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A MULTI-CRITERIA DECISION MAKING FOR RENEWABLE ENERGY SELECTION USING Z-NUMBERS IN UNCERTAIN ENVIRONMENT

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Abstract. In recent era of globalization, the world is perceiving an alarming rise in its energy consumption resulting in shortage of fossil fuels in near future. Developing countries like India, with fast growing population and economy, is planning to explore among its existing renewable energy sources to meet the acute shortage of overall domestic energy supply. For balancing diverse ecological, social, technical and economic features, selection among alternative renewable energy must be addressed in a multi-criteria context considering both subjective and objective criteria weights. In the proposed COPRAS-Z methodology, Z-number model fuzzy numbers with reliability degree to represents imprecise judgment of decision makers' in evaluating the weights of criteria and selection of renewable energy alternatives. The fuzzy numbers are defuzzified and renewable energy alternatives are prioritized as per COmplex PropoRtional ASsessment (COPRAS) decision making method in terms of significance and utility degree. A sensitivity analysis is done to observe the variation in ranking of the criteria, by altering the coefficient of both subjective and objective weight. Also, the proposed methodology is compared with existing multi-criteria decision making (MCDM) methods for checking validity of the obtained ranking result.

Keywords: renewable energy, multi-criteria decision making (MCDM), COPRAS, Z number, fuzzy number.

JEL Classification: D81, D70, P48, Q20, Q30.

Introduction

In the present world, fossil fuels such as coal, gasoline and natural gas obtained as per natural processes are primary sources of global energy (81% of total energy mix), that presume to run out in following years (EC 2003). Many countries are undergoing collaborative research in developing safe, low-cost, sustainable alternative energy sources to replace traditional sources of energy thereby reducing greenhouse gas emissions. India accounts 17% of the world's population but only 4% of the world primary energy consumptions (Pillai, Banerjee

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2009). In renewable energy sector, India has vast reserve throughout the country with overall potential more than current energy consumption (Reddy, Painuly 2004). Making a successful transition from fossil fuel energy to renewable energy requires careful energy planning, decision and selection among the most appropriate renewable energy sources. For balancing diverse ecological and socio-economic aspects, the policy formulation for substitution of the fossil fuels energy by renewable energy must be addressed in a multi-criteria context. The complexity of energy planning and energy projects make multi-criteria a valuable tool in energy resource selection under various decision problems. Thus, adopting and choosing non-fossil based energy sources is a multi-dimensional decision making process that involves a number of different characteristics viz. *Economic, technical, social and environmental*.

The decision process becomes more challenging in selecting and prioritizing an appropriate alternative under several qualitative and quantitative criteria. Also, due to inadequate information and vagueness of human thought, fuzzy logic is used in undertaking complex assessment procedures (Kar, Chatterjee 2015). In case of conflicting alternatives, a decision maker must also consider imprecise data. Even though fuzzy numbers are able to deal with human judgment, it does not consider the reliability of information of the decision makers. In order to overcome this limitation Zadeh (2011), introduced Z-number that includes both the *restriction* of the evaluation and *reliability* of the judgment thus producing fuzzy numbers with degree of self-confidence. In comparison to fuzzy number, Z-number having highest expressive power from human perception represents the real-world imperfect data in a more generalized way (Aliev *et al.* 2013).

In recent literature, Z-number is used widely in solving many complicated decision making problems. Kang *et al.* (2012a) suggested a new multi-criteria decision making method based on Z-number for linguistic decision making problem. Azedah *et al.* (2013) suggested a new AHP method based on Z-number to deal with linguistic decision making problems to search criteria's in evaluating alternative universities. Xiao (2014) proposed a MCDM method where Z-number is first transformed to the interval-valued fuzzy set with footprint of uncertainty (FOU) and then defuzzified to crisp mode using K-M algorithm. Zeinalova (2014) developed a utility function in Z-valuation environment using Choquet integral and newly constructed non-additive measure. Mohamad *et al.* (2014) proposed a decision making procedure based on Z-number with ranking fuzzy numbers method to prioritize the alternatives in a risk analysis problem. Aliev *et al.* (2015) presented expected utility paradigm under Z-information with its application in benchmark decision problem. Gardashova (2014) applied expected utility theory in solving multi-criteria decision making problem using Z-numbers. Yaakob and Gegov (2016) modified TOPSIS method to facilitate MCDM problems based on Z-numbers in stock selection proving its validity using spearman rho rank correlation. Kang *et al.* (2016) applied Z-number based genetic algorithm (GA) methodology for finding the optimal priority weight in supplier selection problem. Aliev *et al.* (2016) suggested human-like fundamental approach in ranking Z-numbers by computing its optimality degrees and adjusting it using a human being's opinion formalized by a degree of pessimism.

In typical MCDM approaches, weights of criteria reveal the relative importance of the decision-making process for ranking suitable alternatives. Depending on the information provided, several approaches are proposed to determine criteria weights based on subjective and objective approach (Ma *et al.* 1999). In our paper, both subjective and objective criteria weights are utilized, benefiting decision maker's expertise. The decision matrix and subjective criteria weights are first taken in Z-numbers (*for checking the reliability of information*) and thereby transformed into fuzzy numbers (*Trapezoidal mode*) applying method developed by Kang *et al.* (2012b). The problem involving calculation with Z-number is straightforward to state but very complicated to solve. Transforming Z-number into fuzzy numbers may lead to loss of information but its low computational complexity allows for extensive range of its usage. Recently, Tavakkoli-Moghaddam *et al.* (2015) proposed a Z-number based PROMETHEE multi-criteria group decision-making approach for facility location selection but they have not considered subjective and objective criteria in their selection. Though a considerable amount of research work has already been conducted by past researchers (Cherni, Kentish 2007; Kaya, Kahraman 2010; Cristobal 2011; Kabak, Dagdeviren 2014; Tasri, Susilawati 2014; Sengul *et al.* 2015) on selection of renewable energy using different MCDM methods, there is still need for a simple and systematic mathematical approach for handling ambiguity and fuzziness. In this paper, the COPRAS method developed by Zavadskas *et al.* (1994) is used for group decision making problem under a fuzzy environment taking reliability of decision into account, in choosing suitable *renewable energy* alternatives. COPRAS method has wide application in decision making under uncertain domain, namely, grey number based CORPAS (Zavadskas *et al.* 2009), Interval-valued intuitionistic fuzzy COPRAS (Razavi Hajiagha *et al.* 2013), Interval type-2 fuzzy COPRAS (Keshavarz Ghorabaee *et al.* 2014). From this point of view, the proposed method appears to be a suitable tool to analyze all perspective establishing a relationship between all alternatives and criteria that influence the decision making process in the renewable energy sector.

The remaining of this paper is structured as follows: *Section 1* discusses the concept of Z-number, its conversion to Trapezoidal fuzzy number (TrFN) along with its defuzzification, arithmetic operations of TrFNs, average rating of TrFN, subjective and objective criteria, and Shannon entropy based objective weight. The proposed algorithmic COPRAS-Z methodology, is discussed stepwise in *Section 2*, considering both subjective and objective criteria weights. *Section 3* comprises an illustrative case study detailing renewable energy sources and evaluation criteria identified from the view of Indian perspective, for validating the proposed methodology. *Section 4* showcase the result discussion part, summarizing all the findings in the background of renewable energy sector. Final section provides the conclusion along with future direction of this research.

1. Preliminaries

1.1. Concept of Z-number

In real world problems, decision making chain are fed by input parameters usually subject to uncertainties and art of handling it is one of the main concerns of the experts (Soroudi, Amaraee 2013). In fuzzy environment, making proper selection depend on various factors limited to human ability and assessment of expert preferences are usually done by *numerical values*. If the experts fails in the above case, *linguistic assessments* are alternatively used to express preference. As per Aliev *et al.* (2013), when dealing with vague and imprecise information, it is not sufficient to take only fuzziness restriction but also its level of reliability.

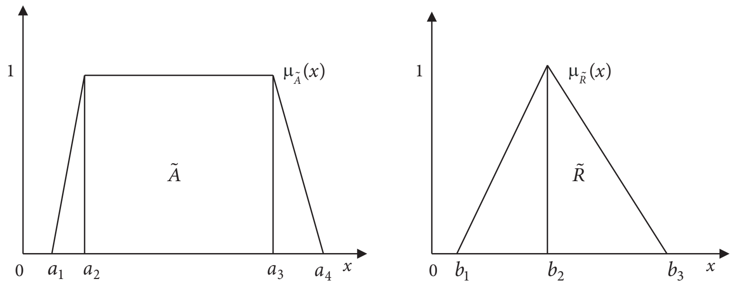

Figure 1. A Simple Z-number $Z=(\tilde{A},\tilde{R})$

For overcoming this limitation, Zadeh (2011), presented a new class of uncertain numbers called Z-number, represented by (1) and shown in Figure 1.

$$Z=\left(\tilde{A},\tilde{R}\right), \tag{1}$$

which includes the restriction of evaluation $\tilde{A}=\{<x,\mu_{\tilde{A}}(x)>| x\in[0,1]\}$ and the reliability of the judgment $\tilde{R}=\{<x,\mu_{\tilde{R}}(x)>| x\in[0,1]\}$; $\mu_{\tilde{A}}(x)$ and $\mu_{\tilde{R}}(x)$ being the trapezoidal and triangular membership functions respectively. In this context, $Z=\left\{x\middle| x\in A \text{ with certainty degree equal to } R\right\}$.

While type 1 and type 2 fuzzy number deals with uncertainty by numerical and interval membership function (Melin, Castillo 2013), Z-number represents reliability of linguistic terms in a more structured way.

1.2. Conversion of Z-number to trapezoidal fuzzy numbers

Lacking of basic properties and complication in arithmetic operation for Z-number forces us to simplify its representation. In order to use Z-number effectively, we use the process of converting Z-numbers to fuzzy numbers on the base of the fuzzy expectation, introduced by Kang *et al.* (2012b), described as follows:

– Transform the reliability $\tilde{R}$ to a crisp value. This computation is made by:

$$\alpha=\frac{\int x\mu_{\tilde{R}}(x)dx}{\int \mu_{\tilde{R}}(x)dx}. \tag{2}$$

Triangular fuzzy number (TFN) is applied here to state the degree of reliability. When $\tilde{R}=\left(b_1,b_2,b_3\right)$, the above formula becomes as (3):

$$\alpha=\frac{b_1+b_2+b_3}{3}. \tag{3}$$

– Add the weight of the second part (reliability $\tilde{R}$) to the first part (constraint $\tilde{A}$). Weighted Z-number can be denoted as:

$$\tilde{Z}^{\alpha}=\left\{\left(x,\mu_{\tilde{A}^{\alpha}}\right)\middle|\mu_{\tilde{A}^{\alpha}}=\alpha\mu_{\tilde{A}},\ x\in\left[0,1\right]\right\} \tag{4}$$

– Then transform the weighted Z-number into a fuzzy number by multiplying $\sqrt{\alpha}$ by:

$$\tilde{Z}'=\sqrt{\alpha}\times\tilde{A}^{\alpha}=\left(\sqrt{\alpha}\times a,\ \sqrt{\alpha}\times b,\ \sqrt{\alpha}\times c,\ \sqrt{\alpha}\times d\right). \tag{5}$$

1.3. Defuzzification of trapezoidal fuzzy number

Let $\tilde{A} = \left(a, b, c, d\right)$ be a trapezoidal fuzzy number (TrFN), whose membership function $f_{\tilde{A}}(x)$ is piecewise linear and defined in (6). $f_{\tilde{A}}^{L}(x):\left[a,b\right]\rightarrow\left[0,1\right]$ *and* $f_{\tilde{A}}^{R}(x):\left[c,d\right]\rightarrow\left[0,1\right]$ are two strictly monotonical and continuous mappings from R to closed interval $\left[0,1\right]$.

$$f_{\tilde{A}}(x) = \begin{cases} f_{\tilde{A}}^{L}(x), & a \le x \le b, \\ 1, & b \le x \le c, \\ f_{\tilde{A}}^{R}(x), & c \le x \le d, \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

where $f_{\tilde{A}}^{L}(x) = \dfrac{x-a}{b-a}$, $f_{\tilde{A}}^{U}(x) = \dfrac{b-x}{b-a}$.

In this paper, we follow centroid formulae presented by Wang *et al.* (2006), to derive the crisp value of any TrFN element (a, b, c, d). Therefore, crisp value for any TrFN $x_{ij} = \left(x_{ij1}, x_{ij2}, x_{ij3}, x_{ij4}\right)$ in matrix $\left[x_{ij}\right]_{m\times n}$ can be expressed as (7).

$$defuzz\left(x_{ij}\right) = \frac{\int x.f_{\tilde{A}}\left(x\right)dx}{\int f_{\tilde{A}}\left(x\right)dx} = \frac{\int\limits_{x_{ij1}}^{x_{ij2}} x.\left(\dfrac{x-x_{ij1}}{x_{ij2}-x_{ij1}}\right)dx + \int\limits_{x_{ij2}}^{x_{ij3}} xdx + \int\limits_{x_{ij3}}^{x_{ij4}} x.\left(\dfrac{x_{ij4}-x}{x_{ij4}-x_{ij3}}\right)dx}{\int\limits_{x_{ij1}}^{x_{ij2}} \left(\dfrac{x-x_{ij1}}{x_{ij2}-x_{ij1}}\right)dx + \int\limits_{x_{ij2}}^{x_{ij3}} dx + \int\limits_{x_{ij3}}^{x_{ij4}} \left(\dfrac{x_{ij4}-x}{x_{ij4}-x_{ij3}}\right)dx} =$$

$$\frac{-x_{ij1}x_{ij2} + x_{ij3}x_{ij4} + \frac{1}{3}\left(x_{ij4}-x_{ij3}\right)^2 - \frac{1}{3}\left(x_{ij2}-x_{ij1}\right)^2}{-x_{ij1} - x_{ij2} + x_{ij3} + x_{ij4}}. \tag{7}$$

1.4. Operations of trapezoidal fuzzy numbers (TrFNs)

Trapezoidal fuzzy numbers (TrFN) can be handled arithmetically and interpreted intuitively. Let $A = \left(a_1, b_1, c_1, d_1\right)$ and $B = \left(a_2, b_2, c_2, d_2\right)$ be two TrFNs. Then the basic arithmetic operations of TrFN are defined as follows (Shemshadi *et al.* 2011):

1. Addition $\oplus$ of two TrFN $A = \left(a_1, b_1, c_1, d_1\right)$ and $B = \left(a_2, b_2, c_2, d_2\right)$
$$A \oplus B = \left(a_1 + a_2,\ b_1 + b_2,\ c_1 + c_2,\ d_1 + d_2\right). \tag{8}$$
2. Subtraction $(-)$ of two TrFN $A = \left(a_1, b_1, c_1, d_1\right)$ and $B = \left(a_2, b_2, c_2, d_2\right)$
$$A\ (-)\ B = \left(a_1 - d_2,\ b_1 - c_2,\ c_1 - b_2,\ d_1 - a_2\right). \tag{9}$$
3. Multiplication $\otimes$ of two TrFN $A = \left(a_1, b_1, c_1, d_1\right)$ and $B = \left(a_2, b_2, c_2, d_2\right)$
$$A \otimes B = \left(a_1 \times a_2,\ b_1 \times b_2,\ c_1 \times c_2,\ d_1 \times d_2\right). \tag{10}$$
4. Division $(\div)$ of two TrFN $A = \left(a_1, b_1, c_1, d_1\right)$ and $B = \left(a_2, b_2, c_2, d_2\right)$
$$A\ (\div)\ B = \left(a_1 \div d_2,\ b_1 \div c_2,\ c_1 \div b_2,\ d_1 \div a_2\right). \tag{11}$$

5. Scalar Multiplication of TrFN $B=(a_2, b_2, c_2, d_2)$

$$kB=k(a_2, b_2, c_2, d_2)=(ka_2, kb_2, kc_2, kd_2). \tag{12}$$

6. Inverse of TrFN $A=(a_1, b_1, c_1, d_1)$

$$A^{-1}=\left(\frac{1}{d_1}, \frac{1}{c_1}, \frac{1}{b_1}, \frac{1}{a_1}\right). \tag{13}$$

1.5. Aggregate fuzzy ratings of TrFNs

For an expert group having K decision makers (DMs), fuzzy rating of each DM D_k $(k=1, 2,..., K)$ can be represented in positive TrFN $R_k=(a_k, b_k, c_k, d_k)$ for $k=1, 2,..., K$. Hence, the aggregated subjective fuzzy rating (R) for TrFN $R_k=(a_k, b_k, c_k, d_k)$ is defined as per Shemshadi *et al.* (2011) as follows:

$$R=(a, b, c, d), \tag{14}$$

where $a=\min\limits_{k=1,2,....K}\{a_k\}$, $b=\frac{1}{K}\sum_{k=1}^{K} b_k$, $c=\frac{1}{K}\sum_{k=1}^{K} c_k$, $d=\min\limits_{k=1,2,....K}\{d_k\}$. (15)

1.6. Subjective and objective attributes

In typical MCDM criteria evaluation, weights of criteria reflect varied opinions and meanings as it is not of equal importance. Majority of the decision making approaches to determine criteria weights, are classified into two categories, namely subjective and objective (Ma *et al.* 1999). Subjective approach reflect intuition and judgment of decision makers influenced by his lack of knowledge or experience, while objective approach determine weight by mathematical models (Deng *et al.* 2000). Both the methods are utilized in the comparison to overcome the shortage that occurs in either of them (Zoraghi *et al.* 2013).

1.7. Shannon Entropy and objective weight

Entropy concept (Shannon 1948) measure the uncertainty in information in terms of probability. As per Zeleny (1996), the entropy concept measures the relative intensities of criteria to represent the average intrinsic information transferred to the decision maker. Shannon's entropy calculates objective weighting of the criteria through the following steps (Zitnick, Kanade 2004):

– Normalize the array of decision matrix (evaluation index) as:

$$P_{ij}=\frac{x_{ij}}{\sum_j x_{ij}}. \tag{16}$$

– Compute entropy measure e_j of every index using the following equation:

$$e_j=-k\sum_{j=1}^{n} P_{ij}\ln(P_{ij}) \text{ where } k=(\ln(m))^{-1}. \tag{17}$$

– Define the divergence div_j that indicates the importance of j^{th} criterion:

$$div_j=|1-e_j|. \tag{18}$$

– Define the objective weight, based on the entropy concept, as in (19):

$$w_j = \frac{div_j}{\sum_j div_j}. \tag{19}$$

2. Proposed methodology

In this section, we propose COPRAS-Z methodology that integrates subjective and objective weight in fuzzy environment, taking reliability of information into account. The proposed approach takes both the expertise and involvement of decision maker's (DMs) in the whole decision making process. Shannon's entropy is adopted to evaluate objective weights of criteria effectively balancing the influence of subjective criteria weights determined by decision makers, providing a more comprehensive methodology for decision making process. The step-by-step methodology of the proposed model is given as follows:

Step 1: *Specify the criteria and alternatives most considerable for the experts*

Form a group of decision maker's (*DMs*) for sorting out the criteria and alternatives for the decision making problem. Two set of appropriate linguistic variables and their relevant membership functions are identified to estimate the important weight of each criterion and fuzzy rates of alternatives assigned by *DMs*. The details given in Table 3 and 4 respectively.

Step 2: Develop a decision matrix

Assume that there is a set of m alternatives $A_i\left(i=1,2,.....m\right)$ evaluated against n selection criteria $C_j\left(j=1,2,.....n\right)$. We utilize p^{th} decision-maker $D_p\left(p=1,2,....,k\right)$ for determining the weighting matrix $DW_p\left(p=1,2,....,k\right)$ of the attributes and the evaluating matrix $Y_p\left(p=1,2,....,k\right)$ of the alternatives, based on linguistic terms expressed in Z-number. In Z-number, $Z\left(\tilde{A},\tilde{R}\right)$, the restriction part $\tilde{A}$, of the Z-number, is taken in trapezoidal fuzzy number (TrFN) and $\tilde{R}$ the reliability part of the Z-numbers, taken in triangular fuzzy number (TFN).

$$Y_p = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{bmatrix} \tilde{y}_{11}^p & \tilde{y}_{12}^p & \cdots & \tilde{y}_{1n}^p \\ y_{21}^p & y_{22}^p & \cdots & y_{2n}^p \\ \vdots & \vdots & \ddots & \vdots \\ y_{m1}^p & y_{m2}^p & \cdots & y_{mn}^p \end{bmatrix}_{m\times n} \end{array} \quad \text{where} \quad \tilde{y}_{ij}^p = Z_{ij}^p\left(\tilde{A},\tilde{R}\right); \tag{20}$$

$$DW_p = \left[\tilde{w}_1^p \quad \tilde{w}_2^p \quad \cdots \quad \tilde{w}_n^p\right]_{1\times n} \quad \text{where} \quad w_j^p = Z_j^p\left(\tilde{A},\tilde{R}\right). \tag{21}$$

Step 3: Construct an aggregated fuzzy decision matrix $\tilde{D}$

Step 3.1: For p^{th} decision maker, the elements $\tilde{y}_{ij}^p = Z_{ij}^p\left(\tilde{A},\tilde{R}\right)$ of $Y_p\left(p=1,2,....,k\right)$ for i^{th} alternative as per j^{th} criterion are transformed to TrFN $\tilde{x}_{ij}^p = \left(\tilde{x}_{ij1}^p,\tilde{x}_{ij2}^p,\tilde{x}_{ij3}^p,\tilde{x}_{ij4}^p\right)$, applying eqns. (2)–(5) of section 1.2. Then fuzzy decision making matrix $X_p = \left[\tilde{x}_{ij}^p\right]_{m\times n}$ is formed and represented by (22).

$$X_p = \begin{bmatrix} \tilde{x}_{11}^p & \tilde{x}_{12}^p & \cdots & \tilde{x}_{1n}^p \\ \tilde{x}_{21}^p & \tilde{x}_{22}^p & \cdots & \tilde{x}_{2n}^p \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{x}_{m1}^p & \tilde{x}_{m2}^p & \cdots & \tilde{x}_{mn}^p \end{bmatrix}_{m\times n} \quad \text{where } \tilde{x}_{ij}^p = \left(\tilde{x}_{ij1}^p, \tilde{x}_{ij2}^p, \tilde{x}_{ij3}^p, \tilde{x}_{ij4}^p\right). \tag{22}$$

Step 3.2: Hence, the aggregated fuzzy rating $\left(x_{ij}\right)$ with respect to criterion $C_j \; \left(j=1,2,\ldots,n\right)$ is calculated as:

$$x_{ij} = \left\{\left(\tilde{x}_{ij1}, \tilde{x}_{ij2}, \tilde{x}_{ij3}, \tilde{x}_{ij4}\right) \middle| \; i=1,2,\ldots,m;\; j=1,2,\ldots,n\right\}, \tag{23}$$

where $\tilde{x}_{ij1} = \min_{p=1,2,\ldots k}\left\{x_{ij1}^p\right\},\; \tilde{x}_{ij2} = \frac{1}{k}\sum_{p=1}^{k} x_{ij2}^p,\; \tilde{x}_{ij3} = \frac{1}{k}\sum_{p=1}^{k} x_{ij3}^p,\; \tilde{x}_{ij4} = \max_{p=1,2,\ldots k}\left\{x_{ij4}^p\right\}.$

Thus the aggregated fuzzy decision matrix $\tilde{D}$ is concisely expressed as:

$$\tilde{D} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix}_{m\times n} . \tag{24}$$

Step 4: Normalize the aggregated fuzzy decision matrix

Assume for each criterion $C_j \; \left(j=1,2,\ldots,n\right)$ scaled between 0 and 1, have values in same measurement range. The normalization of decision matrix $\tilde{D} = \left[x_{ij}\right]_{m\times n}$ for each criterion is done separately increasing the criteria have positive (benefit) concepts and decreasing the negative (cost) concept.

For benefit based j^{th} criterion in the decision matrix $\tilde{D}$, each element $x_{ij} = \left(\tilde{x}_{ij1}, \tilde{x}_{ij2}, \tilde{x}_{ij3}, \tilde{x}_{ij4}\right)$ is normalized by dividing by maximum of their right hand members, shown in (25).

$$\hat{x}_{ij} = \left(\frac{\tilde{x}_{ij1}}{\max_i\left(\tilde{x}_{ij4}\right)}, \frac{\tilde{x}_{ij2}}{\max_i\left(\tilde{x}_{ij4}\right)}, \frac{\tilde{x}_{ij3}}{\max_i\left(\tilde{x}_{ij4}\right)}, \frac{\tilde{x}_{ij4}}{\max_i\left(\tilde{x}_{ij4}\right)}\right), \; j \in \text{Benefit related criteria} . \tag{25}$$

For cost based j^{th} criterion in the decision matrix $\tilde{D}$, each element $x_{ij} = \left(\tilde{x}_{ij1}, \tilde{x}_{ij2}, \tilde{x}_{ij3}, \tilde{x}_{ij4}\right)$ is normalized by dividing minimum of their left hand members by each element, in reverse order, shown in (26).

$$\hat{x}_{ij} = \left(\frac{\min_i\left(\tilde{x}_{ij1}\right)}{\tilde{x}_{ij4}}, \frac{\min_i\left(\tilde{x}_{ij1}\right)}{\tilde{x}_{ij3}}, \frac{\min_i\left(\tilde{x}_{ij1}\right)}{\tilde{x}_{ij2}}, \frac{\min_i\left(\tilde{x}_{ij1}\right)}{\tilde{x}_{ij1}}\right), \; j \in \text{Cost related criteria} . \tag{26}$$

Then the aggregated normalized fuzzy decision matrix $\tilde{N} = \left[\hat{x}_{ij}\right]_{m\times n}$ can be expressed as:

$$\tilde{N} = \begin{bmatrix} \hat{x}_{11} & \hat{x}_{12} & \cdots & \hat{x}_{1n} \\ \hat{x}_{21} & \hat{x}_{22} & \cdots & \hat{x}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \hat{x}_{m1} & \hat{x}_{m2} & \cdots & \hat{x}_{mn} \end{bmatrix}_{m\times n} \quad \text{where } \hat{x}_{ij} = \left(\hat{x}_{ij1}, \hat{x}_{ij2}, \hat{x}_{ij3}, \hat{x}_{ij4}\right) . \tag{27}$$

Step 5: Subjective weighting method and entropy based objective weighting method

For subjective weight

These weights reflect the subjective judgment of decision makers (DMs) *without considering the alternatives.* For p^{th} decision maker, subjective weighting matrix $DW_p\left(p=1,2,....,k\right)$ for criteria C_j based on Z-number, (*shown in* (21)), are transformed to its TrFN counterpart, applying Eqns. (2)–(5) as described in Section 1.2. Thus the fuzzy weighted decision matrix W_p is represented as:

$$W_p=\left[\hat{w}_j^p\right]_{1\times n}=\left[\hat{w}_1^p \quad \hat{w}_2^p \quad \cdots \quad \hat{w}_n^p\right]_{1\times n}, \tag{28}$$

$$\text{where } \hat{w}_j^p=\left(\hat{w}_{j1}^p,\hat{w}_{j2}^p,\hat{w}_{j3}^p,\hat{w}_{j4}^p\right) \text{ for } j=1,2,...,n;\ \ p=1,2,...,k. \tag{29}$$

These TrFN based criteria weight $\hat{w}_j^p\left(j=1,2,...,n;\ p=1,2,...,k\right)$ are transformed to aggregate weight w_j^s for each criteria $C_j\left(j=1,2,...,n\right)$, using (14)–(15) of Section 1.5, to form as subjective weighted matrix $\left(W_s\right)$, as shown in (30).

$$W_s=\left[w_j^s\right]_{1\times n}=\left[w_1^s \quad w_2^s \quad \cdots \quad w_n^s\right]_{1\times n}, \tag{30}$$

$$\text{where } w_j^s=\left\{\left(w_{j1}^s,w_{j2}^s,w_{j3}^s,w_{j4}^s\right)\middle|\, j=1,2,.....,n\right\}. \tag{31}$$

For objective weights

The objective approach select criteria weights through mathematical calculation, *neglecting any subjective judgment information of DMs.* The objective weight for the j^{th} criterion with regard to p^{th} decision maker, is calculated using Eqns. (16)–(19) of entropy measure, described in Section 1.7. The objective weight $w_j^o\left(j=1,2,...,n\right)$ for each criterion $C_j\left(j=1,2,...,n\right)$ is represented in (32) and its corresponding weighted matrix W_o in (33).

$$w_j^o=\frac{div_j}{\sum_{j=1}^{n} div_j}; \tag{32}$$

$$W_o=\left[w_j^o\right]_{1\times n}=\left[w_1^o \quad w_2^o \quad \cdots \quad w_n^o\right]_{1\times n} \text{ for } j=1,2,...,n. \tag{33}$$

Step 6: *Calculate the overall performance evaluation*

Step 6.1: The elements $\left(\hat{x}_{ij}\right)\left(i=1,2,...,m,\ j=1,2,...,n\right)$ of normalized trapezoidal fuzzy decision matrix $\left(\tilde{N}\right)$ are multiplied with TrFN s*ubjective criteria weight* $\left(w_j^s\right)$ to obtain weighted decision matrix $\left(F\right)$, using fuzzy multiplicative operator $\otimes$ of TrFN, discussed in (10) of section 1.4.

$$F=\left[f_{ij}\right]_{m\times n}=\begin{bmatrix} \hat{x}_{11}\otimes w_1^s & \hat{x}_{12}\otimes w_2^s & \cdots & \hat{x}_{1n}\otimes w_n^s \\ \hat{x}_{21}\otimes w_1^s & \hat{x}_{22}\otimes w_2^s & \cdots & \hat{x}_{2n}\otimes w_n^s \\ \vdots & \vdots & \ddots & \vdots \\ \hat{x}_{m1}\otimes w_1^s & \hat{x}_{m2}\otimes w_2^s & \cdots & \hat{x}_{mn}\otimes w_n^s \end{bmatrix}_{m\times n}, \tag{34}$$

where $f_{ij}=\hat{x}_{ij}\otimes w_j^s$, $\hat{x}_{ij}=\left(\hat{x}_{ij1},\hat{x}_{ij2},\hat{x}_{ij3},\hat{x}_{ij4}\right)$ and $w_j^s=\left(w_{j1}^s,w_{j2}^s,w_{j3}^s,w_{j4}^s\right)$; $i=1,2,...,m,\ j=1,2,...,n.$

Step 6.2: Applying (7) of section 1.3, the TrFNs $f_{ij} = \left(f_{ij1}, f_{ij2}, f_{ij3}, f_{ij4}\right)$ in decision matrix $F = \left[f_{ij}\right]_{m\times n}$ are converted to defuzzified mode $\hat{f}_{ij}$ corresponding its weighted decision matrix $\left(\hat{F}\right)$ and shown in (35).

$$\hat{F} = \left[\hat{f}_{ij}\right]_{m\times n} = \begin{bmatrix} \hat{f}_{11} & \hat{f}_{12} & \cdots & \hat{f}_{1n} \\ \hat{f}_{21} & \hat{f}_{22} & \cdots & \hat{f}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \hat{f}_{m1} & \hat{f}_{m2} & \cdots & \hat{f}_{mn} \end{bmatrix}_{m\times n}. \tag{35}$$

Step 6.3: Taking *objective criteria weight* $w_j^o\left(j = 1,2,...,n\right)$ into account, the above *defuzzified matrix* $\left(\hat{F}\right)$ is multiplied with $w_j^o\left(j = 1,2,...,n\right)$, to form total weighted decision matrix $\left(T\right)$. As weight in objective weighted matrix W_o and normalized weighted decision matrix $\left(\hat{F}\right)$ are expressed in crisp mode, simple multiplicative operator '$\times$' is applied here. The result is defuzzified total weighted decision matrix $\left(T\right)$, the elements $t_{ij}\ \left(i = 1,2,...,m,\ j = 1,2,...,n\right)$ which are also in crisp mode, shown in (36).

$$T = \left[t_{ij}\right]_{m\times n} = \begin{bmatrix} \hat{f}_{11}\times w_1^o & \hat{f}_{12}\times w_2^o & \cdots & \hat{f}_{1n}\times w_n^o \\ \hat{f}_{21}\times w_1^o & \hat{f}_{22}\times w_2^o & \cdots & \hat{f}_{2n}\times w_n^o \\ \vdots & \vdots & \ddots & \vdots \\ \hat{f}_{m1}\times w_1^o & \hat{f}_{m2}\times w_2^o & \cdots & \hat{f}_{mn}\times w_n^o \end{bmatrix}_{m\times n}, \tag{36}$$

where $t_{ij} = \hat{f}_{ij}\times w_j^o,\ i = 1,2,...,m,\ j = 1,2,...,n$.

Step 7: Determine the relative significance $\left(Q_i\right)\left(i = 1,2,...,m\right)$ *of each alternative*

Taking total weighted decision matrix $T = \left[t_{ij}\right]_{m\times n}$ compute the values of Q_i as follows

$$P_i = \sum_{j=1}^{k} t_{ij};\quad k = \text{number of criteria to be maximized}; \tag{37}$$

$$R_i = \sum_{j=k+1}^{n} t_{ij};\quad (n-k) = \text{number of criteria to be minimized}; \tag{38}$$

$$R_{\min} = \min_i R_i;\ \left(i = 1,2,...,m\right); \tag{39}$$

$$Q_i = P_i + \frac{R_{\min}\sum_{i=1}^{m} R_i}{R_i\sum_{i=1}^{m}\frac{R_{\min}}{R_i}} \text{ or denoted by } Q_i = P_i + \frac{\sum_{i=1}^{m} R_i}{R_i\sum_{i=1}^{m}\frac{1}{R_i}}. \tag{40}$$

Step 8: Determine the optimality criterion K

$$K = \max_i Q_i\quad \left(i = 1,2,...,m\right). \tag{41}$$

Step 9: Determine the utility degree $\left(N_i\right)\left(i = 1,2,...,m\right)$ *of each alternative*

Taking into account relative significance $\left(Q_i\right)\left(i = 1,2,...,m\right)$ of each alternative, calculate utility degree $\left(N_i\right)\left(i = 1,2,...,m\right)$ of each alternative, as follows:

$$N_i = \left(\frac{Q_i}{Q_{\max}} \right) \times 100\%, \quad i = 1,2,\ldots,m. \tag{42}$$

Step 10: *Rank the alternatives sorting by values* Q_i and $N_i \left(i = 1,2,\ldots,m \right)$ *in an ascending order.*

3. Case study: prioritization of renewable energy sources for India

India has a renewable energy potential of around 85.000 MW from commercially exploitable sources, i.e. (*Wind, 45.000 MW; Small hydro, 15.000 MW; Biomass, 25.000 MW*) and potential to generate 35 MW per square kilometer using solar photovoltaic and thermal energy (Kumar *et al.* 2010). Of the different areas covered under Renewable energy project, this paper has selected a case study for multi-criteria decision making (MCDM) problem in prioritizing of renewable alternatives for electric generation, considering both benefit and cost/risky criteria. Based on Table 1, the energy alternatives considered here are Geothermal energy (A_1), Solar energy (A_2), Tidal power (A_3), Hydro power (A_4) and Wind power (A_5) and twelve different criteria categorized under four category namely, technical (C_1), socio & political (C_2) economic & financial (C_3), environmental (C_4), in prioritizing renewable energy sources, shown in Table 2. The main objective for a renewable energy sources in India is to ensure increase in level of percent share of electricity production by 2023. An alternative energy source will reduce import and reduce green gas emission. The details of these secondary energy resources in Indian perspective is given below.

Table 1. Brief summary of India's renewable energy potential (Luthra *et al.* 2015)

Sl. No.	Renewable Energies in India	Available	Being used
1	Solar energy	700–2100 GW	2.2 GW
2	Wind energy	102 GW	21.1 GW
3	Hydro energy	150 GW	39.7 GW
4	Geothermal energy	10.6 GW	0 GW
5	Biomass energy	23 GW	1.2 GW
6	Tidal power	8 GW	–
7	Wave energy	40 GW	0.01

3.1. Evaluation of renewable energy alternative sources

Secondary energy source, such as renewable energy, are available in the form of geothermal, hydro power, solar, biomass and wind energy, the status discussed in *Indian* perspective (Luthra *et al.* 2015).

Few works has been done to prioritize renewable energy sources based on multi-criteria decision making methods. Cristobal (2011) applied AHP along with VIKOR method for selection among renewable energy like wind power, hydroelectric, solar thermal, biomass, and biofuel in *Spain*. Sengul *et al.* (2015) applied fuzzy TOPSIS method for ranking among renewable energy like Hydropower, Geothermal, Wind, solar, Biofuel energy in *Turkey's* perspective. Tasri and Susilawati (2014) selected the appropriate renewable energy in form of solar, hydro-power, geothermal, wind energy and biomass through fuzzy analytic hierarchy process for *Indonesia*. Kabak and Dagdeviren (2014) proposed a hybrid model based on BOCR and ANP to prioritize *Turkey's* energy alternatives from among five RE sources. Luthra *et al.* (2015) does a literature review on renewable energies alternative's available in Indian perspective (Table 1).

Based on the above research papers this paper consider top five alternative renewable energy viz. Geothermal energy (A_1), Solar energy (A_2), Tidal power (A_3), Hydro power (A_4) and Wind power (A_5). As Biomass consume vast farmland and native habitat resulting in greenhouse gas emission, Tidal energy (only 8%), it is preferred over Biomass energy (23 GW) despite of its low availability (Ratha, Prasanna 2012).

The brief description of above renewable alternatives are discussed below.

Geothermal energy (A_1)

As per Geological society of India, geothermal resources in India estimating around *10.600 MW* (Mahesh, Shoba Jasmin 2013). Indian Government has projected first geothermal power plant in Balrampur district in Chhattisgarh (Luthra *et al.* 2015).

Solar energy (A_2)

In spite of high cost of electricity generation and wide area coverage by solar panels, India' expects to increase its installed grid connected solar power from 2208.36 MW to 20.000 MW by 2022 (Khare *et al.* 2013). Taking advantage of its geographical location, India has high potential for solar energy to decrease the adverse impacts on environment, lower carbon footprints and create balanced regional development.

Tidal power (A_3)

India has an expected potential of 8000 MW tidal energy along 7500 km stretch of coastline including Gulf of Cambay (7000 MW), Gulf of Kutch (1200 MW) and (100 MW) in Sunderban region (Baba *et al.* 2013). New projects are coming up at Mandavi in Kutch (250 MW) and Sunderban (3.75 MW) (Luthra *et al.* 2015).

Hydro-power (A_4)

The total hydro-potential in the country is estimated about 150.000 MW but existing capacity (up to year 2013) is 39.788 MW which is 17.4% of total electricity generation (Kumar, Katoch 2014). In global scenario, India *rank's fifth* in terms of exploitable hydro-potential and by 2017, Indian government has set up a target of expanding hydro capacity to 7 GW (Luthra *et al.* 2015).

Wind energy (A_5)

In the last decade, global wind market grew by an average of 28% per year in terms of total installed capacity (Kumar *et al.* 2010). As per statistics of Indian Ministry of New and renewable energy (IMNRE), 2014, India occupies *fourth place* in the world in wind energy generation installing more than 21136.3 MW.

3.2. Evaluation of renewable energy supply system criteria

The draft of the criteria is verified through a literature review and then reviewed by group of experts, consisting of academics, renewable energy practitioners and government decision makers. This paper chooses criteria based on the research work of the following practitioners. Zhang *et al.* (2015) proposed four criteria (*Technical, Economic, Environmental and Social*) and seven sub-criteria (*TRL, Safety and Security Cost, FIT, CO_2 emissions, Land use and Job creation*) for evaluating clean energy alternatives for Jiangsu, China. For selection among renewable energy in Indonesia based on fuzzy AHP, Tasri and Susilawati (2014) applied five main criteria and fifteen sub-criteria namely, Sustainability, durability, distance to user under *Quality of energy source*; Government policy, labor impact, social acceptance under *Socio-political criteria*; Implementation cost, Economic value, Affordability under *Economic criteria*; Continuity and predictability of performance, risk, local technical knowledge under *Technological* category; Pollutant emission, land requirement, requirement for waste disposal under *Environmental* category. Based on data from various official institutions in Turkey for ranking renewable energy systems, Sengul *et al.* (2015) selected five criteria and nine sub-criteria namely: Efficiency, installed capacity, amount of energy produced under *technical category*; Investment cost, Operation and maintenance cost, payback period under *Economic category*, Land use, value of CO_2 emission under Environmental criteria and Job creation under *Social category*. As per Wang *et al.* (2009) in aid of sustainable energy decision-making, the criteria are classified mainly into four types along with twenty-four sub-criteria. Kabak and Degdeviren (2014) proposed a control hierarchy which consists of four kinds of sub -networks: BOCR and five strategic criteria: Technology, Economy, Security, Global effect and Human Wellbeing to prioritize renewable energy sources for Turkey. In Indian context, Luthra *et al.* (2015) categorized twenty-eight barriers into seven dimensions from an extensive literature review. The brief description of the criteria used to evaluate renewable energy alternatives in India, are explained briefly. While some criteria with positive impact are maximized in decision-making problems while negative impact criteria are minimized. In this study, the criteria with *positive impact* are Energy Efficiency (C_{11}), National Infrastructure (C_{12}), Job creation (C_{21}), Government Policy (C_{22}), Consumer Awareness (C_{23}). The criteria with *negative impact* are the Technology Complexity (C_{13}), Investment Cost (C_{31}), Operation and maintenance Cost (C_{32}), Financial mechanism (C_{33}), Land Use (C_{41}), CO_2 emission (C_{42}), and Safety and ecological issue (C_{43}). These 12 criteria categorized in four category viz. Technical (C_1) , Socio-political (C_2) , Economic & Financial (C_3) and Environmental (C_4), shown in Table 2, the details of which are explained below.

Technical Category (C_1)**:** Under this category we have three criteria, details given below

Energy Efficiency (C_{11})

Energy Efficiency refers to energy obtain taking second law of thermodynamics into consideration (Wang *et al.* 2009). It is one technical criteria to assess country's energy systems to meet requirement potential.

National Infrastructure (C_{12})

To explore and develop these renewable energy resources, there is no clear division of authority between state and national level (Cherni, Kentish 2007). Shortage of institutional mechanisms failed to provide after-sale support due to limited private sector participation (Blachandra 2009). The regulatory barrier resulted in problems in land acquisition whereas a lack of infrastructure added to the cost (Reddy, Painuly 2004).

Technology complexity (C_{13})

Renewable energy is currently in its development phase due to technical complexity and cost disadvantage

(Painuly 2001). Lack of technology transfer, geographical restrictions as well as complex structural constraints are reasons behind rejection of technological potential of renewable energy in Indian perspective (Wilkins 2012).

Table 2. Criteria taken into account to select the best renewable energy

Category	Criteria	References
Technical (C_1)	Energy Efficiency (C_{11}) National Infrastructure (C_{12}) Technology complexity (C_{13})	Wang *et al.* 2009; Cherni, Kentish 2007; Blachandra 2009; Kumar *et al.* 2010; Painuly 2001
Socio & political (C_2)	Job creation (C_{21}) Government Policy (C_{22}) Consumer awareness (C_{23})	Kaya, Kahraman 2010; Wang *et al.* 2009; Khare *et al.* 2013; Harish, Kumar 2014; Reddy, Painuly 2004; Sawin 2003
Economic & Financial (C_3)	Investment cost (C_{31}) Operation and maintenance cost (C_{32}) Financial mechanism (C_{33})	Wang *et al.* 2009; Kaya, Kahraman 2010; Hirmer, Cruickshank 2014; Karakosta *et al.* 2010; Reddy, Painuly 2004; Nguyen *et al.* 2010
Environmental (C_4)	Land use (C_{41}) CO_2 emissions (C_{42}) Safety and ecological issue (C_{43})	Wang *et al.* 2009; Kaya, Kahraman 2010; Evans *et al.* 2009; Tsoutsos *et al.* 2005; Srivastava, Sharma 2013

Socio & Political Category (C_2)**:** This category is also categorized into three sub-parts, detailed below

Job creation (C_{21})

Because of the country's dense population and current economic situation in India, job creation is also considered an important criterion. In the decision making process of local and regional government, *job creations* in renewable energy supply can be made available from installation process to maintenance work in renewable energy sector (Kaya, Kahraman 2010).

Government policy (C_{22})

Political instability, government intervention in domestic markets, corruptions in civil society are major barriers to adoption of separate policy for renewable energy in India. The renewable energy technology is still in development stage due to mismatch in existing policies to facilitate the growth of renewable technologies (Khare *et al.* 2013).

Consumer awareness (C_{23})

As per Sawin (2003), information about government incentives in renewable energy can reach the masses through proper education about various renewable technologies. Lack of awareness and interest in promoting renewable energy technology results in uncertainty on new and efficient products among the stakeholders (Harish, Kumar 2014).

Economic **&** ***Financial category*** (C_3)**:** This category is sub-divided into three sub-parts, as follows

Initial Investment cost (C_{31})

The investors must maintain balance in the investment costs and the benefits, as it is the most used economic criterion to evaluate the energy systems (Kaya, Kahraman 2010). Higher initial investment in imported technology is not accepted by consumers, who tends to minimize the initial cost rather than operating costs (Karakosta *et al.* 2010).

Operation and maintenance cost (C_{32})

Maintenance costs viability depend on the geographical condition and far away point of availability from point of consumption lead to high transmission and distribution losses. Barrier to access to incentives (*in form of subsidy and low interest loan*) affect the economic feasibility of businesses and affordability of maintenance services for renewable energy projects (Nguyen *et al.* 2010).

Financial mechanism (C_{33})

Economic and financial issues plays a crucial role as high investments cost in mass manufacturing remains as barriers due to lack of sufficient financial mechanism to promote adoption of renewable energy technologies (Nguyen *et al.* 2010). Customers are unwilling to invest initially due to large physical distance from a renewable energy projects, low per capita income and low priority to environmental issue. Recently, Indian government is providing financial support for solar appliances (Kumar *et al.* 2010).

Environmental Category (C_4)**:** This category is sub-divided into following three criteria, as follows

Land use (C_{41})

Land is one of scarcer resources in India due to vast human population and directly linked to ecological balance. The environmental and landscape are affected directly by the land occupied by the clean energy systems and must be considered by energy experts (Wang *et al.* 2009). The land acquisition for renewable energy projects is a matter of great concern as different energy systems may occupy different land while the products are same (Kaya, Kahraman 2010).

CO_2 emissions (C_{42})

This criterion is taken into account to produce clean energy and decrease CO_2 emission level released through fossil fuel. The carbon market representing all the greenhouse gases is an important tool in harmful emissions to work in accordance with the market rules (Luthra *et al.* 2015). Penalizing those who release more than the limit imposed and rewarding those who have less emissions should be adopted for reducing the amount of emissions (Kaya, Kahraman 2010).

Safety and ecological issue (C_{43})

Safety is both a *technical* and also a *social criteria evaluation criteria* of applied technology to show the effect of various energy systems to all section of society and its people (Wang *et al.* 2009). In *wind energy* technology there is a high probability of risk due to bird strikes as well as unpopular visual effects and noise pollution. The potential environmental impacts associated with *solar power* are land use and habitat loss, water use and use of hazardous materials in manufacturing (Tsoutsos *et al.* 2005). In regard to *hydro power* there are social problems like rehabilitation policies (Srivastava, Sharma 2013). For un-interrupted and continuous power supply, storage device are required in form of rechargeable batteries, the disposal of which is a major environmental issue.

3.3. Application of the proposed method in prioritization of renewable energy alternatives

In this section, the proposed model is applied in selection of renewable energy, based on the steps of the methodology given in Section 2.

Step 1

In the first step, an expert team consisting of three experts $D_i\left(i=1,2,3\right)$, form a committee to act as decision makers (DMs). *First expert is an* academic researcher having publication in energy policy, *second* is *an expert* on energy affairs in Ministry of Energy and Natural Resources of Indian government; and *remaining expert* view are joint views of the authors of this paper. The communication among the experts are based on Questionnaire form, Interview mode and collecting data from government websites and research papers.

Step 2

After determining the evaluation criteria and the alternatives, the algorithmic steps of the integrated COPRAS-Z methodology are implemented. To determine the importance of each criterion, and rating of alternatives based on criteria, the experts employed a *seven point scale* given in Table 3 and Table 4 respectively. In order to establish the decision matrix for each decision maker, fuzzy linguistic terms are applied where restriction (TrFN) and reliability part (TFN) of the information are taken simultaneously.

Step 3

While evaluating the alternatives, the DMs classify the criteria into benefit and cost criteria to be maximized and minimized simultaneously. Each DM (decision maker) rate each criterion weight (*Subjective*) with respect to linguistic terms (Table 5) and then analyze each alternative with respect to evaluation criteria, shown in Table 6.

Table 3. Fuzzy linguistic terms and correspondent fuzzy numbers of each criterion

Importance	Abbreviation	*For Restriction Part*	*For Reliability Part*
		Trapezoidal Fuzzy Number (TrFN)	Triangular Fuzzy Number (TFN)
Very Low	VL	(0.0, 0.0, 0.1, 0.2)	(0.0, 0.0, 0.2)
Low	L	(0.1, 0.2, 0.2, 0.3)	(0.05, 0.2, 0.35)
Medium Low	ML	(0.2, 0.3, 0.4, 0.5)	(0.2, 0.35, 0.5)
Medium	M	(0.4, 0.5, 0.5, 0.6)	(0.35, 0.5, 0.65)
Medium High	MH	(0.5, 0.6, 0.7, 0.8)	(0.5, 0.65, 0.8)
High	H	(0.7, 0.8, 0.8, 0.9)	(0.65, 0.8, 0.95)
Very High	VH	(0.8, 0.9, 1.0, 1.0)	(0.8, 1.0, 1.0)

Table 4. Fuzzy linguistic terms and correspondent fuzzy numbers of each alternative

For Restriction Part		*For Reliability Part*	
Rank	Trapezoidal Fuzzy Number (TrFN)	Importance	Triangular Fuzzy Number (TFN)
Very Poor (VP)	(0.0, 0.0, 0.1, 0.2)	Very Low (VL)	(0.0, 0.0, 0.2)
Poor (P)	(0.1, 0.2, 0.2, 0.3)	Low (L)	(0.05, 0.2, 0.35)
Medium Poor (MP)	(0.2, 0.3, 0.4, 0.5)	Medium Low (ML)	(0.2, 0.35, 0.5)
Medium (M)	(0.4, 0.5, 0.5, 0.6)	Medium (M)	(0.35, 0.5, 0.65)
Medium Good (MG)	(0.5, 0.6, 0.7, 0.8)	Medium High (MH)	(0.5, 0.65, 0.8)
Good (G)	(0.7, 0.8, 0.8, 0.9)	High (H)	(0.65, 0.8, 0.95)
Very Good (VG)	(0.8, 0.9, 1.0, 1.0)	Very High (VH)	(0.8, 1.0, 1.0)

Table 5. Importance weight of Subjective criteria assessed by decision makers

Category	Criteria	D_1	D_2	D_3
C_1	C_{11}	(M, H)	(MH, H)	(M, H)
	C_{12}	(MH, MH)	(MH, M)	(ML, H)
	C_{13}	(H, MH)	(M, H)	(L, H)
C_2	C_{21}	(H, ML)	(MH, M)	(VL, M)
	C_{22}	(MH, VH)	(MH,VH)	(MH,H)
	C_{23}	(VH, H)	(H, VH)	(H, H)
C_3	C_{31}	(VH, ML)	(L, ML)	(VL, M)
	C_{32}	(H, VH)	(H, VH)	(VL,H)
	C_{33}	(M, M)	(ML, H)	(ML, H)
C_4	C_{41}	(ML, H)	(MH, VH)	(ML, VH)
	C_{42}	(ML, VH)	(M, H)	(ML, H)
	C_{43}	(MH, H)	(H, MH)	(MH, MH)

Table 6. Rating of suppliers with respect to criteria assessed by decision makers

Criteria	Experts	A_1	A_2	A_3	A_4	A_5
C_{11}	D_1	(MP, H)	(MG, VH)	(G, VH)	(G, VH)	(MG, VH)
	D_2	(MP, H)	(VG, H)	(P, ML)	(MP, M)	(VG, H)
	D_3	(P, H)	(VG, ML)	(M, H)	(G, VH)	(VG, ML)
C_{12}	D_1	(VP, M)	(G, VH)	(MG, MH)	(VG, M)	(MP, M)
	D_2	(MG,H)	(MP, M)	(G, MH)	(G, H)	(G, VH)
	D_3	(G, H)	(G, VH)	(G, ML)	(MG, H)	(VG, M)
C_{13}	D_1	(VP, M)	(VP, M)	(MG, VH)	(G, VH)	(G, H)
	D_2	(VP, H)	(G, H)	(VG, H)	(G, MH)	(MG, H)
	D_3	(MP, H)	(MG, H)	(G, VH)	(VG, VH)	(G, H)

End of Table 6

Criteria	Experts	A_1	A_2	A_3	A_4	A_5
C_{21}	D_1	(G, ML)	(G, H)	(G, MH)	(VG, M)	(MG, VH)
	D_2	(MG, VH)	(G, VH)	(VG, VH)	(MG, M)	(VG, H)
	D_3	(VG, H)	(P, ML)	(VG, M)	(MP, H)	(VG, ML)
C_{22}	D_1	(VG, ML)	(G, VH)	(MG, M)	(MP, H)	(MG,VH)
	D_2	(MG,VH)	(P, ML)	(M, H)	(P, H)	(G, VH)
	D_3	(G, VH)	(G, VH)	(MG, MH)	(VP, M)	(P, ML)
C_{23}	D_1	(P, ML)	(MP, H)	(G, MH)	(MG,H)	(G, VH)
	D_2	(G, VH)	(MG, VH)	(G, ML)	(G, H)	(MP, H)
	D_3	(MP, H)	(MP, H)	(MG, VH)	(VP, M)	(MG, VH)
C_{31}	D_1	(MG, VH)	(MP, H)	(VG, H)	(VP,H)	(G, VH)
	D_2	(G, VH)	(P, H)	(VG, ML)	(MP, H)	(P, ML)
	D_3	(MP, M)	(VP, M)	(G, VH)	(G, VH)	(MG, MH)
C_{32}	D_1	(G, VH)	(MG,H)	(MP, M)	(G, MH)	(G, MH)
	D_2	(VG, M)	(G, H)	(G, VH)	(VG, VH)	(G, ML)
	D_3	(G, H)	(VP, M)	(VG, M)	(VG, M)	(MG, VH)
C_{33}	D_1	(MG, H)	(VP,H)	(G, H)	(MG, M)	(VG, H)
	D_2	(G, H)	(MP, H)	(MG, H)	(P, ML)	(VG, ML)
	D_3	(MG, VH)	(G, VH)	(G, H)	(G, VH)	(G, VH)
C_{41}	D_1	(VG, H)	(G, MH)	(MP, H)	(MP, H)	(P, ML)
	D_2	(VG, ML)	(VG, VH)	(MP, H)	(MG, VH)	(MG, VH)
	D_3	(MG, MH)	(VG, M)	(P, H)	(G, VH)	(VG, H)
C_{42}	D_1	(G, MH)	(MG, M)	(VG, M)	(MP, M)	(VG, ML)
	D_2	(G, ML)	(MG, VH)	(MG,H)	(G, VH)	(G, VH)
	D_3	(MG, VH)	(VG, H)	(G, H)	(VG, M)	(G, MH)
	D_4	(MG, H)	(MG, H)	(MG, VH)	(VP, M)	(MG, VH)
C_{43}	D_1	(VG, H)	(VG, ML)	(VP, M)	(G, H)	(VG, VH)
	D_2	(G, VH)	(G, VH)	(VP, H)	(MG, H)	(VG, M)
	D_3	(P, ML)	(P, ML)	(MP, H)	(G, H)	(MG, M)

Step 4

Utilizing p^{th} decision-maker $D_p\left(p=1,2,3\right)$, the weighting matrix $DW_p\left(p=1,2,3\right)$ of the criteria are evaluated by transforming Z-number to Trapezoidal fuzzy number (TrFN) and further aggregated (using Eqns. 28–29) to get average subjective weighted value $w_j^s\left(j=1,2,...,12\right)$ of criteria (Table 7). For objective part, Entropy value E_j, degree of divergence $div\left(E_j\right)$ $\left(j=1,2,...,12\right)$ and objective weight $w_j^o\left(j=1,2,...,12\right)$ are calculated and shown in Table 8.

Table 7. Aggregated subjective criteria weights

Criteria	Average value in TrFN $\left(w_j^s\right)$
C_{11}	(0.36, 0.48, 0.51, 0.72)
C_{12}	(0.18, 0.39, 0.47, 0.64)
C_{13}	(0.09, 0.42, 0.42, 0.71)
C_{21}	(0.00, 0.30, 0.35, 0.57)
C_{22}	(0.45, 0.57, 0.66, 0.77)
C_{23}	(0.63, 0.76, 0.79, 0.89)
C_{31}	(0.00, 0.22, 0.26, 0.59)
C_{32}	(0.00, 0.52, 0.55, 0.87)
C_{33}	(0.18, 0.30, 0.36, 0.45)
C_{41}	(0.18, 0.38, 0.47, 0.77)
C_{42}	(0.18, 0.34, 0.47, 0.54)
C_{43}	(0.40, 0.56, 0.61, 0.73)

Table 8. Calculated entropy measure, divergence and objective weight for each criterion

Criteria	E_j	$div\left(E_j\right)$	w_j^o
C_{11}	0.9706	**0.02936**	**0.1633**
C_{12}	0.9985	0.00151	0.0084
C_{13}	0.9734	**0.02664**	**0.1482**
C_{21}	0.9885	0.01148	0.0639
C_{22}	0.9727	**0.02734**	**0.1521**
C_{23}	0.9942	0.00577	0.0321
C_{31}	0.9866	0.01342	0.0746
C_{32}	0.9932	0.00679	0.0378
C_{33}	0.9934	0.00661	0.0367
C_{41}	0.9679	**0.03205**	**0.1783**
C_{42}	0.9980	0.00195	0.0109
C_{43}	0.9831	0.01686	0.0938

Step 5. Calculate the relative significance and utility degree of each alternative.

Utilizing p^{th} decision-maker $D_p\left(p=1,2,3\right)$, the evaluating matrix $Y_p\left(p=1,2,3\right)$ of the alternatives in Z-number is first transform to TrFN decision matrix $\left(X_p\right)\left(p=1,2,3\right)$, then aggregated to decision matrix $\tilde{D}$ (*using eqn.* 24) and further normalized to fuzzy decision matrix $\tilde{N}$ (*using eqn.* 27). Then calculating as per Steps 6-10 of the proposed methodology (Section 2), find the *relative significance* $\tilde{Q}_i\left(i=1,2,...,5\right)$ and the utility *degree* $N_i\left(i=1,2,...,5\right)$ per alternative $A_i\left(i=1,2,...,5\right)$. Result shown in Table 11.

4. Result discussion

In this paper, we combine defuzzified subjective weight $\left(\hat{w}_j^s\right)$ and objective weight $\left(w_j^o\right)$ of the twelve criteria (Table 9) using formula proposed by Ma *et al.* (1999), shown in (43) as follows:

$$w_j^T = \alpha \times \left(w_j^o\right) + \beta \times \left(\hat{w}_j^s\right);\ \alpha + \beta = 1. \tag{43}$$

Giving equal priority to objective coefficient value α and subjective coefficient value β respectively viz. $\alpha = 0.5$ and $\beta = 0.5$, we get the total criteria weight $\left(w_j^T\right)\left(j = 1,2,\ldots,12\right)$. Result shown in Table 9.

Table 9. Subjective. $\left(\hat{w}_j^s\right)$, Objective $\left(w_j^o\right)$ and Total weights $\left(w_j^T\right)$ of the criteria

Category	List of Criteria	Defuzzified *Subjective weight* $\left(\hat{w}_j^s\right)$		Crisp based *Objective weight* $\left(w_j^o\right)$		Combined *Total weight* $\left(w_j^T\right)$*	
		Weight	Rank	weight	Rank	Weight	Rank
C_1	C_{11}	**0.5206**	**4**	**0.1633**	**2**	**0.3419**	**3**
	C_{12}	0.4196	7	0.0084	12	0.2140	8
	C_{13}	0.4055	**8**	**0.1482**	4	0.2769	6
C_2	C_{21}	0.2971	11	0.0639	7	0.1805	10
	C_{22}	**0.6110**	**2**	**0.1521**	**3**	**0.3815**	**2**
	C_{23}	**0.7672**	1	0.0321	**10**	**0.3997**	**1**
C_3	C_{31}	0.2754	12	0.0746	6	0.1750	12
	C_{32}	0.4676	5	0.0378	8	0.2527	7
	C_{33}	0.3183	10	0.0367	9	0.1776	11
C_4	C_{41}	0.4571	**6**	**0.1783**	1	0.3177	5
	C_{42}	0.3609	9	0.0109	11	0.1859	9
	C_{43}	**0.5716**	3	0.0938	**5**	**0.3327**	**4**

Note: * $w_j^T = \alpha \times \left(w_j^o\right) + \beta \times \left(\hat{w}_j^s\right)$, $\alpha = \beta = 0.5$ (Ma *et al.* 1999).

The coefficient α is dedicated on how sensitive *each objective weight* is while the second coefficient β focuses on the *subjective weight* to analyze their significant effect on the total criteria weight $\left(w_j^T\right)$. Hence, we perform sensitivity analysis to check the variation in ranking of the weights of the criteria, when both the coefficient values α and β are changed in the range from 0 to 1, (with step length 0.1), under constraint $\alpha + \beta = 1$. Details shown in Table 10.

Based on defuzzified weighted decision making matrix, ranking of each five alternative renewable energy (*Geothermal, Solar, Tidal, Hydro and Wind*), in Indian perspective, is evaluated by calculating the *relative significance* $\left(\tilde{Q}_i\right)\left(i = 1,2,\ldots,5\right)$ and *utility degree* $\left(N_i\right)\left(i = 1,2,\ldots,5\right)$ per alternative, shown in Table 11. *Solar energy* (A_2) tops the chart with 100% utility degree, followed by *Hydro energy* (A_4) (97%) and *Wind energy* (A_5) (93%). *Tidal energy* (A_3) shows mixed response (89%) while *geothermal energy* (A_1) shows poor response (82%) due to lack of awareness and government initiatives (Table 11). As for statistics drawn

Table 10. Sensitivity analysis of criteria total weight $\left(w_j^T\right)$ ranking as per variation in coefficient values

Criteria	$\alpha=1$ $\beta=0$ w_j^T	$\alpha=0.9$ $\beta=0.1$ w_j^T	$\alpha=0.8$ $\beta=0.2$ w_j^T	$\alpha=0.7$ $\beta=0.3$ w_j^T	$\alpha=0.6$ $\beta=0.4$ w_j^T	$\alpha=0.5$ $\beta=0.5$ w_j^T	$\alpha=0.4$ $\beta=0.6$ w_j^T	$\alpha=0.3$ $\beta=0.7$ w_j^T	$\alpha=0.2$ $\beta=0.8$ w_j^T	$\alpha=0.1$ $\beta=0.9$ w_j^T	$\alpha=0$ $\beta=1$ w_j^T
C_{11}	2	2	2	2	3	3	4	4	4	4	4
C_{12}	12	11	11	10	8	8	8	8	8	8	7
C_{13}	4	4	4	6	6	6	6	7	7	7	8
C_{21}	7	8	9	9	9	10	11	11	11	11	11
C_{22}	3	3	1	1	1	2	2	2	2	2	2
C_{23}	10	6	6	4	2	1	1	1	1	1	1
C_{31}	6	7	8	8	10	12	12	12	12	12	12
C_{32}	8	9	7	7	7	7	7	6	6	6	5
C_{33}	9	10	10	11	12	11	10	10	10	10	10
C_{41}	1	1	3	3	4	5	5	5	5	5	6
C_{42}	11	12	12	12	11	9	9	9	9	9	9
C_{43}	5	5	5	5	5	4	3	3	3	3	3

Note: $w_j^T = \alpha \times \left(w_j^o\right) + \beta \times \left(\hat{w}_j^s\right)$; $\alpha+\beta=1$; $j=1,2,\ldots,12$.

from Luthra *et al.* (2015) given in Table 1 and data drawn from official website of Government of India, Ministry of Renewable Energy, the proposed ranking matches nearly 100%.

In Indian perspective, *Solar energy* (A_2) is available in range of 700–2100 GW (Highest among the renewable alternatives) and used only 2.2 GW (Table 1) and as per our result it has been *ranked 1*, considering the above 12 criteria under four aspects. *Hydro energy* (A_4) is next available energy resource (150 GW) and used 39.7 GW in India, and as per our result it has come under *2^nd^ ranking*. *Wind energy* (A_5) is available next to Hydro-energy (102 GW) and used only 21.1 GW, and *ranking 3^rd^* in our proposed model, prove the closeness of our result to real data. *Tidal energy* (A_3) has not been exploited so far in mass production of electricity, besides having a vast source of it. India has currently only 8GW of tidal energy as per record and has not been used so far. In our result, it has been *ranked 4^th^* due to its non -pollutant nature and it does not acquire any land for its production. This validates the result. *Geothermal energy* (A_1) is available in India in a total of 10.6 GW, but is left unused. Geothermal energy is depended on various geographical factors, and so it has been *ranked 5^th^*.

Table 11. The values of $\tilde{P}_i$, $\tilde{R}_i$, $\tilde{Q}_i$ and N_i along with ranking of RE alternatives $\left(A_i\right)$

RE alternatives	P_i	R_i	Q_i	N_i	Ranking
A_1 (Geothermal Energy)	0.1447	0.0917	0.2050	82	5
A_2 (Solar Energy)	0.1689	0.0683	0.2502	100	1
A_3 (Tidal Energy)	0.1534	0.0813	0.2216	89	4
A_4 (Hydro Energy)	0.1286	0.0488	0.2421	97	2
A_5 (Wind Energy)	0.1727	0.0930	0.2323	93	3

A sensitivity analysis of alternative ranking is conducted based on change in *subjective* criteria weight, taken on priority basis, to evaluate which criterion has major effect on the ranking, and shown in Table 12. In last part of proposed COPRAS-Z methodology, based on defuzzified decision making matrix, comparison of alternative ranking in COPRAS method is done with existing VIKOR and TOPSIS MCDM methods (Table 13). To validate and confirm the computation result, relations are calculated, using spearman's rank correlation coefficient, among alternative ranking provided by every possible pairs of applied MCDM methods (Antucheviciene *et al.* 2011). Based on Table 13, priorities of alternatives computed by COPRAS provide significant relations with VIKOR (0.7) and TOPSIS (0.5), showing reliability in our proposed renewable energy alternatives ranking. The details shown in Figure 2.

Table 12. Sensitivity of alternative ranking to changes in criterion weights taken on priority basis

Scenarios	Priority based criteria				Ranking of RE Alternatives				
					A_1	A_2	A_3	A_4	A_5
1	C_{23}	C_{22}	C_{43}	C_{11}	5	1	4	2	3
2	C_{32}	C_{23}	C_{41}	C_{21}	5	2	4	1	3
3	C_{12}	C_{33}	C_{21}	C_{31}	5	2	3	1	4
4	C_{11}	C_{31}	C_{22}	C_{13}	5	1	4	3	2
5	C_{11}	C_{43}	C_{13}	C_{23}	5	2	4	1	3
6	C_{21}	C_{32}	C_{11}	C_{22}	5	2	4	3	1

Table 13. Comparison of COPRAS with other MCDM methods

Renewable Energy Alternatives in Indian Perspective	COPRAS	VIKOR			TOPSIS
	Ranking as per utility degree	*Ranking as per*			*Ranking as per Closeness Coefficient*
	(N_i)	S_i	R_i	Q_i	(CC_i)
A_1 (Geothermal Energy)	5	5	4	5	3
A_2 (Solar Energy)	1	1	1	1	1
A_3 (Tidal Energy)	4	4	2	2	5
A_4 (Hydro Energy)	2	3	3	3	4
A_5 (Wind Energy)	3	2	5	4	2

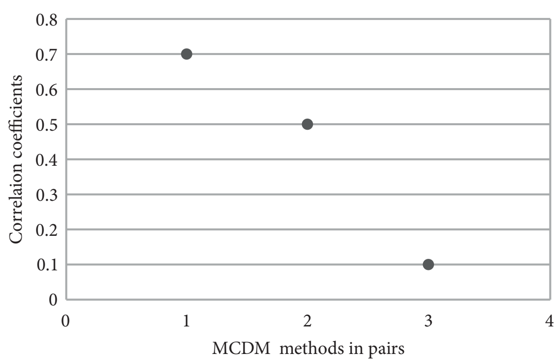

Figure 2. Spearman's rank correlation coefficients between ranking results of two MCDM methods (1 – COPRAS and VIKOR, 2 – COPRAS and TOPSIS, 3 – VIKOR and TOPSIS)

Conclusions and future direction

Prioritizing among renewable energy alternatives for investment projects requires involvement of different groups of decision-makers (DMs). The fact that socio-political, economic, technological and environmental factors considered in the decision making, make the process more complex. The policy formulation for fossil fuels energy substitution by renewable energy be addressed in a multi-criteria context involving group decision makers to avoid bias and minimize partiality in the decision process. Taking the comment of experts from different sectors along with its reliability, proves the effectiveness and correctness of the decision.

In many developing countries, renewable energy can make significant contributions to the economy by providing the energy needed for creating new businesses and employment. India, being a developing country is extensively dependent on energy imports to meet the soaring demand for energy consumed by the dense population of the country due to shortage of domestic fossil fuels. Besides, India is a rich region for purpose of renewable energy generation. Considering the future needs of the region, our study focus on the selection of the most appropriate renewable energy investment considering various benefit and cost criteria. A selection among the renewable energy alternatives is made using COPRAS-Z methodology considering both subjective and objective criteria in Z-number where reliability of fuzzy numbers, given by expert decision makers, is checked. A comparative analysis is conducted on COPRAS with existing TOPSIS and VIKOR MCDM methods in defuzzified environment to check the reliability in proposed renewable energy alternatives ranking.

Therefore, the Indian government and policy makers' should continue to encourage and support the alternative energy (viz. *hydro, solar, wind, geothermal and biomass*) policies and strategies. Finally, it should be noted that the model application is country specific, since the strategies and criteria depend on country's specific energy characteristics, development needs and geographical perspectives. So, the result will vary for different countries based on same criteria. In future, this proposed methodology will be applied in other decision making areas as project selection, green supplier selection, and bio-medical instruments selection.

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