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Intuitionistic fuzzy multi-criteria decision making framework based on life cycle environmental, economic and social impacts: The case of U.S. wind energy

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ABSTRACT

Intuitionistic Fuzzy Set theory can be used in conjunction with environmentally extended input–output based life cycle assessment (EE-IO-LCA) models to help decision makers to address the inherent vagueness and uncertainties in certain sustainable energy planning problems. In this regard, the EE-IO-LCA model can be combined with an intuitionistic fuzzy set theory for a multi-criteria decision making (MCDM) application with a set of environmental and socio-economic indicators. To achieve this goal, this study proposes the use of the Technique for Order of Preference by Similarity to Ideal Solution method to select the best wind energy alternative for a double layer MCDM problem, which requires expert judgments to simultaneously apply appropriate weighting to each life cycle phase and sustainability indicator to be considered. The novelty of this research is to propose a generic 9-step fuzzy MCDM method to solve sustainable energy decision-making problems using a combination of three different techniques: (1) an intuitionistic fuzzy entropy method to identify the individual importance of phases and criteria; (2) an IFWGA operator to establish a sub-decision matrix with the weights applied to all relevant attributes; and (3) an IFWAA operator to build a super-decision matrix with the weights applied to all of the life-cycle phases considered. This proposed method is then applied as a case study for sustainable energy planning, specifically for the selection of V80 and V90 onshore and offshore wind turbines to be installed in the United States. It is strongly believed that this methodology will provide a vital guidance for LCA practitioners in the future for selecting the best possible energy alternative under an uncertain decision-making scenario.

Keywords: Multi-criteria decision making; Intuitionistic fuzzy sets; Aggregation operator; TOPSIS; Life cycle sustainability assessment; Wind energy

1. Introduction

1.1. Wind energy and life cycle assessment

The environmental, economic, and social problems associated with the US energy industry create tremendous challenges and opportunities, requiring a holistic sustainability assessment of different energy policies for decision-making problems and other practical applications associated with the US energy sector (Anadon et al., 2009). The US energy industry will inevitably require a technological revolution to address its many current challenges, including issues related to energy security, environmental sustainability, and economic

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competitiveness (Anadon et al., 2011). In the US, there is currently an unprecedented interest in wind energy technologies as a very promising sustainable energy alternative. According to the US Department of Energy (DOE)'s futuristic scenario, 20% of the US power grid mix will be obtained from onshore and offshore wind power plants by 2030. To achieve this goal, The US government will need to supply 300,000 MW (megawatts) of additional wind generation capacity (US Department of Energy, 2008). Inevitably, the growing share of wind energy in the US electrical power grid will require a greater understanding of the environmental, economic, and social (a.k.a. the triple-bottom-line, or TBL) impacts of wind energy projects. To analyze the total social, economic, and environmental impacts of wind energy technologies, a thorough life cycle assessment (LCA) is used to quantify the total cradle-to-grave environmental impacts of a predetermined functional unit of energy, accounting for impacts from various life cycle phases such as raw material extraction, production, construction, use, and final disposal (Pehnt et al., 2008; Martinez et al., 2009; Weinzettel et al., 2009; Gujba et al., 2010; Santoyo-Castelazo et al., 2011).

Process-based LCA (P-LCA) is the most commonly used method in current LCA literature, having been used extensively for various environmental analyses of wind energy and other applications (Lenzen and Munksgaard, 2002), but the P-LCA methodology is subject to "truncation errors" due to narrowly defined system boundaries (Onat et al., 2014a,b; Cellura et al., 2012; Kucukvar et al., 2015). In P-LCA models, mostly onsite impacts are considered without a full coverage of all upstream supply chain contributions (Kucukvar and Samadi, 2015; Lenzen, 2000; Onat et al., 2015a). To address these limitations, Environmentally-Extended Economic Input–Output based LCA (EE-IO-LCA) approaches have been proposed to quantify the environmental burdens of the systems being analyzed by tracing their entire supply chain and accounting for the corresponding (Cellura et al., 2011; Kucukvar and Tatari, 2011; Egilmez et al., 2013, 2014; Kucukvar et al., in press). Several studies have used the P-LCA method, the EE-IO-LCA method, and/or a combination of both methods in LCA analyses of wind energy alternatives (Park et al., 2015; Wiedmann et al., 2011). For instance, Jungbluth et al. (2014) used the P-LCA method to analyze the environmental impacts of four different onshore wind turbines, each with different capacities ranging from 30 to 800 kW, and one offshore wind turbine with a capacity of 2 MW. Lenzen and Wachsmann (2004) focused on a particular wind turbine located in Brazil and Germany and estimated the effects of geographic factors on its energy consumption and carbon dioxide (CO_2) emissions. Ardente et al. (2008) developed a P-LCA model to evaluate the energy and environmental impacts of a wind farm consisting of 11 wind turbines, each with an individual capacity of 660 kW. Atilgan and Azapagic (2015) investigated the life cycle environmental impacts of electricity generation from fossil fuel power plants in Turkey, including 16 lignite power plants, eight hard coal power plants, and 187 gas power plants. In another study, Martinez et al. (2009) developed P-LCA model for a 2-MW offshore wind turbine installed in Spain. Weinzettel et al. (2009) utilized the LCA methodology for a floating wind turbine, and the results were compared with those of conventional offshore wind turbines and of electricity from a natural combined gas cycle. In a recent study, Noori et al. (2015a) developed an EE-IO-LCA model to compare the environmental impacts of V80 and V90 onshore and offshore wind turbines installed in the US.

Although LCA literature is abundant with studies addressing the life-cycle impacts of wind energy technologies, only a handful of works concentrated on the socio-economic implications of wind energy in addition to the environment (Noori et al., 2015b; Slattery et al., 2011). Triple bottom line (TBL) impacts, which cover all three dimensions of sustainability, are therefore a critical concept for policy-makers to quantify trade-offs between different dimensions of sustainability (Jeswani et al., 2010). The TBL concept focuses on the three main dimensions of sustainable development (environment, economy, and society) (Elkington, 1997; Wiedmann et al., 2009) and has also been integrated into EE-IO-LCA analyses to capture all direct and indirect environmental and socio-economic impacts. For instance, Foran et al. (2005a,b) developed a TBL model of the industrial sectors of Australia's entire economy, including environmental, economic, and social metrics for 135 sectors. Researchers from the University of Sydney constructed the TBL-EIO model and created the BottomLine[3] software for the economies of Australia, the UK, and Japan (Wiedmann and Lenzen, 2009). Several studies have also used the TBL-EIO methodology for sustainability analysis of supply chains (Foran et al., 2005a,b), companies (Wiedmann et al., 2009), buildings (Onat et al., 2014a), electric vehicles (Onat et al., 2014c; Onat, 2015a), energy (Malik et al., in print), pavement alternatives (Kucukvar et al., 2014a,b), and construction sectors (Kucukvar and Tatari, 2013; Kucukvar et al., 2014c). In a recent work, Noori et al. (2015b) constructed a hybrid LCA model by combining a TBL analysis with the EE-IO-LCA method to compare the ecological and socio-economic sustainability performance of V80 and V90 onshore and offshore wind turbines installed in the US.

1.2. *Multi-criteria decision making*

In current literature, the multi-criteria decision-making (MCDM) method is used to select the most feasible energy alternative based on different environmental, economic and social indicators of sustainability. The MCDM literature for energy-related decision making problems mainly focuses on ranking renewable energy alternatives, determining optimal energy resource allocations, and planning various projects (Ardente et al., 2004). A comprehensive review of studies on MCDM approaches for energy planning showed that the Analytic Hierarchy Process (AHP), Preference Ranking Organization Method for Enrichment of Evaluations (PROMETHEE), the Elimination and Choice Translating Reality (ELECTRE) method, the weighted sum method, the weighted product method, compromise programming, and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) are among the most widely used MCDM methodologies in the literature (Greening and Bernow, 2006; Kucukvar et al., 2014b; Løken, 2007; Pohekar and Ramachandran, 2004; Wang et al., 2009a,b; Onat et al., 2016a), and these MCDM techniques have been extensively applied for ranking the best energy alternatives. For instance, Wang et al. (2009a,b) focused on the benefits of MCDM analyses in sustainable energy decision-making and presented a comprehensive review on commonly-used MCDM approaches and indicators. San Cristóbal (2011) applied a combination of compromised ranking and the AHP method to the selection of renewable energy projects in Spain. Furthermore, MCDM methods are frequently used to compare different alternatives for electricity and heat supply, assess the feasibility of wind turbines for an island in Italy (Cavallaro and Ciraolo, 2005), and select the best wind farm

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project in China (Lee et al., 2009). Azapagic et al. (2016) also proposed a novel decision support framework, namely DESIRES which includes a suite of tools such as scenario analysis, life cycle costing, life cycle assessment, social sustainability assessment, system optimization, and multi-attribute decision analysis.

The TOPSIS method, first introduced by Hwang and Yoon (1981), is one of the most well-known classical multi-criteria decision making (MCDM) approaches. The primary goal of the TOPSIS method is to find the alternative with the shortest distance from the positive ideal solution as well as the longest distance from the negative ideal solution (Hwang and Yoon, 1981; Chen and Tzeng, 2004). TOPSIS method and its applications are widely utilized in the literature. For example, Lai et al. (1994) extended the TOPSIS approach to overcome a multiple objective decision making problem. In another example, Chen and Tzeng (2004) combined the TOPSIS method and gray relation analysis to evaluate and choose the best alternative. In a later study, Jahanshahloo et al. (2006a) introduced an extension of the TOPSIS method for decision-making problems to account for the use of interval data as needed for a given problem.

1.3. *The fuzzy set theory and aggregation operators*

Uncertainty and vagueness are inevitable in real-world decision making problems, making it very difficult to determine crisp, easily applicable numbers for the criteria in question and thereby make an exact evaluation and performance ranking of the decision making alternatives being compared (Egilmez et al., in print, 2015; Kahraman et al., 2009). Therefore, most of the selection parameters cannot be given precise values, and decision makers usually must express the evaluation data of the alternatives' suitability for various subjective criteria and the weights of said criteria in linguistic terms (Wang et al., 2009a,b; Doukas et al., 2007; Kaya and Kahraman, 2011; Heo et al., 2010; Talinli et al., 2010). For this reason, the theory of fuzzy sets introduced by Zadeh has achieved a great success in different areas like MCDM problems (Zadeh, 1965; Ardente et al., 2004).

The TOPSIS method is a widely accepted multi-attribute decision-making technique due to its simultaneous consideration of the ideal and anti-ideal solutions, as well as its easily programmable computation procedure. In the fuzzy TOPSIS method, linguistic preferences can easily be converted into fuzzy numbers that can be more readily used in subsequent calculations. Chen (2000) introduced a TOPSIS methodology that defined the rating of each alternative and the weight of each criterion with linguistic terms presented in triangular fuzzy numbers, and a vertex method was developed to calculate the distance between any two triangular fuzzy numbers. Jahanshahloo et al. (2006b) introduced a generalization of the TOPSIS method for decision-making problems using fuzzy data. Yang and Hung (2007) also used the fuzzy TOPSIS method as a decision-making method for layout design problems.

In fuzzy set theory, every element of a particular non-fuzzy set has a membership degree between 0 and 1, and each element's non-membership degree is equal to 1 minus its corresponding membership degree. On the other hand, the sum of the membership and non-membership degrees of an element in a fuzzy set can be less than 1, in which case a hesitation degree must be defined. To illustrate this concept, Atanassov proposed the idea of Intuitionistic Fuzzy Sets (IFSs), which are an extension of the concept of fuzzy sets, in 1986 (Atanassov, 1986). Different research studies on MCDM problems have also been found that have utilized the TOPSIS method based on an intuitionistic fuzzy environment. For instance, Atanassov et al. (2005) discussed intuitionistic fuzzy interpretations of the processes of multi-person and multi-measurement MCDM tools. Liu and Wanga (2007) presented novel methods for solving MCDM problems in an intuitionistic fuzzy environment, and also defined a number of new score and evaluation functions to measure the degrees of decision maker's requirements. Li (2005) and Lin et al. (2007) each introduced new methods to solve single-person MCDM problems based on IFSs and partial weight information. Wei (2008) studied intuitionistic fuzzy MCDM methods based on information about criteria weights that are completely unknown or incompletely known, and introduced a maximizing deviation method-based approach. Boran et al. (2009) proposed a TOPSIS methodology that combined intuitionistic fuzzy sets and intuitionistic fuzzy weighted averaging (IFWA) operators for supplier selection problems. Li et al. (2009) proposed a new methodology for MCDM problems using IFSs; in their method, for each expert in the group, two auxiliary fractional programming models were derived from the TOPSIS method to determine the relative closeness coefficient intervals of each alternative. Kucukvar et al. (2014a,b) proposed a fuzzy MCDM methodology for ranking the life cycle sustainability performance of different pavement alternatives, using two important methods (including the TOPSIS method) to select the best pavement alternative, and using the intuitionistic fuzzy entropy method to identify the importance of different criteria and life cycle phases. Onat et al. (2015b) used the intuitionistic fuzzy MCDM and TOPSIS methods to rank the life cycle sustainability performance of alternative passenger vehicles. In a recent paper, Egilmez et al. (2015) also proposed a multi-criteria intuitionistic fuzzy decision making model, using the fuzzy set and TOPSIS methods as multi-criteria decision making tools to rank the environmental performance of the 27 US and Canada metropoles. Several studies can also be found in the literature in which MCDM problems are analyzed using intuitionistic fuzzy set theory (Su et al., 2011; Wang, 2009).

The field of MCDM is more suitable for using fuzzy and intuitionistic fuzzy aggregation operators, so researchers have developed many aggregation operators for applications in this area of study. For instance, Xu and Yager (2006) introduced new geometric aggregation operators, including intuitionistic fuzzy ordered weighted geometric (IFOWG) operators, intuitionistic fuzzy weighted geometric (IFWG) operators, and intuitionistic fuzzy hybrid geometric (IFHG) operators. Xu (2007a) introduced intuitionistic fuzzy weighted arithmetic averaging (IFWAA) operators based on arithmetic aggregation operators, as well as intuitionistic fuzzy weighted geometric averaging (IFWGA) operators based on the geometric aggregation operators. In addition, Xu (2007b) defined arithmetic aggregation operators such as IFWA operators, intuitionistic fuzzy ordered weighted averaging (IFOWA) operators, and intuitionistic fuzzy hybrid aggregation (IFHA) operators. In another study, Xu (2009) proposed intuitionistic fuzzy aggregation operators based on Choquet integrals, such as intuitionistic fuzzy correlated averaging (IFCA) operators and intuitionistic fuzzy correlated geometric (IFCG) operators, among others. The aforementioned operators not only consider the importance of the elements in question or their ordered positions, but can also highlight correlations among these elements and/or their ordered positions.

1.4. A fuzzy MCDM methodology for sustainable energy planning

The use of MCDM in sustainable energy planning has gained a tremendous degree of interest in recent literature, and many researchers have used a combination of MCDM and fuzzy methods to select the best possible energy options among the considered set of alternatives. The following important studies have used a fuzzy MCDM approach to select optimal energy alternatives for different scenarios (Kaya and Kahraman, 2011; Heo et al., 2010):

- Kahraman and Kaya (2010) applied a fuzzy MCDM methodology in order to rank the best energy alternatives based on various types of criteria (environmental, socio-political, economic, and technological) and constructed a modified fuzzy AHP framework to identify the priority weights of different energy policy options. In this fuzzy AHP framework, experts assigned a definite number on a 1–9 scale to a pairwise comparison matrix in order to determine the priority vector. The results found wind energy to be the best energy policy compared to energy from other alternatives such as solar, biomass, geothermal, hydropower, natural gas, coal, lignite, and nuclear-oil.
- Kaya and Kahraman (2010) developed an integrated approach by combining fuzzy set theory with the VIKOR & AHP methods to determine the best renewable energy alternative for Istanbul, Turkey among alternative energy production sites in the same city. In the algorithm used in this study, the AHP method was used to determine the weights of each criterion with pairwise comparison matrices. During the pairwise comparison process, linguistic terms were linked with fuzzy numbers to enable decision makers to give more comfortable judgments. Wind energy was found to be the most convenient renewable energy source, and the Çatalca region was found to be the best place among the available locations for setting up the wind turbines.
- Kaya and Kahraman (2011) used a modified fuzzy TOPSIS methodology to identify the most feasible energy alternative. First, fuzzy pairwise comparison matrices were used to determine the weights of the selection criteria. The evaluation criteria for alternative energy alternatives were then categorized under four categories: social, economic, environmental, and technological. The selected main indicators for the problem set were efficiency, cost of investment, operation & maintenance cost, nitrogen oxide (NO_x) emissions, CO_2 emissions, land use, social adoption, and employment. Based on the fuzzy TOPSIS results, wind energy was once again selected as the best energy option.
- Heo et al. (2010) built a fuzzy-AHP framework to select a set of renewable energy dissemination programs for Korea with which to increase the share of renewable energy resources to 33 Million tons-of-oil-equivalents (TOEs). Five criteria categories (technological, market-related, economic, environmental, and policy-related) and a total of seventeen different factors were selected after a comprehensive literature review. The results showed economic feasibility to be the most important area to focus on for the successful dissemination of energy alternatives, followed by global market size and technological feasibility, respectively.
- Boran et al. (2012) concentrated on the renewable energy development in Turkey, and built an intuitionistic fuzzy TOPSIS model to evaluate the long-term sustainability performance of several renewable energy technologies for electricity production, including solar, hydro, wind, and geothermal energy. These energy technologies were evaluated based on five criteria (price, carbon emissions, resource availability, efficiency, and negative social costs), and the importance of each criterion was evaluated based on the intuitionistic fuzzy set. The results ranked hydropower as the best alternative, followed by wind energy due to its high degree of public acceptance and greater resource availability in Turkey.

1.5. Research objectives and contribution to the state-of-the-art

The majority of the reviewed studies are case studies of energy decision-making problems using expert judgments for a predetermined set of sustainability indicators. However, the reviewed EE-IO-LCA models, which quantitatively measure the sustainability impacts of energy alternatives, are subject to significant uncertainties due to sector aggregation, data quality limitations, and linearity assumptions, and these uncertainties are not sufficiently integrated with a fuzzy MCDM model alone. Also, the results of LCA analyses are commonly presented in terms of the contributions of separate life cycle phases for each sustainability performance metric. This makes a double-layer MCDM analysis well suited to fully integrate the results of a LCA analysis into fuzzy models (Kucukvar et al., 2014a,b). The current fuzzy MCDM problem is therefore solved using a double-layer MCDM model, since the weights of each life cycle phase and each of the measured environmental and socio-economic indicators must be separately determined with intuitionistic values based on expert opinions. Hence, the overarching goals of this study are to present a fuzzy MCDM method combining the EE-IO-LCA results and to develop a TOPSIS method with which to rank and select the best of the considered alternatives for a double layer MCDM problem, based on intuitionistic fuzzy entropy and intuitionistic fuzzy averaging operators.

To achieve these goals, the intuitionistic fuzzy entropy method is used to identify important evaluation phases and attributes, after which an IFWGA operator is applied to establish a sub-decision making matrix based on the weights applied to each of the attributes, while an IFWAA operator is used to build a super-decision matrix based on the weights of individual life cycle phases. The TOPSIS method is a widely used multi-attribute decision-making approach, and has been selected for this study because it simultaneously considers both the ideal solution and the worst possible non-ideal solution. The TOPSIS method also has an easy computational procedure using excel spreadsheets, allowing linguistic preferences to be easily converted into fuzzy numbers for a fuzzy TOPSIS analysis.

In this research, the MCDM framework includes several sustainability indicators and life cycle phases, including phases corresponding to manufacturing, construction, transportation, and use. Two types of fuzzy data have been created to deal with uncertain parameters, such as the fuzzy weights of sustainability indicators and the fuzzy data of sustainability impacts for each life cycle phase. First, the fuzzy weights of the indicator categories are determined using a linguistic

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approach based on expert judgments. Second, the environmental and socio-economic impact data for each life cycle phase associated with wind power plants are collected and transformed into a single fuzzy dataset, as such compatibility makes the assessment more robust in terms of dealing with the inherent uncertainty associated with sustainability impact data and expert opinions. Consequently, the developed intuitionistic fuzzy MCDM model differs from the previous fuzzy MCDM approaches by (a) using the results of a holistic EE-IO-LCA study on environmental and socio-economic impacts of offshore and onshore wind turbines installed in US (Noori et al., 2015b), (b) constructing a double layer fuzzy MCDM model specific to this problem, as the weights of each life cycle phase and each social, economic, and/or environmental indicator are to be determined based on expert opinions with intuitionistic values, and (3) performing the EE-IO-LCA-based ranking of V80 and V90 onshore and offshore wind turbines, as wind power was selected as the best energy option in a majority of the reviewed studies.

The rest of the paper is organized as follows. First, definitions relating to IFSs, IFWAA operators, IFWGA operators, and fuzzy entropy are presented in Section 2. Second, the steps of the proposed method are given Section 3. Third, a case study for the application of the proposed method and the results thereof are given in Sections 4 and 5, respectively. Finally, conclusions and recommendations for future work are presented in Section 6.

2. Preliminaries

2.1. *Intuitionistic fuzzy sets*

Some basic concepts and definitions of IFSs are presented as follows:

Definition 1. Let X be a fixed set. An IFS α is an object having the form (Atanassov, 1986):

$$\alpha = \{\langle x, \mu_\alpha(x), \nu_\alpha(x)\rangle \mid x \in X\} \tag{1}$$

where the mappings are presented as "μ_α: $X \to [0, 1]$" and "ν_α: $X \to [0, 1]$" under the condition "$0 \le \mu_\alpha(x) + \nu_\alpha(x) \le 1$" for each $x \in X$. $\mu_\alpha(x)$ and $\nu_\alpha(x)$ are defined as the degree of membership and the degree of non-membership, respectively, of element $x \in X$ to set α.

Obviously, if $\nu_\alpha(x) = 1 - \mu_\alpha(x)$, then every IFS ($\alpha$) on a nonempty set X becomes a Fuzzy Set.

Definition 2. Let X be a fixed set where α is an IFS in X. The intuitionistic fuzzy hesitation (a.k.a. the non-determinacy or uncertainty) degree of whether or not x belongs to α is defined as follows:

$$\pi_\alpha(x) = 1 - \mu_\alpha(x) - \nu_\alpha(x). \tag{2}$$

This degree arises due to lack of knowledge, or 'personal error'. Clearly, if

$$\pi_\alpha(x) = 1 - \mu_\alpha(x) - \nu_\alpha(x) = 0.$$

For every $x \in X$, the IFS α becomes a fuzzy set where $0 \le \pi_\alpha(x) \le 1$ (Atanassov, 1986).

Definition 3. Let $\alpha = (\mu_\alpha(x), \nu_\alpha(x), \pi_\alpha(x))$ be an intuitionistic fuzzy number (IFN) where $\mu_\alpha(x) \in [0, 1]$, $\nu_\alpha(x) \in [0, 1]$, $0 \le \mu_\alpha(x) + \nu_\alpha(x) \le 1$, and $\pi_\alpha(x) = 1 - \mu_\alpha(x) - \nu_\alpha(x)$.

Definition 4. Let: $\alpha = (\mu_\alpha, \nu_\alpha, \pi_\alpha)$ and $\beta = (\mu_\beta, \nu_\beta, \pi_\beta)$ be two IFNs in X. Then the following three statements are true:

$$(1)\ \alpha \otimes \beta = (\mu_\alpha\mu_\beta, \nu_\alpha + \nu_\beta - \nu_\alpha\nu_\beta, 1 - \mu_\alpha\mu_\beta - \nu_\alpha - \nu_\beta + \nu_\alpha\nu_\beta),$$

$$(2)\ \alpha^\lambda = \left((\mu_\alpha)^\lambda, 1 - (1 - \nu_\alpha)^\lambda, (1 - \nu_\alpha)^\lambda - (\mu_\alpha)^\lambda\right), \quad \lambda > 0,$$

$$(3)\ \lambda\alpha = \left(1 - (1 - \mu_\alpha)^\lambda, (\nu_\alpha)^\lambda, (1 - \mu_\alpha)^\lambda - (\nu_\alpha)^\lambda\right), \quad \lambda > 0.$$

This study will use a normalized Euclidean distance of two IFSs. According to Szmidt and Kacprzyk (2000):

Definition 5. If $A = \{\langle x, (\mu_\alpha(x), \nu_\alpha(x), \pi_\alpha(x))\rangle \,|x \in X\}$ and $B = \{\langle x, (\mu_\beta(x), \nu_\beta(x), \pi_\alpha(x))\rangle \,|x \in X\}$ are two IFSs in $X = \{x_1, x_2, \ldots, x_m\}$, then the normalized Euclidean distance between A and B is given as follows:

$$d(A, B) = \left[\frac{1}{2m}\sum_{j=1}^{m}\left(\left(\mu_\alpha(x_j) - \mu_\beta(x_j)\right)^2 + \left(\nu_\alpha(x_j) - \nu_\beta(x_j)\right)^2 + \left(\pi_\alpha(x_j) - \pi_\beta(x_j)\right)^2\right)\right]^{1/2} \tag{3}$$

where $\pi_\alpha = 1 - \mu_\alpha - \nu_\alpha$ and $\pi_\beta = 1 - \mu_\beta - \nu_\beta$.

2.2. *Intuitionistic fuzzy weighted averaging operators*

Now, definitions will be provided for intuitionistic fuzzy arithmetic weighted averaging (IFWAA) operator and intuitionistic fuzzy geometric weighted averaging (IFWGA) operators (Xu, 2007a,b):

Definition 6. Assuming that $\alpha_1, \alpha_2, \ldots, \alpha_p$ is an IFS, where $\alpha_i = (\mu_{\alpha_i}, \nu_{\alpha_i}, \pi_{\alpha_i})$ and $i = 1, 2, \ldots, p$, the IFWAA operator is defined as follows:

$$\text{IIFWAA}_\omega(\alpha_1, \alpha_2, \ldots, \alpha_p) = \sum_{i=1}^{p}\omega_i\alpha_i = \left(1 - \prod_{i=1}^{p}(1 - \mu_{\alpha_i})^{\omega_i}, \prod_{i=1}^{p}(\nu_{\alpha_i})^{\omega_i}, \prod_{i=1}^{p}(1 - \mu_{\alpha_i})^{\omega_i} - \prod_{i=1}^{p}(\nu_{\alpha_i})^{\omega_i}\right), \tag{4}$$

where ω_i is the weight of α_i, $0 \le \omega_i \le 1$ and $\sum_{i=1}^{p}\omega_i = 1$.

Definition 7. Assuming that $\alpha_1, \alpha_2, \ldots, \alpha_p$ is an IFS, where $\alpha_i = (\mu_{\alpha_i}, \nu_{\alpha_i}, \pi_{\alpha_i})$ and the degree of hesitation for α_i is $\pi_{\alpha_i} = 1 - \mu_{\alpha_i} - \nu_{\alpha_i}$ where $i = 1, 2, \ldots, p$, the IFWGA operator is defined as follows:

$$\text{IFWGA}_\omega(\alpha_1, \alpha_2, \ldots, \alpha_p) = \sum_{i=1}^{p}\alpha_i^{\omega_i} = \left(\prod_{i=1}^{p}(\mu_{\alpha_i})^{\omega_i}, 1 - \prod_{i=1}^{p}(1 - \nu_{\alpha_i})^{\omega_i}, \prod_{i=1}^{p}(1 - \nu_{\alpha_i})^{\omega_i} - \prod_{i=1}^{p}(\mu_{\alpha_i})^{\omega_i}\right). \tag{5}$$

When we look the aggregation results of IFWAA and IFWGA operators, we can see that these operators are still IFSs. In addition, these operators emphasize different points. The IFWAA operator emphasizes the group's influence, and therefore this operator is not very sensitive to $\alpha_i \in$ IFS ($i = 1, 2, \ldots, p$). On the other hand, the IFWGA operator emphasizes the individual influence, therefore this operator is more sensitive to $\alpha_i \in$ IFS ($i = 1, 2, \ldots, p$). Consequently, IFWAA operator is used to calculate the super decision matrix based on weights of phases. IFWGA operator is then used to calculate an aggregated intuitionistic fuzzy sub-decision matrix.

2.3. *Intuitionistic fuzzy entropy*

Shannon (1948) proposed the entropy function as a measure of uncertainty in a discrete distribution based on the Boltzmann entropy of classical statistical mechanics. De Luca and Termini (1972) introduced the axiom construction of fuzzy entropy and referred to Shannon's probability entropy as a measure of the amount of knowledge. Szmidt and Kacprzyk (2001) extended the axioms of De Luca and Termini (1972) to introduce the new definition for an entropy measure on IFSs. Vlachos and Sergiadis (2007) proposed a useful definition of intuitionistic fuzzy entropy, accounting for the hesitation degree, consisting of the fuzziness degree and the hesitation degree of the IFS. To determine the entropy weights with respect to a set of criteria represented by IFSs, Ye (2010) introduced an entropy weight model, which can be utilized to find the optimal criteria weights, and proposed an assessment formula for a weighted correlation coefficient between a particular alternative and the hypothetical ideal alternative. An entropy weight model is established to determine criteria weights when knowledge of such weights is definitely unknown, in which case the criteria values take the form of IFNs. In this study, the entropy weights method was used to assign weights to each of the specified life cycle phases and to each sustainability indicator measured for the considered alternatives (Vlachos and Sergiadis, 2007; Ye, 2010).

Definition 8. Let $C = \{C_1, C_2, \ldots, C_n\}$ be the set of criteria and $\gamma = \{\gamma_1, \gamma_2, \ldots, \gamma_k\}$ be the set of decision makers, whereas the decision of the dth decision maker regarding the ith criterion is an IFS where $\alpha = (\mu_d(C_i), \nu_d(C_i), \pi_d(C_i))$. Then,

$$H_i = -\frac{1}{k\ln 2}\sum_{d=1}^{k}[\mu_d(C_i)\ln\mu_d(C_i) + \upsilon_d(C_i)\ln\upsilon_d(C_i) - (1-\pi_d(C_i))\ln(1-\pi_d C_i) - \pi_d(C_i)\ln 2]. \quad (6)$$

Definition 9. Let $C = \{C_1, C_2, \ldots, C_n\}$ be the set of criteria with weights $W = \{w_1, w_2, \ldots, w_n\}$. The weight of the ith criterion is determined with the exact model of entropy weights as shown below:

$$w_i = \frac{1-H_i}{n - \sum_{i=1}^{n} H_i} \quad \text{where } \sum_{i=1}^{n} w_i = 1. \quad (7)$$

If $\mu_{w_i} = 0$, $\upsilon_{w_i} = 0$ and $\pi_{w_i} = 1$ then $\mu_{w_i}\ln\mu_{w_i} = 0$, $\upsilon_{w_i}\ln\upsilon_{w_i} = 0$ and $(1-\pi_{w_i})\ln(1-\pi_{w_i}) = 0$.

3. Research methodology

This section describes the TOPSIS method proposed in this study for double layer MCDM problems based on intuitionistic fuzzy entropy and intuitionistic fuzzy averaging operators to select the most appropriate alternative, in which linguistic terms take the form of Intuitionistic fuzzy numbers (IFNs) that are used for evaluations. This method is modeled for a double layer MCDM problem using the EE-IO-LCA results for each decision-making alternative. The required definitions for the introduced method are as follows:

(i) γ_d, $(d = 1, 2, \ldots, k)$, a discrete set of k decision makers,
(ii) $\wp_s$, $(s = 1, 2, \ldots, \ell)$, a finite set of s phases with a weights vector of $\varpi = [\varpi_1, \varpi_2, \ldots, \varpi_\ell]$, where $\varpi_s = (\mu_{\varpi_s}(\wp_s), \nu_{\varpi_s}(\wp_s), \pi_{\varpi_s}(\wp_s))$. For the remainder of this study, this weights vector will be defined as $\varpi_s = (\mu_{\varpi_s}, \nu_{\varpi_s}, \pi_{\varpi_s})$
(iii) C_i, $(i = 1, 2, \ldots, n)$, a finite set of n criteria in every life cycle phase, with a weights vector of $W = [w_1, w_2, \ldots, w_n]$, where $w_i = (\mu_{w_i}(C_i), \nu_{w_i}(C_i), \pi_{w_i}(C_i))$. For the remainder of this study, this weights vector will be defined as $w_i = (\mu_{w_i}, \nu_{w_i}, \pi_{w_i})$.
(iv) α_j, $(j = 1, 2, \ldots, p)$ a discrete set of p alternatives.

This study will integrate the fuzzy entropy method, the intuitionistic geometric average operator (IFWGA), the dynamic intuitionistic fuzzy operator (IFWAA), and the TOPSIS method into a nine-step fuzzy MCDM method to rank and select the most suitable alternative. Fig. 1 presents an illustration of the problem and the steps of the proposed method.

3.1. *A 9-step fuzzy MCDM model*

Step 1: Evaluate phases and indicators by decision makers:

Decision makers evaluate criteria and phases using linguistic terms linked with IFNs.

Step 2: Obtain the weights of indicators and phases, where $\wp_s$, $(s = 1, 2, \ldots, \ell)$ is a finite set of s phases with a weights vector of $\varpi = [\varpi_1, \varpi_2, \ldots, \varpi_\ell]$, where $\varpi_s = (\mu_{\varpi_s}, \nu_{\varpi_s}, \pi_{\varpi_s})$, and C_i, $(i = 1, 2, \ldots, n)$ is a finite set of n criteria in every phase with a weights vector of $W = [w_1, w_2, \ldots, w_n]$, where $w_i = (\mu_{w_i}, \nu_{w_i}, \pi_{w_i})$. To obtain the weight vectors (ϖ and W), the exact model of entropy weights in an IFS (Eqs. (6)–(7)) is used as follows:

$$\overline{H}_s = -\frac{1}{\ell\ln 2}\sum_{s=1}^{\ell}[\mu_{\varpi_s}\ln\mu_{\varpi_s} + \upsilon_{\varpi_s}\ln\upsilon_{\varpi_s} - (1-\pi_{\varpi_s})\ln(1-\pi_{\varpi_s}) - \pi_{\varpi_s}\ln 2] \quad (8)$$

$$H_i = -\frac{1}{n\ln 2}\sum_{i=1}^{n}[\mu_{w_i}\ln\mu_{w_i} + \upsilon_{w_i}\ln\upsilon_{w_i} - (1-\pi_{w_i})\ln(1-\pi_{w_i}) - \pi_{w_i}\ln 2]. \quad (9)$$

If $\mu_{\varpi_s} = 0$, $\upsilon_{\varpi_s} = 0$ and, $\pi_{\varpi_s} = 1$ then $(1-\pi_{\varpi_s})\ln(1-\pi_{\varpi_s}) = 0$, $\mu_{\varpi_s}\ln\mu_{\varpi_s} = 0$ and $\upsilon_{\varpi_s}\ln\upsilon_{\varpi_s} = 0$, respectively. This can also be written as, if $\mu_{w_i} = 0$, $\upsilon_{w_i} = 0$ and $\pi_{w_i} = 1$ then $\mu_{w_i}\ln\mu_{w_i} = 0$, $\upsilon_{w_i}\ln\upsilon_{w_i} = 0$ and $(1-\pi_{w_i})\ln(1-\pi_{w_i}) = 0$ respectively. The entropy weights of the sth phase and the ith criterion are defined as follows:

$$\varpi_s = \frac{1-\overline{H}_s}{\ell - \sum_{s=1}^{\ell}\overline{H}_s} \quad \text{where } \sum_{s=1}^{\ell}\varpi_s = 1 \quad (10)$$

$$\omega_i = \frac{1-H_i}{n - \sum_{i=1}^{n}H_i} \quad \text{where } \sum_{i=1}^{n}\omega_i = 1. \quad (11)$$

Step 3: Evaluate alternatives with decision makers in terms of each criterion: Decision makers evaluate the alternatives using linguistic terms linked with IFNs.

Step 4: Construct an aggregated IF sub-decision matrix for every phase based on the opinions of decision makers.

Let $R_s = \left[\left(r_{ij}\right)_s\right]_{n\times p}$ be an sth aggregated IF sub-decision matrix of decision maker ratings $(s = 1, 2, \ldots, \ell)$, and let $\alpha = (\alpha_1, \alpha_2, \ldots, \alpha_p)$ be a discrete set representing p alternatives. Decision maker evaluations of alternatives with linguistic terms will allow for an easier decision-making process. Every linguistic term corresponds to an IFN with its own specific membership and non-membership degrees. Therefore, the elements that comprise the sub-decision matrix are themselves composed of IFNs. The term $\left(r_{ij}^d\right)_s$ represents the assessment of the dth decision maker based

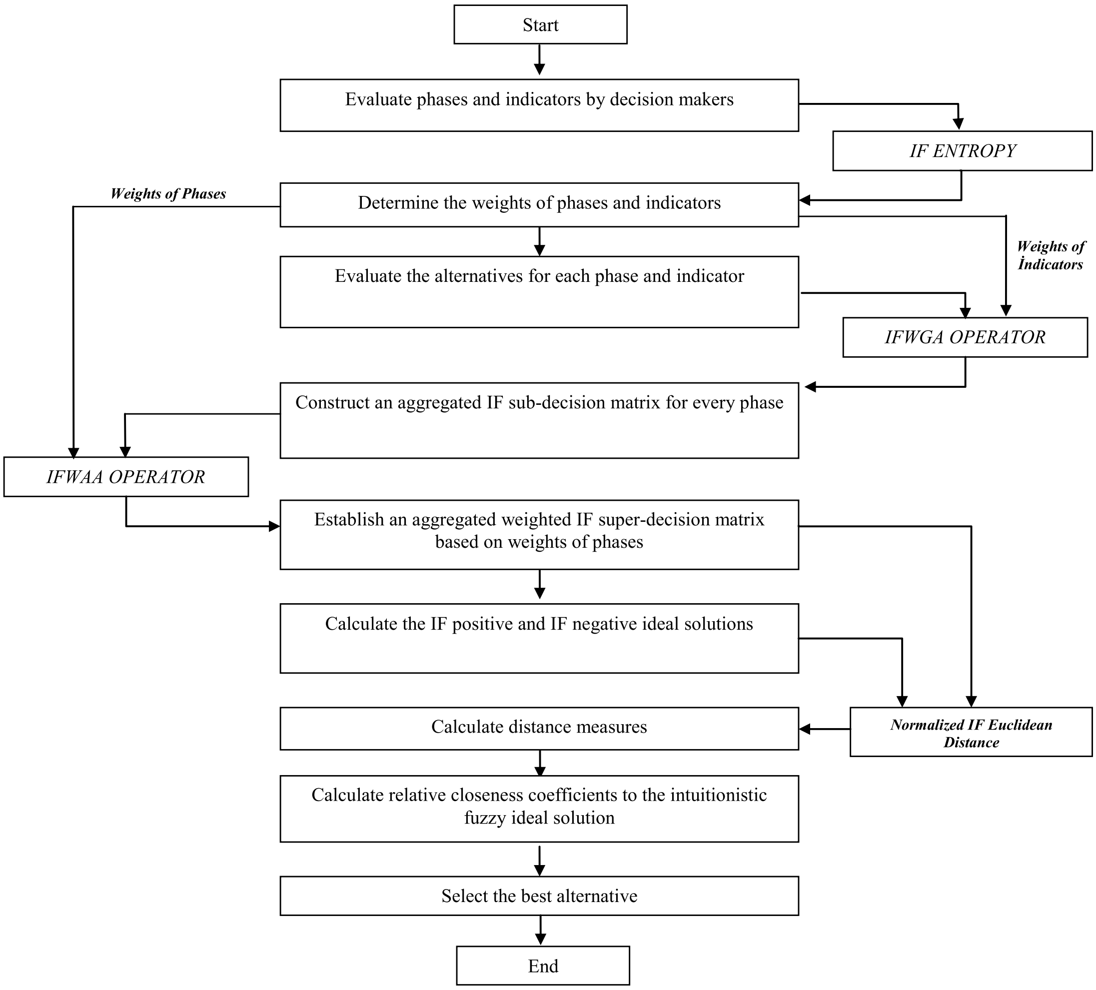

Fig. 1 – The steps of proposed method (IFWAA: Intuitionistic fuzzy arithmetic weighted averaging; IFWGA: Intuitionistic fuzzy geometric weighted averaging).

on the jth criteria regarding the ith alternative in the sth phase of the life cycle, and is also an IFN such that $\left(r_{ij}^{d}\right)_s = \left(\left(\mu_{ij}^{d}\right)_s, \left(\nu_{ij}^{d}\right)_s, \left(\pi_{ij}^{d}\right)_s\right)$, where the degree of hesitation for $\left(r_{ij}^{d}\right)_s$ is calculated as $\left(\pi_{ij}^{d}\right)_s = 1 - \left(\mu_{ij}^{d}\right)_s - \left(\nu_{ij}^{d}\right)_s$, where $i = 1, 2, \ldots, n$, $d = 1, 2, \ldots, k$, $j = 1, 2, \ldots, p$, and $s = 1, 2, \ldots, \ell$. The weights vector of the nth criterion is $W = [w_1, w_2, \ldots, w_n]$, where $w_i = (\mu_{w_i}, \nu_{w_i}, \pi_{w_i})$. To construct the aggregated IF sub-decision matrix, all individual decision makers' opinions have to be merged to one final group decision, so the IFWGA operator will be used for this purpose. The aggregated IF sub-decision matrix is represented with the term $R_s = \left[\left(r_{ij}\right)_s\right]_{n\times p}$, and is calculated as follows:

$$\begin{aligned}
\left(r_{ij}^{d}\right)_s &= \mathrm{IFWGA}_W\left(\left(r_{ij}^{1}\right)_s, \left(r_{ij}^{2}\right)_s, \ldots, \left(r_{ij}^{k}\right)_s\right)\\
&= \prod_{d=1}^{k}\left(\left(r_{ij}^{d}\right)_s\right)^{w_i} = \left(\left(r_{ij}^{1}\right)_s\right)^{w_i} \otimes \left(\left(r_{ij}^{2}\right)_s\right)^{w_i}\\
&\quad \otimes \cdots \otimes \left(\left(r_{ij}^{k}\right)_s\right)^{w_i}\\
&= \left(\prod_{d=1}^{k}\left(\left(\mu_{ij}^{d}\right)_s\right)^{w_i}, 1 - \prod_{d=1}^{k}\left(1-\left(\nu_{ij}^{d}\right)_s\right)^{w_i},\right.\\
&\quad \left.\prod_{d=1}^{k}\left(1-\left(\nu_{ij}^{d}\right)_s\right)^{w_i} - \prod_{d=1}^{k}\left(\left(\mu_{ij}^{d}\right)_s\right)^{w_i}\right). \qquad (12)
\end{aligned}$$

Here $(r_{ij})_s = ((\mu_{ij})_s, (\nu_{ij})_s, (\pi_{ij})_s)$, $i = 1, 2, \ldots, n$, $j = 1, 2, \ldots, p$, and $s = 1, 2, \ldots, \ell$. The aggregated intuitionistic fuzzy sub-decision matrix for each period can therefore be represented as follows:

$$R_s = \left[\left(r_{ij}\right)_s\right]_{n\times p}$$

$$= \begin{bmatrix}
(r_{11})_s & (r_{12})_s & (r_{13})_s & \cdots & \left(r_{1p}\right)_s\\
(r_{21})_s & (r_{22})_s & (r_{23})_s & \cdots & \left(r_{2p}\right)_s\\
(r_{31})_s & (r_{32})_s & (r_{33})_s & \cdots & \left(r_{3p}\right)_s\\
\vdots & \vdots & \vdots & \ddots & \vdots\\
(r_{n1})_s & (r_{n2})_s & (r_{n3})_s & \cdots & (r_{np})_s
\end{bmatrix}_{n\times p}. \qquad (13)$$

Step 5: Establish the aggregated weighted IF super decision matrix.

Using the weights of different life cycle phases (Step 2) and the corresponding R_s sub-decision matrix of these phases (Step 4), the aggregated weighted IF super decision matrix can be established using an IFWAA operator. For this matrix, the following operation is used:

$$\bar{R} = \left[\bar{r}_{ij}\right]_{n\times p}$$

$$\begin{aligned}
\bar{r}_{ij} &= \mathrm{IFWAA}_{\varpi}\left(r_{ij}^{1}, r_{ij}^{2}, \ldots, r_{ij}^{\ell}\right)\\
&= \left(1 - \prod_{s=1}^{\ell}\left(1-\mu_{\left(r_{ij}\right)_s}\right)^{\varpi_s}, \prod_{s=1}^{\ell}\left(\nu_{\left(r_{ij}\right)_s}\right)^{\varpi_s},\right.\\
&\quad \left.\prod_{s=1}^{\ell}\left(1-\mu_{\left(r_{ij}\right)_s}\right)^{\varpi_s} - \prod_{s=1}^{\ell}\left(\nu_{\left(r_{ij}\right)_s}\right)^{\varpi_s}\right) \qquad (14)
\end{aligned}$$

where ϖ_s, $(s = 1, 2, \ldots, \ell)$ represents the weights of the sth phase, resulting in a weights vector of $\varpi =$

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$[\varpi_1, \varpi_2, \ldots, \varpi_\ell]$ where $\varpi_s = (\mu_{\varpi_s}, \nu_{\varpi_s}, \pi_{\varpi_s})$. The weighted complex intuitionistic fuzzy super decision matrix is then written as follows:

$$\bar{R} = \left[\bar{r}_{ij}\right]_{n\times p} = \begin{bmatrix} \bar{r}_{11} & \bar{r}_{12} & \bar{r}_{13} & \cdots & \bar{r}_{1p} \\ \bar{r}_{21} & \bar{r}_{22} & \bar{r}_{23} & \cdots & \bar{r}_{2p} \\ \bar{r}_{31} & \bar{r}_{32} & \bar{r}_{33} & \cdots & \bar{r}_{3p} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \bar{r}_{n1} & \bar{r}_{n2} & \bar{r}_{n3} & \cdots & \bar{r}_{np} \end{bmatrix}_{n\times p}. \quad (15)$$

Step 6: Calculate the ideal solutions.

Let δ_1 and δ_2 represent benefit and cost criteria, respectively, and let φ^- be intuitionistic fuzzy negative-ideal solution (IFNIS) and φ^+ be intuitionistic fuzzy positive-ideal solution (IFPIS). Then φ^- and φ^+ are calculated as follows:

$$\varphi^+_{C_i} = \left(\mu_{\varphi^+_i}(C_i), \nu_{\varphi^+_i}(C_i), \pi_{\varphi^+_i}(C_i)\right) \quad (16)$$

$$\varphi^-_{C_i} = \left(\mu_{\varphi^-_i}(C_i), \nu_{\varphi^-_i}(C_i), \pi_{\varphi^-_i}(C_i)\right) \quad (17)$$

$$\mu_{\varphi^+_i}(C_i) = \left(\left(\max_j \mu_{\bar{r}_{ij}}(C_i)\,|i \in \delta_1\right), \left(\min_j \mu_{\bar{r}_{ij}}(C_i)|i \in \delta_2\right)\right) \quad (18)$$

$$\nu_{\varphi^+_i}(C_i) = \left(\left(\min_j \nu_{\bar{r}_{ij}}(C_i)\,|i \in \delta_1\right), \left(\max_j \nu_{\bar{r}_{ij}}(C_i)|i \in \delta_2\right)\right) \quad (19)$$

$$\mu_{\varphi^-_i}(C_i) = \left(\left(\min_j \mu_{\bar{r}_{ij}}(C_i)\,|i \in \delta_1\right), \left(\max_j \mu_{\bar{r}_{ij}}(C_i)|i \in \delta_2\right)\right) \quad (20)$$

$$\nu_{\varphi^-_i}(C_i) = \left(\left(\max_j \nu_{\bar{r}_{ij}}(C_i)\,|i \in \delta_1\right), \left(\min_j \nu_{\bar{r}_{ij}}(C_i)|i \in \delta_2\right)\right). \quad (21)$$

Step 7: Calculate the distance measures.

The distances between alternatives are measured based on the IFS, and different methods are available with which to measure these distances; this study will use the intuitionistic fuzzy normalized Euclidean distance method. The positive distance measure (d_j^+) and negative distance measure (d_j^-) of each alternative are calculated using Eqs. (22) and (23), respectively:

$$d_j^+ = \left[\frac{1}{2n}\sum_{i=1}^{n}\left(\left(\mu_{\bar{r}_{ij}}(C_i) - \mu_{\varphi^+_i W}(C_i)\right)^2 + \left(\nu_{\bar{r}_{ij}}(C_i) - \nu_{\varphi^+_i W}(C_i)\right)^2 + \left(\pi_{\bar{r}_{ij}}(C_i) - \pi_{\varphi^+_i W}(C_i)\right)^2\right)\right]^{1/2} \quad (22)$$

$$d_j^+ = \left[\frac{1}{2n}\sum_{i=1}^{n}\left(\left(\mu_{\bar{r}_{ij}}(C_i) - \mu_{\phi^-_i W}(C_i)\right)^2 + \left(\nu_{\bar{r}_{ij}}(C_i) - \nu_{\phi^-_i W}(C_i)\right)^2 + \left(\pi_{\bar{r}_{ij}}(C_i) - \pi_{\phi^-_i W}(C_i)\right)^2\right)\right]^{1/2}. \quad (23)$$

Step 8: Calculate the closeness coefficients.

The closeness coefficient of jth alternative, α'_j, is calculated by using the IF positive-ideal solution (d_j^+) and IF negative-ideal solution (d_j^-) as follow:

$$\alpha'_j = \frac{d_j^-}{d_j^+ + d_j^-}, \quad \text{where } 0 \le \tilde{x}_j \le 1. \quad (24)$$

Step 9: Select the most appropriate alternative.

After determining the closeness coefficients of all considered alternatives, $\alpha'_j (j = 1, 2, \ldots, p)$, the closeness coefficients are all ranked accordingly, and the alternative with the highest closeness coefficient is selected as the most suitable alternative.

4. The case for onshore and offshore wind power plants

For purposes of this study, a wind turbine selection problem is selected as a case study, due to the environmental and socio-economic implications of wind turbines observed from a comprehensive EIO-LCA analysis. In this case study, the decision makers desire to choose the best wind turbine alternative with which to generate electric power for the US power grid. Four wind turbine alternatives from VESTAS (α_1 = V80-2.0 MW onshore, α_2 = V90-3.0 MW onshore, α_3 = V80-2.0 MW offshore, and α_4 = V90-3.0 MW offshore) are selected as alternatives for this problem (Vestas Wind Systems A/S, 2006; Elsam, 2004). These wind turbines are represented by V90-3.0 MW and V80-2.0 MW turbines, which are assumed to be installed both onshore and offshore in the US. The EE-IO-LCA methodology is applied to quantify the environmental and socio-economic impacts of each wind turbine prior to the decision making process (Kucukvar and Tatari, 2013; Noori et al., 2015b). Three experts from the Sustainable Systems Analysis Research Group at the University of Central Florida are assigned as decision makers to evaluate the weights of the considered impacts for each LCA phase and the weights of the relevant criteria using the results of LCA, after which the decision makers' linguistic evaluations are aggregated to yield a mean value for each pairwise comparison. Several other researchers have applied a similar weighting strategy likewise based on expert judgments (Kahraman et al., 2009; Kahraman and Kaya, 2010; Kucukvar et al., 2014a; Wang et al., 2009a,b). The decision makers will evaluate the selected wind turbines based on 9 different sustainability indicators (attributes): (1) C_1: employment; (2) C_2: government tax; (3) C_3: income; (4) C_4: business profit; (5) C_5: import; (6) C_6: land footprint; (7) C_7: water withdrawal; (8) C_8: energy use; and (9) C_9: greenhouse gas (GHG) emissions. In this problem, the first five criteria (C_1, C_2, C_3, C_4, C_5) represent benefit attributes, while the remaining four criteria (C_6, C_7, C_8, C_9) are cost attributes. Hence, $\delta_1 = \{C_1, C_2, C_3, C_4, C_5\}$ and $\delta_2 = \{C_6, C_7, C_8, C_9\}$.

4.1. *Indicator selection*

This research uses five socio-economic indicators (business profit, import, income, government tax, and employment) and four environmental indicators (carbon footprint, energy use, water withdrawal, and land footprint). The authors' reasons for selecting these indicators are briefly explained in the following two subsections.

4.1.1. *Socio-economic indicators*

Social and economic sustainability indicators are an integral part of any life-cycle sustainability assessment model (Kloepffer, 2008; Stamford and Azapagic, 2012). For evaluations of energy systems, socio-economic indicators (including job creation, income, and profit) are extensively used (Wang et al., 2009a,b). In addition, according to the Policy and Operations Evaluation Department of the Netherlands' Ministry of Foreign Affairs, there is a two-way relationship between household income and renewable energy consumption for

Table 1 – Definitions of linguistic variables for the importance of phases and sub criteria and evaluation of alternatives.

Linguistic terms (Evaluation of alternatives)	Linguistic terms (Weights of phases and indicators)	IFN
Very Very Good (VVG)/Very Very High (VVH)	Very Very Important (VVI)	(0.95, 0.05)
Very Good (VG)/Very High (VH)	Very Important (VI)	(0.75, 0.15)
Good (G)/High (H)	Important (I)	(0.65, 0.25)
Medium (M)	Mid-Level Importance (M)	(0.50, 0.35)
Bad (B)/Low (L)	Unimportant (UI)	(0.35, 0.55)
Very Bad (VB)/Very Low (VL)	Very Unimportant (VUI)	(0.15, 0.75)
Very Very Bad (VVB)/Very Very Low (VVL)	Very Very Unimportant (VVUI)	(0.05, 0.95)

Table 2 – Evaluation and weights of phases.

	DM1	DM2	DM3
$\wp_1$: Manufacturing	VI	VVI	VI
$\wp_2$: Construction	M	I	VI
$\wp_3$: Transportation	M	VI	M
$\wp_4$: Use	UI	UI	UI

Table 3 – Evaluation and weights of criteria.

	DM1	DM2	DM3
C_1: Employment	I	VI	VVI
C_2: Government tax	M	M	I
C_3: Income	I	VI	VVI
C_4: Business profit	M	UI	M
C_5: Import	UI	UI	M
C_6: Land footprint	UI	UI	M
C_7: Water withdrawal	VI	M	I
C_8: Energy use	VI	I	VI
C_9: Total GHG	VI	VI	VVI

any given country, and each energy system creates many jobs during the construction, maintenance, and end-of-life phases of its life cycle. In fact, a majority of the reviewed studies considered income and employment as a useful social indicator for selecting renewable energy technologies (Afgan and Carvalho, 2004; Chatzimouratidis and Pilavachi, 2008; Santoyo-Castelazo and Azapagic, 2014).

4.1.2. *Environmental indicators*

The United Nations Environmental Programme (UNEP) has listed water scarcity, climate change, energy resource depletion, and ecological land degradation among the most important issues related to sustainable development (UNEP, 2012), and several studies have considered environmental impact categories to evaluate the sustainability energy systems. For instance, life-cycle energy consumption and GHG emissions have often been considered in previous studies as evaluation criteria for energy systems (Atilgan and Azapagic, 2015; Dimitriou et al., 2015; Lenzen, 2008; Kouloumpis et al., 2015), and accounting for interactions regarding water, energy, and land is critical for a comprehensive energy alternative analysis (Evans et al., 2009; Zhang and Anadon, 2013; Zomer et al., 2008). Urban sprawl is also one of the most significant challenges of urbanization, which requires the expansion of urban cities into agricultural land. Moreover, energy systems will have a certain land footprint, and the required amount of land for each power plant is an important indicator for a proper sustainability evaluation of any energy system (Jacobson and Delucchi, 2011).

5. An application and results

Step 1: Evaluate phases and indicators by decision makers.

Linguistic terms corresponding to the IFNs in this study are presented in Table 1. These terms are used to assess the life-cycle phases and indicators. The importance of the indicators and phases is identified by the decision makers and summarized in Tables 2 and 3.

Step 2: Obtain the weights of indicators and phases.

Using fuzzy entropy (Eqs. (8)–(11)), we can calculate the weights of indicators and phases, which are shown in Fig. 2.

Step 3: Evaluate alternatives by decision makers in terms of each criterion.

The decision makers evaluated all alternatives for each life-cycle phase with the linguistic terms presented in Table 1, using IFNs corresponding to the degree of importance with respect to each alternative. The decision makers' evaluation is summarized in Tables 4 through 7 for each phase.

Step 4: Construct an aggregated IF sub-decision matrix for each phase based on the decision makers' evaluations from Step 3.

The sth aggregated weighted IF sub-decision matrix, $R_S = \left[\left(r_{ij}\right)_S\right]_{n\times p}$, was calculated using the IFGWA operator as presented in Eq. (12). Tables 8 through 11 present the aggregated weighted IF sub-decision matrices for each phase.

Step 5: Establish an aggregated weighted IF super decision matrix.

The aggregated weighted IF super decision matrix $\bar{R} = \left[\bar{r}_{ij}\right]_{n\times p}$ was calculated using the IFGAA operator as presented in Eq. (14). Table 12 presents the aggregated weighted IF super decision matrix $\bar{R}$.

Step 6: Calculate the ideal solutions.

The first five attributes selected for this analysis $(C_1, C_2, C_3, C_4, C_5)$ are assumed to be benefit attributes, and the remaining four attributes (C_6, C_7, C_8, C_9) are assumed to be cost attributes. In other words, $\delta_1 = \{C_1, C_2, C_3, C_4, C_5\}$ and $\delta_2 = \{C_6, C_7, C_8, C_9\}$. Then φ^+, the collection of IIF positive-ideal solutions, and φ^-, the collection of IIF negative-ideal solutions, are both determined using Eqs. (18)–(21) as follows:

$$\begin{aligned}\varphi^+ &= \left\{\varphi^+_{c_1}, \varphi^+_{c_2}, \varphi^+_{c_3}, \varphi^+_{c_4}, \varphi^+_{c_5}, \varphi^+_{c_6}, \varphi^+_{c_7}\right\} \\ &= \left\{\begin{array}{c}(0.843, 0.101), (0.983, 0.011), (0.888, 0.080), \\ (0.965, 0.025), (0.995, 0.004), (0.969, 0.021) \\ (0.806, 0.136), (0.656, 0.267), (0.520, 0.368)\end{array}\right\}\end{aligned}$$

$$\begin{aligned}\varphi^- &= \left\{\varphi^+_{c_1}, \varphi^+_{c_2}, \varphi^+_{c_3}, \varphi^+_{c_4}, \varphi^+_{c_5}, \varphi^+_{c_6}, \varphi^+_{c_7}\right\} \\ &= \left\{\begin{array}{c}(0.596, 0.291), (0.910, 0.068), (0.616, 0.267), \\ (0.991, 0.006), (0.968, 0.022), (0.995, 0.004) \\ (0.935, 0.043), (0.903, 0.061), (0.846, 0.112)\end{array}\right\}.\end{aligned}$$

Step 7: Calculate distance measures.

The positive distance measure (d_j^+) and the negative distance measure (d_j^-) of each alternative were calculated

Table 4 – Evaluation of alternatives for the manufacturing phase.

	V80 onshore			V90 onshore			V80 offshore			V90 offshore		
	DM1	DM2	DM3	DM1	DM2	DM3	DM1	DM2	DM3	DM1	DM2	DM3
C_1	G	G	G	VG	VVG	G	G	M	G	M	M	M
C_2	VG	VVG	VG	M	VG	G	P	P	P	P	P	P
C_3	VG	VVG	G	VG	VVG	G	M	M	M	M	M	M
C_4	VG	VVG	VG	VVG	VVG	VVG	G	G	G	G	P	M
C_5	H	VH	VH	H	VH	H	M	M	M	M	M	L
C_6	VVH	VVH	VVH	VVH	VVH	VVH	VH	VH	H	H	M	H
C_7	H	VH	H	H	H	H	M	M	M	L	M	M
C_8	VH	VH	VVH	VH	VH	VH	M	M	M	L	L	L
C_9	VVH	H	VVH	H	H	H	M	M	M	M	L	M

Table 5 – Evaluation of alternatives for the construction phase.

	V80 onshore			V90 onshore			V80 offshore			V90 offshore		
	DM1	DM2	DM3	DM1	DM2	DM3	DM1	DM2	DM3	DM1	DM2	DM3
C_1	VG	VVG	VG	VG	VG	VG	P	M	M	P	P	M
C_2	VG	VVG	VG	VVG	VVG	VVG	M	M	G	M	P	M
C_3	G	VG	G	VG	VG	VG	P	M	M	P	P	P
C_4	VG	G	VG	VVG	VVG	VVG	M	M	M	M	M	M
C_5	VVH	VVH	VH	H	VH	H	L	H	L	L	L	L
C_6	VH	VVH	VH	VH	VH	VH	L	M	M	L	L	M
C_7	VVH	VH	VVH	VH	VH	VH	M	M	L	L	M	L
C_8	H	H	H	VH	E	VH	M	H	M	M	M	M
C_9	L	VL	L	L	L	L	H	M	M	H	H	M

Table 6 – Evaluation of alternatives for the transportation phase.

	V80 onshore			V90 onshore			V80 offshore			V90 offshore		
	DM1	DM2	DM3	DM1	DM2	DM3	DM1	DM2	DM3	DM1	DM2	DM3
C_1	VG	VVG	VG	VG	VVG	VG	P	P	M	P	P	P
C_2	VVG	VVG	VG	VVG	VVG	VVG	M	M	M	P	P	P
C_3	VG	VG	VVG	VG	G	VG	M	M	M	P	P	P
C_4	M	M	M	VG	VVG	VG	P	M	P	P	P	P
C_5	VH	VVH	VVH	VH	VVH	VVH	L	L	L	L	L	L
C_6	VH	VH	VH	VH	VH	VH	L	M	M	L	L	M
C_7	VVH	VVH	VH	VVH	VVH	VVH	M	M	M	M	M	M
C_8	VVH	VH	VH	VH	VH	VH	M	M	M	L	L	L
C_9	H	H	VH	H	H	H	M	M	M	M	L	L

Table 7 – Evaluation of alternatives for the use phase.

	V80 onshore			V90 onshore			V80 offshore			V90 offshore		
	DM1	DM2	DM3	DM1	DM2	DM3	DM1	DM2	DM3	DM1	DM2	DM3
C_1	VG	VG	VG	G	G	G	VG	VG	VG	M	M	P
C_2	VVG	VVG	VVG	M	G	M	VVG	VVG	VG	M	M	P
C_3	VG	VG	VG	M	M	M	M	M	M	M	M	M
C_4	VG	VG	VG	G	G	G	G	G	M	M	M	M
C_5	VVH	VVH	VVH	M	M	H	M	M	M	L	L	L
C_6	VH	VH	VH	VH	H	H	VH	VH	H	M	M	M
C_7	VH	VH	VH	H	H	H	H	H	H	M	L	M
C_8	VH	VVH	VVH	H	H	H	H	H	H	M	M	M
C_9	VVH	VVH	VVH	H	VH	H	VVH	VVH	VH	L	L	L

Table 8 – The aggregated IF decision matrix for the manufacturing phase $\left(R_1^T\right)$.

	V80 onshore	V90 onshore	V80 offshore	V90 offshore
C_1	(0.75, 0.17, 0.07)	(0.84, 0.10, 0.05)	(0.71, 0.20, 0.09)	(0.63, 0.25, 0.12)
C_2	(0.98, 0.10, 0.01)	(0.96, 0.03, 0.02)	(0.90, 0.07, 0.02)	(0.90, 0.07, 0.02)
C_3	(0.84, 0.10, 0.06)	(0.84, 0.10, 0.06)	(0.63, 0.25, 0.12)	(0.63, 0.25, 0.12)
C_4	(0.99, 0.01, 0.00)	(0.99, 0.01, 0.00)	(0.97, 0.02, 0.01)	(0.97, 0.02, 0.01)
C_5	(0.99, 0.01, 0.00)	(1.00, 0.00, 0.00)	(0.98, 0.01, 0.01)	(0.97, 0.02, 0.01)
C_6	(1.00, 0.00, 0.00)	(1.00, 0.00, 0.00)	(0.98, 0.01, 0.01)	(0.98, 0.02, 0.01)
C_7	(0.90, 0.06, 0.03)	(0.89, 0.07, 0.03)	(0.83, 0.11, 0.06)	(0.81, 0.14, 0.06)
C_8	(0.91, 0.05, 0.03)	(0.88, 0.07, 0.05)	(0.74, 0.17, 0.09)	(0.64, 0.29, 0.07)
C_9	(0.87, 0.09, 0.03)	(0.72, 0.20, 0.08)	(0.59, 0.28, 0.13)	(0.54, 0.34, 0.12)

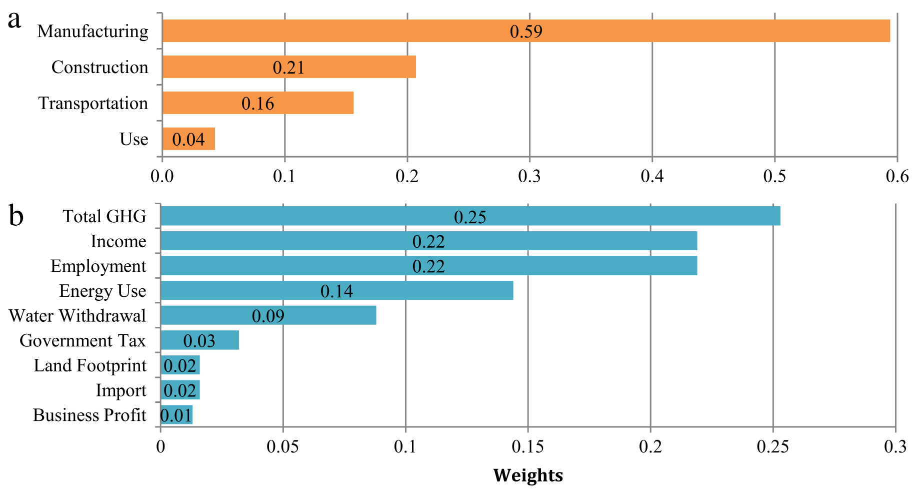

Fig. 2 – Weights of (a) life cycle phase, and (b) criteria.

Table 9 – The aggregated IF decision matrix for the construction phase $\left(R_2^T\right)$.

	V80 onshore	V90 onshore	V80 offshore	V90 offshore
C_1	(0.87, 0.08, 0.05)	(0.83, 0.10, 0.07)	(0.59, 0.30, 0.11)	(0.54, 0.36, 0.10)
C_2	(0.98, 0.01, 0.01)	(1.00, 0.00, 0.00)	(0.94, 0.04, 0.02)	(0.93, 0.05, 0.02)
C_3	(0.80, 0.13, 0.07)	(0.97, 0.03, 0.00)	(0.63, 0.25, 0.12)	(0.63, 0.25, 0.12)
C_4	(0.99, 0.01, 0.00)	(0.99, 0.01, 0.00)	(0.97, 0.02, 0.01)	(0.96, 0.03, 0.01)
C_5	(0.98, 0.01, 0.01)	(0.99, 0.01, 0.00)	(0.96, 0.03, 0.01)	(0.95, 0.04, 0.01)
C_6	(0.99, 0.01, 0.00)	(0.99, 0.01, 0.00)	(0.96, 0.03, 0.01)	(0.96, 0.03, 0.01)
C_7	(0.97, 0.02, 0.01)	(0.93, 0.04, 0.03)	(0.81, 0.14, 0.06)	(0.78, 0.16, 0.05)
C_8	(0.83, 0.12, 0.05)	(0.91, 0.05, 0.03)	(0.77, 0.15, 0.08)	(0.70, 0.21, 0.08)
C_9	(0.75, 0.17, 0.08)	(0.72, 0.20, 0.08)	(0.54, 0.34, 0.12)	(0.49, 0.40, 0.11)

Table 10 – The aggregated IF decision matrix for the transportation phase $\left(R_3^T\right)$.

	V80 onshore	V90 onshore	V80 offshore	V90 offshore
C_1	(0.87, 0.08, 0.05)	(0.87, 0.08, 0.05)	(0.54, 0.36, 0.10)	(0.50, 0.41, 0.09)
C_2	(0.99, 0.01, 0.00)	(1.00, 0.00, 0.00)	(0.94, 0.04, 0.02)	(0.90, 0.07, 0.02)
C_3	(0.63, 0.25, 0.12)	(0.87, 0.08, 0.05)	(0.54, 0.36, 0.10)	(0.50, 0.41, 0.09)
C_4	(0.99, 0.01, 0.00)	(0.99, 0.01, 0.00)	(0.96, 0.03, 0.01)	(0.96, 0.03, 0.01)
C_5	(0.99, 0.01, 0.00)	(0.98, 0.01, 0.01)	(0.97, 0.02, 0.01)	(0.95, 0.04, 0.01)
C_6	(0.99, 0.01, 0.00)	(0.99, 0.01, 0.00)	(0.96, 0.03, 0.01)	(0.96, 0.03, 0.01)
C_7	(0.97, 0.02, 0.01)	(0.99, 0.01, 0.00)	(0.83, 0.11, 0.06)	(0.83, 0.11, 0.06)
C_8	(0.91, 0.05, 0.03)	(0.88, 0.07, 0.11)	(0.74, 0.17, 0.09)	(0.64, 0.29, 0.07)
C_9	(0.75, 0.17, 0.08)	(0.72, 0.20, 0.08)	(0.59, 0.28, 0.13)	(0.49, 0.40, 0.11)

Table 11 – The aggregated IF decision matrix for the use phase $\left(R_4^T\right)$.

	V80 onshore	V90 onshore	V80 offshore	V90 offshore
C_1	(0.83, 0.10, 0.07)	(0.75, 0.17, 0.07)	(0.83, 0.10, 0.07)	(0.59, 0.30, 0.11)
C_2	(1.00, 0.00, 0.00)	(0.94, 0.04, 0.02)	(0.99, 0.01, 0.00)	(0.93, 0.05, 0.02)
C_3	(0.83, 0.10, 0.07)	(0.75, 0.17, 0.07)	(0.71, 0.20, 0.09)	(0.63, 0.25, 0.12)
C_4	(1.00, 0.00, 0.00)	(0.98, 0.01, 0.01)	(0.97, 0.02, 0.01)	(0.96, 0.03, 0.01)
C_5	(0.99, 0.01, 0.00)	(0.98, 0.01, 0.01)	(0.98, 0.01, 0.01)	(0.97, 0.02, 0.01)
C_6	(0.99, 0.01, 0.00)	(0.98, 0.01, 0.01)	(0.98, 0.01, 0.01)	(0.97, 0.02, 0.01)
C_7	(0.93, 0.04, 0.03)	(0.89, 0.07, 0.03)	(0.89, 0.07, 0.03)	(0.81, 0.14, 0.06)
C_8	(0.95, 0.04, 0.02)	(0.83, 0.12, 0.05)	(0.83, 0.12, 0.05)	(0.74, 0.17, 0.09)
C_9	(0.96, 0.04, 0.00)	(0.75, 0.17, 0.08)	(0.91, 0.06, 0.03)	(0.45, 0.45, 0.09)

using the normalized Euclidean distance from Eqs. (22)–(23), and the results are presented in Table 13.

Step 8: Calculate closeness coefficients.

The closeness coefficient of the *j*th alternative, α_j', was determined using the IIF positive-ideal solution (d_j^+) and the IIF negative-ideal solution (d_j^-), and the results are summarized below:

$\alpha_1' = 0.403$, $\alpha_2' = 0.533$, $\alpha_3' = 0.467$, $\alpha_4' = 0.539$.

Step 9: Select the most appropriate alternative.

After ranking the values of α_j' $(j = 1, 2, 3, 4)$ in descending order, the alternative ranking order was found to be such that

Table 12 – Aggregated weighted IF super decision matrix $\bar{R}^T$.

	V80 onshore	V90 onshore	V80 offshore	V90 offshore
C_1	(0.809, 0.127, 0.065)	(0.843, 0.101, 0.056)	(0.673, 0.231, 0.096)	(0.596, 0.291, 0.113)
C_2	(0.983, 0.011, 0.006)	(0.980, 0.015, 0.005)	(0.926, 0.053, 0.021)	(0.910, 0.066, 0.023)
C_3	(0.813, 0.124, 0.064)	(0.888, 0.080, 0.031)	(0.625, 0.259, 0.116)	(0.616, 0.267, 0.117)
C_4	(0.991, 0.007, 0.003)	(0.987, 0.008, 0.004)	(0.970, 0.020, 0.010)	(0.965, 0.025, 0.010)
C_5	(0.989, 0.007, 0.004)	(0.995, 0.004, 0.001)	(0.974, 0.017, 0.009)	(0.968, 0.022, 0.010)
C_6	(0.995, 0.004, 0.001)	(0.995, 0.004, 0.001)	(0.978, 0.014, 0.008)	(0.969, 0.021, 0.010)
C_7	(0.935, 0.043, 0.022)	(0.928, 0.050, 0.022)	(0.831, 0.111, 0.058)	(0.806, 0.136, 0.057)
C_8	(0.903, 0.061, 0.036)	(0.888, 0.066, 0.046)	(0.752, 0.163, 0.085)	(0.656, 0.267, 0.077)
C_9	(0.846, 0.112, 0.042)	(0.722, 0.195, 0.083)	(0.607, 0.273, 0.120)	(0.520, 0.368, 0.113)

Table 13 – Negative and positive distance measures.

	d^+	d^-
A_1	1.719	2.547
A_2	2.250	1.974
A_3	1.762	2.008
A_4	2.505	2.142

$A_4 > A_2 > A_3 > A_1$. A_4 has the highest value, and is therefore the best wind turbine for the objectives previously discussed for this case study.

6. Conclusions and future work

In this study, an intuitionistic fuzzy TOPSIS method was proposed for evaluating wind energy technologies in the US First, the results of an EE-IO-LCA analysis are used to quantify the overall environmental and socio-economic impacts of onshore and offshore wind turbines at each life cycle phase, after which the decision makers evaluated each energy alternative based on the TBL sustainability impacts of each LCA phase. Second, the evaluation results were obtained, taking into account the applicable weight of each specified criterion and each life cycle phase, also using IFWAA and IFWGA operators to account for the influence of individual decision makers on alternatives and the overall group influence on the selection of criteria and life cycle phases for further analysis. Finally, the proposed method was applied to a real case study in which the aim was to rank the performance of wind turbines installed in the US Based on expert evaluations, the manufacturing phase has the highest weight for ranking the sustainability performance of wind energy alternatives, followed by the construction and manufacturing phases, respectively, while the use phase has the lowest weight. Among the environmental impact categories, GHG emissions have the largest importance out of all of the indicators considered in this analysis. The V90 offshore wind turbine was ranked the highest out of the four wind turbine alternatives compared in this study. In addition, wind turbines with a higher power generation capacity (in this case, the V90 onshore and V90 offshore turbines) were found to be better alternatives than those with a lower capacity (the V80 onshore and offshore).

The EE-IO-LCA results in this study are subject to significant uncertainties that may arise from errors in modeling, data collection and/or measurement, meaning that decisions made without sufficiently accounting for these uncertainties may be inherently flawed and thereby lead to incorrect policy conclusions. Therefore, the use of fuzzy MCDM methods is likely to attract more interest as a methodological approach for addressing these uncertainties in sustainable energy decision-making. For this reason, the proposed approach contributes to the emerging field of life cycle sustainability performance benchmarking in that it presents an integrated methodology that includes expert judgments and a fuzzy MCDM analysis, which can be applied in the future to similar problems in which multiple negative and positive sustainability metrics and various life cycle phases must be simultaneously evaluated. The current fuzzy MCDM model can also be extended in the future with other available MCDM methods for the selection of the best energy option from a set of alternatives, thereby a more thorough consideration of all relevant uncertainties and making future models more widely applicable for different alternative-ranking problems.

In the future, the authors aim to broaden and deepen the existing method and apply the improved generalized intuitionistic fuzzy aggregation operator to different decision making problems. Using the life cycle sustainability assessment results of different energy production alternatives with a greater number of socio-economic indicators (injuries, pollution cost, human health, social acceptability, etc.), the proposed methodology can ultimately be used as a generic MCDM approach for energy-related policy-making. However, when the number of indicators, stakeholders, and/or uncertain parameters increases, the expected long-term effects cannot be fully understood using traditional MCDM approaches (Onat et al., 2014d). In such cases, system dynamics modeling should be applied in conjunction with the proposed methodology to further investigate the complex interactions among the relevant social, economic, and environmental impacts and capture feedback mechanisms (Onat et al., 2016b; Onat, 2015b).

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