A multiple criteria decision making method to weight the sustainability criteria of renewable energy technologies under uncertainty

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Abstract

Selecting the most suitable renewable energy technology among feasible alternatives considering conflicting criteria is a Multiple Criteria Decision Making (MCDM) problem. One of the essential stages in the methods used to solve such problems is determining the appropriate weight of each criterion to be considered. The Shannon Entropy method is a frequently used MCDM method to calculate the criteria weights, however it is not suitable to solve problems for which uncertainty in the input data exists. This paper presents a new extended Shannon Entropy method: the Integrated Constrained Fuzzy Shannon Entropy (IC-FSE) method, by which criteria weights are obtained from uncertain input data. To show the applicability of IC-FSE, an illustrative example for the selection of a renewable energy technology in the mining industry is presented, in which three alternative renewable energy technologies, onshore wind, solar photovoltaic and concentrated solar power, were evaluated with respect to technical, social, economic and environmental categories. The results show that IC-FSE can effectively provide appropriate fuzzy solutions for weighting the sustainability criteria for renewable energy technologies. The superiority of this method is showcased by demonstrating that IC-FSE results are more robust than those obtained using other existing methods. The methodology presented can be applied broadly in the renewable energy sector to ensure better informed decision making processes.

Highlights

- A new criteria weighting method for imprecise quantitative data is described.
- The method is used to weight renewable energy technologies' sustainability criteria.
- The normalisation procedure proposed is shown to reduce uncertainty.
- The method yields more appropriate results than existing methods.
- The method yields objective criteria weights, minimising the risk of information loss.

Keywords: Renewable energy technologies; Sustainability criteria; Multiple criteria decision making (MCDM); Uncertainty; Integrated constrained fuzzy Shannon Entropy (IC-FSE); The mining industry

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Abbreviations, units, and nomenclature

AHP, Analytic Hierarchy Process; COA, Centre of Area; CSP, Concentrated Solar Power; ELECTRE, ELimination Et Choix Traduisant la REalité (ELimination and Choice Expressing REality); FAHP, Fuzzy Analytic Hierarchy Process; FSE, Fuzzy Shannon Entropy; FST, Fuzzy Set Theory; GHG, Greenhouse Gas; IC-FSE, Integrated Constrained Fuzzy Shannon Entropy; MCDM, Multiple Criteria Decision Making Method; PV, Photovoltaic; OW, Onshore Wind; TFN, Triangular Fuzzy Number; TOPSIS, Technique for Order of Preference by Similarity to Ideal Solution; l/MWh, litre per megawatt per hour; gCO_2eq/kWh, grams of carbon dioxide equivalent per kilowatt-hour; m^2/kW, square meter per kilowatt; £/MWh, £ per megawatt per hour; Jobs/annual GWh, jobs per annual gigawatt per hour

1. Introduction

Current energy supply is dominated by non-renewable sources, i.e. fossil fuels, most of which are relatively inexpensive to extract [1], but the impact on sustainable development of the extensive use of fossil fuels has raised concerns about the security, reliability, affordability, and environmental impact of energy supplies [2]. One way to respond to these challenges is to significantly increase the use of renewable energy sources and technologies (e.g. wind and solar) that are clean and sustainable [3].

However, it is often challenging to determine the most suitable renewable energy technology to be utilised. Decision makers need to evaluate multiple renewable energy source alternatives with respect to multiple criteria, which often conflict with each other. For example, a renewable energy technology that might help achieve strict environmental regulations (e.g. low GHG emissions, decreasing the reliance on fossil fuel sources) will have costs associated to the additional equipment installation and maintenance, so trade-offs need to be clearly identified during the decision making process.

The selection of the most suitable renewable energy source among a set of feasible alternatives considering multiple conflicting criteria is a Multiple Criteria Decision Making (MCDM) problem. MCDM is a powerful method to find the best alternative when multiple conflicting criteria are involved and need to be evaluated in a scientific manner [4]. MCDM methods have been successfully applied in many fields such as natural resources management [5], environmental science [6], and mining and mineral processing [7], as well as in the area of renewable energy technologies over the past decade.

Researchers' interest in applying MCDM methods in renewable energy area continues to grow, as evidenced by recent literature reviews [8-13]. MCDM methods have been used to: investigate and select the most appropriate site location for renewable energy projects [14, 15], evaluate and select the most suitable photovoltaic technology under uncertainties [16], assess, compare and rank the sustainability of various renewable energy technologies for national-scale assessments under uncertainties [2, 17], analyse and rank the sustainability of different energy storage technologies [18, 19], and evaluate the sustainability of concentrated solar power projects [20].

In general, an MCDM method involves five stages [4, 21-23], namely: (i) weighting the local importance of each criterion with respect to the goal, which is of critical importance as it affects the subsequent stages; (ii) scoring the local preference of each alternative with respect to criteria; (iii) calculating the global weighted scores of alternatives; (iv) ranking of the feasible alternatives based on the global weighted scores; (v) selecting the most suitable alternative, i.e., the highest global weighted score. The final recommendation obtained from any MCDM method usually depends on the criteria against which a set of feasible alternatives are evaluated, the weights (i.e. importance) of the criteria, the local preference scores of alternatives, and the specific algorithm used for aggregating the weights of criteria and the local preferences of alternatives [7].

There are two main methods to determine the criteria weights in MCDM, namely subjective and objective weighting methods. The subjective weighting method relies on decision makers' judgements and can be achieved by means of pairwise comparisons of qualitative or quantitative data. The Analytic Hierarchy Process [21] is the most frequently used subjective weighting method. Although the criteria weights are often obtained using only subjective weighting methods, it is sometimes difficult to obtain reliable judgements from the decision makers, in which case objective weighting methods should be considered.

The objective criteria weights are obtained from the computation of quantitative data, using an algorithm to derive the weights without involving any consideration of decision makers' judgements. The Shannon Entropy method [24] is one of the most frequently used objective methods for deriving the criteria weights. However, in the area of renewable energy, there is a paucity of studies investigating the application of the Shannon Entropy method for objective criteria weighting, an exception being the evaluation of the sustainability of concentrated solar power technologies conducted by Simsek et al. [20].

In cases where the precise values of the relevant input data are available, the evaluation and computation stages in the Shannon Entropy method are applied to express all criteria data and their corresponding weights as crisp values. However, it is often the case that input data are associated with significant uncertainties. For example, Troldborg et al. [2] showed that the data for total power generation, GHG emissions, area requirements and the levelised energy cost, varied widely for each of the eleven renewable energy technologies evaluated. Such variation often results in imprecise input data, which significantly affects the final results and leads to an inaccurate final recommendation [25]. In order to resolve this issue, the imprecise input data can be stated using fuzzy set theory (FST) [26].

A fuzzy set is a group of elements that have degrees of membership over the range 0 and 1, where 0 describes absolutely unlikely or false statements and 1 describes absolutely likely or true statements. The extension of the Shannon Entropy method by means of FST can be termed as a fuzzy Shannon Entropy (FSE) method. In the case when the input data have minimum, most likely and maximum values, a type of ordered fuzzy set, a triangular fuzzy number (TFN), could be used to represent such data.

TFN is one of the most cited fuzzy set types applied to MCDM methods in the literature [27], however, only one fuzzification of the Shannon Entropy method by means of TFN has been proposed [28]. Given that imprecise data is the most common cause of uncertainties in real-world sustainability assessments of renewable energy technologies [11], a more detailed investigation into the reliability and the robustness of the existing extension of the Shannon Entropy method with TFN proposed by Kacprzak [28] is necessary.

Kacprzak [28] developed an FSE method that makes use of standard fuzzy arithmetic. The use of standard fuzzy arithmetic in MCDM methods, however, can lead to inapplicable results for many real-world engineering MCDM problems [29-33]. These inapplicable results arise because a combined method does not take into account the additional information available in real-life situations and ignores known constraints, thus can increase the risk of losing important information about a problem during the computations and result in overestimation of the fuzzy solutions [25, 33, 34]. This is an important issue, since most real-life applications are not constraint-free. Constrained fuzzy arithmetic, on the other hand, can be considered more powerful than standard fuzzy arithmetic [30, 31, 33, 35]. There is therefore scope to improve the fuzzification of the Shannon Entropy method using TFN in order to minimise uncertainty as much as possible by means of constrained fuzzy arithmetic.

In response to the limitations described above, this study proposes a new criteria weighting method: the Integrated Constrained Fuzzy Shannon Entropy (IC-FSE). IC-FSE combines the concepts of constrained fuzzy arithmetic, TFN, and the Shannon Entropy method by taking advantage of their most useful characteristics that can be used to robustly determine the criteria weights for the selection of renewable energy technologies.

The contribution of this study is sixfold: (1) the gap in the Shannon Entropy method literature for problems involving uncertainty due to imprecise input data is addressed; (2) a new MCDM method, IC-FSE, is developed to account for imprecise input data and represent the data by using TFN; (3) the applicability of IC-FSE in weighting the sustainability criteria of renewable energy technologies is showcased; (4) the reliability of IC-FSE compare to stochastic methods is demonstrated; (5) the superiority of the normalisation procedure used in IC-FSE is presented by comparing it to common existing procedures; (6) it is demonstrated that the results obtained from IC-FSE are more robust than those obtained from the only other FSE method reported in the literature. IC-FSE is thus a robust, reliable and superior MCDM method that can be applied broadly in the renewable energy sector to support the decision making process when there is uncertainty in the data.

The remainder of the manuscript is organised as follows: Section 2 provides renewable energy alternatives and criteria in mining and mineral processing; Section 3 provides the theoretical background of TFN, standard fuzzy arithmetic, and constrained fuzzy arithmetic; Section 4 describes the proposed IC-FSE method; Section 5 presents an example of the applicability of the IC-FSE method; Finally, Section 6 provides the final conclusions. Appendix A presents an analysis of normalisation procedures, while in Appendix B provides the comparison of the results obtained from IC-FSE and the only other existing method.

2. Renewable energy technologies and criteria in mining and mineral processing

Mining operations are often located in remote areas where the deposits of mineral resources (coal, metals, industrial minerals, etc.) are found. The remoteness of mine sites frequently results in limited accessibility to energy sources. Because of such circumstances, fossil fuel (e.g. fuel oil, diesel oil, etc.) is in many cases the only feasible choice to power mobile equipment's internal combustion engines and electric power generators [36]. The mining industry still relies heavily on non-renewable energy sources

[37]. It is worth noting that mining operations are very energy intensive; energy costs account for 30–50% of all operating costs [37, 38].

As other industrial operations, mining operations are responsible for producing GHG emissions not only from the use of fossil energy sources for electricity generation but also from operating equipment. As the global demand for metals and minerals steadily increases and the process routes to extract them require larger amounts of energy (due to the need of processing lower grade and finely disseminated ores), higher emissions are produced [39, 40]. In addition, there is a definite correlation between emissions from the mining industry and health risks (e.g. cardiovascular and respiratory diseases) on surrounding communities [41].

In order to address the aforementioned challenges, a number of mining companies worldwide have started to pay more attention to the use of renewable energy technologies in their operations to adhere to the principles of sustainable development [42, 43]. Since energy requirements in mining operations are relatively constant while most renewable energy sources are intermittent, a hybrid scheme that combines renewable sources and diesel generators or electricity from a grid can also be considered for implementation, since energy storage facilities are still relatively expensive [44].

The capability of IC-FSE will be showcased by applying it to weighting the sustainability criteria of renewable energy technologies for mining operations. Sections 2.1 and 2.2 describe the alternatives and criteria used in this work.

2.1. Identification of feasible renewable energy sources

Three renewable energy technologies that have been successfully implemented in the mining industry [37, 45] were considered to be compared. The feasible renewable energy technologies that were considered are summarised as follows:

Onshore wind (OW) — A_1: wind energy is harvested from the movement of air masses to drive wind turbines that provide mechanical power, which is converted to electricity [46]. A number of mining companies have implemented wind power systems at operating mines in Argentina, Canada, and Chile. This has also been done at abandoned mines in the USA to provide electricity to households near the site. The generated power varies from 2 MW to 115 MW in the operating mines and from 29 MW to 237 MW in the abandoned mines [45].

Concentrated solar power (CSP) — A_2: CSP uses reflective surfaces to focus sunlight into a beam to heat a working fluid in a receiver; the steam produced from the heat is utilised to drive a turbine that provides mechanical power, which is converted to electricity [47]. The total installed capacity of CSP in the mining industry in 2016 was 39 MW [37].

Solar photovoltaic (PV) — A_3: solar photovoltaic energy is harvested from the thermal radiation emitted by sunlight by means of photovoltaic cells, which is converted into electric current [48]. A number of mining companies have applied PV technology either at operating mines in the USA, Chile, Australia, South Africa, and Suriname or at abandoned mines in the USA, Germany, Canada, and Korea, where it has been used to provide power to nearby households and for acid mine drainage treatment. The generated power varies from 1MW to 10.6 MW in the operating mines and from 1 MW to 166 MW in the abandoned mines [45].

2.2. Evaluation criteria

There are several studies that list a number of sustainability criteria for assessing renewable energy technologies by means of MCDM methods (e.g. [8, 9, 12, 20, 49-52]). Wang et al. [8] and Simsek et al. [20] present comprehensive lists of frequently used sustainability criteria in MCDM for renewable energy technologies. Those comprehensive lists were used as a basis for determining the criteria considered in the current work. For the purpose of the study, only quantitative criteria were considered. Six evaluation criteria were selected and are summarised in Table 1 and further described below.

Table 1 The evaluation criteria and sources of data used for the current work.

Main categories	Criteria	Units	References
Technical	C_1: Capacity factor	%	[53, 54]
Environmental	C_2: Water consumption	l/MWh	[55, 56]
	C_3: GHG emissions	gCO2eq/kWh	[2]
	C_4: Area requirement	m^2/kW	[2]
Economic	C_5: Levelised energy cost	£/MWh	[2]
Social	C_6: Prospective jobs creation	Jobs/annual GWh	[57, 58]

It is important to mention that quantitative data for the criteria selected were attained from the literature and for consistency, correspond to the same geographical region, i.e. the UK.

1. Technical:

    Capacity factor (C_1) was considered as an important technical criterion. Capacity factor, which is measured as a percentage, defines the ratio between the actual electrical energy production generated by a power plant and the maximum electrical energy output that can be generated over a period of time [52]. A large capacity factor is always desirable; it is important to consider that capacity factors of different power plants vary extensively. The capacity factors of onshore wind, CSP and PV are mainly affected by the weather. For example, when the wind speed is high, the average power generation capacity of wind power plants is high, leading to a greater capacity factor. In addition, since CSP and PV are affected by sunlight, so in summer when daylight time is longer than in winter, the average power generation capacity of CSP and PV power plants is high, and thus leading to a greater capacity factor.

    Based on the literature [53, 54], typical capacity factors for onshore wind, CSP and PV in the UK are about 24–34%, 17–25%, and 5-12%, respectively. It is worth mentioning that the capacity factor of PV is the lowest when compared to all other types of power generation.

2. Environmental:

    Three environmental criteria are used to reflect the effect of renewable energy technologies on environmental sustainability in the mining industry. Three environmental criteria were considered in this work, namely water consumption, GHG emissions and area requirement.

    2.1. Water consumption (C_2).

Water consumption, which is measured in l/MWh, is the amount of withdrawn water obtained from the water reservoir, such as surface water or groundwater, that is not returned to its source during the life cycle of electricity generation [55]. A small amount of water consumption is always desirable. Typical water consumption for onshore wind, CSP and PV in the UK are about 0.4–34 l/MWh, 303–644 l/MWh, and 38-795 l/MWh, respectively [55]. It is worth noting that the maximum estimation of water consumption of PV is higher than that of CSP. The reason for this high use is that when processing silicon into PV equipment, many stages that use much more water than the rest of the manufacturing processes, such as the production of steel components [55], are involved.

2.2. GHG emissions (C_3).

The GHG emissions criterion is one of the most frequently used criteria when evaluating the sustainability of renewable energy technologies [8]. GHG emissions, which are reported as gCO_2eq/kWh, were estimated on the basis of CO_2 and CH_4 emissions of each renewable energy technology, from the commissioning of a plant to the full operation of the technology and the dismantling of the system [59]. A small amount of GHG emissions is always favoured. Typical GHG emissions for onshore wind, CSP and PV in the UK are about 5–70 gCO_2eq/kWh, 15–150 gCO_2eq/kWh, and 20–200 gCO_2eq/kWh, respectively [2].

2.3. Area requirement (C_4).

Another environmental criterion used in this study is the land area required to implement each of the renewable energy technologies. The land area required by each renewable energy technology, which is expressed as m^2/kW, is of great concern for their evaluation in the mining industry. This criterion is important because of concerns that the implementation of renewable energy technologies can often be competing with agriculturally arable land [60] and thus destabilise the flora, the fauna and the ecosystem [61]. Therefore, the smallest area required is always preferred. Based on the literature [2], typical area requirement values for onshore wind, CSP and PV in the UK are about 10–1200 m^2/kW, 10–100 m^2/kW, and 10–500 m^2/kW, respectively.

3. Economic:

The economic criterion is of paramount importance for assessing the sustainability of renewable energy technologies in numerous MCDM studies. The economic criterion considered in the literature often includes the following: capital expenditure (CAPEX), operation and maintenance (O&M) expenditure (OPEX), and fuel costs and levelised energy cost (LEC) [8, 20]. In this work, LEC (C_5), which is measured in £/MWh, was considered as an economic criterion because all the costs over an assumed project's financial life and duty cycle (i.e. CAPEX, OPEX, fuel costs, financing costs, as well as an assumed capacity factor for each plant type) are included in the LEC calculation [47]. Not only that, but LEC is also influenced by the characteristics of the technology, such as efficiency, annual energy production, duration, and energy source [2]. A small amount of LEC is always desirable. Based on the literature [2], typical area requirement values for onshore wind, CSP and PV in the UK are about 25–125 £/MWh, 50–450 £/MWh, and 50–600 £/MWh, respectively. It is clearly noticed that onshore wind has the lowest LEC values, while the solar-based technologies have high LEC values. Since performance variations due to the maturity of technology affects the LEC values [2], LEC values of solar based technologies will tend to decrease in the future if the technologies become more mature.

4. Social:

   The social criterion has been of vital importance for people's acceptance of the application of renewable energy technologies, and has been considered in more detail over the past few decades [8, 20]. Prospective jobs creation, (C6), which is expressed as jobs/annual GWh, is the most frequently used social criterion in the literature [8, 20]; it allows decision makers to consider socioeconomic aspects when deciding which technology can improve the living standards of the surrounding community [61]. This criterion takes into account the potential jobs created during the life cycle of renewable energy technology, from construction and operation until decommissioning. Therefore, the greatest number of job created is favoured. Based on the literature [2], typical prospective job creation values for onshore wind, CSP and PV in the UK are about 0.1–0.6 jobs/annual GWh, 0.2–0.7 jobs/annual GWh, and 0.2–1.3 jobs/annual GWh, respectively.

3. Theory

This section discusses the key theoretical aspects behind the TFN, standard fuzzy arithmetic, and constrained fuzzy arithmetic. The following sub-sections are provided as background for the development of the IC-FSE method in Section 4.

3.1. Triangular Fuzzy Number (TFN)

FST [26] is used to represent the vagueness of statements in natural language into real numbers that have membership function over the range 0 and 1. Bellman and Zadeh [62] first introduced FST into decision making as an approach that can effectively solve problems in a fuzzy environment. This has been followed by numerous approaches in which FST has been applied to existing MCDM methods to solve a variety of problems, with promising outcomes. The following are examples of such approaches found in the literature: fuzzy AHP (FAHP) [63, 64], fuzzy TOPSIS [65, 66], and Fuzzy ELECTRE [67]. The wide application of hybrid FST and MCDM methods to real world problems was surveyed by Kahraman et al. [27] and Mardani et al. [68].

TFN is the most widely used FST for presenting the imprecise input data in real-life MCDM applications because it is easy to apply and thus leads to a straightforward calculation. Kacprzak [28] proposed the first combination of TFN with the Shannon Entropy method. The membership function of TFN $\tilde{A}(x)$ is arranged in the following form:

$$\tilde{A}(x) = \begin{cases} \dfrac{x - c_A^L}{c_A^M - c_A^L}, & c_A^L < x < c_A^M, \\ 1\,, & x = c_A^M, \\ \dfrac{c_A^U - x}{c_A^U - c_A^M}, & c_A^M < x < c_A^U, \\ 0, & \text{otherwise}, \end{cases} \tag{1}$$

where c_A^L and c_A^U are termed as the left and right membership function of TFN $\tilde{A}(x)$ or the lowest and highest boundary values of TFN $\tilde{A}(x)$, while c_A^M is defined as the middle value of TFN $\tilde{A}(x)$. Suppose that a TFN has c_A^L, c_A^M, c_A^U = 2, 3, and 4, respectively, then this TFN can be presented graphically as shown in Fig. 1.

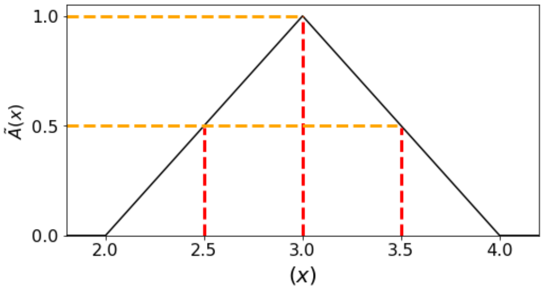

Fig. 1. The membership functions of TFN (2, 3, 4).

In order to obtain a crisp number result of the TFN, the centre-of-area (COA) defuzzification technique, presented by Tzeng and Huang [69], is applied in this paper. The centre of area COA $\tilde{A}(x)$ of a triangular fuzzy number $\tilde{A}(x) = \left(c_A^L, c_A^M, c_A^U\right)$ is formulated in the following form:

$$COA_{\tilde{A}} = \frac{(c_A^U - c_A^L) + (c_A^M - c_A^L)}{3} + c_A^L. \tag{2}$$

3.2. Standard fuzzy arithmetic

In standard fuzzy arithmetic, basic arithmetic operations on real or crisp numbers are extended to operations on TFNs. In this paper, all the positive TFNs are taken into account since all input data are positive numbers. Therefore, the lowest membership number for a TFN is higher than zero.

Suppose that two positive TFNs, namely TFN $\tilde{A}$ and TFN $\tilde{B}$ are defined as, $\tilde{A} = \left(c_A^L, c_A^M, c_A^U\right)$, $\tilde{B} = \left(c_B^L, c_B^M, c_B^U\right)$, the standard arithmetic operations between these two TFNs are as follows:

- Addition (+): $\tilde{A} + \tilde{B} = (c_A^L + c_B^L,\ c_A^M + c_B^M, c_A^U + c_B^U)$. (3)
- Multiplication (x): $\tilde{A} \times \tilde{B} = (c_A^L \times c_B^L,\ c_A^M \times c_B^M, c_A^U \times c_B^U)$. (4)
- Division (/): $\tilde{A}/\tilde{B} = (c_A^L/c_B^U,\ c_A^M/c_B^M, c_A^U/c_B^L)$. (5)

Moreover, the comparison of two TFNs are represented in the following form:

- $\tilde{A} \geq \tilde{B}\ if\ c_A^L \geq c_B^L,\ c_A^M \geq c_B^M, c_A^U \geq c_B^U$. (6)
- $\tilde{A} \leq \tilde{B}\ if\ c_A^L \leq c_B^L,\ c_A^M \leq c_B^M, c_A^U \leq c_B^U$. (7)

3.3. Constrained fuzzy arithmetic

The aforementioned notions of standard fuzzy arithmetic operations can be implemented only in the case when there is no interaction between the fuzzy numbers [35]. For the case when the interaction between fuzzy numbers is involved, the notions of constrained fuzzy arithmetic that are presented in the next paragraphs should be applied.

Suppose that f is a continuous function and $\mathbb{R}$ is the set of real numbers, $f\colon \mathbb{R}^n \rightarrow \mathbb{R}$, and suppose that $\tilde{A}_{\rm i} = \left(A_i^L, A_i^M, A_i^U\right), i = 1, 2, \dots, n$, where n is the amount of positive TFNs. Then, $\tilde{A} = f_F\left(\tilde{A}_1, \tilde{A}_2, \tilde{A}_3, \dots, \tilde{A}_n\right)$ is a TFN $\tilde{A} = (A^L, A^M, A^U)$ whose significant values are derived from the following form

$$A^L = min\,\{f\,(A_1,\ A_2,\ A_3, \dots,\ A_n)\,;\ \ A_i \in \left[A_i^L, A_i^U\right],\ i\ = 1, 2, \dots, n\}, \tag{8}$$

$$A^M = f\,(A_1^M, A_2^M, A_3^M \dots, A_n^M), \tag{9}$$

$$A^U = max\,\{f\,(A_1,\ A_2,\ A_3, \dots,\ A_n)\,;\ \ A_i \in \left[A_i^L, A_i^U\right],\ i\ = 1, 2, \dots, n\}. \tag{10}$$

These basic notions of constrained fuzzy arithmetic will be applied to the TFN arithmetic operations throughout this work.

4. An Integrated Constrained Fuzzy Shannon Entropy (IC-FSE) method

The Shannon Entropy is a widely used MCDM method to obtain the criteria weights by means of objective weight methods. It was initially introduced by Shannon [24] and various modifications have been developed, particularly in normalising a decision matrix [70-72]. This work applies the normalisation procedure that was developed by Nijkamp and Delft [71] mainly because the outcomes obtained by applying this procedure have the lowest degree of uncertainty in comparison to the procedures that were developed by Weitendorf [70] and Voogd [72] (see: Appendix A).

This section describes the application of constrained fuzzy arithmetic to extend the Shannon Entropy method. This is possible when it is difficult to acquire reliable subjective weights, the data that need to be analysed are difficult to be defined precisely, and the input data is presented as ordered fuzzy numbers, such as triangular fuzzy numbers (TFNs).

IC-FSE involves six major steps: (1) defining the problem notions (e.g. determining alternatives and criteria) and developing a fuzzy decision matrix, (2) normalising the fuzzy decision matrix, (3) determining the fuzzy entropy values, (4) computing the local fuzzy criteria weights, (5) defuzzifying the results obtained in step 4, and (6) normalising the crisp values acquired in step 5 in order to obtain the final criteria weights. The mathematical equations for each step of the IC-FSE method are presented below:

1. Developing a fuzzy decision matrix that presents the ratings of different alternatives, $\tilde{A_j}\left(\widetilde{A_1}, \widetilde{A_2} \dots, \widetilde{A_m}\right)$ with respect to predetermined criteria, $\tilde{C_i}\left(\widetilde{C_1}, \widetilde{C_2} \dots, \widetilde{A_n}\right)$; the rating of each alternative is expressed in TFN.

$$\tilde{X} = \left[\widetilde{x_{ji}}\right]_{m\times n} = \begin{array}{c c} & \begin{array}{cccc} C_1 & C_2 & \dots & C_n \end{array} \\ \begin{array}{c} A_1 \\ A_2 \\ \vdots \\ A_m \end{array} & \begin{bmatrix} \widetilde{x_{11}} & \widetilde{x_{12}} & \dots & \widetilde{x_{1n}} \\ \widetilde{x_{21}} & \widetilde{x_{22}} & \dots & \widetilde{x_{2n}} \\ \vdots & \vdots & \ddots & \vdots \\ \widetilde{x_{m1}} & \widetilde{x_{m2}} & \dots & \widetilde{x_{mn}} \end{bmatrix} \end{array}. \tag{11}$$

Note: $\widetilde{x_{ji}}$ is the rating of the alternative j with respect to criterion i. For example: $\widetilde{x_{11}}$ is the rating of the alternative 1 with respect to criterion 1 and the elements of $\widetilde{x_{11}}$ are ${x_{11}}^L, {x_{11}}^M, {x_{11}}^U$, where the superscript indexes L, M, and U refer to the lowest, middle and highest boundary values of TFN $\widetilde{x_{11}}$, respectively.

2. Normalising the fuzzy decision matrix. The normalised elements of TFN $\widetilde{r_{ji}} = \left(r_{ji_L}^C, r_{ji_M}^C, r_{ji_U}^C\right)$, $i\ = 1, \dots, n$ and $j\ = 1, \dots, m$ (where the superscript index C represents the constrained fuzzy arithmetic and the sub-subscript indexes L, M, and U refer to the lowest, middle and highest boundary values) are obtained by using the following equations:

$$r_{ji_L}^{C} = min\left\{\frac{x_{ji}}{\sqrt{\sum_{j=1}^{m} x_{ji}{}^{2}}}; \quad x_{ji}\epsilon\left[x_{ji}{}^{L}, x_{ji}{}^{U}\right]\right\}, \tag{12}$$

$$r_{ji_M}^{C} = \left\{\frac{x_{ji}{}^{M}}{\sqrt{\sum_{j=1}^{m} x_{ji}{}^{M2}}}\right\}, \tag{13}$$

$$r_{ji_U}^{C} = max\left\{\frac{x_{ji}}{\sqrt{\sum_{j=1}^{m} x_{ji}{}^{2}}}; \quad x_{ji}\epsilon\left[x_{ji}{}^{L}, x_{ji}{}^{U}\right]\right\}. \tag{14}$$

3. Determining the fuzzy entropy value $(\widetilde{e_\iota}) = \left(e_{i_L}^{C}, e_{i_M}^{C}, e_{i_U}^{C}\right)$ of each criterion through the following formulae:

$$\widetilde{e_\iota} = -\frac{\sum_{j=1}^{m} \widetilde{f_{J\iota}} \times ln\widetilde{f_{J\iota}}}{\ln m}, \tag{15}$$

$$\widetilde{f_{J\iota}} = \frac{\widetilde{r_{J\iota}}}{\sum_{j=1}^{m} \widetilde{r_{J\iota}}}, \tag{16}$$

$$e_{i_L}^{C} = min\left\{-\frac{\sum_{j=1}^{m}\left(\frac{r_{ji}}{\sum_{j=1}^{m} r_{ji}} \times ln\frac{r_{ji}}{\sum_{j=1}^{m} r_{ji}}\right)}{\ln m}; \quad r_{ji}\epsilon\left[r_{ji}{}^{L}, r_{ji}{}^{U}\right]\right\}, \tag{17}$$

$$e_{i_M}^{C} = -\frac{\sum_{j=1}^{m}\left(\frac{r_{ji}{}^{M}}{\sum_{j=1}^{m} r_{ji}{}^{M}} \times ln\frac{r_{ji}{}^{M}}{\sum_{j=1}^{m} r_{ji}{}^{M}}\right)}{\ln m}, \tag{18}$$

$$e_{i_U}^{C} = max\left\{-\frac{\sum_{j=1}^{m}\left(\frac{r_{ji}}{\sum_{j=1}^{m} r_{ji}} \times ln\frac{r_{ji}}{\sum_{j=1}^{m} r_{ji}}\right)}{\ln m}; \quad r_{ji}\epsilon\left[r_{ji}{}^{L}, r_{ji}{}^{U}\right]\right\}. \tag{19}$$

If $\widetilde{f_{J\iota}}$ are all same, then the fuzzy entropy value of each criterion is the maximum $(\widetilde{e_\iota})$. If $\widetilde{f_{J\iota}}$ is 0, then $\widetilde{f_{J\iota}} \times ln\widetilde{f_{J\iota}}$ is 0.

4. Computing the fuzzy entropy weight $(\widetilde{w_\iota}) = \left(w_{i_L}^{C}, w_{i_M}^{C}, w_{i_U}^{C}\right)$ of each criterion using the following equations:

$$\widetilde{w_\iota} = \frac{1-\widetilde{e_\iota}}{\sum_{i=1}^{n} \widetilde{e_\iota}}, \tag{20}$$

$$w_{i_L}^{C} = min\left\{\left(\frac{1-e_i}{\sum_{i=1}^{n} e_i}\right); \quad e_i\epsilon\left[e_{i_L}^{C}, e_{i_U}^{C}\right]\right\}, \tag{21}$$

$$w_{i_M}^{C} = \frac{1-e_i{}^{M}}{\sum_{i=1}^{n} e_i{}^{M}}, \tag{22}$$

$$w_{i_U}^{C} = max\left\{\left(\frac{1-e_i}{\sum_{i=1}^{n} e_i}\right); \quad e_i\epsilon\left[e_{i_L}^{C}, e_{i_U}^{C}\right]\right\}. \tag{23}$$

5. Defuzzifying the obtained fuzzy entropy weights by using equation (2) in order to obtain the crisp values $(\widetilde{CW}_i)$.

6. Normalising the obtained crisp value of each criterion by means of the distributive mode normalisation technique that is shown in equation (24) in order to attain the weight of the i-th criterion (ObW_i).

$$ObW_i = \widetilde{CW}_i \Big/ \sum_{i=1}^{n} \widetilde{CW}_i . \tag{24}$$

5. IC-FSE for weighting the sustainability criteria of renewable energy technologies in the mining industry

A numerical example of the use of IC-FSE is presented in this section. IC-FSE is used to determine the weights of sustainable criteria in the selection of renewable energy technologies in the mining industry. Three feasible renewable energy technologies were evaluated with respect to six criteria, comprising one technical, three environmental and two socio-economic criteria. For the purpose of this study, an implementation of IC-FSE in Python 3 was used.

The sources of quantitative data for the selected criteria are presented in Table 1 and the data are summarised in Table 2. Columns and rows in Table 2 result in a fuzzy decision matrix that is expressed in TFN.

Table 2 The minimum, most likely and maximum values for each of the feasible renewable energy technologies with respect to each criterion

Alterna-tives	Capacity factor (%)	Water consumption (l/MWh)	GHG emissions (gCO_2eq/kWh)	Area requirement (m^2/kW)	Levelised energy cost (£/MWh)	Prospective jobs (Jobs/annual GWh)
Onshore wind	(24, 28, 34)	(0.4, 4, 34)	(5, 15, 70)	(10, 200, 1200)	(25, 70, 125)	(0.1, 0.2, 0.6)
CSP	(17, 24, 25)	(303, 606, 644)	(15, 40, 150)	(10, 40, 100)	(50, 200, 450)	(0.2, 0.4, 0.7)
PV	(5, 11, 12)	(38, 307, 795)	(20, 60, 200)	(10, 150, 500)	(50, 340, 600)	(0.2, 0.6, 1.3)

5.1. Fuzzy entropy weights

By using equations (12)–(14), the normalised decision matrix in TFN was obtained, the results of which are shown in Table 3. The fuzzy entropy values ($\tilde{e}_i$) were obtained by applying equations (15)–(19), while equations (20)–(23) were used to derive the fuzzy entropy weights ($\tilde{w}_i$). The fuzzy entropy weights were then defuzzified by using equation (2). In order to obtain the crisp criteria weights, equation (24) was then used to normalise the defuzzified entropy weights. The results of the fuzzy entropy values, the fuzzy entropy weights, and the crisp entropy weights are presented in Table 4. Based on the normalised crisp entropy weights (ObW_i), the rank of each criterion is water consumption ≻ area requirement ≻ GHG emissions ≻ levelised energy cost ≻ prospective jobs creation ≻ capacity factor.

Table 3 The normalised fuzzy decision matrix

Alterna-tives	Capacity factor (C_1)	Water consumption (C_2)	GHG emissions (C_3)	Area requirement (C_4)	Levelised energy cost (C_5)	Prospective jobs (C_6)

Onshore wind	(0.65, 0.73, 0.89)	(0.0004, 0.01, 0.1)	(0.02, 0.2, 0.9)	(0.02, 0.8, 1.0)	(0.03, 0.2, 0.9)	(0.1, 0.3, 0.9)
CSP	(0.4, 0.6, 0.7)	(0.4, 0.9, 1.0)	(0.1, 0.5, 1.0)	(0.01, 0.2, 1.0)	(0.1, 0.5, 1.0)	(0.1, 0.5, 1.0)
PV	(0.1, 0.3, 0.4)	(0.1, 0.5, 0.9)	(0.1, 0.8, 1.0)	(0.01, 0.6, 1.0)	(0.1, 0.8, 1.0)	(0.2, 0.8, 1.0)

Table 4 The fuzzy entropy values $(\tilde{e_i})$, fuzzy entropy weights $(\widetilde{w_i})$, normalised crisp entropy weights (ObW_i) and the ranking of criteria obtained from the IC-FSE

	Capacity factor (C1)	Water consumption (C2)	GHG emissions (C3)	Area requirement (C4)	Levelised energy cost (C5)	Prospective jobs (C6)
$(\tilde{e_i})$	(0.67, 0.8, 0.83)	(0.16, 0.45, 0.55)	(0.26, 0.75, 0.79)	(0.07, 0.72, 0.87)	(0.31, 0.72, 0.83)	(0.48, 0.74, 0.87)
$(\widetilde{w_i})$	(0.04, 0.11, 0.23)	(0.12, 0.31, 0.5)	(0.06, 0.14, 0.4)	(0.04, 0.16, 0.44)	(0.05, 0.16, 0.38)	(0.05, 0.12, 0.33)
(ObW_i)	0.1	0.26	0.17	0.18	0.16	0.14
Rank	6	1	3	2	4	5

5.2. Stochastic analysis

In order to capture the uncertainty due to the imprecise input data, the Shannon Entropy method was applied by means of Monte Carlo simulations. Each of the criteria values in Table 2 was randomly sampled for a large number of iterations (i.e. 15,000) and the generated random number was used as input for the Shannon Entropy method. A probabilistic ranking of the weight of each criterion could, therefore, be acquired.

In order to generate a random number $(random_a)$ in a TFN for all of the criteria values, equation (25) was used.

$$random_a = np.random.triangular(min_a, mode_a, max_a), \tag{25}$$

where $np.random.triangular$ denotes a standard function that generates a random number by triangular probability density functions with a $mode_a$ equal to the most likely value and min_a and max_a equal to the lower and upper bound values that are presented in Table 2.

A violin plot was used to visualise the probability density of the simulation results. Fig. 2 shows the violin plot of the weight of each criterion and reveals that the water consumption criterion (C_2) has the highest high probability to be the most important criterion with some overlaps with other five criteria.

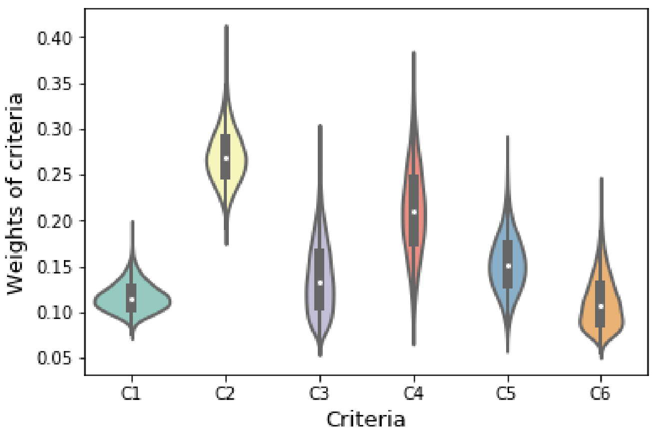

Fig. 2. Violin plot of the weight of each criterion after 15,000 iterations

5.3. Discussion

Table 4 shows the results obtained by applying IC-FSE using the minimum, most likely and maximum values from Table 2. Based on the normalised crisp entropy weights, which are presented in Table 4, the weight of each criterion is water consumption ≻ area requirement ≻ GHG emissions ≻ levelised energy cost ≻ prospective jobs creation ≻ capacity factor.

It can be concluded from the results that the three most important criteria are related to environmental aspects of renewable energy technologies. The total overall weights of these criteria are 0.61. This finding indicates that when choosing renewable energy technologies, water consumption, area requirement, and GHG emissions must be carefully considered, taking into account the specific conditions of the region.

A very interesting finding in the results is that the capacity factor criterion has the lowest weight among all criteria, whereas generally in the literature, this criterion is frequently identified as the most important one. This is probably because the capacity factor's values among the three alternatives are very similar, while the environmental aspects' values vary widely. In addition, since the capacity factor affects levelised energy cost values, so the weight of the levelised energy cost criterion becomes low as well.

Fig. 2 shows the violin plot of the weight of each criterion as calculated from 15,000 Monte Carlo simulations. The results of Monte Carlo simulations applied here explicitly present the uncertainty in the weight of criteria through the overlaps between each criterion. The overlaps indicate that over the range of possible values, any ranking of the five criteria is possible. In fact, all of the criteria have been found to be the most important criterion and the least sustainable criterion in a number of simulations. It is therefore worth noting that the results can indicate the potential variability of the criteria weights in terms of the various data inputs and highlight the effect that the data inputs can have on the results. In addition, based on the results of Monte Carlo simulations, there is a relatively high tendency for water consumption (C_2) to be the most important criterion, whereas the least sustainable criterion is the capacity factor (C_1). Such a tendency is relatively similar to the results obtained from IC-FSE.

It is evident from the aforementioned outcomes that our proposed method, IC-FSE, can be used to assess, weight, compare and rank different criteria in a scientific transparent manner by means of objective methods. Applying IC-FSE can, therefore, be useful to inform the weight of each criterion in order to guide sustainable renewable energy strategies and their implementation. Nevertheless, the results from this work show a limitation in the use of IC-FSE for assessing and weighting the sustainability criteria in evaluating different renewable energy technologies due to the level of uncertainty involved in terms of input data. The input data used in this work were originally collected at a national scale and are therefore relatively generic. From a practical point of view, if a specific renewable energy project in the mining industry were to be considered, the degree of uncertainty in terms of input data is very likely to be smaller than that in the present example. IC-FSE can still be used, by substituting all values in Table 2 as required, and one would expect the set of feasible renewable energy technologies would most probably change. For example, if the mining company is located near a river and there is a high potential to build a hydroelectric power plant (HEPP), then a HEPP might be added into a set of feasible alternatives.

It should be noted that there will always be uncertainties involved in assessing the weights of sustainability criteria in the selection of renewable energy technologies. Uncertainties are mostly associated with the stages of the decision making process [73] and even in its mathematical functions [25]. Therefore, care should be taken when considering the outcomes of MCDM methods.

The uncertainty that is associated with the input data or information can be handled by means of FST, as done in this study, and minimised through prudent assessments of the available data sources in order to ensure that the inputs are representative and reliable. In addition, in order to obtain further information, Monte Carlo simulations can be used to address the associated uncertainties, as done in this work. Nonetheless, IC-FSE has been shown to provide less vague results. In addition, uncertainty often exists in mathematical functions of MCDM methods and thus overestimation of fuzzy results could occur. A method should be therefore capable of minimising the undesired overestimation of results. Undesired results can be avoided by reducing the risk of losing valuable information, which can be achieved by taking into account the interactions among the elements in the calculations. This work showcases the ability of IC-FSE in reducing uncertainty due to mathematical functions by comparing the results obtained from IC-FSE to those obtained from other existing methods (see: Appendix B).

Based on the aforementioned explanation, it can be concluded that the proposed IC-FSE method succeeded in weighting the sustainability criteria in a fuzzy environment based on quantitative data only. However, real-life MCDM problems often also involve qualitative data. It should also be pointed out that this study does not take into account the interaction and dependency between objects (i.e. criteria, sub-criteria, and alternatives). Such dependencies can be accounted by using another MCDM method, such as analytic network process. There is therefore scope to further extend IC-FSE for the case when qualitative and quantitative data, as well as the dependency between objects, are involved.

6. Conclusions

This paper demonstrates the value of applying the concept of constrained fuzzy arithmetic in a fuzzy extension of Shannon Entropy. A hybrid multiple criteria decision making method is developed, namely the Integrated Constrained Fuzzy Shannon Entropy method (IC-FSE). The developed method can be used to determine criteria weights when credible subjective weights are difficult to acquire and the input data that need to be analysed are difficult to define precisely, and thus need to be presented in fuzzy numbers.

In this study, IC-FSE was applied to weight the sustainability criteria of renewable energy technologies in the mining industry. Three feasible renewable energy technologies, namely onshore wind, concentrated solar power, and solar photovoltaic, were examined with respect to six sustainability criteria. The selected criteria were capacity factor, water consumption, GHG emissions, area requirement, levelised energy cost, and prospective jobs creation. The criteria weighting was assessed using data collected from the literature and applied to an illustrative example for the mining industry in the UK. To deal with the uncertainty in the input data, triangular fuzzy numbers were applied to define each of the criteria values. IC-FSE was then used to compute the criteria weights.

The results demonstrate that the environmental criteria associated to renewable energy technologies was the most important aspect to consider. In particular, water consumption was the highest ranked criterion, followed by area requirement and GHG emissions. The latter will continue to be a particularly relevant criterion for the mining industry due to the expected increase in energy demand, combined with the large scale of mining operations. In addition, the technical criterion, i.e. the capacity factor, had the lowest weight among all criteria and as a consequence, the levelised energy cost criterion was also low.

The uncertainty in the input data was also assessed using Monte Carlo simulations to determine probability distributions of criteria weights. The results from the Monte Carlo simulations were then compared to those from IC-FSE in order to obtain insight into the applicability of the latter in overcoming the uncertainty. The results in Sections 5.1 and 5.2 showed that the first and second rank as well as the last rank of criteria were similar. However, it is worth noting that although the uncertainty that is associated with the input data or information can be addressed by means of IC-FSE or Monte Carlo simulations, IC-FSE yields more precise results.

Moreover, when there is uncertainty associated to the method, which can be described mathematically, the method should be capable of minimising the risk of losing important data during the computations and minimising the overestimation of the results. The superiority of IC-FSE over other existing normalisation methods to minimise uncertainty was showcased, demonstrating that IC-FSE's normalisation procedure results in more precise fuzzy weights. In addition, the results acquired from IC-FSE were compared to those obtained from the only other existing method in the literature for criteria weighting that also uses triangular fuzzy numbers, showing that IC-FSE maintains the order of TFN properly. The results derived from IC-FSE show that an appropriate order of TFN in the fuzzy weights of objective criteria with less uncertainty is achieved by taking into account all the information about the uncertainty in the computation process.

In this study, the proposed IC-FSE method succeeded in weighting the sustainability criteria in a fuzzy environment based on quantitative data alone. There is scope to further extend IC-FSE for the case when both qualitative and quantitative data are available, as well as for when there exists a dependency between criteria and alternatives. Further studies to develop such an extended method will be the subject of future work.

This study demonstrates that IC-FSE is a robust method to weight criteria using quantitative and uncertain data. IC-FSE has a broad application potential in other fields to support decision makers in the selection problem when dealing with objective weights under uncertainty.

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Appendix

A) Comparison of normalisation techniques

For deriving fuzzy weights of objective criteria from a decision matrix by means of the Shannon Entropy method, a number of normalisation procedures have been reported in the literature. This section assessed the two most frequently used procedures for normalising a fuzzy decision matrix based on the Shannon Entropy method, namely the Voogd [72] and Weitendorf [70] ratios [74].

The Voogd ratios are formulated in the equation below

$$\widetilde{r_{ji}} = \left(\frac{x_{ji}}{\sum_{j=1}^{m}(x_{ji})}\right). \tag{A.1}$$

The equations (12)–(14) can then substituted by equation (A.1) in order to obtain fuzzy criteria weights based on the Voogd normalisation procedure.

The Weitendorf ratios are expressed in equations (A.2) and (A.3) below.

a. For the beneficial criteria that should be maximised, such as capacity factor (C_1) and prospective jobs creation (C_6), the following equation is applied:

$$\widetilde{r_{ji}} = \frac{x_{ji} - \min(x_{ji})}{\max(x_{ji}) - \min(x_{ji})}. \tag{A.2}$$

b. For the non-beneficial criteria that should be minimised, such as water consumption (C_2), GHG emissions (C_3), area requirement (C_4) and LEC (C_5), the equation below is then applied:

$$\widetilde{r_{ji}} = \frac{\max(x_{ji}) - x_{ji}}{\max(x_{ji}) - \min(x_{ji})}. \tag{A.3}$$

Equations (A.2) and (A.3) were used to substitute equations (12)–(14) in order to obtain fuzzy criteria weights based on the Weitendorf normalisation procedure. A fundamental problem arises when the lowest and/or most likely and/or highest numbers in TFN are the same. The denominator in such a scenario will be zero and the fraction is therefore undefined. In this situation, it is impossible to compute further calculations. For example, in the study presented here, the lowest number in TFN for onshore wind, CSP and PV with respect to area requirement is 10 m^2/kW. For this reason, this work only compared the results obtained from the Voogd normalisation procedure.

Table A.1 shows the results for fuzzy entropy values, fuzzy entropy weights, and crisp entropy weights that are obtained from IC-FSE by using the Voogd normalisation procedure. Based on the crisp entropy weights, the rank of each criterion is water consumption $\succ$ area requirement $\succ$ GHG emissions $\succ$ levelised energy cost $\succ$ prospective jobs creation $\succ$ capacity factor, which is similar to the rank that was obtained from the Nijkamp and Delft's normalisation procedure shown in Table 4. However, it is worth noting that by employing the Nijkamp and Delft's normalisation procedure in equations (12)–(14), the distance between the middle values and lower and upper values of the fuzzy entropy values and the fuzzy entropy weights are smaller than those obtained by applying the Voogd's normalisation procedure. Fig. A.1 shows the comparison of fuzzy entropy weights ($\widetilde{w_i}$) of water consumption and area requirement that are obtained from the Nijkamp and Delft's normalisation procedure and the Voogd normalisation procedure. As can be seen from Fig. A.1, the smaller area of TFN was produced from the Nijkamp and Delft's normalisation. Thus, the Nijkamp and Delft's normalisation results in less vague fuzzy entropy weights than those acquired by the Voogd's normalisation.

Table A.1 The fuzzy entropy values ($\widetilde{e_i}$), fuzzy entropy weights ($\widetilde{w_i}$), normalised crisp entropy weights (ObW_i) and the ranking of criteria obtained from the Voogd normalisation procedure.

	Capacity factor (C_1)	Water consumption (C_2)	GHG emissions (C_3)	Area requirement (C_4)	Levelised energy cost (C_5)	Prospective jobs (C_6)
$(\widetilde{e_i})$	(0.8, 0.94, 0.96)	(0.2, 0.6, 0.71)	(0.32, 0.89, 0.93)	(0.09, 0.86, 1.0)	(0.38, 0.86, 0.96)	(0.55, 0.92, 0.96)
$(\widetilde{w_i})$	(0.01, 0.06, 0.31)	(0.09, 0.42, 0.81)	(0.02, 0.12, 0.63)	(0.0, 0.15, 0.66)	(0.01, 0.15, 0.59)	(0.01, 0.08, 0.51)
(ObW_i)	0.083	0.285	0.166	0.174	0.162	0.13
Rank	6	1	3	2	4	5

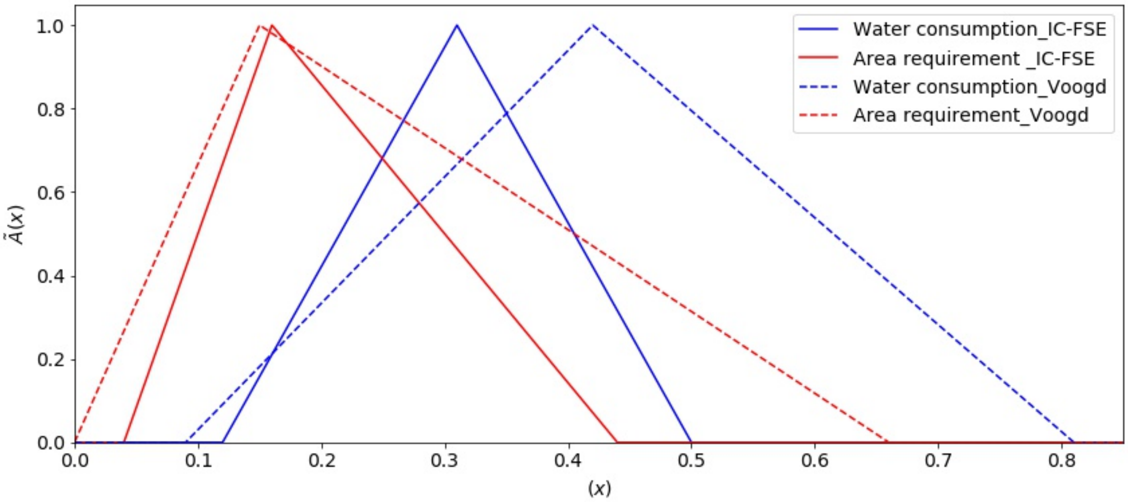

Fig. A.1 The comparison of fuzzy entropy weights $(\widetilde{w_i})$ of water consumption and area requirement criteria that are obtained from the Nijkamp and Delft's normalisation procedure and the Voogd normalisation procedure.

B) A Comparison of IC-FSE with an existing method based on ordered fuzzy numbers

The main differences between the proposed IC-FSE and the existing method based on ordered fuzzy numbers [28] are in the normalisation procedure that is formulated in equations (12)–(14), the computation of the fuzzy entropy values $(\widetilde{e_i})$ that is formulated in equations (15)–(19), and the computation of the fuzzy entropy weights $(\widetilde{w_i})$ that is formulated in equations (20)–(23). In the Kacprzak's method, the Voogd's normalisation procedure is applied to normalise elements of TFN in a fuzzy decision matrix. Equations (B.1)–(B.3) show the algorithms for finding $\widetilde{r_{ji}} = \left(r^K_{ji_L}, r^K_{ji_M}, r^K_{ji_U}\right)$, $i = 1, \ldots, n$ and $j = 1, \ldots, m$ (where the superscript index K represents the fuzzy arithmetic based on the Kacprzak method and the sub-subscript indexes L, M, and U refer to the lowest, middle and highest boundary values).

$$r^K_{ji_L} = \left\{\frac{{x_{ji}}^L}{\sum_{j=1}^{m}\left({x_{ji}}^L\right)}\right\}, \tag{B.1}$$

$$r^K_{ji_M} = \left\{\frac{{x_{ji}}^M}{\sum_{j=1}^{m}\left({x_{ji}}^M\right)}\right\}, \tag{B.2}$$

$$r^K_{ji_U} = \left\{\frac{{x_{ji}}^U}{\sum_{j=1}^{m}\left({x_{ji}}^U\right)}\right\}. \tag{B.3}$$

In addition, the algorithms for obtaining fuzzy entropy values, $(\widetilde{e_i}) = \left(e^K_{i_L}, e^K_{i_M}, e^K_{i_U}\right)$, based on the Kacprzak's method are formulated in the following equations:

$$e_{i_L}^K = \left\{ -\frac{\sum_{j=1}^{m}\left(\frac{r_{ji}{}^L}{\sum_{j=1}^{m} r_{ji}{}^L} \times ln \frac{r_{ji}{}^L}{\sum_{j=1}^{m} r_{ji}{}^L}\right)}{\ln m} \right\}, \tag{B.4}$$

$$e_{i_M}^K = -\frac{\sum_{j=1}^{m}\left(\frac{r_{ji}{}^M}{\sum_{j=1}^{m} r_{ji}{}^M} \times ln \frac{r_{ji}{}^M}{\sum_{j=1}^{m} r_{ji}{}^M}\right)}{\ln m}, \tag{B.5}$$

$$e_{i_U}^K = \left\{ -\frac{\sum_{j=1}^{m}\left(\frac{r_{ji}{}^U}{\sum_{j=1}^{m} r_{ji}{}^U} \times ln \frac{r_{ji}{}^U}{\sum_{j=1}^{m} r_{ji}{}^U}\right)}{\ln m} \right\}, \tag{B.6}$$

while the algorithms for computing the fuzzy entropy weight $(\widetilde{w_i}) = \left(w_{i_L}^K, w_{i_M}^K, w_{i_U}^K\right)$ of each criterion are expressed in the following equations:

$$w_{i_L}^K = \left\{\left(\frac{1 - e_{i_L}^C}{\sum_{i=1}^{n} e_{i_L}^C}\right)\right\}, \tag{B.7}$$

$$w_{i_M}^K = \frac{1 - e_{i_M}^K}{\sum_{i=1}^{n} e_{i_M}^K}, \tag{B.8}$$

$$w_{i_U}^K = \left\{\left(\frac{1 - e_{i_U}^C}{\sum_{i=1}^{n} e_{i_U}^C}\right)\right\}. \tag{B.9}$$

Table B.1 The fuzzy entropy values $(\widetilde{e_i})$ and fuzzy entropy weights $(\widetilde{w_i})$ obtained from the Kacprzak's method

	Capacity factor (C_1)	Water consumption (C_2)	GHG emissions (C_3)	Area requirement (C_4)	Levelised energy cost (C_5)	Prospective jobs (C_6)
$(\widetilde{e_i})$	(0.86, 0.94, 0.93)	(0.33, 0.6, 0.71)	(0.89, 0.89, 0.93)	(1.0, 0.86, 0.72)	(0.96, 0.86, 0.86)	(0.96, 0.92, 0.95)
$(\widetilde{w_i})$	(0.14, 0.06, 0.08)	(0.67, 0.42, 0.32)	(0.11, 0.12, 0.08)	(0.0, 0.15, 0.31)	(0.04, 0.15, 0.15)	(0.04, 0.08, 0.06)

Table B.1 shows the fuzzy entropy values $(\widetilde{e_i})$ and fuzzy entropy weights $(\widetilde{w_i})$ obtained from the Kacprzak's method. As can be observed from Table B.1, the lower, middle and upper values of $(\widetilde{e_i})$ and $(\widetilde{w_i})$ do not follow the notion of TFN that is presented in equation (1). Thus, the results do not represent a fuzzy number; in fact, they are just a triplet of real numbers. In addition, since such triplet of real numbers does not represent a TFN, the fuzzy entropy weights $(\widetilde{w_i})$ cannot be represented graphically and cannot be compared to those obtained from IC-FSE. It can be concluded that by taking into account the interactions among the elements in the calculations, the application of constrained fuzzy arithmetic in IC-FSE results in a correct estimation of the fuzzy entropy weights $(\widetilde{w_i})$.

References

[1] Disli M, Ng A, Askari H. Culture, income, and CO2 emission. Renew Sust Energ Rev. 2016;62:418-28.

[2] Troldborg M, Heslop S, Hough RL. Assessing the sustainability of renewable energy technologies using multi-criteria analysis: Suitability of approach for national-scale assessments and associated uncertainties. Renew Sust Energ Rev. 2014;39:1173-84.

[3] Dincer I. Renewable energy and sustainable development: a crucial review. Renew Sust Energ Rev. 2000;4:157-75.

[4] Roy B. Multicriteria Methodology for Decision Aiding. US: Kluwer Academic Publishers, Dordrecht; 1996.

[5] Mendoza GA, Martins H. Multi-criteria decision analysis in natural resource management: A critical review of methods and new modelling paradigms. Forest Ecol Manag. 2006;230:1-22.

[6] Huang IB, Keisler J, Linkov I. Multi-criteria decision analysis in environmental sciences: ten years of applications and trends. Sci Total Environ. 2011;409:3578-94.

[7] Sitorus F, Cilliers JJ, Brito-Parada PR. Multi-Criteria Decision Making for the Choice Problem in Mining and Mineral Processing: Applications and Trends. Expert Syst Appl. 2019;121:393-417.

[8] Wang J-J, Jing Y-Y, Zhang C-F, Zhao J-H. Review on multi-criteria decision analysis aid in sustainable energy decision-making. Renew Sust Energ Rev. 2009;13:2263-78.

[9] Ramón J, Mateo SC. Multi-Criteria Analysis in the Renewable Energy Industry: Springer-Verlag London; 2012.

[10] Kurka T, Blackwood D. Selection of MCA methods to support decision making for renewable energy developments. Renew Sust Energ Rev. 2013;27:225-33.

[11] Suganthi L, Iniyan S, Samuel AA. Applications of fuzzy logic in renewable energy systems – A review. Renew Sust Energ Rev. 2015;48:585-607.

[12] Strantzali E, Aravossis K. Decision making in renewable energy investments: A review. Renew Sust Energ Rev. 2016;55:885-98.

[13] Kumar A, Sah B, Singh AR, Deng Y, He X, Kumar P, et al. A review of multi criteria decision making (MCDM) towards sustainable renewable energy development. Renew Sust Energ Rev. 2017;69:596-609.

[14] Vafaeipour M, Hashemkhani Zolfani S, Morshed Varzandeh MH, Derakhti A, Keshavarz Eshkalag M. Assessment of regions priority for implementation of solar projects in Iran: New application of a hybrid multi-criteria decision making approach. Energ Convers Manage. 2014;86:653-63.

[15] Yunna W, Geng S. Multi-criteria decision making on selection of solar–wind hybrid power station location: A case of China. Energ Convers Manage. 2014;81:527-33.

[16] van de Kaa G, Rezaei J, Kamp L, de Winter A. Photovoltaic technology selection: A fuzzy MCDM approach. Renew Sust Energ Rev. 2014;32:662-70.

[17] Çolak M, Kaya İ. Prioritization of renewable energy alternatives by using an integrated fuzzy MCDM model: A real case application for Turkey. Renew Sust Energ Rev. 2017;80:840-53.

[18] Ren J. Sustainability prioritization of energy storage technologies for promoting the development of renewable energy: A novel intuitionistic fuzzy combinative distance-based assessment approach. Renew Energ. 2018;121:666-76.

[19] Ren J, Ren X. Sustainability ranking of energy storage technologies under uncertainties. J Clean Prod. 2018;170:1387-98.

[20] Simsek Y, Watts D, Escobar R. Sustainability evaluation of Concentrated Solar Power (CSP) projects under Clean Development Mechanism (CDM) by using Multi Criteria Decision Method (MCDM). Renew Sust Energ Rev. 2018;93:421-38.

[21] Saaty TL. The Analytic Hierarchy Process: McGraw-Hill, New York; 1980.

[22] Keeney RL. Decision Analysis: An Overview. Oper Res. 1982;30:803-38.

[23] Tsoukiàs A. On the concept of decision aiding process: an operational perspective. Ann Oper Res. 2007;154:3-27.

[24] Shannon CE. A Mathematical Theory of Communication. Bell Syst Tech J. 1948;27:379-423.

[25] Sitorus F, Cilliers JJ, Brito-Parada PR. An Integrated Constrained Fuzzy Stochastic Analytic Hierarchy Process Method with Application to the Choice Problem. Expert Syst Appl. 2019;138.

[26] Zadeh LA. Fuzzy sets. Inform Control. 1965;8:338-53.

[27] Kahraman C, Onar SC, Oztaysi B. Fuzzy Multicriteria Decision-Making: A Literature Review. Int J Comput Int Sys. 2015;8:637-66.

[28] Kacprzak D. Objective Weights Based on Ordered Fuzzy Numbers for Fuzzy Multiple Criteria Decision-Making Methods. Entropy. 2017;19:373.

[29] Yager RR. On the lack of inverses in fuzzy arithmetic. Fuzzy Sets Syst. 1980;4: 73-82.

[30] Klir GJ, Cooper JA. On Constrained Fuzzy Arithmetic. Proceedings of 5th international IEEE conference on fuzzy systems. New Orleans, LA, USA, 1996. p. 1285-90.

[31] Klir GJ. Fuzzy arithmetic with requisite constraints. Fuzzy Sets Syst. 1997;91:165-75.

[32] Buckley JJ. Solving fuzzy equations. Fuzzy Sets Syst. 1992;50:1-14.

[33] Enea M, Piazza T. Project Selection by Constrained Fuzzy AHP. Fuzzy Optim Decis Ma. 2004;3:39-62.

[34] Baykasoğlu A, Subulan K. Constrained fuzzy arithmetic approach to fuzzy transportation problems with fuzzy decision variables. Expert Syst Appl. 2017;81:193-222.

[35] Klir GJ, Pan Y. Constrained fuzzy arithmetic: Basic questions and some answers. Soft Comput. 1998;2:100-8.

[36] Paraszczak J, Fytas K. Renewable energy sources – a promising opportunity for remote mine sites? Renew Energ Power Qual. 2012;1:251-6.

[37] Zharan K, Bongaerts JC. Survey on Integrating of Renewable Energy into the Mining Industry. J Environ Account Manage. 2018;6:149-65.

[38] Vyhmeister E, Aleixendri Muñoz C, Bermúdez Miquel JM, Pina Moya J, Fúnez Guerra C, Rodríguez Mayor L, et al. A combined photovoltaic and novel renewable energy system: An optimized techno-economic analysis for mining industry applications. J Clean Prod. 2017;149:999-1010.

[39] Mudd GM. The Environmental sustainability of mining in Australia: key mega-trends and looming constraints. Resour Policy. 2010;35:98-115.

[40] Mason L, Prior T, Mudd G, Giurco D. Availability, addiction and alternatives: three criteria for assessing the impact of peak minerals on society. J Clean Prod. 2011;19:958-66.

[41] Ruiz-Rudolph P, Arias N, Pardo S, Meyer M, Mesias S, Galleguillos C, et al. Impact of large industrial emission sources on mortality and morbidity in Chile: A small-areas study. Environ Int. 2016;92-93:130-8.

[42] McLellan BC, Corder GD, Giurco DP, Ishihara KN. Renewable energy in the minerals industry: a review of global potential. J Clean Prod. 2012;32:32-44.

[43] Zharan K, Bongaerts JC. Decision-making on the integration of renewable energy in the mining industry: A case studies analysis, a cost analysis and a SWOT analysis. J Sustain Min. 2017;16:162-70.

[44] Votteler RG, Brent AC. A literature review on the potential of renewable electricity sources for mining operations in South Africa. J energy South Afr. 2016;27.

[45] Choi Y, Song J. Review of photovoltaic and wind power systems utilized in the mining industry. Renew Sust Energ Rev. 2017;75:1386-91.

[46] Şengül Ü, Eren M, Eslamian Shiraz S, Gezder V, Şengül AB. Fuzzy TOPSIS method for ranking renewable energy supply systems in Turkey. Renew Energ. 2015;75:617-25.

[47] Aman MM, Solangi KH, Hossain MS, Badarudin A, Jasmon GB, Mokhlis H, et al. A review of Safety, Health and Environmental (SHE) issues of solar energy system. Renew Sust Energ Rev. 2015;41:1190-204.

[48] Hernandez RR, Easter SB, Murphy-Mariscal ML, Maestre FT, Tavassoli M, Allen EB, et al. Environmental impacts of utility-scale solar energy. Renew Sust Energ Rev. 2014;29:766-79.

[49] Beccali M, Cellura M, Mistretta M. Decision-making in energy planning. Application of the Electre method at regional level for the diffusion of renewable energy technology. Renew Energ. 2003;28:2063-87.

[50] San Cristóbal JR. Multi-criteria decision-making in the selection of a renewable energy project in spain: The Vikor method. Renew Energ. 2011;36:498-502.

[51] Streimikiene D, Balezentis T, Krisciukaitienė I, Balezentis A. Prioritizing sustainable electricity production technologies: MCDM approach. Renew Sust Energ Rev. 2012;16:3302-11.

[52] Stein EW. A comprehensive multi-criteria model to rank electric energy production technologies. Renew Sust Energ Rev. 2013;22:640-54.

[53] National Statistics UK. National Statistics Energy Trends: UK renewables https://www.gov.uk/government/statistics/energy-trends-section-6-renewables; 2019 [accessed 19 November 2019].

[54] National Statistics UK. National Statistics Digest of UK Energy Statistics (DUKES): renewable sources of energy, https://www.gov.uk/government/statistics/renewable-sources-of-energy-chapter-6-digest-of-united-kingdom-energy-statistics-dukes; 2019 [accessed 19 November 2019].

[55] Meldrum J, Nettles-Anderson S, Heath G, Macknick J. Life cycle water use for electricity generation: a review and harmonization of literature estimates. Environ Res Lett. 2013;8.

[56] Shmelev SE, van den Bergh JCJM. Optimal diversity of renewable energy alternatives under multiple criteria: An application to the UK. Renew Sust Energ Rev. 2016;60:679-91.

[57] UKERC. Low carbon jobs: The evidence for net job creation from policy support for energy efficiency and renewable energy. UK Energy Research Centre Technology and Policy Assessment Function; 2014.

[58] Cameron L, van der Zwaan B. Employment factors for wind and solar energy technologies: A literature review. Renew Sust Energ Rev. 2015;45:160-72.

[59] Amponsah NY, Troldborg M, Kington B, Aalders I, Hough RL. Greenhouse gas emissions from renewable energy sources: A review of lifecycle considerations. Renew Sust Energ Rev. 2014;39:461-75.

[60] Evans A, Strezov V, Evans TJ. Assessment of sustainability indicators for renewable energy technologies. Renew Sust Energ Rev. 2009;13:1082-8.

[61] Chatzimouratidis AI, Pilavachi PA. Multicriteria evaluation of power plants impact on the living standard using the analytic hierarchy process. Energ Policy. 2008;36:1074-89.

[62] Bellman RE, Zadeh LA. Decision Making Fuzzy Environment. Manage Sci. 1970;17:141-64.

[63] Heo E, Kim J, Boo K-J. Analysis of the assessment factors for renewable energy dissemination program evaluation using fuzzy AHP. Renew Sust Energ Rev. 2010;14:2214-20.

[64] Van Laarhoven PJM, Pedrycz W. A fuzzy extension of Saaty's priority theory. Fuzzy Sets Syst. 1983;11:229-41.

[65] Cayir Ervural B, Zaim S, Demirel OF, Aydin Z, Delen D. An ANP and fuzzy TOPSIS-based SWOT analysis for Turkey’s energy planning. Renew Sust Energ Rev. 2018;82:1538-50.

[66] Kahraman C. Fuzzy multi-criteria decision making : theory and applications with recent developments. New York: Springer; 2008.

[67] Mousavi M, Gitinavard H, Mousavi SM. A soft computing based-modified ELECTRE model for renewable energy policy selection with unknown information. Renew Sust Energ Rev. 2017;68:774-87.

[68] Mardani A, Jusoh A, Zavadskas EK. Fuzzy multiple criteria decision-making techniques and applications – Two decades review from 1994 to 2014. Expert Syst Appl. 2015;42:4126-48.

[69] Tzeng G-H, Huang J-J. Multiple Attribute Decision Making: Methods and applications: Taylor & Francis Group, LLC; 2011.

[70] Weitendorf D. Beitrag zur optimierung der räumlichen Struktur eines Gebäude 1976.

[71] Nijkamp P, Delft Av. Multi-Criteria Analysis and Regional Decision-Making: Springer US; 1977.

[72] Voogd JH. Multicriteria evaluation for urban and regional planning. Delft: Delftsche Uitgevers Maatschappij 1982.

[73] Zardari NH, Ahmed K, Shirazi SM, Yusop ZB. Weighting Methods and their Effects on MultiCriteria Decision Making Model Outcomes in Water Resources Management: Springer; 2015.

[74] Brauers WKM, Zavadskas EK. The MOORA method and its application to privatization in a transition economy. Control Cybern. 2006;35:445-69.