Solving renewable energy source selection problems using a q-rung orthopair fuzzy-based integrated decision-making approach

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Abstract

This paper proposes an integrated decision-making framework for the systematic selection of a renewable energy source (RES) from a set of RESs based on sustainability attributes. A real case study of RES selection in Karnataka, India, using the framework is demonstrated, and the results are compared with state-of-the-art methods. The main reason for developing this framework is to handle uncertainty and vagueness effectively by reducing human intervention. Systematic selection of RESs also reduces inaccuracies and promotes rational decision-making. In this paper, q-rung orthopair fuzzy information is adopted to minimize subjective randomness by providing a flexible and generalized preference style. Further, the study found systematic approaches for imputing missing values, calculating attributes' and decision-makers' weights, aggregation or preferences, and prioritizing RESs, which are integrated into the framework. . Comparing the proposed framework with state-of-the-art-methods shows that (i) biomass and solar are suitable RESs for the process under consideration in Karnataka, (ii) the proposed framework is consistent with state-of-the-art methods, (iii) the proposed framework is sufficiently stable even after weights of attributes and decision makers are altered, and (iv) the proposed framework produces broad and sensible rank values for efficient backup management. These results validate the significance of the proposed framework.

Keywords: Gini index; Muirhead mean; q-rung orthopair fuzzy set; Renewable energy; TODIM method; MADM.

1. Introduction

Developing countries, including India, need abundant energy for growth and development, which can be provided with renewable energy sources (RESs) (Rani et al., 2019). RESs are clean and sustainable, which helps to reduce greenhouse gas emissions and various types of secondary waste (Indragandhi et al., 2017). Examples of RESs are solar energy, water, wind, and biomass (Bevrani et al., 2010). In general, the evaluation of RESs is a typical multi-attribute decision-making (MADM) problem, which can be solved rationally using MADM approaches (Yuan et al., 2018).

Since hesitation/confusion are implicit factors in the selection of RESs (Zhang et al., 2019), capturing them is essential. To do so, Yager (2017) proposed a generalized preference style called q-rung orthopair fuzzy sets (q-ROFSs), which offer a flexible preference space for decision-makers (DMs) to share their preferences for each RES. A fundamental property of q-ROFS is that $\mu^q + \upsilon^q \leq 1$, where q is a controlling factor that expands the preference space as the value monotonically increases. When $q = 1$, the q-ROFSs are reduced to intuitionistic fuzzy sets (IFSs) (Atanassov, 1986), and when $q = 2$, the q-ROFSs are reduced to Pythagorean fuzzy sets (PFSs) (Yager, 2014).

To demonstrate the flexibility of a q-rung orthopair fuzzy information (q-ROFI), the following example is discussed. Suppose an expert rates the safety level of a power plant as $\mu = 0.8$ and $\upsilon = 0.8$. This may not be allowed in IFS and PFS as the sum of the degree of belongingness μ and degree of non- belongingness υ is greater than one. However, $q = 4$ is allowed by the q-ROFI, and $\mu^4 + \upsilon^4 \leq 1$. Thus, q-ROFIs provides a flexible preference space and enriches the choice of information.

Note: *All abbreviations and their respective expansions are provided in the Supplementary material. Some definitions, theorems and their proofs are also provided in the Supplementary material to enrich better understanding of the work.*

1.1. Literature review related to RES selection

Recently, various decision-making approaches have been developed and applied to the evaluation and selection of RESs. Previous studies identified multiple attributes and aspects that should be used to assess and select the most appropriate RESs. The following section outlines the application of MADM approaches in different uncertain environments. Wu et al. (2014) introduced an approach based on certain operators and used it to evaluate a wind technology project. Long and Geng (2015) developed an integrated entropy-based TOPSIS method for assessing the photovoltaic module within the context of IVIFSs. Zhang et al. (2015) introduced a method that employs integral and fuzzy measures and used it in the assessment and selection of clean energy methods in China. The results of that study showed that the solar photovoltaic method was the optimal choice.

Wu et al. (2016) extended the ELECTRE-III method to intuitionistic fuzzy sets (IFSs) to evaluate and select sites for an offshore wind power station. Gumus et al. (2016) proposed an integrated framework based on the TOPSIS approach, entropy measure, and weighted arithmetic averaging operator for IFSs to assess wind energy resources in the United States. Kahraman et al. (2016) conducted an IVIF benefit-cost study that assessed investments in wind energy methods. The results showed that the technique proposed in this study is a flexible and informative tool for evaluating wind energy technologies. Çolak and Kaya (2017) presented an integrated approach based on the Analytic Hierarchy Process (AHP) and TOPSIS approaches within interval type-2 fuzzy sets and used it to select and evaluate the RES alternatives. The results showed that wind energy was the most suitable choice. Elzarka et al. (2017) presented a model for vague sets to assess onsite RESs for construction facilities. The outcomes of that study indicated that the method was proficient at selecting and evaluating RESs.

Wu et al. (2018) developed a model utilizing AHP and PROMETHEE II methods within the context of triangular IFSs. They used it to evaluate and rank a large-scale rooftop photovoltaic project. Yuan et al. (2018) developed a new method based on a linguistic hesitant fuzzy set and an enhanced Choquet integral procedure and used it to evaluate and rank RESs in Jilin, China. Their findings concluded that biomass energy was the most appropriate option, among other alternatives. Jeong and Ramírez-Gómez (2018) studied an integrated method that is based on the decision making trial and evaluation laboratory (DEMATEL) and geographic information system (GIS) procedures for fuzzy sets (FSs) to assess the most suitable location for biomass plants to serve as a RES. Dincer and Yuksel (2019) evaluated DEMATEL and TOPSIS approaches that were used to assess and select RESs based on specific criteria. Mishra et al. (2019) developed a decision-making framework using the Jensen exponential divergence measure and used it to assess and rank RES alternatives. Aikhuele et al. (2019) presented a dynamic decision model with reliability attributes for RES evaluation using fuzzy numbers. Cavallaro et al. (2019) presented a TOPSIS method based on entropy under IFSs and used it to evaluate and select solar power plans.

Karunathilake et al. (2019) developed a TOPSIS approach and used it to evaluate and choose the most appropriate RES alternative. That study demonstrated that tiny hydro- and solar photovoltaic systems were the most efficient alternatives among all options. Rani et al. (2019) evaluated an integrated method using the VIKOR technique within the context of PFSs and used it to assess and rank RESs in India. The results of that study demonstrated that the developed approach played a valuable role in the process of evaluating and selecting RESs. Rani et al. (2020a) presented an integrated framework by combining SWARA and VIKOR methods to evaluate and choose ideal solar panel within Pythagorean fuzzy sets context. Wang et al. (2020) presented an innovative model based on fuzzy AHP and SWOT approaches and used it to assess and choose strategic RESs in Pakistan. That study demonstrated that socio-political and economic criteria were significant factors in the evaluation of RESs. Ghenai et al. (2020) used SWARA and ARAS techniques to evaluate a novel method for selecting and assessing RESs. The results of that study demonstrated that land-based wind energy is the best alternative. Rani et al. (2020b) used a decision-making framework based on a TOPSIS approach and a fuzzy divergence measure to evaluate and select RESs within a fuzzy environment. The results of that study showed that the developed framework was capable of assessing RES alternatives. Wang et al. (2020) proposed a non-linear multi-dimensional model for analyzing the sustainability attributes of RESs for 27 European Union countries.

Ilababar et al. (2020) proposed a Pythagorean fuzzy-based decision model for the selection of RESs in Turkey. Krishankumar et al. (2020) used the VIKOR and interval-valued probabilistic linguistic standard variance approaches to evaluate an integrated framework within the context of an interval-valued probabilistic linguistic term set. The results of that study indicated that wind energy was the optimal alternative. Fossile et al. (2020) proposed a programming model for the selection of RESs to Brazil's ports. Results indicate that solar energy is most viable for the ports. Mishra et al. (2020a) introduced a combined methodology based on SWARA and COPRAS approaches for assessing bioenergy production processes. Zhang et al. (2020) put forward a hybrid decision model to select appropriate RES for Fujian, China. The results indicated that wind energy is the most suitable choice for Fujian. Butkiene et al. (2020) prepared a detailed review to analyze the importance of MADM methods for the selection of RESs.

1.2. Challenges in the current methods of RES selection

Based on the literature in the review presented above, there are potential challenges/knowledge gaps that may be encountered during RES selection. *Firstly*, due to the implicit hesitation/confusion in the evaluation process, missing values are common. Previous studies revealed that such values are either imputed randomly or ignored, causing inaccuracies in the RES evaluation. *Secondly*, attributes' weights for RES selection are not systematically determined by capturing the variation in the distribution of the information accurately. Additionally, the degrees of hesitation/confusion exhibited by the DMs are not captured during the calculation of the weights of attributes. Kao (2010) investigated different approaches for determining attribute weight and inferred that the systematic calculation of weights mitigates inaccuracies in the MADM process. *Thirdly*, the weights of the DMs reflecting their relative importance to the decision making process (relative importance values) are not computed in a systematic way, which causes inaccuracies to occur during the evaluation. Koksalmis and Kabak (2018) conducted a detailed analysis of various weight calculation methods for DMs and found that systematic calculation mitigates inaccuracies in the decision-making process. *Fourthly*, aggregation of preference information for RES selection is performed without capturing the interrelationship among attributes. As attributes for RES selection often are in conflict and compete with each other, capturing the interrelation is essential. *Finally*, RESs must be prioritized rationally without potential loss of information.

It must be noted that these challenges are addressed by using the novel contributions presented in Section 1.4. Further, for clarity on each method, kindly refer to Section 2.

1.3. A brief discussion of the methods

Before presenting the contributions of this paper, it is essential to discuss the basic idea of the methods adopted in this study's proposed framework.

Firstly, the Gini index (Han et al., 2012) is a concept adopted from data mining, which is used to determine the significance of an attribute. A higher Gini value indicates a higher level of importance of an attribute. Furthermore, the method captures the variations in the distribution of the information. If the variation is high for an attribute, the Gini value is low, indicating the potential hesitation/confusion during preference elicitation. Consequently, when the variation is low, the Gini value is high – suggesting the level of certainty the expert team conveys concerning that attribute.

Secondly, a programming model (Krishankumar et al., 2019) is used to evaluate each expert's relative importance value when the information associated with the DM is partially known. The objective function is formulated by using the operational laws, and a constrained optimization model is framed to compute the weights of the DMs. The main difference between this study's proposed idea and the idea presented in (Krishankumar et al., 2019) is in the formulation of the objective function.

Thirdly, the Muirhead mean (MM) (Muirhead, 1902) operator is used to aggregate preferences by properly handling the interrelationship between criteria. Operators such as arithmetic/geometric mean, Bonferroni mean, and Hamy mean are special cases of MM operators. Based on the properties of MM, various researchers extended it to different fuzzy variants such as Liu et al. (2019) model for air quality evaluation and Wang et al. (2019b) model for investor selection problems.

Finally, the TODIM method (Portuguese for interactive MADM) (Gomes & Lima, 1991) is used to prioritize RESs, based on the prospect theory by Kahneman & Tversky (1979). To handle uncertainty, researchers proposed TODIM under fuzzy (Krohling & De Souza, 2012) and intuitionistic fuzzy contexts (Krohling et al., 2013), both of which use prospect theory to evaluate alternatives.

1.4. Novel contributions of the paper

The novel contributions of this paper are presented here. *First*, missing values are imputed in a systematic manner using a case-based method, which puts ahead four cases that deal with different scenarios. *Secondly,* the weights of attributes are calculated using the Gini index, which effectively captures variation in the distribution and significance of the information. *Thirdly*, DMs' relative importance values are determined using a programming model, formulated by utilizing the partially known information and the operational laws. *Fourthly*, the DMs' relative importance values are utilized to extend the MM operator to a q-ROFI for aggregation. Unlike the work of Wang et al. (2019b), the proposed operator systematically calculates each DM's relative importance value, which mitigates inaccuracies in the decision-making process. *Finally*, RESs are prioritized by extending the TODIM method to a q-ROFS context. The q-ROFI is flexible and provides a generic preference style for usage as compared to its close counterparts, which motivated our focus in this direction.

The remainder of the work is structured as follows. Section 2 proposes a new decision-making framework within the context of q-ROFSs. Section 3 implements the proposed framework in a real case study of RESs selection in Karnataka, India, demonstrating the applicability and strength of the developed method. Section 4 contains a comparative and sensitivity analysis to validate the consistency and robustness of the outcomes from section 3. Section 5 presents the conclusions of the study.

2. Proposed Methods

This section presents the core novel contributions of this paper. At first, missing values are imputed systematically. Later, weights of attributes and DMs are calculated by properly capturing existing hesitation. Preferences from DMs are aggregated by capturing the interrelationship among DMs. Finally, a prioritization method is put forward for prioritizing RESs. The details of the IFS, q-ROFS, and the different operators are provided in the *supplementary material*.

2.1. Research problem

This section provides the research problem that is addressed in this paper. The core research problem is *"to select an appropriate RES from the set of available RESs in Karnataka, India, to* satisfy *its energy demands*." To solve this problem, a novel decision-making framework with integrated MADM methods for q-ROFI is proposed. A detailed explanation of each proposed method is presented in sections 2.2 to 2.6. From the literature related to RES selection in India and a report from the Ministry of New & Renewable Energy (MNRE), popular RESs in Karnataka are solar energy, biomass energy, tidal energy, hydropower, and wind energy. The real case study discussed in Section 3 considers these RESs as potential alternatives, rated by experts based on sustainabilityattributes.

2.2. Imputation of missing values

This section focuses on the imputation of missing values in the decision matrices provided by the DMs. Due to hesitation/confusion, certain preferences cannot be provided. Previous imputation studies either adopted binning methods or random fills, both of which reduces the accuracy of the decision-making process. Moreover, in a MADM context, several different cases of missing values are identified which cannot be filled by existing methods.

This section presents a case-based method, which can impute preference values rationally for different scenarios.

Case 1: Of ll DMs who provide decision matrices, one matrix has a missing instance. To impute the missing value, Equation (1) is applied.

$$R = \left(\prod_{l=1}^{ll^*} \mu_{ij}^{\lambda^l}, \prod_{l=1}^{ll^*} \upsilon_{ij}^{\lambda^l}\right) \tag{1}$$

where ll^* is the number of DMs, which has the value for the specific instance, and $\lambda^l = {}^1/_{ll^*}$ is the unbiased weight vector. Clearly, $ll^* < ll$.

Case 2: A specific value (i, j) is missing from all ll decision matrices. Equation (2) is used to impute value.

$$R = \left(\prod_{l=1}^{m^*} \mu_{ij}^{\lambda^l}, \prod_{l=1}^{m^*} \upsilon_{ij}^{\lambda^l}\right) \tag{2}$$

where m^* is the number of alternatives with the q-ROFI, and $\lambda^l = {}^1/_{m^*}$ is the unbiased weight vector.

Case 3: Of ll decision matrices, only one matrix has the (i, j) position. To impute the remaining values, the value in the (i, j) position is repeated.

Case 4: A particular column is missing in all ll decision matrices. To impute the values, the type of the attribute (column) is identified; *benefit* or *cost*. If the missing column is of benefit type (or cost type), then the average of the values from the remaining benefit type (or cost type) columns (attributes) is taken. If there is only one benefit (or cost) attribute and the values for that attribute are missing, then the adjacent column is arbitrarily selected to impute the values.

Some of the shortcomings of case-based imputation of missing values are *(i) equal weights are assigned to alternatives (RESs) during imputation by case 2, which is often not the case . Methods may be developed to handle unequal weights of alternatives and partial information on each alternative. (ii) case 3 imputes values by repetition, which might cause subjective biases over that particular attribute, and hence, predictive models may be developed to handle the situation*.

2.3. Gini index for attribute weights

A new extension to the Gini index, specifically for q-ROFSs, is discussed in this section. Generally, weights of attributes are estimated in two ways, *partially known weight* *values* and *fully unknown weight values*. Programming models such as the one in Krishankumar et al. (2019) are used for partially known weight values, and capture the partial information in the form of constraints. For fully unknown weight values weights are determined based on entropy (Xia & Xu, 2012), an analytical hierarchy process (Büyüközkan et al., 2019), or weighted arithmetic method (Valipour et al., 2017).

From the analysis, the latter concept can determine weights without any a priori information. Moreover, the Gini index captures the hesitation/confusion during the preference elicitation process. Based on these concerns, the model for the Gini index under q-ROFSs is discussed.

Step 1: An evaluation matrix of $ll \times n$ with q-ROFI is constructed. Here, ll and n are the number of DMs and attributes, respectively.

Step 2: Use a score function to transform the q-ROFI into a single-valued evaluation matrix. Use equation (3) to normalize these values column-wise.

$$R_{ij}^{*} = \frac{R_{ij}}{\sum_{i=1}^{ll} R_{ij}} \tag{3}$$

where R_{ij}^{*} is the normalized value given by the i^{th} DM over the j^{th} attribute.

Step 3: Use equation (4) to apply the Gini index to determine the significance of information of each attribute. A vector of order $(1 \times n)$ is obtained using Equation (4).

$$GI_j = 1 - \sum_{i=1}^{ll} R_{ij}^{*} \tag{4}$$

where GI_j is the Gini index value of the j^{th} attribute.

Step 4: The values of Eq. (4) are normalized utilizing Eq. (5) to obtain the attribute weights. The higher the significance of information for an attribute, the higher is the weight.

$$w_j = \frac{GI_j}{\sum_{j=1}^{n} GI_j} \tag{5}$$

where w_j is the j^{th} attribute weight.

Some shortcomings of Gini index in attribute weight calculation are *(i) when DMs provide similar opinions on attributes, the weights tend to be equal, and hence, the relative importance of DMs might here be considered for more efficient weight calculation*; and *(ii) personal opinion on each attribute is not used by the Gini index, and hence, constrained parametric-methods may be developed to include these*.

2.4. The programming model for DM weights

This section focuses on the identification of DM weights using a programming model with a q-ROFI. Koksalmis and Kabak (2018) explained the importance and usefulness of a systematic evaluation of DM weights in multi-attribute group decision-making (MAGDM). Inspired by this, we attempted to compute the DMs' weights systematically.

Unlike the model presented in (Krishankumar et al., 2019), the proposed programming model formulates an objective function based on the weights of attributes and operational laws. Moreover, partial information about each DM is used to determine the weights.

The procedure for calculating the weights of the DMs is shown below:

Step 1: Calculate the weighted q-ROFI for each matrix using $WR_{ij} = \left(\left(1-\left(1-\mu_{ij}^{q}\right)^{w_j}\right)^{1/q}, \upsilon_{ij}^{q}\right)$ where w_j is the j^{th} attribute weight.

Step 2: Formulate the programming model, as shown below.

Model 1:

$$Max\ Z = \sum_{l=1}^{ll} \varpi_l \left(Accuracy\left(\oplus_{j=1}^{n}\left(WR_{ij}\right)\right)\right)$$

Subject to

$$\varpi_j \in [0,1] \text{ and } \sum_j \varpi_j = 1.$$

The relative importance values of DMs are obtained by solving the model using the optimization toolbox of MATLAB®. Some shortcomings of the mathematical model for DM weight calculation are *(i) attitude of DMs are not taken into consideration during the formulation of the model*; and *(ii) variations in the distribution of preferences are not considered during the model formulation. This may be addressed by considering these measures as constrained parameters*.

2.5. Aggregation of q-ROFI

An extension to MM operators for aggregating a q-ROFI is presented in this section. Previous studies on aggregation operators showed that capturing the interrelationship between criteria is critical for rational aggregation (Mesiar & Calvo, 2008). Based on this claim, several researchers proposed various operators within the context of q-ROFS, viz. Bonferroni mean (Liu & Liu, 2018), Hamy mean (Wang et al., 2019a), Muirhead mean (Wang et al., 2019b), and Maclaurin symmetric mean (Krishankumar et al., 2019).

The MM operator (Wang et al., 2019b) uses DM weights directly without any systematic calculation. Also, Kosalmis & Kabak (2018) claimed that systematic weight calculation is important for rational decision-making. Motivated by this claim and to circumvent this concern, we present an MM operator within the context of q-ROFS which uses DM weights that were evaluated in Section 2.3.

Definition 4: Aggregation of q-ROFI using q-rung orthopair fuzzy weighted MM (q-ROFWMM) operator is a function $Z^n \dashrightarrow Z$ and is given by

$$q - ROFWMM^{(\lambda_1,\lambda_2,\ldots,\lambda_{ll})} = \left(\left(\left(1 - \left(\prod_{l=1}^{ll}\left(1 - \prod_{t=1}^{ll}\mu_{ij}^{\lambda_t q}\right)^{\varpi_l}\right)\right)^{1/q}\right)^{\frac{1}{\sum_t \lambda_t}}, \left(1 - \left(\left(1 - \prod_{l=1}^{ll}\left(1 - \prod_{t=1}^{ll}\left(1 - v_{ij}^{q}\right)^{\lambda_t}\right)^{\varpi_l}\right)\right)^{\frac{1}{\sum_t \lambda_t}}\right)^{1/q}\right) \quad (6)$$

where ll denotes the number of DMs, $\lambda_1, \lambda_2, \ldots, \lambda_{ll}$ are parameters that can have values from the set $\{1,2,\ldots,ll\}$, and ϖ_1, ϖ_2,…, ϖ_{ll} are relative importance values of DMs.

The main shortcoming of the proposed aggregation operator is that the *risk appetite values are not calculated systematically, this may be done by using mathematical models*.

For properties and theorem related to the proposed aggregation operator and its proof, kindly refer to the Supplementary materials.

2.6. Prioritization of RESs

This section presents an extension to the TODIM method for q-ROFIs, taylored for prioritization of RESs. As previously mentioned, the TODIM method (Gomes & Lima, 1991) is associated with the prospect theory; additionally, the prioritization of RESs is based on the dominance concept. The main advantages of the TODIM method are: (i) it is simple and straightforward; (ii) it prioritizes RESs from a pessimistic viewpoint by considering risk, this closely resembles real-time decision-making (Chen, 2011); (iii) reference weights are used to capture information of an attribute during prioritization.

Motivated by these advantages, researchers have extended the TODIM method into several fuzzy variants. Fan et al. (2013) generalized the TODIM approach to random variables, viz. interval, and fuzzy numbers, for MAGDM. Krohling et al. (2013) provided a generalization of Fan et al.'s (2013) approach, they proposed an intuitionistic fuzzy-based TODIM approach for MAGDM. Ren et al. (2016) further generalized Krohling et al.'s (2013) work, and proposed the Pythagorean fuzzy TODIM. Wei (2018) proposed an extension to the TODIM method under a picture fuzzy context and applied it to MAGDM. Xu et al. (2017) proposed using the TODIM method within a neutrosophic fuzzy context, and applied it to

MAGDM. Mishra and Rani (2018) developed a TODIM approach-based biparametric similarity measure for IVIFSs to solve a plant location selection problem. Rani et al. (2019a) proposed an intuitionistic fuzzy TODIM approach with a Shapley divergence measure to address a decision-making problem. Mishra et al. (2020b) reviewed various entropy and divergence measures for IVIFSs and proposed new divergence and entropy measures to mitigate the inadequacies of existing measures. They also reviewed the TODIM method and used it to solve a service quality assessment problem for vehicle insurance companies.

Based on the literature analysis presented above, the q-ROFS-based TODIM method has not yet been suggested by researchers for RES selection. However, the advantages of the TODIM method inspired us to use it in our proposed framework. The proposed idea is a generalization of state-of-the-art methods and offers sensible prioritization based on the prospect theory. The step-by-step procedure is presented below (see Fig. 1):

Step 1: The aggregated matrix and attribute weight vector are obtained as input for the q-ROFSs-based TODIM method.

Step 2: Calculate the reference weight values for the attributes using equation (7).

$$w_j^{ref} = \frac{w_j}{max_j(w_j)} \tag{7}$$

where w_j is the weight value of the j^{th} attribute.

Step 3: Dominance values between RESs are calculated using equations (8)-(9). n matrices of order $m \times m$ are obtained, which are further processed to prioritize RESs.

$$Dom_j(\alpha,\beta) = \begin{cases} \sqrt{\frac{w_j^{ref} d(\alpha,\beta)}{\sum_{j=1}^{n} w_j^{ref}}} & for\ \alpha > \beta \\ 0 & for\ \alpha = \beta \\ \frac{-1}{\theta}\sqrt{\frac{\left(\sum_{j=1}^{n} w_j^{ref}\right) d(\alpha,\beta)}{w_j^{ref}}} & Otherwise \end{cases} \tag{8}$$

$$NetDom(\alpha,\beta) = \sum_{\substack{j\in n \\ \alpha,\beta \in m}} Dom_j(\alpha,\beta) \tag{9}$$

Here, α and β are any two RESs and $d(\alpha,\beta) = \sqrt{\left(\sum_{j=1}^{n}\left(\left(\mu_{ij}^{q(\alpha)} - \mu_{ij}^{q(\beta)}\right)^2 + \left(\upsilon_{ij}^{q(\alpha)} - \upsilon_{ij}^{q(\beta)}\right)^2 + \left(\pi_{ij}^{q(\alpha)} - \pi_{ij}^{q(\beta)}\right)^2\right)\right)}$. θ can take values 1 and 2.5, as shown by Fan et al. (2013). Equation (8) determines the dominance value between RESs for over each attribute. Equation (9) is used to obtain the net dominance value between RESs.

Step 4: RESs are prioritized using equation (10). A vector of order $1 \times m$ is obtained, which is given in descending order to prioritize the RESs; that is, the RES with the highest dominance is ranked first and so on.

$$\varphi_i = \frac{\sum_i NetDom(\alpha,\beta) - min(\sum_i NetDom(\alpha,\beta))}{max(\sum_i NetDom(\alpha,\beta)) - min(\sum_i NetDom(\alpha,\beta))} \tag{10}$$

where φ_i is the dominance value of the i^{th} RES.

Some shortcomings of q-ROFS-based TODIM method are *(i) dominance values are calculated based on the comparison of q-ROFI, which is done using score and accuracy measure that does not consider the degree of hesitancy, causing information loss*; *(ii) rank reversal issues occur when adequate changes are made to the attributes*.

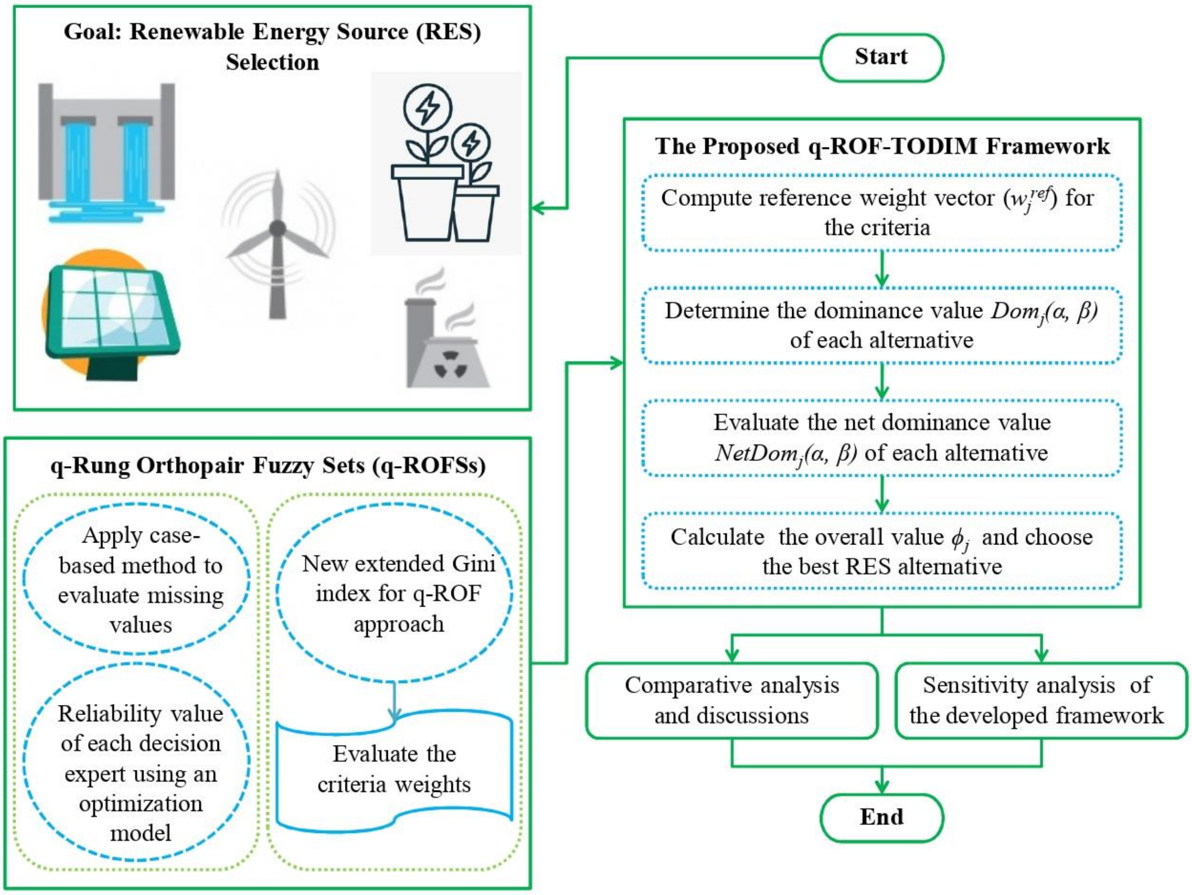

Fig.1 Implementation flowchart of the proposed framework

Fig.1 represents the overall workflow of the developed framework that is used for the rational selection of RES. Initially, DMs provide their linguistic preferences for each RES based on the attributes. To reduce subjective randomness, q-ROFI is adopted for rational decision-making implementation. Since hesitation/confusion are implicit factors in MADM, some values might be missing; thus, a systematic method is used to impute these values.

Next, weights of attributes and DMs are determined systematically by capturing the hesitation and utilizing the partial information provided by the selection committee. Preferences from the DMs are aggregated by capturing the interrelationship among attributes. Unlike existing methods, weights of DMs are rationally calculated and used for aggregation in this framework. Finally, by extending the TODIM method to q-ROFI and with the help of the aggregated matrix and the weight vector of the attributes, prioritization of RESs is performed. To better understand the strengths and weaknesses of the framework, two analyses were conducted; an analysis comparing the framework to existing methods, and a sensitivity analysis with different attributes and DMs weights.

3. A case study in Karnataka: Prioritization of renewable energy sources

This section demonstrates the practicality of the proposed framework by considering a real case study of RESs in Karnataka, India for satisfying its energy demands.

3.1. Introduction to RESs in Karnataka

With an area of around 191,791 square km, Karnataka is the seventh largest state in India – sharing the western boundary with the Arabian Sea and the Laccadive Sea (profile report of Karnataka, 2019). The state has toppled Tamil Nadu to become India's largest renewable energy (RE) generation with an installed capacity of 15.23 GW. This includes 7.27 GW of solar energy, 4.78 GW of wind energy, 1.882 GW of biomass energy and 1.28 GW of small hydropower plants (MNRE Report, 2020). For the past two years, Karnataka has been top ranked in terms of RE generation. The main reasons have been the apt policies and the on-time completion of projects. Convincing farmers to lease their lands for solar and wind power generation is also a crucial task for the government of Karnataka. In addition, Karnataka's biomass generation is growing quicker compared to other states in India.

Solar Energy

High-density solar panels are installed in Karnataka, these produce around 2000 to 2500 KWh solar energy per square meter. 2000 MW of solar power was produced by the Shakti Shala plant in Pavagada during 2018. Around 1,65,000 million Indian rupees (INR) were invested in solar parks to produce power for nearly 700,000 households during this period (Summers, 2019). Karnataka Solar Power Development Corporation Limited (KSPDCL) made an agreement that integrates the solar energy corporation of India and Karnataka Renewable Energy Development Limited (KREDL). This agreement enables large firms to gain access to power from the solar grids (Elavarasan et al, 2020). KREDL promotes the usage of RESs.

Wind Energy

The total installed wind power capacity in Karnataka is 4790.60 MW. Wind speed is a crucial factor for generation of energy from wind farms. Ramachandra and Shruthi (2003) identified that the wind speed must be greater than 5.4 m/s for feasible energy production. Tuppadahalli onshore plant has a potential for 140 GWh per annum and the rotor diameter and height are 82 m and 78 m, respectively (Elavarasan et al, 2020).

Small Hydro Energy

With six percent contribution from water resources to the nation, Karnataka is fortunate to have good conditions for hydropower (Rivers in Karnataka, report, 2019). Out of 939 plants in India, 132 are located in Karnataka, and theese yield a power of about 1230.73 MW (Höffken, 2014).

Biomass Energy

Plants and animals are major sources for biomass energy production, along with waste from agro-industries (Mahishi et al., 2014). Wood and paper industries in Karnataka prepare fuel from combustion processes (KREDL, 2019a). Biomass Energy for Rural India employed a gasification-based power production plant to sate the power demands in the district of Tumkur. Two plants were set, each with a total potential for 240 KW, and the core aim being the reduction of green house-gases (GHG) (Dasappa et al., 2011).

Tidal Energy

With a 320 km coastline, Karnataka can effectively generate energy from the waves (Reddy et al., 2018). There is a potential for 0.2 MW per square meter, but rigid governmental policies reduce possibilities of exploration (Khare, 2019).

3.2. Case Study of RES selection in Karnataka

This section provides an empirical case study of RES selection in Karnataka, India, demonstrating the practical use of the proposed framework. As mentioned earlier, the systematic selection of RESs is important to India; to satisfy the high demand of consumers and to further the country's economic development.

A set of three experts/DMs choose a type of linguistic term as their preference that are transformed into q-ROFI values using Table 1. Let $DM = (dm_1, dm_2, dm_3)$ be a set of DMs who share their preferences for five RESs that are popular in India and evaluated over 12 attributes. Let $RES = (rs_1, rs_2, rs_3, rs_2, rs_5)$ be a set of RESs that are assessed over a set of $AT = (at_1, at_2, at_3, at_4, at_5, at_6, at_7, at_8, at_9, at, at_{11}, at_{12})$ (Rani et al., 2019). The five RESs under consideration are *tidal energy, biomass energy, solar energy, wind energy, and hydropower.* They are selected on the basis of 12 attributes: *air pollutant emissions, need for waste disposal, water pollution, land disruption, land requirement, economic risk, security, sustainable energy, durability, adaptability to energy policy, cost, and feasibility*.

The linguistic rating of each DM is obtained from Rani et al. (2019), and the systematic procedure for rational selection of RES is presented below:

Step 1: Convert the linguistic values provided by each DM into q-ROFI. The linguistic values are obtained from Rani et al. (2019), and Table 1 is used to convert these values into q-ROFI, which are depicted in Table 2.

Table 1: Linguistic to q-ROFNs

Linguistic term	q-ROFN
Absolutely high	(0.98,0.01)
Very high	(0.9,0.6)
High	(0.8,0.65)
Medium-high	(0.75,0.6)
Average	(0.5,0.5)
Medium-low	(0.6,0.7)
Low	(0.7,0.8)
Very low	(0.6,0.9)
Absolutely low	(0.01,0.98)

Step 2: The missing values in these tables are imputed using the procedure proposed in Section 2.2. Table 2 depicts the q-ROFIs related to each linguistic term, and the q-rung is considered to be $q = 3$. Thus, $\mu^3 + v^3 \leq 1$.

Entries are shown as "XX” denotes the missing values, which are imputed using the case-based approach proposed in Section 2.2. Entry (at_4) of dm_1 is imputed as (0.49,0.76) using case 4. Likewise, (at_4) of dm_2 is imputed as (0.47,0.81) using case 4, (at_4) of dm_3 is imputed as (0.51,0.82) using case 4, (rs_1, at_2) of dm is imputed as (0.52,0.91) using case 2, (rs_1, at_2) of dm_2 is imputed as (0.52,0.91) using case 2, (rs_1, at_2) of dm_3 is imputed as (0.52,0.91) using case 2, and (rs_2, at_5) of dm_1 is imputed as (0.49,0.76) using case 1.

Table 2: RES evaluation by the DMs

Attributes	**DMs**	**RESs**				
		rs_1	rs_2	rs_3	rs_4	rs_5
at_1	dm_1	(0.01,0.98)	(0.01,0.98)	(0.6,0.9)	(0.7,0.8)	(0.6,0.9)
	dm_2	(0.01,0.98)	(0.01,0.98)	(0.6,0.9)	(0.6,0.9)	(0.6,0.9)
	dm_3	(0.01,0.98)	(0.6,0.9)	(0.6,0.9)	(0.6,0.9)	(0.6,0.9)
at_2	dm_1	XX	(0.6,0.9)	(0.01,0.98)	(0.7,0.8)	(0.6,0.9)
	dm_2	XX	(0.6,0.9)	(0.01,0.98)	(0.7,0.8)	(0.6,0.9)
	dm_3	XX	(0.01,0.98)	(0.6,0.9)	(0.6,0.9)	(0.01,0.98)
at_3	dm_1	(0.01,0.98)	(0.6,0.9)	(0.6,0.9)	(0.6,0.9)	(0.01,0.98)
	dm_2	(0.6,0.9)	(0.7,0.8)	(0.01,0.98)	(0.6,0.9)	(0.01,0.98)
	dm_3	(0.6,0.9)	(0.7,0.8)	(0.6,0.9)	(0.6,0.9)	(0.6,0.9)
at_4	dm_1	XX	XX	XX	XX	XX
	dm_2	XX	XX	XX	XX	XX
	dm_3	XX	XX	XX	XX	XX
at_5	dm_1	(0.6,0.9)	XX	(0.6,0.9)	(0.6,0.9)	(0.6,0.9)
	dm_2	(0.7,0.8)	(0.01,0.98)	(0.01,0.98)	(0.6,0.9)	(0.7,0.8)
	dm_3	(0.01,0.98)	(0.6,0.9)	(0.01,0.98)	(0.7,0.8)	(0.6,0.9)
at_6	dm_1	(0.75,0.6)	(0.98,0.01)	(0.8,0.65)	(0.8,0.65)	(0.75,0.6)
	dm_2	(0.8,0.65)	(0.9,0.6)	(0.9,0.6)	(0.75,0.6)	(0.75,0.6)
	dm_3	(0.75,0.6)	(0.9,0.6)	(0.9,0.6)	(0.8,0.65)	(0.8,0.65)
at_7	dm_1	(0.6,0.9)	(0.01.0.98)	(0.01,0.98)	(0.6,0.9)	(0.6,0.9)
	dm_2	(0.7,0.8)	(0.01.0.98)	(0.01,0.98)	(0.7,0.8)	(0.6,0.9)
	dm_3	(0.01,0.98)	(0.6.0.9)	(0.6,0.9)	(0.7,0.8)	(0.7,0.8)
at_8	dm_1	(0.6,0.9)	(0.6,0.9)	(0.01,0.98)	(0.7,0.8)	(0.6,0.7)
	dm_2	(0.7,0.8)	(0.7,0.8)	(0.6,0.9)	(0.6,0.9)	(0.7,0.8)
	dm_3	(0.01,0.98)	(0.7,0.8)	(0.6,0.7)	(0.6,0.9)	(0.6,0.9)
at_9	dm_1	(0.5,0.5)	(0.8,0.65)	(0.75,0.6)	(0.75,0.6)	(0.6,0.7)
	dm_2	(0.5,0.5)	(0.8,0.65)	(0.75,0.6)	(0.8,0.65)	(0.5,0.5)
	dm_3	(0.5,0.5)	(0.9,0.6)	(0.8,0.65)	(0.75,0.6)	(0.5,0.5)
at_{10}	dm_1	(0.5,0.5)	(0.75,0.6)	(0.8,0.65)	(0.6,0.7)	(0.5,0.5)
	dm_2	(0.6,0.7)	(0.9,0.6)	(0.75,0.6)	(0.5,0.5)	(0.6,0.7)
	dm_3	(0.5,0.5)	(0.9,0.6)	(0.8,0.65)	(0.6,0.7)	(0.5,0.5)
at_{11}	dm_1	(0.75,0.6)	(0.75,0.6)	(0.75,0.6)	(0.8,0.65)	(0.75,0.6)
	dm_2	(0.5,0.5)	(0.8,0.65)	(0.75,0.6)	(0.8,0.65)	(0.75,0.6)
	dm_3	(0.75,0.6)	(0.9,0.6)	(0.9,0.6)	(0.5,0.5)	(0.5,0.5)
at_{12}	dm_1	(0.5,0.5)	(0.8,0.65)	(0.75,0.6)	(0.75,0.6)	(0.5,0.5)
	dm_2	(0.75,0.6)	(0.75,0.6)	(0.9,0.6)	(0.75,0.6)	(0.75,0.6)
	dm_3	(0.6,0.7)	(0.75,0.6)	(0.5,0.5)	(0.5,0.5)	(0.5,0.5)

Step 3: Preferences of each expert/DM are obtained for each attribute, and, by using the Gini index (Section 2.3), weights are determined.

A matrix of the order *3* × *12* for determining the weights of the attributes is based on Rani et al. (2019). The linguistic terms are converted to their respective q-ROFI based on Table 1, and it is depicted in Table 3.

Table 3: Preferences from DMs for attribute weight calculation

Attributes	**DMs**		
	dm_1	dm_2	dm_3
at_1	(0.9.0.6)	(0.8,0.65)	(0.5,0.5)
at_2	(0.8,0.65)	(0.75,0.6)	(0.5,0.5)
at_3	(0.75,0.6)	(0.8,0.65)	(0.6,0.7)
at_4	(0.8,0.65)	(0.5,0.5)	(0.5,0.5)

at_5	(0.9,0.6)	(0.75,0.6)	(0.5,0.5)
at_6	(0.6,0.7)	(0.7,0.8)	(0.5,0.5)
at_7	(0.8,0.65)	(0.9,0.6)	(0.6,0.7)
at_8	(0.5,0.5)	(0.6,0.7)	(0.6,0.7)
at_9	(0.6,0.7)	(0.7,0.8)	(0.7,0.8)
at_{10}	(0.7,0.8)	(0.6,0.7)	(0.6,0.7)
at_{11}	(0.6,0.7)	(0.9,0.6)	(0.7,0.8)
at_{12}	(0.7,0.8)	(0.9,0.6)	(0.6,0.9)

Gini index is applied to Table 3 in order to determine the weights of the attributes, given by (0.085, 0.085, 0.085, 0.081, 0.085, 0.085, 0.085, 0.085, 0.081, 0.081, 0.081, 0.085, 0.081). Also, the weight values used by Rani et al. (2019) are considered for evaluation and a discussion is presented in the next section.

Step 4: Decision matrices shown in Table 2 are used to obtain the relative importance value of each DM by applying the programming model from section 2.4.

Next, Model 1 is used to obtain the objective function, which is expressed as $0.96\varpi_1 + 1\varpi_2 + 0.96\varpi_3$, and the constraints are $\varpi_1 + \varpi_2 \leq 0.6$, $\varpi_2 + \varpi_3 \leq 0.6$, $\varpi_1 \leq 0.4$, and $\varpi_2 \leq 0.2$. The optimization toolbox from MATLAB is utilized to solve the programming model, and weights were 0.4, 0.2, and 0.4, respectively. Also, DM weights from the work of Rani et al. (2019) were used for evaluation, which is discussed in the next section.

Step 5: Matrix from Table 2 is aggregated using the relative importance vector (from step 4) and the q-ROFWMM operator (from section 2.5), which is shown in Table 4.

The aggregated values from Table 4 are also q-ROFIs and obey the condition $\mu^3 + \nu^3 \leq 1$. The q-ROFWMM operator considers λ_1, λ_2, and λ_3 values to be 2, 2, and 1, and the weights of the DMs are obtained from step 4.

Table 4: The aggregated preferences using q-ROFWMM operator

dm_{123} Aggregated	**RESs**				
	rs_1	rs_2	rs_3	rs_4	rs_5
at_1	(0.32,0.95)	(0.32,0.96)	(0.24,0.96)	(0.35,0.97)	(0.24,0.96)
at_2	(0.29,0.96)	(0.35,0.96)	(0.29,0.97)	(0.35,0.98)	(0.29,0.97)
at_3	(0.29,0.96)	(0.29,0.97)	(0.3,0.96)	(0.36,0.98)	(0.29,0.97)
at_4	(0.3,0.97)	(0.33,0.98)	(0.27,0.98)	(0.41,0.97)	(0.27,0.98)
at_5	(0.27,0.96)	(0.32,0.97)	(0.29,0.97)	(0.36,0.98)	(0.31,0.96)
at_6	(0.32,0.95)	(0.33,0.96)	(0.3,0.96)	(0.4,0.97)	(0.3,0.96)
at_7	(0.33,0.96)	(0.35,0.96)	(0.33,0.96)	(0.41,0.97)	(0.3,0.95)
at_8	(0.3,0.95)	(0.35,0.94)	(0.3,0.95)	(0.42,0.96)	(0.31,0.94)
at_9	(0.3,0.96)	(0.3,0.95)	(0.29,0.96)	(0.4,0.96)	(0.3,0.96)
at_{10}	(0.32,0.96)	(0.33,0.95)	(0.3,0.94)	(0.42,0.97)	(0.31,0.95)
at_{11}	(0.33,0.95)	(0.35,0.96)	(0.29,0.95-)	(0.4,0.96)	(0.31,0.96)
at_{12}	(0.33,0.95)	(0.35,0.96)	(0.3,0.96)	(0.41,0.97)	(0.3,0.96)

Step 6: Prioritize the RESs with the help of the aggregated matrix and attribute weights. The q-ROFS-based TODIM method is applied to prioritize the RESs. Net dominance is calculated

using equations (8)-(9) at $\theta = 1$, as depicted in Table 5. By applying equation (10), the prioritization order for RESs were determined to be $rs_2 = 1 \succ rs_4 = 0.44 \succ rs_3 = 0.35 \succ rs_1 = 0.32 \succ rs_5 = 0$. When $\theta = 2.5$, the net dominance is calculated using equations (8)-(9), as shown in Table 5. Based on the net dominance matrix, the prioritization order is calculated as $rs_3 = 1 \succ rs_4 = 0.72 \succ rs_1 = 0.34 \succ rs_5 = 0.25 \succ rs_2 = 0$.

Table 5: Net Dominance for different values of θ.

RESs	rs_1		rs_2		rs_3		rs_4		rs_5	
	$\theta = 1$	$\theta = 2.5$	$\theta = 1$	$\theta = 2.5$	$\theta = 1$	$\theta = 2.5$	$\theta = 1$	$\theta = 2.5$	$\theta = 1$	$\theta = 2.5$
rs_1	0	0	2.334	2.6568	2.2967	6.1924	2.3093	6.2057	2.2703	3.2447
rs_2	2.3935	5.9706	0	0	2.32	5.8923	2.3313	5.9042	2.3694	5.945
rs_3	2.2436	2.2436	2.332	2.6547	0	0	2.2802	2.2802	2.2578	2.2578
rs_4	2.2431	2.2431	2.3323	2.655	2.2987	6.1945	0	0	2.2574	2.2574
rs_5	2.3641	5.2908	2.3334	2.6561	2.2974	6.1932	2.3099	6.2064	0	0

4. Comparative study: Proposed framework vs. exisisting methods

The current section compares the proposed framework with existing frameworks for RES evaluation. To maintain homogeneity, the proposed framework is compared with methods published on the PF-VIKOR method (Rani et al., 2019), Z-number-based COPRAS method (Chatterjee & Kar, 2018), IF-TOPSIS method (Aikhuele et al., 2019) and PF-WASPAS method (Ilbahar et al., 2020). Based on the investigation, it is evident that the proposed framework is a direct generalization of the work performed by Rani et al. (2019).

Table 6: Aggregated preferences using the q-ROFWMM operator

dm_{123}	rs_1	rs_2	rs_3	rs_4	rs_5
at_1	(0.4477,0.9324)	(0.4244,0.9402)	(0.44,0.9302)	(0.4289,0.9342)	(0.4399,0.9336)
at_2	(0.4583,0.9304)	(0.4305,0.9387)	(0.4421,0.93)	(0.4355,0.9334)	(0.4434,0.933)
at_3	(0.4538,0.93)	(0.4332,0.9377)	(0.4418,0.9284)	(0.4297,0.9334)	(0.4402,0.9324)
at_4	(0.4608,0.9354)	(0.4361,0.9434)	(0.4475,0.9345)	(0.4359,0.9396)	(0.4478,0.9379)
at_5	(0.4502,0.9316)	(0.4233,0.9406)	(0.4338,0.9308)	(0.4295,0.9351)	(0.4396,0.9337)
at_6	(0.4421,0.9419)	(0.4229,0.9425)	(0.4305,0.9418)	(0.4152,0.9469)	(0.4275,0.9453)
at_7	(0.4477,0.931)	(0.4215,0.941)	(0.4338,0.9306)	(0.4269,0.9343)	(0.4391,0.9328)
at_8	(0.4606,0.9296)	(0.4367,0.9377)	(0.4465,0.9285)	(0.4366,0.9332)	(0.4484,0.9311)
at_9	(0.4595,0.9307)	(0.438,0.94)	(0.448,0.9301)	(0.4363,0.9352)	(0.4466,0.9337)
at_{10}	(0.4587,0.932)	(0.4381,0.9409)	(0.4476,0.9316)	(0.4337,0.9368)	(0.4456,0.9344)
at_{11}	(0.4604,0.9302)	(0.4371,0.9389)	(0.4482,0.9292)	(0.4352,0.9343)	(0.4469,0.9326)
at_{12}	(0.466,0.9286)	(0.4414,0.9371)	(0.4525,0.9277)	(0.4414,0.9327)	(0.4528,0.931)

Table 6 depicts the aggregated values when DM weights from the work of Rani et al. (2019) are considered. Based on these values, net dominance is calculated by applying Equations (8)-(10), which is shown in Table 7 at $\theta = 1$ and $\theta = 2.5$, respectively. The weights of the attributes are considered from the work of Rani et al. (2019), and the prioritization orders are given by $rs_2 = 1 \succ rs_1 = 0.71 \succ rs_5 = 0.63 \succ rs_4 = 0.16 \succ rs_3 = 0$ and $rs_3 = 1 \succ rs_4 = 0.71 \succ rs_5 = 0.37 \succ rs_1 = 0.23 \succ rs_2 = 0$.

Table 7: Net Dominance for different values of θ.

RESs	rs_1		rs_2		rs_3		rs_4		rs_5	
	$\theta = 1$	$\theta = 2.5$	$\theta = 1$	$\theta = 2.5$	$\theta = 1$	$\theta = 2.5$	$\theta = 1$	$\theta = 2.5$	$\theta = 1$	$\theta = 2.5$
rs_1	0	0	2.3663	2.6774	2.0406	5.7989	1.9809	5.7279	2.0893	5.5334
rs_2	2.1392	5.5909	0	0	2.095	5.5414	2.046	5.4834	2.089	5.5332
rs_3	2.3467	2.3467	2.3654	2.6766	0	0	2.4115	2.4115	2.3813	2.3813
rs_4	2.3476	2.3476	2.365	2.6762	2.0407	5.7991	0	0	2.3816	2.3816
rs_5	2.2971	2.6101	2.3653	2.6765	2.0412	5.7997	1.9825	5.7298	0	0

Table 8 compares the developed framework with existing frameworks. Certain advantages/innovations of the proposed framework can be seen in Table 8, which are detailed as follows. *Firstly*, the q-ROFI is a flexible preference style that is generalized and allows DMs to express their choice on each alternative freely. *Secondly*, existing methods work on the assumption that all data (preferences) are available. However, in practical MADM problems, this may not be true. Unlike existing methods, the proposed framework considers missing values and imputes them systematically using a case-based method. *Further*, unlike in existing methods, weights are computed by capturing both hesitation and partial information. *Later*, the proposed framework aggregates preferences by accurately capturing the interrelationship among attributes, which is lacking in existing methods. *Finally*, RESs are prioritized by extending the TODIM method to q-ROFI, which utilizes a dominance measure to calculate rank values. This replicates human cognition and produces values that are broader and make backup management sensible and effective.

To establish the efficacy of the proposed framework, it was compared in a sensitivity analysis to the framework by Rani et al. (2019). The weights of attributes and DMs suggested in the work of Rani et al. (2019) were used in the proposed framework. Based on the analysis, the RES ranked highest is rs_2 when $\theta = 1$ and rs_3 when $\theta = 2.5$ remains unaltered even when the weights of attributes and DMs are changed (weights were adopted from Rani et al. (2019)).

Table 8: Investigation of theoretical factors: Proposed vs. Other extant methods

Context	**Methods**					
	Proposed	(Rani et al., 2019)	(Chatterjee & Kar, 2018)	(Rani et al., 2020)	(Zhang et al., 2019)	(Fossile, et al., 2020)
Data	q-ROFI	PFI	Z number	Fuzzy number	Cloud model	Fuzzy number
Missing data	Considered by the framework	Not considered by the methods				
Imputation	Done systematically using a case-based method	Not calculated				
Operator	Muirhead mean	Weighted average	Min-max	Weighted average	No	No
DMs' weights	Programming model	Score measure	No	Score measure	No	No
Attributes' weights	Gini index	Divergence method	Entropy measure	Divergence measure	Mathematical model	Mathematical model
Prioritization	TODIM	VIKOR	COPRAS	TOPSIS	TODIM	Mathematical model
Theme of prioritization	Dominance theory	Compromise solution	Utility theory	Compromise solution	Dominance theory	FI tradeoff
Interrelationship	Captured among attributes	Not captured				
Information on each DM	Partial information about DMs is used	Information not utilized effectively				
Flexibility	High, due to usage of a generalized model	Low, due to usage of a non-generalized model				

To recognize the strengths of the proposed framework compared to existing methods with q-ROFIs, we here discuss several parameters. These values were ranked based on Spearman correlation to determine the consistency of the developed framework. Fig. 2 shows that the proposed framework is highly reliable compared to the already developed methods using q-ROFIs. For a useful and relevant comparison we chose to compare the proposed framework with those of the existing methods that were most similar, thus we considered these methods: q-ROF-WDBA method (Peng et al., 2019), q-ROFI-hybrid method (Liu, et al., 2018), q-ROFI-Muirhead mean (Wang et al., 2019b) and q-ROFI-Bonferroni mean (Liu & Liu, 2018).

Fig. 2 shows that proposed framework is highly consistent with existing methods. The values are given by (1.0, 0.1, 1.0, 0.9, 0.3, 0.9). The prioritization order deviates with variation in the θ values. According to the work of Fan et al. (2013), the values of θ are 1 and 2.5.

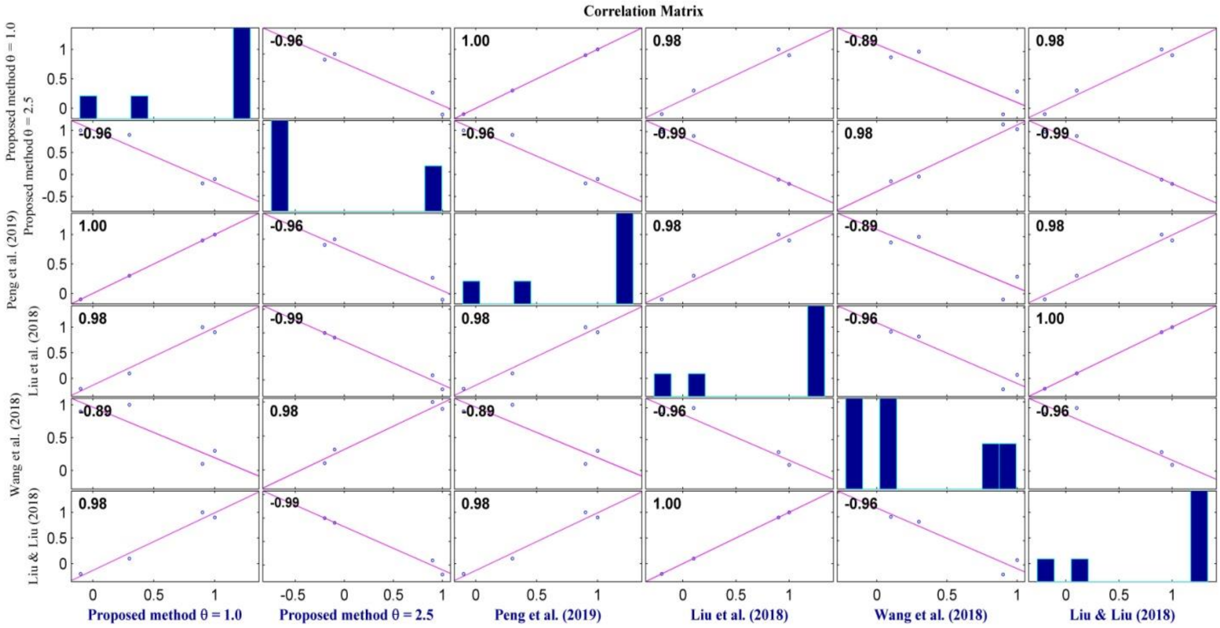

Fig.2 Correlation plot from Spearman correlation – Diagonals are histograms, and Non-diagonals are scatter plots. Values at the top left are $\boldsymbol{R}$ values.

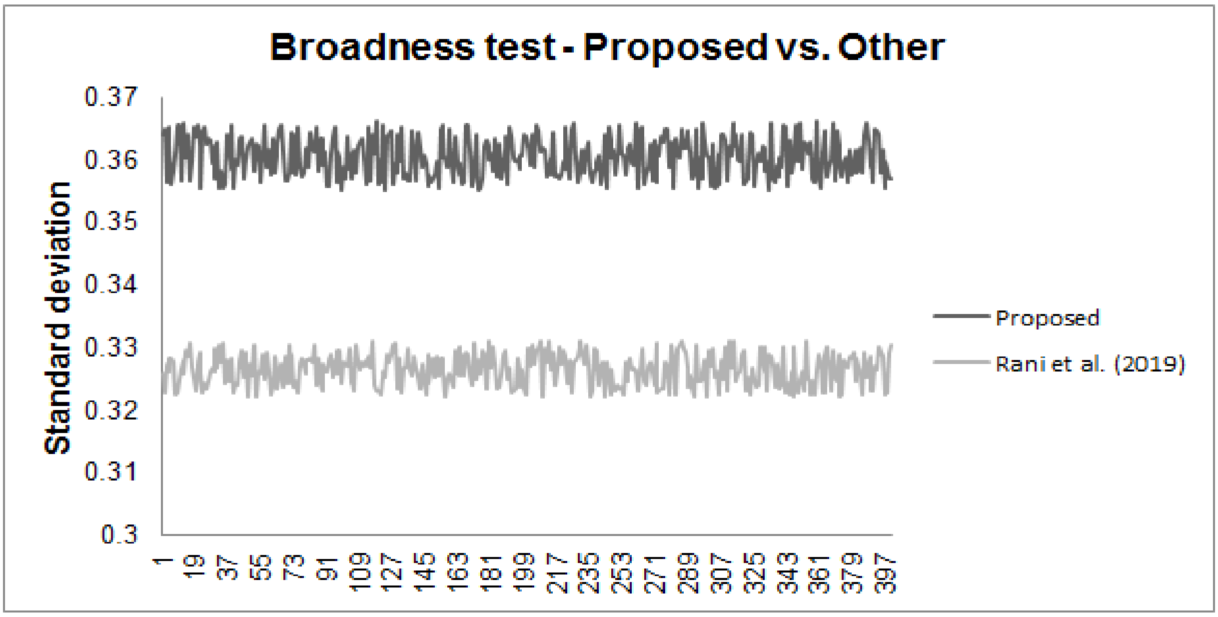

Fig.3 Standard deviation value analysis - Broadness test

Finally, a broadness test is conducted through a simulation study. 400 matrices of order 5×12 are simulated with linguistic information, and its corresponding q-ROFIs and Pythagorean fuzzy information (PFI) are used. A rank value set is determined for each matrix, which forms a vector of order 1×400, whose standard deviation is calculated, shown in Fig. 3. Based on Fig. 3, the proposed framework produces broad rank values compared to its close counterpart Rani et al. (2019). The main reasons for this is the flexibility of q-ROFI over PFI and the capacity of the proposed framework to capture the interrelationship and hesitation among the preference distributions.

5. Conclusion and implications

This section provides the concluding remarks along with valuable policy implications to clearly understand the novelties of the propoed framework and the need for rational selection of RESs.

5.1. The relevance of the proposed framework

In this paper a new decision framework was developed for systematic evaluation of RESs, using q-ROFIs. To reduce subjective randomness, linguistic preferences are transformed into q-ROFIs and are given as input to the framework. Due to hesitation and confusion being common in practical RES selection, missing values are implicit. This problem is addressed in the proposed framework, unlike in the existing selection models for RES. Further, the missing values are imputed systematically using case-based methods. Next, attribute weights and DMs' importance weights are calculated systematically by considering the hesitation and partial information from the DMs. Preferences from DMs are aggregated by reflecting the interdependencies among DMs, this is lacking in existing models. Finally, RESs are prioritized by applying the TODIM method to q-ROFIs. This method prioritizes RESs based on the dominance measure, which closely resembles the human cognition.

From this paper, it is inferred that the proposed framework is *moderately stable* even after suitable deviations are made to the DMs' and attributes' weights. This is evident from the prioritization order obtained by using weights from the proposed framework as well as from Rani et al. (2019); *consistent* with existing methods under q-ROFI. This is inferred from the Spearman correlation (Fig. 2); *produces broad rank values* for effective backup management compared to the decision model of Rani et al. (2019). This is conclusive based on the standard deviation analysis (refer Fig.3).

5.2. Policies implications relevant for RESs in India

Initially, renewable energy (RE), such as wind energy, solar energy, biomass energy, and geothermal heat, is based on natural processes (Kaya & Kahraman, 2010). Various developing nations utilize such types of energy to reduce the carbon footprint, which in turn mitigates global warming and creates societies with sophisticated sustainability. RE is associated with various technologies that enhance efficiency and reduce implementation overhead (Alcayde et al., 2018). RE policies and strategies implemented by a nation can help the energy sector grow. India benefits from a large geographic distribution of ￼To achieve sustainability and environmental goals more RESs are required, and their exploration is a substantial task. A stable increase in the availability of RE was recently achieved, due to effective initiatives from the Indian administration (Mishra et al., 2019).

Official assessments state that by 2022 the overall share of RE will reach 15.9%. In India, three states – Karnataka, Tamil Nadu and Gujarat – mounted as leaders to RES power generation. The three states are the responsible for most of the enormous growth in RESs prospective during last two decades. To achieve India's goal of 175 GW production from RESs by 2022, those three states are working continuously. The Karnataka government promises to offer 24/7 electricity for the whole state by 2020. The government launched “KREDL 2009-2014” to create and employ the produced energy in a creative way. In that five years plan, the target was to reach around 1970 MW. A Green Energy Fund, called “Akshaya Shakthi Nidhi”, has been established by KDREL to assist the development of the project with regards to funding and energy preservation (KREDL report, 2019a).

Solar energy production is one of the encouraged hybrid technologies (Sridharan et al., 2018). For promoting the development of solar power, Jawaharlal Nehru National Solar Mission (JNNSM) was established by the Government of India (GoI) in 2010-2011. Originally, the GOI had a target of employing grid-connected solar power of 20,000 MW by 2020, but in 2015 the goal was extended to 1,00,000 MW (Quitzow, 2015). Karnataka has generated nearly 51 MW through roof-top solar projects (Jakhar et al., 2018). In addition, the Karnataka is manufacturing the world’s largest solar park in Tumkur, to generate 2000 MW of solar power for irrigation (KREDL, 2019b). Furthermore, it is evident that Karnataka is the leading producer of biomass power in India, followed by Tamil Nadu and Gujarat (MNRE, 2019). The main reason for the high generation of biomass power in Karnataka is the availability of high quantity of raw materials from the Western Ghats (Madugundu et al., 2008). A pioneering structure called *tail-end grid* is being proposed by the GoI, and has been adopted on large plants. When considering energy transmission losses, smaller plants would be a better choice for future projects. To illustrate; the smaller plants of 100 KW to 2 MW capacity would mitigate the losses by 5-7% compared with plants with a massive capacity of 50-100 MW – and at the same time, the smaller plants still manage voltage and frequency issues.

By 2022, the projected production potential of small hydro power (SHP) is nearly 15000 MW, and 5718 sites are recognized. Approximately 285 projects of around 940 MW are in introductory stages. The goal is an addition of 300 MW per year, of which 70% is from the private regions (Garg, 2012).

When it comes to solar energy, the production capacity is increased every day. One of the JNNSM's goals is to install 20 million square meters solar thermal collector areas, and to establish 20 million solar lighting systems with an off-grid capacity of 2000 MW by 2022 (Khare et al., 2013).

5.3. On the results of the study

By looking at which attributes received the highest weight value in the study, it was inferred that the following attributes were the most important: *feasibility, pollutant emission, urge for waste disposal, water pollution, economic risk, security,* and *sustainable energy*. These attributes had a relative importance value of 0.085. Following them with a relative importance value of 0.081 were *land disruption, durability, adaptability to energy policy,* and *cost*. Based on these results it is apparent that the DMs have similar hesitation/confusion on each attribute. This iscaptured by the Gini index, and is presented as a relative importance value of each attribute.

Moreover, comparing the proposed framework to existing methods highlights the usefulness of the proposed framework. The comparative study results show that *biomass energy* was the optimal alternative among other RESs when $\theta = 1$, while *solar energy* was the best alternative, when $\theta = 2.5$.

Further, the prioritization order of different methods with q-ROFI was presented, and different factors such as consistency, stability, and broadness of the rank value set were discussed to realize the strengths of the proposed framework.

5.4. General info on the state of RESs in India

In global preference order, the RE sector has been acknowledged as being the fourth most remarkable sector (Sharma, 2017). India was ranked fifth for established RE capacity, mainly hydro-electric energy, in October 2018 (Luthra et al., 2015). In recent years, the amount of RE generators installed has grown considerably, with a compound annual growth rate (CAGR) of 19.78% between 2014 and 2018.

In August 2018, more than 122.1 TWh of electricity was produced, of which 16.3 TWh were from the RE sector. Between 2018 and 2019, the energy generation from RESs for August increased with 51% (IEEFA, 2018). The use of biomass as a RES has increased during the last decade; statistically, it accounts for approximately 14% of total energy utilization worldwide (Parikka, 2004). Researchers have stated that by 2050, almost 15-50% of the prime energy used will be produced from biomass. Several nations apply the use of RE as a part of the political agenda. Each year, power generation from biomass in India receives enormous investments of more than INR 600 crores; it generates over 5,000 million electricity units, which has generated employment of over 10 million man-days per year, predominantly in Indian rural sectors (Kumar et al., 2010).

MNRE has an efficient collaboration with the Indian RE development agency (IREDA) in supporting the use of all solar energy structures and increasing the allocation of REs from the Indian perspective (Mishra, 2018).

Additionally, MNRE has developed a comprehensive plan to make India able to reach the 100 GW target by 2022 (Rani et al., 2019). Plants with a capacity of 23.12GW were installed in India by July 2018. Currently, the 10GW projects are being realized, and plans are being made for the 24.4 GW projects.

India is fortunate to be in the equatorial region with its abundant sunlight; India receives over 5000 trillion kWh of solar enegy per year (Kumar et al., 2010). There is a need for a strategy for the evaluation of combined biomass and solar energy power plants.

5.5. Limitations of the proposed framework

Certain *limitations* of the proposed framework are important to be aware of. A practical difficulty is that DMs must be trained with the preference style to properly utilize the flexibility and potential of q-ROFIs . The shortcomings of the proposed methodologies mentioned in subsections 2.2 to 2.6 should also be considered.

Generalized preference styles, such as interval-valued probabilistic linguistic term sets and double hierarchy hesitant fuzzy linguistic sets, can be adopted as preference information for the evaluation of RESs.

5.6. Suggestions for further research

The proposed framework will serve as a useful tool for selecting the optimal RES under multi-criteria conditions and uncertain environments. In further research, more RESs and more attributes should be evaluated.

Author contribution

The following are the contributions of the authors. All authors had read the manuscript and approve of its submission in the journal. The first two authors prepared the initial prototype of the research model. Later, the two authors made a detailed discussion with the next two authors to develop a workable model of the proposed idea. The first three authors coded the proposed idea, which was fine-tuned by the fourth author. After some brainstorming sessions, the first four authors completed the implementation of the proposed idea. The third and fourth authors supported the data collection process by making discussions with the DMs related to the data. Fifth and sixth authors provided valuable suggestions in fine-tuning the data collection process. Later, the first, third, and fourth authors prepared the initial draft by getting support from the second author, which was completely revised and refined by the fifth and sixth authors. The fifth and sixth authors provided valuable suggestions related to the presentation of the manuscript and helped in language editing and improvement.

Compliance with ethical standards

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