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CODAS METHOD WITH PROBABILISTIC HESITANT FUZZY INFORMATION AND ITS APPLICATION TO ENVIRONMENTALLY AND ECONOMICALLY BALANCED SUPPLIER SELECTION

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Abstract. With the rise of the concept of environmental protection and the attention of all sectors of society to the ecological environment, the selection of green suppliers is a hot topic. In this paper, we develop the combinative distance-based assessment (CODAS) method in the probabilistic hesitant fuzzy sets (PHFSs) to cope with the multiple attributes group decision making (MAGDM). A standardized approach that integrates multiple methods is applied to normalize the original data. Moreover, the statistics variance (SV) method is applied under PHFSs to calculate the objective weighting vector of evaluation criteria. In the end, a case for supplier selection and the comparative analysis are used to confirm the feasibility and utility of this new approach.

Keywords: multiple attributes group decision making (MAGDM), probabilistic hesitant fuzzy sets (PHFSs), CODAS method, supplier selection.

JEL Classification: C43, C61, D81.

Introduction

In a broad sense, a green supply chain refers to the management that requires suppliers to manage their products concerning the environment (Buyukozkan & Cifci, 2012). In addition, the principle of environmental protection is incorporated into the supplier management mechanism, to make their products more environmentally friendly and enhancing the competitiveness of the market (Mousavi et al., 2020). In practice, some enterprises put forward environment-oriented procurement plans, performance principles, or evaluation processes that all, or most suppliers follow (X. L. Wu et al., 2022). Others developed lists of substances that are harmful to the environment and require suppliers to use materials,

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packaging or emissions that do not include such items. Therefore, the selection of green supplier or supplier selection is being an important research topic (H. C. Liao et al., 2020; Ning et al., 2022). The issues of the selection of the green supplier are researched by MADM method (Chatterjee et al., 2018; Wei et al., 2022). For instance, the TODIM method (Gomes & Rangel, 2009; D. Zhang et al., 2022; Zhao et al., 2022), QUALIFLEX method (He et al., 2021; Paelinck, 1978), MOORA method (Liou et al., 2019; Tavana et al., 2021), EDAS method (Keshavarz Ghorabaee et al., 2015; Lei et al., 2022; Su et al., 2022), MABAC method (Jiang et al., 2022; Pamucar & Cirovic, 2015; Zhao et al., 2021), grey relational projection (GRP) method (Wang et al., 2022; Zheng et al., 2010), grey relational analysis (GRA)(H. Zhang et al., 2022), TOPSIS method (Lai et al., 1994; H. Y. Zhang et al., 2022), ELECTRE method (Gegovska et al., 2020; Gitinavard et al., 2018; Qu et al., 2020), the Combined Compromise Solution (CoCoSo) method (Popović, 2021), the simultaneous evaluation of criteria and alternatives (SECA) method (Keshavarz-Ghorabaee et al., 2018), the Copeland method (Özdağoğlu et al., 2021) and so on are applied in different circumstances to solve the green supplier selection problems. Compared to other methods, CODAS method was introduced by Keshavarz Ghorabaee, Zavadskas, Turskis, and Antucheviciene (2016) used the Euclidean distance as the preferred and the Taxicab distance as the second measure. The following is a review of the literature on the application of CODAS method (see Table 1).

According to the literature in the above form, the case study of the green supplier selection using the CODAS method under PHFs hasn't been studied. Thus, we propose the CODAS method under PHFs to solve the MAGDM for green supplier selection. The main contributions of this paper are listed below: (i) the PHF-CODAS method is built for MAGDM issues. (ii) the SV method under PHFs is applied to obtain the weight among criteria. (iii) the Manhattan distance is introduced under PHFs. The writing process of the whole article is as follows. Section 1 introduces the basic concepts and in Section 2 introduces the CODAS method for MAGDM under PHFSs. In Section 3, the newly proposed method is applied in the selection of green suppliers. In Section 4, the comparison with other methods are proposed. Finally, we analyze the shortcoming of this method and the expectation of its application.

Table 1. The pertinent literature of CODAS method under the fuzzy circumstance

Literature	The sets	Case study
Keshavarz Ghorabaee et al. (2017)	Fuzzy Sets (FSs)	market segment selection
Bolturk (2018)	Pythagorean FSs (PFSs)	supplier selection in a manufacturing firm
Bolturk and Kahraman (2018)	Interval-Valued Intuitionistic Fuzzy Sets	wave energy facility location selection
Peng and Garg (2018)	Interval-Valued Fuzzy Soft Sets	emergency decision making
Bolturk and Kahraman (2019)	Interval-Valued Pythagorean Fuzzy Sets	AS/RS technology selection
Karasan et al. (2019)	Interval-Valued Hesitant Fuzzy Sets	Residential construction site selection
Sansabas-Villalpando et al. (2019)	Hesitant Fuzzy Linguistic Term Sets	appraise organizational culture
Lei et al. (2021)	Probabilistic double hierarchy linguistic sets	online shopping platform evaluation

1. Preliminary knowledge

1.1. Probabilistic hesitant fuzzy sets

Definition 1 (Xu & Zhou, 2017)**.** Let Y be a fixed set, and then the PHFS M on Y is defined as the following equations:

$$M_y = \{m_y(q_y^n \mid l_y^n) \mid q_y^n, l_y^n\}, \tag{1}$$

where the function $m_y(q_y^n \mid l_y^n) = \{q_y^n(l_y^n)\}$ which is denoted as $q_y^n(l_y^n)$ to represent the set of probabilistic hesitant fuzzy elements (PHFE), $q_y^n \in R$, $0 \le q_y^n \le 1$,$0 \le l_y^n \le 1, n = 1,2,\cdots \# m$, and $\# m$ is the value of the elements, q_y^n shows the possible membership degrees of the elements, l_y^n is the number of the possibility possible membership degrees, $\sum_{n=1}^{\# m} l_y^n = 1$.

To obtain the same minimum or maximum membership degree in $q^n(l^n)$, Li, Niu, Chen, and Wu (2020) gave a new normalized method which are developed as follows.

Definition 2 (Li, Niu, et al., 2020)**.** Let $m_y(q_y^n \mid l_y^n) = \{q_y^n(l_y^n)\}$ be the PHFEs, where q_y^n is the $n-th$ smallest element in $q_y^n(l_y^n)$. Let $d = \max(\# m_y)$, if $d = \# m_y$, then preliminary form of standardization is equal to the ordinary one. If $d \ne \# m_y$, then the following is the standardizing process:

1. if DM is a risk-seeker, then we have:

$$q_y^n(l_y^n) = \left\{ \underbrace{q_y^1(l_y^1), \cdots q_y^{\# m-1}(l_y^{\# m-1})}_{\# m-1}, \underbrace{q_y^{\# m}\left(\frac{l_y^{\# m}}{d - \# m + 1}\right)}_{d-\# m+1} \right\}, \tag{2}$$

2. if DM is a risk-averter, then we have:

$$q_y^n(l_y^n) = \left\{ \underbrace{q_y^1\left(\frac{l_y^1}{d - \# m + 1}\right)}_{d-\# m+1}, \underbrace{q_y^2(l_y^2), \cdots q_y^{\# m}(l_y^{\# m})}_{\# m-1} \right\}, \tag{3}$$

3. if DM is risk-neutral, then we have:

when $\# m$ is even:

$$q_y^n(l_y^n) = \left\{ \underbrace{q_y^1(l_y^1), q_y^{\frac{\# m}{2}}(l_y^{\frac{\# m}{2}})}_{\frac{\# m}{2}}, \underbrace{q_y^{\frac{\# m+2}{2}}\left(\frac{l_y^{\frac{\# m+2}{2}}}{d - \# m + 1}\right)}_{d-\# m+1}, \underbrace{q_y^{\frac{2d-\# m+4}{2}}(l_y^{\frac{2d-\# m+4}{2}}), \cdots q_y^{\# m}(l_y^{\# m})}_{\frac{\# m-2}{2}} \right\}, \tag{4}$$

when $\# m$ is odd:

$$q_y^n(l_y^n) = \left\{ \underbrace{q_y^1(l_y^1), q_y^{\frac{\# m-1}{2}}(l_y^{\frac{\# m-1}{2}})}_{\frac{\# m-1}{2}}, \underbrace{q_y^{\frac{\# m+1}{2}}\left(\frac{l_y^{\frac{\# m+1}{2}}}{d - \# m + 1}\right)}_{d-\# m+1}, \underbrace{q_y^{\frac{2d-\# m+3}{2}}(l_y^{\frac{2d-\# m+3}{2}}), \cdots q_y^{\# m}(l_y^{\# m})}_{\frac{\# m-1}{2}} \right\}. \tag{5}$$

After the above initial standardization, there are some limitations that the calculation between the probabilities when multiplying two elements. Then we use the normalization method (Li, Chen, et al., 2020).

Definition 3 (Li, Chen, et al., 2020). Let $m_y(q_y^n \mid l_y^n) = \{q_y^n(l_y^n)\}$, $m_1(q_1^a \mid l_1^a) = \{q_1^a(l_1^a)\}$ and $f_2(q_2^b \mid l_2^b) = \{q_2^b(l_2^b)\}$ be three PHFEs respectively, $n = 1,2,\cdots,\#m$, $a = 1,2,\cdots,\#m_1$, $b = 1,2,\cdots,\#m_2$, then the ultima normalization process is defined as:

Step 1. If $l_1^1 < l_2^1$, then $q_1^1(l_1^1) = q_1^1(l_1^1)$ and $q_2^1(l_2^1) = q_2^1(l_2^1)$, otherwise, $q_1^1(l_1^1) = q_1^1(l_2^1)$ and $q_2^1(l_2^1) = q_2^1(l_2^1)$.

Step 2. If $l_1^1 < l_2^1$ and $l_2^1 - l_1^1 \le l_1^2$, then $q_1^2(l_1^2) = q_1^2(l_2^1 - l_1^1)$ and $q_2^2(l_2^2) = q_2^1(l_2^1 - l_1^1)$. If $l_1^1 < l_2^1$ and $l_2^1 - l_1^1 > l_1^2$, then $q_1^2(l_1^2) = q_1^2(l_1^2)$ and $q_2^2(l_2^2) = q_2^1(l_1^2)$. If $l_1^1 \ge l_2^1$ and $l_1^1 - l_2^1 \le l_2^2$, then $q_1^2(l_1^2) = q_1^1(l_1^1 - l_2^1)$ and $q_2^2(l_2^2) = q_2^2(l_1^1 - l_2^1)$. If $l_1^1 \ge l_2^1$ and $l_1^1 - l_2^1 > l_2^2$, then $q_1^2(l_1^2) = q_1^1(l_2^2)$ and $q_2^2(l_2^2) = q_2^2(l_2^2)$.

Step 3. If $l_1^1 \ge l_2^1$, $l_1^1 - l_2^1 \le l_2^2$ and $l_2^1 \le l_2^2 - l_1^1 + l_2^1$, then $q_1^3(l_1^3) = q_1^2(l_1^2)$ and $q_2^3(l_2^3) = q_2^2(l_1^2)$. If $l_1^1 \ge l_2^1$, $l_1^1 - l_2^1 \le l_2^2$ and $l_2^1 > l_2^2 - l_1^1 + l_2^1$, then $q_1^3(l_1^3) = q_1^2(l_2^2 + l_2^1 - l_1^1)$ and $q_2^3(l_2^3) = q_2^2(l_2^2 + l_2^1 - l_1^1)$. If $l_1^1 \ge l_2^1$, $l_1^1 - l_2^1 > l_2^2$ and $l_1^2 \ge l_2^2 + l_2^3$, then $q_1^3(l_1^3) = q_1^2(l_2^3)$ and $q_2^3(l_2^3) = q_2^3(l_2^3)$. If $l_1^1 \ge l_2^1$, $l_1^1 - l_2^1 > l_2^2$ and $l_1^2 < l_2^2 + l_2^3$, then $q_1^3(l_1^3) = q_1^2(l_1^2 - l_2^2)$ and $q_2^3(l_2^3) = q_2^3(l_1^2 - l_2^2)$. If $l_1^1 < l_2^1$, $l_2^1 - l_1^1 \le l_1^2$ and $l_1^2 + l_1^1 \le l_2^2 + l_2^1$, then $q_1^3(l_1^3) = q_1^2(l_1^2 - l_2^1 + l_1^1)$ and $q_2^3(l_2^3) = q_2^2(l_1^2 - l_2^1 + l_1^1)$. If $l_1^1 < l_2^1$, $l_2^1 - l_1^1 > l_1^2$ and $l_2^1 + l_1^2 \le l_1^3 + l_1^1$, then $q_1^3(l_1^3) = q_1^3(l_2^1 - l_1^1 - l_1^2)$ and $q_2^3(l_2^3) = q_2^1(l_2^1 - l_1^1 - l_1^2)$. If $l_1^1 < l_2^1$, $l_2^1 - l_1^1 > l_1^2$ and $l_2^1 + l_1^2 > l_1^3 + l_1^1$, then $q_1^3(l_1^3) = q_1^3(l_1^3)$ and $q_2^3(l_2^3) = q_2^1(l_1^3)$,

where $l_1^1 + l_1^2 + \cdots l_1^{\#a} = 1$ and $l_2^1 + l_2^2 + \cdots l_2^{\#b} = 1$, $\#a = \#b$.

Definition 4 (Xu & Zhou, 2017). The score function of the normalized $m_y(\bar{l}_y^n) = \{\bar{q}_y^n(\bar{l}_y^n)\}$ is obtained:

$$s(\bar{m}_y(\bar{l}_y^n)) = \sum_{n=1}^{\#m} \bar{q}_y^n \bar{l}_y^n, \tag{6}$$

where $\#m$ denotes the number of the diverse membership degrees, $\bar{q}_y^n$ is the $n-th$ largest elements, $\bar{l}_y^n$ denotes the probability of the $n-th$ largest membership degree.

Definition 5 (Xu & Zhou, 2017). For a normalized PHFE $\bar{m}_y(\bar{l}_y^n) = \{\bar{q}_y^n(\bar{l}_y^n)\}$, the deviation degree is obtained by Eq. (7)

$$d(\bar{q}_y^n(\bar{l}_y^n)) = \sum_{n=1}^{\#m} \bar{l}_y^n [\bar{q}_y^n - s(\bar{q}_y^n(\bar{l}_y^n))]^2. \tag{7}$$

Definition 6 (Sha et al., 2021). Compare two elements $\bar{m}_1(\bar{l}_1^a) = \{\bar{q}_1^a(\bar{l}_1^a)\}$ and $\bar{m}_2(\bar{l}_2^b) = \{\bar{q}_2^b(\bar{l}_2^b)\}$:

(1) $\bar{q}_1^a(\bar{g}_1^a) > \bar{q}_2^b(\bar{l}_2^b)$, if $s(\bar{q}_1^a(\bar{l}_1^a)) > s(\bar{q}_2^b(\bar{l}_2^b))$;

(2) $\bar{q}_1^a(\bar{l}_1^a) > \bar{q}_2^b(\bar{l}_2^b)$, if $s(\bar{q}_1^a(\bar{l}_1^a)) > s(\bar{q}_2^b(\bar{l}_2^b))$ and $d(\bar{q}_1^a(\bar{l}_1^a)) > d(\bar{q}_2^b(\bar{l}_2^b))$;

(3) $\bar{q}_1^a(\bar{l}_1^a) = \bar{q}_2^b(\bar{l}_2^b)$, if $s(\bar{q}_1^a(\bar{l}_1^a)) = s(\bar{q}_2^b(\bar{l}_2^b))$ and $d(\bar{q}_1^a(\bar{l}_1^a)) = d(\bar{q}_2^b(\bar{l}_2^b))$;

(4) $\bar{q}_1^a(\bar{l}_1^a) < \bar{q}_2^b(\bar{l}_2^b)$, if $s(\bar{q}_1^a(\bar{l}_1^a)) = s(\bar{q}_2^b(\bar{l}_2^b))$ and $d(\bar{q}_1^a(\bar{l}_1^a)) > d(\bar{q}_2^b(\bar{l}_2^b))$.

Definition 7 (Li, Chen, et al., 2020). Let $\bar{m}(\bar{l}^n) = \{\bar{q}(\bar{l}^n)\}$, $\bar{m}_1(\bar{l}_1^a) = \{\bar{q}_1^a(\bar{l}_1^a)\}$ and $\bar{m}_2(\bar{l}_2^b) = \{\bar{q}_2^b(\bar{l}_2^b)\}$ be two normalized PHFEs, $\#\bar{m}_1 = \#\bar{m}_2 = \#m$ and $\bar{l}_1^a = \bar{l}_2^b = \bar{l}^n$.

(1) $\bar{m}_1^a(\bar{l}_1^a) \oplus \bar{m}_2^b(\bar{g}_2^b) = \cup_{a=1,\cdots,\#\bar{m}_1, b=1,\cdots,\#\bar{m}_2} \{(\bar{q}_1^a + \bar{q}_2^b - \bar{q}_1^a \bar{q}_2^b) \mid \bar{l}^n\}$; (8)

(2) $\bar{m}_1^a(\bar{l}_1^a)\otimes\bar{m}_2^b(\bar{l}_2^b)=\cup_{a=1,\cdots,\#\bar{m}_1,b=1,\cdots,\#\bar{m}_2}\{\bar{q}_1^a\bar{q}_2^b \mid \bar{l}^n\}$; (9)

(3) $(\bar{m})^\lambda=\cup_{n=1,2,\cdots,\#m}\{(\bar{q})^\lambda \mid \bar{l}^n\}$; (10)

(4) $\lambda\bar{m}=\cup_{n=1,2,\cdots,\#m}\{1-(1-\bar{q})^\lambda \mid \bar{l}^n\}$. (11)

Definition 8 (N. Liao et al., 2021, 2022)**.** The probabilistic hesitant fuzzy weighted averaging (PHFWA) operator is defined:

$$PHFWA(\bar{m}_1(\bar{l}_1^a),\bar{m}_2(\bar{l}_2^b),\cdots,\bar{m}_f(\bar{l}_f^n))=\mathop{\oplus}_{e=1}^{f}(\bar{m}_e t_e)=\bigcup_{\bar{q}_1\in\bar{m}_1,\bar{q}_2\in\bar{m}_2,\cdots,\bar{q}_f\in\bar{m}_f}\{1-\prod_{e=1}^{f}(1-\bar{q}_e)^{t_e}(\bar{l}^n)\}, \tag{12}$$

where $t_e=(t_1,t_2,\cdots,t_f)$ is the weight vector of the $\bar{m}_e$, and $\sum_{e=1}^{f}t_e=1$, $t_e\in[0,1]$.

Definition 9 (N. Liao et al., 2021, 2022)**.** The probabilistic hesitant fuzzy weighted geometric (PHFWG) operator is defined.

$$PHFWG=(\bar{m}_1(\bar{l}_1^a),\bar{m}_2(\bar{l}_2^b),\cdots,\bar{m}_f(\bar{l}_f^n))=\mathop{\oplus}_{e=1}^{f}(\bar{m}_e)^{t_e}=\bigcup_{\bar{q}_1\in\bar{m}_1,\bar{q}_2\in\bar{m}_2,\cdots,\bar{q}_f\in\bar{m}_f}\{\prod_{e=1}^{f}(\bar{q}_e)^{t_e}(\bar{l}^n)\}. \tag{13}$$

1.2. Obtain the weights among the attributes

This section, inspired by Liu et al. (2016) , the SV method under PHFSs is used to obtain the objective weights. According to the study (Liu et al., 2016), the PHF-SV method is as follows.

The SV method is defined to calculate the dispersion of every data between the mean value:

$$R_t=\frac{1}{y}\sum_{r=1}^{x}(s(m_{rt})-s(\bar{m}_{rt}))^2,\quad t=1,2,\cdots,y, \tag{14}$$

where $\bar{m}_{rt}$ denotes the average value of the PHEFs. And the weight calculating formula is shown:

$$e_t=\frac{R_t}{\sum_{t=1}^{y}R_t}. \tag{15}$$

1.3. The Euclidean and Taxicab distance for normalized PHFEs

The Euclidean distance (Li, Niu, et al., 2020) was represented by the following equation:

$$D(m_a(l_a),m_b(l_b))=\frac{1}{2}(\sqrt{\frac{1}{\#m}\sum_{n=1}^{\#m}(q_a^n l_a^n-q_b^n l_b^n)^2}+\sqrt{\frac{1}{\#m}\sum_{n=1}^{\#m}(q_a^n-q_b^n)^2 l_a^n l_b^n}). \tag{16}$$

For the normalized PHFEs has the same probabilities which mean that $l_a^n=l_b^n$ (Li, Chen, et al., 2020), the Euclidean distance could be simplified as the following form:

$$D(m_a(l_a),m_b(l_b))=\sqrt{\frac{1}{\#m}\sum_{n=1}^{\#m}(q_a^n-q_b^n)^2\hat{l}^n}\quad \hat{l}_a^n=\hat{l}_a^n=\hat{l}^n. \tag{17}$$

Taxicab distance which is also called Manhattan distance, is coined by Hermann Minkowski in the 19th century. It is a geometrical term used in geometric metric spaces to indicate the absolute wheelbase sum of two points in standard coordinates. Inspired by the extension of the Manhattan distance (Mansouri & Leghris, 2019) in the fuzzy environment We develop the Manhattan distance under PHFSs:

$$d(m_a(l_a), m_b(l_b)) = \sum_{n=1}^{\#m} | q_a^n l_a^n - q_b^n l_b^n |. \tag{18}$$

The normalization form is as follows:

$$d(m_a(l_a), m_b(l_b)) = \sum_{n=1}^{\#m} | \hat{q}_a^n - \hat{q}_b^n | \hat{l}^n,\ \hat{l}_a^n = \hat{l}_a^n = \hat{l}^n. \tag{19}$$

2. CODAS method for probabilistic hesitant fuzzy MAGDM

Set the MAGDM decision matrices be $M^k = [m_{rt}^k(l_{rt})]_{x \times y}$, where $U_r = \{U_1, U_2, \cdots U_x\}$ represents the alternatives, the attributes are represented as $Q_t = \{Q_1, Q_2, \cdots Q_y\}$, and $k = \{k_1, k_2, \cdots k_c\}$ is denoted as the set of DMs. Meanwhile, the weighting of the DMs is $h_k, \sum_{k=1}^{c} h_k = 1, (k = 1, 2, \cdots c)$. Moreover, the weights for $e_t = \{e_1, e_2, \cdots e_y\}$ are totally unknown. The concrete steps of MAGDM under PHSs by using extended CODAS method are given.

Step 1. Normalize decision matrices

The negative criterion is turned into a positive criterion by Eq. (20):

$$\begin{cases} \bar{m}_{rt}(\bar{l}_{rt}) = \{q_{rt}(l_{rt})\} & \text{if the attribute is the positive attribute} \\ \bar{m}_{rt}(\bar{l}_{rt}) = \{(1 - q_{rt})(l_{rt})\} & \text{if the attribute is the negative attribute} \end{cases}. \tag{20}$$

Suppose the experts are all risk-seeker, then the decision matrices are standardized by Definition 2–3.

Step 2. Obtain the integration of the decision matrices

The different DMs' decision matrices are integrated into one overall matrix $\hat{m}_{rt}(\hat{l}_{rt}) = \{\hat{q}_{rt}(\hat{l}_{rt})\}_{x \times y}$ through PHFWA by Eq. (21):

$$PHFWA(\bar{M}_{rt}^1, \bar{M}_{rt}^2, \cdots, \bar{M}_{rt}^c) = \mathop{\oplus}_{k=1}^{c} (\bar{M}_{rt}^k h_k) = \bigcup_{\bar{q}_{rt}^1 \in \bar{m}_{rt}^1, \bar{q}_{rt}^2 \in \bar{m}_{rt}^2, \cdots, \bar{q}_{rt}^c \in \bar{m}_{rt}^c} \{1 - \prod_{k=1}^{c} (1 - \bar{q}_{rt}^k)^{h_k} (\bar{l})\}. \tag{21}$$

Step 3. Calculate the weight among different criterions using Eq. (14) and (15).

Step 4. Construct the weighted normalized decision matrix by using the Eq. (22):

$$\tilde{m}_{rt}(\tilde{l}_{rt}) = \{\hat{e}_t \hat{q}_{rt} \mid \hat{l}_{rt}\}. \tag{22}$$

Step 5. Obtain the score matrix.

$$s(\tilde{m}_{rt}(\tilde{l}_{rt})) = \sum_{n=1}^{\#m} \tilde{q}_{rt}^n \tilde{l}_{rt}^n. \tag{23}$$

Step 6. Determine the negative ideal point (NIP) of each alternative by Eq. (24):

$$\tilde{m}_t^-(\tilde{l}_t) = \min_r s(\tilde{m}_{rt}(\tilde{l}_{rt})). \tag{24}$$

Step 7. Calculate the Euclidean (Li, Chen, et al., 2020) and Taxicab distance of alternatives from NIP by Eq. (25) and (26):

$$D_r = \sqrt{\sum_{t=1}^{y} \frac{1}{\#m} \sum_{n=1}^{\#m} (\tilde{q}_{rt}^{n} - \tilde{q}_{t}^{n-})^{2} \tilde{l}^{n}}, \quad r = 1,2,\cdots,x; \tag{25}$$

$$d_r = \sum_{t=1}^{y} \sum_{n=1}^{\#m} |\tilde{q}_{rt}^{n} - \tilde{q}_{t}^{n-}| \tilde{l}^{n}, \quad r = 1,2,\cdots,x. \tag{26}$$

Step 8. Determine the relative evaluation matrix by Eq. (27):

$$\breve{m}_{rk} = (D_r - D_k) + (\varphi(D_r - D_k) \times (d_r - d_k)), r,k = 1,2,\cdots,x., \tag{27}$$

where $k \in \{1,2,\cdots x\}$, $\varphi(\theta)$ represents the threshold function which is defined:

$$\varphi(\theta) = \begin{cases} 1 & \text{if } |\theta| \geq \tau \\ 0 & \text{if } |\theta| < \tau \end{cases}, \tag{28}$$

where τ is a threshold parameter which is in range 0.01 to 0.05 and the meaning is when the gap of two alternatives is less than τ (we define $\tau = 0.03$ here), then we also compare by Manhattan distance.

Step 9. Calculate the evaluation score of each alternative through Eq. (29):

$$V_r = \sum_{k=1}^{x} \breve{m}_{rk}, \; r = 1,2,\cdots,x. \tag{29}$$

Step 10. Rank the alternatives using the value of the evaluation score.

3. Numerical example

The evaluation of green supply chain management is not only a behavior with significant environmental benefits, but also an effective means for suppliers to obtain significant social and economic benefits. Implementing the environmental assessment of the green supply process can maximize the utilization rate of resources, reduce the consumption of resources, and reduce the manufacturing cost. At the same time, the implementation of green supply process environmental assessment can reduce and avoid the fines caused by environmental problems, reduce unnecessary expenses. Therefore, environmental assessment of the green supply chain is a strategic management decision, which benefits the manufacturer from both economic and social aspects and environmental aspects. The green decision of product supply chain involves many factors, such as Q_1 technology, Q_2 economy, Q_3 enterprise quality, Q_4 enterprise strength, Q_5 environment and Q_6 product characteristics. Moreover, the weight of three decision-makers is $D_c = (0.2, 0.35, 0.45)$. Tables 2–4 show the decision matrix by three DMs under PHFs.

Table 2. Decision matrix K_1 given by the first expert

Alternative	Q_1	Q_2	Q_3
U_1	{0.3(0.1),0.5(0.2),0.6(0.7)}	{0.5(0.5),0.6(0.5)}	{0.5(0.3),0.2(0.1),0.4(0.6)}
U_2	{0.4(0.5),0.5(0.5)}	{0.2(0.1),0.4(0.5),0.3(0.4)}	{0.3(0.6),0.4(0.4)}
U_3	{0.2(0.3),0.4(0.6),0.5(0.1)}	{0.1(0.7),0.4(0.3)}	{0.2(0.4),0.3(0.6)}
U_4	{0.4(0.4),0.2(0.6)}	{0.6(0.1),0.3(0.7),0.2(0.2)}	{0.2(0.2),0.1(0.3),0.5(0.5)}
U_5	{0.3(1)}	{0.3(0.2),0.2(0.8)}	{0.1(0.4),0.4(0.5),0.5(0.1)}
Alternative	Q_4	Q_5	Q_6
U_1	{0.5(0.4),0.2(0.2),0.6(0.4)}	{0.5(0.6),0.4(0.4)}	{0.5(0.6),0.6(0.4)}
U_2	{0.5(0.3),0.3(0.5),0.4(0.2)}	{0.3(0.4),0.4(0.4),0.5(0.2)}	{0.3(0.2),0.5(0.8)}
U_3	{0.3(0.2),0.2(0.8)}	{0.2(0.3),0.3(0.4),0.4(0.3)}	{0.1(0.4),0.5(0.2),0.3(0.4)}
U_4	{0.2(0.4),0.3(0.3),0.4(0.3)}	{0.3(0.4),0.4(0.2),0.5(0.4)}	{0.4(0.5),0.3(0.5)}
U_5	{0.2(0.2),0.3(0.3),0.5(0.5)}	{0.3(0.3),0.4(0.4),0.1(0.3)}	{0.2(0.4),0.4(0.5),0.3(0.1)}

Table 3. Decision matrix K_2 given by the second expert

Alternative	Q_1	Q_2	Q_3
U_1	{0.6(0.2),0.4(0.7),0.5(0.1)}	{0.3(0.5),0.6(0.5)}	{0.3(0.5),0.8(0.2),0.4(0.3)}
U_2	{0.4(0.5),0.3(0.5)}	{0.1(0.6),0.5(0.4)}	{0.2(0.8),0.8(0.2)}
U_3	{0.3(0.2),0.4(0.6),0.1(0.2)}	{0.7(0.2),0.3(0.8)}	{0.4(0.4),0.2(0.3),0.5(0.3)}
U_4	{0.4(0.4),0.1(0.4),0.3(0.2)}	{0.4(1)}	{0.3(0.3),0.6(0.2),0.2(0.5)}
U_5	{0.1(0.2),0.3(0.4),0.5(0.4)}	{0.2(0.3),0.3(0.6),0.4(0.1)}	{0.1(0.5),0.4(0.5)}
Alternative	Q_4	Q_5	Q_6
U_1	{0.3(0.1),0.5(0.5),0.4(0.4)}	{0.4(0.5),0.5(0.5)}	{0.5(1)}
U_2	{0.2(0.5),0.4(0.5)}	{0.3(0.5),0.4(0.3),0.2(0.2)}	{0.3(0.5),0.4(0.2),0.5(0.3)}
U_3	{0.3(0.4),0.7(0.1),0.1(0.5)}	{0.5(0.4),0.3(0.3),0.4(0.3)}	{0.4(0.6),0.2(0.4)}
U_4	{0.5(0.2),0.4(0.1),0.3(0.7)}	{0.3(0.6),0.4(0.4)}	{0.6(0.3),0.3(0.7)}
U_5	{0.2(1)}	{0.1(0.4),0.6(0.6)}	{0.2(0.1),0.3(0.4),0.4(0.5)}

Table 4. Decision matrix K_3 given by the third expert

Alternative	Q_1	Q_2	Q_3
U_1	{0.6(0.4),0.4(0.6)}	{0.6(0.2),0.5(0.5),0.4(0.3)}	{0.5(0.7),0.6(0.3)}
U_2	{0.4(0.2),0.3(0.8)}	{0.3(0.4),0.2(0.5),0.4(0.1)}	{0.2(0.5),0.4(0.5)}
U_3	{0.2(0.3),0.1(05),0.4(0.2)}	{0.4(0.4),0.5(0.1),0.3(0.5)}	{0.6(0.3),0.3(0.6),0.1(0.1)}
U_4	{0.3(1)}	{0.2(0.4),0.3(0.5),0.4(0.1)}	{0.3(0.1),0.4(0.3),0.5(0.6)}
U_5	{0.4(0.1),0.3(0.7),0.4(0.2)}	{0.3(1)}	{0.3(1)}

End of Table 4

Alternative	Q_4	Q_5	Q_6
U_1	{0.6(0.3),0.4(0.3),0.5(0.4)}	{0.7(0.1),0.6(0.5),0.5(0.4)}	{0.5(0.1),0.7(0.7),0.3(0.2)}
U_2	{0.4(0.4),0.5(0.1),0.3(0.5)}	{0.3(0.2),0.5(0.5),0.4(0.3)}	{0.2(0.5),0.4(0.3),0.5(0.2)}
U_3	{0.5(0.3),0.7(0.2),0.2(0.5)}	{0.3(0.7),0.6(0.3)}	{0.4(0.3),0.3(0.5),0.6(0.2)}
U_4	{0.3(0.5),0.4(0.4),0.5(0.1)}	{0.5(0.2),0.4(0.8)}	{0.4(0.1),0.3(0.4),0.5(05)}
U_5	{0.4(0.5),0.2(0.5)}	{0.2(0.3),0.3(0.7)}	{0.1(0.4),0.5(0.3),0.6(0.3)}

Step 1. Obtain the normalized matrix in Table 5 to 7.

Table 5. Normalized decision matrix K_1 given by the first expert

Alternative	Q_1	Q_2
U_1	{0.3(0.1), 0.5(0.2), 0.6(0.2), 0.6(0.15), 0.6(0.15), 0.6(0.1), 0.6(0.1)}	{0.5(0.1), 0.5(0.2), 0.5(0.2), 0.6(0.15), 0.6(0.15), 0.6(0.1), 0.6(0.1)}
U_2	{0.4(0.1), 0.4(0.2), 0.4(0.2), 0.5(0.15), 0.5(0.15), 0.5(0.1), 0.5(0.1)}	{0.2(0.1), 0.4(0.2), 0.4(0.2), 0.3(0.15), 0.3(0.15), 0.3(0.1), 0.5(0.1)}
U_3	{0.2(0.1), 0.2(0.2), 0.4(0.2), 0.4(0.15), 0.4(0.15), 0.5(0.1), 0.4(0.1)}	{0.1(0.1), 0.1(0.2), 0.1(0.2), 0.4(0.15), 0.4(0.15), 0.1(0.1), 0.1(0.1)}
U_4	{0.4(0.1), 0.2(0.2), 0.2(0.2), 0.2(0.15), 0.2(0.15), 0.4(0.1), 0.2(0.1)}	{0.6(0.1), 0.3(0.2), 0.3(0.2), 0.3(0.15), 0.3(0.15), 0.2(0.1), 0.2(0.1)}
U_5	{0.3(0.1), 0.3(0.2), 0.3(0.2), 0.3(0.15), 0.3(0.15), 0.3(0.1), 0.3(0.1)}	{0.3(0.1), 0.2(0.2), 0.2(0.2), 0.2(0.15), 0.2(0.15), 0.2(0.1), 0.3(0.1)}
Alternative	Q_3	Q_4
U_1	{0.5(0.1), 0.5(0.2), 0.4(0.2), 0.4(0.15), 0.4(0.15), 0.4(0.1), 0.2(0.1)}	{0.2(0.1), 0.5(0.2), 0.5(0.2), 0.6(0.15), 0.6(0.15), 0.6(0.1), 0.2(0.1)}
U_2	{0.3(0.1), 0.4(0.2), 0.4(0.2), 0.3(0.15), 0.3(0.15), 0.3(0.1), 0.3(0.1)}	{0.5(0.1), 0.5(0.2), 0.4(0.2), 0.3(0.15), 0.3(0.15), 0.3(0.1), 0.3(0.1)}
U_3	{0.3(0.1), 0.2(0.2), 0.2(0.2), 0.3(0.15), 0.3(0.15), 0.3(0.1), 0.3(0.1)}	{0.3(0.1), 0.2(0.2), 0.2(0.2), 0.2(0.15), 0.2(0.15), 0.2(0.1), 0.3(0.1)}
U_4	{0.1(0.1), 0.1(0.2), 0.2(0.2), 0.5(0.15), 0.5(0.15), 0.5(0.1), 0.5(0.1)}	{0.3(0.1), 0.3(0.2), 0.2(0.2), 0.4(0.15), 0.4(0.15), 0.2(0.1), 0.2(0.1)}
U_5	{0.5(0.1), 0.1(0.2), 0.1(0.2), 0.4(0.15), 0.4(0.15), 0.4(0.1), 0.4(0.1)}	{0.3(0.1), 0.3(0.2), 0.2(0.2), 0.5(0.15), 0.5(0.15), 0.5(0.1), 0.5(0.1)}
Alternative	Q_5	Q_6
U_1	{0.5(0.1), 0.5(0.2), 0.4(0.2), 0.5(0.15), 0.5(0.15), 0.4(0.1), 0.4(0.1)}	{0.5(0.1), 0.6(0.2), 0.6(0.2), 0.5(0.15), 0.5(0.15), 0.5(0.1), 0.5(0.1)}
U_2	{0.5(0.1), 0.3(0.2), 0.2(0.2), 0.4(0.15), 0.4(0.15), 0.4(0.1), 0.5(0.1)}	{0.3(0.1), 0.5(0.2), 0.5(0.2), 0.5(0.15), 0.5(0.15), 0.5(0.1), 0.3(0.1)}
U_3	{0.2(0.1), 0.2(0.2), 0.3(0.2), 0.4(0.15), 0.4(0.15), 0.3(0.1), 0.3(0.1)}	{0.5(0.1), 0.1(0.2), 0.1(0.2), 0.3(0.15), 0.3(0.15), 0.3(0.1), 0.5(0.1)}
U_4	{0.4(0.1), 0.3(0.2), 0.3(0.2), 0.5(0.15), 0.5(0.15), 0.5(0.1), 0.4(0.1)}	{0.3(0.1), 0.3(0.2), 0.3(0.2), 0.4(0.15), 0.4(0.15), 0.4(0.1), 0.4(0.1)}
U_5	{0.3(0.1), 0.3(0.2), 0.4(0.2), 0.1(0.15), 0.1(0.15), 0.4(0.1), 0.4(0.1)}	{0.3(0.1), 0.2(0.2), 0.2(0.2), 0.4(0.15), 0.4(0.15), 0.4(0.1), 0.4(0.1)}

Table 6. Normalized decision matrix K_2 given by the second expert

Alternative	Q_1	Q_2
U_1	{0.4(0.1), 0.6(0.2), 0.4(0.2), 0.4(0.15), 0.4(0.15), 0.5(0.1), 0.4(0.1)}	{0.3(0.1), 0.3(0.2), 0.3(0.2), 0.6(0.15), 0.6(0.15), 0.6(0.1), 0.6(0.1)}
U_2	{0.4(0.1), 0.3(0.2), 0.3(0.2), 0.4(0.15), 0.4(0.15), 0.3(0.1), 0.4(0.1)}	{0.1(0.1), 0.5(0.2), 0.5(0.2), 0.1(0.15), 0.1(0.15), 0.1(0.1), 0.4(0.1)}
U_3	{0.4(0.1), 0.3(0.2), 0.1(0.2), 0.4(0.15), 0.4(0.15), 0.4(0.1), 0.4(0.1)}	{0.7(0.1), 0.3(0.2), 0.3(0.2), 0.3(0.15), 0.3(0.15), 0.7(0.1), 0.3(0.1)}
U_4	{0.1(0.1), 0.3(0.2), 0.1(0.2), 0.4(0.15), 0.4(0.15), 0.1(0.1), 0.4(0.1)}	{0.4(0.1), 0.4(0.2), 0.4(0.2), 0.4(0.15), 0.4(0.15), 0.4(0.1), 0.4(0.1)}
U_5	{0.3(0.1), 0.1(0.2), 0.3(0.2), 0.5(0.15), 0.5(0.15), 0.3(0.1), 0.5(0.1)}	{0.2(0.1), 0.2(0.2), 0.3(0.2), 0.3(0.15), 0.3(0.15), 0.3(0.1), 0.4(0.1)}
Alternative	Q_3	Q_4
U_1	{0.8(0.1), 0.4(0.2), 0.4(0.2), 0.3(0.15), 0.3(0.15), 0.3(0.1), 0.3(0.1)}	{0.3(0.1), 0.4(0.2), 0.4(0.2), 0.5(0.15), 0.5(0.15), 0.5(0.1), 0.5(0.1)}
U_2	{0.8(0.1), 0.2(0.2), 0.2(0.2), 0.2(0.15), 0.2(0.15), 0.2(0.1), 0.8(0.1)}	{0.2(0.1), 0.2(0.2), 0.2(0.2), 0.4(0.15), 0.4(0.15), 0.4(0.1), 0.4(0.1)}
U_3	{0.2(0.1), 0.2(0.2), 0.4(0.2), 0.5(0.15), 0.5(0.15), 0.4(0.1), 0.4(0.1)}	{0.7(0.1), 0.3(0.2), 0.3(0.2), 0.1(0.15), 0.1(0.15), 0.1(0.1), 0.1(0.1)}
U_4	{0.3(0.1), 0.3(0.2), 0.6(0.2), 0.2(0.15), 0.2(0.15), 0.2(0.1), 0.2(0.1)}	{0.4(0.1), 0.5(0.2), 0.3(0.2), 0.3(0.15), 0.3(0.15), 0.3(0.1), 0.3(0.1)}
U_5	{0.1(0.1), 0.1(0.2), 0.1(0.2), 0.4(0.15), 0.4(0.15), 0.4(0.1), 0.4(0.1)}	{0.2(0.1), 0.2(0.2), 0.2(0.2), 0.2(0.15), 0.2(0.15), 0.2(0.1), 0.2(0.1)}
Alternative	Q_5	Q_6
U_1	{0.4(0.1), 0.4(0.2), 0.4(0.2), 0.5(0.15), 0.5(0.15), 0.5(0.1), 0.4(0.1)}	{0.5(0.1), 0.5(0.2), 0.5(0.2), 0.5(0.15), 0.5(0.15), 0.5(0.1), 0.5(0.1)}
U_2	{0.3(0.1), 0.3(0.2), 0.3(0.2), 0.4(0.15), 0.4(0.15), 0.2(0.1), 0.2(0.1)}	{0.5(0.1), 0.5(0.2), 0.4(0.2), 0.3(0.15), 0.3(0.15), 0.3(0.1), 0.3(0.1)}
U_3	{0.3(0.1), 0.3(0.2), 0.5(0.2), 0.4(0.15), 0.4(0.15), 0.5(0.1), 0.5(0.1)}	{0.4(0.1), 0.4(0.2), 0.2(0.2), 0.4(0.15), 0.4(0.15), 0.2(0.1), 0.2(0.1)}
U_4	{0.3(0.1), 0.4(0.2), 0.4(0.2), 0.3(0.15), 0.3(0.15), 0.3(0.1), 0.3(0.1)}	{0.3(0.1), 0.3(0.2), 0.3(0.2), 0.6(0.15), 0.6(0.15), 0.3(0.1), 0.3(0.1)}
U_5	{0.6(0.1), 0.6(0.2), 0.1(0.2), 0.6(0.15), 0.1(0.15), 0.1(0.1), 0.1(0.1)}	{0.2(0.1), 0.3(0.2), 0.3(0.2), 0.4(0.15), 0.4(0.15), 0.4(0.1), 0.4(0.1)}

Table 7. Normalized decision matrix K_3 given by the third expert

Alternative	Q_1	Q_2
U_1	{0.6(0.1), 0.6(0.2), 0.4(0.2), 0.4(0.15), 0.4(0.15), 0.6(0.1), 0.4(0.1)}	{0.4(0.1), 0.4(0.2), 0.6(0.2), 0.5(0.15), 0.5(0.15), 0.5(0.1), 0.5(0.1)}
U_2	{0.4(0.1), 0.3(0.2), 0.3(0.2), 0.3(0.15), 0.3(0.15), 0.4(0.1), 0.3(0.1)}	{0.4(0.1), 0.3(0.2), 0.3(0.2), 0.2(0.15), 0.2(0.15), 0.2(0.1), 0.2(0.1)}
U_3	{0.2(0.1), 0.2(0.2), 0.4(0.2), 0.5(0.15), 0.5(0.15), 0.4(0.1), 0.5(0.1)}	{0.5(0.1), 0.4(0.2), 0.4(0.2), 0.3(0.15), 0.3(0.15), 0.3(0.1), 0.3(0.1)}
U_4	{0.3(0.1), 0.3(0.2), 0.3(0.2), 0.3(0.15), 0.3(0.15), 0.3(0.1), 0.3(0.1)}	{0.4(0.1), 0.2(0.2), 0.2(0.2), 0.3(0.15), 0.3(0.15), 0.3(0.1), 0.3(0.1)}
U_5	{0.4(0.1), 0.4(0.2), 0.3(0.2), 0.3(0.15), 0.3(0.15), 0.3(0.1), 0.3(0.1)}	{0.3(0.1), 0.3(0.2), 0.3(0.2), 0.3(0.15), 0.3(0.15), 0.3(0.1), 0.3(0.1) }

End of Table 7

Alternative	Q_3	Q_4
U_1	{0.5(0.1), 0.5(0.2), 0.5(0.2), 0.6(0.15), 0.6(0.15), 0.5(0.1), 0.5(0.1)}	{0.6(0.1), 0.6(0.2), 0.5(0.2), 0.4(0.15), 0.4(0.15), 0.5(0.1), 0.5(0.1)}
U_2	{0.2(0.1), 0.2(0.2), 0.2(0.2), 0.4(0.15), 0.4(0.15), 0.4(0.1), 0.4(0.1)}	{0.5(0.1), 0.4(0.2), 0.4(0.2), 0.3(0.15), 0.3(0.15), 0.3(0.1), 0.3(0.1)}
U_3	{0.6(0.1), 0.6(0.2), 0.3(0.2), 0.3(0.15), 0.3(0.15), 0.3(0.1), 0.1(0.1)}	{0.5(0.1), 0.5(0.2), 0.7(0.2), 0.2(0.15), 0.2(0.15), 0.2(0.1), 0.2(0.1)}
U_4	{0.4(0.1), 0.4(0.2), 0.5(0.2), 0.5(0.15), 0.5(0.15), 0.5(0.1), 0.3(0.1)}	{0.5(0.1), 0.4(0.2), 0.4(0.2), 0.3(0.15), 0.3(0.15), 0.3(0.1), 0.3(0.1)}
U_5	{0.3(0.1), 0.3(0.2), 0.3(0.2), 0.3(0.15), 0.3(0.15), 0.3(0.1), 0.3(0.1)}	{0.2(0.1), 0.2(0.2), 0.2(0.2), 0.4(0.15), 0.4(0.15), 0.4(0.1), 0.4(0.1)}
Alternative	Q_5	Q_6
U_1	{0.7(0.1), 0.5(0.2), 0.5(0.2), 0.6(0.15), 0.6(0.15), 0.6(0.1), 0.6(0.1)}	{0.5(0.1), 0.3(0.2), 0.7(0.2), 0.7(0.15), 0.7(0.15), 0.7(0.1), 0.7(0.1)}
U_2	{0.4(0.1), 0.4(0.2), 0.3(0.2), 0.5(0.15), 0.5(0.15), 0.5(0.1), 0.5(0.1)}	{0.4(0.1), 0.4(0.2), 0.5(0.2), 0.2(0.15), 0.2(0.15), 0.2(0.1), 0.2(0.1)}
U_3	{0.3(0.1), 0.3(0.2), 0.3(0.2), 0.6(0.15), 0.6(0.15), 0.3(0.1), 0.3(0.1)}	{0.4(0.1), 0.4(0.2), 0.6(0.2), 0.3(0.15), 0.3(0.15), 0.3(0.1), 0.3(0.1)}
U_4	{0.5(0.1), 0.4(0.2), 0.4(0.2), 0.4(0.15), 0.4(0.15), 0.4(0.1), 0.5(0.1)}	{0.4(0.1), 0.3(0.2), 0.3(0.2), 0.5(0.15), 0.5(0.15), 0.5(0.1), 0.5(0.1)}
U_5	{0.2(0.1), 0.2(0.2), 0.3(0.2), 0.3(0.15), 0.3(0.15), 0.3(0.1), 0.3(0.1)}	{0.5(0.1), 0.5(0.2), 0.1(0.2), 0.6(0.15), 0.6(0.15), 0.1(0.1), 0.1(0.1)}

Step 2. Obtain the integrated decision matrix in Table 8.

Table 8. Aggregated decision matrix

Alternative	Q_1	Q_2
U_1	{0.444(0.1), 0.572(0.2), 0.469(0.2), 0.469(0.15), 0.469(0.15), 0.563(0.1), 0.469(0.1)}	{0.396(0.1), 0.396(0.2), 0.465(0.2), 0.572(0.15), 0.572(0.15), 0.572(0.1), 0.572(0.1)}
U_2	{0.400(0.1), 0.332(0.2), 0.332(0.2), 0.405(0.15), 0.405(0.15), 0.396(0.1), 0.405(0.1)}	{0.231(0.1), 0.416(0.2), 0.416(0.2), 0.194(0.15), 0.194(0.15), 0.194(0.1), 0.381(0.1)}
U_3	{0.287(0.1), 0.242(0.2), 0.294(0.2), 0.432(0.15), 0.432(0.15), 0.432(0.1), 0.432(0.1)}	{0.514(0.1), 0.279(0.2), 0.279(0.2), 0.332(0.15), 0.332(0.15), 0.462(0.1), 0.245(0.1)}
U_4	{0.261(0.1), 0.271(0.2), 0.194(0.2), 0.315(0.15), 0.315(0.15), 0.261(0.1), 0.315(0.1)}	{0.469(0.1), 0.315(0.2), 0.315(0.2), 0.342(0.15), 0.342(0.15), 0.315(0.1), 0.315(0.1)}
U_5	{0.332(0.1), 0.261(0.2), 0.300(0.2), 0.388(0.15), 0.388(0.15), 0.300(0.1), 0.388(0.1)}	{0.262(0.1), 0.231(0.2), 0.271(0.2), 0.271(0.15), 0.271(0.15), 0.271(0.1), 0.342(0.1)}

End of Table 8

Alternative	Q_3	Q_4
U_1	{0.653(0.1), 0.462(0.2), 0.432(0.2), 0.435(0.15), 0.435(0.15), 0.396(0.1), 0.341(0.1)}	{0.384(0.1), 0.497(0.2), 0.462(0.2), 0.506(0.15), 0.506(0.15), 0.532(0.1), 0.424(0.1)}
U_2	{0.559(0.1), 0.266(0.2), 0.266(0.2), 0.295(0.15), 0.295(0.15), 0.295(0.1), 0.595(0.1)}	{0.397(0.1), 0.363(0.2), 0.327(0.2), 0.342(0.15), 0.342(0.15), 0.342(0.1), 0.342(0.1)}
U_3	{0.376(0.1), 0.350(0.2), 0.315(0.2), 0.388(0.15), 0.388(0.15), 0.342(0.1), 0.290(0.1)}	{0.549(0.1), 0.341(0.2), 0.435(0.2), 0.161(0.15), 0.161(0.15), 0.161(0.1), 0.194(0.1)}
U_4	{0.279(0.1), 0.279(0.2), 0.473(0.2), 0.397(0.15), 0.397(0.15), 0.397(0.1), 0.332(0.1)}	{0.405(0.1), 0.416(0.2), 0.304(0.2), 0.332(0.15), 0.332(0.15), 0.271(0.1), 0.271(0.1)}
U_5	{0.300(0.1), 0.165(0.2), 0.165(0.2), 0.372(0.15), 0.372(0.15), 0.372(0.1), 0.372(0.1)}	{0.231(0.1), 0.231(0.2), 0.200(0.2), 0.363(0.15), 0.363(0.15), 0.363(0.1), 0.363(0.1)}
Alternative	Q_5	Q_6
U_1	{0.539(0.1), 0.462(0.2), 0.432(0.2), 0.532(0.15), 0.532(0.15), 0.506(0.1), 0.469(0.1)}	{0.500(0.1), 0.483(0.2), 0.599(0.2), 0.571(0.15), 0.571(0.15), 0.571(0.1), 0.571(0.1)}
U_2	{0.396(0.1), 0.332(0.2), 0.300(0.2), 0.432(0.15), 0.432(0.15), 0.363(0.1), 0.397(0.1)}	{0.416(0.1), 0.472(0.2), 0.462(0.2), 0.341(0.15), 0.341(0.15), 0.341(0.1), 0.271(0.1)}
U_3	{0.271(0.1), 0.271(0.2), 0.388(0.2), 0.469(0.15), 0.469(0.15), 0.388(0.1), 0.388(0.1)}	{0.432(0.1), 0.322(0.2), 0.327(0.2), 0.342(0.15), 0.342(0.15), 0.262(0.1), 0.332(0.1)}
U_4	{0.396(0.1), 0.372(0.2), 0.372(0.2), 0.396(0.15), 0.396(0.15), 0.396(0.1), 0.396(0.1)}	{0.332(0.1), 0.300(0.2), 0.300(0.2), 0.517(0.15), 0.517(0.15), 0.396(0.1), 0.396(0.1)}
U_5	{0.418(0.1), 0.418(0.2), 0.261(0.2), 0.397(0.15), 0.397(0.15), 0.261(0.1), 0.261(0.1)}	{0.332(0.1), 0.341(0.2), 0.214(0.2), 0.469(0.15), 0.469(0.15), 0.322(0.1), 0.322(0.1)}

Step 3. Calculate the weight through Eqs (14)–(15), and the results is $e_t = \{0.182, 0.218, 0.100, 0.166, 0.234\}$.

Step 4. Construct the weighted normalized decision matrix in Table 9.

Table 9. Weighted decision matrix

Alternative	Q_1	Q_2
U_1	{0.101(0.1), 0.143(0.2), 0.109(0.2), 0.109(0.15), 0.109(0.15), 0.140(0.1), 0.109(0.1)}	{0.104(0.1), 0.104(0.2), 0.127(0.2), 0.169(0.15), 0.169(0.15), 0.169(0.1), 0.169(0.1)}
U_2	{0.089(0.1), 0.071(0.2), 0.071(0.2), 0.090(0.15), 0.090(0.15), 0.088(0.1), 0.090(0.1)}	{0.056(0.1), 0.110(0.2), 0.110(0.2), 0.046(0.15), 0.046(0.15), 0.046(0.1), 0.099(0.1)}
U_3	{0.060(0.1), 0.049(0.2), 0.062(0.2), 0.098(0.15), 0.098(0.15), 0.098(0.1), 0.098(0.1)}	{0.145(0.1), 0.069(0.2), 0.069(0.2), 0.084(0.15), 0.084(0.15), 0.126(0.1), 0.0599(0.1)}
U_4	{0.054(0.1), 0.056(0.2), 0.039(0.2), 0.067(0.15), 0.067(0.15), 0.054(0.1), 0.067(0.1)}	{0.129(0.1), 0.079(0.2), 0.079(0.2), 0.087(0.15), 0.087(0.15), 0.079(0.1), 0.079(0.1)}
U_5	{0.071(0.1), 0.054(0.2), 0.063(0.2), 0.086(0.15), 0.086(0.15), 0.063(0.1), 0.086(0.1)}	{0.064(0.1), 0.056(0.2), 0.067(0.2), 0.067(0.15), 0.067(0.15), 0.067(0.1), 0.087(0.1)}
Alternative	Q_3	Q_4
U_1	{0.101(0.1), 0.060(0.2), 0.055(0.2), 0.056(0.15), 0.056(0.15), 0.049(0.1), 0.041(0.1)}	{0.077(0.1), 0.108(0.2), 0.098(0.2), 0.110(0.15), 0.110(0.15), 0.118(0.1), 0.087(0.1)}
U_2	{0.079(0.1), 0.031(0.2), 0.031(0.2), 0.034(0.15), 0.034(0.15), 0.034(0.1), 0.087(0.1)}	{0.088(0.1), 0.079(0.2), 0.070(0.2), 0.073(0.15), 0.073(0.15), 0.073(0.1), 0.073(0.1)}
U_3	{0.046(0.1), 0.042(0.2), 0.037(0.2), 0.048(0.15), 0.048(0.15), 0.041(0.1), 0.034(0.1)}	{0.135(0.1), 0.073(0.2), 0.099(0.2), 0.032(0.15), 0.032(0.15), 0.032(0.1), 0.039(0.1)}
U_4	{0.032(0.1), 0.032(0.2), 0.062(0.2), 0.049(0.15), 0.049(0.15), 0.049(0.1), 0.040(0.1)}	{0.090(0.1), 0.093(0.2), 0.064(0.2), 0.071(0.15), 0.071(0.15), 0.056(0.1), 0.056(0.1)}
U_5	{0.035(0.1), 0.018(0.2), 0.018(0.2), 0.045(0.15), 0.045(0.15), 0.045(0.1), 0.045(0.1)}	{0.047(0.1), 0.047(0.2), 0.040(0.2), 0.079(0.15), 0.079(0.15), 0.079(0.1), 0.079(0.1)}
Alternative	Q_5	Q_6
U_1	{0.074(0.1), 0.060(0.2), 0.055(0.2), 0.073(0.15), 0.073(0.15), 0.068(0.1), 0.061(0.1)}	{0.150(0.1), 0.143(0.2), 0.193(0.2), 0.180(0.15), 0.180(0.15), 0.180(0.1), 0.180(0.1)}
U_2	{0.049(0.1), 0.040(0.2), 0.035(0.2), 0.055(0.15), 0.055(0.15), 0.044(0.1), 0.049(0.1)}	{0.118(0.1), 0.139(0.2), 0.135(0.2), 0.093(0.15), 0.093(0.15), 0.093(0.1), 0.072(0.1)}
U_3	{0.031(0.1), 0.031(0.2), 0.048(0.2), 0.061(0.15), 0.061(0.15), 0.048(0.1), 0.048(0.1)}	{0.124(0.1), 0.087(0.2), 0.089(0.2), 0.093(0.15), 0.093(0.15), 0.069(0.1), 0.090(0.1)}
U_4	{0.049(0.1), 0.045(0.2), 0.045(0.2), 0.049(0.15), 0.049(0.15), 0.049(0.1), 0.049(0.1)}	{0.090(0.1), 0.080(0.2), 0.080(0.2), 0.157(0.15), 0.157(0.15), 0.111(0.1), 0.111(0.1)}
U_5	{0.053(0.1), 0.053(0.2), 0.030(0.2), 0.049(0.15), 0.049(0.15), 0.030(0.1), 0.030(0.1)}	{0.090(0.1), 0.093(0.2), 0.055(0.2), 0.138(0.15), 0.138(0.15), 0.087(0.1), 0.087(0.1)}

Step 5. Obtain the score matrix in Table 10.

Table 10. The score of the aggregated decision matrix

	Q_1	Q_2	Q_3	Q_4	Q_5	Q_6
U_1	0.118	0.141	0.059	0.102	0.065	0.172
U_2	0.082	0.078	0.043	0.075	0.046	0.111
U_3	0.077	0.086	0.042	0.064	0.047	0.091
U_4	0.056	0.086	0.046	0.073	0.048	0.110
U_5	0.071	0.066	0.033	0.061	0.042	0.097

Step 6. Determine the NIP of each alternative by Eq. (24) in Table 11:

Table 11. The negative ideal solution

Q_1	Q_2	Q_3	Q_4	Q_5	Q_6
{0.054(0.1)	{0.064(0.1)	{0.035(0.1)	{0.047(0.1)	{0.053(0.1)	{0.090(0.1)
0.056(0.2),	0.056(0.2),	0.018(0.2),	0.047(0.2),	0.053(0.2),	0.093(0.2),
0.039(0.2),	0.067(0.2),	0.018(0.2),	0.040(0.2),	0.030(0.2),	0.055(0.2),
0.067(0.15),	0.067(0.15),	0.045(0.15),	0.079(0.15),	0.049(0.15),	0.138(0.15),
0.067(0.15),	0.067(0.15),	0.045(0.15),	0.079(0.15),	0.049(0.15),	0.138(0.15),
0.054(0.100),	0.067(0.100),	0.045(0.100),	0.079(0.100),	0.030(0.100),	0.087(0.100),
0.067(0.100)}	0.087(0.100)}	0.045(0.100)}	0.079(0.100)}	0.030(0.100)}	0.087(0.100)}

Step 7. Calculate the Euclidean (Li, Chen, et al., 2020) and Taxicab distance of alternatives between the NIP and the results are shown in Tables 12–13.

Table 12. The Euclidean distance

U_1	U_2	U_3	U_4	U_5
0.145	0.074	0.078	0.050	0.017

Table 13. The Manhattan distances

U_1	U_2	U_3	U_4	U_5
0.302	0.146	0.154	0.088	0.016

Step 8. Determine the relative evaluation matrix in Table 14.

Table 14. The relative evaluation matrix

	U_1	U_2	U_3	U_4	U_5
U_1	0.00	0.23	0.21	0.31	0.41
U_2	–0.23	0.00	0.00	0.02	0.19
U_3	–0.21	0.00	0.00	0.03	0.20
U_4	–0.31	–0.02	–0.03	0.00	0.11
U_5	–0.41	–0.19	–0.20	–0.11	0.00

Step 9. Calculate the evaluation score of each alternative:

$$V_1 = 1.16, V_2 = -0.02, V_3 = 0.02, V_4 = -0.25, V_5 = -0.90.$$

Step 10. Rank the alternatives and the superiority order is:

$$r(U_1) \succ r(U_3) \succ r(U_2) \succ r(U_4) \succ r(U_5).$$

4. Comparative analysis

In this part, the PHF-TODIM method (W. K. Zhang et al., 2018), PHFWA operator (Xu & Zhou, 2017), PHFWG operator (Xu & Zhou, 2017) and PHF-TOPSIS method (J. Wu et al., 2019) is used to compare with the PHF-CODAS method.

4.1. Compare with PHF-TODIM

The PHF-TODIM method (W. K. Zhang et al., 2018) is used to compare with PHF-CODAS method. The PHF-TODIM method has the following calculating results (Table 15):

Table 15. The results of PHF-TODIM method

	Expression	The results
Relative weights	e_t^*	$e_t^* = (0.777, 0.929, 0.427, 0.706, 0.427, 1.000)$
Overall degree	$\vartheta(U_r)$	$\vartheta(U_1) = 1.000, \vartheta(U_2) = 0.427, \vartheta(U_3) = 0.418, \vartheta(U_4) = 0.492, \vartheta(U_5) = 0.000$
The result		$r(U_1) \succ r(U_4) \succ r(U_2) \succ r(U_3) \succ r(U_5)$

4.2. Compare with the PHF aggregation operators (see Table 16–17)

Table 16. The outcome about PHFWA operator

Alternative	Overall values	Score
U_1	{{0.474(0.1),0.481(0.2),0.494(0.2),0.527(0.15),0.527(0.15),0.542(0.1),0.501(0.1)}	0.505
U_2	{0.389(0.1),0.385(0.2),0.374(0.2),0.330(0.15),0.330(0.15),0.320(0.1),0.383(0.1)}	0.360
U_3	{0.430(0.1),0.300(0.2),0.336(0.2),0.350(0.15),0.350(0.15),0.349(0.1),0.315(0.1)}	0.341
U_4	{0.366(0.1),0.324(0.2),0.313(0.2),0.392(0.15),0.392(0.15),0.336(0.1),0.338(0.1)}	0.349
U_5	{0.308(0.1),0.278(0.2),0.241(0.2),0.380(0.15),0.380(0.15),0.314(0.1),0.345(0.1)}	0.315
The result	$r(U_1) \succ r(U_2) \succ r(U_4) \succ r(U_3) \succ r(U_5)$	

Table 17. The outcome of PHFWG operator

Alternative	Overall values	Score
U_1	{{0.461(0.1),0.475(0.2),0.486(0.2),0.522(0.15),0.522(0.15),0.536(0.1),0.489(0.1)}	0.497
U_2	{0.369(0.1),0.376(0.2),0.364(0.2),0.314(0.15),0.314(0.15),0.308(0.1),0.367(0.1)}	0.347
U_3	{0.408(0.1),0.297(0.2),0.329(0.2),0.327(0.15),0.327(0.15),0.320(0.1),0.299(0.1)}	0.326
U_4	{0.354(0.1),0.319(0.2),0.300(0.2),0.380(0.15),0.380(0.15),0.328(0.1),0.333(0.1)}	0.339
U_5	{0.301(0.1),0.266(0.2),0.236(0.2),0.370(0.15),0.370(0.15),0.310(0.1),0.342(0.1)}	0.307
The result	$r(U_1) \succ r(U_2) \succ r(U_4) \succ r(U_3) \succ r(U_5)$	

4.3. Compare with the PHF-TOPSIS method

The PHF-TOPSIS method (J. Wu et al., 2019) is used to compare with PHF-CODAS method. The calculating results of PHF-TOPSIS method is listed in Table 18.

Table 18. The outcomes about PHF-TOPSIS method

Title	Sign	The results
Distance	D_r^+ D_r^-	$D_r^+ = (0.00, 0.84, 0.92, 0.87, 1.09)$ $D_r^- = (1.16, 0.48, 0.26, 0.36, 0.22)$
Relative closeness coefficients	G^*	$G_1^* = 1.00, G_2^* = 0.36, G_3^* = 0.22, G_4^* = 0.29, G_5^* = 0.17$
The result		$r(U_1) \succ r(U_2) \succ r(U_4) \succ r(U_3) \succ r(U_5)$

Through the above methods to the same raw data processing comparison, the final results below have some differences from each other because of the characteristics of each method. Though the result of the new method has some differences from other methods, the best solution is U_1.

Conclusions

In this paper, the proposed PHF-CODAS method measures the full performance by the Euclidean and Taxicab distances between the negative ideal solution. The principle of PHF-CODAS method is if the Euclidean distances of two alternatives are very close to each other, the Taxicab distance is used to compare them. In this paper, we apply PHF-CODAS method for MAGDM under PHFSs. In the end, a case for supplier selection and the comparative analysis are used to confirm the feasibility and utility of this new approach. The superiorities of the extended method are as follows: (1) the PHF-CODAS method is built to solve the probabilistic hesitant fuzzy MAGDM; (2) It uses the SV method to measure the weight of each attributes under the PHFSs; (3) the comparative analysis is given to show the feasibility of this extended method; (4) This extended method in the PHF environment can be applied in the selection of the green supplier which may meet the needs of production to the greatest extent while paying attention to environmental protection. In our subsequent research, the proposed methods and algorithm would be meaningful for other real decision-making problems and the developed approaches can also be extended to other unpredictable and uncertain information.

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