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# The selection of renewable energy technologies using a hybrid subjective and objective multiple criteria decision making method

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ABSTRACT

The use of renewable energy technologies is a key factor for sustainable development but their selection from several alternatives is a difficult task that relies on the careful assessment of relevant criteria. While Multiple Criteria Decision Making (MCDM) methods have been used successfully in various renewable energy technology selection problems, the decision process becomes more challenging when preferential judgements are made on the basis of non-homogenous and imprecise input data, and when there is uncertainty due to disparities among decision makers. This paper presents a hybrid MCDM method capable of overcoming these problems by taking into account quantitative and qualitative data under a probabilistic environment in the context of group decision making. In this method, qualitative data is fuzzified and used along with quantitative data to develop a hybrid model. A coefficient factor allows decision makers to vary the weight of each quantitative model so that the resultant criteria weights and overall alternatives' scores consider both subjective considerations and objective information. An example is presented to showcase the usability of the method developed for ranking and evaluating renewable energy technologies in the mining industry. In addition, the impact of different coefficient factors on the final results was assessed by means of sensitivity analysis. The results indicate that the method developed is able to minimise the loss of valuable objective information, caused by the subjective bias of qualitative weights during the evaluations, by adjusting the coefficient factors of the hybrid model during the calculations.

## 1. Introduction

Energy-generating technologies that depend on non-renewable fossil fuels result in significant environmental challenges, such as increasing greenhouse gas (GHG) emissions, which lead to climate change (Disli et al., 2016; Li et al., 2020). In response to these challenges, it is important to better exploit renewable energy technologies (e.g. wind and solar), which are low-cost, clean and sustainable (Cunden et al., 2020; Dincer, 2000).

The selection of renewable energy technologies is a complex and multidisciplinary problem that mainly refers to the performance of the technologies concerning multiple criteria such as environmental, social, technical and economic (Wu et al., 2018). In order to evaluate holistically and select the technologies that have a higher performance appropriately, decision makers need to have methodological tools that incorporate both quantitative and qualitative analyses of the multiple criteria. Decision makers should, therefore, make use of the best tools available to evaluate the performance criteria of renewable energy technologies. Choosing the best renewable energy technology to use among various alternatives considering conflicting criteria is thus considered a Multiple Criteria Decision Making (MCDM) problem (Büyüközkan & Güleryüz, 2017).

Since the 1970 s, a variety of MCDM methods have been developed and extensively applied in many fields and for a wide range of case

*Abbreviations, units, and nomenclature:* AHP, Analytic Hierarchy Process; CSP, Concentrated Solar Power; FAHP, Fuzzy Analytic Hierarchy Process; GHG, Greenhouse Gas; IC-FSAHP, Integrated Constrained Fuzzy Stochastic Analytic Hierarchy Process, IC-FSE, Integrated Constrained Fuzzy Shannon Entropy; LEC, levelised energy cost; MCDM, Multiple Criteria Decision Making Method; NV, Normalised Vector; OW, Onshore Wind; PV, Photovoltaic; SE, Shannon Entropy; TFN, Triangular Fuzzy Number; WSM, Weighted Sum Model; $gCO_2eq/kWh$, 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.

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studies (Sitorus et al., 2019b). An MCDM selection problem is often arranged as a decision matrix in which alternatives are evaluated with respect to conflicting criteria. Most of MCDM methods have algorithms for determining the criteria weights that represent the relative importance or significance of each criterion to others. Algorithms are also applied to determine the weights of alternatives, usually referred to as alternatives' scores, which represent the relative preference of each alternative to others. The weighting methods in MCDM can be classified into two types: subjective methods, which are obtained from decision makers' opinions (i.e. qualitative), and objective methods, which are acquired purely from calculations (i.e. quantitative).

Many studies have demonstrated the successful application of MCDM methods for the selection of renewable energy technologies, as evidenced by extensive literature reviews provided by Wang et al. (2009) and Kumar et al. (2017). There is, however, a paucity of studies addressing the development and application of MCDM methods for problems in which preferential judgements are made based on non-homogenous data (i.e. quantitative and qualitative) (Ma et al., 1999; Rao & Patel, 2010; Rao et al., 2011), uncertain input data (i.e. probabilistic) (Ullah et al., 2021; Kotb et al., 2021; Krejčí, 2018; Troldborg et al., 2014; Zimmermann, 2000), and uncertainty caused by different decision makers' opinions (Ivanco et al., 2017; Sitorus et al., 2019a).

Even though there is a need for adequate mathematical tools to support the decision making process under the aforementioned circumstances, there has been no study on the development of decision tools that can be used to overcome complex selection problems, such as the selection of renewable energy technology. Consequently, in view of this lack of existing methods, the main research questions that need to be addressed are as follows:

1. What are the most suitable subjective and objective methods that can be used for the selection of renewable energy technologies?
2. What are the main shortcomings of the most suitable subjective and objective methods identified?
3. What are the notions and the applicability of the combined subjective and objective weights into a single framework?

In line with the aforementioned research questions, the objective of this work is to propose a systematic MCDM method for evaluating renewable energy technologies from a sustainability perspective and identifying the most appropriate alternative considering non-homogenous data (i.e. quantitative and qualitative), uncertainties due to imprecise input data and disparities among decision makers.

An integrated MCDM method is presented that takes into account quantitative and qualitative data under uncertainty in the context of group decision making. To this end, the proposed method combines a subjective method (i.e. Integrated Constrained Fuzzy Stochastic Analytic Hierarchy Process (IC-FSAHP)) (Sitorus & Brito-Parada, 2020a; Sitorus et al., 2019a) and objective methods (i.e. Integrated Constrained Fuzzy Shannon Entropy (IC-FSE) (Sitorus & Brito-Parada, 2020b), Normalised Vector (NV) (Voogd, 1982) and Weighted Sum Model (WSM)) (Fishburn, 1967). In order to showcase its capabilities, the method developed is applied to an example for the ranking and evaluation of renewable energy technologies in the mining industry.

The contribution of this paper is fourfold: (1) the gap in MCDM methods for problems involving quantitative and qualitative data under uncertainties due to imprecise data and different opinions among decision makers is explored; (2) a new method that combines IC-FSAHP, IC-FSE, NV, and WSM is presented; (3) the usability of the method developed is showcased and the outcomes obtained from the method are analysed; (4) a methodology for the carrying out of sensitivity analysis by varying the coefficient factors of subjective and objective weights, including the assessment of its results, is presented. It is demonstrated that the proposed method is a robust MCDM method that can be applied broadly in the renewable energy sector to support the process of decision making when there is uncertainty in the non-homogenous input data.

## 2. Literature review

An MCDM method involves four important steps (Roy, 1996), namely: (i) determining the local criteria weight; (ii) calculating the local alternatives' score; (iii) measuring the overall weighted alternatives' scores; (iv) selecting the best alternative which has the greatest overall weighted score. The final results obtained from any MCDM method mainly depend on the criteria, the criteria weights, the local and overall alternatives' scores, and the specific algorithm applied for calculating the criteria weights and the alternatives' scores (Sitorus et al., 2019b).

There are two main MCDM methods for deriving the criteria weights and the alternatives' scores, namely subjective and objective methods. In the subjective methods, the criteria weights and the alternatives' scores are acquired from decision makers' judgements and preferences via pairwise comparisons. One of the most widely applied subjective methods is the Analytic Hierarchy Process (AHP), developed by Saaty (1980). Despite its popularity, the application of AHP has been frequently criticised when uncertainty caused by the lack of information and uncertainty caused by various decision makers' opinions are present. The extension of AHP by coupling it with the fuzzy set theory is one of the most popular techniques to overcome the uncertainty problem caused by the lack of information. Moreover, stochastic simulation can be coupled with fuzzy AHP methods in order to capture uncertainty caused by opinions from multiple decision makers. Sitorus et al. (2019a) showed that IC-FSAHP is capable of minimising uncertainty and not only yielded more precise results than AHP and its variants, but also enhanced the reliability of decisions taken under uncertainty by means of multiple criteria group decision making.

Unlike the subjective methods, the criteria weights and the alternatives' scores in objective methods are obtained from the computation of quantitative data, using mathematical algorithms or models to derive the weights and scores without considering the decision makers' judgements and preferences. One of the most widely used objective methods is the Shannon Entropy method (SE) (Shannon, 1948). Regardless of its popularity, the application of SE has been often criticised when uncertainty caused by the imprecise input data is present. The extension of SE by combining it with the fuzzy set theory is one of the most popular techniques to overcome the uncertainty problem. The IC-FSE method, which has been developed by Sitorus and Brito-Parada (2020b), is able to reduce uncertainty and resulted in more accurate and precise results than existing methods.

It is worth noting that both weighting methods (i.e. for subjective and objective weights) have limitations. In order to comprehensively take into account the decision makers' opinions and reduce subjectivity, the opinions of decision makers and the objective information should be comprehensively considered to determine the criteria weights and alternatives' scores by means of combining both subjective and objective weights into a single framework. The notions and the applicability of the combined subjective and objective weights into a single framework are interesting and important aspects to study. One of the aims of this work is to present the notions and the applicability of such a combined method.

The use of renewable energy technologies (e.g. wind power and solar power) has gained enormous interest due to an increasing environmental awareness and the need to avoid the negative impacts of non-renewable fossil fuels on the environment (i.e. producing GHG emissions which lead to global warming and climate change) (Strantzali & Aravossis, 2016). Expanding the application of renewable energy technologies in many sectors, particularly in large energy consuming industries, is of vital importance. Renewable energy technologies are environmentally friendly and able to compete with fossil fuels in a wide variety of applications at reasonable prices (Rani et al., 2020; Rani et al., 2019).

The use of renewable energy sources is a key factor for sustainable development (Sánchez-Lozano et al., 2016). However, there are several aspects linked to the implementation of renewable energy technologies that need to be considered. Among those factors are their high initial cost (Solangi et al., 2019), potential capacity limitations (e.g. inconsistent energy source input) (Sitorus & Brito-Parada, 2020b), infrastructure management (e.g. land area required) (Yuan et al., 2018), and social impacts management (e.g. the acceptance and understanding by the public of some renewable energy technologies) (Yuan et al., 2018).

Moreover, it is vital to understand and assess the trade-offs between the aforementioned aspects associated with different renewable energy technologies. The selection of a renewable energy technology for a given application often requires a careful management of conflicting technical, environmental, and socio-economic criteria (Sitorus & Brito-Parada, 2020b). For example, the use of renewable energy technologies reduces GHG emissions but can be costly and may have impacts on land use or habitats. There is thus a need for adequate tools that can deal with these conflicts and trade-offs when evaluating and selecting the most suitable renewable energy technologies at a given location.

In many cases, the selection of the most suitable renewable energy technology involves several challenges, such as non-homogenous input data and uncertainties due to either imprecise input data or to divergent opinions from decision makers. These challenges can make the selection process significantly more difficult. The benefit of MCDM, compared to single criterion decision analysis, is that the methods take into account multiple conflicting criteria to attain an integrated decision result (Kumar et al., 2017).

MCDM methods have been successfully applied in a number of different aspects in renewable energy, such as selection of on/off grid hybrid solar, wind, hydro, biomass clean electricity supplies using an integrated Fuzzy-AHP/TOPSIS/EDAS/MOORA (Ullah et al., 2021), selection of optimal design of solar, wind, diesel-based RO desalination integrating flow-battery and pumped-hydro storage using an integrated Fuzzy-AHP and Fuzzy-VIKOR (Kotb et al., 2021), selection of renewable energy sources employing Fuzzy TOPSIS (Rani et al., 2020) and using an integrated AHP-CODAS Method (Ali et al., 2020), renewable energy technologies evaluation using Fuzzy VIKOR (Rani et al., 2019), selection of optimal design of sustainable energy system using AHP, TOPSIS, VIKOR, CODAS, WASPAS (Elkadeem et al., 2021a), optimal sites selection for photovoltaic solar farms using two different MCDM methods, namely TOPSIS and ELECTRE TRI (Sánchez-Lozano et al., 2016) and optimal sites selection for solar and wind energies using an integrated a GIS-based MCDM model (Elkadeem et al., 2021b), sustainable energy planning strategies evaluation by means of an integrated AHP and Fuzzy TOPSIS method (Solangi et al., 2019), and the evaluation of a renewable energy project performance using an extended TODIM (Zhang et al., 2019). In all the aforementioned cases, MCDM supported decision makers in determining the importance of criteria and the preference of alternatives, and in making a proper selection based on the rank order of the alternatives.

MCDM methods can be classified into subjective and objective methods, depending on the type of weighting considered. Table 1 shows successful examples of the most frequently used subjective (i.e. AHP based) and objective (i.e. SE based) methods for the selection of renewable energy technology.

Ali et al. (2020) and Elkadeem et al. (2021a) successfully applied AHP, the most frequently used subjective method, to determine the most suitable renewable energy sources and the optimal design of sustainable energy system, respectively. It should be noted that Ali et al. (2020) and Elkadeem et al. (2021a) assumed that the input data, all criteria weights and alternatives' scores were expressed as crisp values. However, it is often the case that selection problems are associated with uncertainties due to imprecise input data, and thus all criteria weights and alternatives' scores are expressed in fuzzy numbers. In this regard, Kotb et al. (2021) and Ullah et al. (2021) showed the successful development and application of combined Fuzzy AHP methods to select the most optimal design of solar, wind, diesel-based RO desalination integrating flow-battery and pumped-hydro storage and to select the optimal type of on/off grid hybrid solar, wind, hydro, biomass clean electricity supplies to be used, respectively. It should be noted that while Kotb et al. (2021) and Ullah et al. (2021) made use of experts' opinions to determine the importance of criteria and preference of alternatives, they did not take into account uncertainties associated to the various opinions from the experts. Sitorus et al. (2019a) developed a method that makes use of stochastic simulations to capture the various opinions from the experts in assessing selection problems that are associated with the imprecise input data.

**Table 1**
Examples of successful application of the most frequently used subjective MCDM methods (i.e. AHP based) and objective MCDM methods (i.e. SE based) for the selection of renewable energy technology.

| Subjective methods | Criteria | Alternatives | Scope |
|---|---|---|---|
| An integrated AHP-CODAS method (Ali et al., 2020). | 13 sub-criteria under the following aspects:<br>1. Technical,<br>2. Economic,<br>3. Environmental,<br>4. Socio-political. | 3 feasible alternatives such as:<br>1. Solar-wind hybrid energy system,<br>2. Solar mini-grid,<br>3. Wind mini-grid. | Evaluating and selecting the most suitable renewable energy sources. |
| An integrated Fuzzy AHP (FAHP) and Fuzzy-VIKOR (Kotb et al., 2021). | 10 key performance criteria (KPC) covering the following aspects:<br>1. Economic,<br>2. Environmental,<br>3. Energy. | 10 feasible alternatives (i.e. from case 0 to case 9). | Selecting an optimal design of solar, wind, diesel-based RO desalination integrating flow-battery and pumped-hydro storage. |
| AHP, TOPSIS, VIKOR, CODAS, WASPAS (Elkadeem et al., 2021a). | 12 sub-criteria based on the following aspects:<br>1. Energy,<br>2. Economic,<br>3. Environmental,<br>4. Social. | 11 energy system alternatives (i.e. from case 1 to case 11). | Selecting the optimal design of sustainable energy system. |
| An integrated Fuzzy-AHP/TOPSIS/EDAS/MOORA (Ullah et al., 2021). | 5 criteria such as:<br>1. Economy,<br>2. Reliability,<br>3. Ecology,<br>4. Society,<br>5. Topography. | 12 energy system alternatives (i.e. from case A1 to case A12). | Selecting on/off grid hybrid solar, wind, hydro, biomass clean electricity supplies. |
| Objective methods | Criteria | Alternatives | Scope |
| SE (Simsek et al., 2018). | 10 sub-criteria based on the following aspects:<br>1. Technical,<br>2. Economic,<br>3. Environmental,<br>4. Social. | 11 schemes including:<br>1. Morocco_160,<br>2. India_125,<br>3. Israel_120,<br>4. Abu Dhabi_100,<br>5. China_50,<br>6. India_50<br>7. India_25<br>8. Thailand_5<br>9. Chile_4.2<br>10. India_3<br>11. Lebanon_2.2 | Evaluating the sustainability of concentrated solar power technologies. |
| Fuzzy SE (Sitorus & Brito-Parada, 2020b). | 6 criteria such as:<br>1. Capacity factor,<br>2. Water consumption,<br>3. GHG emissions,<br>4. Area requirement,<br>5. Levelised Energy Cost,<br>6. Prospective jobs. | 3 alternatives including:<br>1. Onshore wind<br>2. CSP<br>3. PV | Weighting the sustainability criteria of wind and solar power technologies. |

Simsek et al. (2018) successfully implemented SE, the most frequently used objective method, to evaluate the sustainability of concentrated solar power technologies. It is worth mentioning that Simsek et al. (2018) assumed that all input data were expressed as crisp values. As previously mentioned, the input data to be analysed are often imprecise and thus the use of crisp SE is not sufficient. Sitorus and Brito-Parada (2020b) developed a method that combines ordered fuzzy numbers and the SE method (i.e. IC-Fuzzy SE) to weight the sustainability criteria of wind and solar power technologies.

It is worth highlighting that the successful examples discussed above did not consider the case when non-homogeneous data, uncertainties due to imprecise input data and disparities among decision makers are involved. There is scope to develop a method capable of dealing with such cases.

Mining operations are very energy intensive, with energy costs typically accounting for 30–50% of all operating costs (Zharan & Bongaerts, 2018). Mining operations are often located in remote areas where the mineral deposits are discovered. Due to the remoteness of mine sites, accessibility to energy sources is usually limited, which results in fossil fuels being the only readily available option to power equipment (Paraszczak & Fytas, 2012); in fact, this contributes to the mining industry heavy dependence on non-renewable energy sources (Zharan & Bongaerts, 2018).

Mining operations are noticeably responsible for producing greenhouse gas (GHG) emissions not only from the use of fossil fuels for operating equipment but also for power generation. Moreover, as the global demand for minerals continues to increase and the process to extract and separate them require greater amounts of energy (due to the need of mining lower grade and finely disseminated ores), greater emissions are produced (Mason et al., 2011). In order to address the aforementioned concerns, many mining companies have started to give greater consideration to the use of renewable energy technologies in their operations (McLellan et al., 2012; Moreno-Leiva et al., 2020; Vyhmeister et al., 2017).

MCDM methods have been successfully used in a number of different aspects in the mining industry, including the assessment of mine closure risk using an integrated AHP, PROMETHEE, and TOPSIS method (Amirshenava & Osanloo, 2018), sustainable water management in a mining complex by means of AHP (Freitas & Magrini, 2013), corporate social responsibility strategies evaluation in the mining industry employing fuzzy DEMATEL (Govindan et al., 2014). While previous studies in the literature have emphasised the importance of applying MCDM methods in evaluating and selecting renewable energy technologies, no study has yet done so for the mining industry.

There are, however, other tools that have been used in the literature to evaluate the performance of renewable energy technologies and select the best alternative in the mining industry. Mostert (2014) adopted the triple bottom line (i.e. financial, social, and environmental) accounting method to evaluate the sustainability of a project in order to select the best renewable energy technology in the mining industry. The financial, social, and environmental values were engineered in order to determine a monetary value for a renewable energy project. However, Mostert (2014) recommends that a monetary value alone is not sufficient to base a decision on, and a combination of qualitative measures to be used in conjunction with the triple bottom line are advocated. A different decision-making approach to implement renewable energy technologies in the mining industry, namely the use of cost analysis and SWOT analysis, was applied by Zharan and Bongaerts (2017). Both Mostert (2014) and Zharan and Bongaerts (2017) considered mainly the financial value on a decision. It is worth noting, however, that there were no multiple conflicting criteria involved in their evaluation. Because of the complexity of decision analysis, primarily in terms of problem analysis and structuring, the aforementioned tools (i.e. those in Mostert (2014) and Zharan and Bongaerts (2017)), tend not to be sufficient to support decision makers in the evaluation of more complex selection problems. An appropriate tool, such as MCDM methods, would therefore be required to better support decision makers in selecting renewable energy technologies in the mining industry.

## 3. Research framework

In line with the challenges discussed in Sections 1 and 2, the research framework for this study, as shown in Fig. 1, is as follows: first, the development of novel hybrid MCDM method including the workflows and equations of the novel method is presented; second, the applicability of the novel hybrid method in an illustrative example is showcased; finally, the conclusions of the current work are provided.

## 4. MCDM methodology

The following sub-sections discuss the key theoretical aspects behind Triangular Fuzzy Number (TFN), Integrated Constrained Fuzzy Stochastic AHP (IC-FSAHP), Integrated Constrained Fuzzy Shannon Entropy (IC-FSE), Normalised Vector (NV), and Weighted Sum Model (WSM)) and the proposed hybrid method. TFN is used to represent the uncertain data as ordered real numbers, consisting of minimum, medium and maximum numbers, IC-FSAHP is used to calculate the criteria weights and the alternatives' scores in a subjective manner, while an objective procedure makes use of IC-FSE to determine the criteria weights, with the NV and WSM methods used to calculate the local and overall alternatives' scores, respectively.

### 4.1. TFN

The order of membership function of TFN $\widetilde{A}(x)$ is expressed in the following form:

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

where $c_A^L$ and $c_A^U$ are the lowest and highest values of TFN $\widetilde{A}(x)$, while $c_A^M$ is the middle value of TFN $\widetilde{A}(x)$. Fig. 2 shows an example of a TFN which has a membership function of 2, 3, and 4.

In this work, a crisp number value of the TFN is obtained using the centre-of-area (COA) defuzzification approach, proposed by Tzeng and Huang (2011), and is expressed in the following form:

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

### 4.2. Subjective weighting method

In the current work, IC-FSAHP was used as a subjective weighting method for obtaining the criteria weights and the overall alternatives' scores. Sitorus et al. (2019a) showed that IC-FSAHP was able to reduce uncertainties caused by imprecise input data and various judgements among decision makers.

The following steps to apply the IC-FSAHP method are: (i) the notions of a decision problem are defined; (ii) the local fuzzy criteria weights and the local fuzzy alternatives' scores are calculated; (iii) the overall alternatives' scores are calculated; (iv) the results are synthesised; (v) the alternatives are ranked. Fig. 3 shows the workflow of the IC-FSAHP method. The reader is referred to Sitorus et al. (2019a) for a full description of the steps.

For the simplicity of data collection and analysis, a scale of seven linguistic variables used in Sitorus and Brito-Parada (2020a) was applied

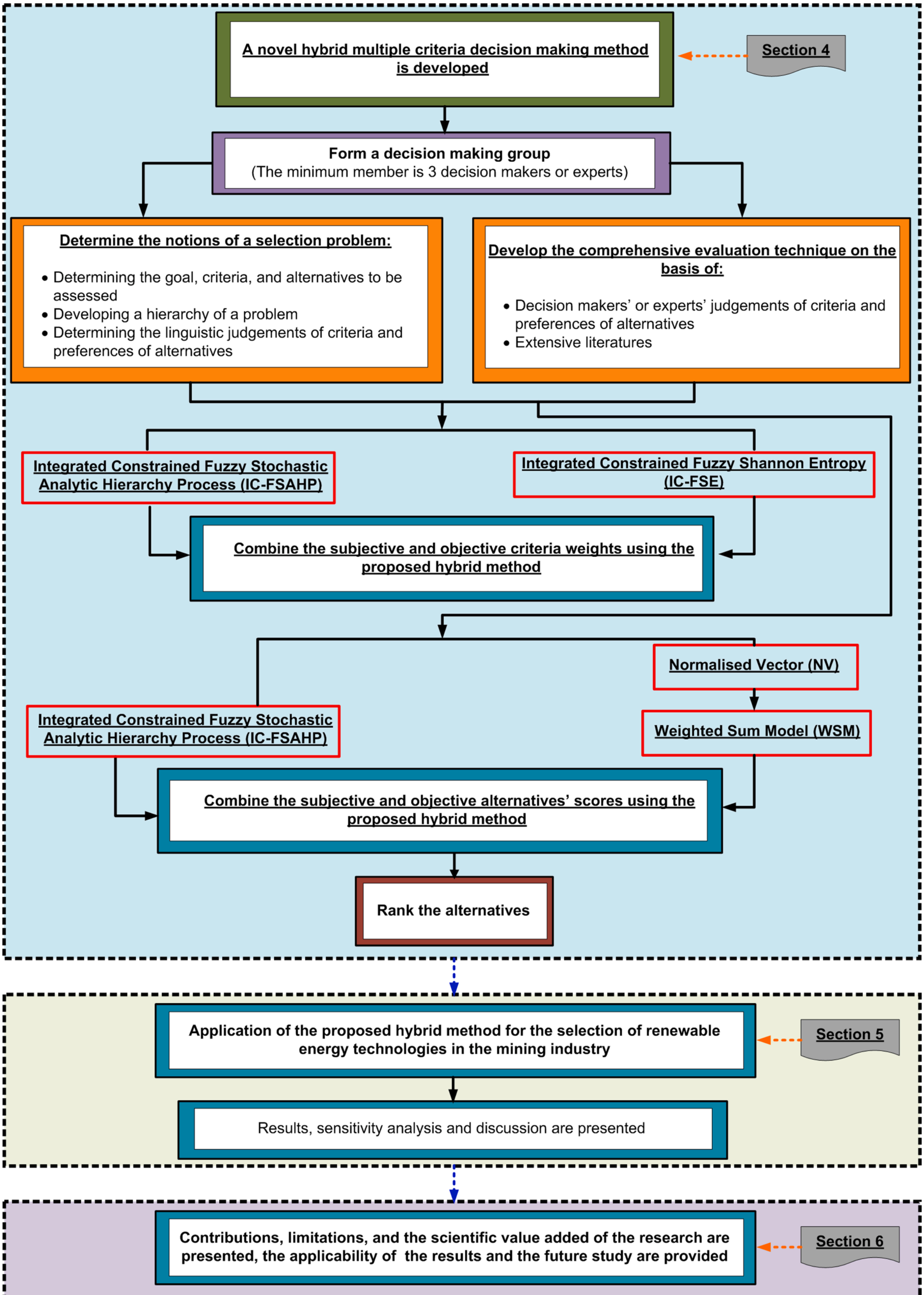


**Fig. 1.** Flowchart of the research in this work.

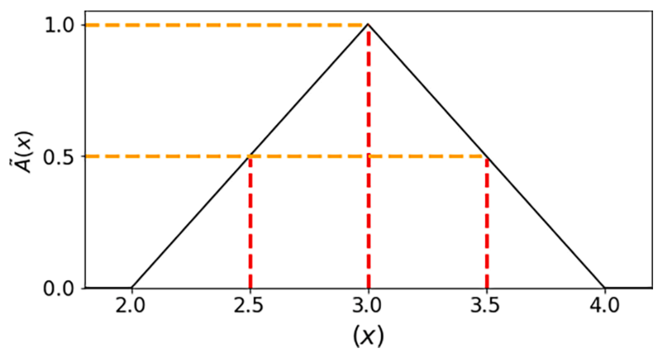


**Fig. 2.** Membership function of a TFN (2, 3, 4).

in this work. Fig. 4 presents the membership functions for the TFN scale levels.

It is worth noting that the weights of criteria and the overall scores of alternatives obtained from IC-FSAHP are expressed as $We_i^S$ and $OSc_k^S$, respectively. $We_i^S$ is the defuzzified value of $We_{iL}^S$, $We_{iM}^S$ and $We_{iU}^S$, which are obtained from the following equations:

$$We_{iL}^S = min\left\{\frac{\sqrt[n]{\Pi_{j=1}^n a_{ij}}}{\sum_{i=1}^n \sqrt[n]{\Pi_{j=1}^n a_{ij}}}; \begin{array}{l} a_{ij}\in[a_{ijL}, a_{ijU}], \forall j > i, \\ a_{ji} = \dfrac{1}{a_{ij}}, \forall j < i, \\ a_{jj} = 1, \forall j \end{array}\right\}, \tag{3}$$

$$We_{iM}^S = \left\{\frac{\sqrt[n]{\Pi_{j=1}^n a_{ijM}}}{\sum_{i=1}^n \sqrt[n]{\Pi_{j=1}^n a_{ijM}}}\right\}, \tag{4}$$

$$We_{iU}^S = max\left\{\frac{\sqrt[n]{\Pi_{j=1}^n a_{ij}}}{\sum_{i=1}^n \sqrt[n]{\Pi_{j=1}^n a_{ij}}}; \begin{array}{l} a_{ij}\in[a_{ijL}, a_{ijU}], \forall j > i, \\ a_{ji} = \dfrac{1}{a_{ij}}, \forall j < i, \\ a_{jj} = 1, \forall j \end{array}\right\}, \tag{5}$$

where the superscript $S$ represents the subjective weighting method, the subscripts $L$, $M$ and $U$ describe the lowest, middle, and highest numbers in TFN and $a_{ij}$ represents the extent to which a criterion $i$ is more important than a criterion $j$ $(i = j = 1, 2, \cdots, n)$ with respect to the goal.

Furthermore, $OSc_k^S$ is the defuzzified value of $OSc_{kL}^S$, $OSc_{kM}^S$ and $OSc_{kU}^S$, which are determined from the following formulas:

$$OSc_{kL}^S = min\left\{\frac{\sum_{i=1}^n \sqrt[n]{\Pi_{j=1}^n a_{ij}} LSc_{kL}^S}{\sum_{i=1}^n \sqrt[n]{\Pi_{j=1}^n a_{ij}}}; \begin{array}{l} a_{ij}\in[a_{ijL}, a_{ijU}], \forall j > i, \\ a_{ji} = \dfrac{1}{a_{ij}}, \forall j < i, \\ a_{jj} = 1, \forall j \end{array}\right\}, \tag{6}$$

$$OSc_{kM}^S = \frac{\sum_{i=1}^n \sqrt[n]{\Pi_{j=1}^n a_{ijM}} LSc_{kM}^S}{\sum_{i=1}^n \sqrt[n]{\Pi_{j=1}^n a_{ijM}}}, \tag{7}$$

$$OSc_{kU}^S = max\left\{\frac{\sum_{i=1}^n \sqrt[n]{\Pi_{j=1}^n a_{ij}} LSc_{kU}^S}{\sum_{i=1}^n \sqrt[n]{\Pi_{j=1}^n a_{ij}}}; \begin{array}{l} a_{ij}\in[a_{ijL}, a_{ijU}], \forall j > i, \\ a_{ji} = \dfrac{1}{a_{ij}}, \forall j < i, \\ a_{jj} = 1, \forall j \end{array}\right\}, \tag{8}$$

where $LSc$ describes the local scores of alternatives which are acquired by using equations (3) – (5) (i.e. $a_{ij}$ represents the extent to which each alternative $i$ is more important than an alternative $j$ $(i = j = 1, 2, \cdots, m)$ with respect to each criterion $(1, 2, \cdots, n)$, and $k$ represents the $k$-th alternative $(k = 1, 2, \cdots, m)$.

### 4.3. Objective weighting method

In the objective weighting method, three approaches were applied for determining the criteria weights, the local and overall alternatives' scores. IC-FSE was used for calculating the criteria weights while NV and WSM were used for determining the local and overall alternatives' scores, respectively.

#### 4.3.1. Objective criteria weighting method

IC-FSE was used to determine the criteria weights when subjective weights are difficult to be acquired and the input data that need to be evaluated are difficult to be defined precisely (thus need to be presented in TFN). Sitorus and Brito-Parada (2020b) showcased that IC-FSE was able to produce precise fuzzy weights with less uncertainty and could maintain the order of TFN properly.

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 weights of criteria. Fig. 5 presents the framework of the IC-FSE method, a detailed explanation of which can be found in Sitorus and Brito-Parada (2020b).

It is worth mentioning that the weights of criteria obtained from IC-FSE are expressed as $We_i^O$. $We_i^O$ is the defuzzified value of $We_{iL}^O$, $We_{iM}^O$ and $We_{iU}^O$, which are obtained from the following equations:

$$We_{iL}^O = min\{(\frac{1 - e_i}{\sum_{i=1}^n e_i}); e_i\in[e_{i_L}^C, e_{i_U}^C]\}, \tag{9}$$

$$We_{iM}^O = \frac{1 - e_i{}^M}{\sum_{i=1}^n e_i{}^M}, \tag{10}$$

$$We_{iU}^O = max\{(\frac{1 - e_i}{\sum_{i=1}^n e_i}); e_i\in[e_{i_L}^C, e_{i_U}^C]\}, \tag{11}$$

where the superscript $O$ represents the objective weighting method and $e_i$ is the fuzzy entropy value of the $i$-th criterion $(i = 1, 2, \cdots, n)$.

#### 4.3.2. Objective local priorities of alternatives scoring method

Each alternative is evaluated with regard to its data corresponding to every criterion. The local scores of alternatives $(LSc_k^O)$ are obtained from the NV method.

For the beneficial criteria that should be maximised, such as potential total power generation ($C_1$) and prospective jobs creation ($C_5$), the direct NV method formulated in the following equation is applied:

$$LSc_k^O = (\frac{x_{ki}}{\sum_{k=1}^m (x_{ki})}). \tag{12}$$

For the non-beneficial criteria that should be minimised, such as GHG emissions ($C_2$), area requirement ($C_3$) and LEC ($C_4$), the reciprocal NV method formulated in the equation below is applied:

$$LSc_k^O = (\frac{1/x_{ki}}{\sum_{k=1}^m 1/(x_{ki})}). \tag{13}$$

The superscript $O$ in $LSc_k^O$ represents the objective weighting method and $x_{ki}$ is the defuzzified rating of the $k$-th alternative with respect to the $i$-th criterion.

#### 4.3.3. Objective overall priorities of alternatives scoring method

Based on the aforementioned description, each criterion has an objective weight obtained from IC-FSE $(We_i^O)$ and each alternative has a local score obtained from NV $(LSc_k^O)$. The overall alternatives' scores $(\widetilde{OSc_k^O})$ are obtained by aggregating the local alternatives' scores with the criteria weights by means of the WSM formulated in the following

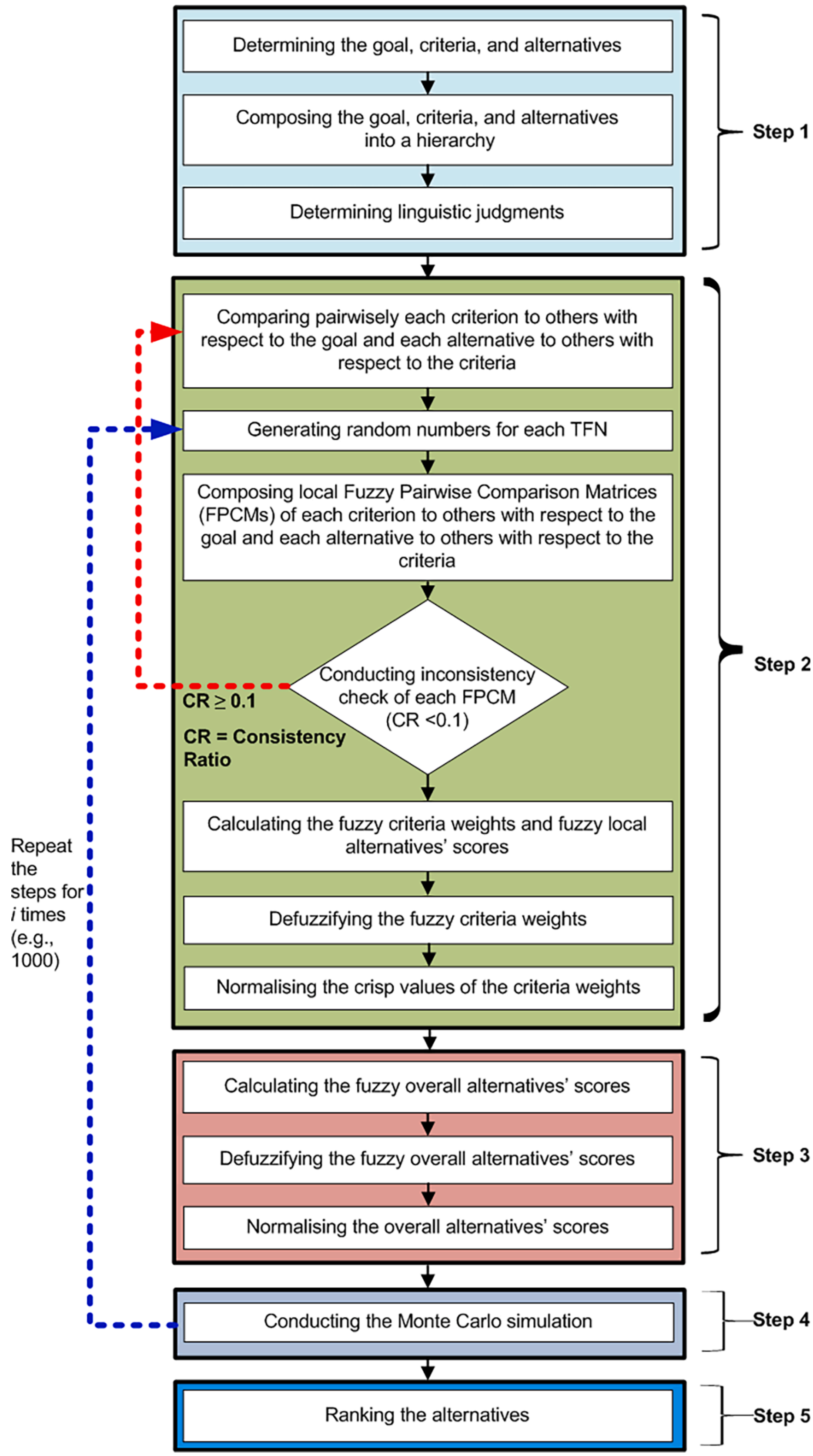


**Fig. 3.** The workflow of the IC-FSAHP method (Sitorus et al., 2019a).

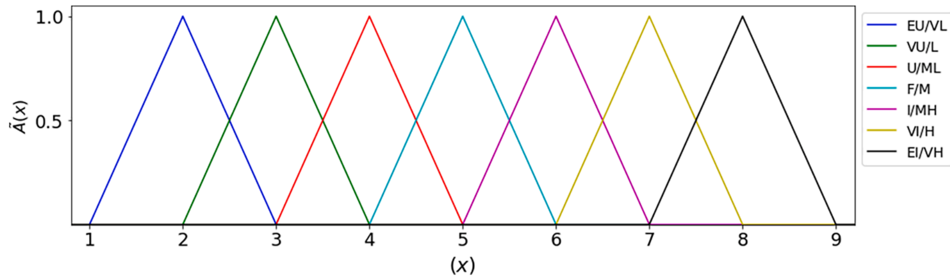


**Fig. 4.** Membership functions of the TFN scale levels used in evaluating the criteria and alternatives (note: EU: Extremely Unimportant, VU: Very Unimportant, U: Unimportant, F: Fair, I: Important, VI: Very Important, EI: Extremely Important, VL: Very Low, L: Low, ML: Medium Low, M: Medium, MH: Medium High, H: High, and VH: Very High).

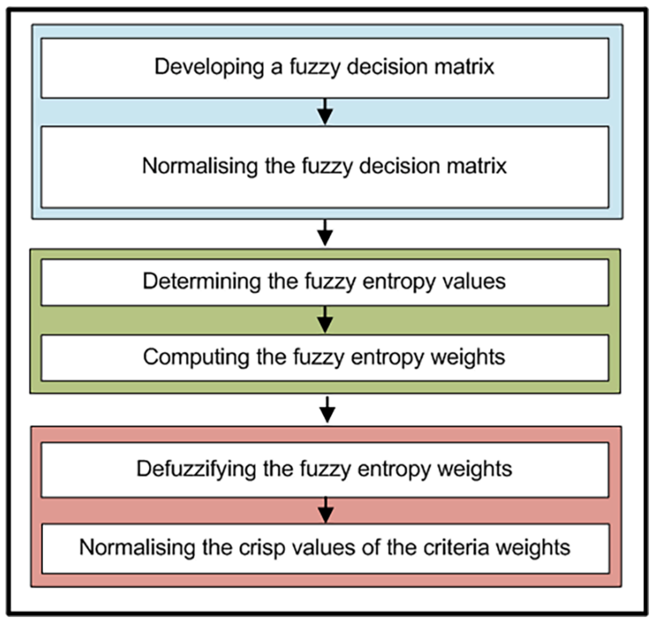


**Fig. 5.** The framework of the IC-FSE method (Sitorus & Brito-Parada, 2020b).

form:

$$\widetilde{OSc_k^O} = \sum_{i=1}^{n} We_i^O LSc_k^O. \tag{14}$$

Furthermore, the normalised overall score of the $k$-th alternative ($OSc_k^O$) is obtained using the distributive mode approach expressed in the equation below

$$OSc_k^O = \frac{\widetilde{OSc_k^O}}{\sum_{k=1}^{m} \widetilde{OSc_k^O}}. \tag{15}$$

### *4.4. Proposed combined method*

In line with the descriptions in Sections 4.1, 4.2 and 4.3, in the case when decision makers need to use both objective and subjective weighting methods, the following combined methodology is proposed.

a. For the combined weights of criteria ($We_i^C$), the following equation is applied:

$$We_i^C = (\alpha We_i^S) + (\beta We_i^O); \alpha + \beta = 1. \tag{16}$$

b. For the combined overall scores of alternatives ($OSc_k^C$), the equation below is applied:

$$OSc_k^C = (\alpha OSc_k^S) + (\beta OSc_k^O); \alpha + \beta = 1. \tag{17}$$

The superscript $C$ in $We_i^C$ and $OSc_k^C$ represents the combined subjective and objective weights while $\alpha$ and $\beta$ are the coefficient factors given to the subjective and objective weights, respectively. The coefficient factors $\alpha$ and $\beta$ thus enable decision makers to determine how much importance they intend to assign to the subjective and objective weights. In this paper, $\alpha = \beta = 0.5$ was used for the base case calculations. In order to show the impact of the changes of coefficient factor $\alpha$ on the final results, six values of $\alpha$ were considered for a sensitivity analysis, namely 0, 0.2, 0.4, 0.6, 0.8, 1.

The detailed flowcharts of the proposed novel hybrid MCDM method for weighting the criteria and scoring the alternatives are shown in Figs. 6 and 7, respectively.

## 5. Application of the method developed to the selection of renewable energy technologies in the mining industry

There is a need for adequate MCDM methods to support decision makers in selecting renewable energy technologies in the mining industry when preferential judgements are made based on non-homogenous data (i.e. quantitative and qualitative), uncertain input data (i.e. probabilistic), and uncertainty because of different decision makers' opinions. In this section, the applicability of the novel MCDM method is showcased.

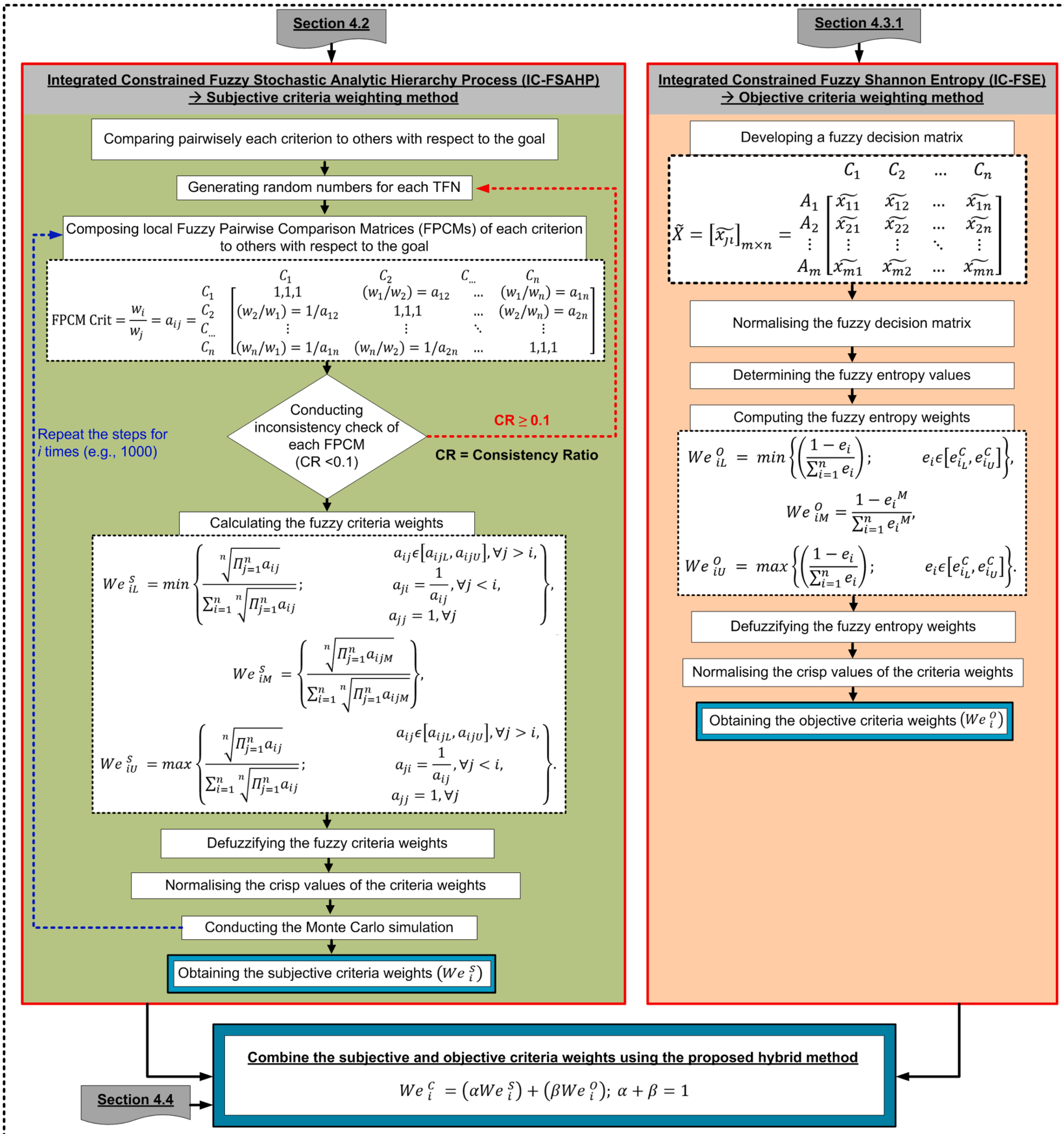


**Fig. 6.** Flowchart of proposed novel hybrid MCDM method for weighting the criteria.

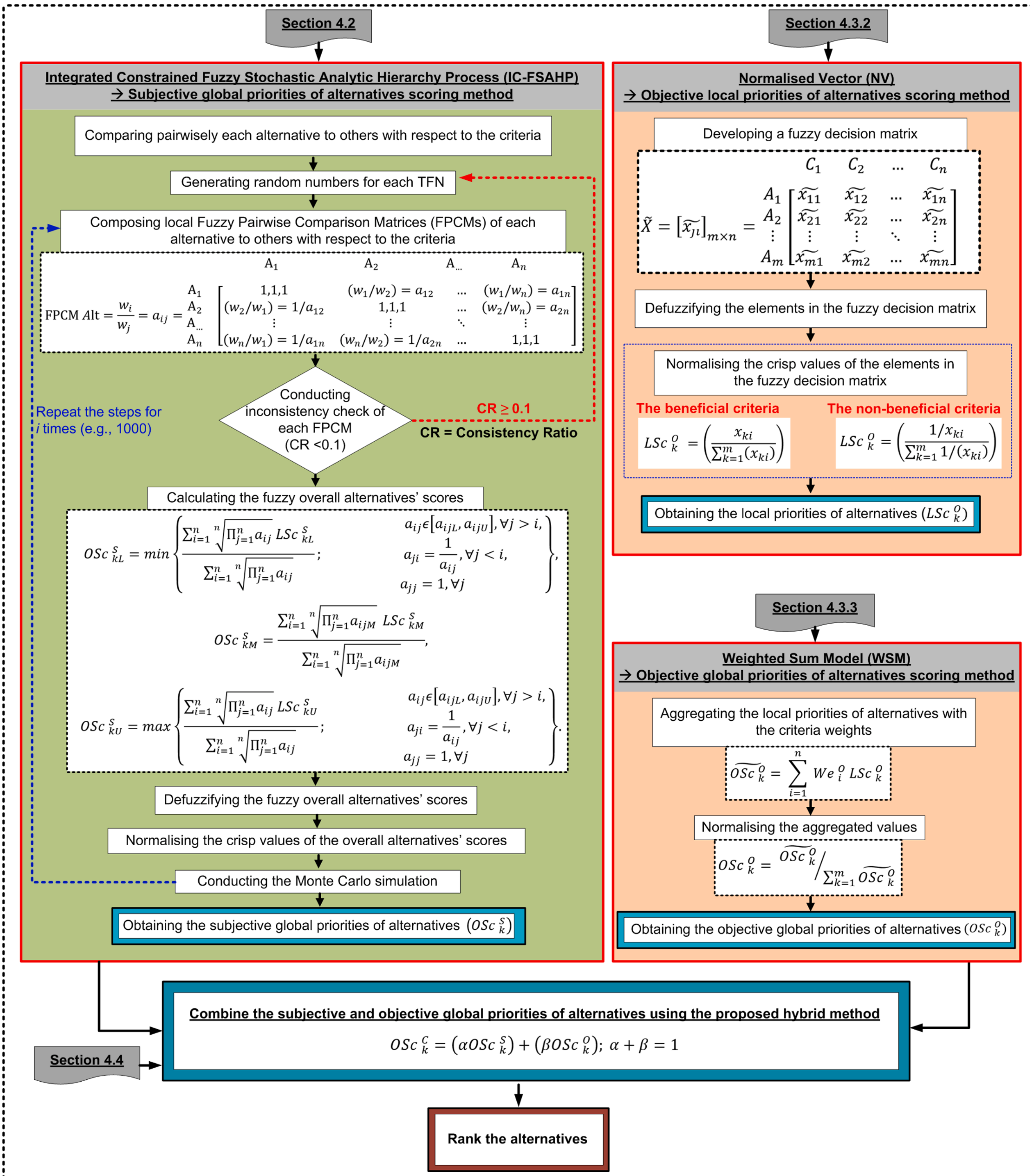


**Fig. 7.** Flowchart of proposed novel hybrid MCDM method for scoring the alternatives.

**Table 2**
The evaluation criteria and sources of quantitative data used for the current work.

| Category | Criteria | Units | References |
|---|---|---|---|
| Technical | $C_1$: Potential total power generation | TWh/yr | (Troldborg et al., 2014) |
| Environmental | $C_2$: GHG emissions | $gCO_2eq/kWh$ | (Troldborg et al., 2014) |
| | $C_3$: Area requirement | $m^2/kW$ | (Troldborg et al., 2014) |
| Economic | $C_4$: Levelised energy cost | \$/MWh | (Troldborg et al., 2014) |
| Social | $C_5$: Prospective jobs creation | Jobs/annual GWh | (UKERC, 2014) |

### 5.1. The notions of the selection problem

Suppose that a mining company would like to select the most suitable renewable energy technology for one of its operations. For this purpose, five criteria were considered: potential total power generation ($C_1$), GHG emissions ($C_2$), area requirement ($C_3$), levelised energy cost (LEC) ($C_4$), and prospective jobs creation ($C_5$). Furthermore, three feasible alternatives were examined, namely Onshore wind (OW) — $A_1$, Concentrated solar power (CSP) — $A_2$, Solar photovoltaic (PV) — $A_3$. Sections 5.1.1 and 5.1.2 provide the detailed description of different criteria and alternatives considered in this work.

In this work, the decision making process was conducted through an objective assessment first, followed by subjective judgements. For the purpose of this work, an implementation of the method in Python 3 was used.

#### 5.1.1. Sustainability criteria

Five sustainability criteria (Ci) were selected and are summarised in Table 2 and further described below. It is worth to emphasise that quantitative data for the criteria selected were obtained from the literature and, for consistency, correspond to the same geographical region, i.e. the UK.

1. Technical:

Potential total power generation ($C_1$) was considered as an important technical criterion. Potential total power generation (TWh/yr) ($C_1$) is the quantity of energy that can be delivered by each of the renewable energy technologies per year (Troldborg et al., 2014). The great value of the potential total power generation is always preferred.

2. Environmental:

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

2.a) GHG emissions ($C_2$).

The GHG emissions criterion is one of the most frequently used criteria when assessing renewable energy technologies (Wang et al., 2009). GHG emissions, which are measured in $gCO_2eq/kWh$, are estimated by $CO_2$ and $CH_4$ emissions of each renewable energy technology, from the commissioning of a power plant to its full operation and the dismantling stage of the power plant (Amponsah et al., 2014). The target should be eliminating GHG emissions or reducing them as much as possible.

2.b) Area requirement ($C_3$).

The extension of land required by each renewable energy technology, which is reported as $m^2/kW$, is of vital importance for their evaluation in the mining industry because of concerns that the implementation of renewable energy technologies can frequently be competing with agriculturally arable land (Evans et al., 2009) and thus destabilise the ecosystem (Chatzimouratidis & Pilavachi, 2008). The decision making process would therefore always favour alternatives that require the smallest area.

3. Economic:

Economic considerations are of utmost importance for evaluating the sustainability of renewable energy technologies in various MCDM studies. In this work, levelised energy cost (LEC) (C4), which is expressed as \$/MWh, was considered as an economic criterion because all the costs over an assumed project's financial life and duty cycle are included in the LEC calculation (Aman et al., 2015). The aforementioned costs include capital expenditure (CAPEX), operation and maintenance (O&M) expenditure (OPEX), fuel costs, financing costs, as well as an assumed capacity factor for each plant type. In addition, LEC takes into account the attributes of the technology, such as energy source, annual energy production, efficiency, and duration (Troldborg et al., 2014). Reducing LEC is always advantageous.

4. Social:

A range of social aspects have been of enormous significance for people's acceptance of the implementation of renewable energy technologies. Prospective jobs creation (C5), which is reported as jobs/annual GWh, is the most commonly used social criterion in the literature (Wang et al., 2009); it allows decision makers to consider socioeconomic aspects when determining which technology can enhance the living standards of the surrounding population (Chatzimouratidis & Pilavachi, 2008). This criterion considers the prospective jobs generated during the life cycle of a renewable energy technology, from construction and operation to decommissioning. A large number of jobs created is, of course, desirable.

#### 5.1.2. Feasible renewable energy technologies

Three renewable energy technologies that have been successfully applied in the mining industry (Choi & Song, 2017; Zharan & Bongaerts, 2018) were considered as alternatives (Ai) for the assessment in this work and are summarised as follows:

1. 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 into electricity (Şengül et al., 2015). Several mining companies have applied OW power systems at operating mines in Argentina, Canada, and Chile. This has also been implemented at abandoned mines in the USA to provide electricity to households surrounding the site. The generated power in the operating mines varies from 2 MW to 115 MW and in the abandoned mines from 29 MW to 237 MW (Choi & Song, 2017).

2. Concentrated solar power (CSP) — $A_2$

Concentrated solar power utilises reflective surfaces to concentrate sunlight into a beam to heat a working fluid in a receiver and produce the steam that is employed to drive a turbine that provides mechanical power, which is then converted to electricity (Aman et al., 2015). The installed capacity of concentrated solar power in the mining industry in 2016 was 39 MW (Zharan & Bongaerts, 2018). Even though the existing installed capacity is relatively low, several mining companies in Chile

**Table 3**
The minimum, most likely and maximum values for each of the considered renewable energy technologies with respect to each criterion.

| Alternatives | Total power generation (TWh/yr) | GHG emissions ($gCO_2eq$/kWh) | Area requirement ($m^2$/kW) | Levelised energy cost ($/MWh) | Prospective jobs (Jobs/annual GWh) |
|---|---|---|---|---|---|
| Onshore wind | (25, 45, 125) | (5, 15, 70) | (10, 200, 1200) | (32, 90, 160) | (0.1, 0.2, 0.6) |
| CSP | (2.5, 11, 20) | (15, 40, 150) | (10, 40, 100) | (64, 256, 576) | (0.2, 0.4, 0.7) |
| PV | (2.5, 20, 70) | (20, 60, 200) | (10, 150, 500) | (64, 435, 768) | (0.2, 0.6, 1.3) |

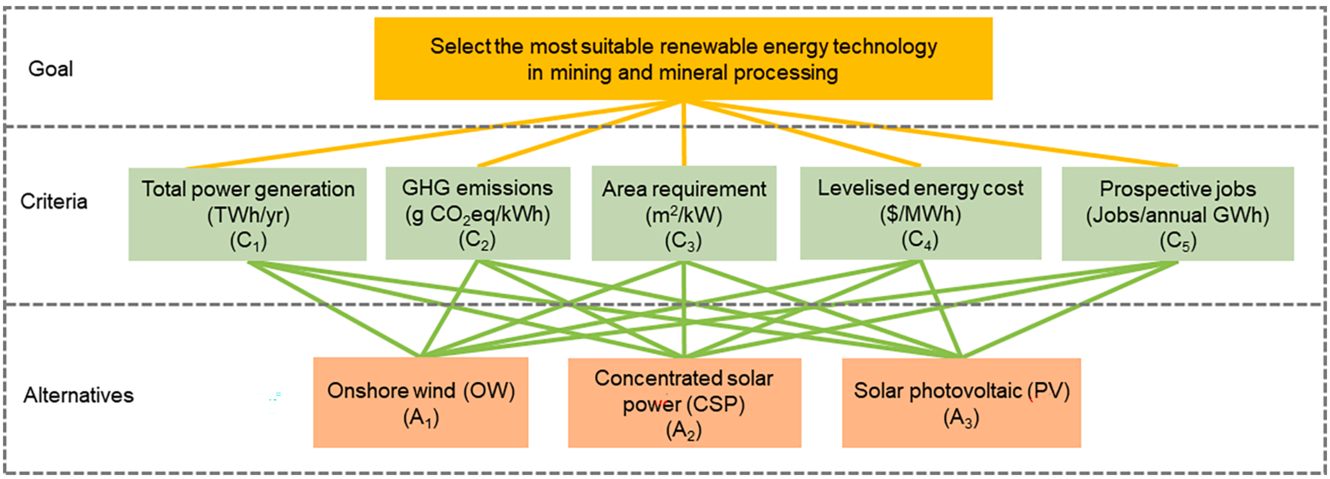


**Fig. 8.** Hierarchy structure for choosing the most suitable renewable energy technology in the mining industry.

**Table 4**
The experts' assessment of the significance of the criteria with respect to the goal.

| Experts | Total power generation (TWh/yr) | GHG emissions ($gCO_2eq$/kWh) | Area requirement ($m^2$/kW) | Levelised energy cost ($/MWh) | Prospective jobs (Jobs/annual GWh) |
|---|---|---|---|---|---|
| $E_1$ | VI | EI | VI | VI | I |
| $E_2$ | EI | EI | EI | EI | EI |
| $E_3$ | I | I | U | EI | I |
| $E_4$ | VI | VI | U | EI | VI |

have investigated a future potential concentrated solar power plant installation with high capacity (up to 50 MW) to support their operations (Parrado et al., 2016).

3. Solar photovoltaic (PV) — $A_3$

Solar photovoltaic energy is another renewable source of electricity generation harvested from the thermal radiation produced by sunlight through photovoltaic cells, which is converted into electric current (Hernandez et al., 2014). Several mining companies have implemented solar photovoltaic power systems at operating mines in the USA, Chile, Australia, South Africa, and Suriname. Solar photovoltaic technology has also been implemented at abandoned mines in the USA, Germany, Canada, and Korea, where it has been used for acid mine drainage

**Table 6**
Results from the first iteration of random TFNs aggregated from the assessment of the importance of the criteria with respect to the goal, using the modified beta-PERT distribution.

| $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ |
|---|---|---|---|---|
| (6.466, 6.751, 7.112) | (6.713, 7.070, 8.721) | (3.452, 4.893, 7.187) | (6.996, 7.503, 8.715) | (5.303, 6.197, 7.001) |

**Table 7**
Results from the first iteration of random TFNs aggregated from the assessment of the preference of alternatives with respect to each criterion, using the modified beta-PERT distribution.

| Alternatives | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ |
|---|---|---|---|---|---|
| $A_1$ | (4.000, 6.575, 7.506) | (5.331, 5.888, 7.796) | (5.928, 6.914, 8.460) | (6.552, 7.914, 8.447) | (6.500, 7.962, 8.756) |
| $A_2$ | (6.616, 6.814, 8.767) | (6.622, 6.941, 8.760) | (4.803, 5.288, 8.186) | (3.704, 5.288, 7.772) | (6.441, 7.024, 8.391) |
| $A_3$ | (6.599, 7.573, 7.789) | (5.409, 6.927, 8.988) | (6.429, 6.974, 7.584) | (6.567, 7.403, 7.703) | (6.558, 7.345, 8.153) |

**Table 5**
Preference assessment of the alternatives with respect to each criterion by four experts.

| Alternatives | Total power generation (TWh/yr) | GHG emissions ($gCO_2eq$/kWh) | Area requirement ($m^2$/kW) | Levelised energy cost ($/MWh) | Prospective jobs (Jobs/annual GWh) |
|---|---|---|---|---|---|
| Onshore wind | (H, VH, M, M) | (H, VH, H, M) | (MH, VH, MH, L) | (H, VH, VH, M) | (VH, VH, M, H) |
| CSP | (H, VH, H, L) | (H, VH, H, M) | (VH, VH, H, M) | (H, VH, H, L) | (H, VH, M, H) |
| PV | (VH, VH, M, H) | (VH, VH, H, MH) | (VH, VH, H, M) | (VH, VH, H, MH) | (H, VH, M, H) |

treatment and to provide power to households near the site. The power generated in the operating mines varies from 1 MW to 10.6 MW and in the abandoned mines from 1 MW to 166 MW (Choi & Song, 2017).

### 5.2. Input data

The sources of quantitative data for the five criteria are presented in Table 2 and the data are summarised in Table 3. These data were used as a basis for obtaining the criteria weights and the alternatives' scores using the objective weight. Columns and rows in Table 3 result in a fuzzy decision matrix that is expressed in TFN.

In order to obtain the criteria weights and the alternatives' scores using the subjective weight, the hierarchy of this renewable energy technologies selection problem was constructed and is presented in Fig. 8. It is worth noting that the IC-FSAHP method succeeded in solving an MCDM problem under a fuzzy environment when the decision makers' or experts' opinions have the least, the highest and the most likely values. These values are required for generating random numbers. In order to get these values, the minimum number of decision makers or experts is three. A group of four experts was invited to participate the current work.

Four experts were selected for a survey, who had the following criteria: a university degree in mining, mineral processing, extractive metallurgy, chemical engineering, or related discipline; a minimum 5 years operational experience in the mining industry or 5 years working in academia; had practical experience in the selection of renewable energy technologies in the mining industry, or had experience in research on the selection of renewable energy technologies in the mining industry. In addition, the experts (two from academia and two from the mining industry), denoted by $E_1$, $E_2$, $E_3$ and $E_4$, were asked for their judgements and preferences through a survey conducted via online questionnaires in November 2019. The pairwise comparison of the criteria and the alternatives that were examined by the four experts are shown in Table 4 and Table 5, respectively. Furthermore, the scale of linguistic variables, shown in Fig. 4, was applied to compare pairwise the significance of the criteria and preference of the alternatives.

### 5.3. Results

Based on the workflow of the IC-FSAHP method (Sitorus et al., 2019a), shown in Fig. 3, the assessments shown in Tables 4 and 5 were aggregated by using the modified beta-PERT distribution (Sitorus et al., 2019a) in order to generate random numbers. The number of iterations used for this work was 1000. Tables 6 and 7 show the first iterations of the random TFNs that were aggregated from Tables 4 and 5, respectively.

To obtain the Fuzzy Pairwise Comparison Matrices (FPCMs) that are described in Fig. 3, the elements in each FPCM, $a_{ij} = (a_{ijL}, a_{ijM}, a_{ijU})$, were derived from the division formula of two TFNs for upper triangular FPCM (Sitorus et al., 2019a) and the reciprocation formula of a TFN for lower triangular FPCM (Sitorus et al., 2019a). For example, the FPCM of alternatives $A_1$, $A_2$, and $A_3$ with respect to $C_1$ is shown in equation (18).

$$a_{ij} = \begin{array}{cccc} Criteria1 & A_1 & A_2 & A_3 \\ A_1 & (1,1,1) & \dfrac{(4.000,6.575,7.506)}{(6.616,6.814,8.767)} & \dfrac{(4.000,6.575,7.506)}{(6.599,7.573,7.789)} \\ A_2 & [\dfrac{(4.000,6.575,7.506)}{(6.616,6.814,8.767)}]^{-1} & (1,1,1) & \dfrac{(6.616,6.814,8.767)}{(6.599,7.573,7.789)} \\ A_3 & [\dfrac{(4.000,6.575,7.506)}{(6.599,7.573,7.789)}]^{-1} & [\dfrac{(6.616,6.814,8.767)}{(6.599,7.573,7.789)}]^{-1} & (1,1,1) \end{array} \tag{18}$$

Since the consistency ratios of all FPCMs were less than 0.1, and thus acceptable, it was possible to then calculate the fuzzy criteria weights ($We_i^S$) fuzzy alternatives local priorities ($LSc_k^S$) and overall scores ($OSc_k^S$).

Based on the workflow of the IC-FSE method (Sitorus & Brito-Parada, 2020b), presented in Fig. 5, the normalised decision matrix in TFN, the fuzzy entropy values ($\widetilde{e_i}$), fuzzy entropy weights $(\widetilde{w_i})$, normalised crisp entropy weights ($We_i^O$), and the ranking of criteria obtained from the IC-FSE were presented in Tables 8 and 9.

By using equations (12) and (13), the objective local priorities of alternatives ($LSc_k^O$) with respect to criteria were obtained by means of NV, the results of which are shown in Table 10. Moreover, Table 11 shows the overall scores of alternatives ($OSc_k^O$) obtained from WSM, calculated by using equations (14) and (15).

Furthermore, by applying equations (16) and (17), the results of overall criteria weights and overall alternatives' scores from the first iteration for $\alpha = 0.5$ were obtained, the results of which are shown in Tables 12 and 13, respectively.

**Table 9**
The fuzzy entropy values ($\widetilde{e_i}$), fuzzy entropy weights ($\widetilde{w_i}$), normalised crisp entropy weights ($We_i^O$) and the ranking of criteria obtained from the IC-FSE.

| | Total power generation ($C_1$) | GHG emissions ($C_2$) | Area requirement ($C_3$) | Levelised energy cost ($C_4$) | Prospective jobs ($C_5$) |
|---|---|---|---|---|---|
| ($\widetilde{e_i}$) | (0.143, 0.729, 0.73) | (0.263, 0.749, 0.793) | (0.073, 0.717, 0.866) | (0.312, 0.721, 0.825) | (0.431, 0.78, 0.815) |
| $\widetilde{w_i}$ | (0.085, 0.208,0.55) | (0.064, 0.193, 0.491) | (0.045, 0.217, 0.526) | (0.053, 0.214, 0.463) | (0.055, 0.169, 0.42) |
| ($We_i^O$) | 0.225 | 0.199 | 0.210 | 0.195 | 0.171 |
| Rank | 1 | 5 | 2 | 3 | 4 |

**Table 8**
The normalised fuzzy decision matrix.

| Alterna-tives | Total power generation ($C_1$) | GHG emissions ($C_2$) | Area requirement ($C_3$) | Levelised energy cost ($C_4$) | Prospective jobs ($C_5$) |
|---|---|---|---|---|---|
| Onshore wind | (0.325, 0.892, 1.0) | (0.02, 0.204, 0.942) | (0.02, 0.79, 1.0) | (0.033, 0.176, 0.87) | (0.068, 0.248, 0.892) |
| CSP | (0.017, 0.218, 0.623) | (0.071, 0.543, 0.991) | (0.008, 0.158, 0.99) | (0.081, 0.499, 0.992) | (0.119, 0.566, 0.941) |
| PV | (0.02, 0.396, 0.941) | (0.12, 0.815, 0.997) | (0.008, 0.592, 1.0) | (0.106, 0.848, 0.996) | (0.251, 0.786, 0.989) |

**Table 10**

Objective local priorities ($LSc_k^O$) of alternatives with respect to criteria obtained NV.

| Alterna-tives | Total power generation ($C_1$) | GHG emissions ($C_2$) | Area requirement ($C_3$) | Levelised energy cost ($C_4$) | Prospective jobs ($C_5$) |
|---|---|---|---|---|---|
| Onshore wind | 0.607 | 0.578 | 0.08 | 0.65 | 0.192 |
| CSP | 0.104 | 0.236 | 0.75 | 0.205 | 0.338 |
| PV | 0.288 | 0.186 | 0.17 | 0.145 | 0.47 |

**Table 11**

The overall scores of alternatives ($OSc_k^O$) obtained from WSM.

| | OW ($A_1$) | CSP ($A_2$) | PV ($A_3$) |
|---|---|---|---|
| ($OSc_k^O$) | 0.428 | 0.326 | 0.246 |
| Rank | 1 | 2 | 3 |

**Table 12**

Results of overall criteria weights obtained from the first iteration for $\alpha = 0.5$.

| $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ |
|---|---|---|---|---|
| 0.200 | 0.214 | 0.177 | 0.228 | 0.181 |

**Table 13**

Results of overall alternatives' scores obtained from the first iteration for $\alpha = 0.5$.

| $A_1$ | $A_2$ | $A_3$ |
|---|---|---|
| 0.318 | 0.325 | 0.357 |

Violin plots were used to show the probability density of the local criteria weights and the overall alternatives' scores for different $\alpha$ after 1000 iterations. Fig. 9.a) and b) show the violin plots of the criteria weights and the overall alternatives' scores obtained from the proposed combined method for $\alpha = 0.5$ after 1000 iterations. The results indicate that total power generation ($C_1$) was the highest prioritised criterion and the onshore wind technology ($A_1$) was the most suitable alternative. Moreover, Fig. 9.b) showcases that the ranking of alternatives can be determined as onshore wind ($A_1$) $\succ$ concentrated solar power ($A_2$) $\succ$ solar photovoltaic ($A_3$).

### 5.4. Sensitivity analysis

A sensitivity analysis of the decision making results was conducted by applying different values of $\alpha$ in the interval [0, 1] to the proposed combined method. In this study, six values of coefficient $\alpha$ were used, namely 0, 0.2, 0.4, 0.6, 0.8, and 1.

In the case when decision makers intend to obtain results from only applying the objective weighting method, which means that the final recommendations do not take into account the subjective judgements or preferences obtained from decision makers, $\alpha = 0$ is then applied. Tables 9 and 11 show the criteria weights ($We_i^O$) and the overall alternatives' scores ($OSc_k^O$) obtained from the objective weighting method, respectively. It can be seen from Tables 9 and 11 that the most prioritised criterion is total power generation ($C_1$) and the rank of each alternative is in the following order: onshore wind ($A_1$) $\succ$ concentrated solar power ($A_2$) $\succ$ solar photovoltaic ($A_3$). In addition, it is worth highlighting that for this case when $\alpha = 0$ the most important criterion and the rank of each alternative are similar to those of when $\alpha = \beta = 0.5$.

On the other hand, when the subjective weighting method needs to be used, $\alpha = 1$ is applied. By applying $\alpha = 1$ or fully subjective weighting method, the final outcomes consider only the subjective judgements or preferences obtained from decision makers. Fig. 10.a) and b) show the violin plots of the criteria weights and the overall alternatives' scores obtained from the proposed combined method for $\alpha = 1$ after 1000 iterations. LEC ($C_4$) was the most prioritised criterion and solar photovoltaic ($A_3$) was the most suitable renewable energy technology. Moreover, Fig. 10.b) shows that the ranking of alternatives can be determined as solar photovoltaic ($A_3$) $\succ$ concentrated solar power ($A_2$) $\succ$ onshore wind ($A_1$). It can be concluded that by applying the fully subjective weight, the final recommendations are different from those obtained when applying the fully objective weight.

After obtaining the results from the fully objective weighting method ($\alpha = 0$) or the fully subjective weighting method ($\alpha = 1$), four other values of coefficient $\alpha$ were used for further analysis, namely 0.2, 0.4, 0.6, 0.8. Figs. 11 and 12 provide violin plots of the criteria weights and the overall alternatives' scores based on the various values of $\alpha$, respectively. Fig. 11 showcases that when the coefficient $\alpha$ increases, the importance of the criteria is slightly changed (i.e. the most prioritised criterion was changed from total power generation ($C_1$) to LEC ($C_4$)). This means that the influence of the objective weights on the importance of the criteria increases when $\alpha$ is increased. In addition, Fig. 12 shows that the increase of the coefficient $\alpha$ does not change the most suitable

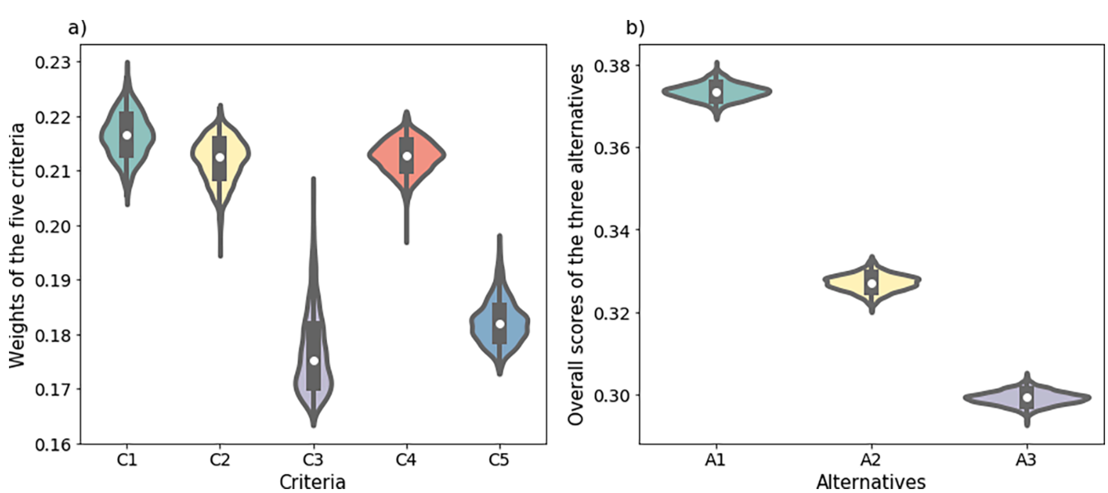


**Fig. 9.** Violin plots of a) the criteria weights and b) the overall alternatives' scores obtained from the proposed combined method for $\alpha = 0.5$ after 1000 iterations.

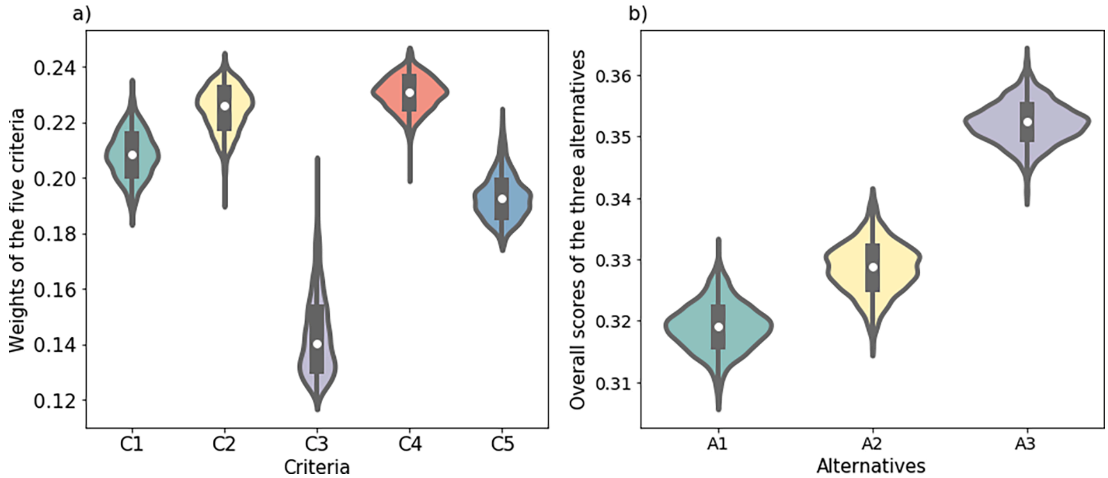


**Fig. 10.** Violin plots of a) the criteria weights, and b) the overall alternatives scores obtained from the proposed combined method for $\alpha = 1$ after 1000 iterations.

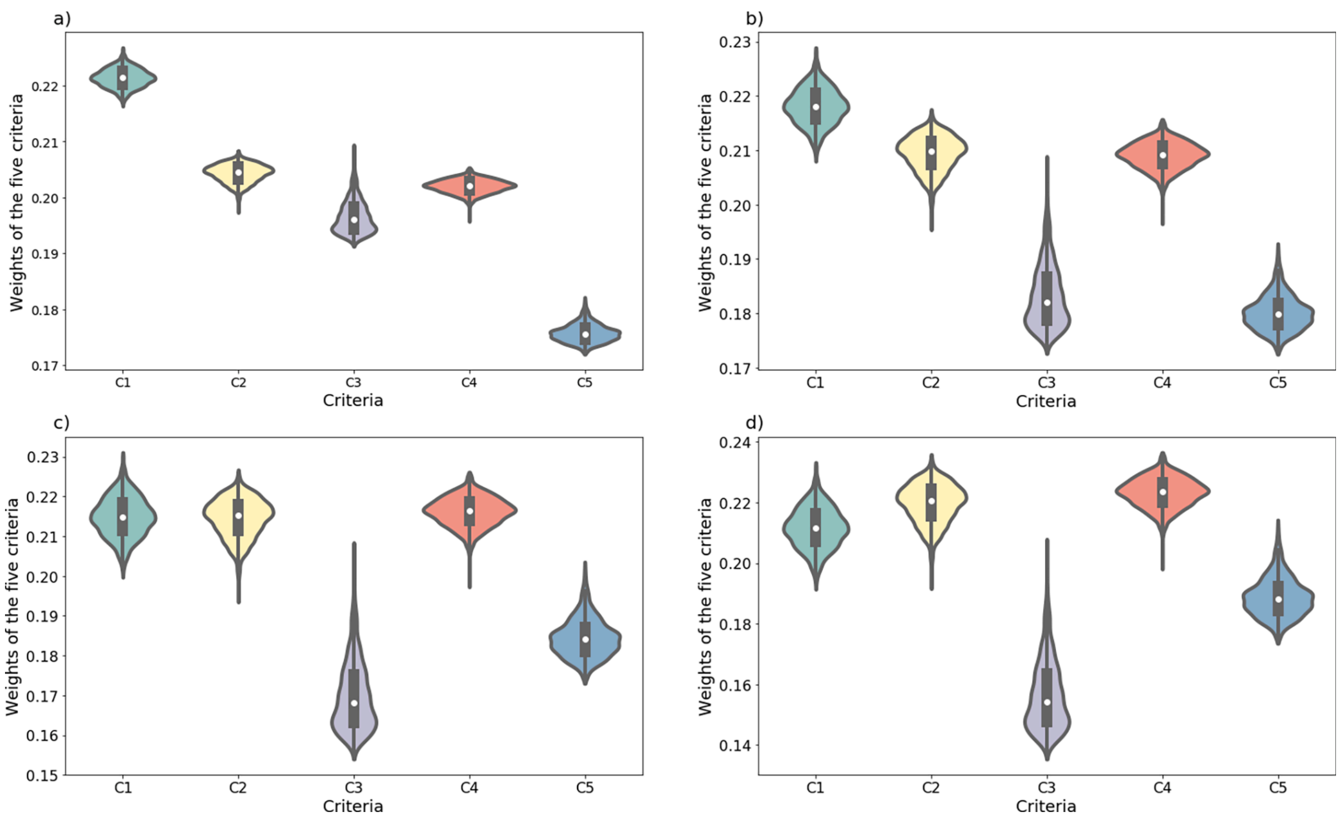


**Fig. 11.** Violin plots of the criteria weights obtained from the proposed combined method for a) $\alpha = 0.2$; b) $\alpha = 0.4$; c) $\alpha = 0.6$; d) $\alpha = 0.8$ after 1000 iterations.

alternative (i.e. the onshore wind technology ($A_1$)), thus indicating that the objective weights have a powerful influence on the overall alternatives' scores.

Based on the example presented above, it is worth considering that the uncertainty is not only associated with the imprecise input data, which can be minimised by means of TFN, and associated with the different decision makers' opinions, which can be captured by Monte Carlo simulations, as done in this study. The uncertainty can be also associated with ill-judged assessments when decision makers do not take into account the available data sources and mostly use their subjective opinion in decision making analysis.

For example, Figs. 9–12 as well as Tables 9 and 11 show that the criteria weights and the overall alternatives' scores obtained by different coefficient factors ($\alpha$) result in different outcomes that reflect both subjective preferences and the objective weight. The results from Figs. 9, 11 and 12 show that the objective weight dominates the final criteria weights and overall alternatives' scores. The best alternative shown in these figures is the onshore wind ($A_1$) technology. This result is completely different from that shown in Fig. 10, when the fully subjective weighting method was applied, resulting in the solar photovoltaic ($A_3$) technology being the best alternative. The difference in the results obtained can arguably be linked to the fact that the experts did not consider the objective information. Their judgements and preferences were made on the basis of their knowledge and experience. This circumstance can lead to potential bias during the evaluation and affect the final results. For example, a very interesting finding can be observed

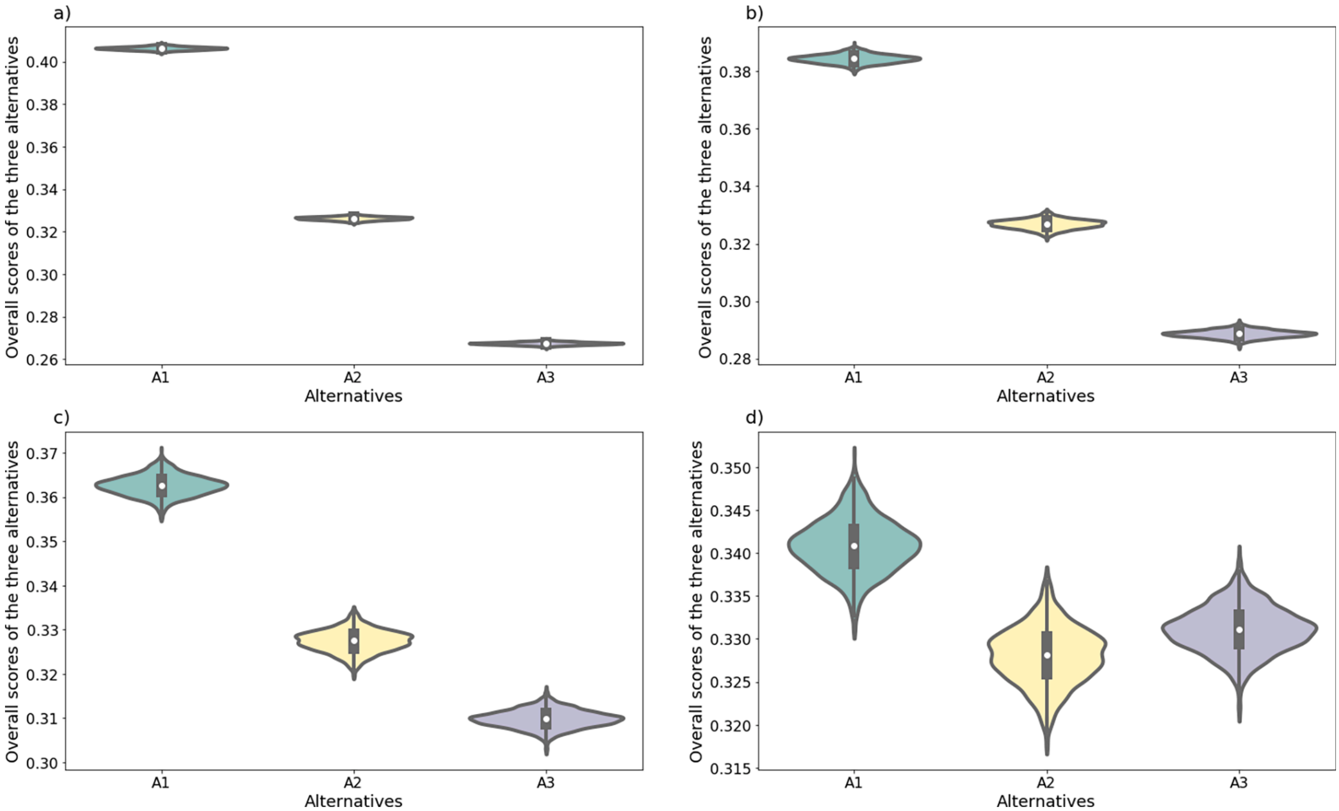


**Fig. 12.** Violin plots of the alternatives' scores obtained from the proposed combined method for a) $\alpha = 0.2$; b) $\alpha = 0.4$; c) $\alpha = 0.6$; d) $\alpha = 0.8$ after 1000 iterations.

in the evaluation of the renewable energy technologies considered with respect to the LEC criterion. Despite the quantitative data presented in Table 3, showing that solar based technologies (solar photovoltaic ($A_3$) and concentrated solar power ($A_2$)) have higher LEC than the onshore wind ($A_1$) technology, Table 5 indicates that the experts regard solar based technologies as not being dissimilar to onshore wind with regards to LEC. Therefore, choosing the right coefficient factor for the objective weight is critical to avoid subjective bias during the evaluations.

This work also showcases the applicability of the proposed hybrid approach in capturing uncertainty due to ill-judged assessments. The proposed hybrid method determines criteria weights and alternatives' scores by solving a comprehensive mathematical programming model which considers both subjective and objective factors. It overcomes the shortcomings which possible arise in either a subjective weighting approach or an objective weighting approach.

### 5.5. Discussion

It is evident from the aforementioned outcomes that the proposed method can be used to evaluate different criteria and alternatives under uncertainties in the context of group decision making in a scientific transparent manner by means of subjective weights (i.e. Integrated Constrained Fuzzy Stochastic Analytic Hierarchy Process (IC-FSAHP)) and objective weights (i.e. Integrated Constrained Fuzzy Shannon Entropy (IC-FSE), Normalised Vector (NV), and Weighted Sum Model (WSM)). It is worth noting that when evaluating such complex selection problems, one criterion (i.e. cost or monetary value) is not sufficient to base a decision on. In fact, multiple criteria that are often conflicting are involved. Therefore, the triple bottom line approach or the cost analysis proposed by Mostert (2014), Zharan and Bongaerts (2017), respectively, which are based on a monetary value, are unable to assess the complex selection problem comprehensively. A combination of MCDM methods with the triple bottom line or with cost analysis is thus suggested in order to analyse the problem holistically.

In MCDM problems, uncertainty due to imprecise input data are often present and quantifying such input data is challenging. In the current study, the proposed combined method is capable of quantifying these types of data by means of triangular fuzzy numbers. This evidenced that the proposed hybrid method is superior to those developed by Ma et al. (1999) and Rao and Patel (2010), which did not take into account the risk of imprecise input data.

Furthermore, the proposed method can capture inconsistencies of decision makers as a group, which are caused by decision makers having different points of view in judging their preference, by means of stochastic methods in IC-FSAHP. This feature was missing in the methods proposed by Ma et al. (1999), Rao and Patel (2010) and Rao et al. (2011). Since the proposed hybrid method in this work does not have the aforementioned shortcomings, it is deemed superior to other MCDM methods in its capability of dealing with uncertainties.

Further, combining subjective and objective weighting methodologies enhances the capability of the proposed method in terms of determining the criteria weights and alternatives' scores through the use of coefficient factors. The coefficient factors are able to be adjusted for balancing the decision makers' opinions and the objective information or quantitative data involved, and thus reduce the subjectivity of decision makers in assessing the selection problem.

Regarding the coefficient factors, decision makers or experts should discuss and adjust the coefficients that will be used. They can freely choose adjusting coefficients according to the particular characteristics of the decision makers or experts and input data. Selecting the adjusting coefficients depends on the background, expertise and experience of decision makers or experts and the availability of quantitative data. For example: if the decision makers or experts have a lot of experience with the high success rate on the selection of renewable energy technologies in the same type of mineral being processed and in the same country, it is possible to use a very low coefficient on objective weights (less than0.5) and the very high coefficient on subjective weights (>0.5).

It should also be indicated that this work does not consider the interaction and dependency between criteria, sub-criteria, and alternatives. Such dependencies can be handled by using another MCDM method, such as Analytic Network Process (ANP). There is therefore scope to further extend the proposed method for the case when non-homogeneous data and uncertainties due to imprecise input data and various decision makers' opinions, as well as the dependency between criteria and alternatives, are involved.

## 6. Conclusions

A hybrid MCDM method was proposed and was applied to the selection of renewable energy technologies in the mining industry, which faces an increase in energy demand as high grade ores are depleted and the demand for metals and minerals, including those required for renewable energy technologies, increases. The large scale of mining operations makes it very important to consider renewable energy options in order to contribute to the sustainability of the operations.

Three renewable technology alternatives, namely onshore wind, concentrated solar power, and solar photovoltaic, were assessed taking into account both subjective considerations and objective information with respect to five sustainability criteria. The selected criteria were potential total power generation, GHG emissions, area requirement, levelised energy cost, and prospective jobs creation. An objective weight was obtained using data compiled from the literature, whereas a subjective weight was obtained from the judgements and preferences of four experts. The proposed method was then employed to compute the criteria weights and the alternatives' scores.

The results when the same coefficient factors of subjective and objective weights were applied show that total power generation ($C_1$) was the most important criterion and the onshore wind technology ($A_1$) was the most suitable alternative. Furthermore, from the sensitivity analysis results, it can be summarised that the criteria weights and the overall alternatives' scores obtained by various coefficient factors yield different results. Despite the different results, the ranking of alternatives obtained with the proposed method reflects both subjective preferences and the objective weight. Moreover, the proposed method is also able to minimise the loss of valuable objective information, which is caused by the subjective bias of qualitative weights during the evaluations, by adjusting the coefficient factors of both quantitative and qualitative data in the hybrid model during the calculations.

The outcomes have shown the usability of the proposed method in selecting renewable energy technologies in the mining industry in a fuzzy environment based on quantitative and qualitative data in the context of group decision making. In addition, the method can be used in other areas to support decision makers in the selection problem under the aforementioned circumstances.

Nevertheless, the outcomes from this work show that there is some uncertainty in the quantitative input data used. The input data used in this study were originally compiled at a national scale and are therefore relatively generic. In terms of the application of objective weighting methods, 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 lower than that in the present example. The proposed method can be applied by substituting all values in Table 3 as required, and amending the set of feasible renewable energy technologies to be considered. For example, if a mining company is located nearby geothermal energy resources and there is a high potential to build a geothermal power plant (GPP), then a GPP might be added into a set of feasible alternatives.

The use of coefficient factors can be extended to other MCDM methods that combine objective and subjective weighting. It is worth highlighting that in such cases, the outcome for the preferred renewable energy system might differ to that obtained in the present study, unless there is a high level of consistency in the process of decision making.

This study has shown that the proposed hybrid method is a robust method to identify and screen the criteria, weight the criteria and rank the alternatives when decision makers face a complex problem that requires to consider non-homogenous input data and uncertainties due to imprecise input data and different decision makers' opinions. The proposed method has a broad application potential in other sectors to support decision makers in dealing with a selection problem with the aforementioned characteristics. In addition, there is scope to further extend the proposed hybrid method for the case when there exists a dependency between criteria and alternatives. Further studies to develop such an extended method will be the subject of future work.

## CRediT authorship contribution statement

**Fernando Sitorus:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Writing – original draft, Writing – review & editing. **Pablo R. Brito-Parada:** Conceptualization, Writing – review & editing, Supervision.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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