AHP and Intuitionistic Fuzzy TOPSIS Methodology for SCM Selection

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1 Introduction

Multi-Criteria Decision-Making (MCDM) is a modeling and methodological tool for dealing with complex engineering problems [1]. Many mathematical programming models have been developed to address MCDM problems. However, in recent years, MCDM methods have gained considerable acceptance for judging different proposals. Intuitionistic fuzzy set (IFS) theory introduced by Atanassov [2] is an extension of the classical Fuzzy Set (FS), which is a suitable tool to deal with the vagueness and uncertainty decision information [2]. Recently, some researchers have shown interest in the IFS theory and applied it in the field of MCDM [3–10]. However, IFS has also been applied to many areas, such as medical diagnosis [11–13] decision-making problems [6–8, 14–31], pattern recognition [33–38], supplier sélection [39, 40], entreprise partners selection [41], personnel selection [42], evaluation of renewable energy [43], facility location selection [44], web service selection [45], printed circuit board assembly [46], management information system [47] and project selection [48].

The AHP proposed by Saaty [49] is one of the most popular methods in the based on the preference relation in the decision-making process [49]. The AHP is a well-known method for solving decision-making problems. In this method, the decision-maker (DM) performs pair-wise comparisons and, then, the pair-wise comparison matrix and the eigenvector are derived to specify the weights of each parameter in the problem. The weights guide the DM in choosing the superior alternative.

We study the AHP-IFT methodology here where all the values are expressed in Intuitionistic fuzzy numbers collected. To do that, we first present the concept of AHP and determine the weight of the criteria based on the opinions of decision-

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makers. Then, we introduce the concept of IFT and develop a model based on such opinions. The rest of the paper is organized as follows: Sect. 2 provides the materials and methods—mainly AHP, Fuzzy Set Theory (FST) and Intuitionistic Fuzzy Set (IFS). The AHP-IFT methodology is introduced in Sect. 3. How the proposed model is used in a numerical example is explained in Sect. 4. The conclusions are provided in the final section.

2 Preliminaries

2.1 Basic Concept of AHP

The AHP is a general theory of measurement. It is used to derive relative priorities on absolute scales from both discrete and continuous paired comparisons in multilevel hierarchic structures. These comparisons may be taken from a fundamental scale that reflects the relative strength of preferences. The AHP has a special concern with deviation from consistency and the measurement of this deviation, and with dependence within and between the groups of elements of its structure. It has found its widest applications in MCDM. Generally, the AHP is a nonlinear framework for carrying out both deductive and inductive thinking without the use of syllogism [50].

The AHP proposed by Saaty [49] is a flexible method for selecting among alternatives based on their relative performance with respect to a given criteria [51, 52]. AHP resolves complex decisions by structuring alternatives into a hierarchical framework. Such hierarchy is constructed through pair-wise comparisons of individual judgments rather than attempting to prioritize the entire list of decisions and criteria. This process has been given as follows [53]:

Describe the unstructured problem; Detail the criteria and alternatives; Recruit pair-wise comparisons among decision elements; Use the Eigen-value method to predict the relative weights of the decision elements; Compute the consistency properties of the matrix, and Collect the weighted decision elements.

The AHP techniques form a framework of the decisions that use a one-way hierarchical relation with respect to decision layers. The hierarchy is constructed in the middle level(s), with decision alternatives at the bottom. The AHP method provides a structured framework for setting priorities at each level of the hierarchy using pair-wise comparisons that are quantified using a 1–9 scale as demonstrated in Table 1.

Table 1 The fundamental scale

Importance intensity	Definition
1	Equal importance
3	Moderate importance of one over another
5	Strong importance of one over another
7	Very strong importance of one over another
9	Extreme importance of one over another
2, 4, 6, 8	Intermediate values

2.2 FST

Zadeh [54] introduced the FST to deal with uncertainty and vagueness. A major contribution of FST is capability in representing uncertain data. FST also allows mathematical operators and programming to be performed in the fuzzy domain. An FS is a class of objects with a continuum of grades of membership. Such a set is characterized by a membership function, which assigns to each object a grade of membership ranging "between" zero and one [55, 56].

A tilde '~' will be placed above a symbol if the symbol shows an FST. A Triangular Fuzzy Number (TFN) $\widetilde{M}$ is shown in Fig. 1. A TFN is denoted simply as (a,b,c). The parameters a, b and c $(a \le b \le c)$, respectively, denote the smallest possible value, the most promising value, and the largest possible value that describe a fuzzy event. The membership function of TFN is as follows:

Each TFN has linear representations on its left and right side, such that its membership function can be defined as

$$\mu\left(\frac{x}{\widetilde{M}}\right) = \begin{cases} 0, & x < a, \\ (x-a)/(b-a), & a \le x \le b, \\ (c-x)/(c-b), & b \le x \le c, \\ 0, & x > c. \end{cases} \tag{1}$$

The left and right representation of each degree of membership as in the following:

$$\widetilde{M} = M^{l(y)}, M^{r(y)} = (a + (b-a)y, c + (b-c)y), \quad y \in [0,1] \tag{2}$$

where $l(y)$ and $r(y)$ denote the left-side representation and the right-side representation of a fuzzy number(FN), respectively. Many ranking methods for FNs have

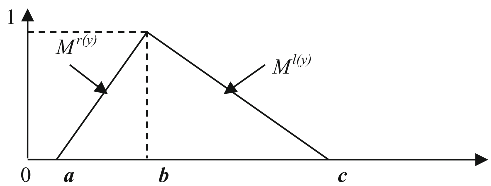

Fig. 1 A TFN $\widetilde{M}$

been developed in the literature. These methods may provide different ranking results [57].

While there are various operations on TFNs, only the important operations used in this study are illustrated. Two positive TFNs (a_1, b_1, c_1) and (a_2, b_2, c_2) have been given as follows:

$$\begin{aligned}(a_1, b_1, c_1) + (a_2, b_2, c_2) &= (a_1 + a_{2,}, b_1 + b_2, c_1 + c_2),\\ (a_1, b_1, c_1) - (a_2, b_2, c_2) &= (a_1 - a_{2,}, b_1 - b_2, c_1 - c_2),\\ (a_1, b_1, c_1) * (a_2, b_2, c_2) &= (a_1 * a_{2,}, b_1 * b_2, c_1 * c_2),\\ (a_1, b_1, c_1)/(a_2, b_2, c_2) &= \left(a_{1/}c_{2,}, b_{1/}b_2, c_1/a_2\right).\end{aligned} \tag{3}$$

2.3 Basic Concept of IFS

The following formulas briefly introduce some necessary introductory basic concepts of IFS. IFS A in a finite set R can be written as:

$$\chi_{ij} = \left(\mu_{ij}, v_{ij}, \pi_{ij}\right),$$

Where,
$\boldsymbol{\mu_{ij}}$: Degree of membership of the the i_{th} alternative with respect to j_{th} criteria
$\boldsymbol{v_{ij}}$: Degree of non-membership of i_{th} alternative with respect to j_{th} criteria
$\boldsymbol{\pi_{ij}}$: Degree of hesitation of the i_{th} alternative with respect to the j_{th} criteria
R is an intuitionistic fuzzy decision matrix.

$$\begin{aligned}&A = \{\langle r, \mu_A(r), v_A(r)\rangle | r \in R\}\\ &where\\ &\mu_A(r) : \mu_A(r) \in [0, 1], R \rightarrow \quad [0, 1]\\ &v_A(r) : v_A(r) \in [0, 1], R \rightarrow \quad [0, 1]\end{aligned} \tag{4}$$

μ_A and v_A are the membership function and non-membership function, respectively, such that

$$0 \le \mu_A(r) \oplus v_A(r) \le 1 \quad \forall r \in R \quad R \rightarrow \quad [0, 1] \tag{5}$$

A third parameter of IFS is $\pi_A(r)$, known as the intuitionistic fuzzy index or hesitation degree of whether r belongs to A or not

$$\pi_A(r) = 1 - \mu_A(r) - v_A(r) \tag{6}$$

$\pi_A(r)$ is called the degree of indeterminacy of r to A.

It is obviously seen that for every $r \in R$:

$$0 \leq \pi_A(r) \leq 1 \quad \pi_A(r) \tag{7}$$

If $\pi_A(r)$ is small the knowledge about r is more certain. However, if $\pi_A(r)$ is great, this knowledge is rather uncertain. Obviously, when

$$\mu_A(r) = 1 - v_A(r) \tag{8}$$

For all elements of the universe, the ordinary FST concept is recovered [46].

Let A and B are IFSs of the set R. Then, the multiplication operator is defined as follows (2).

$$A \otimes B = \{\mu_A(r).\mu_B(r), v_A(r) + v_B(r) - v_A(r).v_B(r) | r \in R\} \tag{9}$$

3 AHP-IFT Hybrid Method

To rank a set of alternatives, the AHP-IFT methodology as an outranking relation theory is used to analyze the data of a decision matrix. We assume m alternatives and n decision criteria. Each alternative is evaluated with respect to the n criteria. All the values assigned to the alternatives with respect to each criterion form a decision matrix.

In this study, our model integrates two well-known models, AHP and IFT. The evaluation of the study based on this hybrid methodology is given in Fig. 2. The procedure for AHP-IFT methodology ranking model has been given as follows:

Let $A = \{A_1, A_2, \ldots, A_m\}$ be a set of alternatives and $C = \{C_1, C_2, \ldots, C_n\}$ be a set of criteria. It should be mentioned here that the presented approach mainly utilizes the IFT method proposed in [39, 42–44, 48]. The procedure for AHP-IFT methodology is conducted in seven steps presented as follows:

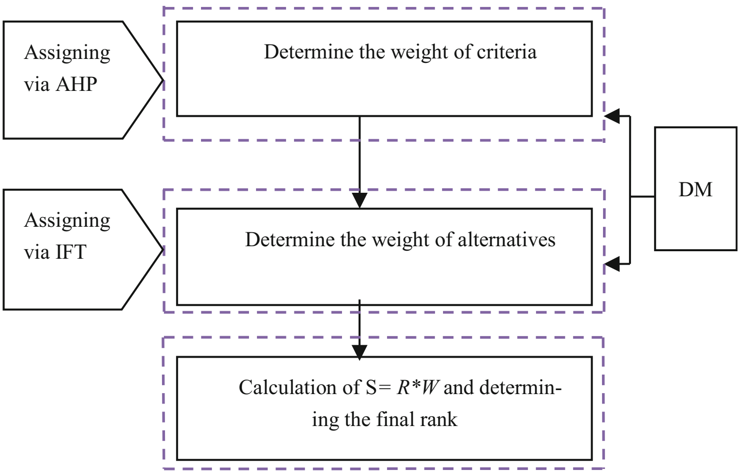

Fig. 2 Schematic diagram of the AHP–IFT

Table 2 Fundamental scale of absolute numbers

Importance intensity	Definition	Definition
1	Very Bad (VB)	Equal importance
3	Bad(B)	Moderate importance of one over another
5	Medium Best(MB)	Strong importance of one over another
7	Good(G)	Very strong importance of one over another
9	Very Good(VG)	Extreme importance of one over another

Step 1

Determine the weight of the criteria based on the opinion of decision-makers (W).

In the first step, we assume that the decision group contains $\mathrm{l} = \{\mathrm{l}_1, \mathrm{l}_2, \ldots, \mathrm{l}_\mathrm{l}\}$ DMs. The DMs is given the task of forming individual pair-wise comparisons by using standard scale as in Table 2.

Step 2

Determine the weights of importance of DMs:

In the second step, we assume that the decision group contains $l = \{l_1, l_2, \ldots, l_l\}$ DMs. The importance's of the DMs are considered as linguistic terms which are assigned to IFNs. Let $D_l = [\mu_l, v_l, \pi_l]$ be an intuitionistic fuzzy number for rating of k_{th} DM. Then, the weight of l_{th} DM can be calculated as:

$$\lambda_l = \frac{\left(\mu_l + \pi_l\left(\frac{\mu_l}{\mu_l + v_l}\right)\right)}{\sum_{l=1}^{k}\left(\mu_l + \pi_l\left(\frac{\mu_l}{\mu_l + v_l}\right)\right)} \quad where\, \lambda_l \in [0, 1] \quad and \quad \sum_{l=1}^{k} \lambda_l = 1. \tag{10}$$

Step 3

Determine the Intuitionistic Fuzzy Decision Matrix (IFDM).

Based on the weight of DMs, the aggregated intuitionistic fuzzy decision matrix (AIFDM) is calculated by applying the intuitionistic fuzzy weighted averaging (IFWA) operator Xu [58]. In a group decision-making process, all the individual decision opinions need to be fused into a group opinion to construct AIFDM [58].

Let $R^{(l)} = (r_{ij}^{(l)})_{m \times n}$ be an IFDM of each DM. $\lambda = \{\lambda_1, \lambda_2, \lambda_3, \ldots, \lambda_k\}$ is the weight of DM as result, are equal.

$$R = \left(r_{ij}\right)_{m\times n},$$

Where

$$\begin{aligned} r_{ij} &= IFWA_\lambda\left(r_{ij}^{(1)}, r_{ij}^{(2)}, \ldots, r_{ij}^{(l)}\right) \\ &= \lambda_1 r_{ij}^{(1)} \oplus \lambda_2 r_{ij}^{(2)} \oplus \lambda_3 r_{ij}^{(3)} \oplus \ldots \oplus \lambda_k r_{ij}^{(k)} \\ &= \left[1 - \prod_{l=1}^{k}\left(1 - \mu_{ij}^{(l)}\right)^{\lambda_l}, \prod_{l=1}^{k}\left(v_{ij}^{(l)}\right)^{\lambda_l}, \prod_{l=1}^{k}\left(1 - \mu_{ij}^{(l)}\right)^{\lambda_l} - \prod_{l=1}^{k}\left(v_{ij}^{(l)}\right)^{\lambda_l}\right]. \end{aligned} \tag{11}$$

Step 4
Calculate $S = R^*W$:

In the step 4, a weight of criteria (W) with respect to IFDM (R) is defined as follows:

$$S = R * W \tag{12}$$

Step 5
Determine the intuitionistic fuzzy positive and negative ideal solutions:

In this step, the intuitionistic fuzzy positive ideal solution (IFPIS) and intuitionistic fuzzy negative ideal solution (IFNIS) have to be determined. Let J_1 and J_2 be the benefit criteria and cost criteria, respectively. A^* is IFPIS and A^- is IFNIS. Then, A^* and A^- are equal to:

$$A^* = \left(r_1^{'*}, r_2^{'*}, \ldots, r_n^{'*}\right), r_j^{'*} = \left(\mu_j^{'*}, v_j^{'*}, \pi_j^{'*}\right), j = 1, 2, \ldots, n \tag{13}$$

and

$$A^- = \left(r_1^{'-}, r_2^{'-}, \ldots, r_n^{'-}\right), r_j^{'-} = \left(\mu_j^{'-}, v_j^{'-}, \pi_j^{'-}\right), j = 1, 2, \ldots, n \tag{14}$$

Where

$$\mu_j^{'*} = \left\{\left(\max_i \left\{\mu_{ij}^{'}\right\} j \in J_1\right), \left(\min_i \left\{\mu_{ij}^{'}\right\} j \in J_2\right\}, \tag{15}$$

$$v_j^{*} = \left\{\left(\min_i \left\{v_{ij}^{'}\right\} j \in J_1\right), \left(\max_i \left\{v_{ij}^{'}\right\} j \in J_2\right\}, \tag{16}$$

$$\pi_j^{'*} = \left\{\left(1 - \max_i \left\{\mu_{ij}^{'}\right\} - \min_i \left\{v_{ij}^{'}\right\} j \in J_1\right), \left(1 - \min_i \left\{\mu_{ij}^{'}\right\} - \max_i \left\{v_{ij}^{'}\right\} j \in J_2\right\}, \tag{17}$$

$$\mu_j^{'-} = \left\{\left(\min_i \left\{\mu_{ij}^{'}\right\} j \in J_1\right), \left(\max_i \left\{\mu_{ij}^{'}\right\} j \in J_2\right\}, \tag{18}$$

$$v_j^{'-} = \left\{ \left(\max_i \left\{ v_{ij}^{'} \right\} j \in J_1 \right), \left(\min_i \left\{ v_{ij}^{'} \right\} j \in J_2 \right\}, \tag{19}$$

$$\pi_j^{'-} = \left\{ \left(1 - \min_i \left\{ \mu_{ij}^{'} \right\} - \max_i \left\{ v_{ij}^{'} \right\} j \in J_1 \right), \left(1 - \max_i \left\{ \mu_{ij}^{'} \right\} - \min_i \left\{ v_{ij}^{'} \right\} j \in J_2 \right\}. \tag{20}$$

Step 6

Determine the separation measures between the alternative:

We can make use of the separation between alternatives on IFS, distance measures proposed by Atanassov [59], Szmidt and Kacprzyk [60], and Grzegorzewski [61] including the generalizations of Hamming distance, Euclidean distance and their normalized distance measures. After selecting the distance measure, the separation measures, S_i^* and S_i^-, of each alternative from IFPIS and IFNIS, are calculated:

$$S_i^* = \frac{1}{2} \sum_{j=1}^{n} \left[\left| \mu_{ij}^{'} - \mu_j^{'*} \right| + \left| v_{ij}^{'} - v_j^{'*} \right| + \left| \pi_{ij}^{'} - \pi_j^{'*} \right| \right] \tag{21}$$

$$S_i^- = \frac{1}{2} \sum_{j=1}^{n} \left[\left| \mu_{ij}^{'} - \mu_j^{'-} \right| + \left| v_{ij}^{'} - v_j^{'-} \right| + \left| \pi_{ij}^{'} - \pi_j^{'-} \right| \right] \tag{22}$$

Step 7

Make the final ranking

In the final step, the relative closeness coefficient of an alternative A_i with respect to the IFPIS A^* is defined as follows:

$$C_i^* = \frac{S_i^-}{S_i^* + S_i^-} where 0 \leq C_i^* \leq 1. \tag{23}$$

The alternatives are ranked according to the descending order of C_i^*'s score.

4 Numerical Examples

In this section, we describe how an AHP-IFT methodology is applied via an example. The criteria to be considered in the selection of projects are determined by an expert team from the decision group. In our study, we employ six evaluation criteria. The attributes which are considered here in the assessment of A_i (i = 1,2,. . .,6) are: (1) C_1 as benefit; (2) C_2,.., C_6 as cost. The committee evaluates the performance of alternatives A_i (i = 1,2,. . .,4) according to the attributes C_j (j = 1,2,. . .,6), respectively. Therefore, one cost criterion, C_1, and five benefit criteria, C_2,. . .,C_6 are considered. After preliminary screening, four alternatives

Table 3 The importance weight of the criteria

Criteria	DM_1	DM_2	DM_3	DM_4
C_1	G	VG	VG	MB
C_2	VG	VG	VG	VG
C_3	MB	G	VG	MB
C_4	G	G	VG	G
C_5	G	VG	MB	G
C_6	MB	G	MB	VG

Table 4 Linguistic term for rating DMs

Linguistic terms	IFNs
Very Important	(0.80, 0.10)
Important	(0.50, 0.20)
Medium	(0.50, 0.50)
Bad	(0.3, 0.50)
Very Bad	(0.20, 0.70)

A_1, A_2, A_3, and A_4, remain for further evaluation. A team of four DMs,—such as; DM_1, DM_2, DM_3, and DM_4—is formed to select the most suitable alternative.

The importance weight of the criteria given by the four DMS appear in Table 3.

The opinions of the DMs on the criteria are aggregated to determine the weight of each criterion.

$$W_{\{R_1,R_2,R_3,R_4,R_5,R_6\}} = \begin{bmatrix} 0,170 \\ 0,205 \\ 0,148 \\ 0,170 \\ 0,159 \\ 0,148 \end{bmatrix}^T$$

Also, the degree of the DMs on group decision, shown in Table 4, and the linguistic terms used for the ratings of the DMs, appear Table 5.

We construct the aggregated IFDM based on the opinions of DMs. The linguistic terms are shown in Table 6.

The ratings given by the DMs to six alternatives appear in Table 7.

The aggregated IFDM based on aggregation of DMs' opinions is constructed as follows:

Table 5 The importance of DMs and their weights

	DM_1	DM_2	DM_3	DM_4
Linguistic terms	Very important	Medium	Important	Important
Weight	0.342	0.274	0.192	0.192

Table 6 Linguistic terms for rating the alternatives

Linguistic terms	IFNs
Extremely good (EG)	[1.00; 0.00;0.00]
Very good (VG)	[0.85;0,05; 0.10]
Good (G)	[0.70; 0.20;0.10]
Medium bad (MB)	[0.50; 0.50;0.00]
Bad (B)	[0.40; 0.50;0.10]
Very bad (VB)	[0.25; 0.60;0.15]
Extremely bad (EB)	[0.00, 0.90,0.10]

$$R = \begin{array}{c c} & \begin{array}{cccccc} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 \end{array} \\ \begin{array}{c} A_1 \\ A_2 \\ A_3 \\ A_4 \\ A_5 \\ A_6 \end{array} & \begin{bmatrix} (0.80,0.08,0.12) & (0.69,0.20,0.11) & (0.76,0.12,0.12) & (0.80,0.09,0.11) & (0.78,0.11,0.11) & (0.69,0.20,0.11) \\ (0.68,0.20,0.12) & (0.78,0.11,0.11) & (0.74,0.13,0.13) & (0.78,0.11,0.11) & (0.69,0.21,0.10) & (0.75,0.13,0.12) \\ (0.82,0.07,0.11) & (0.79,0.10,0.11) & (0.79,0.10,0.11) & (0.84,0.05,0.11) & (0.84,0.05,0.11) & (0.84,0.05,0.11) \\ (0.83,0.16,0.1) & (0.75,0.14,0.11) & (0.70,0.19,0.11) & (0.81,0.08,0.11) & (0.82,0.07,0.11) & (0.85,0.05,0.10) \\ (0.55,0.38,0.07) & (0.42,0.52,0.06) & (0.64,0.40,0.06) & (0.55,0.33,0.12) & (0.54,0.33,0.13) & (0.40,0.54,0.06) \\ (0.75,0.13,0.12) & (0.69,0.19,0.12) & (0.75,0.13,0.12) & (0.75,0.13,0.12) & (0.85,0.05,0.10) & (0.78,0.11,0.11) \end{bmatrix} \end{array}$$

After the weights of the criteria and the rating of the projects were determined, the aggregated weighted IFDM was constructed as follows:

$$R = \begin{array}{c c} & \begin{array}{cccccc} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 \end{array} \\ \begin{array}{c} A_1 \\ A_2 \\ A_3 \\ A_4 \\ A_5 \\ A_6 \end{array} & \begin{bmatrix} (0.136, 0.0136, 0.020) & (0.141, 0.041, 0.023) & (0.112, 0.018, 0.018) & (0.136, 0.015, 0.019) & (0.124, 0.017, 0.017) & (0.102, 0.030, 0.016) \\ (0.116, 0.034, 0.020) & (0.160, 0.023, 0.023) & (0.110, 0.019, 0.019) & (0.133, 0.019, 0.019) & (0.110, 0.033, 0.016) & (0.111, 0.019, 0.018) \\ (0.139, 0.012, 0.019) & (0.162, 0.021, 0.023) & (0.117, 0.015, 0.016) & (0.143, 0.009, 0.019) & (0.134, 0.008, 0.017) & (0.124, 0.007, 0.016) \\ (0.141, 0.027, 0.017) & (0.154, 0.029, 0.023) & (0.104, 0.028, 0.016) & (0.138, 0.014, 0.019) & (0.130, 0.011, 0.017) & (0.126, 0.007, 0.015) \\ (0.094, 0.065, 0.012) & (0.086, 0.107, 0.012) & (0.095, 0.059, 0.009) & (0.094, 0.056, 0.020) & (0.086, 0.052, 0.021) & (0.059, 0.080, 0.009) \\ (0.128, 0.022, 0.020) & (0.141, 0.039, 0.025) & (0.111, 0.019, 0.018) & (0.128, 0.022, 0.020) & (0.135, 0.008, 0.016) & (0.115, 0.016, 0.016) \end{bmatrix} \end{array}$$

Then IFPIS and IFNIS are provided as follows:

$$\begin{aligned} A^* = \{&(0.141, 0.012, 0.847), (0.162, 0.021, 0.817), (0.117, 0.015, 0.868), \\ &(0.143, 0.009, 0.848), (0.135, 0.008, 0.857), (0.126, 0.007, 0.867)\} \\ A^- = \{&(0.094, 0.065, 0.841), (0.086, 0.107, 0.807), (0.095, 0.059, 0.846), \\ &(0.094, 0.056, 0.850), (0.086, 0.052, 0.862), (0.059, 0.080, 0.861)\} \end{aligned}$$

The negative and positive separation measures based on normalized Euclidean distance for each alternative, and the relative closeness coefficient are calculated as Table 8.

Table 7 Ratings of the alternatives

Alternative	Criteria	DM_1	DM_2	DM_3	DM_4
A_1	C_1	*VG*	*VG*	*G*	*G*
	C_2	*G*	*VG*	*MB*	*MB*
	C_3	*VG*	*G*	*B*	*VG*
	C_4	*VG*	*VG*	*G*	*G*
	C_5	*VG*	*VG*	*MB*	*G*
	C_6	*G*	*VG*	*MB*	*MB*
A_2	C_1	*G*	*VG*	*MB*	*B*
	C_2	*VG*	*VG*	*G*	*MB*
	C_3	*VG*	*VG*	*B*	*B*
	C_4	*VG*	*VG*	*MB*	*G*
	C_5	*G*	*G*	*G*	*G*
	C_6	*VG*	*VG*	*MB*	*B*
A_3	C_1	*VG*	*VG*	*G*	*VG*
	C_2	*VG*	*G*	*G*	*VG*
	C_3	*VG*	*G*	*VG*	*G*
	C_4	*VG*	*VG*	*VG*	*VG*
	C_5	*VG*	*VG*	*VG*	*VG*
	C_6	*VG*	*VG*	*VG*	*VG*
A_4	C_1	*MB*	*G*	*MB*	*VG*
	C_2	*G*	*VG*	*G*	*G*
	C_3	*MB*	*VG*	*G*	*G*
	C_4	*VG*	*G*	*VG*	*VG*
	C_5	*VG*	*VG*	*G*	*VG*
	C_6	*VG*	*VG*	*VG*	*VG*

Table 8 Separation measures and relative closeness coefficient of each alternative

Alternatives	S^*	S^-	C_i^*
A_1	2,563	2,737	0.516
A_2	2,570	2,725	0.515
A_3	2,500	2,798	0.528
A_4	2,530	2,773	0.523

5 Conclusion

In this paper, AHP-IFT methodology is incorporated in selecting Supply Chain (SCM). The purpose of the study was to use an MCDM Method which combines AHP and IFT to evaluate a set of alternatives in order to reach the most suitable alternative. In the evaluation process, the ratings of each alternative, given by Intuitionistic fuzzy information, are represented as IFNs. AHP is used to assign weights to the criteria while IFT is employed to calculate the full-ranking of the alternatives. The AHP-IFT methodology was used to aggregate rating DMs.

Multiple DMs are often preferred rather than a single DM to avoid minimizes partiality in the decision process. Therefore, group decision making process for alternative selections considered effective. This is because it combines the idea of different DMs using a scientific MCDM method. In real life, information and performances regarding different settings are usually uncertain. Therefore, the DMs are unable to express their judgments on the best alternatives and/or criteria with crisp values, and such evaluation are very often expressed in linguistic terms, instead AHP and IFT are suitable ways to deal with MCDM because the contains a vague perception of DMs' opinions. A numerical example is illustrated and finally, the, results indicate that Among six alternatives with respect to six criteria, after using this methodology, the best ones are three, four, six, one, two and, five. The presented approach not only validates the methods, but also considers a more extensive list of benefit—and—cost oriented criteria suitable selecting the best. The AHP-IFT methodology has potential to deal with similar types of situations with uncertainty in MCDM problems.

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