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Original paper

Sustainability performance assessment with intuitionistic fuzzy composite metrics and its application to the motor industry

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Abstract

The performance assessment of companies in terms of sustainability requires to find a balance between multiple and possibly conflicting criteria. We here rely on composite metrics to rank a set of companies within an industry considering environmental, social and corporate governance criteria. To this end, we connect intuitionistic fuzzy sets and composite programming to propose novel composite metrics. These metrics allow to integrate important environmental, social and governance principles with the gradual membership functions of fuzzy set theory. The main result of this paper is a sustainability assessment method to rank companies within a given industry. In addition to consider multiple objectives, this method integrates two important social principles such as maximum utility and fairness. A real-world example is provided to describe the application of our sustainability assessment method within the motor industry. A further contribution of this paper is a multicriteria generalization of the concept of magnitude of a fuzzy number.

Keywords: Composite programming, intuitionistic fuzzy numbers, parametric distance functions, magnitude.

1 Introduction

Performance is no longer a single objective problem. Sustainability has become the usual standard for measuring performance in many industries. The concept of sustainability implies the consideration of environmental, social and corporate governance criteria (ESG). These general criteria have been materialized by United Nations into a set of Sustainable Development Goals as a blueprint to achieve a better and more sustainable future for all. They address global challenges such as poverty, inequality, climate change, environmental degradation, peace and justice. It is likely that the achievement of some of these criteria may intersect with one another to produce a win-win sustainable situation. In other cases, conflict between criteria may require to find a compromise solution in the design of public policies and individual decision-making. Furthermore, corporate claims about sustainability and greenwashing have increased rapidly in recent years. An example in the automotive industry is the scandal of Wolkswagen in 2015. As a result, there is a need for assessing sustainability performance. However, we also face some challenges because sustainability is a multidimensional concept and, at the same time, we usually find problems of reliability in the information used to measure multiple criteria.

Since the pioneering work by Zadeh [50], fuzzy set theory has been broadly employed in various research fields involving uncertainty. In recent years, several authors have attempted to expand the classical fuzzy set theory by developing alternative fuzzy sets (FS) such as: interval-valued fuzzy sets (IVFS) [42, 51], intuitionistic fuzzy sets (IFS) [5], neutrosophic fuzzy sets (NFS) [40], hesitant fuzzy sets (HFS) [41], picture fuzzy sets (PFS) [16], Pythagorean fuzzy sets (PFS) [48], hexagonal fuzzy sets (HFS) [35], interval-valued generalized hexagonal fuzzy numbers (IVGHFN) [24], spherical fuzzy sets [22] or spherical fuzzy Nsoft expert sets [1].

In this paper, we deal with IFS within the context of multicriteria decision making (MCDM). To this end, we use Intuitionistic Analytic Hierarchy Process (IAHP) combined with novel Intuitionistic Fuzzy Composite Metrics

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(IFCM). An IFS is characterized by a membership function (e.g., the percentage of people who voted for the current government), but also by a non-membership function (e.g., the percentage of people who voted for other parties outside the government). As a result, the definition of these two functions results in the consideration a third group of elements, those not covered by the membership and non-membership functions, hence non-determined (e.g., the percentage of people who did not vote at all). On the other hand, the Analytic Hierarchy Process (AHP) proposed by [39] provides a comprehensive framework for solving complex decision problems. Furthermore, fuzzy extensions of AHP (F-AHP) become an effective tool to sort out such complex situations.

A non-membership function in an IFS describes any fuzzy concept with more neutrality and realism [11]. The main advantage of an IFS is that it may express more abundant and flexible information as compared with a conventional fuzzy set. Many recent works used IFS to solve multicriteria fuzzy decision-making problems. [46] proposed an IF programming method for group decision making, [15] integrated the intuitionistic fuzzy weighted averaging method and the soft set with imprecise data in multicriteria supplier selection problems, [13] proposed a group decision-making methodology combining AHP and VIKOR (VIsekriterijumska optimizacija i KOmpromisno Resenje) under an IF environment for waste management, [34] developed an IF Additive Ratio Assessment (IF-ARAS) method for multicriteria personnel selection, and [36] used F-AHP and F-VIKOR and triangular fuzzy numbers for multicriteria group decision making to deal with the COVID 19 pandemic. The methodology, type of fuzzy sets used and applications of the previous studies and other related works are summarized in Table 1. However, an important shortcoming of these papers is that, after the application of fuzzy logic, decision makers are limited by usually rigid multicriteria methodologies that lack of flexibility and explainability. Here explainability means the ability of parameters of decision-making models to support the results according to the preferences of decision-makers.

In order to provide flexibility and explainability, we here rely on compromise programming (CP) as one of the most widely used multiple criteria decision making (MCDM) techniques [8]. The presence of multiple objectives is common in many areas of research and an equilibrium or compromise solution is sought. CP is based on the concept of distance to the ideal point, usually infeasible, where the maximum for each criterion is attained [53, 49]. By giving different values to a parameter in the Minkowski distance function, a number of appealing metrics can be devised to find compromise solutions, hence offering a higher degree of flexibility and explainability. Moreover, a convex combination of distances with different parameters [38, 19] leads to composite metrics used to solve MCDM problems by exploiting the explainable features of different metrics. As an example, the linear metric represents the principle of maximum utility and the infinite metric represents the principle of maximum fairness [19].

Table 1: Survey on recent works about fuzzy MCDM

Reference	Methodology	Application
[46]	IF programming	Electronic commerce
[4]	IF-AHP and IF-MOORA	Product selection
[18]	MOLP and TOPSIS	Project portfolio selection
[13]	IF-AHP and IF-VIKOR	Waste management
[15]	IF-WAM-SSM	Supplier selection
[3]	IF-AHP and IF-VIKOR	Logistics operations
[25]	IF-AHP and IF-VIKOR	Transport
[34]	IF-ARAS	Personnel selection
[36]	F-AHP and F-VIKOR	COVID 19
This paper	IFCM	Sustainability assessment

IF-MOORA: Intuitionistic fuzzy multibjective optimization based on ratio analysis
MOLP: Multiobjective linear programming
IF-WAM-SSM: Intuitionistic fuzzy weighted averaging and soft set method
IFCM: Intuitionistic fuzzy composite metrics

The combination of fuzzy set theory and CP led to the introduction of fuzzy CP [10, 18, 26, 33]. However, there is a lack of research on the use of IF composite metrics. In this paper, we argue that there is a potential to develop intuitionistic fuzzy composite metrics to cover a wider range of decisions making problems by combining the generality of IFS and the explainability of composite programming metrics. More precisely, we here propose two IF composite metrics as a natural extension of composite programming within an intuitionistic fuzzy environment. To this end, we rely on the concept of magnitude of a fuzzy number proposed by [21] as a way to rank fuzzy numbers. However, the notion of magnitude is clearly a bicriteria concept because it combines the mean and the standard deviation in the possibilistic context of fuzzy numbers. As a result, we generalize the definition of magnitude of a fuzzy number as a multicriteria concept that enables us to consider a new way to represent and study fuzzy numbers.

Summarizing, this paper contributes to the development of intuitionistic fuzzy set theory and composite programming by means of:

- A linear-infinite metric combining the principles of maximum utility and maximum fairness.
- A linear-quadratic metric combining the principles of maximum utility and minimum deviation.
- A multicriteria generalization of the concept of magnitude of a fuzzy number.

In addition to this introduction, Section 2 provides useful background on intuitionistic fuzzy set theory. Section 3 describes how to rank alternatives using intuitionistic fuzzy composite metrics. Section 4 illustrates our approach by means of a case study ranking a set of motor companies. Finally, Section 5 concludes highlighting natural extensions of this work.

2 Useful background on intuitionistic fuzzy sets

Intuitionistic fuzzy sets was proposed by [5, 6] as a generalization of fuzzy set theory by [50]. In this section, we provide basic useful background on intuitionistic fuzzy sets that we later use in our proposal of fuzzy composite metrics.

Definition 2.1. *Let X be a non-empty set, the intuitionistic fuzzy set $\tilde{A}$ is expressed as:*

$$\tilde{A} = \{\langle x, \mu_{\tilde{A}}(x), v_{\tilde{A}}(x)\rangle | x \in X\}. \tag{1}$$

In set X, $\mu_{\tilde{A}}(x)$ and $v_{\tilde{A}}(x)$ are, respectively, the degree of membership and non-membership of element x to $\tilde{A}$, defined as follows:

$$\mu_{\tilde{A}} : X \to [0,1]\,. \tag{2}$$

$$v_{\tilde{A}} : X \to [0,1]\,, \tag{3}$$

which satisfy the condition:

$$0 \leq \mu_{\tilde{A}} + v_{\tilde{A}} \leq 1. \tag{4}$$

As a result, an ordinary fuzzy set can be expressed as:

$$\{\langle x, \mu_{\tilde{A}}(x), 1 - \mu_{\tilde{A}}(x)\rangle | x \in X\}. \tag{5}$$

Definition 2.2. *Let $\tilde{A}$ be an intuitionistic fuzzy set. The value $\pi_{\tilde{A}}(x)$ is called the degree of hesitancy (or uncertainty) of element x belongs to $\tilde{A}$ in X:*

$$\pi_{\tilde{A}}(x) = 1 - \mu_{\tilde{A}}(x) - v_{\tilde{A}}(x). \tag{6}$$

We can express the degree of membership and non-membership by means of triangular intuitionistic fuzzy numbers (TIFN) as proposed by [27].

Definition 2.3. *A TIFN $\tilde{A} = \langle(\underline{a}, a, \overline{a}), w_{\tilde{A}}, u_{\tilde{A}}\rangle$ is a special intuitionistic fuzzy set on a real number set $\mathbb{R}$, whose membership function $\mu_{\tilde{A}}$ and non-membership function $v_{\tilde{A}}$ are defined as follows:*

$$\mu_{\tilde{A}} = \begin{cases} \frac{x-\underline{a}}{a-\underline{a}} w_{\tilde{A}} & \textit{if} \quad \underline{a} \leq x < a, \\ w_{\tilde{A}} & \textit{if} \quad x = a, \\ \frac{\overline{a}-x}{\overline{a}-a} w_{\tilde{A}} & \textit{if} \quad a < x \leq \overline{a}, \\ 0 & \textit{if} \quad x < \underline{a} \text{ or } x > \overline{a}. \end{cases} \tag{7}$$

$$v_{\tilde{A}} = \begin{cases} \frac{a-x+(x-\underline{a})u_{\tilde{A}}}{a-\underline{a}} & \textit{if} \quad \underline{a} \leq x < a, \\ u_{\tilde{A}} & \textit{if} \quad x = a, \\ \frac{x-a+(\overline{a}-x)u_{\tilde{A}}}{\overline{a}-a} & \textit{if} \quad a < x \leq \overline{a}, \\ 1 & \textit{if} \quad x < \underline{a} \text{ or } x > \overline{a}. \end{cases} \tag{8}$$

Values $w_{\tilde{A}}$ and $u_{\tilde{A}}$ represent the maximum degree of membership and the minimum degree of non-membership, respectively, which satisfy the following inequalities:

$$0 \leq w_{\tilde{A}} \leq 1. \tag{9}$$

$$0 \leq u_{\tilde{A}} \leq 1. \tag{10}$$

$$0 \leq w_{\tilde{A}} + u_{\tilde{A}} \leq 1. \tag{11}$$

A TIFN can express a higher degree of uncertainty than an ordinary triangular fuzzy number. Furthermore, the usual arithmetical operations over triangular fuzzy numbers can be generalized to TIFNs. The definitions of possibilistic mean $M(\tilde{A})$ and possibilistic standard deviation $\sigma(\tilde{A})$ of a TIFN are necessary for the understanding of our approach [14, 21, 45].

Definition 2.4. *The possibilistic mean of a TIFN $\tilde{A} = \langle(\underline{a}, a, \overline{a}), w_{\tilde{A}}, u_{\tilde{A}}\rangle$ is given by:*

$$M(\tilde{A}) = \frac{M_\mu(\tilde{A}) + M_v(\tilde{A})}{2}, \tag{12}$$

where $M_\mu(\tilde{A})$ is the possibilistic mean of the membership function and $M_v(\tilde{A})$ is the possibilistic mean of the non-membership function computed as follows:

$$M_\mu(\tilde{A}) = \frac{1}{6}(\underline{a} + 4a + \overline{a})w_{\tilde{A}}. \tag{13}$$

$$M_v(\tilde{A}) = \frac{1}{6}(\underline{a} + 4a + \overline{a})(1 - u_{\tilde{A}}). \tag{14}$$

Definition 2.5. *Given a TIFN $\tilde{A} = \langle(\underline{a}, a, \overline{a}), w_{\tilde{A}}, u_{\tilde{A}}\rangle$, the possibilistic standard deviation of a $\tilde{A}$ is given by:*

$$\sigma(\tilde{A}) = \frac{\sigma_\mu(\tilde{A}) + \sigma_v(\tilde{A})}{2}, \tag{15}$$

where $\sigma_\mu(\tilde{A})$ is the possibilistic standard deviation of the membership function and $\sigma_v(\tilde{A})$ is the possibilistic standard deviation of the non-membership function computed as follows:

$$\sigma_\mu(\tilde{A}) = \frac{1}{\sqrt{24}}(\underline{a} - \overline{a})\sqrt{w_{\tilde{A}}}. \tag{16}$$

$$\sigma_v(\tilde{A}) = \frac{1}{\sqrt{24}}(\underline{a} - \overline{a})\sqrt{(1 - u_{\tilde{A}})}. \tag{17}$$

In order to establish direct comparisons between a pair of TIFNs, different distance functions can be applied [20]. In addition, [21] introduced the concept of magnitude $\mathrm{Mag}(\tilde{A})$ of a fuzzy number that we here particularize for a TIFN:

Definition 2.6. *Given a TIFN $\tilde{A} = \langle(\underline{a}, a, \overline{a}), w_{\tilde{A}}, u_{\tilde{A}}\rangle$, its magnitude $\mathrm{Mag}(\tilde{A})$ is expressed by:*

$$\mathrm{Mag}(\tilde{A}) = M(\tilde{A}) + \sigma(\tilde{A}), \tag{18}$$

where $M(\tilde{A})$ is the possibilistic mean and $\sigma(\tilde{A})$ is the standard deviation of $\tilde{A}$.

The use of a measure such as the magnitude of a fuzzy number presents some advantages such as integrity of ordering relation, transitivity of ordering relation and independence of irrelevant fuzzy numbers [21]. The mean and the standard deviation have the same dimension and the resulting scalar value can be used to rank fuzzy numbers. As a result, it is a synthetic measure that allows direct comparisons to rank alternatives by means of TIFN.

3 Ranking alternatives using intuitionistic fuzzy composite metrics

In this section, we first introduce basic concepts of compromise programming and we also describe how compromise programming can be extended by means of different composite metrics derived from the crucial notion of distance. We rely on distances between fuzzy numbers computed by means of the concept of magnitude, which we here generalize as a multicriteria concept.

3.1 From compromise programming to composite metrics

Multiple criteria decision making (MCDM) techniques aim to solve the conflict among many different and possibly non-commensurate objectives by finding an equilibrium solution. Compromise Programming (CP) is an MCDM technique based on the concept of distance to the ideal point, usually infeasible, where the maximum for each criterion is attained [49, 53].

By assuming that we want to maximize all criteria, we can use the following normalization for each criterion x:

$$y_j = \frac{g_j(x) - g_{j,min}}{g_{j,max} - g_{j,min}}, \tag{19}$$

where $g_{j,max}$ and $g_{j,min}$ are, respectively, the maximum and minimum value achievement as measured by $g_j(x)$ objective function. As a result, all criteria achievements are restricted to the interval $[0, 1]$. By combining all criteria measurements, the ideal point in a bicriteria space is given by $\boldsymbol{y}* = (1, 1)$ and the anti-ideal point by $\boldsymbol{y}_* = (0, 0)$. Finally, the Zeleny's axiom of choice stating that alternatives that are closer to the ideal point are preferred to those that are further is used to select alternatives. To this end, the Minkowski distance function of order p from any point $\boldsymbol{y} \in \mathbb{R}^q$ to the ideal point is used as a loss function to be minimized:

$$\mathcal{L}_p = \left[\sum_{j=1}^{q} \rho_j^p |1 - y_j|^p \right]^{1/p}, \tag{20}$$

where q is the number of criteria under consideration and ρ_j is the weight attached to the j-th criterion.

By setting parameter p in the Minkowski distance function to different values, a number of appealing metrics can be devised to find compromise solutions with a different degree of balance:

1. The linear metric ($p = 1$) implies full compensability among achievements for different criteria and tends to produce more unbalanced solutions:
$$\mathcal{L}_1 = \sum_{j=1}^{q} \rho_j (1 - y_j). \tag{21}$$

2. The quadratic metric ($p = 2$) considers the Euclidean distance the ideal point and compensability among criteria is reduced because large deviations are squared:
$$\mathcal{L}_2 = \left[\sum_{j=1}^{q} \rho_j^2 (1 - y_j)^2 \right]^{1/2}. \tag{22}$$

3. The infinite metric ($p = \infty$) only considers the weighted maximum deviation from the ideal:
$$\mathcal{L}_\infty = \lim_{p \to \infty} \left[\sum_{j=1}^{q} \rho_j^p (1 - y_j)^p \right]^{1/p} = \max_j \left[\rho_j (1 - y_j) \right]. \tag{23}$$

By considering a convex combination of the linear and infinite metric, composite programming has been proposed as a suitable way to include not only one metric but two in the selection of the best alternative [2, 19, 38]:

$$\mathcal{L}_{1,\infty} = \lambda \sum_{j=1}^{q} \rho_j (1 - y_j) + (1 - \lambda) \max_j \left[\rho_j (1 - y_j) \right], \tag{24}$$

where parameter $\lambda \in [0,1]$ controls the degree in which the linear term is more important than the infinite term.

Following a different approach, [7] proposed a linear quadratic composite metric for utility functions with non-null second derivative such as the Cobb-Douglas utility function. Along the lines of equation (24), a straightforward way to overcome this limitation is the use of a convex combination of the linear and quadratic losses encoded in equations (21) and (22):

$$\mathcal{L}_{1,2} = \lambda \sum_{j=1}^{q} \rho_j (1 - y_j) + (1-\lambda) \left[\sum_{j=1}^{q} \rho_j^2 (1-y_j)^2 \right]^{1/2}. \tag{25}$$

3.2 Generalized magnitude of fuzzy numbers

The notion of magnitude from Definition 2.6 is clearly a bicriteria concept including the possibilistic mean and the standard deviation as critical dimensions. Furthermore, the possibilistic mean and standard deviation are also related to the parameters of value and ambiguity in [17]. This fact motivates us to generalize its definition as a multicriteria concept.

Definition 3.1. *Given a generalized fuzzy number $\tilde{A}$, its multicriteria magnitude* $\mathrm{MMag}(\tilde{A})$ *is expressed by:*

$$\mathrm{MMag}(\tilde{A}) = f(x_1(\tilde{A}), x_2(\tilde{A}), \ldots, x_m(\tilde{A})), \tag{26}$$

where $f(x_1(\tilde{A}), x_2(\tilde{A}), \ldots, x_m(\tilde{A}))$ is a function $f : \mathbb{R}^m \to \mathbb{R}$ considering an m-dimensional set of features of $\tilde{A}$, denoted by $x_1(\tilde{A})$, $x_2(\tilde{A})$, ..., $x_m(\tilde{A})$.

Note that when $x_1(\tilde{A})$ is the possibilistic mean of $\tilde{A}$, $x_2(\tilde{A})$ is the possibilistic standard deviation of $\tilde{A}$, and the rest of features up to m are null, the multicriteria magnitude corresponds to the initial definition of magnitude proposed in [21] if $f(\cdot)$ is an additive function. Two features are often enough to describe a fuzzy number [17], but the concept of multicriteria magnitude is able to include as many other features as required to a thorough description. Some examples of these other features are the maximum and minimum support values of membership functions. Other examples are measures of kurtosis or skewness of fuzzy numbers in a similar way as in probability distributions. Finally, the concept of multicriteria magnitude in Definition 3.1 allows users to attach a different weight to each of the parameters or aspects included in its mathematical expression. There is no need to assume that the possibilistic mean and the standard deviation have the same importance in all cases. On the contrary, a decision maker may consider that the mean value is twice more important than the spread of a fuzzy number.

3.3 Intuitionistic fuzzy composite metrics

In this section, we propose to build the intuitionistic fuzzy counterparts of equations (24) and (25). To this end, we use distances or deviations computed based on the concept of generalized magnitude of a fuzzy number. The rationale behind our approach is that composite metrics described in Section 3.1 are indeed deviations from an ideal point.

Let us first assume that the ideal point can be represented as the following TIFN:

$$\gamma^+ = ((1,1,1),1,0). \tag{27}$$

Next, we define a distance function $d(\gamma^+, \tilde{y}_j)$ measuring the deviation from the ideal (γ^+) to any fuzzy achievement ($\tilde{y}_j$) based on the concept of magnitude from equation (18) as particular case of Definition 3.1:

$$d(\gamma^+, \tilde{y}_j) = |\,\mathrm{Mag}(\gamma^+) - \mathrm{Mag}(\tilde{y}_j)| = |M(\gamma^+) + \sigma(\gamma^+) - M(\tilde{y}_j) - \sigma(\tilde{y}_j)|. \tag{28}$$

From Definitions 2.4 and 2.5 and equation (28), we next derive the triangular intuitionistic fuzzy counterparts of the linear-infinite and linear-quadratic composite metrics. First, we compute the the possibilistic mean and standard deviation of $\tilde{y}_j = ((\underline{y}_j, y_j, \overline{y}_j), w_{\tilde{y}_j}, u_{\tilde{y}_j})$:

$$M(\tilde{y}_j) = \frac{1}{12}(\underline{y}_j + 4y_j + \overline{y}_j)(1 - u_{\tilde{y}_j} + w_{\tilde{y}_j}), \tag{29}$$

$$\sigma(\tilde{y}_j) = \frac{(\overline{y}_j - \underline{y}_j)}{2\sqrt{24}}(\sqrt{w_{\tilde{y}_j}} + \sqrt{1 - u_{\tilde{y}_j}}). \tag{30}$$

Since $\mathrm{Mag}(\gamma^+) = M(\gamma^+) + \sigma(\gamma^+) = 1 + 0 = 1$, we can compute the distance from the ideal γ^+ to any TIFN $\tilde{y}_j$ by means of the following expression:

$$d(\gamma^+, \tilde{y}_j) = 1 - \frac{1}{12}(\underline{y}_j + 4y_j + \overline{y}_j)(1 - u_{\tilde{y}_j} + w_{\tilde{y}_j}) - \frac{(\overline{y}_j - \underline{y}_j)}{2\sqrt{24}}(\sqrt{w_{\tilde{y}_j}} + \sqrt{1 - u_{\tilde{y}_j}}). \tag{31}$$

As a result, if the achievement for each goal is measured by a TIFN $\tilde{y}_j$, the composite linear-infinite loss function described in equation (24) can be expressed as follows:

$$\mathcal{L}_{1,\infty} = \lambda \sum_{j=1}^{q} \rho_j d(\gamma^+, \tilde{y}_j) + (1 - \lambda) \max_j \left[\rho_j d(\gamma^+, \tilde{y}_j)\right]. \tag{32}$$

The intuitionistic fuzzy linear-infinite composite metric presents the advantage of integrating two important social principles such as maximum utility and fairness as suggested by [19]. Furthermore, by incorporating fuzzy set theory, we benefit from the the ability of gradual membership and non-membership functions to support multiple criteria decision-making with sufficient generality.

Similarly, the composite linear-quadratic loss function described in equation (25) can be expressed as:

$$\mathcal{L}_{1,2} = \lambda \sum_{j=1}^{q} \rho_j d(\gamma^+, \tilde{y}_j) + (1 - \lambda) \left[\sum_{j=1}^{q} \rho_j^2 d(\gamma^+, \tilde{y}_j)^2\right]^{1/2}. \tag{33}$$

The intuitionistic fuzzy linear-quadratic composite metric combines the notion of maximum utility and minimum deviation by relying on a convex combination of intuitionistic fuzzy distance functions to a multidimensional ideal point.

Assuming that we know the priorities for each indicator, we are in a position to rank alternatives by means of the intuitionistic fuzzy composite metrics. To this end, we propose the following steps:

Step 1 Quantification. We first obtain a set of crisp indicators representing criteria and subcriteria in either a flat or a hierarchical structure. Each indicator is a quantitative measure assessing the degree in which a particular attribute is fulfilled. For instance, the environmental performance of a given company.

Step 2 Normalization. In order to avoid meaningless comparison among indicators, we normalize the set of indicators. Several normalization techniques in a multiple criteria decision making context can be found in [52] and [43]

Step 3 Construction of the decision matrix. We construct a normalized fuzzy decision matrix by setting each element of the matrix to a fuzzy number. In the case of TIFN, values $w_{\tilde{y}_j}$ and $u_{\tilde{y}_j}$ are estimated according to the degree of reliability introduced by the quality of information provided by each indicator.

Step 4 Ranking. Finally, we use a intuitionistic fuzzy composite metric to derive a ranking of alternatives.

In what follows, we take advantage of these composite metrics to illustrate our intuitionistic fuzzy approach to rank alternatives.

4 Case study: sustainability performance assessment of motor companies

In this case study, we aim to rank the performance of the main motor companies worldwide. To this end, we select firms with more than USD 100,000 million in 2019 revenues as summarized in Tables 4, 5, 6 and 7.

4.1 Motivation, criteria, structure and priorities

As mentioned in the introduction, sustainability has become the usual standard for measuring performance in many industries. The concept of sustainability implies the consideration not only of economic aspects but also the consideration of environmental, social and corporate governance criteria. Then, we are dealing with a multiple criteria decision-making problem in which we must find a balance among the different criteria under consideration when seeking a compromise solution.

On the other hand, the motor industry is one of the most relevant industries around the world [23, 31]. In addition, the motor industry is a key player in the environmental impact due to global warming emissions. As a result, the main reason to select the motor industry in our sustainability performance assessment method is that we consider this industrial sector a big influencer in the sustainability of the global economic system.

In this study, we consider both financial and non-financial criteria to represent the multidimensional concept of sustainability. Financial criteria include aspects such as solvency, profitability, cash-flow and liquidity. These indicators provide useful information about critical aspects to assess the financial situation of a company and are commonly used in the corporate finance and financial analysis literature [9, 12, 32, 37]. We obtain data from the public financial statements of the selected motor companies. On the other hand, we obtain non-financial criteria from EIKON-Thomson Reuters database. Along the lines of the selection of the financial criteria, the set of non-financial criteria are assumed to faithfully represent the environmental, social and government performance for assessment and comparative purposes. The full list of criteria, subcriteria and 26 indicators is as follows:

1. Non-financial
   (a) Environmental (E)
      i. Resource Use (E1)
      ii. Emissions (E2)
      iii. Environmental innovation (E3)
   (b) Social (S)
      i. Workforce (S1)
      ii. Human rights (S2)
      iii. Community (S3)
      iv. Product responsibility (S4)
   (c) Governance (G)
      i. Management (G1)
      ii. Shareholders (G2)
      iii. CSR strategy (G3)
2. Financial
   (a) Solvency (SO)
      i. Liability to assets ratio (SO1)
      ii. Debt to equity ratio (SO2)
      iii. Net debt to EBITDA ratio (SO3)
      iv. Interest expense to revenue ratio (SO4)
   (b) Profitability (P)
      i. ROA (P1)
      ii. ROE (P2)
      iii. Assets turnover (P3)
      iv. Operating margin (P4)
   (c) Cash-flow (CF)
      i. Net income to cash operating activities (CF1)
      ii. Debt to cash operating activities (CF2)
      iii. Liabilities to cash operating activities (CF3)
   (d) Liquidity (L)
      i. Current ratio (L1)
      ii. Quick ratio (L2)
      iii. Average inventory days (L3)
      iv. Average receivables days (L4)
      v. Average payable days (L5)

In order to establish the priorities for criteria and subcriteria we follow the next steps:

Step 1: Representation of expert opinions. We ask three experts to express their opinions about the importance of criteria and subcriteria following an Intuitionistic Fuzzy Analytic Hierarchy Process Approach (IF-AHP) as described in [47]. These opinions are represented as an intuitionistic fuzzy evaluation value $\tilde{r}_{ijk} = (\mu_{r_{ijk}}, v_{r_{ijk}})$ according to the linguistic scale summarized in Table 2. Other values between 0 and 1 can be used to express any intermediate preference between two consecutive linguistic scales. In words, $\tilde{r}_{ijk} = (\mu_{r_{ijk}}, v_{r_{ijk}})$ represents the judgment about the preference of criterion i over criterion j as expressed by expert k.

Step 2: Aggregation of priorities. The information provided by the experts is aggregated according to the following expression:

$$\tilde{r}_{ij} = (\frac{1}{3}\sum_{k=1}^{3}\mu_{r_{ijk}}, \frac{1}{3}\sum_{k=1}^{3}v_{r_{ijk}}). \tag{34}$$

Table 2: IF-AHP semantics

Scale	**Linguistic scales**
0.1	Extremely not preferred
0.2	Very strongly not preferred
0.3	Strongly not preferred
0.4	Moderately not preferred
0.5	Equally preferred
0.6	Moderately preferred
0.7	Strongly preferred
0.8	Very strongly preferred
0.9	Extremely preferred

Step 3: Priority calculation. In order to compute priority vector $\omega = (\omega_1, \omega_2, \dots, \omega_n)$, we use the linear programming model Optima Priority Optimization (OPO) described in [28]. This model elicits exact priorities from the matrix of intuitionistic fuzzy preferences relations (IFPR).

$$\begin{aligned}
&\max \tau \\
&1 - [(0.42 - 1)\omega_1 + 0.42\omega_2] \geq \tau \\
&1 - [(0.67 - 1)\omega_1 + 0.67\omega_3] \geq \tau \\
&1 - [(0.67 - 1)\omega_2 + 0.67\omega_3] \geq \tau \\
&1 - [0.55\omega_1 + (0.55 - 1)\omega_2] \geq \tau \\
&1 - [0.30\omega_1 + (0.30 - 1)\omega_3] \geq \tau \\
&1 - [0.32\omega_2 + (0.32 - 1)\omega_3] \geq \tau \\
&0 \leq \omega_i \leq 1 \quad i = 1, 2, 3. \\
&\sum_{i=1}^{3}\omega_i = 1.
\end{aligned} \tag{35}$$

The optimal solution for program (35) is $\omega^* = (0.37, 0.44, 0.19)$ with objective function value $\tau^* = 0.9938 \approx 1$. This result implies complete consistency for the non-financial criteria.

Step 4: Consistency checking. In pairwise comparisons, inconsistent preference relations can generate misleading results. In case of values of τ^* far below one, experts should be asked again in order to repair the inconsistency of the preferences until an acceptable value is obtained. However, it is possible that experts refuse to be re-checked and inconsistency can be repaired automatically following the algorithm proposed by [47].

Step 5: Global priority vector. In our case study, the optimal priority vector for categories is given by:

$$\omega^* = (\omega_F^*, \omega_{NF}^*), \tag{36}$$

$$\omega^*_{NF} = (\omega^*_E, \omega^*_S, \omega^*_G), \tag{37}$$

$$\omega^*_F = (\omega^*_{SO}, \omega^*_P, \omega^*_{CF}, \omega^*_L). \tag{38}$$

In addition, each indicator I_j has local priority vector ω_{jI_j} for each subcriteria $j \in \{E, S, G, SO, P, CF, L\}$:

$$\omega^*_j = (\omega^*_{j1}, \omega^*_{j2}, \dots, \omega^*_{jI_j}). \tag{39}$$

We obtain the global weight of indicator I_j for subcriteria j by multiplying priorities for each criteria, subcriteria and indicator:

$$\overline{\omega}^* = (\overline{\omega}^*_1, \overline{\omega}^*_2, \dots, \overline{\omega}^*_{26}), \tag{40}$$

with:

$$\sum_{c=1}^{26} \overline{\omega}^*_c = 1. \tag{41}$$

As an example, global priority value for indicator Workforce (S1) is computed as follows:

$$\overline{\omega}^*_{S1} = \omega^*_{NF} \cdot \omega^*_S \cdot \omega^*_{S1} = 0.358 \cdot 0.437 \cdot 0.254 = 0.040. \tag{42}$$

Summarizing, local and global weights and consistency indexes are shown in Table 3. Consistency indexes are not shown for economy of space but all values are above 0.98.

Table 3: Local and global weights.

Criteria	ω^*	Subcriteria	ω^*_j	Indicator	$\omega^*_{jI_j}$	$\overline{\omega}^*_c$
NF	0.358	E	0.369	E1	0.248	0.033
				E2	0.261	0.035
				E3	0.491	0.065
		S	0.437	S1	0.254	0.040
				S2	0.357	0.056
				S3	0.180	0.028
				S4	0.209	0.033
		G	0.194	G1	0.619	0.043
				G2	0.232	0.016
				G3	0.149	0.010
F	0.642	SO	0.417	SO1	0.366	0.098
				SO2	0.240	0.064
				SO3	0.201	0.054
				SO4	0.192	0.052
		P	0.289	P1	0.355	0.066
				P2	0.329	0.061
				P3	0.164	0.030
				P4	0.152	0.028
		CF	0.119	CF1	0.489	0.037
				CF2	0.232	0.018
				CF3	0.279	0.021
		L	0.174	L1	0.327	0.037
				L2	0.237	0.027
				L3	0.173	0.019
				L4	0.151	0.017
				L5	0.112	0.013

4.2 Ranking alternatives

Once we know the priorities for each indicator, we are in a position to derive a ranking for motor companies by means of the intuitionistic fuzzy composite metrics proposed in Section 3.3. To this end, we use the following steps:

Step 1: Quantification. The set of crisp indicators is obtained and denoted by i_{gct} where $g = 1, 2, \ldots, 9$ indexes the set of firms, $c = 1, 2, \ldots, 26$ indexes the set of indicators, and $t = 1, 2, 3$ indexes the years under consideration, namely, 2017, 2018 and 2019.

Step 2: Normalization. The set of crisp indicators is normalized by means of equation (19) to obtain normalized indicators n_{gct}.

Step 3: Construction of the decision matrix. A normalized fuzzy decision matrix $\tilde{N}$ is built by setting element $\tilde{n}_{gc}$ to the following TIFN:

$$\tilde{n}_{gc} = ((\min_t n_{gct}, \frac{1}{3}\sum_{t=1}^{3} n_{gct}, \max_t n_{gct}), w_{\tilde{n}_{gc}}, u_{\tilde{n}_{gc}}). \tag{43}$$

Values $w_{\tilde{n}_{gc}}$ and $u_{\tilde{n}_{gc}}$ are estimated according to the degree of reliability of each indicator. In our case study, we obtain the set of non-financial indicators from EIKON database provided by Thomson Reuters. These indicators are not verified by any third party institution. There is no commonly accepted method of measuring sustainability. In addition to lack of transparency, corporate social responsibility evaluations present weaknesses such as full compensability of high scores for one domain with low scores in another domain [44]. Concerns about reliability of the information provided due to eventual greenwashing practices add more difficulties. As a result, it seems reasonable to set $w_{\tilde{n}_{gc}} = 0.7$ and $u_{\tilde{n}_{gc}} = 0.2$ in the case of non-financial indicators ($c = 1, 2, \ldots, 10$).

On the other hand, financial indicators have been retrieved from accounting public information under the control of supervising authorities or, more specifically, of the stock market regulator in the case of listed companies such as Volkswagen and Ford. As a result, it seems reasonable to set $w_{\tilde{n}_{gc}} = 0.9$ and $u_{\tilde{n}_{gc}} = 0.05$ in the case of financial indicators ($c = 11, 12, \ldots, 26$).

Step 4: Ranking. By means of the intuitionistic fuzzy composite metrics introduced in Section 3.3, a ranking of motor companies is derived. More precisely, we use the linear-infinite composite metric encoded in equation (32) and the linear-quadratic metric encoded in equation (33). In addition, we use different values of parameter λ to analyze its impact in the final ranking. We also control the impact of degree of reliability about the quality of the information by considering cases: a) full reliability $w_{\tilde{n}_{gc}} = 1$ and $u_{\tilde{n}_{gc}} = 0$; and b) some degree of reliability expressed by $w_{\tilde{n}_{gc}} \neq 1$ and $u_{\tilde{n}_{gc}} \neq 0$.

In Table 4, we present the ranking results when using the linear-infinite composite metric for different values of parameter λ and in the case of full reliability ($w_{\tilde{n}_{gc}} = 1$ and $u_{\tilde{n}_{gc}} = 0$). In general, we observe a correlation between the rankings for different values of λ. However, we must highlight that when we overweight utility and underweight fairness ($\lambda = 0.75$), Honda is no longer the first in the ranking but Stellantis is.

Table 4: Linear-infinite composite metric ranking with full reliability

Company	$\mathcal{L}_{1,\infty}$ ($\lambda = 0.25$)	**Rank**	$\mathcal{L}_{1,\infty}$ ($\lambda = 0.5$)	**Rank**	$\mathcal{L}_{1,\infty}$ ($\lambda = 0.75$)	**Rank**
Volkswagen	0.255	6	0.370	7	0.484	7
Toyota	0.200	3	0.293	3	0.386	3
Daimler	0.237	5	0.341	5	0.444	4
Ford	0.270	9	0.379	9	0.487	8
Honda	0.179	1	0.261	1	0.343	2
GM	0.256	7	0.363	6	0.470	6
Stellantis	0.188	2	0.265	2	0.342	1
SAIC	0.258	8	0.375	8	0.493	9
BMW	0.236	4	0.340	4	0.444	5

In Table 5, we present the ranking results when using the linear-infinite composite metric for different values of parameter λ and in the case of a given degree of reliability ($w_{\tilde{n}_{gc}} \neq 1$ and $u_{\tilde{n}_{gc}} \neq 0$). Again, we observe a strong correlation between the rankings for different values of λ. However, when we overweight utility and underweight fairness

Table 5: Linear-infinite composite metric ranking with a degree of reliability

Company	$\mathcal{L}_{1,\infty}$ ($\lambda = 0.25$)	**Rank**	$\mathcal{L}_{1,\infty}$ ($\lambda = 0.5$)	**Rank**	$\mathcal{L}_{1,\infty}$ ($\lambda = 0.75$)	**Rank**
Volkswagen	0.196	7	0.330	6	0.464	7
Toyota	0.154	3	0.262	3	0.370	3
Daimler	0.186	5	0.307	5	0.427	5
Ford	0.221	9	0.346	9	0.471	8
Honda	0.141	1	0.236	1	0.330	2
GM	0.209	8	0.332	7	0.454	6
Stellantis	0.152	2	0.241	2	0.330	1
SAIC	0.192	6	0.332	8	0.471	9
BMW	0.182	4	0.304	4	0.426	4

($\lambda = 0.75$), the differences between the first and the second position in the ranking reduces to a minimum.

By comparing Tables and 4 and 5, we observe a different ranking for the three values of parameter λ. These results show that the introduction of some degree of reliability in the quality of the information expressed by a TIFN has an impact in the ranking. Changes are not radical but remarkable, specially for those companies whose positions in the ranking changed. In the case of a limited number of companies applying for public funds, this change may be relevant.

In Table 6, we present the ranking results when using the linear-quadratic composite metric for different values of parameter λ in the case of full reliability ($w_{\tilde{n}_{gc}} = 1$ and $u_{\tilde{n}_{gc}} = 0$). We find no difference in the first two companies of the ranking (Honda and Stellantis) with respect to the linear-infinite composite metric. However, we observe differences in the case of the worst companies of the ranking (Ford and SAIC). When using the linear-quadratic metric, Ford improves its ranking when utility is overweighed.

Table 6: Linear-quadratic composite metric ranking with full reliability

Company	$\mathcal{L}_{1,2}$ ($\lambda = 0.25$)	**Rank**	$\mathcal{L}_{1,2}$ ($\lambda = 0.5$)	**Rank**	$\mathcal{L}_{1,2}$ ($\lambda = 0.75$)	**Rank**
Volkswagen	0.224	6	0.317	7	0.410	7
Toyota	0.164	3	0.235	3	0.306	3
Daimler	0.204	5	0.282	4	0.361	4
Ford	0.242	9	0.328	8	0.415	8
Honda	0.141	1	0.199	1	0.257	2
GM	0.225	7	0.309	6	0.394	6
Stellantis	0.151	2	0.200	2	0.250	1
SAIC	0.241	8	0.350	9	0.458	9
BMW	0.203	4	0.283	5	0.364	5

In Table 7, we present the ranking results when using the linear-quadratic composite metric for different values of parameter λ in the case of presence some degree of reliability ($w_{\tilde{n}_{gc}} \neq 1$ and $u_{\tilde{n}_{gc}} \neq 0$). When using the linear-quadratic metric with reliability, Stellantis is the best company in the ranking when utility has the same importance as deviation ($\lambda = 0.5$) and when utility is overweighed ($\lambda = 0.75$). On the contrary, Honda loses the first position. Again, the introduction of a degree of reliability results in a different ranking with the exception of the case for $\lambda = 0.75$.

In sum, these results show that different composite metrics reflecting different social principles (utility, fairness and deviation) and the introduction of degree of reliability may have an impact in the ranking results. As a result, we argue that the definition of an intuitionistic fuzzy composite metric must consider all the aspects described in this paper when ranking alternatives.

Table 7: Linear-quadratic composite metric ranking with a degree of reliability

Company	$\mathcal{L}_{1,2}$ ($\lambda = 0.25$)	**Rank**	$\mathcal{L}_{1,2}$ ($\lambda = 0.5$)	**Rank**	$\mathcal{L}_{1,2}$ ($\lambda = 0.75$)	**Rank**
Volkswagen	0.170	6	0.281	6	0.392	7
Toyota	0.129	3	0.212	3	0.295	3
Daimler	0.158	5	0.252	5	0.345	4
Ford	0.197	9	0.299	8	0.400	8
Honda	0.113	1	0.180	2	0.247	2
GM	0.184	8	0.282	7	0.380	6
Stellantis	0.120	2	0.180	1	0.240	1
SAIC	0.180	7	0.309	9	0.438	9
BMW	0.153	4	0.250	4	0.348	5

4.3 Discussion and insights

From the results of this case study, we find that fuzzy composite metrics represent a suitable option to introduce flexibility and to enhance explainability and meaning in fuzzy MCDM. By ranking alternatives using a distance function to the ideal point in a multidimensional space, we need to define a particular function. For instance, the TOPSIS method is based on the relative closeness to the ideal solution using the Euclidean distance function ($p = 2$) in equation (20)). Similarly, the VIKOR method is based on a weighted average of the Manhattan distance ($p = 1$ in equation (20)) and the Tchebychev distance ($p = \infty$ in equation (20)). However, previous works such as [13] and [36] used intuitionistic fuzzy methods to solve multiple criteria decision-making problems restricted to a given metric and without considering critical principles that support the whole decision-making process. As a result, the set of intuitionistic fuzzy composite metrics used in this paper are an extension of TOPSIS and VIKOR [30] approaches that provide flexibility and explainability to the decision-making process within a fuzzy environment.

On the flexibility side, we allow practitioners not only to select among any possible combination of $p = 1$ and $p = \infty$ using the linear-infinite composite metric, but also among any possible combination of $p = 1$ and $p = 2$ using the linear-quadratic composite metric. Other possible combination of particular values of p would lead to alternative composite metrics. As a result, the water resource planning problem described in [29], the waste management case study in [13], or the prioritizing of pandemic prevention strategies in [36] could be enhanced by considering alternative composite metrics according to the decision-making principles integrated in these metrics. This reasoning leads us to the explainability advantages introduced by our composite metrics.

On the explainability perspective, the selection of any particular combination of the metrics proposed in this paper implies the use of different decision-making principles. According to [38] and [19], by using the linear-infinite metric, decisions will cover the whole range starting from the principle of maximum utility ($p = 1$) and ending in the maximum fairness principle ($p = \infty$). On the other hand, by using the linear-quadratic metric, decisions will be made on the vicinity of maximum utility because parameter p is restricted to values 1 and 2. However, the linear term pursues achievement while the quadratic one pursues more balanced solutions [7], by minimizing the squared deviation to the ideal point. These principles support decision-makers in the sense that they are allowed to integrate critical aspects such as achievement or utility ($p = 1$), deviation or imbalance ($p = 2$), fairness or maximum regret minimization ($p = \infty$).

As a result, by providing an expression of these composite metrics within an IF environment, we move one step further in generality to cover a wider range of decision-making situations. In addition, decision-makers have now the possibility to add meaning to the selection of alternatives by integrating critical principles in the decision-making process.

5 Concluding remarks

In this paper, we have introduced intuitionistic fuzzy composite metrics as a natural way to combine the generality of fuzzy set theory and the explainability of composite metrics derived from compromise programming. Most of the existing compromise programming methods rank alternatives based on crisp numbers and a single distance function. To develop more general decision-making tools, we propose a composite metric by integrating the linguistic features expressed in the form of an intuitionistic fuzzy number and compromise programming.

This paper contributes to enhance existing knowledge in two different ways. On the one hand, we describe a method on how to rank alternatives by means of intuitionistic fuzzy composite metrics. By means of an illustrative case study about the motor industry, we show how analysts and practitioners can use this method in practice. With respect to other ranking methods, fuzzy composite metrics result in two main advantages. On the one hand, we can express basic principles such as maximum utility and fairness, and minimum absolute deviations by a convex combination of distance functions to a multidimensional ideal point. On the other hand, by proposing the intuitionistic fuzzy counterpart of usual composite metrics, we allow to control for the degree of reliability of the information included in common sustainability reports. In order to allow the application of our proposal, we describe the main steps to follow. For simplicity, we here consider control parameter λ in an intuitionistic fuzzy composite metric as a crisp number. However, the analysis described in this paper can be easily extended to consider parameter λ as an intuitionistic fuzzy number.

Summarizing, we here propose the connection of intuitionistic fuzzy numbers with compromise programming by means of two composite metrics: a linear-infinite metric combining the principles of maximum utility and maximum fairness; and a linear-quadratic metric combining the principles of maximum utility and minimum deviation. We then use these metrics as a key element for a new method to rank alternatives in terms of sustainability considering multiple criteria such as environmental, social and corporate governance criteria.

A further contribution of this paper is a multicriteria generalization of the concept of magnitude of a fuzzy number. This general concept is applicable to each type of fuzzy number (ordinary, Pythagorean, neutrosophic, spherical, ...) and allows researchers and practitioners to design new features to better represent fuzzy numbers in a synthetic but informative way. Finally, we consider that engineering new expressions of the concept of magnitude to adapt the representation of a fuzzy number in a specific context is an interesting future line of research.

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