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A new last aggregation compromise solution approach based on TOPSIS method with hesitant fuzzy setting to energy policy evaluation

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Abstract

Utilizing renewable energies is one of the most important issues for economical and social significance in future human life. Choosing the best renewable energy among all other candidates is very important in this area. To address the issue, multi-criteria group decision making (MCGDM) methods with imprecise information could be employed to solve these problems. The aim of this paper is to propose a new compromise solution approach based on technique for order preference by similarity to ideal solution (TOPSIS) method under evaluations of a group of experts with hesitant fuzzy information. The hesitant fuzzy set (HFS) is a new fuzzy set which could help the experts by providing some membership degrees for renewable energy candidates under the evaluation criteria to margin of errors. Also, weights of each expert and criterion are determined by proposing extended hesitant fuzzy entropy and maximizing deviation methods based on hesitant fuzzy Euclidean-Hausdorff distance measure. In addition, the judgments (preferences) of experts are aggregated in the final step to prevent the loss of data. Finally, an illustrative example about the energy policy selection is presented to demonstrate the performance of the proposed decision approach. Also, a comparative analysis is provided with the recent decision methods of the literature to show the capability of the proposed approach.

Keywords: Energy policy evaluation, compromise solution approach, hesitant fuzzy sets, last aggregation, individual regret, weighting methods.

1- Introduction

Using the renewable energy resources leads to prevention of the environmental pollutions, reducing the production costs, saving the non-renewable energies, etc. (Kaygusuz, 2002; Keyhani et al., 2010; Ulutaş, 2005; Zamani, 2007). Choosing the most suitable candidate energies such as wind, geothermal, solar, biomass and hydropower among the conflicted criteria is a main energy issue for developing countries. To cope with the issue, the multi-criteria decision making (MCDM) techniques can be considered appropriately. Also, a group of experts may be established to assess the energy

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problems which lead to utilize the multi-criteria group decision making (MCGDM) techniques. However, different decision making methods are considered by some researchers to solve their energy problems in the last decade.

The analytical hierarchy process (AHP) method was implemented by Akash et al. (1999) to report and compare the electricity power production elements in Jordan. Afgan and Carvalho (2002) based on the synthesis and analysis of parameters provided the choice of criteria for evaluations of the renewable energy technologies by regarding environment capacity, economic indicators, energy resources, and social indicators. Also, the analytical network process (ANP) method was used by Ulutas (2005) to evaluate the energy policy selection problem and to specify the appropriate energy resources candidate under the conflicted criteria in Turkey. Patlitzianas et al. (2007) presented an integrated decision making approach by utilizing the ordered weighted average of qualitative opinions to assess the renewable energy producers in the European Union accession. Wang et al. (2010) presented a decision making model in hierarchical structure to assess the renewable and nonrenewable energy resources in the China. In addition, Erol and Kılkıs (2012) by using the AHP method evaluated the energy source policy under three candidates as sustainable, long-term and robust in the Turkey.

Yazdani-Chamzini et al. (2013) chose the most suitable renewable energy project by presenting the integrated complex proportional assessment (COPRAS) and AHP methods. Doukas et al. (2014) proposed a transparent and coherent methodological MCDM framework based on utilizing linguistic variables for achieving the companies' energies and environmental corporate policies. Georgiou et al. (2015) compared the results of ranking the renewable energies by applying the preference ranking organization method for enrichment of evaluation (PROMETHEE) and AHP methods.

In real decision problems, parameters may be imprecise or uncertain, and experts cannot determine their performance values or opinions by crisp values. Thus, the preferences of experts' judgments about the candidate energies versus the selected criteria can be expressed under a fuzzy environment. In this regard, the traditional / new fuzzy set theories and their extensions are useful tools to cope with the imprecise condition for solving the decision-making problems in the field of energy. For instance, the PROMETHEE method was developed by Goumas and Lygerou (2000) based on fuzzy input information to sort the energy exploitation schemes candidates in geothermal field. Meixner (2009) presented an AHP method based on fuzzy information to choose the suitable energy source candidate. In addition, Kaya and Kahraman (2010) proposed an integrated method by considering the VIKOR and AHP methods under a fuzzy environment to select the best renewable energy candidate in Turkey. Also, a modified TOPSIS method was proposed by Kaya and Kahraman (2011) based on fuzzy sets theory to choose the most appropriate energy technology candidate by regarding to determine the criteria' weights by fuzzy pair-wise comparison matrices.

Sadeghi et al. (2012) presented the fuzzy AHP method to compute the criteria' weights, and then the technique for order preference by similarity to ideal solution (TOPSIS) method under a fuzzy environment was provided to choose the proper renewable energy sources candidate versus the selected criteria in Iran. Also, Jing et al. (2012) presented an integrated assessment model based on the fuzzy sets theory and MCDM procedure to achieve the comprehensive benefits of combined cooling, heating and power systems. Ansari and Ashraf (2012) provided the application of a fuzzy MCDM method for choosing the appropriated energy sources to electricity generation in India. Cavallaro (2013) presented a TOPSIS method based on fuzzy sets theory to evaluate the nuclear energy competiveness. Sianaki and Masoum (2013) considered a fuzzy TOPSIS method for assessing the preferences, and indicated that the proposed approach could help householders so that their participations in demand response were maximized.

The review of the decision making techniques in energy decision problems under uncertainty has demonstrated that the fuzzy approach has been appropriate for dealing with uncertainty and has been attended by some researchers in recent years. In this study, the hesitant fuzzy set (HFS), which has been introduced by Torra and Narukawa (2009) and Torra (2010), is provided to allow the experts to express their judgments by some membership degrees for a candidate energy under evaluation criteria for margin of errors. In recent years, the HFS tool is more utilized by some researchers to cope with uncertainty in their problems. Wang et al. (2014) introduced the dominance and opposition relations for HFSs which inspired by classical ELECTRE methods. In addition, they proposed an outranking approach for MCDM problems in hesitant fuzzy setting for ranking the candidate alternatives. Wu et al. (2014) proposed an approach based on the generalized prioritized aggregation operator of hesitant fuzzy linguistic numbers for solving the MCDM problems, in which the criteria are various priority levels. Xu and Zhang (2013) presented an MCDM approach based on the TOPSIS method by utilizing the hesitant fuzzy information to specify the most appropriate energy policy candidate. Hence, the optimal criteria weights were computed by proposing the maximizing deviation method respecting to incomplete information. Zhang and Xu (2014) based on concept of linear programming proposed an interval programming method under hesitant fuzzy environment to select the best energy project. Investigating the literature has indicated that the weights of criteria and experts have poor attention for considering in the procedures of proposed decision approaches simultaneously. In addition, the HFS as an efficient tool to handle uncertainty has not been widely utilized in energy decision problems. Therefore, this study presents a new compromise solution based on the TOPSIS under hesitant fuzzy environment, in which the experts and criteria' weights are computed by new indexes and are considered in the procedure of the proposed compromise solution approach. In addition, the experts' judgments (preferences) are aggregated in the last step to avoid the loss of information as one of the innovations of this study. In sums, the main merits of this study are expressed as follows:

(1) A new compromise solution approach is presented based on the concept of TOPSIS method under hesitant fuzzy environment;
(2) A group of experts is established to evaluate the energy policy selection problem by assigning some membership degrees for an energy candidate to margin of errors;
(3) Weights of experts and criteria are computed based on a developed hesitant fuzzy entropy method and an extended hesitant fuzzy maximizing deviation method respectively;
(4) Opinions of experts are aggregated in final step to prevent the loss of data; and
(5) A new compromise solution index is proposed to rank the energy alternatives.

The rest of this paper is outlined as follows: in section 2, the definition of HFS is expressed and some operations about this new fuzzy set are described. In section 3, proposed last aggregation compromise solution approach is introduced under a hesitant fuzzy environment. In section 4, an illustrative example for the energy decision problem is provided to indicate the procedure and to show the performance of proposed approach. Finally, some concluding remarks and future directions are given in section 5.

2- Preliminaries

Definition 1. Reference set is indicated by X , Xia and Xu (2011) represented the HFS by a function as $h_E(\mathrm{x})$ which X returns to [0, 1].

$$E = \{< x, h_E(\mathrm{x}) > | \mathrm{x} \in \mathrm{X}\} \tag{1}$$

where $h_E(\mathrm{x})$ is defined as the set of membership degrees for an element under [0,1], denoting the membership degree of element $x \in X$ to E .

Definition 2. The basic operators are defined by Xia and Xu (2011) as below:

$$\tilde{h}_1 \oplus \tilde{h}_2 = \cup_{\gamma_1 \in \tilde{h}_1, \gamma_2 \in \tilde{h}_2} \left\{\gamma_1 + \gamma_2 - \gamma_1 . \gamma_2\right\} \tag{2}$$

$$\tilde{h}_1 \otimes \tilde{h}_2 = \cup_{\gamma_1 \in \tilde{h}_1, \gamma_2 \in \tilde{h}_2} \left\{\gamma_1 . \gamma_2\right\} \tag{3}$$

$$h^\lambda = \cup_{\gamma \in h} \left\{\gamma^\lambda\right\} \tag{4}$$

$$\lambda h = \cup_{\gamma \in h} \left\{1 - (1-\gamma)^\lambda\right\} \tag{5}$$

Definition 3. Xu and Xia (2011) suggested some hesitant fuzzy distance measures. In addition, the general hesitant fuzzy Hausdorff distance measure is proposed as follows:

$$d_{ghh}\left(h_M, h_N\right)=\left(\max_j\left|h_{ij}^{\sigma(\lambda)}-h_{kj}^{\sigma(\lambda)}\right|^{\lambda}\right)^{\frac{1}{\lambda}} \tag{6}$$

where if $\lambda=1$, then the hesitant fuzzy Hamming-Hausdorff distance measure is obtained and if $\lambda=2$, the hesitant fuzzy Euclidean-Hausdorff distance measure is achieved.

Definition 4. The hesitant fuzzy aggregation operations are described by Xia and Xu (2011). In this regard, the hesitant fuzzy weighted averaging (HFWA) and the hesitant fuzzy averaging (HFA) relations are shown respectively as follows:

$$HFWA\left(h_1, h_2, ..., h_n\right)=\underset{j=1}{\overset{n}{\oplus}}\left(w_j h_j\right)=\cup_{\gamma_1\in h_1,\gamma_2\in h_2,...,\gamma_n\in h_n}\left\{1-\prod_{j=1}^{n}\left(1-\gamma_j^{\lambda}\right)^{w_j}\right\} \tag{7}$$

$$HFA\left(h_1, h_2, ..., h_n\right)=\underset{j=1}{\overset{n}{\oplus}}\left(\frac{1}{n}h_j\right)=\cup_{\gamma_1\in h_1,\gamma_2\in h_2,...,\gamma_n\in h_n}\left\{1-\prod_{j=1}^{n}\left(1-\gamma_j^{\lambda}\right)^{\frac{1}{n}}\right\} \tag{8}$$

where $w=\left(w_1, w_2, ..., w_n\right)^T$ are the weight vector of $h_j\ \left(j=1,2,...,n\right)$.

Definition 5. The normalized hesitant fuzzy decision matrix $\left(B=\left(b_{ij}\right)_{m\times n}\right)$ relations is defined by Zhu et al. (2012). In this case, a hesitant fuzzy decision matrix is indicated by $H=\left(h_{ij}\right)_{m\times n}$, then:

$$b_{ij}=\cup_{t_{ij}\in b_{ij}}=\begin{cases}\left\{\gamma_{ij}\right\} & \text{for possitive criteria}\\ \left\{1-\gamma_{ij}\right\} & \text{for negative criteria}\end{cases}\quad \forall i=1,...,m;\ j=1,...,n \tag{9}$$

3 - Proposed hesitant fuzzy compromise solution approach

In this section, hesitant fuzzy compromise solution approach with last aggregation based on TOPSIS method is presented and also the overall structure of the proposed approach is depicted in Figure 1.

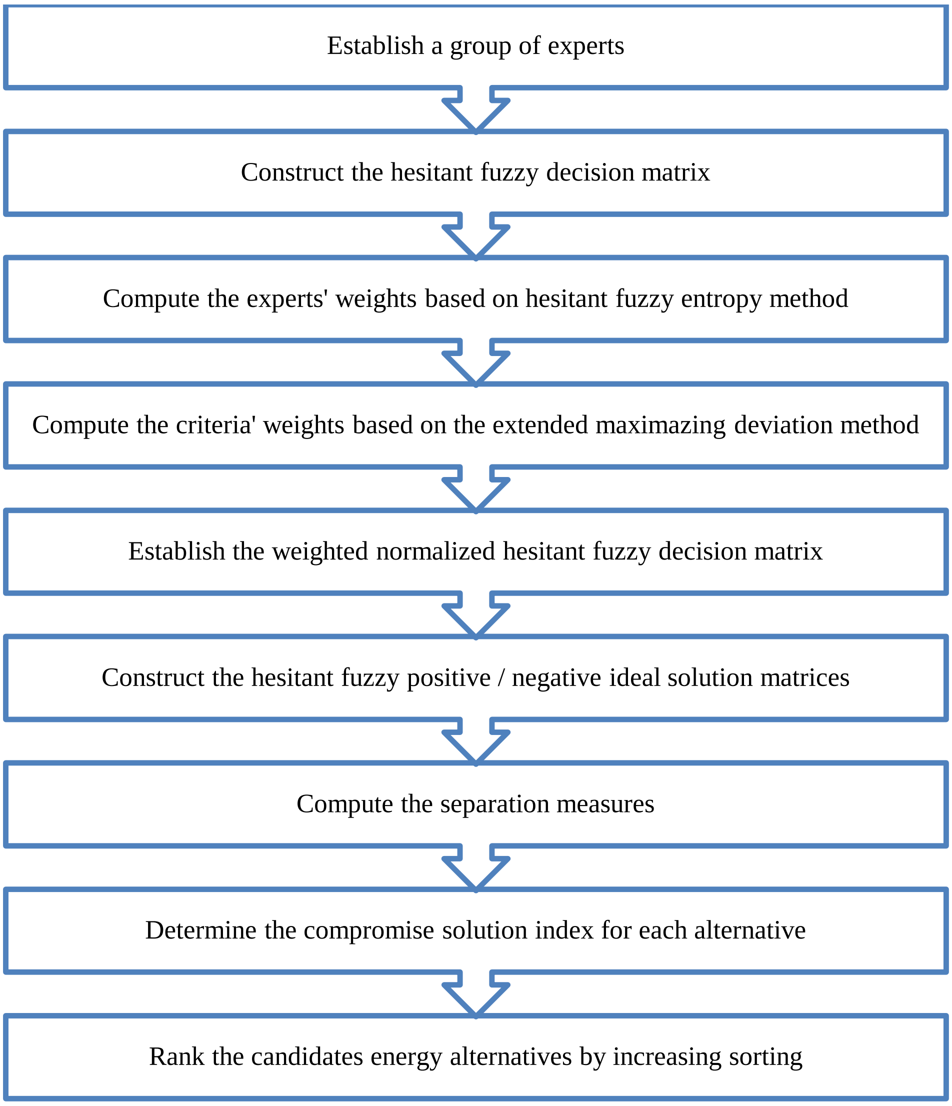

Figure 1. The procedure of the proposed approach

Step 1. The hesitant fuzzy decision matrix could be established based on the group experts' judgments as follows:

	C_1	C_1	$\cdots$	C_n
A_1	$\{\mu_{11}^1, \mu_{11}^2, \ldots, \mu_{11}^k\}$	$\{\mu_{12}^1, \mu_{12}^2, \ldots, \mu_{12}^k\}$	$\cdots$	$\{\mu_{1n}^1, \mu_{1n}^2, \ldots, \mu_{1n}^k\}$
A_2	$\{\mu_{21}^1, \mu_{21}^2, \ldots, \mu_{21}^k\}$	$\{\mu_{22}^1, \mu_{22}^2, \ldots, \mu_{22}^k\}$	$\cdots$	$\{\mu_{2n}^1, \mu_{2n}^2, \ldots, \mu_{2n}^k\}$
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$
A_m	$\{\mu_{m1}^1, \mu_{m1}^2, \ldots, \mu_{m1}^k\}$	$\{\mu_{m2}^1, \mu_{m2}^2, \ldots, \mu_{m2}^k\}$	$\cdots$	$\{\mu_{mn}^1, \mu_{mn}^2, \ldots, \mu_{mn}^k\}$

Step 2. Weights of experts are determined based on proposed extended hesitant fuzzy entropy method as follows:

Step 2.1. Normalize the hesitant fuzzy decision matrix by utilizing definition 5.

$$P_k = \begin{array}{c} \\ A_1 \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{pmatrix} \mu_{11} & \mu_{12} & \cdots & \mu_{1n} \\ \vdots & \vdots & \ddots & \vdots \\ \mu_{m1} & \mu_{m2} & \cdots & \mu_{mn} \end{pmatrix}_{m\times n} \end{array} \tag{10}$$

Step 2.2. Establish the $\left[\eta^k\right]_{m\times n}$ matrix for each expert by the following relation:

$$\eta_{ij}^k = \frac{\mu_{ij}^k}{1-\prod_{i=1}^{m}(1-\mu_{ij}^k)} \tag{11}$$

Step 2.3. Specify the final weight of each expert based on the hesitant fuzzy entropy index as below:

$$\varpi_k = \frac{1-\left[\prod_{i=1}^{m}\left(\prod_{j=1}^{n}\left(1-\eta_{ij}^k\right)^{Ln\left(\eta_{ij}^k\right)}\right)\right]^{-\frac{1}{Ln(m)}}}{\sum_{k=1}^{K}\left(1-\left[\prod_{i=1}^{m}\left(\prod_{j=1}^{n}\left(1-\eta_{ij}^k\right)^{Ln\left(\eta_{ij}^k\right)}\right)\right]^{-\frac{1}{Ln(m)}}\right)} \tag{12}$$

Step 3. A maximizing deviation method is extended based on the hesitant fuzzy Euclidean-Hausdorff distance measure and experts' opinions to calculate criteria' weights as follows:

$$\vartheta_j^* = \frac{\prod_{k=1}^{K}\left(\frac{\sum_{i=1}^{m}\sum_{l=1}^{m}\left(\sqrt{\max_j\left|h_{ij}^{k\sigma(\lambda)}-h_{lj}^{k\sigma(\lambda)}\right|^2}\right)}{\sqrt{\sum_{j=1}^{n}\left(\sum_{i=1}^{m}\sum_{l=1}^{m}\left(\sqrt{\max_j\left|h_{ij}^{k\sigma(\lambda)}-h_{lj}^{k\sigma(\lambda)}\right|^2}\right)\right)^2}}\right)^{\varpi_k}}{\sum_{j=1}^{n}\left[\prod_{k=1}^{K}\left(\frac{\sum_{i=1}^{m}\sum_{l=1}^{m}\left(\sqrt{\max_j\left|h_{ij}^{k\sigma(\lambda)}-h_{lj}^{k\sigma(\lambda)}\right|^2}\right)}{\sqrt{\sum_{j=1}^{n}\left(\sum_{i=1}^{m}\sum_{l=1}^{m}\left(\sqrt{\max_j\left|h_{ij}^{k\sigma(\lambda)}-h_{lj}^{k\sigma(\lambda)}\right|^2}\right)\right)^2}}\right)^{\varpi_k}\right]} \tag{13}$$

Step 4. Construct the weighted normalized hesitant fuzzy decision matrix for each expert as follows:

$$\theta_k = \begin{bmatrix} \vartheta_1^*.\mu_{A_1}(x_1) & \vartheta_2^*.\mu_{A_1}(x_2) & \cdots & \vartheta_n^*.\mu_{A_1}(x_n) \\ \vartheta_1^*.\mu_{A_2}(x_1) & \vartheta_2^*.\mu_{A_2}(x_2) & \cdots & \vartheta_n^*.\mu_{A_2}(x_n) \\ \vdots & \vdots & \ddots & \vdots \\ \vartheta_1^*.\mu_{A_m}(x_1) & \vartheta_2^*.\mu_{A_m}(x_2) & \cdots & \vartheta_n^*.\mu_{A_m}(x_n) \end{bmatrix} \forall k \tag{14}$$

Step 5. The hesitant fuzzy positive / negative ideal solution matrices are established by the following relations:

$$\varphi^* = \left(\mu_{ij}^*\right)_{m\times n} = \begin{array}{c c} & \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{array}{c} A_1 \\ \vdots \\ A_m \end{array} & \begin{pmatrix} \mu_{11}^* & \mu_{12}^* & \cdots & \mu_{1n}^* \\ \vdots & \vdots & \ddots & \vdots \\ \mu_{m1}^* & \mu_{m2}^* & \cdots & \mu_{mn}^* \end{pmatrix}_{m\times n} \end{array} \tag{15}$$

and

$$\varphi^- = \left(\mu_{ij}^-\right)_{m\times n} = \begin{array}{c c} & \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{array}{c} A_1 \\ \vdots \\ A_m \end{array} & \begin{pmatrix} \mu_{11}^- & \mu_{12}^- & \cdots & \mu_{1n}^- \\ \vdots & \vdots & \ddots & \vdots \\ \mu_{m1}^- & \mu_{m2}^- & \cdots & \mu_{mn}^- \end{pmatrix}_{m\times n} \end{array} \tag{16}$$

where in aforementioned matrices:

$$\mu_{ij}^* = \underset{k}{Max}\left\{\mu_{ij}^k\right\} \tag{17}$$

and

$$\mu_{ij}^- = \underset{k}{Min}\left\{\mu_{ij}^k\right\} \tag{18}$$

Step 6. Distance between hesitant fuzzy positive / negative ideal solution matrices and the weighted normalized hesitant fuzzy decision matrix (separation measures) are determined for each expert based on the hesitant fuzzy Euclidean-Hausdorff distance measure as follows:

$$\hbar_i^{*k} = \sum_{j=1}^{n} \sqrt{\max_j \left|\theta_{ij}^{k\sigma(\lambda)} - \varphi_{ij}^{*\sigma(\lambda)}\right|^2} \quad \forall i,k \tag{19}$$

and

$$\hbar_i^{-k} = \sum_{j=1}^{n} \sqrt{\max_j \left|\theta_{ij}^{k\sigma(\lambda)} - \varphi_{ij}^{-\sigma(\lambda)}\right|^2} \quad \forall i,k \tag{20}$$

Step 7. The compromise solution index is introduced as follows:

$$\xi_i = \prod_{k=1}^{K}\left[\frac{\left(\max_{\lambda}\left|\hbar_i^{*k\sigma(\lambda)}-\left(\max_{k}\left\{\hbar_i^{*k\sigma(\alpha)}\right\}\right)\right|\right)^2+\left(\max_{\lambda}\left|\hbar_i^{-k\sigma(\lambda)}-\left(\max_{k}\left\{\hbar_i^{-k\sigma(\lambda)}\right\}\right)\right|\right)^2}{\max_{\lambda}\left|\hbar_i^{*k\sigma(\lambda)}-\left(\max_{k}\left\{\hbar_i^{*k\sigma(\lambda)}\right\}\right)\right|+\max_{\lambda}\left|\hbar_i^{-k\sigma(\lambda)}-\left(\max_{k}\left\{\hbar_i^{-k\sigma(\lambda)}\right\}\right)\right|}\right]^{\varpi_k} \quad \forall i \tag{21}$$

Step 8. Rank the candidates by increasing sorting of compromise solution index values. Thus, the best candidate could have a minimum value of compromise solution index.

4 - Practical example for the evaluation of energy policy

In this section, a practical example for the selection of best energy policy from the recent literature (Xu and Zhang, (2013) is presented to indicate the process and the application of the proposed approach. This problem is about the energy policy selection which has been established by five candidate energy projects $\left(A_i(i=1,2,...,m)\right)$, and four criteria$\left(C_j\left(j=1,2,...,n\right)\right)$ under the several experts' judgments$\left(DM_k\left(k=1,2,...,K\right)\right)$ as follows:

C_1: technological,

C_2: environmental,

C_3: socio-political,

and

C_4: economic.

As represented in Table 1, the hesitant fuzzy decision matrix based on the preference judgments of experts is established. In this case, the length of some sets may be different because the decision makers may be expert in this area and may be assign a same value of membership degrees, and versus if the decision makers are unfamiliar with this area, and then express their opinions by different membership degrees. Thus, the times of repeated values for membership degrees have not been demonstrated, while it has more significance than other membership degrees repeated less times (Xu and Zhang, 2013). Consequently, the repeated values of membership degrees are eliminated from the sets. In addition, the sets should be extended until the same lengths are obtained. To address the issue, the risk preferences of each expert could be regarded. In this study, the experts are considered pessimistic and then the minimal values of membership degrees for each set should be added to the set. The results are given in Table 2.

Table 1. The hesitant fuzzy decision matrix

	C_1	C_2	C_3	C_4
A_1	{0.5, 0.4, 0.3}	{0.9, 0.8, 0.7, 0.1}	{0.5, 0.4, 0.2}	{0.9, 0.6, 0.5, 0.3}
A_2	{0.5, 0.3}	{0.9, 0.7, 0.6, 0.5, 0.2}	{0.8, 0.6, 0.5, 0.1}	{0.7, 0.4, 0.3}
A_3	{0.7,0.6}	{0.9, 0.6}	{0.7, 0.5, 0.3}	{0.6, 0.4}
A_4	{0.8, 0.7, 0.4, 0.3}	{0.7, 0.4, 0.2}	{0.8, 0.1}	{0.9, 0.8, 0.6}
A_5	{0.9, 0.7, 0.6, 0.3, 0.1}	{0.8, 0.7, 0.6, 0.4}	{0.9, 0.8, 0.7}	{0.9, 0.7, 0.6, 0.3}

Table 2. The hesitant fuzzy decision matrix based on the risk preferences of experts

	C1	***C2***	***C3***	***C4***
A_1	{0.5, 0.4, 0.3, 0.3, 0.3}	{0.9, 0.8, 0.7, 0.1, 0.1}	{0.5, 0.4, 0.2, 0.2, 0.2}	{0.9, 0.6, 0.5, 0.3. 0.3}
A_2	{0.5, 0.3, 0.3, 0.3, 0.3}	{0.9, 0.7, 0.6, 0.5, 0.2}	{0.8, 0.6, 0.5, 0.1, 0.1}	{0.7, 0.4, 0.3, 0.3, 0.3}
A_3	{0.7, 0.6, 0.6, 0.6, 0.6}	{0.9, 0.6, 0.6, 0.6, 0.6}	{0.7, 0.5, 0.3, 0,3, 0.3}	{0.6, 0.4, 0.4, 0.4, 0.4}
A_4	{0.8, 0.7, 0.4, 0.3, 0.3}	{0.7, 0.4, 0.2, 0.2, 0.2}	{0.8, 0.1, 0.1, 0.1, 0.1}	{0.9, 0.8, 0.6, 0.6, 0.6}
A_5	{0.9, 0.7, 0.6, 0.3, 0.1}	{0.8, 0.7, 0.6, 0.4, 0.4}	{0.9, 0.8, 0.7, 0.7, 0.7}	{0.9, 0.7, 0.6, 0.3, 0.3}

The weight of each expert is computed based on the proposed extended hesitant fuzzy entropy method. In this case, the hesitant fuzzy decision matrix is normalized based on definition 5 and then the $\left[\eta^k\right]_{m\times n}$ matrix is constructed for each expert by utilizing Eq. (11).

Hence, the final experts' weights are determined by applying the hesitant fuzzy entropy index in Eq. (12). In addition, the maximizing deviation method is developed and proposed based on the hesitant fuzzy Euclidean-Hausdorff distance measure and preferences experts' judgments to calculate the criteria' weights.

The computational results of experts and criteria' weights are indicated in Table 3. Also, the weighted normalized hesitant fuzzy decision matrix is specified for each expert and then the hesitant fuzzy positive / negative ideal solution matrices are determined based on Eqs. (15)-(18).

Hence, the distance between hesitant fuzzy positive / negative ideal solution matrices and the weighted normalized hesitant fuzzy decision matrix are obtained by using Eqs. (19) and (20), and are demonstrated in Table 4.

Table 3. The computational results of criteria and experts' weights

Experts	ϖ_k	C_j	ϑ_j^*
k_1	0.19870	C_1	0.22204
k_2	0.20031	C_2	0.23585
k_3	0.20043	C_3	0.33771
k_4	0.20030	C_4	0.20440
k_5	0.20028		

Table 4. Distance between hesitant fuzzy positive / negative ideal solution matrices and the weighted normalized hesitant fuzzy decision matrix

Experts	A_i	$\hbar_i^{*k}$	$\hbar_i^{-k}$
	A_1	0.00000	0.67605
	A_2	0.00000	0.72640
k_1	A_3	0.00000	0.51858
	A_4	0.00000	0.72571
	A_5	0.00000	0.66329
	A_1	0.37534	0.56228
	A_2	0.46951	0.55427
k_2	A_3	0.44875	0.25989
	A_4	0.59144	0.42055
	A_5	0.37768	0.54526
	A_1	0.52407	0.42707
	A_2	0.54611	0.47898
k_3	A_3	0.51858	0.00000
	A_4	0.71025	0.14901
	A_5	0.49259	0.44419
	A_1	0.67605	0.00000
	A_2	0.67595	0.26600
k_4	A_3	0.51858	0.00000
	A_4	0.72571	0.00000
	A_5	0.64633	0.14901
	A_1	0.67605	0.00000
	A_2	0.72640	0.00000
k_5	A_3	0.51858	0.00000
	A_4	0.72571	0.00000
	A_5	0.66329	0.00000

Finally, the candidates for energy policies are ranked based on the new compromise solution index (Eq. (21)). In this respect, the fifth candidate is the most suitable and the fourth candidate is the worst. In addition, the proposed last aggregation compromise solution approach is compared to Xu and Zhang (2013) method and show somewhat same results in the ranking of the energy policy candidates. The aforementioned results are given in Table 5.

Hence, the determination of the weights of experts is considered in the proposed approach, and also the judgments (preferences) of the experts are aggregated in the last step of the proposed new hesitant fuzzy compromise solution relation, while Xu and Zhang (2013) method did not consider these features. In addition, Xu and Zhang (2013) method proposed the maximizing deviation method based on incomplete weight information; but, this study has extended the maximizing deviation method based on the hesitant fuzzy Euclidean-Hausdorff distance measure by regarding the experts' opinions and their weights. In sums, the main merits and advantages of this paper versus the recent decision making methods in the literature and Xu and Zhang (2013) method are outlined as follows: (1) the entropy method is developed with hesitant fuzzy setting to obtain the experts' weights; (2) the proposed approach is prepared based on the last aggregation approach to decrease the loss of data under hesitant fuzzy environment ; and (3) the experts’ judgments and their weights are considered in determining the criteria' weights under uncertainty.

Table 5. The values of compromise solution index and ranking of energy policy candidates

A_i	ξ_i	Ranked by the proposed approach hesitant fuzzy compromise solution	Ranked by Xu and Zhang (2013) method
A_1	0.43890	4	4
A_2	0.40402	2	3
A_3	0.43616	3	2
A_4	0.55826	5	5
A_5	0.39985	1	1

5 - Conclusions and future directions

Selecting the most suitable renewable energy could reduce the production costs and the environmental pollutions. This study has proposed a new last aggregation compromise solution approach based on TOPSIS method under hesitant fuzzy environment to select the best energy policy. In addition, an entropy method has been developed based on the HFS to determine the experts’ weights, and also the maximizing deviation method have been extended based on the hesitant fuzzy Euclidean-Hausdorff distance measure to compute the criteria' weights. Hence, the weights of experts and criteria have been considered in the procedure of the proposed hesitant fuzzy compromise solution approach to decrease the errors. Also, assessments by a group of experts have been aggregated in the last step to decrease the loss of information. These features of the proposed approach have led to be powerful than the imprecise / precise decision methods. Finally, the presented practical example for the evaluation of energy policy candidates has showed the proposed approach's implementation step by step, and ranking results of the proposed approach has been compared with a decision method from the recent literature. For future directions, considering the hierarchical structure for the criteria could improve the efficiency of the proposed approach. In addition, it can be tailored based on the interval-valued hesitant fuzzy sets that help experts to express their judgments by some interval-values for an element under a set to margin of errors.

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