) \\ \vdots & \ddots & \vdots \\ \Delta(\tilde{A}_{r1}^\mu, \tilde{A}_1^{-\mu}) & \dots & \Delta(\tilde{A}_{rs}^\mu, \tilde{A}_s^{-\mu}) \end{pmatrix}_{r \times s} \quad (20)$$

$$\Delta^{-v} = [\Delta_{ij}^{-v}] = \begin{pmatrix} \Delta(\tilde{A}_{11}^v, \tilde{A}_1^{-v}) & \dots & \Delta(\tilde{A}_{1s}^v, \tilde{A}_s^{-v}) \\ \vdots & \ddots & \vdots \\ \Delta(\tilde{A}_{r1}^v, \tilde{A}_1^{-v}) & \dots & \Delta(\tilde{A}_{rs}^v, \tilde{A}_s^{-v}) \end{pmatrix}_{r \times s} \quad (21)$$

**Step 5.4.** The collective index ( $C$ ) is obtained by Eq. 32.

For this reason, the  $\zeta_i^\mu$  and  $\zeta_i^v$  are computed based on Eqs. 22 and 23.

$$\varsigma_i^\mu(\Delta^{*\mu}, \Delta^{-\mu}) = \left( \sum_{j=1}^L \frac{\Delta_{ij}^{*\mu}}{\Delta_{ij}^{-\mu}} \right)^{\frac{1}{L}} + G_{ij}^\mu \quad \forall i \quad (22)$$

$$\varsigma_i^v(\Delta^{*v}, \Delta^{-v}) = \left( \sum_{j=1}^L \frac{\Delta_{ij}^{*v}}{\Delta_{ij}^{-v}} \right)^{\frac{1}{L}} + G_{ij}^v \quad \forall i \quad (23)$$

When the  $\Delta_{ij}^{-\mu} > 0$  and  $\Delta_{ij}^{-v} > 0$ , the first terms are obtained; but when the  $\Delta_{ij}^{-\mu} = 0$  or  $\Delta_{ij}^{-v} = 0$ , these cases are computed by Eqs. 24 and 25.

$$G_{ij}^\mu = \left( \left( \max_j \frac{\Delta_{ij}^{*\mu}}{\Delta_{ij}^{-\mu}} \right) \right)^{\frac{1}{\max_j W_j}} \quad (24)$$

$$G_{ij}^v = \left( \left( \max_j \frac{\Delta_{ij}^{*v}}{\Delta_{ij}^{-v}} \right) \right)^{\frac{1}{\max_j W_j}} \quad (25)$$

Also,  $\chi_i^\mu$  and  $\chi_i^v$  are obtained from Eqs. 26 and 27.

$$\chi_i^\mu(\Delta^{*\mu}, \Delta^{-\mu}) = \left( \sum_{j=1}^L \Delta_{ij}^{*\mu} \right)^{\frac{1}{r}} + \left( \sum_{j=1}^L \frac{1}{\Delta_{ij}^{-\mu}} \right)^{\frac{1}{L}} + Q_{ij}^\mu \quad \forall i \quad (26)$$

$$\chi_i^v(\Delta^{*v}, \Delta^{-v}) = \left( \sum_{j=1}^L \Delta_{ij}^{*v} \right)^{\frac{1}{r}} + \left( \sum_{j=1}^L \frac{1}{\Delta_{ij}^{-v}} \right)^{\frac{1}{L}} + Q_{ij}^v \quad \forall i \quad (27)$$

When  $\Delta_{ij}^{-\mu} > 0$  and  $\Delta_{ij}^{-v} > 0$ , the first terms are obtained; but when the  $\Delta_{ij}^{-\mu} = 0$  or  $\Delta_{ij}^{-v} = 0$ , these points are computed by Eqs. 28 and 29.

$$Q_{ij}^\mu = \left( \left( \min_j \Delta_{ij}^{-\mu} \right) \right)^{\frac{1}{\max_j W_j}} \quad (28)$$

$$Q_{ij}^v = \left( \left( \min_j \Delta_{ij}^{-v} \right) \right)^{\frac{1}{\max_j W_j}} \quad (29)$$

The collective index ( $C$ ) is calculated using Eqs. 30-32. The collective index can be the summation of two membership and non-membership collective indexes because these two measures are different in nature.

$$C^\mu = \varsigma_i^\mu + \chi_i^\mu \quad (30)$$

$$C^v = \varsigma_i^v + \chi_i^v \quad (31)$$

$$C = C^\mu + C^v \quad (32)$$

**Step 6.** The priority alternatives are ranked with the collective index computation.

Finally, the framework of the proposed approach is shown in Fig. 1.

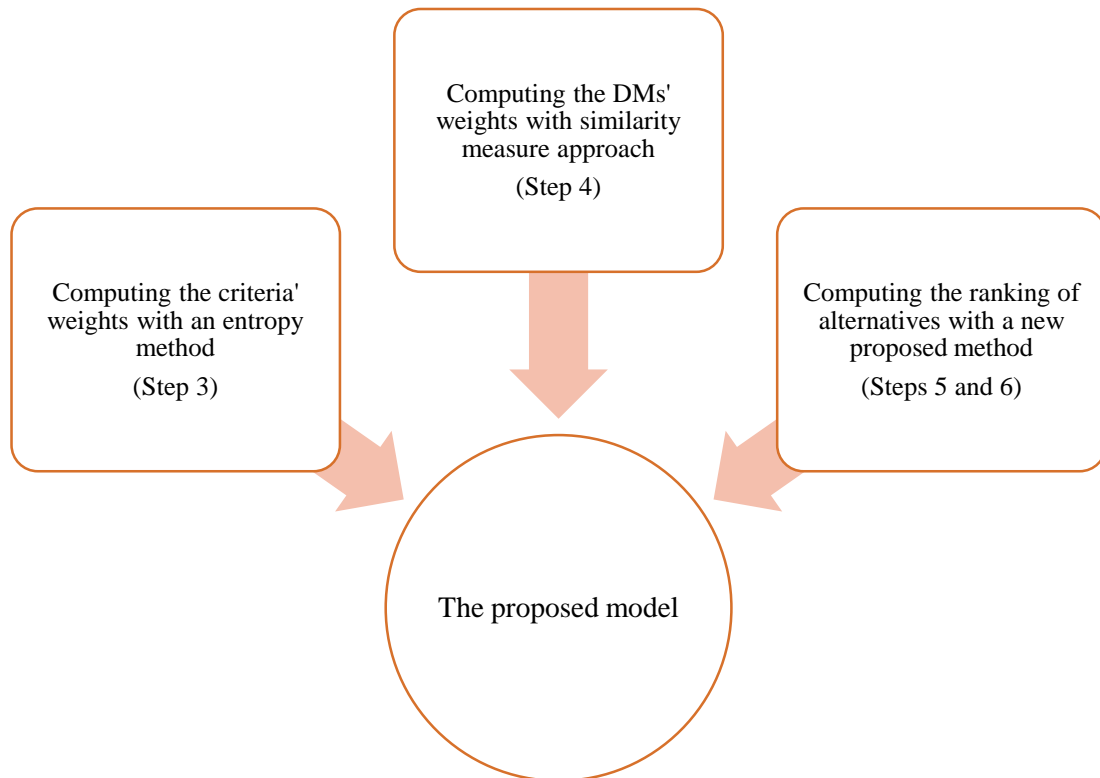


Fig. 1. The structure of the proposed approach

## Case study

This section provides the selecting HWR facility within an MCDM framework to consider the efficiency of the proposed approach. According to the recent literature, a case study is introduced for Indian Health Service (IHS) in the Albuquerque region [41]. It is the target to evaluate the health and safety condition in the case of chosen HWR facilities through the structure applied in the presented study. The official liability of IHS is to improve the American Indians and Alaska Natives physically, mentally, socially, and spiritually to the maximum levels with culturally proper personal and public health services.

Five alternative facilities are chosen from the proposed area via the IHS officials, which are Jicarilla Service Unit ( $A_1$ ), Ute Mountain Ute Service Unit ( $A_2$ ), Zuni Comprehensive Health Center ( $A_3$ ), New Sunrise Regional Treatment Center ( $A_4$ ), and Taos-Picuris Service Unit ( $A_5$ ). In addition, the paper selects three professional experts, which are chosen from the IHS opinion ( $DM_1$ ), invited from the Division of Facilities Planning Construction ( $DM_2$ ), and another colleague from the Division of Environmental Health Services ( $DM_3$ ). Furthermore, the evaluation team agrees to engage the linguistic variables that are existed in Table 1 in the definition of significant weights of criteria and the ratings of the HWR facility alternative, respectively.

Also, this paper has organized the four criteria to assess the potential safety and health hazards in waste recycling facilities that include the intensity of incident ( $C_1$ ), time of disposal ( $C_2$ ), failure to find the risk ( $C_3$ ), and protective and preventive measures ( $C_4$ ). It is notable that the three first criteria have the benefits nature, and the fourth criterion has the cost essence. Hence, the scale of the criteria is determined by [0.4,0.6], [0.1,0.3], [0.15,0.3] and [0.15,0.45], respectively. In addition, the proposed approach is used to compute the weights of criteria and DMs and also to obtain the ranking of the alternatives. In addition, Table 1 provides the linguistic values to evaluate the criteria and alternatives with DMs' opinions [42].

**Table 1.** Linguistic values for alternative rates

Linguistic variables	Intuitionistic fuzzy values
Extremely high (EH)	[0.95, 0.05]
Very very high (VVH)	[0.90, 0.10]
Very high (VH)	[0.80, 0.10]
High (H)	[0.70, 0.20]
Medium high (MH)	[0.60, 0.30]
Medium (M)	[0.50, 0.40]
Medium low (ML)	[0.40, 0.50]
Low (L)	[0.25, 0.60]
Very low (VL)	[0.10, 0.75]
Very very low (VVL)	[0.10, 0.90]

In the following, the comparison decision matrix based on the linguistic judgment of the DMs within the HWR alternatives and the criteria is generated in [Table 2](#).

**Table 2.** Comparison decision matrix of HWR facilities alternatives with linguistic terms

Alternatives	DMs	$C_1$	$C_2$	$C_3$	$C_4$
$A_1$	$DM_1$	MH	VVH	H	M
	$DM_2$	H	MH	ML	MH
	$DM_3$	ML	H	L	H
$A_2$	$DM_1$	VH	ML	ML	VVL
	$DM_2$	MH	VVL	H	L
	$DM_3$	M	VL	VL	VL
$A_3$	$DM_1$	M	H	VVL	VH
	$DM_2$	ML	H	EH	M
	$DM_3$	L	ML	VH	H
$A_4$	$DM_1$	H	MH	M	ML
	$DM_2$	M	L	VH	ML
	$DM_3$	MH	M	H	VL
$A_5$	$DM_1$	MH	EH	VH	VH
	$DM_2$	H	VH	H	MH
	$DM_3$	ML	VVH	VVH	H

In this regard, the normalized decision matrix is computed by [Eqs. 2-4](#), and the weights of criteria ( $W_j$ ) are obtained based on [Eq. 6](#). Also, these are determined in [Tables 3 and 4](#), respectively. [Table 5](#) illustrates that the fourth index has a high value than the other criteria. This criterion is related to the protective and preventive measures, which have a high effect on the HWR process by the most weighting measure. Afterward, the first, third, and second indexes have a high weighted measure, respectively.



**Table 3.** Normalized decision-making matrix

Alternatives	DMs	$C_1$	$C_2$	$C_3$	$C_4$
$A_1$	$DM_1$	0.250000	0.333333	1.000000	1.000000
	$DM_2$	1.000000	1.000000	0.666667	0.666667
	$DM_3$	0.333333	0.250000	1.000000	1.000000
$A_2$	$DM_1$	1.000000	1.000000	0.428571	0.500000
	$DM_2$	0.833333	0.857143	0.000000	0.000000
	$DM_3$	1.000000	1.000000	0.000000	0.000000
$A_3$	$DM_1$	0.571429	0.625000	0.857143	0.875000
	$DM_2$	0.000000	0.000000	0.545455	0.666667
	$DM_3$	0.000000	0.000000	0.272727	0.200000
$A_4$	$DM_1$	1.000000	1.000000	0.666667	0.666667
	$DM_2$	0.833333	0.818182	0.666667	0.636364
	$DM_3$	0.833333	0.818182	0.666667	0.636364
$A_5$	$DM_1$	0.000000	0.000000	1.000000	1.000000
	$DM_2$	0.500000	0.500000	1.000000	1.000000
	$DM_3$	0.000000	0.000000	1.000000	1.000000

**Table 4.** Criteria weights

Criteria	$W_j$
$C_1$	0.250375
$C_2$	0.248874
$C_3$	0.250373
$C_4$	0.250378

On the other hand, one of the most important factors is relevant to the weights of DMs ( $\varpi_p$ ). This measure is calculated based on Eq. 13 in Table 5.

**Table 5.** Weights of DMs

DMs	$S_m(D_p, D^*)$	$\varpi_p$
$DM_1$	0.449647	0.392418
$DM_2$	0.335163	0.292505
$DM_3$	0.361027	0.315077

Table 5 shows that the first DM has a high value than each other. This DM is selected based on the IHS opinions, and he has the most affected on the HWR problem. Finally, the ranks of the alternative are introduced based on matrix  $\Delta^{*\mu}$ ,  $\Delta^{-\mu}$ ,  $\Delta^{*v}$ , and  $\Delta^{-v}$  with Eqs. 18-21 that are determined in Tables B1 to B4 (See Appendix B). Also, the collective measure ( $C$ ) and the final ranking are reported based on Eq. 32 in Table 6.

**Table 6.** Final ranking of the alternatives

Alternatives	$C^\mu$	$C^v$	$C$	Final rank
$A_1$	6.199864	6.164206	12.364070	2
$A_2$	2.625564	2.606210	5.231775	5
$A_3$	6.515078	6.783930	13.299008	1
$A_4$	4.638159	4.541787	9.179946	3
$A_5$	3.822490	3.934950	7.757440	4

The final ranking shows that the third alternative, which is related to Zuni Comprehensive Health Center, has a higher value than the other options.

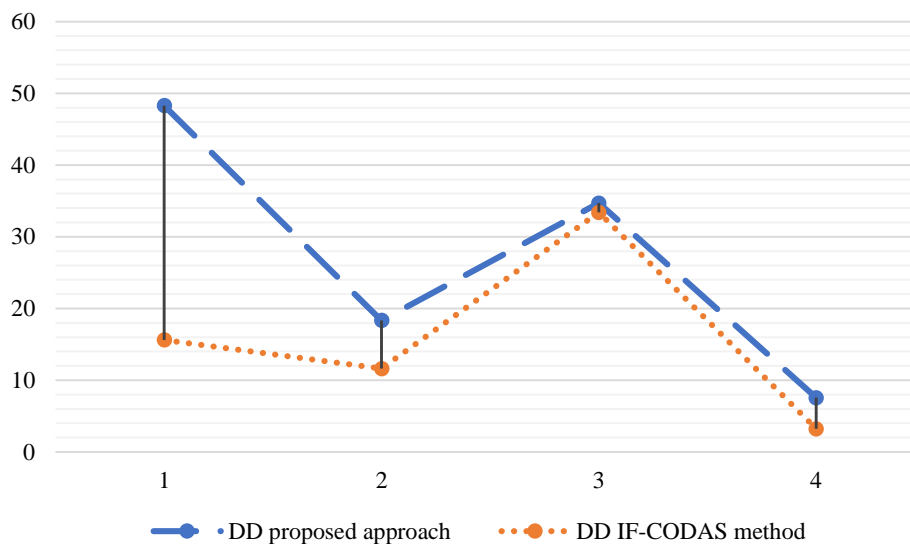
**Comparative analysis:** A comparative analysis is provided to validate the performance of the proposed approach by comparing the introduced model with the recent method (i.e., IF-combinative distance-based assessment (CODAS)) [43]. The final alternatives' ranking results verify the efficiency and performance of the proposed approach that is given in Table 7. Also, Table 7 determines the different degrees (DDs) between the alternatives' values; for instance, this measure is computed by Eq. 33 for alternatives' values  $A$  and  $B$  that is  $A > B$ .

$$DD = \frac{A - B}{B} \times 100 \quad (33)$$

**Table 7.** DDs values of the presented method and IF-CODAS approach

Alternatives	IF-CODAS score	IF-CODAS ranking	IF-CODAS DD values	Proposed method score	Proposed method ranking	Proposed method DD values
$A_2$	3.98294	5	15.61460	5.231775	5	48.27549
$A_5$	4.60486	4	11.60951	7.757440	4	18.33731
$A_4$	5.13947	3	33.40710	9.179946	3	34.68565
$A_1$	6.85641	2	3.21873	12.364070	2	7.56173
$A_3$	7.07710	1		13.299008	1	

When the results of the decision approaches are the same, the method with a higher DD is better than others [44]. The model with a higher DDs presents more particular among the final values of alternatives. Hence, the DDs values of the proposed approach are higher than the IF-CODAS method, which demonstrates the reliability and effectiveness of the introduced approach. Also, Fig. 2 illustrates the scattering rate of responses between the two various methods. This figure shows that the proposed approach has a higher scattering rate based on DDs values and better performance than the IF-CODAS method.



**Fig. 2.** Scattering rates based on DDs between two different decision methods

**Sensitivity analysis:** To sensitivity analysis of the proposed method, the weight of each index is changed, which has been computed by the entropy approach. In this regard,  $C_{ij}$  determines the criteria' weights values that change from  $i$  to  $j$ . Thus, Fig. 3 determines the final rankings' values, which do not change with the different criteria' weights, and these values are

independent of criteria' weights and are reliable in all stages. Hence, Fig. 3 verifies the final ranking results, showing that the third alternative has higher priority than other alternatives.

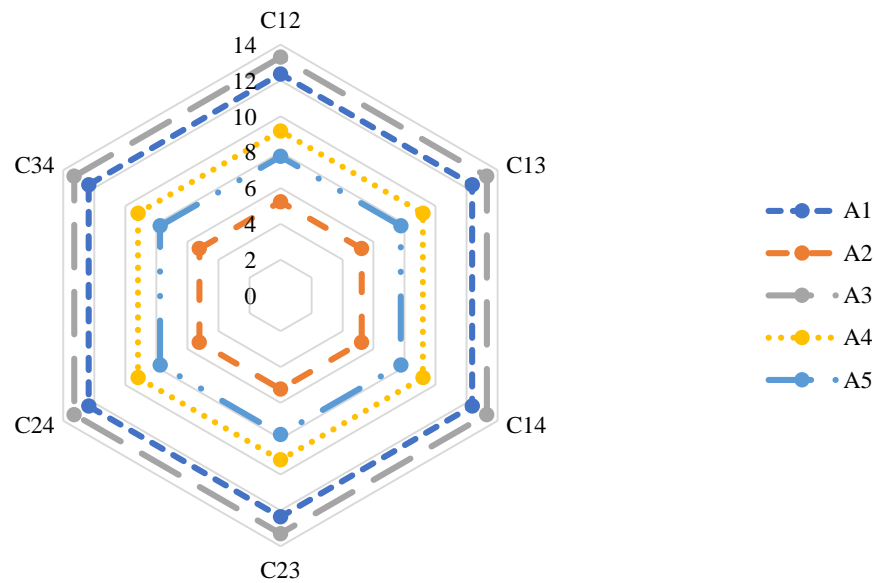


Fig. 3. Impact of criteria' weights on final ranking results

## Conclusion

This paper provides an intuitionistic fuzzy (IF) analysis approach assisting to take an appropriate and real decision and applies a case study of healthcare waste recycling (HWR) to determine the verification and efficiency of the proposed model under IF conditions. Subjective opinions and vagueness in deciding the appearance of conditions recommend the necessity of using an analytical approach. Intuitionistic fuzzy sets (IFSs) present a mathematical model of serving, like ambiguities, where the uncertainty arises from the incapability to achieve sufficient quantities. Hence, IFSs are suitable tools to apply and control uncertain and vague data in a multitude of multi-criteria decision making (MCDM) problems by using the membership degree and non-membership degree that provides the real-world conditions to cope with an uncertain situation. The IF data has been used in abundant areas likewise decision-making, image processing, and medical diagnosis. This paper presented a new method to compute the weights of criteria, decision-makers (DMs), and the ranking of alternatives. The main advantage of the proposed approach was respected to utilize the new ranking technique that was able to rank the alternatives and to compute weights of the DMs and criteria under an IF condition. The IFS in the proposed decision model could deal with real-world problems properly. The analysis showed that the proposed method was verified by comparing with the IF-combinative distance-based assessment (CODAS) approach, and different degrees (DDs) measure was applied to determine the performance of using the decision approach. Moreover, the sensitivity analysis was introduced based on the real case study to determine the utility of the extended IF-data measures over the existing ones. To validate the consequences of the proposed approach, the weight of criteria was shifted among each other. The final results of ranking the alternatives were denoted that the outcome was not modified with changing the situation, and the proposed method was reliable. Finally, it was illustrated that the third alternative with a high degree has the highest ranking than other options and highest priority in the HWR problem. Finally, the proposed approach has a high performance to deal with real-world requirements and uncertain conditions using the IFSs with membership and non-

membership degrees. Also, this method can use in various types of healthcare systems for the DMs and managers of organizations to make suitable decisions in uncertain environments.

The presented proposed approach in this study has its limitations. In this study, four principal criteria were used to examine healthcare hazardous waste recycling operations, while other significant factors could be regarded for this approach. Also, the outcomes of this study cannot be generalized as a current limitation of using non-probability procedures. Developments in support of a broader range of experts, which appear in more experience-based feedback, would assist future research results towards generalizing the decisions' outcomes. For future suggestions, the extended MCDM model can be major extensible to picture fuzzy sets, Pythagorean fuzzy sets, hesitant fuzzy sets, and hesitant fuzzy sets. Furthermore, various hybrid MCDM platforms along with the presented model can be used to choose the most suitable HWR facility selection.

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## Appendix A

In this section, an IFS is presented to grasp the real-world environment with independent criteria better. Hence, the basic formulation of the IF method is generated in the following:

**Definition A.1.** [45]. Let  $X$  be a universe discourse. The IFS  $P$  from  $X$  is an aim introduced below.

$$P = \{ \langle x, \mu_R(x), v_R(x), \pi_R(x) \rangle | x \in X \}$$

The value of the membership function  $\mu_A: X \rightarrow [0,1]$  that means a rate of membership of the value  $x$  and non-membership function  $v_A: X \rightarrow [0,1]$ , which means a degree of non-membership of it in the set  $P$ . Nevertheless, for each  $x \in X$  exists  $0 \leq \mu_R(x) + v_R(x) \leq 1, \pi_R = 1 - \mu_R - v_R$ .

**Definition A.2.** [46,47]. Let  $P$  and  $Q$  be two IFSs from a set of  $X$ ; though the relations between them are described below.

$$\begin{aligned} \bar{P} &= \{ \langle x, v_P(x), \mu_Q(x) \rangle | x \in P \} \\ P \oplus Q &= \{ \langle x, \mu_P(x) + \mu_Q(x) - \mu_P(x) \cdot \mu_Q(x), v_P(x) \cdot v_Q(x), 1 - \mu_P(x) - \mu_Q(x) + \mu_P(x)\mu_Q(x) - v_P(x)v_Q(x) \rangle \} \\ P \otimes Q &= \{ \langle x, \mu_P(x) \cdot \mu_Q(x), v_P(x) + v_Q(x) - v_P(x) \cdot v_Q(x), 1 - \mu_P(x)\mu_Q(x) - v_P(x) - \mu_Q(x) + v_P(x)v_Q(x) \rangle \} \\ P^\lambda &= \{ \langle x, \mu_P(x)^\lambda, 1 - (1 - v_P(x)^\lambda) \rangle | x \in P \}, \lambda > 0; \\ \lambda P &= \{ \langle x, 1 - (1 - \mu_P(x)^\lambda), v_P(x) \rangle | x \in P \}, \lambda > 0; \end{aligned}$$

**Definition A.3.** Hamming distance and Euclidean distance are obtained for  $X = \{x_1, x_2, \dots, x_N\}$  [48].

$$\begin{aligned} d_H(P, Q) &= \sum_{i=1}^N \frac{1}{2n} (|\mu_P(x_i) - \mu_Q(x_i)| + |v_P(x_i) - v_Q(x_i)| + |\pi_P(x_i) - \pi_Q(x_i)|) \\ d(P, Q) &= \sqrt{\frac{1}{2n} \sum_{i=1}^N ((\mu_P(x_i) - \mu_Q(x_i))^2 + (v_P(x_i) - v_Q(x_i))^2 + (\pi_P(x_i) - \pi_Q(x_i))^2)} \end{aligned}$$

**Definition A.4.** The IF aggregation operator (IFAO) is computed below [47].

$$IFAO(\tilde{a}_1, \tilde{a}_2, \dots, \tilde{a}_i) = \langle 1 - \prod_{i=1}^r (1 - \mu_{ij})^{\frac{1}{r}}, \prod_{i=1}^r v_{ij}^{\frac{1}{r}} \rangle$$

**Definition A.5.** Matrixes of positive and negative for normalized IF  $l_{ij}$  are introduced below ( $\forall i = 1, 2, \dots, r; j = 1, 2, \dots, s$ ) [47].

$$l_{ij} = \begin{cases} \{ \{ \mu_{ij}, v_{ij} \} & \text{for positive criteria} \\ \{ \{ 1 - \mu_{ij}, 1 - v_{ij} \} \} & \text{for negetive criteria} \end{cases}$$

## Appendix B

**Table B1.** The ideal separation matrix  $\Delta^{*\mu}$

Alternatives	$C_1$	$C_2$	$C_3$	$C_4$
$A_1$	0.026171	0.045588	0.117125	0.161024
$A_2$	0.000000	0.242616	0.128490	0.000000
$A_3$	0.094125	0.098279	0.009297	0.189579
$A_4$	0.017498	0.152498	0.045612	0.056605
$A_5$	0.026171	0.000000	0.000000	0.197453

**Table B2.** The anti-ideal separation matrix  $\Delta^{-\mu}$

Alternatives	$C_1$	$C_2$	$C_3$	$C_4$
$A_1$	0.067954	0.197028	0.011364	0.036429
$A_2$	0.094125	0.000000	0.000000	0.197453
$A_3$	0.000000	0.144337	0.119193	0.007875
$A_4$	0.076627	0.090118	0.082877	0.140848
$A_5$	0.067954	0.242616	0.128490	0.000000

**Table B3.** The ideal separation matrix  $\Delta^{*\nu}$

Alternatives	$C_1$	$C_2$	$C_3$	$C_4$
$A_1$	0.028914	0.036183	0.093867	0.159599
$A_2$	0.000000	0.218096	0.104554	0.000000
$A_3$	0.093444	0.067908	0.013825	0.190871
$A_4$	0.021039	0.119023	0.026166	0.059222
$A_5$	0.028914	0.000000	0.000000	0.197336

**Table B4.** The anti-ideal separation matrix  $\Delta^{-\nu}$

Alternatives	$C_1$	$C_2$	$C_3$	$C_4$
$A_1$	0.064530	0.181913	0.010688	0.037738
$A_2$	0.093444	0.000000	0.000000	0.197336
$A_3$	0.000000	0.150188	0.090729	0.006466
$A_4$	0.072405	0.099073	0.078389	0.138114
$A_5$	0.064530	0.218096	0.104554	0.000000



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