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The selection of healthcare waste treatment technologies by a multi-criteria group decision-making method with intuitionistic fuzzy sets

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Abstract

Nowadays, healthcare waste (HCW) management has been received attention by increasing the rate of the population and the usage of services. Meanwhile, one of the significant challenges is to select the appropriate treatment technology for decision-makers (DMs) in the HCW industry. In this respect, this paper proposes a new multi-criteria decision-making (MCDM) approach to compute criteria weights, DMs' weights, and alternative ranking methods for assessing and selecting the best HCW treatment technology from various stakeholders. The proposed structure deals with uncertain evaluations of alternatives by using intuitionistic fuzzy (IF)' linguistic variables to show criteria weights and to extend two new weighting and ranking methods to obtain DMs' weight and rank the HCW disposal alternatives based on uncertain conditions. Eventually, an empirical case in Shanghai, China, from the recent literature, is applied to determine the feasibility, validation, and effectiveness of the proposed model. Results demonstrate that the introduced model is proper and efficient to handle the HCW treatment technology selection problem under an uncertain information condition. According to the final comparative results, the first alternative and the first DM have a high preference than others, respectively. Furthermore, the sensitivity analysis determines that the final ranking results are reliable with changing the criteria' weights regarding four various kinds of states.

Keywords: Healthcare waste management, technology selection, intuitionistic fuzzy sets, weights of decision-makers, ranking method

1-Introduction

In today's world, one of the most important subjects is the growing population rapidly. Based on this issue, the rate of healthcare facilities and the demand for medical services increased, creating healthcare wastes (HCWs) (Aghajani Mir et al., 2016; Windfeld and Brooks, 2015). In developing countries, the HCW management has been changed to a complex challenge for municipalities. For instance, China is one of those countries where health waste is a combination, and its separation is a problematic issue (Ruoyan et al., 2010). The World Health Organization (WHO) defined HCW as the waste created from the diagnosis, therapy, or immunization of human beings or animals, consists of sharps, blood, organs, chemicals, pharmaceuticals, medical devices, and radioactive materials (Komilis et al., 2012).

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The disposal of HCWs is a high preference social health and environmental worry all over the universe. If not adequately controlled, it introduces a considerable risk of infection or hurt to healthcare staff and social persons (Giacchetta, 2013). For this purpose, the HCW management has been changed to an important global issue (Caniato et al., 2015).

HCW management starts with the collection of waste from facilities. After that, the waste is transferred to the disposal site with the appropriate treatment technology selected to be treated. Finally, energy recovery occurs. The suitable technology selection has a high impact on the ecological and financial, and it has been of interest to researchers recently. In this regard, multi-criteria decision-making (MCDM) helps to select an appropriate alternative in a healthcare treatment technology selection problem (Lu et al., 2016). Moreover, in a multitude of HCW treatment technology selection problems, DMs may have difficulty in assessing alternatives with particular crisp values due to the vagueness of human minding. Moreover, the evaluation information was given by DMs that should be occurred with linguistic terms in view of the complexity of specific HCW treatment technology selection problems (Liu et al., 2015).

One of the major challenges of managers to take the appropriate decision is related to the uncertainty condition of real-world applications (Dorfeshan et al., 2020; Mousavi et al., 2020). The theory of fuzzy sets (FSs) was introduced by Zadeh (1965) that has arrived at good achievement in several areas. Meanwhile, intuitionistic fuzzy sets (IFSs) were proposed by Atanassov (1986) and were presented to be many benefits to deal with uncertainty. In this respect, the usage of the IF near the MCDM problem has a high position to make appropriate decisions (Mousavi et al., 2019, 2021; Davoudabadi et al., 2019, 2020; Moghiseh et al., 2019). Hence, Shi et al. (2017) proposed an integrated decision approach to select the suitable technology for treatment in healthcare waste management. Adaar and Telise (2019) proposed the MC-HFLTS method to select the suitable technology for healthcare waste system. Mishra et al. (2020) introduced the technology selection decision for waste management in the healthcare industries under IF conditions. Mishra et al. (2021) proposed the location decision problem for disposal management in the healthcare system under Fermatean fuzzy environment. Torkayesh et al. (2021) introduced the landfill location in the healthcare disposal location selection problem. This paper used the BWM-grey MARCOS model based on GIS to take an appropriate decision.

Liu et al. (2014) proposed the application of interval 2-tuple linguistic MULTIMOORA approach for healthcare waste treatment technology assessment and selection. Hence, it is clear that the approaches of addressing HCW treatment technology selection problems are not still quite developed, and there is a requirement to propose new and efficient methods for the evaluation of HCW disposal methods with uncertain linguistic information. Xiao (2018) proposed an MCDM method to evaluate the healthcare waste technology selection based on D numbers. Moreover, Rani et al. (2020) proposed the Paythagorean fuzzy set in the healthcare waste treatment problem. Ghram and Farikha (2020) proposed an evaluation method under ARAS-H fuzzy environment to assess the healthcare waste treatment technologies. Also, this paper used the real-case study in Tunisia to validate the efficiency of the proposed approach. Ghram and Farikha (2020) introduced the evaluation technique to assess the healthcare waste technologies under ARAS-H fuzzy condition. Pamučar et al. (2021) proposed a combination MCDM method that was created based on BWM-MABAC approach with a D-number. Moreover, this approach was used to evaluate HCW management. Torkayesh et al. (2021) generated the stratified best-worst multi-criteria decision-making method to take a sustainable waste disposal technology selection decision. Ouyang et al. (2021) introduced an information fusion FMEA method to evaluate the healtcare risk management. This method used 2-tuple linguistic values and interval probability. Liu et al. (2021) analyzed a Pythagorean fuzzy method that was combined with a compromise solution method to evaluate the treatment technology selection in the medical waste area.

This paper proposes a new MCDM method under IF requirements to select the appropriate technology in the treatment process of the HCW problem. Meanwhile, the proposed method is consisting of the three main parts that are included in calculations of criteria weights, DMs' weights, and alternatives rankings, respectively. The criteria weights are obtained from the linguistic judgment of the experts with Shannon entropy method, and the weights of the DMs are extended by a new decision method. Afterward, the ranking of alternatives is calculated with a new proposed approach. Finally, an empirical case is generated to validate the efficiency of the proposed model. The main innovations of the paper are presented in the following: (1) Applying IF-Shannon entropy method to compute the weights of criteria; (2) Developing a new DMs' weighting method based on computing the closeness degree from the average ideal solution and maximum negative and positive ideal solutions distances; and (3) Proposing a new alternative ranking method with aggregating two collective indexes based on negative and positive ideal solutions distances and weights of cost and benefit criterion, respectively. Furthermore, the principal motivation of this study is to use the new MCDM methodology based on a new DMs' weighting approach that is created with an obtaining the closeness degree from average, positive, and negative ideal solutions distances and also, a new ranking method that is provided with an aggregating the two collective indexes under IF conditions. This model is a reliable approach to coping with various requirements and can aid the DMs in making appropriate decisions in different situations.

The rest of this paper is formed as follows: Section 2 depicts IF preliminaries, and section 3 presents the proposed model. Section 4 determines the numerical example from the recent literature to show the performance of the new approach. Section 5 introduces the sensitivity analysis, and finally, the conclusions are presented in section 6.

2-Preliminary

In this section, some basic descriptions regarding IF formulation that are useful in this paper are provided. Moreover, the main advantages of IFS are described in the following:

- IFSs consider both advantages (memberships) and disadvantages (non-memberships) of a supposed solution, and the vague region is taken into account as well (Szmidt and Baldwin, 2006).
- IFSs convert a vague pattern division problem into a specific and well-describe optimization problem.
- IFSs, unlike usual fuzzy sets, maintain a measured degree of uncertainty (Khatibi and Montazer, 2009).
- IFS divides the positive and negative data for membership of a factor in the set (Kumar et al., 2013).

Definition 1. (Atanassov, 1986). Let X be a universe discourse. The IFS T from X is an aim that is presented in equation (1).

$$P = \{\langle x, \mu_T(x), v_T(x), \pi_T(x)\rangle | x \in X\} \tag{1}$$

$\mu_T: X \to [0,1]$ and $v_T: X \to [0,1]$ are the values of membership and non-membership functions, respectively. Also, π_T is relevant to the hesitance degree. Hence, for each $x \in X$ exists $0 \le \mu_T(x) + v_T(x) \le 1$. $\pi_T = 1 - \mu_T - v_T$.

Definition 2. (Atanassov, 1994; Xu & Yager, 2006) Let T and U are two IFSs from a set of X; Hence, the significant operators are described in equations (2)-(8).

$$T \cup U = \left\{\langle x. max\left(\mu_T(x), \mu_U(x)\right). min(v_T(x), v_U(x))\ \rangle | x \in T\right\} \tag{2}$$

$$T \cap U = \left\{\langle x. min\left(\mu_T(x), \mu_U(x)\right). max(v_T(x), v_U(x))\rangle | x \in T\right\} \tag{3}$$

$$\bar{T} = \{\langle x, v_T(x). \mu_U(x)\rangle | x \in T\} \tag{4}$$

$$\begin{aligned} \mathrm{T} \oplus \mathrm{U} = \{\langle x, \mu_T(x) + \mu_U(x) - \mu_T(x). \mu_U(x), v_T(x). v_U(x), 1 - \mu_T(x) - \mu_U(x) \\ + \mu_T(x)\mu_U(x) - v_T(x)v_U(x)\rangle\} \end{aligned} \tag{5}$$

$$T \otimes U = \{\langle x, \mu_T(x).\mu_U(x), v_T(x) + v_T(x) - v_U(x).v_U(x), 1 - \mu_T(x)\mu_U(x) - v_T(x) - \mu_U(x) + v_T(x)v_U(x)\rangle\} \quad (6)$$

$$T^H = \{\langle x.\mu_T(x)^H.1 - (1 - v_T(x)^H)|x \in T\rangle\}, H > 0; \quad (7)$$

$$HT = \{\langle x, 1 - (1 - \mu_T(x))^H, v_T(x)|x \in T\rangle\}, H > 0; \quad (8)$$

Definition 3. (Szmidt & Kacprzyk, 2000). Hamming distance and Euclidean distance are computed with equations (9) and (10) for $X = \{x_1.x_2.\dots.x_m\}$.

$$dis_H(T, U) = \sum_{i=1}^{m} \frac{1}{2n}(|\mu_T(x_i) - \mu_U(x_i)| + |v_T(x_i) - v_U(x_i)| + |\pi_T(x_i) - \pi_U(x_i)|) \quad (9)$$

$$dis(T, U) = \sqrt{\frac{1}{2n}\sum_{i=1}^{m}((\mu_T(x_i) - \mu_U(x_i))^2 + (v_T(x_i) - v_U(x_i))^2 + (\pi_T(x_i) - \pi_U(x_i))^2)} \quad (10)$$

3-The proposed model

In this section, the proposed method is presented for the HCW technology selection problems with the vague information by using IFSs. The proposed decision approach develops an extended DM weighting method and a new alternative ranking approach. The core of this paper is based on four recent related studies on group decision-making and MCDM problems (i.e., Yue, 2014; Wan et al., 2013; Dorfeshan and Mousavi, 2019; Kuo, 2016).

In multi-attribute group decision-making problems $A = \{A_1, A_2, \dots\dots, A_m\}$ is the alternatives set, $C = \{C_1, C_2, \dots\dots, C_n\}$ will be the criteria set, and $DM = \{DM_1, DM_2, \dots\dots, DM_t\}$ will be the DMs' set. The judgment of the DM d ($d \in \{1,2,\dots,t\}$) develops the assessment of criteria j ($j \in \{1,2,\dots,n\}$) for the alternative i ($i \in \{1,2,\dots m\}$) by using the IF information that is depicted as $\tilde{Z}_{ij}^d = [\mu_{ij}^d, v_{ij}^d]$.

Step 1. Constructing the decision matrix with gathering expert linguistic term opinions under the IF condition for the k^{th} DM is called Y_k and established as follows:

$$Y_k = (\tilde{Y}_{ij}^d)_{m \times n} = \begin{bmatrix} [\mu_{11}^d, v_{11}^d] & [\mu_{12}^d, v_{12}^d] & \dots & [\mu_{1n}^d, v_{1n}^d] \\ [\mu_{21}^d, v_{21}^d] & [\mu_{22}^d, v_{22}^d] & \dots & [\mu_{2n}^d, v_{2n}^d] \\ \vdots & \vdots & & \vdots \\ [\mu_{m1}^d, v_{m1}^d] & [\mu_{m2}^d, v_{m2}^d] & \dots & [\mu_{mn}^d, v_{mn}^d] \end{bmatrix}, \quad (11)$$

Step 2. Calculating the criteria weights with Shannon entropy method.

Entropy value is obtained from equation (12), and the final weights of criteria based on DMs opinions are computed with equation (13).

$$E_j^d = -\frac{1}{m \ln 2}\sum_{i=1}^{m}[\mu_{ij}^d \ln \mu_{ij}^d + v_{ij}^d \ln v_{ij}^d] \quad (12)$$

$$W_j^d = \frac{\left(1 - E_j^d\right)}{\sum_{j=1}^{n}\left(1 - E_j^d\right)} \tag{13}$$

Step 3. Constructing the normalized decision matrix with equations (14)-(16).

$$P_k = \left(\tilde{P}_{ij}^d\right)_{m\times n} = \begin{bmatrix} P_{11}^d & P_{12}^d & \cdots & P_{1n}^d \\ P_{21}^d & P_{22}^d & \cdots & P_{2n}^d \\ \vdots & \vdots & & \vdots \\ P_{m1}^d & P_{m2}^d & \cdots & P_{mn}^d \end{bmatrix}, \tag{14}$$

$$P_{ij}^d = \frac{Y_{ij}^d - \min_i Y_{ij}^d}{\max_i Y_{ij}^d - \min_i Y_{ij}^d}, \qquad \textit{for the benefit criteria} \tag{15}$$

$$P_{ij}^d = \frac{\max_i Y_{ij}^d - Y_{ij}^d}{\max_i Y_{ij}^d - \min_i Y_{ij}^d}, \qquad \textit{for the cost criteria} \tag{16}$$

Step 4. Computing the weights of DMs.

The DMs' weight is computed with means of the closeness to the ideal average solution and maximum distance from negative and positive ideal solutions.

Step 4.1. The best alternative (A^*), right ideal and left ideal best alternatives (A_R^-, A_L^-) are obtained from equations (17)-(22), respectively.

$$A^* = \begin{bmatrix} P_{11}^* & \cdots & P_{1n}^* \\ \vdots & \ddots & \vdots \\ P_{m1}^* & \cdots & P_{mn}^* \end{bmatrix} \tag{17}$$

$$A_{ij}^* = \left(\frac{1}{d}\sum_{d=1}^{D} \mu_{P_{ij}^d}, \frac{1}{d}\sum_{d=1}^{D} \upsilon_{P_{ij}^d}\right) \tag{18}$$

$$A_L^- = \begin{bmatrix} P_{L11}^- & \cdots & P_{L1n}^- \\ \vdots & \ddots & \vdots \\ P_{Lm1}^- & \cdots & P_{Lmn}^- \end{bmatrix} \tag{19}$$

$$P_{Lij}^- = \min_d\left\{\tilde{P}_{ij}^d\right\} \tag{20}$$

$$A_R^- = \begin{bmatrix} P_{R11}^- & \cdots & P_{R1n}^- \\ \vdots & \ddots & \vdots \\ P_{Rm1}^- & \cdots & P_{Rmn}^- \end{bmatrix} \tag{21}$$

$$P_{Rij}^- = \max_d\left\{\tilde{P}_{ij}^d\right\} \tag{22}$$

Step 4.2. Calculating the distance of matrixes from average, left, and right negative ideal solutions with equations (23)- (25).

$$DisA_d^* = \sum_{i=1}^{m}\sum_{j=1}^{n}\sqrt{\frac{1}{2}\left[\left({\mu_{P_{ij}^d}}^2 - \left(\frac{1}{d}\sum_{d=1}^{D}\mu_{P_{ij}^d}\right)^2\right)^2 + \left({\upsilon_{P_{ij}^d}}^2 - \left(\frac{1}{d}\sum_{d=1}^{D}\upsilon_{P_{ij}^d}\right)^2\right)^2\right]} \quad \forall d \in D \tag{23}$$

$$DisA_{Ld}^- = \sum_{i=1}^{m}\sum_{j=1}^{n}\sqrt{\frac{1}{2}\left[\left({\mu_{P_{ij}^d}}^2 - \left(\min_d \mu_{\tilde{P}_{ij}^d}\right)^2\right)^2 + \left({\upsilon_{P_{ij}^d}}^2 - \left(\min_d \upsilon_{\tilde{P}_{ij}^d}\right)^2\right)^2\right]} \quad \forall d \in D \tag{24}$$

$$DisA_{Rd}^{-} = \sum_{i=1}^{m}\sum_{j=1}^{n}\sqrt{\frac{1}{2}\left[\left({\mu_{P_{ij}^{d}}}^{2}-\left(\max_{d}\mu_{\tilde{P}_{ij}^{d}}\right)^{2}\right)^{2}+\left({v_{P_{ij}^{d}}}^{2}-\left(\max_{d}v_{\tilde{P}_{ij}^{d}}\right)^{2}\right)^{2}\right]} \qquad \forall d \in D \tag{25}$$

Step 4.3. The final value of each DM is computed from equation (26).

$$\emptyset_{d} = DisA^{d-} + \frac{\sum_{d=1}^{D} DisA_{d}^{*}}{DisA_{d}^{*}\sum_{d=1}^{D}\frac{1}{DisA_{d}^{*}}} \tag{26}$$

$$DisA^{d-} = max\{DisA_{Ld}^{-}, DisA_{Rd}^{-}\} \tag{27}$$

Step 4.4. The final weight of the *dth* DM is obtained with equation (28).

$$\partial_{d} = \frac{\emptyset_{d}}{\sum_{d=1}^{D}\emptyset_{d}} \tag{28}$$

Step 5. Aggregating the normalized decision matrix from equation (29).

$$\tilde{\rho}_{ij} = \frac{\sum_{d=1}^{D}\partial_{d}P_{k}}{\sum_{d=1}^{D}\partial_{d}} = \frac{\sum_{d=1}^{D}\left[\sqrt{1-\left(1-\left(\mu_{P_{ij}^{d}}\right)^{2}\right)^{\partial_{d}}}, {v_{P_{ij}^{d}}}^{\partial_{d}}\right]}{\sum_{d=1}^{D}\partial_{d}} \tag{29}$$

Step 6. The criteria' weight is aggregated and normalized with equations (30) and (31), respectively.

$$\widetilde{w}_{j} = \frac{\widetilde{W}_{1}^{d} \oplus \widetilde{W}_{2}^{d} \oplus \ldots \oplus \widetilde{W}_{j}^{d}}{d} \qquad \forall j \tag{30}$$

$$\widetilde{W}_{j} = \frac{\widetilde{w}_{j}}{\sum_{j=1}^{n}\widetilde{w}_{j}} \tag{31}$$

Step 7. The weighted normalized decision matrix is computed from equation (32).

$$\sigma_{ij} = \tilde{P}_{ij} \otimes \widetilde{W}_{j} \tag{32}$$

Step 8. The positive and negative ideal solutions are obtained from equations (33)- (36).

$$\sigma_{ij}^{+} = \left[\max_{i}\mu_{\sigma_{ij}}, \min_{i}v_{\sigma_{ij}}\right] \qquad for\ j \in benefit \tag{33}$$

$$\sigma_{ij}^{+} = \left[\min_{i}\mu_{\sigma_{ij}}, \max_{i}v_{\sigma_{ij}}\right] \qquad for\ j \in cost \tag{34}$$

$$\sigma_{ij}^{-} = \left[\min_{i}\mu_{\sigma_{ij}}, \max_{i}v_{\sigma_{ij}}\right] \qquad for\ j \in benefit \tag{35}$$

$$\sigma_{ij}^{-} = \left[\max_{i}\mu_{\sigma_{ij}}, \min_{i}v_{\sigma_{ij}}\right] \qquad for\ j \in cost \tag{36}$$

Step 9. The distance from positive and negative ideal solutions is obtained from equations (37) and (38).

$$\Delta_{ij}^{-} = \sqrt{\frac{1}{2}\left[\left({\mu_{\sigma_{ij}}}^{2}-\left(\min_{i}\mu_{\sigma_{ij}}\right)^{2}\right)^{2}+\left({v_{\sigma_{ij}}}^{2}-\left(\max_{i}v_{\sigma_{ij}}\right)^{2}\right)^{2}\right]} \qquad for\ j \in benefit \tag{37}$$

$$\Delta_{ij}^{+} = \sqrt{\frac{1}{2}\left[\left({\mu_{\sigma_{ij}}}^{2}-\left(\max_{i}\mu_{\sigma_{ij}}\right)^{2}\right)^{2}+\left({v_{\sigma_{ij}}}^{2}-\left(\min_{i}v_{\sigma_{ij}}\right)^{2}\right)^{2}\right]} \qquad for\ j \in benefit \tag{38}$$

Step 10. The initial collective index is computed from equations (39)- (41)

$$\psi_i = \left(\frac{\sum_{j=1}^{n} \Delta_{ij}^{+}}{\sum_{j=1}^{n} \Delta_{ij}^{-}}\right)^{\frac{1}{j}} \tag{39}$$

$$\varsigma_i = \sum_{j=1}^{n} \Delta_{ij}^{-} + \frac{\sum_{i=1}^{m}\sum_{j=1}^{n} \Delta_{ij}^{+}}{\sum_{j=1}^{n} \Delta_{ij}^{+} * \sum_{i=1}^{m}\sum_{j=1}^{n} \frac{1}{\Delta_{ij}^{+} + Q_{ij}}} \tag{40}$$

$$\theta_i = \varsigma_i + \frac{1}{\psi_i} \tag{41}$$

where $\Delta_{ij}^{+} > 0$, the first terms are computed, but when the $\Delta_{ij}^{+} = 0$ these cases are obtained with equation (42).

$$Q_{ij} = \left(\left(\min_{j} \Delta_{ij}^{+}\right)\right)^{\frac{1}{\max_{j} W_j}} \tag{42}$$

Step 11. The new method to obtain the collective index is proposed with equation (43) based on the cost and benefit weights of the criterion $\left(W_j^{-}, W_j^{+}, W_j^{+} + W_j^{-} = 1\right)$.

$$\varrho_i = \sum_{j=1}^{n} W_j^{+} \left(\frac{\Delta_{ij}^{-}}{\sum_{i=1}^{m} \Delta_{ij}^{-}}\right) - \sum_{j=1}^{n} W_j^{-} \left(\frac{\Delta_{ij}^{+}}{\sum_{i=1}^{m} \Delta_{ij}^{+}}\right) \tag{43}$$

Step 12. The final collective index is shown in equation (45).

$$C_i = \frac{\theta_i + \varrho_i}{2} \tag{44}$$

Finally, the alternatives are ranked in descending order.

4- Empirical case

In this section, the empirical case is provided that is related to Shanghai, China, from the recent literature to validate the ability and effectiveness of the proposed approach for the HCW treatment technology selection problem (Shi et al., 2017). Shanghai is one of the most polluted cities of China, in which the capacities of the available incineration plants are confined and cannot cope with all the wastes created in the healthcare organizations. Hence, it should be determined the suitable treatment technology for HCW's problem with the proposed decision-making process. Based on initial studies, four HCW treatment technologies are shown as the alternatives, which are Incineration (A_1), Steam sterilization (A_2), Microwave (A_4), and Landfill (A_4). Furthermore, this case analyzes the eight various criteria in the four fields economy, environment, technology, and society, which are indicated in table 1. Eventually, three types of the stakeholders (DM_1, DM_2, DM_3) are used to determine their opinions with the linguistic terms that are shown in table 2 (Rouyendegh et al., 2020).

Table 1. The definition of the criteria

Segments	Criteria description
Economy	Cost of net per ton (C_1)
Environment	Residuals of the waste (C_2)
	Health effect release (C_3)
Technology	Reliability (C_4)
	Effectiveness of the treatment (C_5)
Society	Admission of the society (C_6)

Table 2. The linguistic value of alternatives rate

Linguistic variables	Intuitionistic fuzzy values
Very good (VG)	$[9.00, 0.10]$
Good (G)	$[0.85, 0.05]$
Medium good (MG)	$[0.70, 0.20]$
Medium (M)	$[0.50, 0.50]$
Medium poor (MP)	$[0.40, 0.50]$
Poor (P)	$[0.25, 0.60]$
Very poor (VP)	$[0.10, 0.90]$

Furthermore, table 3 generates the evaluation of experts from alternatives and criteria.

Table 3. The linguistic judgments DMs

DMs	Alternatives	Criteria					
		C_1	C_2	C_3	C_4	C_5	C_6
DM_1	A_1	G	P	VG	VG	MG	VG
	A_2	M	P	P	M	G	P
	A_3	MP	P	P	M	MG	P
	A_4	M	M	G	P	VP	G
DM_2	A_1	G	M	G	G	G	G
	A_2	M	VP	P	G	VG	P
	A_3	M	P	MP	MG	M	MP
	A_4	P	M	G	G	MP	G
DM_3	A_1	G	P	G	G	G	G
	A_2	P	M	VP	G	M	P
	A_3	M	P	P	M	M	P
	A_4	P	M	M	M	P	VG

Hence, the criterion weights based on *dth* expert' opinions are computed based on equation (13) that is shown in table 4. Afterward, the aggregated normalized criteria' weights are obtained from equations (30) and (31), and is determined in table 5.

Table 4. The weights of criteria

DMs	Criteria					
	C_1	C_2	C_3	C_4	C_5	C_6
DM_1	0.86104	0.95663	0.69219	0.85279	0.63339	0.69219
DM_2	0.83939	0.85279	0.70043	0.51769	0.72829	0.70043
DM_3	0.82494	0.97109	0.70664	0.70770	0.83939	0.69219

Table 5. The normalized aggregation criteria weights

Criteria	Normalized aggregated criterion weight
C_1	0.18341
C_2	0.20194
C_3	0.15246
C_4	0.15093
C_5	0.15985
C_6	0.15141

Furthermore, the weights of the DMs are calculated with equations (17)-(28). For this reason, the best alternative (A^*), right ideal alternatives (A_R^-) and left ideal best alternatives (A_L^-) are presented in tables 6-8, respectively.

Table 6. The best alternative values

Alternatives	Criteria					
	C_1	C_2	C_3	C_4	C_5	C_6
A_1	[0.00000,1.00000]	[0.33333,0.66667]	[1.00000,0.03030]	[1.00000,0.00000]	[0.90000,0.05882]	[0.97436,0.03030]
A_2	[0.78704,0.06061]	[0.33333,0.66667]	[0.00000,1.00000]	[0.79487,0.26667]	[0.80556,0.30976]	[0.00000,1.00000]
A_3	[0.72222,0.12121]	[0.12500,0.75000]	[0.15000,0.82175]	[0.12821,0.93333]	[0.47222,0.66488]	[0.08333,0.93939]
A_4	[0.92593,0.00000]	[1.00000,0.00000]	[0.81880,0.17647]	[0.33333,0.66667]	[0.00000,1.00000]	[0.97436,0.03030]

Table 7. The left ideal alternative values

Alternatives	Criteria					
	C_1	C_2	C_3	C_4	C_5	C_6
A_1	[0.00000,1.00000]	[0.00000,0.00000]	[1.00000,0.03030]	[1.00000,0.00000]	[0.80000,0.00000]	[0.92308,0.00000]
A_2	[0.58333,0.00000]	[0.00000,0.00000]	[0.00000,1.00000]	[0.38462,0.00000]	[0.41667,0.00000]	[0.00000,1.00000]
A_3	[0.58333,0.00000]	[0.00000,0.25000]	[0.00000,0.64706]	[0.00000,0.80000]	[0.20000,0.17647]	[0.00000,0.81818]
A_4	[0.77778,0.00000]	[1.00000,0.00000]	[0.53333,0.00000]	[0.00000,0.00000]	[0.00000,1.00000]	[0.92308,0.00000]

Table 8. The right ideal alternative values

Alternatives	Criteria					
	C_1	C_2	C_3	C_4	C_5	C_6
A_1	[0.00000,1.00000]	[1.00000,1.00000]	[1.00000,0.09091]	[1.00000,0.00000]	[1.00000,0.17647]	[1.00000,0.09091]
A_2	[1.00000,0.18182]	[1.00000,1.00000]	[0.00000,1.00000]	[1.00000,0.80000]	[1.00000,0.81818]	[0.00000,1.00000]
A_3	[1.00000,0.18182]	[0.37500,1.00000]	[0.25000,1.00000]	[0.38462,1.00000]	[0.80000,1.00000]	[0.25000,1.00000]
A_4	[1.00000,0.00000]	[1.00000,0.00000]	[1.00000,0.52941]	[1.00000,1.00000]	[0.00000,1.00000]	[1.00000,0.09091]

The average, left, and right ideal negative distances are computed from equations (23)-(25). Also, the final value of each DM ($\emptyset_d$), and the final weights of DM (∂_d) are computed from equation (28). These results are shown in table 9.

Table 9. The weights of DM

DMs	$DisA_d^*$	$DisA_{Ld}^-$	$DisA_{Rd}^-$	$\emptyset_d$	∂_d
DM_1	3.91089	11.61023	9.97844	15.95863	0.34100
DM_2	4.42518	11.21916	9.82386	15.06220	0.32185
DM_3	4.05216	11.58145	9.79888	15.77825	0.33715

Table 9 determines that the first DM has a high priority than other experts, and this point introduces the importance degree of this expert over others. In addition, the computational results of the ranking method are presented in tables 10-12. The distance from positive and negative ideal solutions is depicted in tables 10 and 11. Nevertheless, the values of θ_i, ϱ_i, C_i, and final rankings are provided in table 12.

Table 10. The distance from positive ideal solution (Δ_{ij}^+)

Alternatives	Criteria					
	C_1	C_2	C_3	C_4	C_5	C_6
A_1	0.00000	0.25791	0.00209	0.00000	0.00510	0.00284
A_2	0.22245	0.25791	0.20841	0.06629	0.03129	0.18705
A_3	0.16017	0.25814	0.14681	0.14412	0.07716	0.11714
A_4	0.26207	0.00000	0.08152	0.14407	0.18176	0.00288

Table 11. The distance from negative ideal solution (Δ_{ij}^{-})

Alternatives	Criteria					
	C_1	C_2	C_3	C_4	C_5	C_6
A_1	0.26207	0.02746	0.20695	0.15786	0.17925	0.18471
A_2	0.06801	0.02746	0.00000	0.09405	0.15552	0.00000
A_3	0.10718	0.11397	0.14682	0.06358	0.14853	0.14556
A_4	0.00000	0.28274	0.15269	0.01525	0.00000	0.18482

Table 12. The final rank of the alternatives

Alternatives	θ_i	ϱ_i	C_i	Final rank
A_1	0.96359	0.28776	0.62568	1
A_2	1.02923	0.08598	0.55760	4
A_3	1.00611	0.20005	0.60308	2
A_4	1.00156	0.17303	0.58730	3

5- Sensitivity analysis

In this section, the sensitivity analysis is introduced to demonstrate the reliability of the proposed method. For this respect, the criteria weights change in various ranges, and their impacts on the final ranking results are determined. At the initial state, the first weight index is shifted to the fourth weight, and the third weight is changed with the sixth weight simultaneously. At the second state, along with the changes to the first issue, by increasing the changing of the weights with shifting the second weight to the fifth weight, the final ranking results do not change. Also, at the third state, the weight of the first criterion varies with the second index, and the third indicator changes with the fourth index. In addition, the weight of the fifth criterion shifts to the sixth index, respectively. Eventually, in the fourth state, the weights of the criteria take the equal values $\frac{1}{6}$. In this regard, the final rank is reliable simultaneously. The final results of ranking the alternatives are given in table 13.

Table 13. The final results of the ranking with changing the criteria weights

State	Alternatives	θ_i	ϱ_i	C_i	Final rank
First state	A_1	0.96385	0.28278	0.62331	1
	A_2	1.02618	0.09190	0.55904	4
	A_3	1.00678	0.19719	0.60199	2
	A_4	1.00052	0.17392	0.58722	3
Second state	A_1	0.95005	0.30348	0.62676	1
	A_2	1.01798	0.11652	0.56725	4
	A_3	1.00349	0.20701	0.60525	2
	A_4	1.00979	0.14146	0.57563	3
Third state	A_1	0.94583	0.30578	0.62580	1
	A_2	1.03491	0.07182	0.55337	4
	A_3	1.00280	0.21103	0.60691	2
	A_4	0.99629	0.18589	0.59109	3
Fourth state	A_1	0.95215	0.30326	0.62770	1
	A_2	1.02743	0.09094	0.55919	4
	A_3	1.00435	0.20601	0.60518	2
	A_4	1.00311	0.16576	0.58443	3

According to table 13, the results of the θ_i, ϱ_i, and C_i change from initial values, but the final rank is reliable with each change.

7- Conclusions

In this paper, a new group decision-making model is proposed. In the first stage, the weight of the criteria is computed based on Shannon entropy method with the uncertain information. In the group decision-making approach, an extended new weighting method was introduced to compute the weight of DMs based on means of the closeness to the ideal average solution and maximum distance from a negative ideal solution and positive ideal solution. Afterward, the new ranking method was proposed based on aggregating two collective indexes that computed negative and positive ideal solutions distance and weights of cost and benefit criterion. On the one hand, this problem was regarded under intuitionistic fuzzy (IF) conditions to cope with an uncertain environment of real-world applications. On the other hand, this paper solved an empirical case from the recent literature in HCW technology selection with four kinds of alternatives, and some analyses were clearly explained. After computing the problem with a proposed approach, it determined the first alternative that had a high priority than others. This alternative was relevant to the incineration of the healthcare waste. Moreover, this study introduced a sensitivity analysis to demonstrate that the final ranking method was reliable with changing the weights of criteria. For this reason, the four states with various types of conditions were explained, and all of them determined that the final ranking results were reliable with changes in criteria' weights.

For future suggestions, the introduced method can be extended to interval-valued IF sets. Hence, in the future, approaches to compute the objective criteria weights can be introduced when the information of criteria weight is entirely unknown or unavailable. A new optimization method can be used to obtain the weights of the DMs. Furthermore, a computer-based application system is to explain, which can accelerate the execution of the introduced model. Also, the proposed method is capable of use in various types of industries.

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