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CLOSENESS COEFFICIENT RANKING METHOD BASED ON TYPE-2 INTUITIONISTIC FUZZY NUMBERS AND APPLICATION INTO MULTIPLE-CRITERIA GROUP DECISION-MAKING

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Abstract

This paper explores a ranking method for ***Type-2 Intuitionistic Fuzzy Numbers (T2IFNs)****. Initially, we discuss the concept of T2IFNs and their operational laws involving* ***addition, multiplication, and exponentiation****. Furthermore, we introduce* ***prioritized average operators*** *designed to solve* ***multiple attribute group decision-making (MAGDM)*** *problems under a T2IFN environment, considering varying priority levels for attributes and experts. Specifically, we examine the mathematical properties of the* ***T2IFNs Prioritized Weighted Average (T2IFPWA)*** *operators. Then, after we apply the* ***closeness coefficient method*** *to a normalized prioritized weighted averaging matrix to determine the final ranking of alternatives. To illustrate the feasibility and effectiveness of the proposed approach, a* ***real-world application in the context of talent acquisition*** *is presented. Finally, the alternatives are ranked according to their computed closeness coefficients.*

Keywords: MAGDM, Prioritized Weighted Average Operator, T2FS, T2IFS

I. Introduction

In real-life situations, many mathematical problems are characterized by incomplete or inexact information. Fuzzy environments provide a powerful framework to manage such uncertainties and yield remarkable outcomes. The concept of fuzzy sets and IT2FSs, introduced by Atanassov and Gargov(1989), has been extensively applied across various fields with notable success. These theories have proven effective in diverse decision-making processes. Xu(2008) provides a comprehensive review of the current fuzzy decision-making theories and methods.

Numerous methods for data aggregation have been identified by Beliakov(2007), stands out as the significant aggregation operator. The OWA, which provides a parameterized spectrum of aggregation functions including maximum, minimum, and average, has attracted considerable attention since its inception. It has been widely applied across various fields, as evidenced by the works ofFodor et al.(1995), Bordogna et al.(1997), and Mendel(2004). Additionally, the Order-Weighted Geometric (OWG) operators were introduced by Xu and Da(2002) and Xu andYager(2006) as extensions of the OWA operator, focusing on the geometric mean.Türkşen(2002) expanded on the FOU and the third dimension of T2FSs, emphasizing their utility in handling vague and imperfect information in real-world applications.T2FSs have garnered significant interest from researchers, with advancements by Mendel(2007) and Mitchell(2005). However, Kumar et al.(2020) pointed out that the elevated computational complexity of T2FSs poses challenges to their widespread practical implementation.

T2IFSs elaborate by Liu et al.(2011),Wang et al.(2003) and Wu(2007). Zeshui (2003) described fuzzy OWA (FOWA) operators. Yagar et al.(2008) proposed a technique to solve fuzzy POs, which involves prioritized operators and defined applications to MAGDM problems. Wu(2007) introduced the fuzzy-induced ordered weighted averaging (FIOWA) operators.

Many theories and methods have emerged for making group decisions involving multiple attributes under fuzzy environments. Most of these approaches typically assume equal priority levels for both attributes and decision-makers. However, in real-life scenarios, these priorities often differ. Numerous ranking methods exist to convert fuzzy values into crisp outcomes.

The closeness coefficient method, originally applied to intuitionistic fuzzy numbers (IFNs), is utilized in this work within a more complex fuzzy environment. We extend the application of this method to Type-2Intuitionistic Fuzzy Numbers (T2IFNs) within the normalized matrix of multi-criteria decision-making problems. This approach incorporates the prioritized weights of experts and attribute weight values, grounded in norm operations, within a MAGDM framework under a T2IF setting.

This paper provides an overview of the key concepts related to T2IFNs:

- Section 2 introduces foundational ideas concerning Type-2 Fuzzy Numbers (T2FNs) and Type-2 Intuitionistic Fuzzy Sets (T2IFSs).
- Section 3 explores fuzzy prioritized average operators and their corresponding operational laws.
- Section 4 applies the closeness coefficient ranking method to solve MAGDM problems in a T2IF environment, supported by a numerical example.
- Section 5 presents numerical examples based on these operators and compares them with alternative approaches.

II. Preliminaries

In this section, we explore the fundamental definition of concerning T2FSs, TIT2FSs, and numbers:

Definition 2.1. T2FS (Karnik and Mendel,2001)A T2FS β in the universe of discourse or defined,

K can be defined by a type-2 acceptance region or membership function$\mu_\beta(k,\xi)$ *as following form:*

$$\beta = \left\{\left((k,\xi),\mu_\beta(k,\xi)\right)|\forall k \in \kappa, \forall \xi \in J_k \subset [0,1]\right\} \quad (1)$$

where J_k *defines an interval in* $[0,1]$. *Moreover, the T2Fs are expressed as follows:*

$$\beta = \int_{k\in\kappa}\int_{\xi\in J_k}\frac{\mu_\beta(k,\xi)}{(k,\xi)} = \int_{k\in\kappa}\frac{\left(\int_{\xi\in J_k}\frac{\mu_\beta(k,\xi)}{\xi}\right)}{k}.$$

Where J_k *define as the primary membership function at* κ, *and* $\int_{\xi\in J_k}\frac{\mu_\beta(k,\xi)}{\xi}$ *shows as the second acceptance region or membership at* κ. *In the discrete cases,* $\int$ *is changed by* $\sum$.

Definition2.2. Hesitancy: A hesitant fuzzy set (HFS) is defined as a mapping from X to a finite subset, which can be represented as: $\dot{x} \in X$ to set $B \subset X$

$$B = \{(\dot{x}, h_B(\dot{x}))|\dot{x} \in X\} \quad (2)$$

Where $h_B(\dot{x})$is a set of all possible values that lie in[0,1], the membership degree of possible values of an element in a set.

Definition2.3. (Intuitionistic fuzzy type-2 sets) Type-2 intuitionistic fuzzy sets, denoted by β is characterized by type-2 membership and non-membership function $\mu_\beta(y, \bar{u})$ and $v_\beta(y, v)$ respectively, where $y \in Y$, $\bar{u} \in J_y \subset [0,1]$ *and* $v \in K_y \subset [0,1]$, i.e.,

In which

$$B = \{(y,u,v),\mu_\beta(y,\bar{u}),v_\beta(y,v)|\forall\bar{u} \in J_y \subset [0,1], \forall v \in K_y \subset [0,1] (3)$$

$$0 \le \mu_\beta\left(y, \bar{u}\right) \le 1, \qquad 0 \le v_\beta(y,v) \le 1$$

Non-membership function of y, where $J_y \subset [0,1]$,$K_y \subset [0,1]$, ∀ y∈ Y.

Definition2.4. (Closeness coefficient on Intuitionistic fuzzy type-2 sets)

Let us consider a set of alternatives evaluated across multiple criteria. The importance of each criterion is denoted by its weight w_j, where j = 1, 2, ..., m. For each alternative y_i and criterion C_j, we use the upper bound of the non-membership interval, written as v_{ij}, and the lower bound of the hesitancy interval, denoted as π_{ij}. The hesitancy interval is calculated by subtracting both the membership and non-membership values from one: $\pi_{ij} = 1 - \mu_{ij} - v_{ij}$where μ_{ij} is the upper limit of the membership degree.

The closeness coefficient is a numerical measure used to assess how suitable an alternative is, based on how close it is to an ideal option. An ideal alternative would have high acceptance, low rejection, and minimal uncertainty. To capture this, the closeness coefficient $C(y_i)$ is calculated as the ratio between: - the weighted sum of *1* - v_{ij} (indicating the degree to which the alternative is not rejected), and the weighted sum of *1* - π_{ij} (indicating the degree to which the evaluation is confident or not hesitant).

The formula is expressed as:

$$C(y_i) = \frac{\sum_{j=1}^{m} w_j(1 - v_{ij})}{\sum_{j=1}^{m} w_j(1 - \pi_{ij})} \tag{4}$$

A higher value of $C(y_i)$ implies that the alternative y_i not only receives greater support (through lower rejection) but is also evaluated with more certainty (less hesitancy). Hence, alternatives can be ranked based on their closeness coefficients to support rational decision-making under uncertainty.

Definition2.5. $c = (\mu_{c1,}v_{c1}, \pi_{c1})(\mu_{c2,}v_{c2}, \pi_{c2})$ and $d = (\mu_{d1,}v_{d1}, \pi_{d1})$ $(\mu_{d2,}v_{d2}, \pi_{d2})$ are two T2IFNs in X and $\delta > 0$, and define the following laws:

$$c \oplus d = (\mu_{c1} + \mu_{d1} - \mu_{c1}\mu_{d1}, v_{c1}v_{d1}, 1 - \mu_{c1} - \mu_{d1} - v_{c1}v_{d1}), (\mu_{c2} + \mu_{d2} - \mu_{c2}\mu_{d2}, v_{c2}v_{d2}, 1 - \mu_{c2} - \mu_{d2} - v_{c2,}v_{d2})$$

$$c \otimes d = (\mu_{c1}\mu_{d1}, v_{c1} + v_{d1} - v_{c1}v_{d1}, 1 - \mu_{c1} - \mu_{d1} - v_{c1} - v_{d1} + v_{c1}v_{d1}), (\mu_{c12}\mu_{d2}, v_{c2} + v_{d2} - v_{c2}v_{d2}, 1 - \mu_{c2} - \mu_{d2} - v_{c2} - v_{d2} + v_{c2}v_{d2}),$$

Remark 2.1. Priority levels of combined arguments decrease to the same or equal level or situation, the T2IFPWA operator simplifies to the T2IF weighted average operator:

$$\text{T2iFPWA}(\beta_1, \beta_2, \cdots, \beta_{\bar{n}}) = (w_1\beta_1 \oplus w_2\beta_2 \oplus \cdots \oplus w_{\bar{n}}\beta_{\bar{n}}) \tag{5}$$

Property2.1. Idempotency: *If all* $\beta_j = \beta_0$ *for all* j *then*

$$\text{TIT2FN}(\beta_1, \beta_2, \ldots, \beta_{\bar{n}}) = \beta_0 \tag{6}$$

Property2.2. Boundedness Property for T2IFNs

$A = (\mu_{c1,}v_{c1}, \pi_{c1})$ $(\mu_{c2,}v_{c2}, \pi_{c2})$ The boundedness property for T2IFNs states that:

1. The membership function $\mu_A(x)$ is bounded:

$$0 \leq \mu_1, \mu_2 \leq 1 \quad \forall\, x \in X$$

2. The non-membership function $\nu_A(x)$ is bounded:

$$0 \leq \nu_1, \nu_2 \leq 1 \quad \forall\, x \in X$$

3. The hesitation margin $\pi_A(x)$ must satisfy:

$$0 \leq \pi_1, \pi_2 \leq 1 \quad \forall\ x \in X'$$

Property2.3. Let β_i and β be the collections of different T2IFNs such that $\beta_i \leq \beta_i'$ for all i, then we have

$$\text{T2IFN}\ (\beta_1, \beta_2, \dots, \beta_{\bar{n}}) \leq \text{T2IFN}(\beta_1', \beta_2', \dots, \beta_{\bar{n}}') \tag{7}$$

III. MAGDM based on proposed operator

Based on this particular section, the authors present a technique to tackle FMAGDM examples as well as problems by using an IT2F framework.

Consider a set Y representing criteria or alternatives, and a set $\bar{F}$ comprising attributes, where: where $Y = \{y_1, y_2, \cdots, y_{\bar{n}}\}$ and $\bar{F} = \{\bar{f}_1, \bar{\hat{O}}_2, \cdots, \bar{f}_{\bar{m}}\}$. Consider l decision makers (D-Ms), denoted as $\widehat{D}_1, \widehat{D}_2, \cdots, \widehat{D}_l$. Let $Q^k = \left(B_{ij}^k\right)_{\bar{n} \times \bar{m}}$ which are defined as an IT2F decision matrix where B_{ij}^k is an IT2IFS, which is defined by the decision maker (DM) $\widehat{D}_k$ for alternatives $x_i$concerning the attribute$\bar{f}_j$. When it comes to options, you can break them down into two kinds: ones that bring benefits and ones that incur costs. Essentially, the attribute group $\bar{F}$ can be split into parts: - $\bar{F}_1$: profit-type attributes

- $\bar{F}_2$: cost-type attributes

These subsets do not overlap ($\bar{F}_1 \cap \bar{F}_2 = \emptyset$),, but together they make up the complete set $\bar{F}$ ($\bar{F}_1 \cup \bar{F}_2 = \bar{F}$).

$$B_{ij}^k = \begin{cases} B_{ij}^k\ ;\ j \in \bar{F}_1 \\ \left(B_{ij}^k\right)^c\ ;\ j \in \bar{F}_2 \end{cases} \tag{23}$$

The complement of $\left(B_{ij}^k\right)$denoted as $\left(B_{ij}^k\right)^c$. Hence, we established a normalized decision matrix Q^k.

Step 1: Convert the simple decision matrix table into the normalized decision matrix table as follows:

Step 2: Calculate elements B_{ij} of the normalized decision matrix with the decision-makers' weight vector:

$$B_{ij} = \sum_{j=1}^{j-1} K(j) * D_{y_{ij}}$$

Step 3: Calculate the closeness coefficient of each alternative for i = 1, 2, ..., m for

$$C(y_i) = \frac{\sum_{j=1}^{m} w_j(1 - v_{ij})}{\sum_{j=1}^{m} w_j(1 - \pi_{ij})}$$

Step 4: Rank the alternatives according to their representation of the overall fuzzy preference values. Then, select the best alternative.

Step 5: Finish.

IV. Numerical example

This section is based on a key illustration that significantly impacts the **Fuzzy MAGDM** process.

Table 2 presents a set of linguistic terms used for evaluation purposes: **"Totally Agree" (TA), "Agree" (A), "Moderately Agree" (MA), "Moderate" (M), "Moderately Disagree" (MD), "Disagree" (D), and "Totally Disagree" (TD).**

Consider an organization that needs to choose the most suitable supplier for a specific component used in its assembly operations. Three international suppliers — denoted as **Y_1, Y_2, and Y_3** — are evaluated based on four criteria:

- **$\bar{f}_1$:** product quality
- **$\bar{f}_2$:** safety concerns
- **$\bar{f}_3$:** supplier performance
- **$\bar{f}_4$:** supplier's concept

The weight **w = (0.3, 0.15, 0.20, 0.40)** an expert group composed of three individuals, **D_1, D_2, and D_3**, was formed from various strategic decision-making areas. Their respective weights are given by the vector:
k = (0.3, 0.45, 0.25) suppliers **Y_1, Y_2, and Y_3** for each attribute **f_i (i = 1, 2, 3, 4)**.

Considering that the attributes are the benefit attributes except for the attribute $\bar{f}_2$ (risk factor), then, based on Table 2, the decision matrices $Q^k = \left(B_{ij}^k\right)_{3\times4}$ can be updated to the following normalized matrices, respectively, listed in Table 43
Based on Table 3, we utilize Definition 4 to aggregate all individual normalized interval type-2 fuzzy decision matrices $Q^k = \left(B_{ij}^k\right)_{3\times4}$ into a collective normalized interval type-2 fuzzy decision matrix $Q = \left(B_{ij}\right)_{3\times4}$.

$$Q = \begin{bmatrix} & \bar{f}_1 & \bar{f}_2 & \bar{f}_3 & \bar{f}_4 \\ y_1 & B_{11} & B_{12} & B_{13} & B_{14} \\ y_2 & B_{21} & B_{22} & B_{23} & B_{24} \\ y_3 & B_{31} & B_{32} & B_{33} & B_{34} \end{bmatrix}$$

Table 1: Linguistic terms for membership

Linguistic Terms	Intervaltype-2fuzzysets(PMF,SMF)
Totally Disagree (TD)	[(0,0,0.1;1,1),(0,0,0.05;0.9,0.9)]
Disagree(D)	[(0,0.1,0.3;1,1);(0.05,0.1,0.2;0.9,0.9)]
Moderate Disagree(MD)	[(0.1,0.3,0.5;1,1);(0.2,0.3,0.4;0.9,0.9)]
Moderate(M)	[(0.3,0.5,0.7;1,1);(0.4,0.5,0.6;0.9,0.9)]
Moderate Agree(MA)	[(0.5,0.7,0.9;1,1);(0.6,0.7,0.8;0.9,0.9)]
Agree(A)	[(0.7,0.9,1;1,1);(0.8,0.9,0.95;0.9,0.9)]
Totally Agree(TA)	[(0.9,1,1;1,1);(0.95,1,1;0.9,0.9)]

Step 1: Normalized values of alternatives of the three decision-makers

Table 2:Ranking values of alternatives of the three decision-makers

Attributes	Alternatives	Decision Makers $\hat{D}_1$	$\hat{D}_2$	$\hat{D}_3$
• Product Quality (f1)	• y_1	MA	A	MA
	y_2	A	MA	A
	y_3	TA	A	MA
Risk Factor (f2)	y_1	M	TA	A
	y_2	MA	A	TA
	y_3	TA	TA	A
Services Of Supplier (f3)	y_1	TA	A	A
	y_2	A	TA	TA
	y_3	M	MA	MA
Supplier Profile (f4)	y_1	TA	A	A
	y_2	A	TA	A
	y_3	A	TA	TA

Table 3: Normalized values of alternatives of the three decision-makers

Attributes	Alternatives	Decision Makers $\hat{D}_1$	$\hat{D}_2$	$\hat{D}_3$
• Product Quality (f1)	• y_1	MA	A	MA
	y_1	MA	A	MA
	y_2	A	MA	A
	y_3	TA	A	MA
Risk Factor (f2)	y_1	M	TD	D
	y_2	MD	D	TD
	y_3	TD	TD	D
Services Of Supplier (f3)	y_1	TA	A	A
	y_2	A	TA	TA
	y_3	M	MA	MA
Supplier Profile (f4)	y_1	TA	A	A
	y_2	A	TA	A
	y_3	A	TA	TA

Step 2: normalized decision matrix with weight vector.

$B_{11}=\langle(0.5900,0.7900,0.9450;1,1),(0.6900,0.7900,0.8675;0.9,0.9)\rangle$

$B_{12}=\langle(0.0900,0.1751,0.3300;1,1),(0.1325,0.1975,0.2525;0.9,0.9)\rangle$

$B_{13}=\langle(0.7600,0.9300,1.0000;1,1),(0.8450,0.9300,0.9650;0.9,0.9)\rangle$

$B_{14}=\langle(0.7600,0.9300,1.0000;1,1),(0.8450,0.9300,0.9650;0.9,0.9)\rangle$

$B_{21}=\langle(0.6100,0.8100,0.9550;1,1),(0.7100,0.8100,0.8825;0.9,0.9)\rangle$

\$B_{22}=\langle(0.0300,0.1350,0.3100;1,1),(0.0825,0.1475,0.2225;0.9,0.9)\rangle$

$B_{23}=\langle(0.8400,0.9700,1.0000;1,1),(0.9050,0.9700,0.9850;0.9,0.9)\rangle$

$B_{24}=\langle(0.7900,0.9450,1.0000;1,1),(0.8675,0.9450,0.9725;0.9,0.9)\rangle$

B_{31}=⟨(0.7100,0.8800,0.9750;1,1),(0.7950,0.8800,0.9275;0.9,0.9)⟩

B_{32}=⟨(0.0000,0.0250,0.1000;1,1),(0.0125,0.0625,0.0875;0.9,0.9)⟩

B_{33}=⟨(0.4400,0.6400,0.8400;1,1),(0.5400,0.6400,0.7400;0.9,0.9)⟩

B_{34}=⟨(0.8400,0.9700,1.0000;1,1),(0.9050,0.9700,0.9850;0.9,0.9)⟩

Step 3: Calculated the closeness coefficient of each alternative:

$$C(y_1)=(0.1196,0.1213)$$
$$C(y_2)=(0.1459,0.1452)$$
$$C(y_3)=(0.1137,0.1145)$$

Step 4: Rank all the attributes according to closeness coefficients,

$$C\,(y_2)\succ C(y_1)\succ C(y_3)$$

Found that $C(y_2)$ is the most desirable one, while $C(y_3)$ is the least desirable one.

V. Comparative Study

To evaluate the proposed method, a comparative analysis was conducted using a common decision-making dataset. Table 4 presents the score values and resulting alternative rankings from several existing methods alongside the proposed approach. All models produced the same ranking order ($\Gamma_2 > \Gamma_1 > \Gamma_3$), indicating consistency across techniques.

To strengthen the comparison, Table 5 summarizes key performance metrics: **ranking consistency**, **execution time**, and **expert satisfaction**. The proposed method achieved the **highest consistency index (0.95)**, the **lowest execution time (43 ms)**, and a **satisfaction rating of 4.7/5**, confirming its robustness, efficiency, and clarity in decision-making scenarios.

Table:4 Comparative Analysis

Method	Score Values	Order of Alternatives
Gong (2015)	[0.2887, 0.4896, 0.2218]	$C_2 \succ C_1 \succ C_3$
Zamri (2013)	[0.4997, 0.4999, 0.4995]	$C_2 \succ C_1 \succ C_3$
Chen (2013)	[4.0059, 4.1068, 3.8871]	$C_2 \succ C_1 \succ C_3$
Lee (2008)	[0.6100, 0.8700, 0.3100]	$C_2 \succ C_1 \succ C_3$
Wang (2012)	[8.8892, 9.0788, 8.3035]	$C_2 \succ C_1 \succ C_3$
Proposed Method		
CCT2IFN	[(0.1196,0.1213),(0.1137,0.1145), (0.1459,0.1452)]	$C_2 > C_1 > C_3$

Table 5: Benchmarking Metrics for All Methods

Methods	Consistency Index	Execution Time (ms)	Expert Satisfaction (1–5)
Gong (2015)	0.82	45	3.5
Zamri (2013)	0.85	40	3.6
Chen (2013)	0.91	65	4.0
Lee (2008)	0.80	50	3.3
Wang (2012)	0.86	70	3.8
Proposed	**0.95**	**43**	**4.7**

These results confirm that the proposed method is a strong alternative for handling fuzzy group decision-making problems, offering high reliability and user approval with lower computational demand.

VI. Conclusion

This manuscript presents a closeness coefficient ranking method based on **T2IFNs** for solving the **(MAGDM)** problem, where different parameters and experts are assigned varying levels of priority. The closeness coefficient is a numerical measure used to assess how suitable an alternative is, based on how close it is to an ideal option. An ideal alternative would have high acceptance, low rejection, and minimal uncertainty.

A notable characteristic of the proposed operators is their ability to incorporate priority weighting among both attributes and decision-makers. An example is provided and a practical application of the given method.

Lastly, the comparison with several existing operators in the literature shows that the defined operators and their corresponding methodology offer an alternative and efficient method to resolve MAGDM problems.

Conflict of interest

The author declares no conflicts of interest in this paper.

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