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TRIZ-driven assessment of sector-wise investment decisions in renewable energy projects through a novel integrated q-ROF-DEMATEL-SRP model

Serhat Yüksel [a,d], Fatih Ecer [b,*], Raghunathan Krishankumar [c], Hasan Dinçer [a,d], Yaşar Gökalp [e]

[a] The School of Business, Istanbul Medipol University, Istanbul, Turkey
[b] Sub-Department of Operations Research, Faculty of Economics and Administration, Afyon Kocatepe University, Afyonkarahisar, Turkey
[c] Information Technology Systems and Analytics Area, Indian Institute of Management Bodh Gaya, Bodh Gaya, 824234, Bihar, India
[d] Clinic of Economics, Azerbaijan State University of Economics (UNEC), Istiqlaliyyat Str. 6, Baku, AZ1141, Azerbaijan
[e] The School of Health, Istanbul Medipol University, Istanbul, Turkey

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ABSTRACT

Necessary actions should be taken to improve renewable energy investments to minimize the carbon emission problem. In this process, the most significant determinants should be identified for some reasons, such as using human and financial resources more effectively. However, there are limited studies in the literature that prioritize the analysis of these items. This situation can be accepted as a missing gap in the literature. Accordingly, this study evaluates sector-wise investment decisions in renewable energy projects. To do so, a novel integrated q-rung orthopair fuzzy set (q-ROFS) decision-making model has been generated. Firstly, the weights of the theory of the solution of inventive problems (TRIZ)-driven criteria are computed via the q-ROF decision-making trial and evaluation laboratory (DEMATEL) methodology. The second stage of the proposed model consists of selecting the most appropriate investment alternatives with the help of the q-ROFS-based simple ranking process (q-ROF SRP). The main contribution of this study is that key sector-wise investment decisions in renewable energy projects can be identified by establishing a novel decision-making model. The main superiority of the proposed model is that the DEMATEL method is extended to the q-ROFS context to determine the weights of the factors. With the help of this issue, uncertainties and subjective randomness in the decision-making process can be minimized. In addition to this situation, causal directions between these indicators can be taken into consideration for this condition. The findings indicate that possible extension with modularity is the most critical indicator for this situation. Similarly, resource efficiency is also found to be the most influencing item. In addition to them, the ranking results demonstrate that waste-to-energy technologies and energy storage systems are the most critical investment alternatives.

Nomenclature

Abbreviation	Expansion
q-ROFS	q-Rung orthopair fuzzy set
q-ROF	q-Rung orthopair fuzzy
TRIZ	Theory of inventive problem solving
DEMATEL	Decision making trial and evaluation laboratory
SRP	Simple ranking process
q-ROF – SRP	q-Rung orthopair fuzzy – simple ranking procedure
MCDM	Multi-criteria decision-making
AHP	Analytical hierarchy process
BWM	Best worst method
IFS	Intuitionistic fuzzy set
PFS	Pythagorean fuzzy set
FFS	Fermatean fuzzy set
q-RFD	q-Rung orthopair fuzzy data
COVID-19	Corona virus disease of 2019
WASPAS	Weighted aggregated sum product assessment
CRADIS	Compromise ranking of alternatives from distance to ideal solution
IoT	Internet of things
VIKOR	Visekriterijumska optimizacija i kompromisno resenje
EXPROME – II	Extended preference ranking organization method for enrichment evaluation – II
TODIM	Tomada de decisão interativa multicritério (Portuguese word)

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* Corresponding author.
E-mail addresses: fecer@aku.edu.tr (F. Ecer), raghunathan.k@iimbg.ac.in (R. Krishankumar).

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(*continued*)

Nomenclature	
Abbreviation	Expansion
q-ROFN	q-Rung orthopair fuzzy number
REP	Renewable energy project
PCM	Pairwise comparison matrix
DM	Decision matrix
Symbol	Meaning
μ	Membership or preference grade
υ	Non-membership or non-preference grade
Q	q-Rung orthopair fuzzy set
q	A factor that can have integer values greater than zero
β	Any scalar quantity greater than zero
t	Number of experts
m	Number of criteria
n	Number of alternatives
i	Index for elements in the row of a matrix
j	Index for elements in the column of a matrix
k	Index for expert
$AQ_{ij}^{'}$	Aggregated q-ROFN when alternative i is rated by criterion j
λ_k	Weight of expert k
AQ_{ij}	Accuracy value of aggregated q-ROFN
F_{ij}	Total relationship matrix
I	Identity matrix
R_i	Row sum
C_j	Column sum
w_j	Weight of criterion j
O_i	Rank order of alternative i
N_i	Weighted rank order sum value of alternative i
M_i	Final rank value of alternative i

1. Introduction

Correct investment decisions must be made on a sector basis to ensure the effectiveness of renewable energy projects. This is primarily necessary for a good understanding of the market and demand. Energy demands may vary across different sectors. Therefore, the right energy resources must align with the sectors. This situation is of vital importance for both the sustainability and profitability of investments. In addition to this issue, making the right investment decisions on a sector basis is also necessary for compatibility with the technology infrastructure [1]. The type of energy that should be used in this process may differ depending on the sectors. Therefore, taking into account sector-specific technical requirements and infrastructure can increase the success of projects. Investments made in the right sectors can also contribute to financial efficiency. This can significantly contribute to reducing the costs of projects [2]. On the other hand, renewable energy projects play an essential role in managing environmental impacts [3,4]. In this context, environmental negative impacts can be minimized by selecting suitable projects according to sectors [5].

Many factors need to be considered when making the right investment decisions on a sector basis in renewable energy projects. In this context, a clear understanding of market expectations is critical. Market expectations determine which sectors will see more demand for renewable energy projects. This contributes to understanding which types of renewable energy are needed more. Similarly, market expectations also indicate which sectors are competitive [6]. This situation allows the right investment decisions to be made. Ensuring resource efficiency is also paramount in making the right investment decisions on a sector basis in renewable energy projects. Efficient use of resources allows the costs of projects to be reduced. This situation supports increasing investments. Technology and infrastructure compatibility are other factors that should be considered when making the right investment decisions. Since the availability of infrastructure will affect the choice of technology, this is crucial in making the investment decision. Regulation and incentives in countries are another vital variable in this context [7]. The sector's current or future regulatory environment in which investment will be made should be considered.

There are different investment alternatives in renewable energy projects on a sector basis. The vital thing in this process is to find the proper investment projects. Businesses may encounter different unpredictable costs if these investment decisions are made incorrectly. This situation may negatively affect the effectiveness and efficiency of the projects. In summary, in making correct investment decisions, it is essential to determine the foremost criteria that influence this process and select investment alternatives concerning the sectors. The companies have limited financial and human resources. Hence, these limited resources should be used effectively to improve the performance of the companies. On the other hand, if the most important factors are not determined, businesses will implement the wrong investment strategies. This situation can cause businesses to experience some important problems. Therefore, the most effective factors must be determined to make the right investment decisions. Although many studies in the literature highlight the importance of renewable energy projects, a limited number of studies analyze the importance of these factors. This can be defined as a critical gap in the literature on this subject. Therefore, this problem should be overcome with new studies.

Accordingly, this study aims to evaluate sector-wise investment decisions in renewable energy projects. Hence, the main research question of this study is to understand which criteria have the highest significance and which sector-wise investment alternatives play the most crucial role in this framework. For this purpose, a novel fuzzy decision-making model has been constructed. TRIZ-based criteria are first weighted using the decision-making trial and evaluation laboratory (DEMATEL) methodology in this process. In the second stage of the proposed model, selected investment alternatives are ranked with the help of the simple ranking process (SRP) technique. Within this context, q-ROFSs minimize uncertainties in the decision-making process. The primary motivation of this work is the necessity of a new study to define the most critical performance indicators of renewable energy investment projects. Owing to this issue, more effective investment strategies can be identified. This situation can positively influence the performance improvements of these projects. Otherwise, companies can face some financial difficulties because of this situation. This issue can negatively affect the profitability of the companies. To find the most critical determinants, decision-making models can be taken into consideration. However, there are lots of criticisms for these models, such as failure to manage uncertainties effectively and choosing appropriate techniques according to the subjects of the study. These criticisms should be taken into consideration to generate an effective model.

Some popular methods in the multi-criteria decision-making (MCDM) field are the analytical hierarchy process (AHP), best-worst method (BWM), entropy, and stepwise weight assessment ratio analysis (SWARA). In this work, authors use DEMATEL, which is from the no-prior information category. The method considers a pairwise comparison matrix as input. It is used to determine the criteria weights [8]. It also helps to determine the causal relationship, which is lacking in the extant techniques. Besides, the approach utilizes matrix formulation and, hence, is straightforward in terms of formulation. The simple ranking process (SRP) method [9] is a novel ranking approach that determines the rank values of alternatives to rank the alternatives based on the values. Specifically, it is inferred that (i) SRP is a simple yet elegant approach for ranking alternatives; (ii) SRP mitigates the normalization process in the ranking approach, which is common in multiple ranking approaches; and (iii) SRP considers the type of criteria during rank estimation. Driven by these features, for the first time in the literature, the q-ROF-DEMATEL-SRP framework is introduced. q-ROFS provides a rational context for modeling uncertainty and flexibility for experts to share their degrees of preference and degrees of non-preference. Specifically, q-ROFS is a generalized fuzzy set that can represent its predecessor fuzzy variants, such as intuitionistic fuzzy set (IFS), Pythagorean fuzzy set (PFS), and Fermatean fuzzy set (FFS) as special cases by assigning specific integer values to the factor q. Readers can realize this in the upcoming section. Though these fuzzy sets are orthopair forms that allow preference and non-preference degrees, in q-ROFS, experts gain an advantage to flexibly control/manage the rating window by assigning different values to q, which is impossible in the predecessor fuzzy variants. Consider a situation where an expert is rating a location for setting up a hydropower plant, and she provides her preference and non-preference degrees as (0.85, 0.90). Earlier variants, such as IFS, PFS, and FFS, cannot accept this orthopair rating as their respective inequality constraints do not hold true. As a result, q-ROFS is considered a valid structure for accepting the above-mentioned rating information.

In sum, the primary motivation for making this study is identifying critical sector-wise investment decisions in renewable energy projects. It is necessary to improve renewable energy investments to minimize the carbon emission problem more effectively. Moreover, the methodological contributions and novelties of the proposed model are given below.

(i) The DEMATEL method is extended to the q-ROFS context to determine the weights of TRIZ-driven criteria methodically, along with their causal relationship.
(ii) The SRP method is extended to the q-ROFS context to rank the renewable energy investment projects sector-wise for effectively reducing carbon emissions.
(iii) The q-ROF-DEMATEL-SRP framework is offered to solve complex real-world problems.

Consequently, this work addresses the research gap by proposing a novel decision-making framework that prioritizes sector-wise investment decisions, providing practical insights and a methodological contribution to the field. Without understanding these sector-specific factors, businesses risk implementing inefficient investment strategies, which could lead to increased costs and reduced project effectiveness. So, the sector-specific investments ensure that the appropriate energy solutions are applied, maximizing the effectiveness and profitability of these projects.

Some rationale behind the selection of these approaches for developing the present decision framework is as follows:

- Generalized orthopair fuzzy variant – q-ROFS is considered for data interpretation, which enables interpretation of data in two dimensions, i.e., preference or membership and non-preference or non-membership with a factor *q* that can aid in managing the grades/values, thereby supporting the effective expression of experts' rating information.
- DEMATEL can consider a pairwise comparison matrix as input. Besides, the DEMATEL method allows experts to understand the causal relationship among entities and the weight determination for criteria, which other approaches lack.
- SRP is a simple, elegant, and recent method that reduces normalization overhead, which other methods do not handle adequately. It further offers experts easy-to-implement steps for practical usage and better decision-making.
- There are also some advantages to using the TRIZ technique in determining variables. TRIZ brings a systematic approach to the problem-solving process. In this process, it identifies the contradictions encountered in the analysis process and offers creative strategies for resolving them. In this way, it is possible to achieve more successful analysis results.

The developed model considers q-ROFS structure based on DEMATEL and SRP procedures for rational ranking renewable energy projects. In general, it must be noted that the proposed integrated model can be extended to different decision fields, provided appropriate rating information is given as input to the model. In this research work, a specific case of renewable energy project selection is presented and from the earlier studies, it is inferred that managing uncertainty, handling the causal relationship of criteria, and determining ranks with less computational complexity is lacking, which acts as a primary motivation for proposing this integrated approach in this research and showcasing its usage through renewable energy project selection to facilitate sector-wise investment.

The literature review section is given in the second section. The proposed model is explained in the part next to the review section. Moreover, the fourth part consists of the results of the analysis. Discussion and conclusion are given in the final sections.

2. Literature review

2.1. Research on renewable energy projects

One factor influencing the effectiveness of renewable energy projects is the complex market needs. This relates to how renewable energy projects can respond to the diverse and dynamic demands of the market [10]. Market expectations can be focused on sustainability and environmental compliance, as well as energy security [11]. Moreover, the continuous development of technology requires renewable energy projects to keep pace with advancing technology [12]. Cui and Zhao [13] conducted a study to analyze the environmental impacts of renewable energy projects in the maritime sector. The study results show that marine renewable energies should be increased to achieve the sustainable target and reduce marine pollution. Kou et al. [14] carried out a study with an MCDM model to determine the optimal renewable energy project selection. It is emphasized that market expectations play a significant role in selecting the appropriate project.

The effectiveness of renewable energy projects is directly related to resource efficiency. Ensuring resource efficiency is essential for the sustainability of renewable energy projects [15]. Similarly, it also contributes to reducing energy production costs. In addition, efficiency in energy storage and distribution processes makes it possible to use renewable energies more effectively [16]. Agu et al. [17] examined renewable energy use in Canada until 2050. It is underlined that efficiency must be ensured for renewable energy use to be at the desired level. Yang et al. [18] aimed to identify China's green growth potential. Accordingly, the relationship between financial development and natural resource productivity is analyzed. The study's results, using data from 2000 to 2019, show that resource efficiency should be ensured to realize green growth quickly.

The compatibility of renewable energy projects with other systems and projects is another factor affecting their effectiveness. Energy is the building block for many sectors to continue their activities. Accordingly, energy generation, distribution, and storage must be compatible with other projects [19]. Moreover, the compatibility of renewable energy projects with other projects directly affects energy efficiency, security, and sustainability [20]. Rodríguez-Segura et al. [21] examined the relationship between renewable energy development and social acceptance in Spain. The results of the study highlighted that the compatibility of olive cultivation and renewable electricity generation is crucial for the development of projects. Prayogo et al. [22] conducted research with a hybrid MCDM approach to develop renewable energy integration. They stated that compatibility with renewable energy sources and environmental considerations are vital for integration.

The modular structure of renewable energy projects contributes positively to their effectiveness. Modular design of these projects can reduce the risks and costs [23]. Apart from that, having a modular structure facilitates the installation and maintenance of the project. The modular structure provides easier integration to possible technological developments. In addition, it makes it easier to integrate different renewable energy sources and projects [24]. Gaidzik et al. [25] researched the development of energy cooperatives in Poland. It is argued that the modularity of renewable energy projects contributes to the development of enterprises. Olabi et al. [26] aimed to reveal the contribution of wind energy to sustainable development goals. The survey results in London indicate that renewable energy projects are simple to set up and administer thanks to their modular structure.

The focus of this research is to present an integrated decision model for ranking renewable energy projects that could potentially aid investors in their investment process. Researchers have earlier presented studies on risk evaluation/assessment, factors' ranking, project assessment via decision-making approaches in the context of renewable energy. Adoption of TRIZ factors for ranking projects that could help in sector-wise investment in renewable energy is novel and some research gaps that could be identified from the methodological perspective is given in Table 1.

From Table 1, the following points can be seen:

- Uncertainty handling from two dimensions provides better scope than a single dimension. Generally, orthopair variants of fuzzy aid in two-dimensional uncertainty modeling.
- Many studies encourage consideration of causal relationships during criteria weight calculation, and prominently, DEMATEL and ANP methods are utilized
- Ranking methods consider normalization, increasing the decision model's computational complexity. In this study, the SRP method is extended to q-ROFS, which nullifies this issue by eliminating the normalization phase in the ranking algorithm. As a result, the computational complexity of the model is low, and the feasibility of the model is improved.

The unique proposition of the proposed model is to consider the best of breed from the decision-making process and combine the methods to form a decision framework that can combat different challenges/lacunae. The present model can interpret uncertainty from two dimensions, consider causal relationships during criteria weight calculations, explain the cause and effect from the list of factors/criteria by considering the total relationship values, and significantly reduce the complexity of ranking by eliminating the normalization phase. The combination of these features enables the policymakers to use the model better for the task at hand.

2.2. Research on q-ROFSs

q-ROFS, proposed by Yager [27], is a generalized fuzzy structure that can effectively represent other orthopair fuzzy forms as special cases. The q-ROFS considers a factor q, which can take positive integer values, and when the values are 1, 2, and 3, they denote IFS, PFS, and FFS, respectively. As discussed earlier, certain orthopair values cannot be accepted by the predecessor fuzzy forms. Hence, there is a need for q-ROFS, which can flexibly accommodate diverse degrees of preference and non-preference. Yet, one potential limitation of q-ROFS is that it cannot accept the preference and the non-preference degree to 1. In other words, full membership and non-membership grades are unacceptable for a specific instance. However, this is an extreme case, and as a result, the q-ROFS gained popularity in the decision-making field, and its ability to allow both preference and non-preference degrees facilitated the decision-making process.

This section briefly reviews q-ROFS-based decision models for diverse decision applications to provide a sense of the set's usefulness in decision applications. Alkan and Kahraman [28] put forward the TOPSIS method with q-rung orthopair fuzzy data (q-RFD) for ranking different government strategies toward the control of the COVID-19 outbreak. Krishankumar et al. [29] developed an integrated model with the WASPAS method for ranking cloud vendors to support medical centers. Limboo and Dutta [30] determined the basic probability under the q-ROFS context for medical diagnosis applications. IoT service providers are selected for eco-friendly transport planning by extending the CRADIS method to q-ROFS [31]. Jabeen et al. [32] extended the power of the Bonferroni mean operator to the q-ROFS context and presented some properties of the function and its usage in disease diagnosis. A new score function is developed, and BWM is extended to q-RFD for manufacturer selection [33]. To support the idea of agri-food 4.0, unmanned aerial vehicles are graded by extending the VIKOR method to q-ROFS [34]. Kumar and Chen [35] presented aggregation functions and proved their fundamental properties for the helpful application of aggregation in the decision process under the q-ROFS context. Likewise, Farid and Riaz [36] presented the Aczel-Alsina aggregation function with their fundamental properties in the q-ROFS context. Li et al. [37] developed conflict analysis and resolution methods in the three-way context by utilizing q-RFD. Cao et al. [38] ranked different food waste treatment methods by considering the TODIM method with a weighted power geometric function in the context of complex q-RFD.

Besides these recent advancements in the theory of q-ROFS and its usage in different fields, there are specific works from energy-related decision applications in the context of q-ROFS. Krishankumar and Pamucar [39] assessed diverse barriers that hinder clean energy usage via integrated CRITIC and WASPAS methods under the q-ROFS context. A new norm-based distance measure is developed, and specific properties are discussed by considering q-RFD, and its practical use is presented through clean energy selection [40]. Naz et al. [41] developed a decision model with 2-tuple q-ROFS by considering DEMATEL and TOPSIS methods to select renewable energy resources. Mushtaq et al. [42] graded different thermal energy storage approaches via q-ROF Einstein-ordered aggregation function. Recently, Parthasarathy and Narayanamoorthy [43] prioritized strategies for green energy via the q-ROF EXPROME-II method. The risk involved in clean/renewable energy projects is prioritized by the prospect theory-driven TODIM method with q-RFD.

Table 1
Research gaps from methodological viewpoint in the renewable energy sector.

Sources	Uncertainty modelling	Causal relationship	Computational complexity of ranking
Martinez et al. (2023)	Two dimensions	No	High
Kou et al. (2023)	Two dimensions	Yes	High
Zhou et al. (2021)	One dimension	Yes	High
Hashemizadeh et al. (2021)	One dimension	Yes	High
Kul et al. (2020)	One dimension	No	High
Ilbahar et al. (2022)	Two dimensions	No	High
Karatop et al. (2021)	One dimension	No	High
Agyekum et al. (2021)	N/A	No	High
Proposed	*Two dimensions*	*Yes*	*Low*

2.3. Research inferences from earlier studies

As a result of a comprehensive literature review, the following conclusions are reached. (i) Renewable energy projects (REPs) are one of the most popular investments in recent times. (ii) However, these projects have the characteristics of high initial investment cost, long payback period, and high technology requirements. These characteristics drive researchers and investors to look for ways to increase the efficiency of renewable energy projects. (iii) Yet, many factors influence the efficiency of these projects. (iv) Nevertheless, it is not possible for managers to address all these factors simultaneously. This would require a lot of time, workforce, and money. (v) Further, these factors have different importance, and it is essential to determine their importance. (vi) q-ROFS supports experts in better handling uncertainty and provides a flexible window for eliciting both preference and non-preference degrees during rating. (vii) To date, causal relationships among TRIZ-driven criteria have not been considered. Consequently, this study aims to develop prioritized strategies to promote the grading of REPs and offers a new integrated decision-making model.

3. Research methodology

3.1. Preliminaries

One of the most recent extensions of fuzzy sets, qROFS, has been used to solve many decision-making problems successfully to date [44–46]. In this section, some basic concepts of orthopair fuzzy sets are discussed.

Definition 1. [47]: A is a fixed set, and $B \subset A$ is also fixed. Then, an IFS $\overline{B}$ in A is given by;

$\overline{B} = \{a, \mu_{\overline{B}}(a), \upsilon_{\overline{B}}(a) | a \epsilon A\}$ (1) where $\mu_B(a)$, $\upsilon_{\overline{B}}(a)$, and $\pi_{\overline{B}}(a) = 1 - (\mu_{\overline{B}}(a) + \upsilon_{\overline{B}}(a))$ are the degree of membership, non-membership, and hesitancy, respectively. All these values are in the unit interval, and $\mu_{\overline{B}}(a) + \upsilon_{\overline{B}}(a) \leq 1$.

Definition 2. [27]: A is a fixed set and $a \in A$. Then, the q-ROFS Q on A is considered as;

$Q = \{a, \mu_Q(a), \upsilon_Q(a) | a \epsilon A\}$ (2) where $\mu_Q(a), \upsilon_Q(a)$ are in the 0 to 1 range, and referred as the degree of membership and non-membership. Also, $0 \leq (\mu_Q(a))^q + (\upsilon_Q(a))^q \leq 1$.

Note 1: In this study, $Q = (\mu_k, \upsilon_k)\ \forall k = 1, 2, \ldots, \tau$ is referred as q-rung orthopair fuzzy number (q-ROFN), and collectively they form q-ROFS.

Definition 3. [48]: Q_1 and Q_2 are two q-ROFNs. Arithmetic operations with q-ROFNs are given by;

$$Q_1^\beta = \left(\mu_1^\beta, \left(1 - (1 - \upsilon_1^q)^\beta\right)^{1/q}\right), \beta > 0 \tag{3}$$

$$\beta Q_1 = \left(\left(1 - (1 - \mu_1^q)^\beta\right)^{1/q}, \upsilon_1^\beta\right), \beta > 0 \tag{4}$$

$$Q_1 \bigoplus Q_2 = \left((1 - (1 - \mu_1^q)(1 - \mu_2^q))^{1/q}, \upsilon_1 \upsilon_2\right) \tag{5}$$

$$Q_1 \bigotimes Q_2 = \left(\mu_1 \mu_2, (1 - (1 - \upsilon_1^q)(1 - \upsilon_2^q))^{1/q}\right) \tag{6}$$

$$A(Q_1) = \mu_1^q + \upsilon_1^q \tag{7}$$

$$S(Q_2) = \mu_2^q - \upsilon_2^q \tag{8}$$

Arithmetic operations are shown in Eqs. (3)–(8) and they denote power operator, scalar multiplication, ring sum, ring product, accuracy, and score, respectively.

3.2. Criteria weight with the q-ROF DEMATEL approach

In this section, a step-by-step procedure for weight calculation using the q-ROF DEMATEL method is put forward. Notably, weights are associated with the relative importance of criteria, and as a result, a higher weight value denotes higher importance. In practical decision problems, criteria have unequal importance owing to different trade-offs, hesitation, and/or cognitive thoughts of the experts. Generally, weights are calculated with some prior knowledge or no prior knowledge. In the former case, some additional input is required that shares certain information about the criteria, whereas, in the latter case, there is no such additional input in the formulation. Thus, some basic definitions that support understanding the DEMATEL approach are given below.

Definition 1. A direct relationship between two objects is asymmetric. A pairwise comparison matrix $m \times m$ is obtained with each entry d_{ij} representing the degree to which criterion j affects criterion i. The value denotes influence and direction with an outcome, $D = [d_{ij}]_{m \times m}$.

Definition 2. Experts rate criteria in a pairwise comparison manner. Consider t matrices of $m \times m$ order as input to the procedure presented below.

Driven by these features, the authors extend DEMATEL to q-ROFSs. The step-by-step procedure for weight estimation is provided below.

Step 1: Collect rating information using the Likert scale to form an $m \times m$ pairwise comparison matrix. If there are t experts, each expert forms an $m \times m$ pairwise comparison matrix.

Transform the qualitative terms to q-ROFN based on the conversion values (readers can refer to the case example section for clarity). The q-ROFN corresponding to a particular qualitative term takes the form specified in Eq. (2) and Note 1.

Step 2: Aggregate these pairwise comparison matrices using Eq. (9), and as a result, a single pairwise comparison matrix of $m \times m$ order is obtained.

$AQ'_{ij} = \left(\prod_{k=1}^{t} \left(\mu_{ij}\right)^{\lambda_k}, \prod_{k=1}^{t} \left(\upsilon_{ij}\right)^{\lambda_k}\right)$ (9) where λ_k is the weight of the expert k.

Eq. (9) depicts the simple weighted geometry aggregation operator that considers the q-ROFN from each expert and the weight of each expert as input. Besides, the operator ensures that the resultant membership and non-membership values follow the q-ROFN form. So, if t pairwise comparison matrices of order $m \times m$ are given as input, Eq. (9) yields one pairwise comparison matrix of order m × m, and the values in the matrix follow q-ROFN form.

Step 3: Apply Eq. (7) to determine the accuracy values of the aggregated matrix. The accuracy matrix is formed, which is of order $m \times m$.

Based on Eq. (7), accuracy values are determined, which yields results in the unit interval, and an accuracy matrix is obtained that is of order $m \times m$. These are normalized.

Step 4: Determine total relational values using Eq. (10), which is of order $m \times m$.

$F_{ij} = AQ_{ij} * (I - AQ_{ij})^{-1}$ (10) where I is the identity matrix that is also of $m \times m$ order, * denotes matrix multiplication, $(a)^{-1}$ is inverse of matrix a, and F_{ij} is the total relational value matrix.

It can be noted that Eq. (10) yields the total relational values by considering the direct and indirect relational values. Since the qualitative terms are considered in the study, we do not have full membership or full non membership values.

Step 5: Calculate the sum of values row-wise and column-wise to form two vectors of order $1 \times m$. These two vectors are used to determine the net relational value, which is further normalized to obtain the weight vector of the criteria (Eqs. (11)–(13)).

$$R_i = \sum_{j=1}^{m} M_{ij} \tag{11}$$

$$C_j = \sum_{i=1}^{m} M_{ij} \tag{12}$$

$$w_j = \frac{\sum_{i,j=1}^{m} (R_i + C_j)}{\sum_i \sum_{i,j=1}^{m} (R_i + C_j)} \tag{13}$$

where R_i and C_j sum values row wise and column wise, respectively and w_j is the weight of criterion j.

It must be observed that Eq. (11) yields a row vector of 1 × m order, and likewise, Eq. (12) produces a column vector of $1 \times m$ order, which is finally fed to Eq. (13) for weight calculation. These weight values generally range from 0 to 1 and sum to unity.

3.3. Ranking with the novel q-ROF SRP approach

SRP is an easy and young MCDM method [49]. To date, it has not been extended to q-ROFS. In this section, a ranking algorithm known as

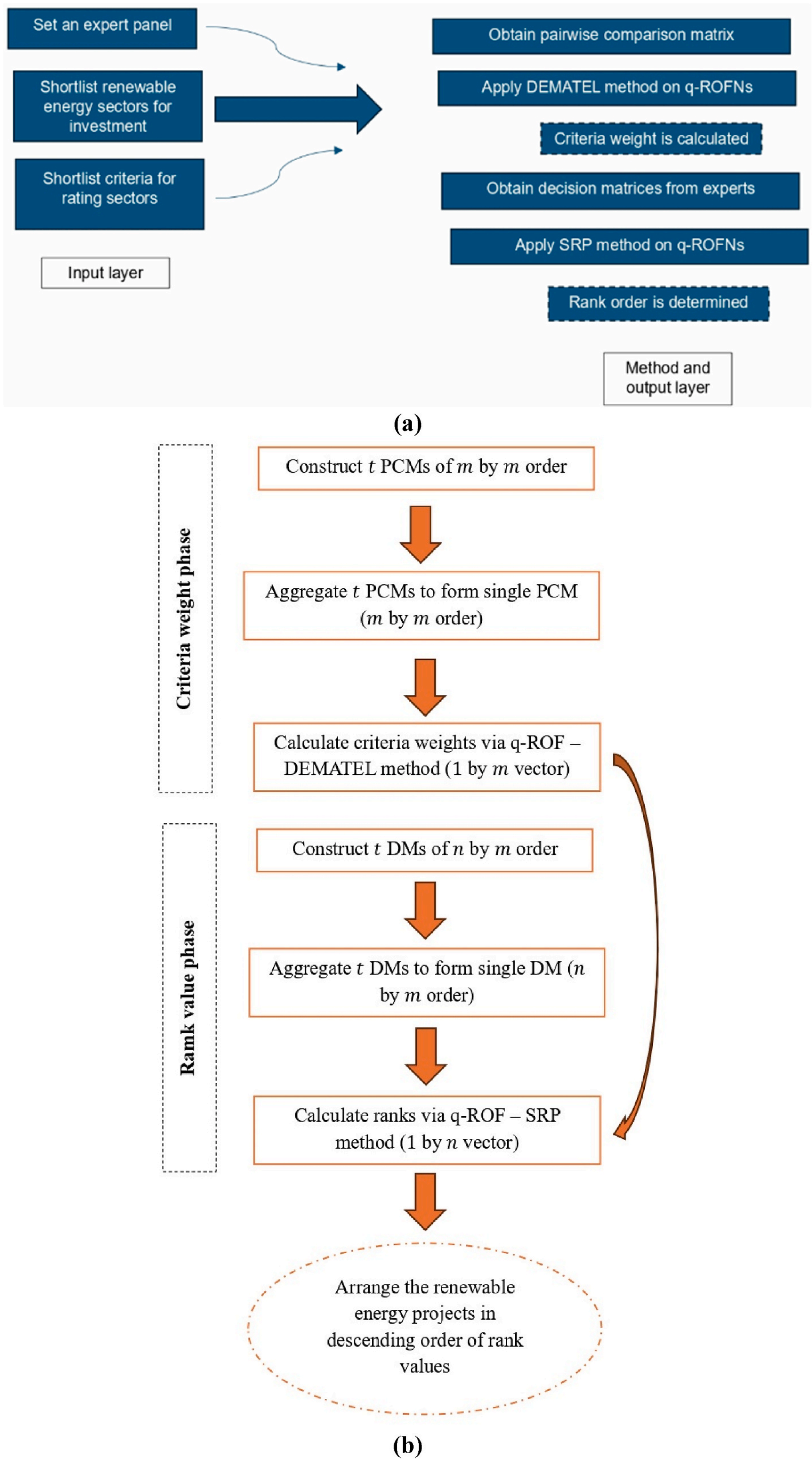

Fig. 1. (a) The developed integrated decision model with q-ROFSs and (b) workflow of it.

SRP is extended to the q-ROFS context for the first time. The algorithm procedure developed is presented below.

Step 1: Consider t matrices of order $n \times m$ where t is the number of experts, n is the number of alternatives, and m is the number of criteria. Initially, the rating is in the form of a Likert scale, and based on the value presented above, the terms are converted to q-ROFNs.
Step 2: Apply Eq. (9) to determine the net decision matrix based on the input obtained from Step 1. Experts' weights are considered in the unit interval range, and an aggregated matrix of $n\times m$ order is obtained.

As discussed earlier, the simple weighted geometry operator is used to aggregate q-ROFN-based rating information. As a result, an aggregated matrix of $n \times m$ order is obtained. The weights of experts used in Section 3.1 can be used here as well.

Step 3: Apply Eq. (7) to calculate the accuracy measure based on the input from Step 2. The order of this matrix is also $n \times m$.

An accuracy matrix is obtained with all values in the unit interval range, and this matrix, along with the criteria weight vector, is fed as input to the further steps.

Step 4: Considering the type of criteria, the rank order is determined for alternatives using Eq. (14).

$$O_i = \begin{cases} max(a_{ij}) \text{ if } j \text{ is benefit} \\ min(a_{ij}) \text{ if } j \text{ is cost} \end{cases} \tag{14}$$

where a_{ij} is the accuracy value and O_i is the rank order of the alternative i.

Eq. (14) infers that if there are two criteria, one benefit-type and another cost-type, and three alternatives, the benefit-type criterion will set rank orders in the descending order of accuracy values. Moreover, rank orders are assigned based on the ascending order of accuracy values for the cost-type criterion. In other words, if the criterion is benefit type, the alternative with maximum accuracy gets the top rank, and the ordering follows. In contrast, if the criterion is of cost type, then the alternative with minimum accuracy value gets the top rank, and the ordering follows.

Step 5: Determine the net weighted rank of alternatives using Eq. (15). A vector of $1 \times n$ is obtained that is used by Eq. (16) for determining the final ranks of alternatives.

$$N_i = \sum_j w_j . O_i \tag{15}$$

$$M_i = n - N_i \tag{16}$$

where w_j is the weight of criterion j, n is the number of alternatives.

From Eq. (15), the net weighted rank of alternative i is obtained, and eventually, N_i yields a vector of order $1 \times n$, which is further utilized by Eq. (16) for determining the final rank values of alternatives. Arrange the values of M_i in descending order to obtain the final ranking order of alternatives. In other words, the higher the value of M_i, the higher the priority of alternative i.

In Fig. 1(a), a block diagram is provided by considering two key layers, i.e., the input layer and the method/output layer. In the input layer, an expert panel is formed that is responsible for shortlisting the criteria and the renewable energy projects for sector-wise investment. Later, in the method/output layer, weights of criteria are determined and rank values of renewable energy projects are calculated by interpreting the data as q-ROFN. This conversion supports effective modeling of uncertainty from two dimensions, i.e., preference and non-preference dimensions. In Fig. 1(b) a workflow of the developed model is depicted that clarifies the working of the model. A panel is formed by inviting t experts who support the current decision problem of ranking REPs for potential sector-wise investment. The experts shortlisted n potential projects/sectors and identified m criteria that could be used to rate these sectors. The experts provide their pairwise comparison concerning the m criteria and provide their rating on projects/sectors based on each criterion. As a result, t pairwise comparison matrices (PCMs) and t decision matrices (DMs) are obtained. Pairwise comparison matrices are given as input to the criteria weight assessment procedure, and based on the algorithm, the weights are calculated, which is of $1 \times m$ order. This weight vector, along with the decision matrices of $n \times m$ order is given as input to the proposed ranking algorithm, and the rank order is determined based on the ranking algorithm. Thus, a vector of $1 \times n$ is obtained.

Before presenting the case study where the usefulness of the developed model is testified, it must be noted that the presented integrated approach q-ROFS-DEMATEL-SRP is a novel model presented by authors for the first time (to the best of their knowledge). From the data side, q-ROFS provides a rational context for modeling uncertainty and allows flexibility experts to share their degree of preference and non-preference. Further, the DEMATEL approach is a potential method for determining criteria weights methodically. SRP is a simple and elegant method for determining the rank values of alternatives. A combination of these in the form of a decision model provides an exciting tool for investors to plan their investment sector-wise in renewable energy projects rationally. A systematic framework mitigates bias and subjectivity and offers a supportive tool for experts to gain confidence during their investment.

4. Case study

In this section, criteria weights and alternative rankings are computed first. After that, a sensitivity analysis is conducted. Next, a comparative evaluation is performed. Finally, the main findings of the model are discussed by comparing them with the results of the previous similar studies.

4.1. Criteria weighting and alternative ranking

TRIZ technique is considered for the selection of the criteria set. This approach is designed to systematize innovation processes. In this way, effective and innovative solutions can be developed to solve the problem. TRIZ offers 40 general innovation principles for solving frequently encountered problems. These factors provide solution proposal alternatives suitable for the type of problems. In this way, it is possible to solve the problems more effectively and in a shorter time. On the other hand, the contradiction matrix is used in the analysis performed with the TRIZ technique. This matrix indicates the negative effects of improving a feature in the system. This helps to take the most correct actions. After a detailed literature survey, the TRIZ-driven criteria set is formed as follows.

C1. Possible extension with modularity
C2. Complexity based on the market needs
C3. Resource efficiency
C4. Compatibility with other systems and projects
C5. Uniqueness with asymmetry and originality
C6. Synergy using feedback mechanism and local sources

Modularity is becoming an important factor in the development of renewable energy projects. With these systems, installation processes can be carried out more quickly. Thanks to this, the time it takes to put projects into operation can be shortened. Complexity based on market needs is an important factor in developing renewable energy projects. This helps to adapt more easily to changing market demands. Energy markets show different demands according to different conditions. Projects gain competitive advantage by dynamically adapting to the market's changing needs. Resource efficiency is essential for the development of renewable energy projects. Initial costs are usually high in renewable energy projects. When efficiency is achieved, it makes projects more financially attractive. Compatibility with other systems and projects is also important for the performance of these projects. Thanks to compatibility, it is possible for renewable energy sources to provide uninterrupted electricity. This reduces energy supply interruptions and increases customer expectations. Uniqueness with asymmetry and originality should also be taken into consideration in this framework. Asymmetric and unique designs make projects different and competitive. Synergy using feedback mechanisms and local sources is another important factor. Feedback mechanisms provide the opportunity to monitor and evaluate energy production processes instantly. This supports the detection of potential problems at a very early level. Moreover, renewable energy project set for sector-wise investment is constructed as follows.

A1. Renewable plants
A2. Waste-to-energy technologies
A3. Energy storage systems
A4. Electrified mobility
A5. Efficiency technologies

This study considers a 7-Likert scale where "0″ refers to none, "1″ is worst, "2″ is worse, "3″ is bad, "4″ is good, "5″ is better, and "6″ is best. The q-ROFN corresponding to these terms are (0,0) for "0″, (0.6, 0.9) for "1″, (0.7, 0.8) for "2″, (0.6, 0.8) for "3″, (0.6, 0.7) for "4″, (0.5, 0.5) for "5″, and (0.9, 0.6) for "6". From the criteria weight matrix point of view, "0″ is none, "1″ is lowest preference, "2″ is lower preference, "3″ is low preference, "4″ is high preference, "5″ is higher preference, and "6″ is highest preference. Three experts are denoted as R1, R2, and R3, five renewable energy projects as T1, T2, T3, T4, and T5, and six criteria as C1, C2, C3, C4, C5, and C6. Except for the criterion C2, the other criteria are benefit type. All experts are assigned equal weights, and the value is considered as $\frac{1}{3}$ for each expert. The step-by-step procedure for determining the rank values via the developed framework follows.

Step 1: Three experts rate five alternatives based on six criteria. The rating is given as a Likert scale (refer to Table 2), which is transformed to its respective q-ROFN based on the above values.
Step 2: Likewise, three experts give their rating in pairwise comparison for six criteria (refer Table 3).
Step 3: Determine the criteria weights by applying the procedure in Section 3.2. A vector of 1×6 is obtained. The data for the method is obtained from Step 2.

The data from Step 2 is provided as input to the procedure presented in Sect. 3.2. Eq. (10)–(13) are used for determining the weights of criteria. As shown in Table 4, analysis results of qROF-DEMATEL show that the criteria weights are 0.184 (C1), 0.153 (C2), 0.156 (C3), 0.162 (C4), 0.169 (C5), and 0.176 (C6), respectively. Thus, "possible extension with modularity" (C1) is the most crucial criterion, followed by "synergy using feedback mechanism and local sources" (C6), "uniqueness with asymmetry and originality" (C5), "compatibility with other systems and projects" (C4), "resource efficiency" (C3), and "complexity based on the market needs" (C2). Table 4 also informs about the causal directions. As per q-ROF-DEMATEL, "resource efficiency" (C3) and "complexity based on the market needs" (C2) are the most influencing criteria. Further, "resource efficiency" affects all other criteria. However, "uniqueness

Table 2
Rating from experts for alternatives.

Alternatives	Experts	Criteria					
		C1	C2	C3	C4	C5	C6
T1	DM1	5	4	5	4	3	4
	DM2	5	4	5	4	3	4
	DM3	5	5	5	4	3	5
T2	DM1	3	3	4	3	3	5
	DM2	4	3	4	4	4	5
	DM3	4	4	4	3	3	5
T3	DM1	4	4	5	5	4	3
	DM2	4	4	5	4	4	4
	DM3	4	5	5	5	4	3
T4	DM1	5	4	5	4	5	4
	DM2	5	4	5	4	5	4
	DM3	5	5	5	4	5	4
T5	DM1	4	4	5	4	4	4
	DM2	4	4	5	4	4	4
	DM3	4	4	5	4	4	4

Table 3
Rating from experts for criteria.

Criteria	Experts	Criteria					
		C1	C2	C3	C4	C5	C6
C1	DM1	0	3	2	3	3	2
	DM2	0	4	2	4	3	2
	DM3	0	3	5	3	3	3
C2	DM1	3	0	3	5	4	4
	DM2	3	0	4	5	4	4
	DM3	4	0	3	5	4	4
C3	DM1	4	5	0	4	5	4
	DM2	4	5	0	4	5	4
	DM3	4	5	0	5	5	4
C4	DM1	3	4	2	0	3	4
	DM2	4	4	2	0	3	4
	DM3	3	5	3	0	3	5
C5	DM1	3	2	2	3	0	3
	DM2	4	4	4	3	0	4
	DM3	3	3	3	3	0	3
C6	DM1	3	3	2	3	4	0
	DM2	3	3	2	3	4	0
	DM3	3	3	3	3	5	0

Table 4
Influence and weights of the criteria.

	R	C	R + C	R-C	Weight	Rank of criteria	Impact directions
C1	6.225	5.911	12.136	0.314	0.184	1	C1 → (C2, C3)
C2	4.996	5.074	10.070	−0.078	0.153	6	–
C3	3.969	6.311	10.280	−2.343	0.156	5	–
C4	5.530	5.171	10.700	0.359	0.162	4	C4 → (C3)
C5	6.187	4.950	11.137	1.238	0.169	3	C5 → (C2, C3)
C6	6.054	5.543	11.597	0.511	0.176	2	C6 → (C2, C3)

Note: C2 and C3 are effects, and the remaining are causes.

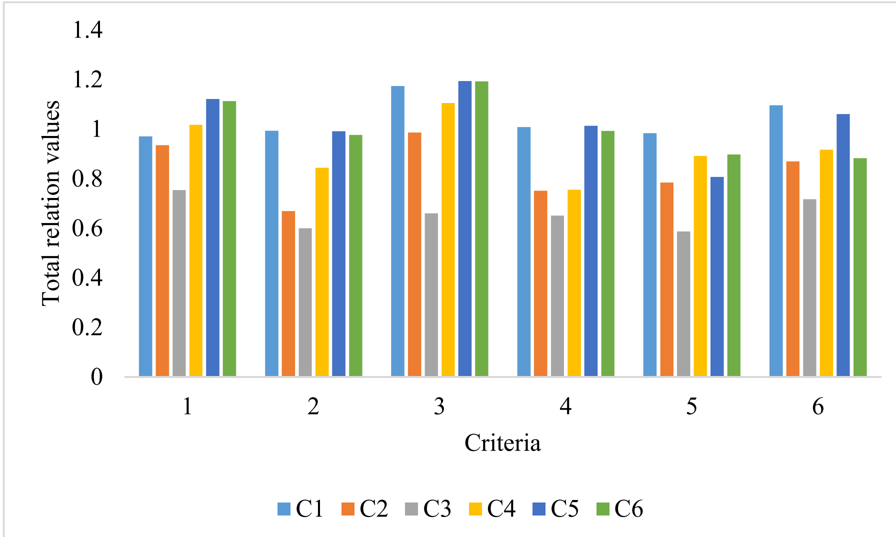

Fig. 2. Total relation values of criteria.

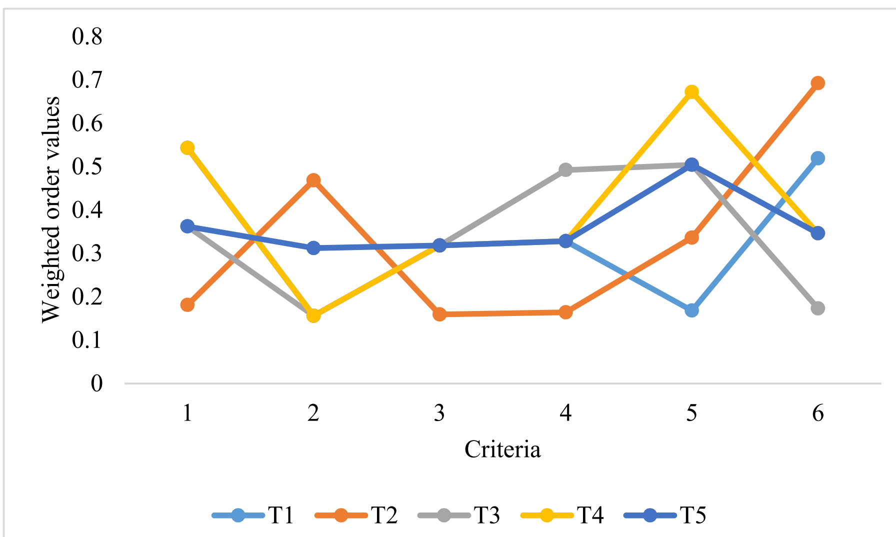

Fig. 3. Weighted order values of REPs.

Table 5
Aggregated q-ROFS decision matrix.

REP	e1	e2	e3	e4	e5	e6	e7	e8	e9	e10	e11	e12
T1	0.5	0.5	0.56	0.62	0.5	0.5	0.6	0.7	0.6	0.8	0.56	0.62
T2	0.6	0.73	0.6	0.76	0.6	0.7	0.6	0.76	0.6	0.76	0.5	0.5
T3	0.6	0.7	0.56	0.62	0.5	0.5	0.53	0.56	0.6	0.7	0.6	0.76
T4	0.5	0.5	0.56	0.62	0.5	0.5	0.6	0.7	0.5	0.5	0.6	0.7
T5	0.6	0.7	0.6	0.7	0.5	0.5	0.6	0.7	0.6	0.7	0.6	0.7

Note: (e1, e2) denotes the preference and non-preference grades of C1, (e3, e4) denotes the preference and non-preference grades of C2, (e5, e6) denotes the preference and non-preference grades of C3, (e7, e8) denotes the preference and non-preference grades of C4, (e9, e10) denotes the preference and non-preference grades of C5, and (e11, e12) denotes the preference and non-preference grades of C6.

with asymmetry and originality" (C5) is influenced by all other criteria.

The impact is determined from the total relationship matrix, and based on R-C values, it is clear that C2 and C3 are effects and the rest are causes. Also, C5 is more influential than C6 and C1. M_{ij} values are depicted pictorially in Fig. 2, obtained from the q-ROF-DEMATEL approach and further used for determining the criteria weights.

Step 4: Determine the rank values by applying the procedure in Sect. 3.3 and using data from Step 1. A rank vector of 1×5 is obtained.

Data from Step 1 and the criteria vector calculated in Step 3 are utilized as input by the procedure presented in Section 3.3. Eq. (14)–(16) is applied to determine the rank values of REP and is calculated as 2.968, 3.000, 2.995, 2.637, and 2.83, respectively. Based on the value, the

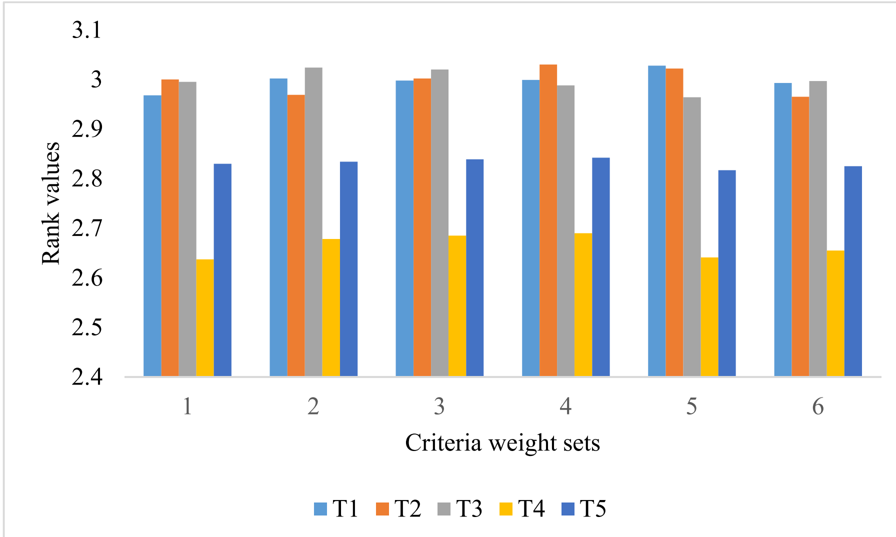

Fig. 4. Sensitivity analysis of criteria weights.

alternatives are ordered as T2 > T3 > T1 > T5 > T4. Weighted ordering values calculated via Eq. (15) are depicted in Fig. 3.

Table 5 shows the aggregated matrix obtained by applying Eq. (9) to the data presented in Table 2. Initially, the data in Table 2 is transformed to q-ROFN based on the corresponding orthopair values given above, and later, by applying Eq. (9), the data is aggregated and shown in Table 5.

4.2. Sensitivity analysis

In this section, a sensitivity analysis is conducted using varying criteria weights and attempts to understand its effect on the rank order of alternatives. Six criteria weight sets are obtained by conducting rotation operations on the weight vector. In this way, six weight vectors are generated, and the idea is to assign each criterion with every weight value calculated so that the effect of weights of criteria can be effectively investigated in the ranking process. Six weight vectors are obtained since there are six criteria. These six vectors are given as input along with the rating data to the ranking algorithm. The rank values are determined for each alternative, which is further used to rank options for potential investment.

Based on the result (Fig. 4), the final rank order obtained is T2 $\geq$ T3 $\geq$ T1 > T5 > T4. From this, there is evident competition among the first three renewable energy projects. However, the rank order of renewable energy projects T4 and T5 remains intact even after adequate changes to the criteria weights are made.

4.3. Comparative analysis

The rank order obtained from the developed model is compared with extant models from the q-ROFN context to understand the consistency of the proposed model. Extant models such as the Deveci et al. [50] model use the q-ROFN-based WASPAS method, and Pinar's [51] model uses the q-ROFN-based COPRAS methodology. The data and the weight vector are sent as input to the respective ranking algorithm, and the rank orders of alternatives are obtained, which are further given to Spearman correlation for determining the coefficients. From the value, it is clear that the orders are consistent. Coefficient values are provided in the form of a matrix below, and from the values, it is clear that the ranking order obtained from the proposed model is consistent with the rank orders received from other models.

$$\rho = \begin{pmatrix} 1 & 0.7 & 0.7 \\ 0.7 & 1 & 1 \\ 0.7 & 1 & 1 \end{pmatrix}$$

The first row of the matrix concerns the proposed versus other models, i.e., q-ROFN-based WASPAS and q-ROFN-based COPRAS. Likewise, the second row concerns q-ROFN-based WASPAS and other models, that is proposed and q-ROFN-based COPRAS, and the last row concerns q-ROFN-based COPRAS and other models, that is proposed and q-ROFN-based WASPAS. From the coefficient values, it is inferred that the proposed model yields a rank order consistent with the other rank orders yielded by extant methods.

Apart from the methodical comparison that infers the consistent rank orders from proposed and extant methods, an application-based comparison helps readers understand the efficacy of the developed decision model for supporting rational renewable energy project selection towards effective sector-wise investment. Table 1 presented above provides a summarized view of the research gaps in extant renewable energy sector models, which are resolved via the proposed framework. Some merits of the proposed framework are:

- Uncertainty is interpreted from two dimensions based on the qualitative rating information given by experts. Further, the q-ROFS structure allows flexible interpretation of uncertainty by managing the window of expression of preference and non-preference grades via the factor q..
- DEMATEL is extended to q-ROFS, which offers promising features such as methodical estimation of criteria weights, determination of causal relationships among criteria, and quantification of influence by criteria.
- Finally, the SRP method is extended to q-ROFS for ranking, which enables computationally feasible ranking of alternative renewable energy projects that would aid investors in planning their sector-wise

investments. By eliminating the normalization phase of ranking, SRP allows computationally feasible determination of rank values.

4.4. Discussion

Possible extension with modularity is an important issue when making the right investment decisions on a sector basis in renewable energy projects. A modular approach contributes to making projects more scalable. This way, more straightforward adaptation can be achieved to changing needs and increasing demand. On the other hand, modularity can reduce the cost and time required for projects. Verma and Álvarez-Miranda [52] stated that this contributes significantly to increasing the profitability of projects. Another advantage of this situation is related to risk management. This helps the projects be safer, allowing more investors to choose these projects. Similarly, dos Santos Junior et al. [53] identified that resource efficiency is essential in making the right investment decisions on a sector basis in renewable energy projects. Resource efficiency increases efficiency in energy production and consumption. This contributes significantly to more effective management of the costs of projects. Moreover, Heidari and Heravi [54] concluded that more efficient energy production processes could also help reduce emissions.

Waste-to-energy technologies can be taken into consideration when making the right investment decisions on a sector basis in renewable energy projects. This technology significantly supports the efficient conversion of waste into energy. In this way, waste can be disposed of without harming nature. According to Waidelich and Steffen [55], this situation is necessary to diversify energy sources. This can increase the security of energy supply and reduce dependence on fossil fuels. Glockner et al. [56] discussed that another benefit of waste-to-energy production is reducing the amount of waste. This situation can reduce the costs of both storage and disposal of waste. Furthermore, by converting waste into energy, potentially large amounts of electricity can be produced. On the other hand, Subramaniam and Loganathan [57] highlighted that energy storage systems are critical in making the right investment decisions on a sector basis in renewable energy projects. Owing to this situation, a safer environment can be created by balancing energy supply and demand. In addition, Liu et al. [58] determined that energy storage systems allow renewable energy resources to be used more effectively. Similarly, energy storage systems enable innovative technological developments.

5. Conclusion and policy implications

This study aims to examine sector-wise investment decisions in renewable energy projects. Within this scope, a novel fuzzy decision-making model has been generated. In the first stage, the weights of the TRIZ-driven criteria are computed via the q-ROF DEMATEL methodology. On the other hand, the second stage of the proposed model includes the selection of the most appropriate investment alternatives ranked with the help of q-ROF SRP. It is concluded that possible extension with modularity is the most critical indicator for this situation. Similarly, resource efficiency is also found to be the most influencing item. In addition, the ranking results demonstrate that waste-to-energy technologies and energy storage systems are the most critical investment alternatives.

To realize modularity-focused renewable energy projects, some policy practices can be determined. Tax deductions should be provided for the development and implementation of modular renewable energy technologies. These incentives significantly reduce the initial costs. As a result, investors focus more on these projects. In addition, regulations should be developed to ensure the standardization of modular components. In this way, the compatibility of modular systems can be increased. This allows operational costs to be significantly reduced. Moreover, special insurance practices should be developed for modular systems. This supports the more successful management of risks in the process. On the other hand, it is also possible to develop policy practices to increase resource efficiency. Recycling of equipment used in renewable energy projects should be ensured. In this way, natural resource consumption can be reduced. Similarly, since the costs of the materials used will also decrease, it is possible to increase the financial profitability of businesses.

The main theoretical contribution of this study is that key sector-wise investment decisions in renewable energy projects are identified. It is quite necessary to improve renewable energy investments so that the carbon emission problem can be minimized more effectively. The main limitation of this study is that a general evaluation is conducted for renewable energy projects. However, the results can change based on different types of renewable energy projects. Thus, in the following studies, solar or wind energy projects can be analyzed precisely. On the other side, the proposed model has some limitations. In this model, DEMATEL and SRP are taken into consideration. However, these techniques are criticized for some reasons. Therefore, for future research direction, some improvements should be made to these methods to handle these criticisms. One possible criticism of the DEMATEL method is its inability to consider partial information about entities.

Furthermore, the result from the approach is dependent on the consistency of the pairwise data. Though the SRP method is simple, it considers subjective grading in the formulation, which leads to a certain level of bias in the decision system. Plans are being made to alleviate these criticisms. Besides, plans are being made to extend the proposed framework to different interval-valued and probabilistic fuzzy variants to understand the framework's potential. Also, the authors plan to expand the decision model to diverse decision problems within the field of energy science and other application domains such as sustainability, healthcare, industry and automation, supply chain management, and so on. The authors also plan to combine the concepts of machine learning and recommendation systems to facilitate large-scale decision-making in real-time scenarios.

CRediT authorship contribution statement

Serhat Yüksel: Writing – review & editing, Writing – original draft, Project administration, Investigation, Data curation, Conceptualization. **Fatih Ecer:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Formal analysis. **Raghunathan Krishankumar:** Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Formal analysis. **Hasan Dinçer:** Writing – review & editing, Writing – original draft, Project administration, Data curation, Conceptualization. **Yaşar Gökalp:** Writing – review & editing, Writing – original draft, Investigation, Data curation, Conceptualization.

Declaration of competing interest

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

Appendix

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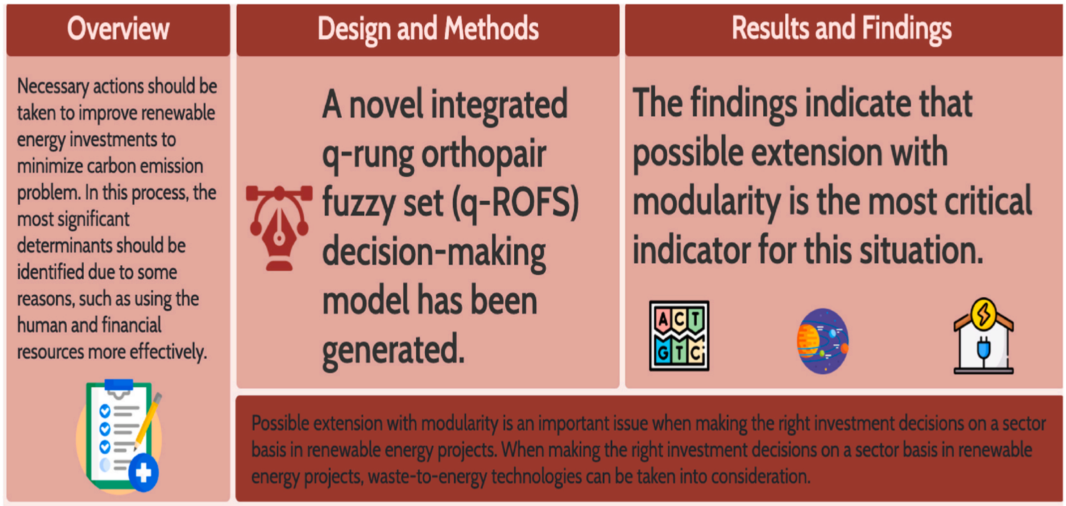

Fig. A1. Graphical Abstract.

Data availability

Data will be made available on request.

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