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An Integrated Intuitionistic Fuzzy Closeness Coefficient-Based OCRA Method for Sustainable Urban Transportation Options Selection

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Abstract: Transportation systems play a key role in urban development by providing access for people to markets and education, employment, health care, recreation, and other key services. However, uncontrolled urban population and fast growth of vehicle mobility inevitably lead to unsustainable urban transportation systems in terms of economic, technical, social, and geographical aspects of sustainability. Thus, there is a need to select suitable sustainable urban transportation (SUT) alternatives, which can contributed to the technological advancement of a city and changes in societal necessities, mitigating the climate change impact from transport and transforming living habits, in the context of high urban population growth. Therefore, this paper aims to introduce an integrated multi-attribute decision analysis (MADA) framework for assessing and ranking the sustainable urban transportation (SUT) options under an intuitionistic fuzzy sets (IFSs) context. In this regard, firstly IF-distance measures and their properties are developed to obtain the criteria weight. Second, an IF-relative closeness coefficient-based model is presented to find the criteria weights. Third, the operational competitiveness rating (OCRA) model is introduced with the IF-score function-RS-based decision experts' weighing model and the relative closeness coefficient-based criteria weight determination model under the IFSs environment. To exemplify the utility and effectiveness of the developed IF-relative closeness coefficient-based OCRA methodology, a case study ranking the different SUT bus options is presented from an intuitionistic fuzzy perspective. A comparison with different models is made to prove the superiority and solidity of the obtained outcome. Moreover, the comparative analysis outperforms the other extant MADA models, as it can provide more sound outcomes than others, and thus it is more suitable and efficient to elucidate uncertain information in handling practical MADA problems. In this study, we analyze and determine the most suitable and sustainable SUT by considering the economic, technical, environmental, and social dimensions of sustainability and also make a significant contribution to the current scientific knowledge by providing a novel decision support system from an uncertainty perspective.

Keywords: intuitionistic fuzzy sets; sustainable urban transportation; multi-attribute decision analysis (MADA); closeness coefficient; operational competitiveness rating (OCRA)

MSC: 94D05; 94A17; 90B50

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1. Introduction

The idea of "sustainable development (SD)" has become a well-known catchphrase in current development discourse, which seeks to incorporate social progress with environmental concerns and economic development of any country [1]. The transportation sector makes up 30% of the worldwide energy consumption. National urban transport policy envisages quick, reasonable, safe, comfortable, reliable, and sustainable urban transportation (SUT). The underlying theme of sustainable transportation (ST) refers to a low impact on the environment, affordable modes of transport, and energy-efficiency [2–5]. The behavior of urban transportation procedures is developing, mainly in terms of associated externalities, namely, traffic, energy consumption, and air quality [6–8]. The SUT is an exciting region of study with various concerns being taken into consideration, which can be studied in the ensuing four pillars, namely, economic, technical, social, and environmental concerns [9,10].

Selection of a SUT structure considers various indicators/criteria, including energy efficiency, technology, cost, and facilities. Since the selection of the SUT option involves numerous criteria and uncertainty, it can therefore be considered as an uncertain "multi-attribute decision analysis (MADA)" problem [4]. To accommodate this, the present article utilizes an MADA tool. It is worth mentioned that a solution that functions well with some attributes but fails at other attributes is not adequate. As "compromising solutions (CSs)" are chosen in these cases, interrelationships among the considered attributes become important. These interrelationships are often ignored in several MADA models [11–13]. Most of the conventional tools disregard the interrelationships with the considered attributes. Moreover, few authors consider the interrelationship between attributes without taking uncertainty into account [14–16].

Numerous researchers utilize the conventional "fuzzy set (FS)" [17] doctrine, owing to its resemblance to human thinking, to choose an option with diverse choices. However, when compared with the FS, the concept of "intuitionistic fuzzy set (IFS)" [18] has more benefits in dealing with the subjectivity of the human mind and uncertain information [19,20]. Consequently, this study suggests a relative closeness coefficient [21] supported with an MADA tool under the IFSs perspective in order tackle vagueness and diminish the biases in MADA procedures. In this study, the interrelationships with considered indicators are adequately measured, and DEs' opinions are accurately taken. Thus, IFSs are appropriate to explore the vagueness and fuzziness in DEs' decisions, where the FSs prove inadequate.

1.1. Needs of the Paper

Based on the existing studies, we identified the following challenges and motivations for this study:

i. Distance measures are essential tools for IFSs. In the literature, several distance measures have been introduced by the researchers. However, there is a need to develop an improved intuitionistic fuzzy distance measure for the betterment of existing measures.
ii. To evade the redundant influence of subjective DEs' significances on the decision result, there is an urgent need to derive the weights of the DEs' opinions.
iii. In the context of intuitionistic fuzzy MADA tools, most of the earlier studies have discussed either objective weighting methods or subjective weighting methods. To avoid the shortcomings of objective or subjective weighting models, there is a need to present a weighting model for finding the indicator weights. However, extant subjective weighting tools hardly consider the relative closeness coefficient degree as a degree for weighting from an intuitionistic fuzzy setting.
iv. There is no study to present the operational competitiveness rating (OCRA) method from an intuitionistic fuzzy perspective to determine the MADA problems.
v. In the literature, a single article [1] has implemented the choquet integral-TOPSIS method in the evaluation of SUT options over a finite number of criteria. However, this method has limitations in solving the multiple criteria SUT assessment problem under an intuitionistic fuzzy environment.

1.2. Research Contributions

We present the notable research contributions of the paper as follows:

- To measure the degree of discrimination, a new IF-distance measure was proposed with enviable properties with the use of flexible parameters.
- For the first time, this paper proposed a generalized score value and rank sum model-based weighting approach to derive the DEs' weights within the IFS environment.
- In order to consider the relative closeness coefficient of indicators, this paper presented a new intuitionistic fuzzy divergence measure-based model and further used it to compute the weights of the indicators.
- The present study proposed an OCRA model based on a combination of a distance measure and relative closeness coefficient, which can better describe the uncertainty of practical decision-making problems.
- This study implements the proposed IF-closeness coefficient-OCRA method on a case study of SUT assessment problems within the IFS context.

1.3. Organizations of This Study

The remaining part of this work is summarized in the following manner: Section 2 discusses the literature related to the SUTs and MADA method with uncertainty. Section 3 presents the fundamental ideas of IFSs and a new IF-distance measure with their properties. Section 4 introduces an integrated IF-closeness coefficient-OCRA model based on the proposed distance measure and the relative closeness coefficient. Section 5 uses the developed model on a case study of different SUT options and also discusses comparative analysis. Finally, Section 6 presents the conclusions and further research recommendations.

2. Literature Review

2.1. Sustainable Transportation and Alternative Fuel Technologies

The ST as a conception entails a holistic tool because of the requirement of combination when several structures interrelate. Various scholars have given their consideration to the area of sustainability in transportation. Yedla and Shrestha [22] evaluated diverse ST options for Delhi, India. Awasthi et al. [23] discussed an MADA tool for selecting ST from vagueness perspectives. Their study considered the phase of the SUT structures by evaluating various indicators of sustainability and employed the TOPSIS tool on FSs to choose the suitable ST option. Verma et al. [24] planned a model to evaluate the outcomes of diverse public transportation strategies using different sustainability pillars. They used the "composite sustainability index (CSI)" with the weighted sum model to develop an integrated framework. In the SUT context, Onat et al. [25] developed a hybrid model using the TOPSIS model under IFSs. Further, Onat et al. [26] generalized their work, including 16 indicators of sustainability of 7 passenger cars using "life-cycle assessment (LCA)" with MADA. Various scholars such as Karlson et al. [27], Miller et al. [28], and Rajak et al. [29] have assessed the performance of sustainability options in public transportation.

The SUT-related studies with diverse purposes, namely, policy implication evaluations, are also presented by [30,31]. Büyüközkan et al. [1] presented the TOPSIS-based framework for the SUT alternatives assessment problem. Recently, Melkonyan [32] developed a decision support system for sustainable urban mobility using integrated policy. Verma et al. [33] highlighted the momentous transportation issues encountered in India and evolved how the government transportation division policy interventions for cities. Pamucar et al. [3] gave a decision support system for prioritizing alternative fuel vehicles for ST based on a full consistency model and measurement alternatives and ranking based on a compromise solution framework on a neutrosophic set. Liang et al. [20] gave an integrated tool with the fuzzy set to assess the AFVs problem with four dimensional criteria. An extension of the WISP model on q-ROFSs was proposed by Deveci et al. [4] for assessing and prioritizing SUT in the metaverse with uncertainty. Hezam et al. [5] developed a hybrid CRITIC-SWARA-DNMA model for prioritizing the digital technologies under ST for persons with disabilities under a "fermatean fuzzy sets (FFSs)" context.

2.2. MADA Methods with Uncertainties

In order to treat with ambiguity, FSs [17] have received considerable attention from researchers [34]. Further, several generalizations of FSs have been developed [18,35–37]. As a generalization of FSs, IFSs have received much attention from distinct intellectuals. They have a strong capability to describe the vagueness of the data in comparison with the FS theory. In IFSs, an element is considered by the "membership grade (MG)", "non-membership grade (NG)", and "indeterminacy grade (IG)" to express the uncertain information more systematically [18]. A decision-making methodology using Markowitz and DEA cross-efficiency tools has been developed to evaluate the portfolios under the IFS context [38]. In one study, Chen and Liu [39] proposed a similarity measure for IFSs and applied pattern recognition problems. In the past few years, many theories and applications about IFSs have been discussed [40–43]. Ecer [21] presented an IF-closeness coefficient-based multi-attribute ideal-real comparative analysis to evaluate COVID-19 vaccines over diverse considered criteria.

The operational competitiveness rating (OCRA) method [44] can be considered as the agreement of a simple averaging weight tool with a max–min normalization process. Madic et al. [45] discussed the OCRA model for solving nonconventional machining process (NCMP) selection problems. Stanujkic et al. [46] discussed the enhanced OCRA model to assess the linear performance grades for benefit and cost criteria. Roman-Liu et al. [47] analyzed the convergence of the OCRA and the upper limb risk assessment to assess the risks of developing musculoskeletal disorders at 18 repetitive task workstations. Ulutas [48] discussed an integrated analytic hierarchy process and the OCRA models on FSs to treat supplier selection for the Turkish textile industry. Ulutas et al. [49] gave a hybrid model on grey pivot pairwise relative criteria importance assessment and OCRA methods for personnel selection. Candan [50] presented economic research performance in 15 OECD associate countries and assessed the bibliometric features for the duration of 2010–2017 with the analytic hierarchy process OCRA model by considering the opinions of 5 different DEs opinions. To prioritize the suppliers, Mohammed et al. [51] presented a hybrid MABAC-OCRA-TOPSIS-VIKOR (MOTV) approach with a criteria weighting model. Stanujkic et al. [52] discussed the comparison of various methods with OCRA to show the effectiveness and usefulness of the MADA model.

3. IFSs and Parametric Distance Measure

3.1. Preliminaries

This section shows the notions related to the IFSs.

Definition 1. [18]. *An IFS L on $O = \{o_1,\ o_2,\ \ldots,\ o_t\}$ is given by*

$$L = \{(o_k,\ \mu_L(o_k),\ \nu_L(o_k))\ :\ o_k \in O\}, \tag{1}$$

where $\mu_L : O \to [0,\ 1]$ and $\nu_L : O \to [0,\ 1]$ signify the MG and NG of o_k to L in O, with the condition $0 \le \mu_L(o_k) + \nu_L(o_k) \le 1, \forall\, o_k \in O$. An IG of an object $o_k \in O$ to L is discussed as $\pi_L(o_k) = 1 - \mu_L(o_k) - \nu_L(o_k)$ and $0 \le \pi_L(o_k) \le 1, \quad \forall\, o_k \in O$. Xu [53] presented the IFN $\zeta = (\mu_\zeta,\ \nu_\zeta)$ with the constraint $\mu_\zeta,\ \nu_\zeta \in [0,\ 1]$ and $0 \le \mu_\zeta + \nu_\zeta \le 1$.

Definition 2. [53,54]. *Let $\zeta = (\mu_\zeta,\ \nu_\zeta)$ be an IFN. Then*

$$\mathbb{S}(\zeta) = \frac{1}{2}((\mu_\zeta - \nu_\zeta) + 1),\ \ H(\zeta) = (\mu_\zeta + \nu_\zeta), \tag{2}$$

are said to be score and accuracy degrees, respectively.

Definition 3. [54]. *Suppose $\zeta_k = (\mu_k,\ \nu_k), k = 1, 2, \cdots, t$ are the IFNs. An improved score value (ISV) is given by*

$$\mathbb{S}(\zeta_k) = \mu_k[1 + (\varepsilon_1\ +\ \varepsilon_2)(1 - \mu_k - \nu_k)], \tag{3}$$

where in $\varepsilon_1 + \varepsilon_2 = 1$, $\varepsilon_1, \varepsilon_2 > 0$ denotes the attitudinal feature of the ISV, presenting the grade of weighted averaging of IG between the MG and NG on IFNs.

Definition 4. [53]. *For a set of IFNs $\zeta_k = (\mu_k, \nu_k), k = 1, 2, \cdots, t$, the intuitionistic fuzzy weighted averaging operator (IFWAO) and intuitionistic fuzzy weighted geometric operator (IFWG) on IFNs are defined as*

$$IFWAO_w(\zeta_1, \zeta_2, \ldots, \zeta_t) = \overset{t}{\underset{k=1}{\oplus}} w_k \zeta_k = \left[1 - \prod_{k=1}^{t} (1 - \mu_k)^{w_k},\ \prod_{k=1}^{t} {\nu_k}^{w_k}\right], \tag{4}$$

$$IFWGO_w(\zeta_1, \zeta_2, \ldots, \zeta_k) = \overset{t}{\underset{k=1}{\otimes}} w_k \zeta_k = \left[\prod_{k=1}^{t} {\mu_k}^{w_k},\ 1 - \prod_{k=1}^{t} (1 - \nu_k)^{w_k}\right], \tag{5}$$

where $w = (w_1, w_2, \ldots, w_k)^T$ is a weight vector of ζ_k, $k = 1, 2, \ldots, t$, with $\sum_{k=1}^{t} w_k = 1$, $w_k \in [0,\ 1]$.

Definition 5. [55]. *A real function $d : IFS(O) \times IFS(O) \to [0, 1]$ is said to be distance measure on IFS (O) if d fulfills the following postulates: for any A, B, C on IFS (O),*

(D1): $0 \le d(A,\ B) \le 1$,

(D2): $d(A,\ B) = 0$ if and only if A = B,

(D3): $d(A,\ B) = d(B,\ A)$,

(D4): $d(A,\ B) \le d(A,\ C)$ and $d(B,\ C) \le d(A,\ C)$ with the condition $A \subseteq B \subseteq C$.

3.2. Proposed Parametric IF-Distance Measure

In this section, utilizing the representation of IFSs, we develop a new formula to estimate the discrimination between the IFNs by adding the diverse parameters known as the parametric IF-distance measure as follows: for any *A*, *B* on *IFS (O)*, a parametric IF-distance measure is developed as

$$d(A,\ B) = \sqrt[p]{\frac{1}{2n\ (t+1)^p} \sum_{i=1}^{n} \begin{pmatrix} |(t + 1 - a)\ (\mu_A(o_i) - \mu_B(o_i)) - a\ (\nu_A(o_i) - \nu_B(o_i))|^p + \\ |(t + 1 - b)\ (\nu_A(o_i) - \nu_B(o_i)) - b\ (\mu_A(o_i) - \mu_B(o_i))|^p \end{pmatrix}} \tag{6}$$

where "p" is the L_p-norm, t, a and b signify the uncertainty level with the condition $a + b \le t + 1,\ 0 \le a, b \le t + 1,\ t > 0$.

Theorem 1. *The expression $d(A,\ B)$ is a valid IF-distance measure.*

Proof. To prove the validity of $d(A,\ B)$, we show that it fulfills the axioms (d1)–(d4) of Definition 5. For two IFSs *A* and *B*, we have

(d1).

$$\begin{aligned} & |(t + 1 - a)\ (\mu_A(o_i) - \mu_B(o_i)) - a\ (\nu_A(o_i) - \nu_B(o_i))| \\ = & \ |((t + 1 - a)\ (\mu_A(o_i) - a\ \nu_A(o_i))) - ((t + 1 - a)\ (\mu_B(o_i) - a\ \nu_B(o_i)))|, \\ & |(t + 1 - b)\ (\nu_A(o_i) - \nu_B(o_i)) - b\ (\mu_A(o_i) - \mu_B(o_i))| \\ = & \ |((t + 1 - b)\ (\nu_A(o_i) - b\ \mu_A(o_i))) - ((t + 1 - b)\ (\nu_B(o_i) - b\ \mu_B(o_i)))|. \end{aligned}$$

In IFS, we know that $0 \le \mu_A(o_i), \mu_B(o_i), \nu_A(o_i), \nu_B(o_i) \le 1$, and therefore we have

$$\begin{aligned} -a \le ((t + 1 - a)\ (\mu_A(o_i) - a\ \nu_A(o_i))) \le (t + 1 - a), \\ -(t + 1 - a) \le ((t + 1 - a)\ (\mu_B(o_i) - a\ \nu_B(o_i))) \le a. \end{aligned}$$

Therefore, we have

$$-(t + 1) \le ((t + 1 - a)\ (\mu_A(o_i) - a\ \nu_A(o_i))) - ((t + 1 - a)\ (\mu_B(o_i) - a\ \nu_B(o_i))) \le t + 1.$$

It implies that

$$0 \leq |((t+1-a)(\mu_A(o_i) - a\,\nu_A(o_i))) - ((t+1-a)(\mu_B(o_i) - a\,\nu_B(o_i)))|^p \leq (t+1)^p.$$

Likewise, we can prove that

$$0 \leq |((t+1-b)(\nu_A(o_i) - b\,\mu_A(o_i))) - ((t+1-b)(\nu_B(o_i) - b\,\mu_B(o_i)))|^p \leq (t+1)^p.$$

Hence, $0 \leq d(A, B) \leq 1$.

(d2). It is easy to prove that $d(A, B) = d(B, A)$.

(d3).

$$d(A, A^c) = 1 \Leftrightarrow \sqrt[p]{\frac{1}{n}\sum_{i=1}^{n} |\mu_A(o_i) - \nu_A(o_i)|^p} = 1 \Leftrightarrow |\mu_A(o_i) - \nu_A(o_i)|^p = 1$$

$\Leftrightarrow \mu_A(o_i) = 1,\ \nu_A(o_i) = 0$ or $\mu_A(o_i) = 1,\ \nu_A(o_i) = 0 \Leftrightarrow A$ is a crisp set.

Additionally, if $A = B$, then $\mu_A(o_i) = \mu_A(o_i)$ and $\nu_A(o_i) = \nu_B(o_i),\ \forall i = 1, 2, \ldots, n$. Then, Equation (6) becomes $d(A, B) = 0$. Conversely, assume that $d(A, B) = 0$, which implies that

$$|(t+1-a)(\mu_A(o_i) - \mu_B(o_i)) - a(\nu_A(o_i) - \nu_B(o_i))|^p = 0 \tag{7}$$

and

$$|(t+1-b)(\nu_A(o_i) - \nu_B(o_i)) - b(\mu_A(o_i) - \mu_B(o_i))|^p = 0. \tag{8}$$

Solving Equations (7) and (8), we obtain $\mu_A(o_i) - \mu_B(o_i) = 0$ and $\nu_A(o_i) - \nu_B(o_i) = 0$, which implies that $\mu_A(o_i) = \mu_B(o_i)$ and $\nu_A(o_i) = \nu_B(o_i)$.

(d4). For $A, B, C \in IFSs(O)$,

$$d(A, B) = \sqrt[p]{\frac{1}{2n\,(t+1)^p}\sum_{i=1}^{n} \begin{pmatrix} |(t+1-a)(\mu_A(o_i) - \mu_B(o_i)) - a(\nu_A(o_i) - \nu_B(o_i))|^p + \\ |(t+1-b)(\nu_A(o_i) - \nu_B(o_i)) - b(\mu_A(o_i) - \mu_B(o_i))|^p \end{pmatrix}},$$

$$d(A, C) = \sqrt[p]{\frac{1}{2n\,(t+1)^p}\sum_{i=1}^{n} \begin{pmatrix} |(t+1-a)(\mu_A(o_i) - \mu_C(o_i)) - a(\nu_A(o_i) - \nu_C(o_i))|^p + \\ |(t+1-b)(\nu_A(o_i) - \nu_C(o_i)) - b(\mu_A(o_i) - \mu_C(o_i))|^p \end{pmatrix}}.$$

since

$$\begin{aligned}
&|(t+1-a)(\mu_A(o_i) - \mu_B(o_i)) - a(\nu_A(o_i) - \nu_B(o_i))| \\
&= |((t+1-a)(\mu_A(o_i) - a\,\nu_A(o_i))) - ((t+1-a)(\mu_B(o_i) - a\,\nu_B(o_i)))|, \\
&|(t+1-b)(\nu_A(o_i) - \nu_B(o_i)) - b(\mu_A(o_i) - \mu_B(o_i))| \\
&= |((t+1-b)(\nu_A(o_i) - b\,\mu_A(o_i))) - ((t+1-b)(\nu_B(o_i) - b\,\mu_B(o_i)))|, \\
&|(t+1-a)(\mu_A(o_i) - \mu_C(o_i)) - a(\nu_A(o_i) - \nu_C(o_i))| \\
&= |((t+1-a)(\mu_A(o_i) - a\,\nu_A(o_i))) - ((t+1-a)(\mu_C(o_i) - a\,\nu_C(o_i)))|, \\
&|(t+1-b)(\nu_A(o_i) - \nu_C(o_i)) - b(\mu_A(o_i) - \mu_C(o_i))| \\
&= |((t+1-b)(\nu_A(o_i) - b\,\mu_A(o_i))) - ((t+1-b)(\nu_C(o_i) - b\,\mu_C(o_i)))|.
\end{aligned}$$

If $A \subseteq B \subseteq C$, we have $\mu_C(o_i) \geq \mu_B(o_i) \geq \mu_A(o_i)$ and $\nu_C(o_i) \leq \nu_B(o_i) \leq \nu_A(o_i)$. Hence,

$$\begin{aligned}
(t+1-a)(\mu_A(o_i) - a\,\nu_A(o_i)) &\leq (t+1-a)(\mu_B(o_i) - a\,\nu_B(o_i)) \leq (t+1-a)(\mu_C(o_i) - a\,\nu_C(o_i)), \\
(t+1-b)(\nu_C(o_i) - b\,\mu_C(o_i)) &\leq (t+1-b)(\nu_B(o_i) - b\,\mu_B(o_i)) \leq (t+1-b)(\nu_A(o_i) - b\,\mu_A(o_i)).
\end{aligned}$$

Consequently,

$$\begin{aligned}
&|((t+1-a)(\mu_A(o_i) - a\,\nu_A(o_i))) - ((t+1-a)(\mu_C(o_i) - a\,\nu_C(o_i)))| \\
&\leq |((t+1-a)(\mu_A(o_i) - a\,\nu_A(o_i))) - ((t+1-a)(\mu_B(o_i) - a\,\nu_B(o_i)))|, \\
&|((t+1-b)(\nu_A(o_i) - b\,\mu_A(o_i))) - ((t+1-b)(\nu_B(o_i) - b\,\mu_B(o_i)))| \\
&\leq |((t+1-b)(\nu_A(o_i) - b\,\mu_A(o_i))) - ((t+1-b)(\nu_C(o_i) - b\,\mu_C(o_i)))|.
\end{aligned}$$

This implies that $d(A, C) \geq d(B, C)$ and $d(A, C) \geq d(A, B)$. Thus, the property (D4) is obtained. Hence, the measure $d(A, B)$ is a valid distance measure on IFSs. □

4. Proposed IF-Closeness Coefficient-OCRA Model

The classical OCRA method has been utilized to determine the relative performances of a set of production units. Further, few authors have extended the classical OCRA under different environments for various purposes. Unfortunately, none of the previous studies has developed an integrated OCRA method based on the IF-closeness coefficient from an IF perspective. This study suggests an integrated decision analysis model known as the IF-closeness coefficient-OCRA with an application in handling MCDM problems. The main benefit of the proposed OCRA model is that it can operate with those MADA conditions in which the relative weights of attributes are dependent upon options, and diverse weight distributions are offered to attributes for diverse options, while some of the attributes are not relevant to all the options either with IF information. The notion of the OCRA tool is to implement the independent assessment of options over beneficial and non-beneficial attributes and lastly to merge these two aggregate grades to determine competitiveness grades, which supports the DEs not to fail information through the MADA procedure [45]. The development of the IF–closeness coefficient–OCRA model is presented and depicted in Figure 1.

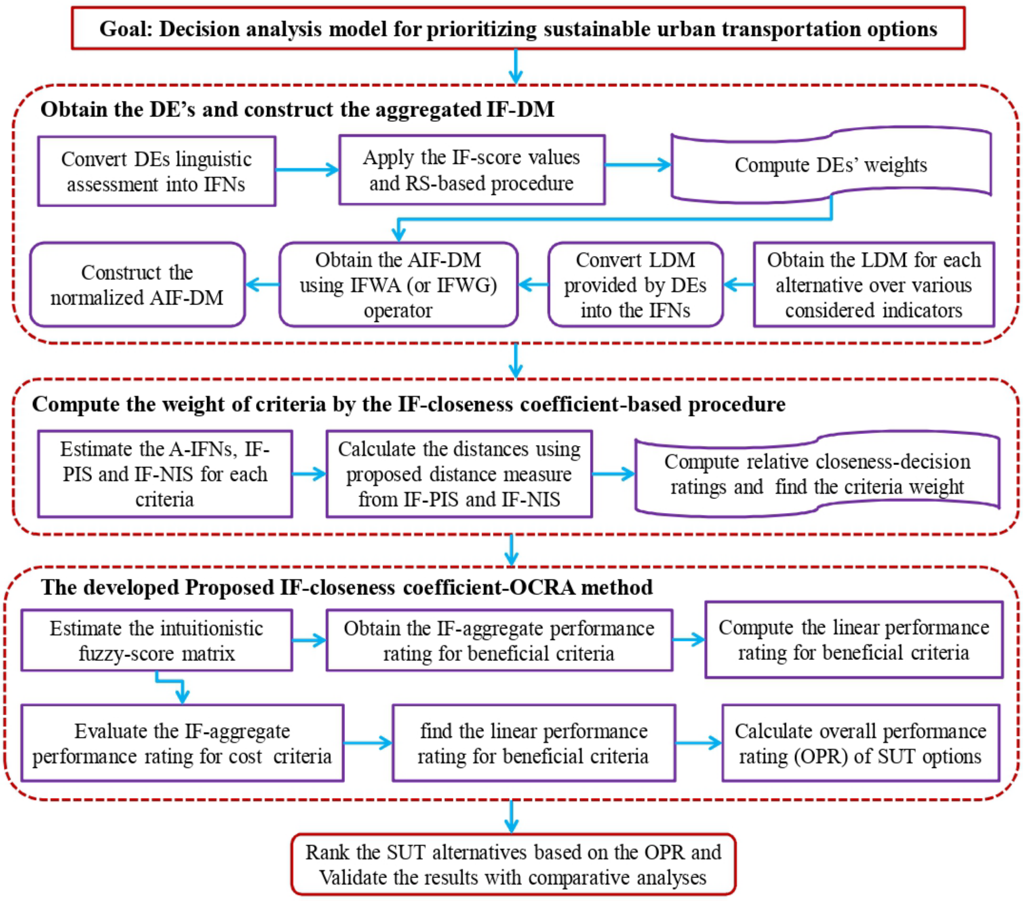

Figure 1. Flowchart of the developed IF–closeness coefficient–OCRA model.

Step 1: Create the "linguistic decision matrix (LDM)".

Consider a set of m options $T = \{T_1, T_2, \ldots, T_m\}$ concerning with attribute set $R = \{r_1, r_2, \ldots, r_n\}$. We make a DEs set $D = \{d_1, d_2, \ldots, d_l\}$ to choose the option(s). Let $Z = \left(\xi_{ij}^{(k)}\right)_{m\times n}$ be the LDM provided by the DEs set in which $\xi_{ij}^{(k)}$ involves the "linguistic rating (LR)" of an option T_i with regard to r_j and is further converted into an "intuitionistic fuzzy-decision matrix (IF-DM)" using Table 1.

Table 1. LVs for prioritizing SUT options.

LVs	IFNs
Absolutely high (AH)	(0.95, 0.05)
Very very high (VVH)	(0.85, 0.1)
Very high (VH)	(0.8, 0.15)
High (H)	(0.7, 0.2)
Slightly high (MH)	(0.6, 0.3)
Average (A)	(0.5, 0.4)
Slightly low (ML)	(0.4, 0.5)
Low (L)	(0.3,0.6)
Very very low (VL)	(0.2, 0.7)
Very low (VVL)	(0.1, 0.8)
Absolutely low (AL)	(0.05, 0.95)

Step 2: Obtain the DEs' weights (λ_k).

Initially, the evaluation ratings of DEs are defined as the LRs and then changed into IFNs. Let $d_k = (\mu_k, \nu_k),\ k = 1, 2, \ldots, l$ be an IFN; then the expression for finding weight is given by

Step 2a: Find the IF-score matrix.

The normalized IF-score value $\left(\overline{d}_k\right)$ of each IFN d_k is calculated as follows:

$$\overline{d}_k = \frac{\mu_k[1 + (\varepsilon_1 + \varepsilon_2)(1 - \mu_k - \nu_k)],}{\sum\limits_{k=1}^{l} (\mu_k[1 + (\varepsilon_1 + \varepsilon_2)(1 - \mu_k - \nu_k)])},\ k = 1, 2, \ldots, l. \tag{9}$$

Step 2b: Estimate the ranking of relevant assessment criteria and find the criteria weight $l - r_k + 1$, where r_k is the priority of k^{th} criterion. Each weight is normalized as follows:

$$\left(\overline{d}_k^r\right) = \frac{l - r_k + 1}{\sum\limits_{k=1}^{l} (l - r_k + 1)}, k = 1, 2, \ldots, l. \tag{10}$$

Step 2c: Calculation of expert weight.

To find the DEs' weights, we combine Equations (9) and (10) as follows:

$$\lambda_k = \frac{1}{2}\left(\left(\overline{d}_k\right) + \left(\overline{d}_k^r\right)\right),\ k = 1, 2, \ldots, l, \text{ where } \lambda_k \geq 0 \text{ and } \sum_{k=1}^{l} \lambda_k = 1. \tag{11}$$

Step 3: Make an "aggregated IF-DM (AIF-DM)".

All the IF-DMs are operated into AIF-DM. The IFWA operator is used to generate the AIF-DM, which is $Z = \left(\xi_{ij}\right)_{m \times n}$, where

$$\xi_{ij} = \left(\mu_{ij}, \nu_{ij}\right) = IFWA_{\lambda_k}\left(\xi_{ij}^{(1)}, \xi_{ij}^{(2)}, \ldots, \xi_{ij}^{(l)}\right) \text{ or } IFWG_{\lambda_k}\left(\xi_{ij}^{(1)}, \xi_{ij}^{(2)}, \ldots, \xi_{ij}^{(l)}\right) \tag{12}$$

Step 4: Find the attribute weight by the IF–relative closeness coefficient-based model.

To obtain the attribute weight, the IF–relative closeness coefficient-based method is applied. Let $w = (w_1, w_2, \ldots, w_n)^T$ be the weight of the attribute set with $\sum\limits_{j=1}^{n} w_j = 1$ and $w_j \in [0,\ 1]$. Then, the process for determining the attribute weight by the IF–relative closeness coefficient-based model is discussed as

Step 4a: Estimate the A-IFNs by combining the LDM assessment degrees provided by DEs using the IFWA operator and obtain $G = \left(z_j\right)_{1 \times n}$.

Step 4b: Describe the IF-reference points.

An IFN has a "positive ideal solution (IF-PIS)" and a "negative ideal solution (IF-NIS)", which consider ratings as ϕ^+ = (1, 0, 0) and ϕ^- = (0, 1, 0), respectively.

Step 4c: Derive the distances of attributes from IF-PIS and IF-NIS.

To compute the distance, the proposed parametric IF-distance measure is applied; p_j^+ and p_j^- are handled in Equation (6) to exemplify positive and negative distances from $G = \left(z_j\right)_{1\times\, n}$, and the IF-PIS and IF-NIS, respectively.

$$p_j^+ = \sqrt[p]{\frac{1}{2n\ (t\ +1)^p} \sum_{i\ =\ 1}^{n} \left(\left|(t\ +\ 1-\ a)\ \left(\mu_{\xi_j} -\ \mu_{\phi^+}\right) - a\ \left(\nu_{\xi_j} -\ \nu_{\phi^+}\right)\right|^p + \left|(t\ +\ 1-\ b)\ \left(\nu_{\xi_j} -\ \nu_{\phi^+}\right) -\ b\ \left(\mu_{\xi_j} -\ \mu_{\phi^+}\right)\right|^p \right)}, \tag{13}$$

$$p_j^- = \sqrt[p]{\frac{1}{2n\ (t\ +1)^p} \sum_{i\ =\ 1}^{n} \left(\left|(t\ +\ 1-\ a)\ \left(\mu_{\xi_j} -\ \mu_{\phi^-}\right) - a\ \left(\nu_{\xi_j} -\ \nu_{\phi^-}\right)\right|^p + \left|(t\ +\ 1-\ b)\ \left(\nu_{\xi_j} -\ \nu_{\phi^-}\right) -\ b\ \left(\mu_{\xi_j} -\ \mu_{\phi^-}\right)\right|^p \right)}, \tag{14}$$

Step 4d: Compute the relative closeness-decision rating (RC-DR).

$$rc_j = \frac{p_j^-}{p_j^- \,+\, p_j^+},\ \ j = 1,2,\ldots,n. \tag{15}$$

Step 4e: Obtain the criteria weight $\left(w_j\right)$ as follows:

$$w_j = \frac{rc_j}{\sum_{j=1}^{n} rc_j}. \tag{16}$$

Step 5: Construct the IF-score matrix (IF-SM).

The IF-SM $\overline{Z} = \left(\eta_{ij}\right)_{m\times\, n}$, is obtained from the AIF-DM $Z = \left(\xi_{ij}\right)_{m\times\, n}$ as

$$\eta_{ij} = \mu_{ij}\left[1 + (\varepsilon_1\ +\ \varepsilon_2)\left(1 - \mu_{ij} - \nu_{ij}\right)\right]. \tag{17}$$

Step 6: Obtain the "IF-performance rating" for beneficial criteria known IF-PRB as

$$P_i = \sum_{j\in p_b} w_j \left(\frac{\eta_{ij} - \min_j \eta_{ij}}{\max_j \eta_{ij} - \min_j \eta_{ij}} \right),\ i = 1,2,\ldots,m. \tag{18}$$

Step 7: Find the "linear performance rating" for benefit criteria known LPRB as

$$\overline{P}_i = P_i - \min_i P_i,\ i = 1,2,\ldots,m. \tag{19}$$

Step 8: Estimate the "IF-performance rating" for cost criteria known IF-PRC as

$$Q_i = \sum_{j\in r_n} w_j \left(\frac{\max_j \eta_{ij} - \eta_{ij}}{\max_j \eta_{ij} - \min_j \eta_{ij}} \right),\ i = 1,2,\ldots,m. \tag{20}$$

Step 9: Find the "linear performance rating" for cost criteria known LPRC as

$$\overline{Q}_i = Q_i - \min_i Q_i,\ i = 1,2,\ldots,m. \tag{21}$$

Step 10: Compute the "overall performance rating (OPR)" of each option as

$$O_i\ =\ \left(\overline{P}_i + \overline{Q}_i\right) - \min_i\left(\overline{P}_i + \overline{Q}_i\right),\ \ i = 1,2,\ldots,m. \tag{22}$$

Step 11: From the OPR $\left(O_i\right)$, the option with the maximum value of OPR is the optimal choice.

The assessment process of the OCRA model considers the utilization of the discrimination to the minimum preferable performances of attributes, i.e., $\max_j \eta_{ij} - \eta_{ij}$ for cost-type, and $\eta_{ij} - \min_j \eta_{ij}$ for benefit-type, which shows a certain resemblance to the conventional TOPSIS and VIKOR models. However, the OCRA model has its accuracies; the precise normalization process discussed in Equations (18) and (20) can be revealed as one of the momentous tool.

5. Case Study: Prioritization of SUT Options

The key objective of the study was the implementation of the IF–closeness coefficient–OCRA model, which is integrated to utilize the SUT alternative selection in IFSs settings.

SUT option solutions are mainly resilient on the fuel mode [1,3–5,32,56,57]. There are various kinds of bus structures for SUT owing to the multi-access features. However, most of them do not encounter the elementary needs of the Delhi Municipal Corporation strategy, and a committee of DEs was selected to establish a limit on the number of options for assessment. After a preliminary evaluation, buses were described for 5 diverse SUT options fuels for further assessments in this case study, namely, liquid propane gas (LPG) (T_1), hybrid electric vehicles (HEVs) (T_2), Diesel engines (DIE) (T_3), CNG (T_4), and electric buses with exchangeable batteries (EEB) (T_5).

To choose the best SUT bus options, a team of four DEs (g_1, g_2, g_3, and g_4) was created. These DEs were from various disciplines comprising researchers on gerontechnology groups/classes, stockholders, professors, and managers. The respondent of each technology group/class assessed the following criteria using an 11-stage scale, where AL means absolutely low and AH means absolutely high. In the study, buses with AFVs were considered and assessed in terms of sustainability perspectives. Corresponding to the assessment, the appropriate option will be chosen with the consideration of various, occasionally conflicting indicators. Apparently, no one option can instantaneously fulfill all decision indicators, which creates the problem of an appropriate choice for the utilization of multi-attribute assessment. Owing to the consequence of a sustainability perspectives of the SUT options, the DEs were invited by the Delhi municipality, India, to do this assessment over sustainability indicators. A wide-ranging literature study and DEs' thoughts were assembled to evaluate the considered indicators. A wider range of indicators could be related with fuel types in sustainability perspectives. However, DEs defined the range of indicators so the most significant indicators could be engaged for the 11 assessment indicators, which were nominated by the DEs [3–5,23,32,58,59]. These indicators were then assembled into economical, technical, environmental, and social pillars. Brief explanations of these indicators are given in Table 2.

Table 2. The inclusive evaluation indicators for SUT options.

Indicators	Sub-Criteria	Type
Economical (I_1)	Energy availability (r_1)	Max
	Energy efficiency (r_2)	Max
	Acquisition cost (r_3)	Min
	Operating cost (r_4)	Min
Technical (I_2)	Vehicle capacity (r_5)	Max
	Road capacity (r_6)	Max
	Flow conformance(r_7)	Max
Environmental factor (I_3)	Noise pollution (r_8)	Min
	Air pollution (r_9)	Min
Social (I_4)	Passenger comfort (r_{10})	Max
	Social impact (r_{11})	Max

Now, the process of the implementation of the IF–closeness coefficient–OCRA model on the present case study is shown as follows:

Steps 1–3: Table 1 is considered to show the LRs and their associated IFNs to determine the DEs' weights and the indicators for prioritizing SUT options [5]. Using Table 2 and Equations (9)–(11), the DEs' weights were computed and are shown in Table 1. Table 3 signifies the LDM by DEs. From Equation (12) and Table 4, the aggregated IF-DM was constructed and is shown in Table 5.

Table 3. Weights of DEs for ranking SUT options.

DEs	g_1	g_2	g_3	g_4
Ratings	VVH (0.85, 0.10)	VH (0.80, 0.15)	AH (0.95, 0.05)	H (0.7, 0.20)
rank	2	3	1	4
λ_k	0.2793	0.2217	0.3376	0.1615

Table 4. LDM for prioritizing SUT options by DEs.

Criteria	T_1	T_2	T_3	T_4	T_5
r_1	(H,VH,MH,H)	(AH,H,H,VH)	(H, MH,A,H)	(AH,H,H,VH)	(H,H,ML,VH)
r_2	(MH,H,A,VH)	(H,H,VVH,MH)	(A,H,MH,ML)	(VH,H,MH,AH)	(VH,MH,H,A)
r_3	(L,VL,ML,ML)	(AL,L,L,VL)	(ML, ML,VL,L)	(VL,ML,L,L)	(VL,L,ML,ML)
r_4	(ML,ML,A,L)	(L,L,VL,ML)	(VVL,A,ML,ML)	(A,VL,ML,ML)	(VL,L,ML,VL)
r_5	(H,MH,A,ML)	(VH,MH,A,A)	(A,MH,H,MH)	(VH,H,AH,MH)	(MH,VH,H,H)
r_6	(AH, MH,VH,A)	(ML,H,A,VH)	(VH,MH,A,H)	(AH,H,A,VH)	(VH,H,MH,A)
r_7	(VVH,MH,ML,L)	(VH,MH,A,ML)	(VH,VH,MH,ML)	(ML,H,VVH,H)	(MH,VH,H,MH)
r_8	(AL,L,ML,VL)	(ML,L,ML,ML)	(VL,L,A,ML)	(AL,VVL,A,L)	(A,VL,VVL,L)
r_9	(VL,L,A,L)	(A,VL,L,VVL)	(AL,MH,VL,L)	(L,AL,VL,ML)	(A,L,VL,VL)
r_{10}	(A,MH,AH,VH)	(AH,H,H,MH)	(MH,ML,VH,H)	(MH,MH,ML,H)	(VH,A,MH,MH)
r_{11}	(VH,H,MH,H)	(MH,H,VH,MH)	(ML,H,AH,H)	(H,MH,H,VH)	(A,A,VH,VVH)

Table 5. AIF-DM for prioritizing SUT options.

Criteria	T_1	T_2	T_3	T_4	T_5
r_1	(0.698, 0.215, 0.087)	(0.830, 0.130, 0.041)	(0.620, 0.276, 0.103)	(0.830, 0.130, 0.041)	(0.645, 0.260, 0.095)
r_2	(0.638, 0.270, 0.092)	(0.751, 0.169, 0.080)	(0.574, 0.323, 0.104)	(0.779, 0.169, 0.052)	(0.690, 0.226, 0.084)
r_3	(0.315, 0.584, 0.101)	(0.221, 0.699, 0.080)	(0.322, 0.577, 0.101)	(0.298, 0.602, 0.101)	(0.327, 0.572, 0.101)
r_4	(0.384, 0.478, 0.139)	(0.286, 0.614, 0.101)	(0.355, 0.543, 0.103)	(0.392, 0.506, 0.102)	(0.295, 0.604, 0.101)
r_5	(0.575, 0.321, 0.104)	(0.632, 0.285, 0.083)	(0.614, 0.283, 0.103)	(0.847, 0.123, 0.030)	(0.703, 0.210, 0.087)
r_6	(0.816, 0.151, 0.033)	(0.595, 0.312, 0.094)	(0.661, 0.255, 0.084)	(0.798, 0.164, 0.039)	(0.679, 0.237, 0.084)
r_7	(0.618, 0.293, 0.088)	(0.621, 0.296, 0.084)	(0.698, 0.230, 0.072)	(0.712, 0.204, 0.084)	(0.689, 0.224, 0.087)
r_8	(0.261, 0.658, 0.082)	(0.379, 0.521, 0.100)	(0.367, 0.530, 0.102)	(0.281, 0.634, 0.085)	(0.286, 0.611, 0.104)
r_9	(0.330, 0.567, 0.103)	(0.316, 0.581, 0.103)	(0.296, 0.616, 0.088)	(0.236, 0.679, 0.085)	(0.319, 0.579, 0.103)
r_{10}	(0.811, 0.159, 0.030)	(0.809, 0.145, 0.046)	(0.669, 0.249, 0.082)	(0.562, 0.334, 0.104)	(0.654, 0.263, 0.083)
r_{11}	(0.705, 0.212, 0.084)	(0.703, 0.217, 0.080)	(0.801, 0.162, 0.037)	(0.701, 0.209, 0.091)	(0.698, 0.230, 0.072)

Step 4: First, the distances of AIF-DM from IF-PIS and IF-NIS were obtained by means of Equations (13) and (14). The IF-relative closeness coefficient rc_j was estimated using Equation (15) and is mentioned in Table 6. The criteria weights were estimated using Equation (16), given as

w_j =(0.0893, 0.0847, 0.0943, 0.0954, 0.0860, 0.0973, 0.0838, 0.0852, 0.1008, 0.0915, 0.0917).

The values of criteria weights are depicted in Figure 2.

Here, Figure 2 shows the criteria weights with respect to the outcome. Air pollution (r_9) with a weight of value 0.1008 came out to be the most important parameter for prioritizing SUT options. Road capacity (r_6), with a weight of 0.0973, was the second-most significant criterion. Operating cost (r_4) was third with a weight value of 0.0954. Acquisition cost (r_3) was ranked fourth with a weight of 0.0943, fifth was social impact (r_{11}) with a weight of 0.0917, and others were considered crucial criteria for the assessment of SUT options.

Steps 5: From Equation (17), the IF-SM $\overline{Z} = \left(\eta_{ij}\right)_{m\times\ n}$, was obtained from AIF-DM and is presented in Table 7.

Steps 6–7: The IF-PRB and LPRB for the beneficial indicators were computed using Equations (18) and (19) and given in Table 8.

Steps 8–9: The IF-PRC and LPRC for the cost indicators were obtained using Equations (20) and (21) and are given in Table 8.

Table 6. Weight of criteria in the form of LTs for prioritizing SUT options.

Criteria	g_1	g_2	g_3	g_4	AIF-DM	p_{ij}^{+}	p_{ij}^{-}	rc_j	w_j
r_1	H	VH	H	A	(0.702, 0.210, 0.088)	0.257	0.743	0.743	0.0893
r_2	MH	A	VH	MH	(0.667, 0.253, 0.080)	0.295	0.705	0.705	0.0847
r_3	VH	ML	VVH	H	(0.753, 0.179, 0.068)	0.215	0.785	0.785	0.0943
r_4	A	A	VVH	AH	(0.770, 0.179, 0.051)	0.206	0.794	0.794	0.0954
r_5	MH	ML	MH	AH	(0.687, 0.252, 0.061)	0.284	0.716	0.716	0.0860
r_6	H	ML	AH	A	(0.793, 0.172, 0.036)	0.191	0.809	0.809	0.0973
r_7	VH	MH	ML	VH	(0.662, 0.263, 0.075)	0.303	0.697	0.697	0.0838
r_8	ML	VH	MH	VVH	(0.672, 0.248, 0.079)	0.291	0.709	0.709	0.0852
r_9	VH	MH	AH	ML	(0.826, 0.147, 0.028)	0.161	0.839	0.839	0.1008
r_{10}	A	VH	VVH	A	(0.728, 0.202, 0.070)	0.239	0.761	0.761	0.0915
r_{11}	VVH	MH	H	MH	(0.724, 0.192, 0.084)	0.237	0.763	0.763	0.0917

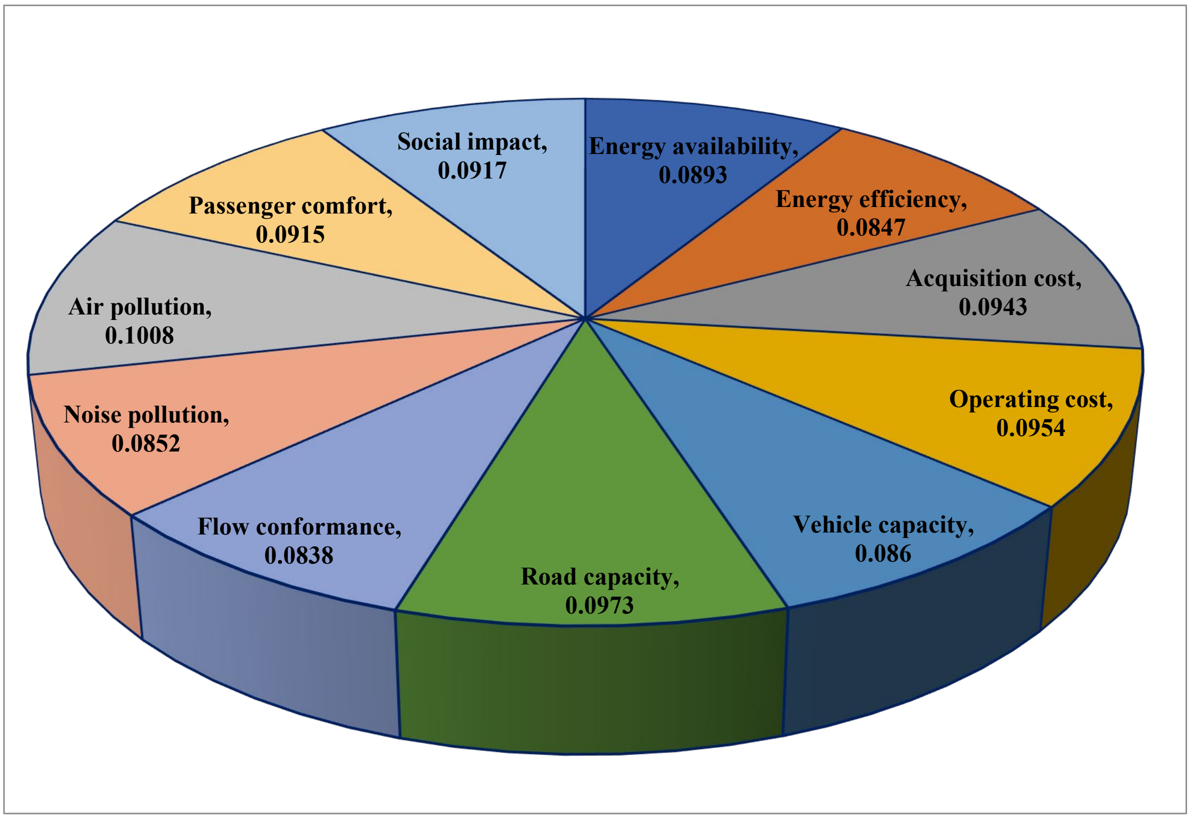

Figure 2. Weight of indicator for prioritizing HSS with the IF–SD–RS model.

Table 7. IF-score values of AIF-DM for prioritizing SUT options.

Criteria	T_1	T_2	T_3	T_4	T_5
r_1	0.759	0.863	0.684	0.863	0.706
r_2	0.697	0.811	0.633	0.819	0.748
r_3	0.347	0.239	0.355	0.328	0.360
r_4	0.437	0.314	0.391	0.432	0.325
r_5	0.635	0.684	0.677	0.872	0.764
r_6	0.843	0.651	0.716	0.828	0.736
r_7	0.673	0.672	0.748	0.771	0.749
r_8	0.282	0.417	0.405	0.305	0.315
r_9	0.364	0.349	0.322	0.256	0.352
r_{10}	0.836	0.846	0.724	0.621	0.708
r_{11}	0.764	0.759	0.831	0.764	0.748

Table 8. The overall performance rating of SUT options.

Options	P_i	$\overline{P_i}$	Q_i	$\overline{Q_i}$	O_i	Ranking
T_1	0.3354	0.0698	0.1881	0.0306	0.0556	2
T_2	0.3064	0.0408	0.1881	0.0305	0.0266	3
T_3	0.2656	0.0000	0.2023	0.0447	0.0000	5
T_4	0.4287	0.1631	0.1576	0.0000	0.1184	1
T_5	0.2938	0.0282	0.1967	0.0392	0.0227	4

Steps 10: The overall performance ratings of alternatives for prioritizing SUT options are determined using Equation (22) and are depicted in Table 8.

Step 11: Hence, the prioritization of options for prioritizing SUT options is $T_4 \succ T_1 \succ T_2 \succ T_5 \succ T_3$, and the CNG ($T_4$) is the best SUT option with the highest OPR.

5.1. Comparison with Other Models

To show the effectiveness of the IF-relative closeness coefficient-DN-WISP framework, we related the outcomes of the developed model with some of the extant models such as the "IF-COPRAS [60]", "IF-WASPAS [11]", "IF-TOPSIS [61]", and "IF-CoCoSo" [62]. The purpose for choosing the IF-COPRAS model is that the approach employs the vector normalization process. The purpose for choosing the WASPAS and CoCoSo models is that both approaches use the linear max normalization process and the integration of WSM and WPM. Additionally, both of them combine the WSM and WPM and use the linear max–min normalization process in which the cost and benefit criteria are treated in a different way.

5.1.1. The IF-TOPSIS Tool

The IF-TOPSIS method contains the following steps:

Steps 1–4: Follow the aforesaid tool.

Step 5: Compute the IF-PIS and IF-NIS.

Let p_b and p_n be the collection of benefits and cost indicators, respectively. Let N_j^+ and N_j^- be the IF-PIS and IF-NIS, respectively, defined by

$$\mathrm{N}_j^+ = \left(\mu_j^+, \nu_j^+\right) = \begin{cases} \max \mathbb{S}(\xi_{ij}), & \text{for benefit criterion} \\ \min \mathbb{S}(\xi_{ij}), & \text{for cos t criterion} \end{cases} \tag{23}$$

$$\mathrm{N}^- = \left(\mu_j^-, \nu_j^-\right) = \begin{cases} \min \mathbb{S}(\xi_{ij}), & \text{for benefit criterion} \\ \max \mathbb{S}(\xi_{ij}), & \text{for cos t criterion} \end{cases}, \tag{24}$$

where $j = 1, 2, \ldots, n$.

Step 6: Evaluation of distances from IF-PIS and IF-NIS.

The weighted distance of the options $t_i (i = 1, 2, \ldots, m)$ from the IF-IS N_j^+ is estimated as

$$D\left(\xi_{ij}, \mathrm{N}_j^+\right) = \sqrt{\frac{1}{2}\sum_{j=1}^{n} w_j\left[\left(\mu_{ij} - \mu_j^+\right)^2 + \left(\nu_{ij} - \nu_j^+\right)^2 + \left(\pi_{ij} - \pi_j^+\right)^2\right]}, \tag{25}$$

and the distance of the options $t_i (i = 1, 2, \ldots, m)$ from the IF-AIS N_j^- is calculated as

$$D\left(\xi_{ij}, \mathrm{N}_j^-\right) = \sqrt{\frac{1}{2}\sum_{j=1}^{n} w_j\left[\left(\mu_{ij} - \mu_j^-\right)^2 + \left(\nu_{ij} - \nu_j^-\right)^2 + \left(\pi_{ij} - \pi_j^-\right)^2\right]}, \tag{26}$$

Step 7: Find the "relative closeness coefficient (RCC)".

Finally, the RCC of each option is obtained as

$$CC_i = \frac{D\left(\xi_{ij},\ \mathrm{N}_j^-\right)}{D\left(\xi_{ij},\ \mathrm{N}_j^-\right) + D\left(\xi_{ij},\ \mathrm{N}_j^+\right)}. \tag{27}$$

Step 8: Choose the appropriate one from the maximum RCC value.

From Table 5, Equations (23) and (24), IF-PIS, and IF-NIS are obtained as

N_j^+ = {(0.830, 0.130, 0.041), (0.779, 0.169, 0.052), (0.221, 0.699, 0.080), (0.286, 0.614, 0.101) (0.847, 0.123, 0.030), (0.816, 0.151, 0.033), (0.712, 0.204, 0.084), (0.261, 0.658, 0.082), (0.236, 0.679, 0.085), (0.809, 0.145, 0.046), (0.801, 0.162, 0.037)},

N_j^- = {(0.620, 0.276, 0.103), (0.574, 0.323, 0.104), (0.327, 0.572, 0.101), (0.392, 0.506, 0.102), (0.575, 0.321, 0.104), (0.595, 0.312, 0.094), (0.621, 0.296, 0.084), (0.379, 0.521, 0.100), (0.330, 0.567, 0.103), (0.562, 0.334, 0.104), (0.698, 0.230, 0.072)}.

Using Equations (25)–(27), the outcomes of the IF-TOPSIS method are depicted in Table 9.

Table 9. The RCC of options for prioritizing SUT options.

Alternative	$D\left(\xi_{ij},\ \mathrm{N}_j^+\right)$	$D\left(\xi_{ij},\ \mathrm{N}_j^-\right)$	CC_i	Ranks
T_1	0.288	0.208	0.4201	3
T_2	0.234	0.257	0.5229	2
T_3	0.357	0.134	0.2736	5
T_4	0.157	0.333	0.6792	1
T_5	0.287	0.203	0.4142	4

Therefore, the ranking of SUT options is $T_4 \succ T_2 \succ T_1 \succ T_5 \succ T_3$, and the CNG ($T_4$) has a higher degree of RCC.

5.1.2. The IF-COPRAS Tool

This method comprises the steps as follows:

Steps 1–4: Follow the aforesaid model.

Step 5: Sum of the ratings of benefit and cost criteria:

$$\alpha_i = \overset{l}{\underset{j=1}{\oplus}} w_j\, \xi_{ij}, \tag{28}$$

$$\beta_i = \overset{n}{\underset{j=l+1}{\oplus}} w_j\, \xi_{ij}. \tag{29}$$

Step 6: Find the "relative degree (RD)" of each option using

$$\gamma_i = \vartheta \mathbb{S}(\alpha_i) + (1-\vartheta) \frac{\sum_{i=1}^{m} \mathbb{S}(\beta_i)}{\mathbb{S}(\beta_i) \sum_{i=1}^{m} \frac{1}{\mathbb{S}(\beta_i)}},\ i = 1, 2, \ldots, m. \tag{30}$$

Step 7: Estimate the "utility degree (UD)" of each option using

$$\delta_i = \frac{\gamma_i}{\gamma_{\max}} \times 100\ \%,\ i = 1, 2, \ldots, m. \tag{31}$$

Applying Equations (28)–(31), the implementation results are mentioned in Table 10. Thus, the CNG (T_4) was obtained as the suitable SUT option with the highest RD (0.7029).

Table 10. The UD of options for prioritizing SUT options.

Options	α_i	$\mathbb{S}(\alpha_i)$	β_i	$\mathbb{S}(\beta_i)$	γ_i	δ_i
T_1	(0.540, 0.389, 0.071)	0.575	(0.137, 0.807, 0.055)	0.165	0.7040	100.00
T_2	(0.544, 0.378, 0.078)	0.583	(0.126, 0.826, 0.048)	0.150	0.7039	99.99
T_3	(0.501, 0.419, 0.080)	0.541	(0.142, 0.808, 0.050)	0.167	0.7003	99.47
T_4	(0.591, 0.344, 0.065)	0.623	(0.127, 0.826, 0.046)	0.150	0.7029	99.84
T_5	(0.509, 0.414, 0.077)	0.548	(0.129, 0.820, 0.051)	0.154	0.6966	98.95

5.1.3. The IF-WASPAS Tool

Steps 1–4: Follow the proposed tool.

Step 5: Find the WSM and WPM degrees by using Equations (32) and (33), respectively,

$$S_i^{(1)} = \overset{n}{\underset{j=1}{\oplus}} w_j \xi_{ij}, \tag{32}$$

$$S_i^{(2)} = \overset{n}{\underset{j=1}{\otimes}} \xi_{ij}^{w_j}. \tag{33}$$

Step 6: Determine the UD of options using

$$Q_i = \hbar\, S_i^{(1)} + (1-\hbar)\, S_i^{(2)}, \ \forall\, i. \tag{34}$$

Step 7: Prioritize the options as per the UD (Q_i).

By means of Equations (32)–(34), the UD for prioritizing SUT options are demonstrated in Table 11.

Table 11. The IF-WASPAS model for prioritizing SUT options.

Options	$S_i^{(1)}$	$S_i^{(2)}$	$\mathbb{S}\left(S_i^{(1)}\right)$	$\mathbb{S}\left(S_i^{(2)}\right)$	$Q_i(\hbar)$
T_1	(0.666, 0.254, 0.080)	(0.642, 0.268, 0.090)	0.706	0.687	0.6965
T_2	(0.683, 0.238, 0.079)	(0.661, 0.255, 0.084)	0.722	0.703	0.7128
T_3	(0.637, 0.277, 0.086)	(0.624, 0.286, 0.091)	0.680	0.669	0.6743
T_4	(0.713, 0.234, 0.054)	(0.685, 0.237, 0.078)	0.740	0.724	0.7317
T_5	(0.649, 0.260, 0.091)	(0.644, 0.264, 0.092)	0.694	0.690	0.6923

Hence, the ranking of the options is $T_4 \succ T_2 \succ T_1 \succ T_5 \succ T_3$, and the CNG ($T_4$) is a suitable choice with maximum UD.

5.1.4. The IF-CoCoSo Tool

Steps 1–5: Similar to the IF-WASPAS model.

Step 6: Estimate the "balanced compromise degrees (BCDs)" of options as

$$Q_i^{(1)} = \frac{\mathbb{S}\left(S_i^{(1)}\right) + \mathbb{S}\left(S_i^{(2)}\right)}{\sum\limits_{i=1}^{m}\left(\mathbb{S}\left(S_i^{(1)}\right) + \mathbb{S}\left(S_i^{(2)}\right)\right)}, \tag{35}$$

$$Q_i^{(2)} = \frac{\mathbb{S}\left(S_i^{(1)}\right)}{\min\limits_i \mathbb{S}\left(S_i^{(1)}\right)} + \frac{\mathbb{S}\left(S_i^{(2)}\right)}{\min\limits_i \mathbb{S}\left(S_i^{(2)}\right)}, \tag{36}$$

$$Q_i^{(3)} = \frac{\vartheta\, \mathbb{S}\left(S_i^{(1)}\right) + (1-\vartheta)\mathbb{S}\left(S_i^{(2)}\right)}{\vartheta \max\limits_i \mathbb{S}\left(S_i^{(1)}\right) + (1-\vartheta)\max\limits_i \mathbb{S}\left(S_i^{(2)}\right)}, \tag{37}$$

Step 8: Assess the "overall compromise degree (OCD)" of options are computed as

$$Q_i = \left(Q_i^{(1)} Q_i^{(2)} Q_i^{(3)}\right)^{1/3} + \frac{1}{3}\left(Q_i^{(1)} + Q_i^{(2)} + Q_i^{(3)}\right). \tag{38}$$

Step 9: Prioritize the options using OCD (Q_i) in decreasing order.

Using Equations (35)–(38), the OCSs are depicted in Table 12. From Table 12, the CNG (T_4) is the best SUT alternative for prioritizing SUT options.

Table 12. The OCS for prioritizing SUT options.

Options	$Q_i^{(1)}$	$Q_i^{(2)}$	$Q_i^{(3)}$	Q_i
T_1	0.1986	2.0657	0.9525	1.8033
T_2	0.2032	2.1139	0.9746	1.8453
T_3	0.1922	2.0000	0.9211	1.7453
T_4	0.2086	2.1701	1.0000	1.8941
T_5	0.1974	2.0534	0.9447	1.7913

The comparative outcomes are displayed in Tables 9–12 and Figure 3. From Tables 9–12, it can be observed that the optimal SUT is T_4 (CNG) for prioritizing SUT options using almost all MCDM tools. The advantages of the developed IF-relative closeness coefficient-OCRA model are presented as follows:

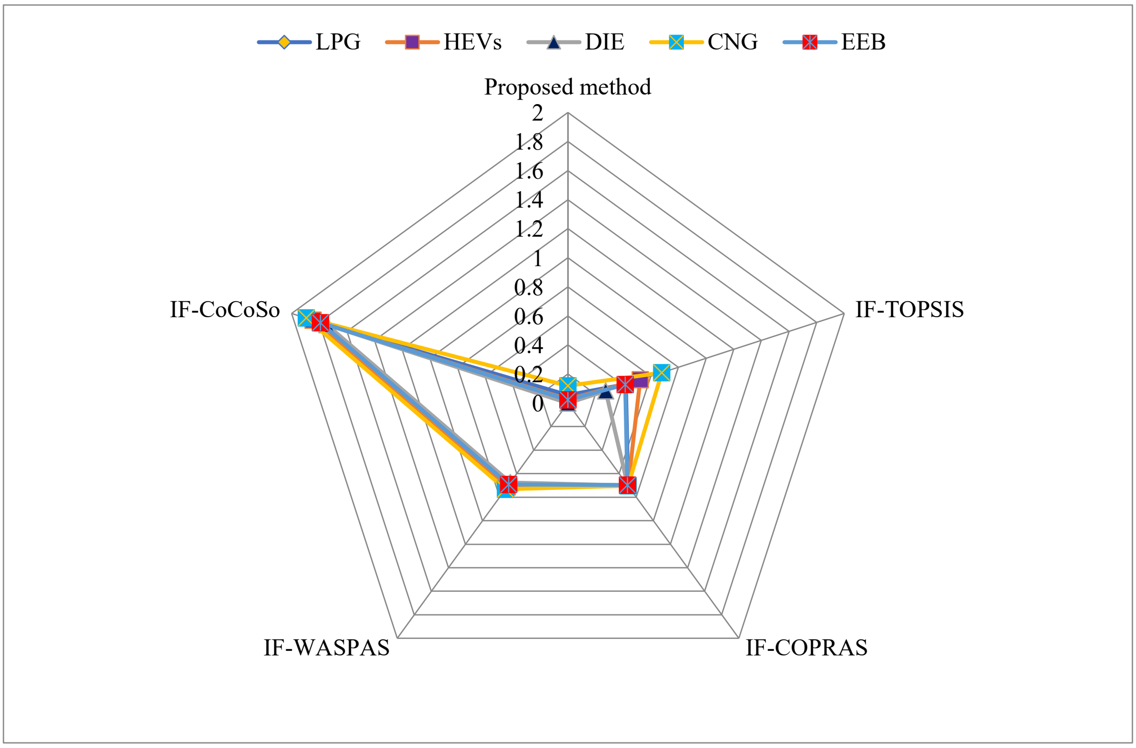

Figure 3. Assessment degrees of alternatives by different methods.

- The proposed method utilizes the linear normalization procedure and relative closeness coefficient, while the IF-COPRAS method utilizes only the vector normalization procedure, where IF-WASPAS, IF-TOPSIS, and IF-CoCoSo use only the linear normalization procedure. Thus, the proposed method avoids the information loss and provides more accurate decision results by means of different criteria.
- The IF-WASPAS, IF-CoCoSo, and the proposed method associate the WSM and WPM to enhance the accuracy of outcomes. In IF-COPRAS, the IFWA operator, utility degrees of options are obtained. In IF-TOPSIS, the closeness coefficients based on

the distance measure of each option are estimated, while the IF–closeness coefficient–OCRA utilizes the performance of independent assessment of options over benefit and cost indicators and combines these two APRs so as to determine OPRs, which supports DEs not to misplace information during the MADA process.

- The systematic assessment of DEs' weights using the IF-score value and IF-rank sum model reduce the imprecision and biases in the MADA procedure.
- The developed method determines the criteria weights by using the IF–relative closeness coefficient-based tool. In contrast, in IF-WASPAS, the criteria weight is obtained with a similarity measure-based tool, in IF-CoCoSo, the criteria weight is obtained using divergence measure and the score function-based approach, and in IF-COPRAS and IF-TOPSIS, the criteria weight is chosen randomly.

6. Conclusions

The evaluation of the SUT selection problem is considered as an intricate MADA problem owing to the presence of multiple qualitative and quantitative indicators. The aim of this work is to introduce an MADA model for assessing and prioritizing SUT options from an IFS perspective. In this regard, a hybrid intuitionistic fuzzy MADA framework was introduced with the integration of the IF-distance measure, IF-relative closeness coefficient-based weight-determining model, and the OCRA approach. In this regard, new parametric IF-distance measure was presented and their properties discussed. In this framework, new formulae were discussed to find the DEs' weights and indicators' weights. To illustrate the reasonableness and utility of the developed framework, a case study of SUT options assessment was taken under IFSs settings. A comparison with extant tools was conducted to expose the rationality and solidity of the obtained outcomes. The findings of the outcomes proved that the presented framework has great significance and strength and is very consistent compared to the prior introduced tools. The main advantages of the proposed framework are the simple computational steps under IFS context and development of weight-determining tools for DEs and indicators during the assessment of SUT options.

However, this method neglects the subjective weights of indicators during the SUT options assessment. In addition, the present work does not consider the target-based indicators. This study is not able to express the indeterminate and inconsistent information in the process of SUT alternatives assessment. In a future study we will try to improve the limitations of this study by developing new models with integrated subjective–objective weights of indicators in SUT assessment. In the future, it would be exciting to use the introduced OCRA model for other decision-making scenarios such as IoT-enabling technologies assessment for the SUT system, waste-to-energy plant selection, biofuel product plant location evaluations. etc. In addition, we will extend the proposed OCRA model under different disciplines, namely, complex q-rung orthopair fuzzy sets, dual probabilistic linguistic term sets, and others.

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