Group decision making by a last aggregation approach under interval-valued Pythagorean fuzzy environment for sustainable project decision

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Abstract

Interval-valued Pythagorean fuzzy sets (IVPFSs) as enhanced type of Pythagorean fuzzy sets (PFSs) improve the expression of the degrees of membership, non-membership and hesitancy in comparison with intuitionistic fuzzy sets (IFSs). In this paper, to use the advantages of IVPFSs a new group decision-making method is introduced based on linear assignment method (LAM). In this approach, subjective and objective weights of criteria are taken into account. Moreover, the method applies a new ranking method for IVPFSs. To avoid the shortcomings of first aggregation methods, the introduced decision-making approach involves a last aggregation approach. Finally, the method is used in a case study of sustainable project evaluation in order to depict the applicability of this method.

Keywords: Group decision making; interval-valued Pythagorean fuzzy sets (IVPFSs); linear assignment method (LAM); last aggregation; ranking IVPFSs; sustainable project evaluation

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1. Introduction

Dealing with uncertainty needs applications of flexible tools [1-3]. Intuitionistic fuzzy sets (IFSs) Atanassov [4] is one of the applicable tools to model uncertainty. These sets are able to model the degree of membership, non-membership and hesitation. Despite this novelty, it should be noted that these sets cannot completely model the opinions of the decision makers (DMs). One example is an occurrence of situations where the aforementioned degrees sum up to a number which is bigger than 1. Yager [5, 6] introduced Pythagorean fuzzy sets (PFSs) to handle such situations. These sets are developed based on IFSs and improve the flexibility and applicability of IFSs.

PFSs are improved forms of IFSs. To put differently, they have the merits of IFSs in addition to offering a wider range to model agreement, disagreement and hesitancy. For instance, when comparing PFSs with classic fuzzy sets, it can be concluded that PFSs have membership, non-membership and hesitancy degrees while classic fuzzy sets can just include a crisp value of membership in the interval [0, 1]. Moreover, PFSs not only address the fuzziness of “agreement” but include the “disagreement” of the experts in the process [7], [8].


A review of PFS and IVPF based methods shows that these sets are still new in decision-making problems and their advantages can be used to address many uncertain decision making situations. One of the decision-making methods that is new to these sets is linear assignment method (LAM) [20]. This method applies a criterion-wise ranking approach by using a set of criterion weights. The LAM applies linear compensatory discipline to handle the interaction and combination of the decision making criteria. Another issue in using PFSs and IVPFSs is presenting proper defuzzification and ranking methods. One approach in this process is using the concept of ideal solutions. Mohagheghi et al. [21] proposed a distance-based
similarity measure between interval type 2 fuzzy numbers (IT2FN) to evaluate the performance of IT2FNs in any comparing application. This approach is simple and applies all the values that characterize a fuzzy number. This approach has not been applied to address IVPFSs. Another approach to improve a decision-making process is using entropy to address weights of criteria. One increasing approach in attending to decision preferences is applying fuzzy entropies to better obtain the weights related to the attributes. One of the main reasons of the practicality of fuzzy entropies is their eligibility for evaluations of fuzziness [22]. However, given the novelty of IVPFSs in decision making this approach is still rather fresh in this area. Another decision-making approach that is new for IVPFSs and PFSs is using last aggregation methods. These methods avoid information loss through delaying the aggregation process. One aggregation method is the WASPAS (weighted aggregated sum product assessment) method presented by Zavadskas et al. [23]. One of the advantages of the WASPAS is proving the possibility of achieving the highest levels of accuracy in assessments by applying the principles of weighted aggregated functions optimization.

To conclude, the main motivations for presenting this paper are as follows:

1. In recent years IVPFSs have been used to extend well-known decision-making methods under a new uncertain environment. This trend provides enhancing the reliability of decision-making methods.

2. The LAM method applies weights of criteria in its computational process, but most of the studies consider the weights given by the experts and do not address it in forms of subjective and objective weights.

3. Most of the proposed group decision-making methods are the first aggregation that could lead to loss of information.

4. Sustainability in projects and project portfolios is a practical trend that requires proper considerations and the application of tools that are capable of addressing complex conditions.

Organizational decision-making processes and situation evaluations are often carried out in groups, and the processes have several uncertain factors [24-27]. Moreover, in multi-criteria group decision making (MCGDM) reaching a preference-based choice over the available alternatives is the main objective [28-31]. The alternatives are investigated by using a number of criteria. Moreover, the entire process is carried out by using a group of experts or DMs [32].

In order to contribute to the improvement of MCGDM under IVPF uncertainty in this paper a new decision-making method is introduced. The method is then applied in sustainable project selection. This paper has the following novelties: (1) the PFS method applies the principles of the well-known method LAM to introduce a last aggregation method for project evaluation; (2) A new ranking method for IVPFSs is introduced that is used in the LAM process; (3) IVPFS entropy is presented to compute the importance of each criterion; (4) Score function of IVPFSs is used to address the LAM method; (5) The method is last aggregation and aggregation is carried out by using the WASPAS method.
The rest of this paper is organized as follows: in section 2 the preliminary knowledge of the method is presented. Section 3 explains the presented method and in section 4 the application process of the method is presented. Eventually, section 5 presents the concluding remarks of the paper.

2. Interval-valued Pythagorean fuzzy sets

PFSs are extensions of IFSs but they offer more flexibility and dominant in the manifestation of uncertainty. The advantages in showing the degrees of membership degree, non-membership hesitancy is actually due to increasing the space for setting such values. One typical example of PFSs advantage over IFSs is when a DM denotes the value to which a candidate satisfies a criterion as $\frac{\sqrt{3}}{2}$ and the values to which it dissatisfies the criterion as $\frac{1}{2}$. In this example, it is obvious that applying IFSs is not possible because $\frac{\sqrt{3}}{2} + \frac{1}{2} > 1$. On the other hand, PFSs are able to illustrate such uncertainties because they have a bigger space for expression of such situations and in this case $(\frac{\sqrt{3}}{2})^2 + (\frac{1}{2})^2 \leq 1$. The PFSs can express higher levels of vagueness in comparison with IFSs. In addition to that, in real world situations where it is necessary to make a choice under uncertainty, PFSs have higher potentials in dealing with the vague and imperfect information when it comes to comparison with IFSs. Figure 1 presents a comparison of PFSs and IFSs [6, 9].

In the following some basic definitions of IFS and PFS are presented:

A given IFS set such as $Q$ in a universe of discourse ($O$) is expressed as:

$$Q = \{x, \mu_q(O), \nu_q(O) : o \in O \}$$

(1)

where $\mu_q : O \rightarrow [0,1]$ shows the membership degree while $\nu_q : O \rightarrow [0,1]$ expresses non-membership value of element $o \in O$ to the set $Q$, respectively under the following condition:

$$0 \leq \mu_q(O), \nu_q(O) \leq 1$$

(2)

The last value in these sets is the degree of indeterminacy $\pi_q(o)$:

$$\pi_q(o) = 1 - \mu_q(O) - \nu_q(O)$$

(3)

{Please insert Figure 1 here.}
IFSs were proposed by Atanassov [4] and instead of only containing the value of membership, possess the values of membership, non-membership and hesitancy. These sets have been applied to address uncertainties of various real-world situations like sustainable supplier selection [33], renewable energy evaluation [34], sustainable project portfolio selection [35], sustainable material selection [36] and evaluation of product end-of-life scenarios [37].

Despite their successful applications, sometimes these sets cannot deal with uncertain elements. In other words, there are conditions where the degrees that a candidate like $Q_i$ satisfies and dissatisfies with respect to attribute $P_j$ add up to a value greater than one. Obviously, it is not feasible to show this situation by application of IFSs. To deal with this matter, PFSs were introduced as follows [5, 6]:

$Q$ as a PFS defined in the universe of discourse ($O$) is set as:

$$Q = \{<x, \mu_Q(O), \nu_Q(O)>| o \in O \}$$  \hspace{1cm} (4)

In Eq. (4), $\mu_Q: O \rightarrow [0,1]$ and $\nu_Q: O \rightarrow [0,1]$ sets the values of membership and non-membership of element $o \in O$ to the set $Q$, respectively. The following condition should hold for the expressed values:

$$0 \leq (\mu_Q(O))^2, (\nu_Q(O))^2 \leq 1$$  \hspace{1cm} (5)

$\pi_Q(O)$ shows the value of indeterminacy and is denoted by the following:

$$\pi_Q(o) = \sqrt{1-(\mu_Q(O))^2-(\nu_Q(O))^2}$$  \hspace{1cm} (6)

One way to enhance PFSs is to use intervals instead of crisp values to address uncertain degrees. Peng and Yang [10] introduced interval-valued Pythagorean fuzzy sets (IVPFSs). The following presents a briefing on these sets:

Interval $[0, 1]$ shows the set of all closed subintervals of $[0,1]$ and $O$ is set as a universe of discourse. As a result, an IVPFS $\tilde{Q}$ in $O$ can be denoted as the following:

$$\tilde{Q} = \{<x, \mu_Q(O), \nu_Q(O)>| o \in O \}$$  \hspace{1cm} (7)
In Eq. (7), \( \mu_{\tilde{q}}: O \rightarrow H_{\text{int}}([0,1]) \) and \( \nu_{\tilde{q}}: O \rightarrow H_{\text{int}}([0,1]) \) denote the membership and non-membership values of the element \( o \) belonging to \( O \) to the set \( \tilde{Q} \), respectively. For each \( o \in O \), \( \mu_{\tilde{q}}(O) \) and \( \nu_{\tilde{q}}(O) \) are closed intervals. The lower and upper bounds are shown by \( \mu_{\tilde{q}}^+(O), \mu_{\tilde{q}}^-(O), \nu_{\tilde{q}}^+(O), \nu_{\tilde{q}}^-(O) \), respectively. \( \tilde{Q} \) can also be expressed as follows:

\[ \tilde{Q} = \left\langle x, [\mu_{\tilde{q}}^-(O), \mu_{\tilde{q}}^+(O)], [\nu_{\tilde{q}}^-(O), \nu_{\tilde{q}}^+(O)] \mid o \in O \right\rangle \]  \hspace{1cm} (8)

The following for \( \tilde{Q} \) should hold:

\[ 0 \leq (\mu_{\tilde{q}}^+(O))^2, (\nu_{\tilde{q}}^+(O))^2 \leq 1 \]  \hspace{1cm} (9)

The degree of indeterminacy is set as the following:

\[ \pi_{\tilde{q}}(o) = \left[ \pi_{\tilde{q}}^-(o), \pi_{\tilde{q}}^+(o) \right] = \left[ \sqrt{1-(\mu_{\tilde{q}}^+(O))^2-(\nu_{\tilde{q}}^-(O))^2}, \sqrt{1-(\mu_{\tilde{q}}^-(O))^2-(\nu_{\tilde{q}}^+(O))^2} \right] \]  \hspace{1cm} (10)

The following presents the score function of \( \tilde{Q} \) [10]:

\[ s(\tilde{Q}) = \frac{1}{2} \left[ (\mu_{\tilde{q}}^+(O))^2 + (\mu_{\tilde{q}}^-(O))^2 - (\nu_{\tilde{q}}^- (O))^2 - (\nu_{\tilde{q}}^+ (O))^2 \right], s(\tilde{Q}) \in [-1,1] \]  \hspace{1cm} (11)

The following shows the accuracy function of \( \tilde{Q} \) [10]:

\[ a(\tilde{Q}) = \frac{1}{2} \left[ (\mu_{\tilde{q}}^+(O))^2 + (\mu_{\tilde{q}}^-(O))^2 + (\nu_{\tilde{q}}^- (O))^2 + (\nu_{\tilde{q}}^+ (O))^2 \right], a(\tilde{Q}) \in [0,1] \]  \hspace{1cm} (12)

The following shows the hesitancy degree of \( \tilde{Q} \) [10]:

\[ h(\tilde{Q}) = \frac{1}{2} \left[ 1-(\mu_{\tilde{q}}^+(O))^2 - (\nu_{\tilde{q}}^- (O))^2 + 1-(\mu_{\tilde{q}}^-(O))^2 - (\nu_{\tilde{q}}^+ (O))^2 \right], h(\tilde{Q}) \in [0,1] \]  \hspace{1cm} (13)

The following computes the distance between two IVPFNs \( \tilde{Q}_1 \) and \( \tilde{Q}_2 \) [10]:

\[ d(\tilde{Q}_1, \tilde{Q}_2) = \frac{1}{4} \left[ \left| (\mu_{\tilde{q}_1})^2 - (\mu_{\tilde{q}_2})^2 \right| + \left| (\mu_{\tilde{q}_1})^2 - (\mu_{\tilde{q}_2})^2 \right| + \left| (\nu_{\tilde{q}_1})^2 - (\nu_{\tilde{q}_2})^2 \right| + \left| (\nu_{\tilde{q}_1})^2 - (\nu_{\tilde{q}_2})^2 \right| \right] \]  \hspace{1cm} (14)

For two PFNs as \( \tilde{Q}_1 = (\mu_{\tilde{q}_1}, \nu_{\tilde{q}_1}) \) and \( \tilde{Q}_2 = (\mu_{\tilde{q}_2}, \nu_{\tilde{q}_2}) \) and \( \rho > 0 \) the following operations are set [10]:
\[ \tilde{Q}_1 \oplus \tilde{Q}_2 = \left[ \frac{Q_1^0 + Q_2^0}{1 - \left( \mu_2^0 \right)^2}, \frac{Q_1^0 + Q_2^0}{1 - \left( \mu_2^0 \right)^2}, \frac{Q_1^0 + Q_2^0}{1 - \left( \mu_2^0 \right)^2}, \frac{Q_1^0 + Q_2^0}{1 - \left( \mu_2^0 \right)^2} \right] \]

(15)

\[ \tilde{Q}_1 \otimes \tilde{Q}_2 = \left[ \left( \mu_2^0 \right)^2, \left( \mu_2^0 \right)^2, \left( \mu_2^0 \right)^2, \left( \mu_2^0 \right)^2, \left( \mu_2^0 \right)^2, \left( \mu_2^0 \right)^2, \left( \mu_2^0 \right)^2, \left( \mu_2^0 \right)^2 \right] \]

(16)

\[ \rho \tilde{Q}_1 = \left[ \left( 1 - \left( \mu_1^0 \right)^2 \right)^\rho, \left( 1 - \left( \mu_1^0 \right)^2 \right)^\rho, \left( 1 - \left( \mu_1^0 \right)^2 \right)^\rho, \left( 1 - \left( \mu_1^0 \right)^2 \right)^\rho \right] \]

(17)

\[ Q_1' = \left[ \left( \mu_1^0 \right)^\rho, \left( \mu_1^0 \right)^\rho \right] \]

(18)

Also, the following operations can be obtained:

\[ \tilde{Q}_1 - \tilde{Q}_2 = \left[ \left( 1 - \left( \mu_2^0 \right)^2 \right)^\rho, \left( 1 - \left( \mu_2^0 \right)^2 \right)^\rho, \left( 1 - \left( \mu_2^0 \right)^2 \right)^\rho, \left( 1 - \left( \mu_2^0 \right)^2 \right)^\rho \right] \]

(19)

\[ \rho \tilde{Q}_1 = \left[ \left( 1 - \left( \mu_1^0 \right)^2 \right)^\rho, \left( 1 - \left( \mu_1^0 \right)^2 \right)^\rho, \left( 1 - \left( \mu_1^0 \right)^2 \right)^\rho, \left( 1 - \left( \mu_1^0 \right)^2 \right)^\rho \right] \]

(20)

3. Proposed methodology

In this section, the presented method of IVPFS-LAM is presented. The method consists of 6 main steps. First the decision matrices are formed. Second, they are normalized. To achieve the required matrices for the IVPFS-LAM method, it is necessary to compare the IVPFS values denoting ratings of alternatives. Therefore, a ranking method for IVPFS is introduced. To better address the importance of criteria weights in this method, an IVPFS entropy method is extended and applied. The matrices required for the LAM method are then made, and the introduced IVPFS-LAM is presented. Given the last aggregation nature of the method, finally, the WASPAS method aggregates the outcomes.
3.1. Description of making IVPFS decision matrices

In this IVPFS based method, DMs should express their opinions in forms of IVPFSs. The condition that for every value of \( o \in O, 0 \leq \sup\{\mu_o(\Theta)^2 + \sup(\mu_o(\Theta)^2) \leq 1\} \) can be easily confirmed by using spreadsheets. As a result, \( DMT^V \) is made as follows:

\[
DMT^V = \begin{bmatrix}
A^V_{11} & \cdots & A^V_{1h} \\
\vdots & \ddots & \vdots \\
A^V_{h1} & \cdots & A^V_{gh}
\end{bmatrix}
\]  

(21)

In this matrix, \( A_1, A_2, \ldots, A_g \) shows the set of possible alternatives that are being evaluated. \( g \) shows the number of alternatives. Set of evaluation criteria is denoted by \( x_1, x_2, \ldots, x_h \). \( h \) also is used to mention the number of criteria. \( A^V_{gh} \) is applied to express the evaluation of candidate \( A_g \) according to criterion \( x_h \) that is expressed by the \( v \)th DM. \( A^V_{gh} \) is denotes as:

\[
A^V_{gh} = \left( \left[ \mu_{x_h}^{V^L}, \mu_{x_h}^{V^U} \right], \left[ V_{x_h}^{V^L}, V_{x_h}^{V^U} \right] \right)
\]

(22)

The subjective importance value of \( x_h \) is expressed as follows:

\[
x^V_h = \left( \left[ \mu_{x_h}^{V^L}, \mu_{x_h}^{V^U} \right], \left[ V_{x_h}^{V^L}, V_{x_h}^{V^U} \right] \right)
\]

(23)

3.2. Normalization process of IVPFS decision matrices

In this step, a normalization process is used. The set of evaluation criteria which is categorized into benefit and cost denoted as \( x_C \) and \( x_B \) respectively, is made dimensionless in this step. The matrices are normalized as follows:

\[
A^V_{gh} = \begin{cases} 
A^V_{gh} ; & h \in x_B \\
(A^V_{gh})^C ; & h \in x_C
\end{cases}
\]

(24)

Where \((A^V_{gh})^C\) denotes the complement of \( A^V_{gh} \).

3.3. Description of IVPFS ranking and defuzzification step

In order to carry out the LAM it is necessary to compare and rank the values of \( A^V_{gh} \). Therefore, in this part a new ranking and comparing method is presented. This method utilizes all the information expressed by an IVPFS. The studies of Deng [38], Mohagheghi et al. [21] formed the basis of this method as introduced in the following:

1. Define the positive ideal solution as \( IVPFS_{\text{max}} \) and the negative ideal solution as \( IVPFS_{\text{min}} \).
2. Compute the distance-based value of similarity between each IVPFS \( (A_g^V) \) \( IV\hat{P}FS_g \ (g = 1, 2, ..., G) \) and the positive ideal solution \( (d_g^+) \) according to Eq. (25):

\[
d_g^+(IV\hat{P}FS_g, IV\hat{P}FS_{max}) = \frac{1}{4} \left[ (\mu_{IV\hat{P}FS_x}^-)^2 - (\mu_{IV\hat{P}FS_{max}}^-)^2 + (\mu_{IV\hat{P}FS_d}^+)^2 - (\mu_{IV\hat{P}FS_{max}}^+)^2 + (v_{IV\hat{P}FS_x}^-)^2 - (v_{IV\hat{P}FS_{max}}^-)^2 + (v_{IV\hat{P}FS_d}^+)^2 - (v_{IV\hat{P}FS_{max}}^+)^2 + (\pi_{IV\hat{P}FS_x}^-)^2 - (\pi_{IV\hat{P}FS_{max}}^-)^2 + (\pi_{IV\hat{P}FS_d}^+)^2 - (\pi_{IV\hat{P}FS_{max}}^+)^2 \right]
\]

3. Compute the value of similarity between each IVPFS \( (A_g^V) \) \( IV\hat{P}FS_g \ (g = 1, 2, ..., G) \) and the negative ideal solution \( (d_g^-) \) according to Eq. (26):

\[
d_g^-(IV\hat{P}FS_g, IV\hat{P}FS_{min}) = \frac{1}{4} \left[ (\mu_{IV\hat{P}FS_x}^-)^2 - (\mu_{IV\hat{P}FS_{min}}^-)^2 + (\mu_{IV\hat{P}FS_d}^+)^2 - (\mu_{IV\hat{P}FS_{min}}^+)^2 + (v_{IV\hat{P}FS_x}^-)^2 - (v_{IV\hat{P}FS_{min}}^-)^2 + (v_{IV\hat{P}FS_d}^+)^2 - (v_{IV\hat{P}FS_{min}}^+)^2 + (\pi_{IV\hat{P}FS_x}^-)^2 - (\pi_{IV\hat{P}FS_{min}}^-)^2 + (\pi_{IV\hat{P}FS_d}^+)^2 - (\pi_{IV\hat{P}FS_{min}}^+)^2 \right]
\]

4. Compute the overall performance of each IVPFS (IVPFSP) by using the following:

\[
IVPFSP_g = \frac{1}{4} \left[ (\mu_{IV\hat{P}FS_x}^-)^2 - (\mu_{IV\hat{P}FS_{max}}^-)^2 + (\mu_{IV\hat{P}FS_d}^+)^2 - (\mu_{IV\hat{P}FS_{max}}^+)^2 + (v_{IV\hat{P}FS_x}^-)^2 - (v_{IV\hat{P}FS_{max}}^-)^2 + (v_{IV\hat{P}FS_d}^+)^2 - (v_{IV\hat{P}FS_{max}}^+)^2 + (\pi_{IV\hat{P}FS_x}^-)^2 - (\pi_{IV\hat{P}FS_{max}}^-)^2 + (\pi_{IV\hat{P}FS_d}^+)^2 - (\pi_{IV\hat{P}FS_{max}}^+)^2 \right], \ g = 1, 2, ..., G
\]

5. Now given the fact that the values are converted into crisp values they can be easily compared. IVPFSs can now be ranked in descending order of IVPFSP\(_g\).
This defuzzification will only be applied to assist a formation of matrices required for making the mathematical model of LAM. In other words, this defuzzification will not affect the fuzziness of the decision-making process.

3.4. Description of IVPFS criteria weights

LAM ranks the alternatives based on criteria weights. In other words, weights of criteria play a vital role in the rankings. So far, in the presented method, subjective weights were gathered from the DMs. For the purpose of improving this process, an entropy-based criteria weight computation is developed. To put differently, subjective and objective weights are used in this process. To compute the entropy of importance of evaluation criteria, the following is proposed [39].

\[
Ent(X^v) = \frac{1}{v} \sum_{v=1}^{V} \frac{D_1 + D_2 + \pi_{x_h}^v + \pi_{x_h}^v}{V_1 + V_2 + \pi_{x_h}^v + \pi_{x_h}^v}
\]  
(28)

Where \( D_1 = \min \left\{ \mu_{x_h}^v, \mu_{x_h}^v \right\}, D_2 = \min \left\{ \mu_{x_h}^v, \mu_{x_h}^v \right\}, V_1 = \min \left\{ v_{x_h}^v, v_{x_h}^v \right\}, V_2 = \min \left\{ v_{x_h}^v, v_{x_h}^v \right\} \)

\( Ent(X^v) \) is then multiplied in \( x^v_h \) to make a novel criteria weights (SOW). It is calculated as follows:

\[
SOW^v_h = \begin{bmatrix}
\frac{1}{V_1 + V_2 + \pi_{x_h}^v + \pi_{x_h}^v} \left[ D_1 + D_2 + \pi_{x_h}^v + \pi_{x_h}^v \right] \left[ 1 - ((1 - (\mu_{x_h}^v)^2) \right]

\frac{1}{V_1 + V_2 + \pi_{x_h}^v + \pi_{x_h}^v} \left[ D_1 + D_2 + \pi_{x_h}^v + \pi_{x_h}^v \right] \left[ 1 - ((1 - (\mu_{x_h}^v)^2) \right]
\end{bmatrix}
\]

\[
\left( v_{x_h}^v \right) \left( v_{x_h}^v \right)
\]

3.5. Description of IVPFS model and solving approach

1. By applying the result of subsection 3-3, g candidates can be ranked with respect to each criterion \( x_h \). A rank frequency matrix \( r^v \) is here defined. This non-negative square \( (g \times g) \) has elements \( r_{g}^v \) that show the frequency in which \( A_g \) is ranked as the \( l \)th criterion-wise ranking. The following matrix is the result of this step:
To illustrate further, \( T^{V}_{11} \) shows the frequency in which alternative \( A_1 \) is ranked as the first alternative in the appraisal of the \( v \)th decision maker.

2. After forming this matrix, it will be used to make a weighted rank frequency matrix (WRFM). It is formed as presented in Eq. (31):

\[
WRFM^{V} = \begin{bmatrix}
WRFM^{V}_{11} & \cdots & WRFM^{V}_{1g} \\
\vdots & \ddots & \vdots \\
WRFM^{V}_{g1} & \cdots & WRFM^{V}_{gg}
\end{bmatrix}
\]

(31)

Where \( WRFM^{V}_{gl} = SOW^{v}_{gl} \oplus SOW^{v}_{g1} \oplus \cdots \oplus SOW^{v}_{gg} \).

It should be mentioned that each one of the values of \( WRFM^{V} \) in the weighted rank frequency matrix \( WRFM^{V} \) denote the value of concordance among all criteria in ranking the \( l \)th option \( l \).

It is possible that \( \sigma \) candidates end up with the same scores according to a criterion. Therefore, the original ranking is departed into \( \sigma! \) equalized rankings. In such case, each of the rankings will receive the weight of \( 1/\sigma! \) [40].

3. After creating the aforementioned matrices, \( A_g \) for each \( l (l=1, 2, \ldots, g) \) must be decided in a way that \( \frac{\sum_{l=1}^{g} s(WRFM^{V}_{gl})}{\sum_{l=1}^{g} s(WRFM^{V}_{gl})} \) is maximized. Here, \( s \) denotes score function and it is used to defuzzify the fuzzy values in the model. Obviously, this problem is an \( g! \) comparison problem. Let define \( \varphi_{gl} \) as a binary variable that is equal to 1 if \( A_g \) is ranked as 1 for \( v \)th DM and 0 otherwise. Consequently, the following linear assignment model is obtained:

\[
\begin{align*}
\max \sum_{g=1}^{G} \sum_{l=1}^{L} \frac{1}{2} \left[ (\mu_{WRFM^{V}_{gl}})^2 + (\mu_{\tilde{WRFM}^{V}_{gl}})^2 \right] - \left( v_{WRFM^{V}_{gl}} \right)^2 = (v_{\tilde{WRFM}^{V}_{gl}})^2] \cdot \varphi_{gl}
\end{align*}
\]

(32)

Subject to:
\[
\sum_{g=1}^{G} \varphi_{gl} = 1, g = 1, 2, \ldots, G, v = 1, 2, \ldots, V \tag{33}
\]

\[
\sum_{g=1}^{G} \varphi_{gl} = 1, l = 1, 2, \ldots, G, v = 1, 2, \ldots, V \tag{34}
\]

\[
\varphi_{gl} = 0 \text{ or } 1 \text{ for all } g \text{ and } v \tag{35}
\]

Eq. (33) assigns alternative \( A_g \) to only one rank. Eq. (34) makes each rank available just for one candidate. The outcome of this step is rankings gathered from each DM. Since this approach is a group decision-making process, an aggregation process is required. \( \text{Rank}_v^g \) is used to show the ranking of alternative \( g \) which is carried out according to judgments of \( v \)th DM.

### 3.6. Description of aggregation based on the WASPAS method

This step is based on the WASPAS method which enables getting to the highest level of accuracy in approximation by using suggested methodology for optimization of weighted aggregated function. Moreover, it is advantageous to most of other available methods since it is able to improve the accuracy of evaluation [41]. The rankings achieved from the previous step are here utilized to reach aggregated decisions. Therefore, the following is presented:

\[
\hat{\varphi}_g = \left( \mathfrak{A} \left( \sum_{v=1}^{V} \left( \text{Rank}_v^g \right) DW_v \right) \right) + \left( 1 - \mathfrak{A} \left( \prod_{v=1}^{V} \text{Rank}_v^g DW_v \right) \right) \tag{36}
\]

where \( DW_v \) is the weight of \( v \)th expert and \( 0 < \mathfrak{A} < 1 \) is applied to express the vitality of each part. It should be noted that \( 0 < DW_v < 1 \) and \( \sum_{v=1}^{V} DW_v = 1 \). Finally, the aggregated rankings \( \hat{\varphi}_g \) are obtained.

### 3.7. Step by step algorithm

**Step 1** Identify the alternatives \( A_g \ (g=1, 2, \ldots, G) \) and evaluation criteria \( X_h \ (h=1, 2, \ldots, H) \).

**Step 2** Form the decision matrix for each DM by using their expertise in the form of IVPFSs.

**Step 3** Gather the information on subjective importance of decision-making criteria in form of IVPFSs.

**Step 4** Form the normalized decision matrices.

**Step 5** Defuzzify the decision matrices by using section 3.3.

**Step 6** Compute the entropy of criteria and form the SOW to address weights of criteria.

**Step 7** Form the rank frequency matrix \( T^V \) for each DM.
Step 8 Form the form weighted rank frequency matrix (WRFM) for each DM.

Step 9 Make and solve the linear assignment model according to each DM separately and obtain the values of $Rank^*_g$.

Step 10 Use the WASPAS based aggregation approach to aggregate the obtained outcomes.

4. Prioritizing projects in a portfolio

Considering sustainability in project and project portfolio environments has formed an essential and applicable direction for researchers and practitioners. Awasthi and Omran [42] regarded sustainable mobility project evaluation under fuzzy uncertainty. Li et al. [43] investigated the problem of sustainable building project evaluation by using the matter-element theory. Also, Lei et al. [44] considered sustainability in investment risk evaluation for renewable energy projects. In this section, the sustainability is considered to evaluate and prioritize projects in a portfolio of projects.

In order to depict the applicability of the presented approach in real-world decision-making problems, this section presents a case study. Projects in a portfolio of an Iranian holding company in the area of gas and oil development are assessed based on the presented method of this paper. The main priority of the studied firm is to invest in the oil, gas and petrochemical sectors. In addition, the firm is trying to reach an active position in the capital market of the country in order to get to its long-term objective of becoming the largest holding in Iran's petrochemical sector. Moreover, the firm wants to increase its presence in local, regional and international markets by obtaining a competitive edge over others. As a result, the firm has kept the data of candidate projects as confidential. Given the confidentiality of the data, the authors had to present limited details of the projects.

Prioritizing the projects of this firm (CP1, CP2, CP3 and CP4) by using sustainability criteria which are as economic (SC1), social (SC2), environmental (SC3), cultural (SC4) and spatial (SC5) benefits was performed. A group of three experts (PME1, PME2 and PME3) was made. Each expert reviewed the projects and the criteria and provided its judgment on project and criteria assessments by using IVPFSs. To properly achieve IVPFS values, the PMEs were given the preliminary knowledge of IVPFSs and were asked to express their judgments by using membership and non-membership degrees. After the required information was gathered, they were checked to see if the constraint was not violated. Consequently, the violated values were returned to be adjusted. Employing IVPFSs provides more space to express agreement, disagreement and hesitancy in comparison with IFSs. In addition to this advantage, IVPFSs carry an advantage in comparison with PFSs which is employing intervals to express uncertain elements.
Table 1 depicts how sustainable the projects are, and Table 2 shows the value of evaluation criteria.

{Please insert Table 1 here.}

{Please insert Table 2 here.}

Since all the evaluation criteria belong to the benefit category, it is not required to perform the normalization step. As a result, the ranking and defuzzification steps are done to get the needed matrices. Initially, positive and negative ideal solutions are set and then the computations for obtaining the values of \( d^*_+(IVPFS, IVPFS_{\text{bon}}) \) and \( d^*_-(IVPFS, IVPFS_{\text{bon}}) \) are done. Finally, the overall performance of each IVPFS is computed. Table 3 presents the results for the first decision maker.

{Please insert Table 3 here.}

In order to use both subjective and objective weights in this process, entropy of criteria weights are computed, then the new weight is constructed. Table 4 presents the entropy and the new weights.

{Please insert Table 4 here.}

In order to form the linear assignment model, it is required to form the matrix of \( T^v \). Based on the defuzzified values presented in Table 3, the matrix for the first DM can be formed.

\[
T^v = \begin{bmatrix}
SOW^1_4 & SOW^1_1 + SOW^1_2 + SOW^1_3 + SOW^1_5 & 0 & 0 \\
SOW^1_5 & SOW^1_4 & SOW^1_1 + SOW^1_2 & SOW^1_3 & SOW^1_1 + SOW^1_2 + SOW^1_3 \\
0 & 0 & SOW^1_3 & SOW^1_4 + SOW^1_5 & SOW^1_4 + SOW^1_5 \\
SOW^1_1 + SOW^1_2 + SOW^1_3 & 0 & SOW^1_4 + SOW^1_5 & 0 & 0
\end{bmatrix} \quad (37)
\]
Then, the values of $T^p$ for each DM are calculated. The resulting values are utilized to make the mathematical model of linear assignment method. For instance, the objective function for the first DM is formed as follows:

$$\max z = 0.03x_{11} + 0.8x_{12} + 0x_{13} + 0x_{14} + 0.039x_{21} + 0.032x_{22} + 0.62x_{23} + 0.04x_{24} + 0x_{31} + 0x_{32} + 0.04x_{33} + 0.77x_{34} + 0.73x_{41} + 0x_{42} + 0.35x_{43} + 0.44x_{44}$$ \hspace{1cm} (38)

After solving the linear assignment models for each DM by using LINGO optimizing software, the following rankings are gained as given in Table 5:

{Please insert Table 5 here.}

In order to reach an aggregated result based on the judgments of all experts, the aggregation process is performed. Sensitivity analysis on the importance of experts was performed, and Table 6 presents the results. Moreover, Figure 2 presents the ranking of alternatives.

{Please insert Table 6 here.}

{Please insert Figure 2 here.}

**Comparative analysis:**

In order to provide a proper comparison and elaborate the novelties of this paper, this part displays a comparative analysis. In detail, first, the results are compared with the results obtained by the method of Oz et al. [45] in Table 7. Then, a comparative analysis of the method with some of the recent papers is presented in Table 8.

{Please insert Table 7 here.}
The results show that both methods yield similar outputs. Therefore, the method provides results that are confirmed with the method of Oz et al. [45]. To show the advantages of the presented method with recent papers, Table 8 is provided. This table presents the finer points of the presented method.

{Please insert Table 8 here.}

5. Conclusion

Real-world decision making involves dealing with various uncertain elements. These uncertain elements could change the outcomes of decision-making process. It is necessary to consider this uncertainty in any real-world cases. Scholars have employed fuzzy sets to enhance the existing decision processes to deal with the vagueness of decision-making environment. To better address uncertainty, fuzzy extensions have been proposed and applied in decision-making studies. Interval-valued Pythagorean fuzzy sets (IVPFSs) as extensions of intuitionistic fuzzy sets (IFSs) enhance the presentation of uncertainty by expressing membership, non-membership and hesitancy in a flexible way. To apply these sets in decision-making process, a new interval valued Pythagorean fuzzy (IVPF) method was proposed. The proposed method was based on the concept of the linear assignment method (LAM). However, this concept was not solely extended to a new environment, but the method is also enhanced in several aspects. Given the importance of criteria weight in the LAM, both subjective and objective weights of criteria were developed to enhance the process. Also, a new ranking method for IVPFSs was introduced which served as a step of this process. Another aspect of development was that the introduced method addressed group decision making through a last aggregation extension of the LAM. This resulted in avoiding information loss. Moreover, the method was further enhanced by considering weights of decision makers in the aggregation process. The WASPAS method was utilized to aggregate the results. In order to investigate the applicability of this method, data from a case study was employed to evaluate and prioritize projects in a portfolio based on sustainable criteria. To better investigate the outcomes of the process, sensitivity analysis on the weights of experts was carried out, and the results were compared with recent studies. Several open questions are left to future research works. First, impacts of using other concepts rather than entropy to consider importance of criteria could be investigated in the method. Second, utilizing subjective and objective data to express an importance of decision makers could be explored in the aggregation part of this paper. The third issue that can be addressed is considering leniency reduction in the linear assignment method. Fourth, the method can be extended using similar fuzzy sets such as spherical and picture fuzzy sets to

16
investigate the impacts of using various tools. Finally, the proposed method could be applied in other case utilizations to assess the features of the method and IVPFSs in different environments.

References


35. Mohagheghi, V. Mousavi, S. M. Siadat, A. "A new approach in considering vagueness and lack of knowledge for selecting sustainable portfolio of production projects". In 2015 IEEE International
43. Li, M. Xu, K. Huang, S. "Evaluation of green and sustainable building project based on extension matter-element theory in smart city application" Computational Intelligence, Article in press. (2020), DOI:10.1111/coin.12286
Figures’ captions

Figure 1. Spaces of PFS and IFS

Figure 2. Priority of projects under different weights of DMs
Tables’ captions

**Table 1.** Projects sustainability assessments results

**Table 2.** Criteria weights applied in sustainable assessment

**Table 3.** The results of ranking step

**Table 4.** Entropy and $SOW^p_h$

**Table 5.** Ranking of each expert

**Table 6.** Aggregated results under different weights of experts

**Table 7.** Comparing the results with the results of Oz et al. (2019)

**Table 8.** Comparing the presented method with similar studies
Figures:

Figure 1.
Tables:

**Table 1.**

<table>
<thead>
<tr>
<th>PME1</th>
<th>SC1</th>
<th>SC2</th>
<th>SC3</th>
<th>SC4</th>
<th>SC5</th>
</tr>
</thead>
<tbody>
<tr>
<td>CP1</td>
<td>([0.55,0.75], [0.25,0.4])</td>
<td>([0.62,0.72], [0.22,0.32])</td>
<td>([0.46,0.49], [0.38,0.48])</td>
<td>([0.71,0.75], [0.23,0.32])</td>
<td>([0.65,0.68], [0.23,0.33])</td>
</tr>
<tr>
<td>CP2</td>
<td>([0.35,0.45], [0.6,0.7])</td>
<td>([0.5,0.6], [0.3,0.35])</td>
<td>([0.07,0.15], [0.8,0.9])</td>
<td>([0.69,0.71], [0.25,0.4])</td>
<td>([0.75,0.78], [0.33,0.43])</td>
</tr>
<tr>
<td>CP3</td>
<td>([0.2,0.4], [0.5,0.6])</td>
<td>([0.45,0.48], [0.35,0.39])</td>
<td>([0.12,0.18], [0.74,0.84])</td>
<td>([0.51,0.55], [0.41,0.45])</td>
<td>([0.41,0.45], [0.56,0.6])</td>
</tr>
<tr>
<td>CP4</td>
<td>([0.6,0.8], [0.3,0.4])</td>
<td>([0.72,0.78], [0.15,0.2])</td>
<td>([0.56,0.66], [0.23,0.43])</td>
<td>([0.55,0.65], [0.23,0.33])</td>
<td>([0.45,0.48], [0.55,0.58])</td>
</tr>
<tr>
<td>PME2</td>
<td>SC1</td>
<td>SC2</td>
<td>SC3</td>
<td>SC4</td>
<td>SC5</td>
</tr>
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<td>CP1</td>
<td>([0.4,0.65], [0.32,0.45])</td>
<td>([0.62,0.78], [0.25,0.4])</td>
<td>([0.48,0.52], [0.41,0.45])</td>
<td>([0.65,0.69], [0.28,0.39])</td>
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<tr>
<td>CP2</td>
<td>([0.33,0.48], [0.55,0.65])</td>
<td>([0.6,0.65], [0.28,0.39])</td>
<td>([0.12,0.18], [0.71,0.75])</td>
<td>([0.55,0.75], [0.29,0.42])</td>
<td>([0.69,0.72], [0.23,0.33])</td>
</tr>
<tr>
<td>CP3</td>
<td>([0.3,0.5], [0.4,0.75])</td>
<td>([0.5,0.55], [0.37,0.47])</td>
<td>([0.18,0.21], [0.7,0.78])</td>
<td>([0.5,0.58], [0.4,0.43])</td>
<td>([0.31,0.42], [0.6,0.69])</td>
</tr>
</tbody>
</table>
\[
\begin{array}{c|cccc}
\text{CP}_{1} & (0.7,0.85) & (0.2,0.4) & (0.79,0.85) & (0.12,0.15) \\
\text{CP}_{2} & (0.68,0.69) & (0.51,0.50) & (0.51,0.53) & (0.42,0.48) \\
\text{CP}_{3} & (0.6,0.65) & (0.3,0.35) & (0.6,0.65) & (0.3,0.35) \\
\text{CP}_{4} & (0.41,0.48) & (0.48,0.55) & (0.41,0.48) & (0.48,0.55) \\
\text{CP}_{5} & (0.85,0.89) & (0.17,0.25) & (0.85,0.89) & (0.17,0.25) \\
\end{array}
\]

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<th>\text{SC}_{2}</th>
<th>\text{SC}_{3}</th>
<th>\text{SC}_{4}</th>
<th>\text{SC}_{5}</th>
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</thead>
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<tr>
<td>\text{CP}_{1}</td>
<td>(0.41,0.72)</td>
<td>(0.2,0.52)</td>
<td>(0.68,0.69)</td>
<td>(0.51,0.50)</td>
<td>(0.51,0.53)</td>
</tr>
<tr>
<td>\text{CP}_{2}</td>
<td>(0.42,0.52)</td>
<td>(0.55,0.72)</td>
<td>(0.61,0.69)</td>
<td>(0.45,0.55)</td>
<td>(0.45,0.53)</td>
</tr>
<tr>
<td>\text{CP}_{3}</td>
<td>(0.31,0.51)</td>
<td>(0.42,0.62)</td>
<td>(0.17,0.22)</td>
<td>(0.65,0.81)</td>
<td>(0.78,0.52)</td>
</tr>
<tr>
<td>\text{CP}_{4}</td>
<td>(0.62,0.91)</td>
<td>(0.18,0.02)</td>
<td>(0.55,0.61)</td>
<td>(0.31,0.41)</td>
<td>(0.70,0.35)</td>
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<td>\text{CP}_{5}</td>
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<td>(0.75,0.8)</td>
<td>(0.68,0.68)</td>
<td>(0.23,0.29)</td>
<td>(0.5,0.5)</td>
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<td>(0.22,0.35)</td>
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<td>(0.68,0.72)</td>
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<td>(0.62,0.75)</td>
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<td>(0.75,0.25)</td>
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**Table 3.**

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<th>\text{CP}_{3}</th>
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<td>(d^{+}_{s})</td>
<td>0.28</td>
<td>1.23</td>
<td>1.36</td>
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</tr>
<tr>
<td>(d^{-}_{s})</td>
<td>1.13</td>
<td>0.66</td>
<td>0</td>
<td>1.36</td>
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<tr>
<td>(IVPFSP_{s})</td>
<td>0.8</td>
<td>0.35</td>
<td>0</td>
<td>1</td>
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<table>
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<tr>
<td>(d^{+}_{s})</td>
<td>0.34</td>
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<td>(d^{-}_{s})</td>
<td>0.8</td>
<td>0.31</td>
<td>0</td>
<td>1.15</td>
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<tr>
<td>(IVPFSP_{s})</td>
<td>0.69</td>
<td>0.27</td>
<td>0</td>
<td>1</td>
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<th>\text{SC}_{3}</th>
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<th>\text{CP}_{2}</th>
<th>\text{CP}_{3}</th>
<th>\text{CP}_{4}</th>
</tr>
</thead>
<tbody>
<tr>
<td>(d^{+}_{s})</td>
<td>0.51</td>
<td>2.19</td>
<td>1.8</td>
<td>0</td>
</tr>
</tbody>
</table>

24
\[ d^+_g = 1.99 \quad 0 \quad 0.38 \quad 2.19 \]

\[ IVPFS_{PSP} = 0.79 \quad 0 \quad 0.17 \quad 1 \]

\begin{table}[h]
\centering
\begin{tabular}{c|cccc}
& SC1 & SC2 & SC3 & SC4 \\
\hline
PME1 & ([0.64,0.69], [0.37,0.5]) & ([0.62,0.68], [0.23,0.29]) & ([0.5,0.6], [0.4,0.5]) & ([0.39,0.49], [0.33,0.38]) & ([0.5,0.59], [0.33,0.42]) \\
PME2 & ([0.57,0.61], [0.25,0.35]) & ([0.55,0.58], [0.31,0.39]) & ([0.43,0.49], [0.3,0.39]) & ([0.45,0.56], [0.33,0.39]) & ([0.45,0.55],[0.25,0.35]) \\
PME3 & ([0.59,0.64], [0.41,0.5]) & ([0.43,0.49], [0.33,0.38]) & ([0.5,0.55], [0.33,0.43]) & ([0.5,0.56],[0.4,0.5]) & ([0.62,0.75],[0.25,0.28]) \\
\hline
Entropy & 0.6424 & 0.822 & 0.905 & 0.918 & 0.8 \\
\end{tabular}
\caption{Table 4.}
\end{table}

\begin{table}[h]
\centering
\begin{tabular}{c|cccc}
& CP1 & CP2 & CP3 & CP4 \\
\hline
PME1 & 2 & 3 & 4 & 1 \\
PME2 & 2 & 4 & 3 & 1 \\
PME3 & 2 & 3 & 4 & 1 \\
\end{tabular}
\caption{Table 5.}
\end{table}

\begin{table}[h]
\centering
\begin{tabular}{c|ccc}
& PME1 & PME2 & PME3 \\
\hline
Weight of expert & (0.33) & (0.33) & (0.33) \\
Project & CP1 & CP2 & CP3 & CP4 \\
\end{tabular}
\caption{Table 6.}
\end{table}
<table>
<thead>
<tr>
<th>Rank</th>
<th>Project</th>
<th>Expert</th>
<th>Weight of expert</th>
<th>Project</th>
<th>Expert</th>
<th>Weight of expert</th>
<th>Project</th>
<th>Expert</th>
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<td>2</td>
<td>CP₁</td>
<td>PME₁</td>
<td>(0.2)</td>
<td>CP₂</td>
<td>PME₂</td>
<td>(0.2)</td>
<td>CP₃</td>
<td>PME₃</td>
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<tr>
<td>3</td>
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<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
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<td></td>
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<td></td>
<td></td>
<td></td>
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<tr>
<td>1</td>
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Table 7. 

<table>
<thead>
<tr>
<th>Rank (Oz et al., 2019)</th>
<th>Presented method of this paper</th>
</tr>
</thead>
<tbody>
<tr>
<td>CP₁</td>
<td>3</td>
</tr>
<tr>
<td>CP₂</td>
<td>2</td>
</tr>
<tr>
<td>CP₃</td>
<td>4</td>
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<tr>
<td>CP₄</td>
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</table>

Table 8. 

<table>
<thead>
<tr>
<th>Aspect</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Uncertainty</td>
<td>Using Pythagorean fuzzy sets that apply the membership, non-membership and hesitancy values with more flexibility in comparison with intuitionistic fuzzy sets.</td>
</tr>
<tr>
<td>Weight of criteria</td>
<td>This paper in comparison with other studies that apply linear assignment uses the weight of criteria that consists of subjective and objective weights of criteria.</td>
</tr>
<tr>
<td>First and last aggregations</td>
<td>The aggregation in this paper is carried out in the final step of this paper. This would result in a reduction of information loss which is caused when the aggregation is carried out in the initial phases.</td>
</tr>
<tr>
<td>Aggregation method</td>
<td>The aggregation is performed based on the WASPAS method. This would provide the step with the benefits of this method.</td>
</tr>
</tbody>
</table>
Biographies:

**Vahid Mohagheghi** is currently a PhD student at the Department of Industrial Engineering, Faculty of Engineering, Shahed University, in Tehran, Iran. He received his MSc degree from the Department of Industrial Engineering, Shahed University, in 2015. His main research interests include quantitative methods in project management, multi-criteria decision making, fuzzy sets theory, and logistics planning. He has published several papers in reputable journals and international conference proceedings.

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