



# Assessing renewable energy alternatives with multi-criteria decision-making techniques based on q-rung orthopair fuzzy sets

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## Abstract

In recent years, countries have prioritized the selection of viable renewable energy alternatives, driven by the urgent need for a transition to sustainable energy. Selecting appropriate energy sources requires careful consideration of social, political, economic, and technological factors. This study proposes a comprehensive framework for evaluating renewable energy alternatives using a combination of the CRITIC (Criteria Importance Through Intercriteria Correlation) and MABAC (Multi-Attributive Border Approximation area Comparison) methods, enhanced by quantum-Rung Fuzzy Sets. A detailed evaluation is performed using 22 sub-criteria, grouped into environmental, technological, economic, and socio-political dimensions, to assess renewable sources such as wind, solar, geothermal, biomass, wave, hydraulic, and hydrogen. Expert input and literature guide the criteria selection. The model is applied in a case study of the Turkish energy sector, revealing hydrogen as the most promising alternative. Sensitivity analysis confirms the robustness of the results, showing no significant changes in the ranking of energy alternatives. To the best of the authors' knowledge, this is the first study to combine CRITIC and MABAC methods within the q-ROFS domain to solve the problem of selecting a renewable energy source. This framework provides valuable insights to policymakers, energy planners, and decision-makers, offering a reliable tool for navigating the complexities of renewable energy selection.

**Keywords** Renewable energy · Energy sources · Fuzzy sets · Q-rung orthopair · Multi-criteria decision-making

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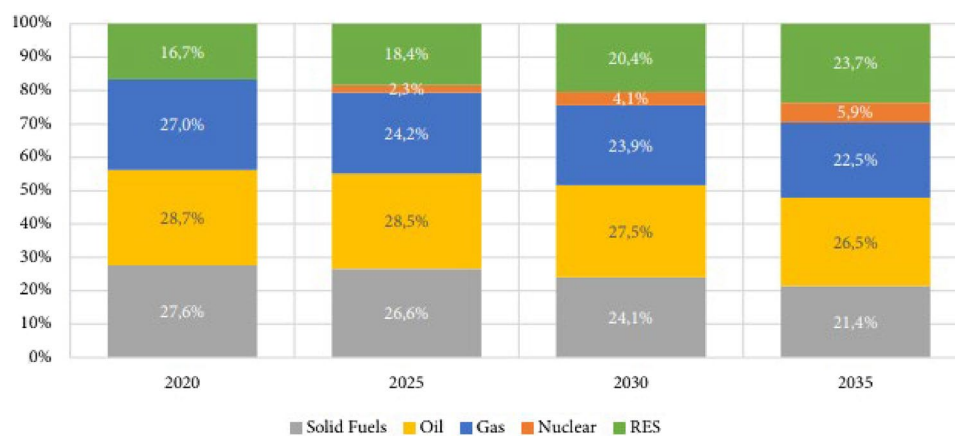
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## 1 Introduction

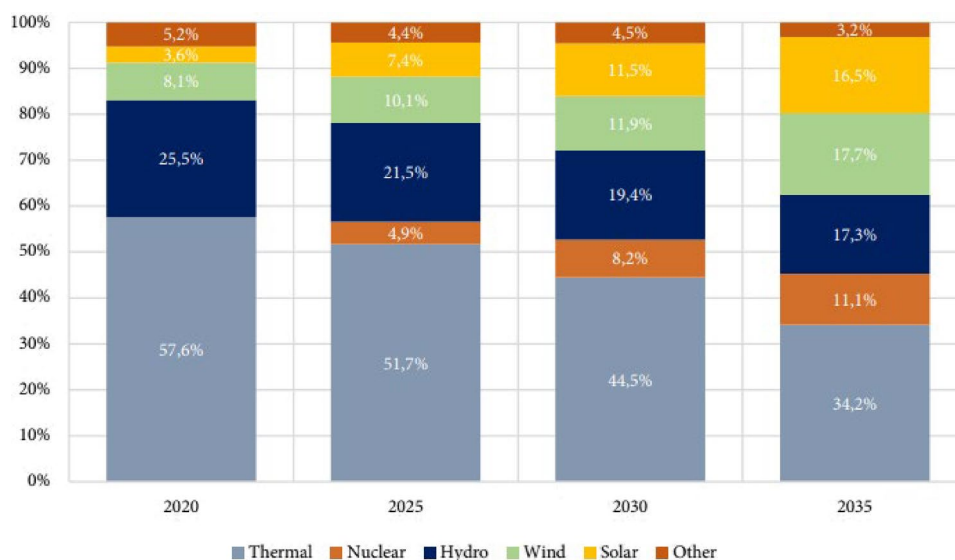
Energy is a fundamental necessity in various aspects of living. The growing global economy and the world's population growth increase the energy demand (Dincer 2001). The energy crisis will lead to an increase in clean energy use over the long term. Because countries around the world are focusing on clean energy transition. This is particularly influenced by factors such as advancements in technology, the global economy, and the need for energy security. Therefore, increasing the use of clean energy transition and production are essential (International energy agency: energy technology perspectives 2023).

Fossil fuels constitute 81% of the energy resource distribution used in the energy sector around the world (EU Commission 2003; Çelikbilek and Tüysüz, 2016). Renewable energy sources are more environmentally friendly than fossil fuels (Shahzad 2012). Increasing the share of renewable energy in total energy production has the potential to significantly improve environmental sustainability and ecological well-being. Moreover, renewable energy

**Fig. 1** Distribution of primary energy consumption by source (Ministry of energy and natural resources: Türkiye national energy plan 2022)



**Fig. 2** Distribution of electricity generation by source (Ministry of energy and natural resources: Türkiye national energy plan 2022)



sources have the capacity to mitigate the worldwide greenhouse gas impact (International renewable energy agency: wind energy: a gender perspective 2020). In modern times, renewable energy production primarily relies on biomass, solar, geothermal, wind, hydroelectric, and tidal energy sources (Shahzad 2012).

Türkiye possesses hydraulic, wind, solar, biomass, and geothermal potential for renewable energy (Yılmaz 2012). Enhancing the renewable energy supply in Türkiye will have a beneficial impact on economic growth, conservation of biodiversity, energy security, and national sovereignty. Türkiye's energy policy prioritises expanding the utilisation of domestic resources, effectively using resources in accordance with geopolitical opportunities, and monitoring global changes (TUBA: Turkish academy of science biomass energy report 2022). There will be a growing inclination towards renewable energy sources in the coming years. This prediction is further corroborated by the "Türkiye's National Energy Plan 2022" (Ministry of energy and natural resources: Türkiye national energy plan 2022). Between 2020 and 2035, primary energy consumption will increase

by 2.2%, as shown in Fig. 1 and 2. In parallel, primary energy consumption increased by an average of 3.1 percent per year between 2000 and 2020. By 2035, a greater proportion of primary energy consumption will be derived from renewable sources, up from 16.7 percent in 2020. Similarly, nuclear energy is projected to attain a 5.9 percent market share by the year 2035. The proportion attributed to fossil resources is projected to decline from 83.3 percent in 2020 to 70.4 percent in 2035.

In a similar fashion, by 2035, 65.8% of electricity generation will be derived from renewable sources, up from 42.4% in 2020. Hydropower, which is approaching its maximum installed capacity and generation potential, will account for 17.3 percent of total installed capacity in 2035, up from its current highest share.

This study proposes a structured framework to identify key criteria for selecting the most suitable renewable energy source to support sustainable energy solutions for Türkiye. Acknowledging the complexity of these decisions, the research incorporates expert insights to assign weights to these criteria. Q-Rung Orthopair Fuzzy Sets (q-ROFS) have

improved flexibility and superior ability to manage uncertainty compared to Intuitive Fuzzy Sets (IFS) and Neutrosophic Sets (NS). Therefore, this study employs q-ROFS. The q-parameter in q-ROFS allows these sets to handle more ambiguity and hesitation in data, making them especially useful in scenarios where traditional models may fall short. Moreover, q-ROFS generalizes both the Pythagorean Fuzzy Set (PFS) and IFS, offering a precise and adaptable framework vital for complex, real-world decision-making problems. This is achieved through the utilization of advanced Multi-Criteria Decision Making (MCDM) techniques, including q-Rung, fuzzy CRITIC, and MABAC. With such advantages, we aim to conduct a comprehensive and unbiased assessment of the various factors influencing renewable energy source selection.

The main contributions of this study are as follows: To the best of authors' knowledge, it is the first study that hybridized CRITIC and MABAC methods on q-ROFS domain, to address renewable energy source selection problem. In the q-ROFS environment, CRITIC and MABAC hybridization contributes to the objectification of criterion weights. This hybrid approach utilizes a robust ranking mechanism for evaluation, thus improving decision consistency and accuracy.

This research could serve as a framework to guide Türkiye's transition to a more sustainable energy system. The findings can offer valuable contributions to enhancing energy resilience, minimizing ecological damage, and fostering economic progress through renewable energy initiatives. These insights can play an important role in shaping long-term national energy policies and achieving sustainable development goals.

The paper is organized as follows: Sect. 2 consists of the evaluation of renewable energy alternatives and the research gap. Section 3 details the methodology used in the study. Section 4 describes the application of methods, sensitivity analysis, and comparative analysis. Section 5 covers discussion, managerial implications, and explains the interpretation of the results along with their practical significance, and Sect. 6 contains the conclusions of the study and recommendations for future research.

## 2 Literature review

This section initially summarises global studies on the selection of renewable energy sources, followed by a summary of similar studies undertaken in Türkiye.

### 2.1 Assessment of renewable energy alternatives

Ahmad and Tahar (2014) used the Analytic Hierarchy Process (AHP) to rank renewable energy alternatives for sustainable electricity generation in Malaysia. Similarly, Kumar and Samuel (2017) combined AHP and VIKOR methods to determine the optimal renewable energy source for an Indian university campus. Ishfaq et al. (2018) evaluated renewable energy options for Pakistan using AHP, VIKOR, and TOPSIS. Lee and Chang (2018) compared renewable energy alternatives in Taiwan through weighted sum, VIKOR, TOPSIS, and ELECTRE methods, with criteria weighted by Shannon entropy.

Fuzzy and grey extensions of MCDM methods have been widely applied in renewable energy evaluation. Xu et al. (2019) developed a two-stage framework for hydrogen production in Pakistan using fuzzy AHP for weighting and DEA for ranking. Wang et al. (2020) analyzed biomass, wind, and solar options for electricity in Sindh and Baluchistan through fuzzy AHP, while Chen et al. (2020) employed PROMETHEE II to assess renewable energy in northern China. Rani et al. (2020) proposed a fuzzy TOPSIS-based divergence measure for ranking under uncertainty, and Wang et al. (2021) utilized grey AHP and WASPAS for renewable energy selection in Vietnam. Similarly, Quteishat and Younis (2023) applied fuzzy ANP and fuzzy TOPSIS, and Ding et al. (2023) integrated DEMATEL with interval regret theory for investment evaluation in Fujian, China. Recent studies have introduced hybrid and novel MCDM approaches. Yazdani et al. (2020) combined Shannon entropy with EDAS in a Saudi Arabian case. Rani et al. (2021) developed a SWARA-CoCoSo hybrid under neutrosophic conditions for India. Sarkodie et al. (2022) used CRITIC with MOORA, TOPSIS, and COPRAS for Ghana's energy ranking. Krishankumar et al. (2022) employed HLEFI and variance-based approaches for sustainable planning in India, while Al-Barakati et al. (2022) applied interval-valued Pythagorean fuzzy WASPAS. Ghose et al. (2022) focused on cost-based fuzzy TOPSIS in Gujarat, and Almutairi et al. (2022) combined SWARA with grey ARAS for Iran. Long et al. (2022) proposed a cognitive fuzzy sustainability assessment model for residential energy production.

Recently, numerous studies have been conducted globally on hydrogen energy. We also reviewed some studies focusing on integrated hydrogen and MCDM. Hosseini Dehshiri and Amiri (2023) studied hydrogen production strategies in Iran. The strategies were evaluated using gray additive ratio assessment, gray TOPSIS, gray COPRAS, and gray simple additive weighting methods. They concluded

that cooperation and coordination between energy investment companies and industries is the most efficient and cost-effective strategy. Ransikarbum et al. (2023) conducted source selection for the hydrogen supply chain in Thailand. A decision framework integrating Fuzzy AHP, and DEA methods was used. Political acceptance was the highest weighted criterion. Natural gas was shown to be a prominent source for hydrogen production. Liu and Lu (2024) conducted to determine the site selection for hybrid offshore wind-photovoltaic-wave-hydrogen production in Hainan Island, China. A three-stage decision framework combining geographic information system and MCDM in a rough-fuzzy environment was presented for this hybrid system.

Olabi et al. (2024) evaluated hydrogen production technologies using WASPAS, the weighted sum model, the weighted product model, and the TOPSIS method. Biomass gasification technology outperformed the others. The contribution of hydrogen production technology to the Sustainable Development Goals by providing a clean and accessible energy source and reducing greenhouse gas emissions was emphasized. Shanian and Savadogo (2024) analyzed the hydrogen production performance of alkaline and proton exchange membrane (PEM) electrolyzers using MCDM methods. TOPSIS, the WASPAS interval method, and the Best Worst Method were used, along with fuzzy logic, in the study. Alkaline and PEM electrolyzers were compared in terms of hydrogen production costs. It was concluded that the electrolyzer selection may vary depending on the specific requirements of the project. Pinto et al. (2025) examined the potential for solar-based green hydrogen production in Tunisia. Land suitability for hydrogen production was assessed using AHP and a geographic information system. The study contributed to an adaptable basis for the North African region.

The increasing number of studies on the selection of hydrogen production technology, the selection of production location, and its integration with renewable energy systems highlights the importance of hydrogen energy.

### 2.1.1 Renewable energy resources evaluation studies in Türkiye

The second decade of the Millennium marks a significant transformation in Türkiye's renewable energy capacity. The rise in research pertaining to Türkiye in this domain further substantiates this.

The objective of the study conducted by Kahraman et al. (2010) was to evaluate and rank renewable energy sources for Türkiye. The Choquet integral method was employed. Çelikbilek and Tüysüz (2016) employed a grey-based integrated DEMATEL, ANP, and VIKOR MCDM methodology for the evaluation of renewable energy resources. In a

further contribution to this field, Büyüközkan and Güleriyüz (2016) investigated the most suitable renewable energy resource selection problem in Türkiye from the perspective of investors. The researchers employed an integrated DEMATEL and ANP MCDM approach. This study represents the inaugural application of the DEMATEL and ANP integrated method in the context of Türkiye. Mousavi et al. (2017) put forward a novel soft computing strategy, modified ELECTRE, in a hesitant fuzzy setting, with the objective of overcoming uncertainty in the domain of renewable energy policy selection. The weights of the criteria were determined by a developed maximisation of deviation method, which was subsequently applied to case studies in Türkiye and Iran. Toklu and Taşkın (2018) proposed a decision model to evaluate renewable energy sources in Türkiye. They determined four criteria, which were further broken down into twelve subcriteria for the study. They used fuzzy AHP to determine criteria weights. Afterward, renewable energy alternatives were ranked using fuzzy TOPSIS. Büyüközkan et al. (2018) proposed an integrated approach to AHP and COPRAS methods in a hesitant fuzzy linguistic environment on a case study from Türkiye. A numerical model is presented in the focus of Sustainable Development Goals. Alkan and Albayrak (2020) determined the criteria weights in their study with the fuzzy entropy method. Fuzzy COPRAS and fuzzy multi-objective optimization by ratio analysis plus the full multiplicative form (MULTIMOORA) are used to rank alternatives by region for potential energy investment. The study is a guide for renewable energy investment. Ecer et al. (2021) applied a case study in Türkiye for the renewable energy source selection. They used the level-based weight assessment (LBWA) and combinative distance-based assessment (CODAS) method based on the interval rough number extension. Yürek et al. (2021) ranked renewable energy sources. Model criteria were created based on the sustainability index. Based on Pythagorean fuzzy sets, AHP and TOPSIS methods are integrated. Bilgili et al. (2022) carried out a study that took into account the sustainable growth constraint of Türkiye and came to the forefront with an evaluation in terms of investment. Within this constraint and certain criteria, the best alternative was determined by the Intuitionistic fuzzy-TOPSIS method. In another academic study conducted in Türkiye, Alkan (2024) evaluated renewable energy alternatives focusing on sustainable development. The CRITIC and SWARA methods determined the weights of the criteria, and CODAS ranked the alternatives with using interval-valued picture fuzzy sets.

Although hydrogen-focused MCDM studies are relatively limited for Türkiye, some recent studies are included below.

Işık et al. (2024) proposed the neutrosophic picture fuzzy set and TOPSIS method and evaluated hydrogen production alternatives in Türkiye. The proposed method was shown to be more reliable when compared with the spherical fuzzy TOPSIS method. Biomass gasification was determined to be the best alternative. Aktekin et al. (2024) presented a hybrid system integrating nuclear, wind, and solar power plants to meet the electrical energy needs of residential buildings in Mersin. Excess electrical energy was converted into hydrogen. Carbon emissions have been shown to be reduced by 236,621 tons. Yılmaz and Uyan (2025) analyzed the most suitable area for solar-powered green hydrogen production in Konya. Geographic Information Systems and the best-worst method were used, and region-specific criteria were included. This study highlighted Konya's strategic potential for green hydrogen production.

The increasing number of studies integrating hydrogen into renewable energy systems is making hydrogen energy more attractive. The results of this study highlight the importance of hydrogen energy and MCDM studies.

## 2.2 Research gap

In the literature, MCDM methods are widely used in research focusing on renewable energy source assessment. The proposed approach guides the decision-making process in a more realistic framework in terms of participation, flexibility, and feasibility.

## 3 Research methodology

This study addresses the sustainable renewable energy source selection problem with a hybridized framework, q-Rung Orthopair Fuzzy CRITIC & MABAC. To enhance the text's readability, we include the preliminaries on q-ROFS in Sect. 3.1. Relevant works can also be consulted by interested readers (Krishankumar et al. 2021; Aytekin et al. 2023; Turan & Boran 2022; Yager 2016; Liu & Wang 2018; Ali 2018; Shaheen et al. 2021; Hussain et al. 2019).

In this study, we use q-ROFS because they offer a greater degree of flexibility. and are capable of modelling higher levels of uncertainty in comparison to IFS. In IFS, the sum of the membership and non-membership must not exceed the specified limit.  $1, \mu(x) + \nu(x) \leq 1$ , while in q-ROFS, the constraint is generalized to  $\mu q(x) + \nu q(x) \leq 1$ , where  $q$  may represent any positive integer. The  $q$ -parameter in q-ROFS provides the ability to handle higher levels of uncertainty. As  $q$  increases, q-ROFS can accommodate more vagueness and hesitation in the data. This makes q-ROFS especially useful in complex decision-making scenarios, where traditional models might fail to capture the

full range of uncertainty (Kumar 2024, 2020; Peng and Luo 2021; Riaz et al. 2020a, b).

Moreover, q-ROFS generalize both Pythagorean fuzzy sets and IFS, making them suitable for applications requiring a high degree of precision and adaptability. This generalization allows q-ROFS to handle more complex uncertainties while maintaining computational efficiency, which is especially important in MCDM field (Riaz et al. 2020a, b; Seikh and Mandal 2022).

The CRITIC method enhances the objectivity in weighting criteria by focusing on the most informative and uncorrelated factors, crucial in energy planning where economic, environmental, and social factors are at play. MABAC further ensures robust and systematic ranking of alternatives, even with incomplete data. The hybridization of q-ROFS with CRITIC and MABAC enhances decision accuracy, combining their strengths to handle uncertainties, determine objective criteria importance, and provide reliable rankings, making it essential for renewable energy decision-making.

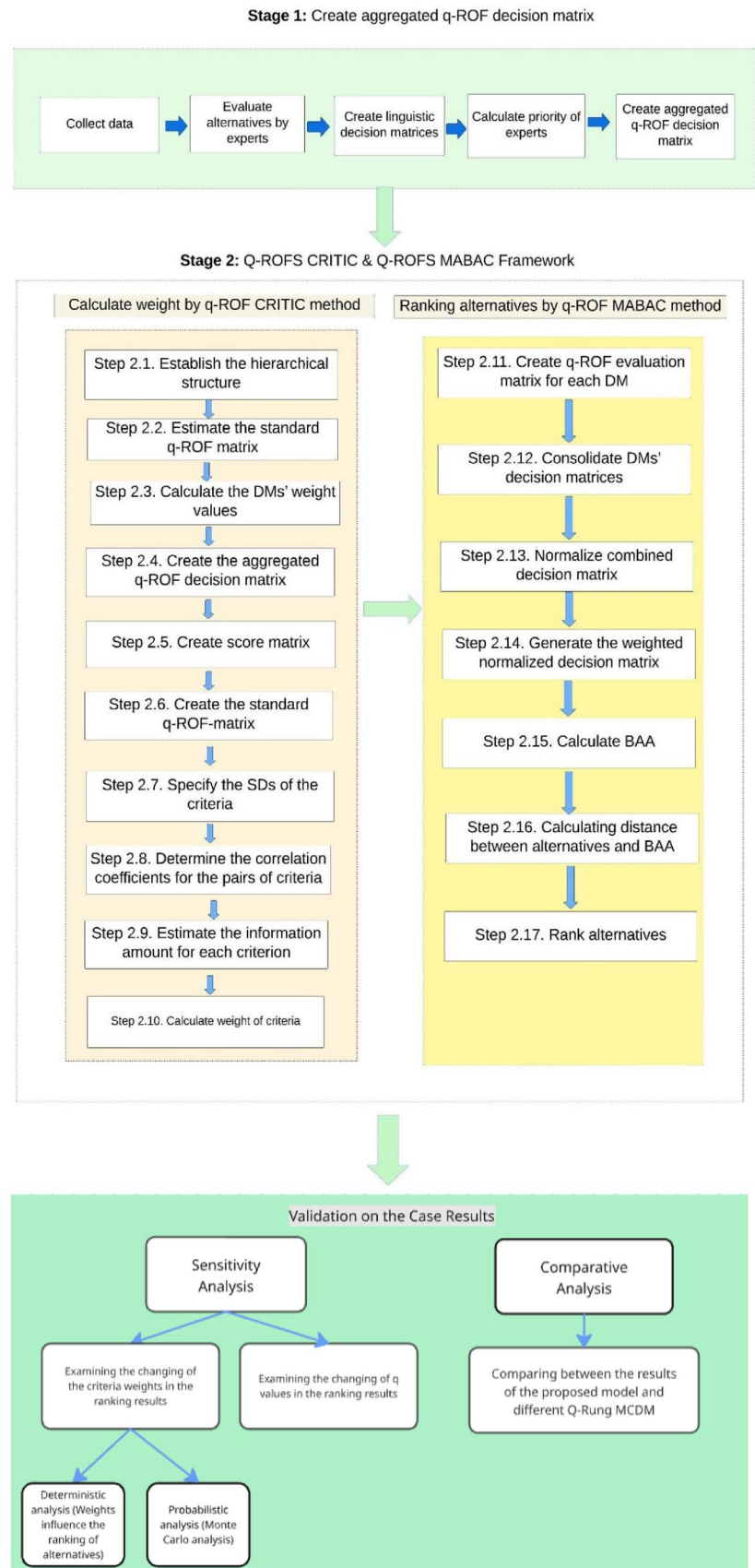
Figure 3 depicts the research framework that includes three main stages and six substages. After data collection and preparation stage, the criterion weights are determined by employing combinative weighting method with q-ROFS CRITIC. q-ROFS MABAC method deploys to rank maintenance strategy selection. Thirdly, to validate the presented framework, sensitivity analyses and comparative analyses are conducted. In sensitivity analysis, one hundred supplementary scenarios were simulated by reducing the significance of the paramount criterion (criterion C) by 1% and adjusting the significance of the other two criteria. The criteria weights in the comparative analysis section were computed independently using q-ROF Grey Relational Analysis (q-ROF GRA) and q-ROF CODAS techniques. Spearman correlation analysis was implemented to assess the efficacy of the evaluation methodology in light of the updated rankings.

### 3.1 Q-rung orthopair fuzzy sets

Yager (2016) initially proposed the q-rung orthopair fuzzy set (q-ROFS) in order to create a preference framework that is more adaptable., enhancing the capacity for expert information evaluation. In this approach, Yager introduced a regulation parameter  $q$ , expanding the preference space through the condition  $\mu^q + \nu^q \leq 1$ , where  $(\mu)$  denotes the membership degree and  $(\nu)$  the non-membership degree. For  $q = 1$ , the q-ROFS model reduces to intuitionistic fuzzy sets (IFS), while  $q = 2$  yields Pythagorean fuzzy sets (PFS) (Gündoğdu et al. 2023; Aytekin et al. 2023; Krishankumar et al. 2021).

A q-ROFS  $B$  in a finite discourse universe  $X = \{x_1, x_2, \dots, x_m\}$  is given by

Fig. 3 Framework of the developed methodology



$$B = \{ \langle x_i, (\mu_B(x_i), v_B(x_i)) \rangle | x_i \in X \}, \tag{1}$$

where  $\mu_B(x_i) \in [0, 1]$  stands for the belongingness degree and  $v_B(x_i) \in [0, 1]$  stands for the degree of non-belongingness of element  $x_i \in X$  to set B given that  $0 \leq (\mu_B(x_i)^q + v_B(x_i)^q) \leq 1$  where  $q \geq 1$ . In addition, the degree of indeterminacy is calculated as follows,

$\pi_B(x_i) = (1 - (\mu_B(x_i))^q + (v_B(x_i))^q)^{1/q}$ . The q-ROFS B is reduced to  $B = (\mu_B(x), v_B(x))$  which is called q-Rung Orthopair Fuzzy Number if the fixed set  $X = \{x_1, x_2, \dots, x_n\}$  has a single element  $X = \{x\}$ ,

Assume that  $a = (\mu_a, v_a)$  and  $b = (\mu_b, v_b)$  are two q-ROFNs. The operations are as follows (Aytekin et al. 2023; Gündoğdu et al. 2023; Ali 2018).

$$a \vee b = (\max(\mu_a, \mu_b), \min(v_a, v_b)),$$

$$a \wedge b = (\min(\mu_a, \mu_b), \max(v_a, v_b)),$$

$$a \oplus b = (\sqrt[q]{(\mu_a)^q + (\mu_b)^q - (\mu_a)^q(\mu_b)^q}, v_a v_b),$$

$$a \otimes b = (\mu_a \mu_b, \sqrt[q]{(v_a)^q + (v_b)^q - (v_a)^q(v_b)^q})$$

$$ma = (\sqrt[q]{1 - (1 - (\mu_a)^q)^m}, (v_a)^m); m \geq 0,$$

$$a^\lambda = ((\mu_a)^\lambda, \sqrt[q]{1 - (1 - (v_a)^q)^\lambda}); \lambda \geq 0$$

$$(a)^c = (v_a, \mu_a),$$

Consider  $a = (\mu_a, v_a)$  as a q-ROFN. The score  $S(a)$  and accuracy  $H(a)$  functions of  $a$  are calculated as follows (Wei et al. 2018):

$$S(a) = \frac{1}{2}(1 + (\mu_a)^q - (v_a)^q); S(a) \in [0, 1] \tag{2}$$

$$H(a) = (\mu_a)^q + (v_a)^q; H(a) \in [0, 1] \tag{3}$$

Note that q-ROFNs depend directly on  $S(a)$  and  $H(a)$ .

If  $a = (\mu_a, v_a)$  and  $b = (\mu_b, v_b)$  be two q-ROFNs, and  $S(a)$  and  $S(b)$  and  $H(a)$  and  $H(b)$

are the score and accuracy functions of  $a$  and  $b$ , then we have (Wang et al. 2019):

- (i) if  $S(a) > S(b) \rightarrow a > b$ ,
- (ii) if  $S(a) = S(b)$  and  $H(a) > H(b) \rightarrow a > b$ ,
- (iii) if  $S(a) = S(b)$  and  $H(a) = H(b) \rightarrow a = b$ .

**Table 1** Linguistic scale for q-ROFNs for criteria (Alkan and Kahraman 2021)

Linguistic Terms	( $\mu, v$ )
Certainly high importance (CHI)	(0.99,0.11)
Very high importance (VHI)	(0.88,0.22)
High importance (HI)	(0.77,0.33)
Above average importance (AAI)	(0.66,0.44)
Average importance (AI)	(0.55,0.55)
Under average importance (UAI)	(0.44,0.66)
Low importance (LI)	(0.33,0.77)
Very low importance (VLI)	(0.22,0.88)
Certainly low importance (CLI)	(0.11,0.99)

The hamming distance,  $hd(a, b)$ , is a distance measure between two q-ROFNs,  $a = (\mu_a, v_a)$  and  $b = (\mu_b, v_b)$ , which is calculated by Eq. (4):

$$hd(a, b) = \frac{1}{2}(|(\mu_a)^q - (\mu_b)^q| + |(v_a)^q - (v_b)^q| + |(\pi_a)^q - (\pi_b)^q|) \tag{4}$$

### 3.2 q-ROFS CRITIC method

The CRITIC method was developed to objectively assign weights to criteria by factoring in the correlation coefficient and standard deviation (SD) (Diakoulaki et al. 1995). Yang et al. (2022) present a succinct explanation of the implementation of the q-ROF CRITIC methodology.

**Step 1.** Establish the hierarchical structure.

**Step 2.** Develop the decision matrix. Formulate the problem.

Let  $O = \{O_1, O_2, \dots, O_m\}$  signify a set of options and  $C = \{C_1, C_2, \dots, C_m\}$  represent a set of criteria. The set of DMs,  $\{D_1, D_2, \dots, D_l\}$ , offer their judgements on all choices  $O_i$  over the criteria  $C_j$  as “linguistic variables (LVs)”. The decision matrix for the  $k^{th}$  decision maker (DM) in q-ROF context can be expressed as;  $N = (\xi_{ij}^{(k)})$ , where  $i = 1, \dots, m, j = 1, \dots, n$  and  $k = 1, \dots, l$ .

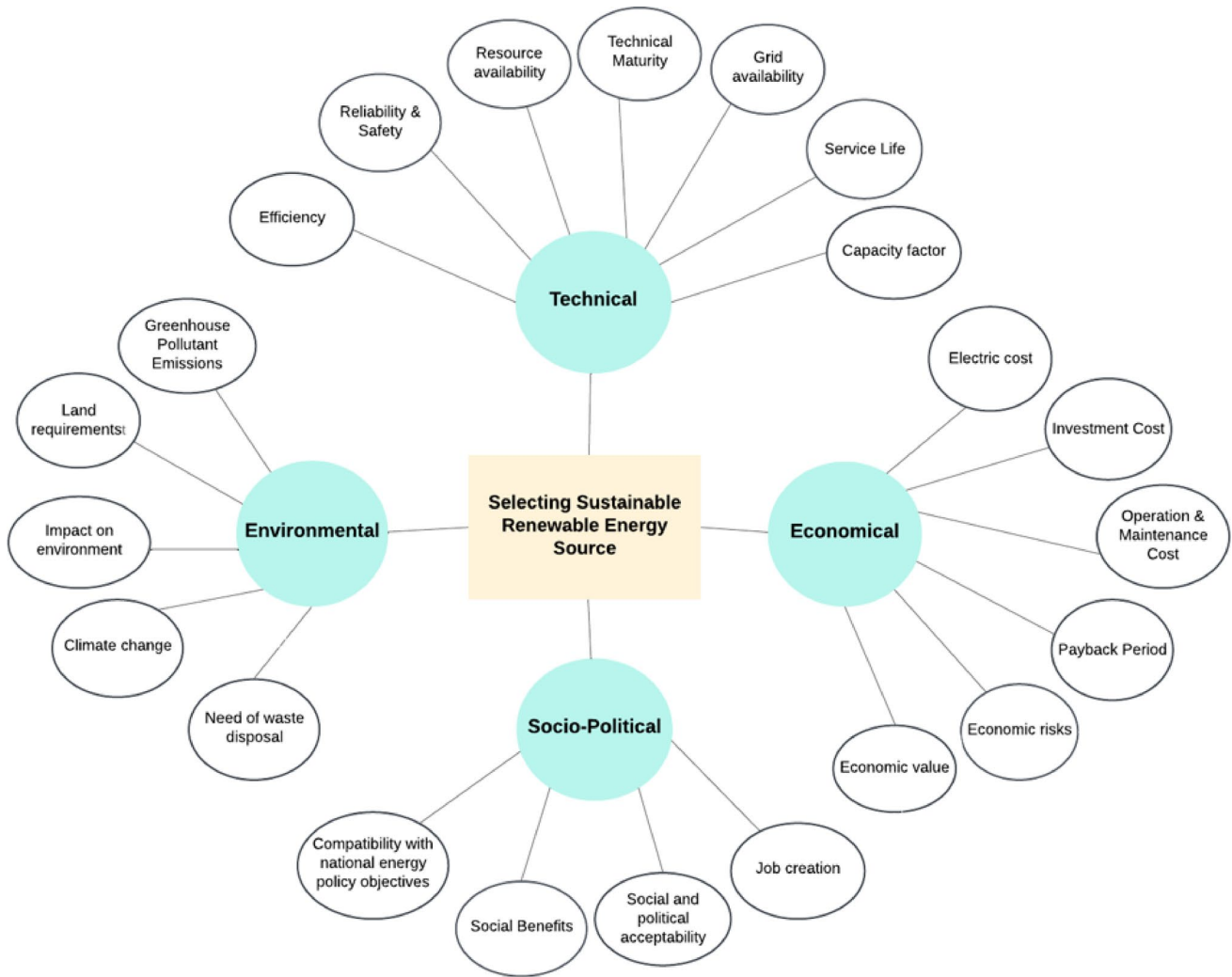
**Step 3.** Calculation of the weight of each decision-maker.

The DMs’ evaluations of the decision problem are assigned weights. The linguistic scale is given in Table 1. Assume that,  $l_k = (\mu_k, v_k)$  stands for the rating of  $k^{th}$  DM defined with q-ROFN, then the weight of the  $k^{th}$  DM,  $\lambda_k$  will be calculated using Eq. (5):

$$\lambda_k = \frac{\frac{1}{2}((\mu_k^q - v_k^q) + 1)}{\sum_{k=1}^l (\frac{1}{2}((\mu_k^q - v_k^q) + 1))} \tag{5}$$

$$\lambda_k \geq 0 \text{ and } \sum_{k=1}^l \lambda_k = 1.$$

**Step 4.** The aggregated q-ROF decision matrix is obtained.



**Fig. 4** Suggested hierarchy for selecting sustainable renewable energy

$$\xi_{ij} = (\mu_{ij}, v_{ij}) = q - ROFW A_{\lambda} \left( \xi_{ij}^{(1)}, \xi_{ij}^{(2)}, \dots, \xi_{ij}^{(l)} \right)$$

$$= \left( \sqrt[q]{1 - \prod_{k=1}^l (1 - (\mu_k^q)^{\lambda_k}), \prod_{k=1}^l (v_k)^{\lambda_k}} \right) \quad (6)$$

**Step 5.** Create score matrix  $S = (x_{ij})_{m \times n}$  with Eq. (7)

$$x_{ij} = \frac{1}{2} \left( (\mu_{ij}^q - v_{ij}^q) + 1 \right) \quad (7)$$

**Step 6.** Determine the standard q-ROF-matrix  $\tilde{S} = (\tilde{x}_{ij})_{m \times n}$  where

$$\tilde{x}_{ij} = \begin{cases} \frac{x_{ij} - x_j^-}{x_j^+ - x_j^-}, j \in C_b \\ \frac{x_j^+ - x_{ij}}{x_j^+ - x_j^-}, j \in C_n \end{cases} \quad (8)$$

Here,  $x_j^+ = \max_i x_{ij}$  and  $x_j^- = \min_i x_{ij}$ .

**Step 7.** Specify the SDs of the criteria with Eq. (9)

$$\sigma_j = \sqrt{\frac{\sum_{i=1}^m (\tilde{x}_{ij} - \bar{x}_j)^2}{m}}, \text{ where } \bar{x}_j = \sum_{i=1}^m \tilde{x}_{ij} / m \quad (9)$$

**Step 8.** Determine correlation coefficients for the pairs of criteria.

$$r_{jt} = \frac{\sum_{i=1}^m (\tilde{x}_{ij} - \bar{x}_j) (\tilde{x}_{it} - \bar{x}_t)}{\sqrt{\sum_{i=1}^m (\tilde{x}_{ij} - \bar{x}_j)^2 \sum_{i=1}^m (\tilde{x}_{it} - \bar{x}_t)^2}} \quad (10)$$

**Step 9.** Estimate the information amount for each criterion with Eq. (11)

$$c_j = \sigma_j \sum_{i=1}^n (1 - r_{jt}) \quad (11)$$

**Table 2** q-ROF-decision matrix

Criteria	(WI)	(SE)	(GE)	(BI)	(WA)	(HC)	(HN)							
C1	0.43	0.70	0.46	0.67	0.53	0.58	0.71	0.43	0.44	0.67	0.68	0.47	0.59	0.52
C2	0.73	0.40	0.61	0.50	0.55	0.56	0.56	0.59	0.57	0.57	0.65	0.49	0.48	0.63
C3	0.66	0.49	0.53	0.59	0.63	0.49	0.73	0.40	0.57	0.57	0.75	0.37	0.48	0.63
C4	0.63	0.49	0.60	0.54	0.56	0.56	0.59	0.53	0.55	0.56	0.57	0.57	0.53	0.58
C5	0.41	0.72	0.41	0.72	0.61	0.53	0.72	0.39	0.48	0.66	0.61	0.53	0.59	0.53
C6	0.70	0.41	0.68	0.43	0.64	0.47	0.66	0.45	0.75	0.37	0.70	0.41	0.70	0.41
C7	0.70	0.41	0.66	0.45	0.68	0.43	0.70	0.41	0.76	0.36	0.72	0.39	0.70	0.41
C8	0.60	0.50	0.56	0.55	0.58	0.53	0.60	0.50	0.64	0.47	0.64	0.47	0.62	0.50
C9	0.56	0.56	0.56	0.56	0.56	0.56	0.57	0.54	0.62	0.48	0.60	0.52	0.67	0.44
C10	0.60	0.50	0.60	0.50	0.60	0.50	0.61	0.50	0.62	0.48	0.61	0.50	0.66	0.45
C11	0.55	0.58	0.57	0.55	0.56	0.55	0.58	0.53	0.58	0.53	0.60	0.50	0.64	0.47
C12	0.66	0.45	0.67	0.43	0.63	0.49	0.64	0.47	0.66	0.45	0.66	0.45	0.66	0.45
C13	0.60	0.52	0.59	0.52	0.60	0.50	0.63	0.49	0.66	0.45	0.67	0.43	0.69	0.43
C14	0.73	0.40	0.73	0.40	0.68	0.43	0.70	0.41	0.79	0.32	0.71	0.42	0.67	0.46
C15	0.59	0.52	0.64	0.47	0.58	0.53	0.66	0.45	0.68	0.44	0.64	0.47	0.73	0.37
C16	0.63	0.49	0.63	0.49	0.57	0.54	0.63	0.49	0.64	0.47	0.64	0.47	0.64	0.47
C17	0.60	0.50	0.60	0.50	0.58	0.53	0.56	0.55	0.62	0.50	0.66	0.45	0.66	0.45
C18	0.59	0.52	0.60	0.50	0.58	0.53	0.58	0.53	0.60	0.50	0.64	0.47	0.68	0.43
C19	0.61	0.50	0.61	0.50	0.62	0.48	0.67	0.43	0.64	0.47	0.62	0.48	0.70	0.41
C20	0.63	0.49	0.64	0.47	0.66	0.45	0.66	0.45	0.53	0.57	0.59	0.52	0.66	0.52
C21	0.59	0.52	0.61	0.50	0.62	0.48	0.67	0.43	0.55	0.55	0.60	0.50	0.61	0.50
C22	0.56	0.56	0.52	0.61	0.57	0.54	0.64	0.47	0.56	0.55	0.66	0.46	0.51	0.00

**Table 3** The standard q-ROF-matrix SD, criteria weights

	(WI)	(SE)	(GE)	(BI)	(WA)	(HC)	(HN)	$\sigma_j$	$C_j$	$w_j$
C1	1.0	3.0	4.0	7.0	2.0	6.0	5.0	0.53	10.41	0.04
C2	1.0	6.0	4.0	3.0	5.0	7.0	1.0	0.33	5.94	0.02
C3	1.0	3.0	5.0	6.0	4.0	7.0	2.0	0.42	7.35	0.03
C4	1.0	7.0	4.0	6.0	3.0	5.0	1.0	0.35	6.26	0.03
C5	1.0	2.0	5.0	7.0	3.0	5.0	4.0	0.53	9.96	0.04
C6	1.0	4.0	2.0	3.0	7.0	5.0	5.0	0.60	12.79	0.05
C7	1.0	2.0	3.0	4.0	7.0	6.0	4.0	0.59	11.70	0.05
C8	1.0	2.0	3.0	4.0	6.0	6.0	5.0	0.64	13.23	0.05
C9	1.0	2.0	2.0	4.0	6.0	5.0	7.0	0.66	15.01	0.06
C10	5.0	5.0	5.0	3.0	2.0	3.0	1.0	0.64	13.33	0.05
C11	1.0	3.0	2.0	4.0	4.0	6.0	7.0	0.64	14.35	0.06
C12	2.0	1.0	7.0	6.0	2.0	2.0	2.0	0.48	9.24	0.04
C13	6.0	7.0	5.0	4.0	3.0	2.0	1.0	0.65	13.86	0.06
C14	3.0	2.0	6.0	5.0	1.0	4.0	7.0	0.44	9.88	0.04
C15	6.0	5.0	7.0	3.0	2.0	4.0	1.0	0.60	12.19	0.05
C16	5.0	5.0	7.0	4.0	2.0	1.0	2.0	0.64	13.54	0.05
C17	4.0	4.0	6.0	7.0	3.0	2.0	1.0	0.54	10.39	0.04
C18	5.0	3.0	6.0	6.0	3.0	2.0	1.0	0.55	11.10	0.04
C19	6.0	6.0	4.0	2.0	3.0	4.0	1.0	0.58	12.64	0.05
C20	5.0	3.0	1.0	1.0	7.0	6.0	4.0	0.53	12.47	0.05
C21	6.0	3.0	2.0	1.0	7.0	5.0	3.0	0.47	11.10	0.04
C22	6.0	7.0	4.0	2.0	5.0	1.0	3.0	0.54	12.96	0.05



**Fig. 5** Relative importance of criteria obtained with the CRITIC technique

**Step 10.** Find the criteria weights using Eq. (12)

$$w_j = \frac{c_j}{\sum_{j=1}^n c_j} \tag{12}$$

### 3.3 q-ROFS MABAC method

The MABAC model was defined and introduced to the literature by Pamučar and Ćirović (Pamučar & Ćirović, 2015).

In the MABAC, the first step is to establish the criterion functions for each decision alternative and the distances of these functions to the Border Approximation Area (BAA). Subsequently, the choice alternatives are prioritized, and the optimal alternative is chosen. (Pamučar & Ćirović, 2015). The MABAC model has many advantages such as consistency, and simplicity. Additionally, it considers the hidden values of losses and gains, and it can be integrated with other views. Therefore, the MABAC method is a good tool

**Table 4** Linguistic scale for q-ROFNs for alternatives. (Alkan and Kahraman 2021)

Linguistic Terms	( $\mu, v$ )
Certainly high value (CHV)	(0.99,0.11)
Very high value (VHV)	(0.88,0.22)
High value (HV)	(0.77,0.33)
Above average value (AAV)	(0.66,0.44)
Average value (AV)	(0.55,0.55)
Under average value (UAV)	(0.44,0.66)
Low value (LV)	(0.33,0.77)
Very low value (VLV)	(0.22,0.88)
Certainly low value (CLV)	(0.11,0.99)

for obtaining acceptable decisions (Turan & Boran 2022). The steps for the q-ROF MABAC method are as follows:

**Step 1.** Create q-ROF evaluation matrix for each DM.

$$R^k = [A_{ij}^k]_{m \times n} = R^k = \begin{matrix} A_1 & \left( \begin{matrix} (\mu_{11}^k, v_{11}^k) & \cdots & \mu_{1n}^k, v_{1n}^k \\ \vdots & \vdots & \ddots & \vdots \\ A_m & (\mu_{m1}^k, v_{m1}^k) & \cdots & \mu_{mn}^k, v_{mn}^k \end{matrix} \right) \end{matrix} \quad (13)$$

where  $A_{ij}^k = (\mu_{ij}^k; v_{ij}^k)$  defines the q-ROF knowledge of alternative on criteria  $C_j^k$  by DM  $k$ .

**Step 2.** Consolidate DMs' decision matrices.

DM's evaluation matrices are integrated using q-ROFWA (q-ROF Weighted Average) or q-ROFWG (q-ROF Weighted Geometric) aggregating operators using with Eq. (14).

$$r = [A_{ij}]_{m \times n} = \begin{matrix} A_1 & \left( \begin{matrix} (\mu_{11}^k, v_{11}^k) & \cdots & \mu_{1n}^k, v_{1n}^k \\ \vdots & \vdots & \ddots & \vdots \\ A_m & (\mu_{m1}^k, v_{m1}^k) & \cdots & \mu_{mn}^k, v_{mn}^k \end{matrix} \right) \end{matrix} \quad (14)$$

**Step 3.** Normalize the combined decision matrix with Eq. (15) and Eq. (16).

For benefit criteria;  $N_{ij} = A_{ij} = (\mu_{ij}; v_{ij}) \quad (15)$

For cost criteria;  $N_{ij} = (A_{ij})^{cost} = (v_{ij}; \mu_{ij}) \quad (16)$

**Step 4.** Generate the weighted normal decision matrix. Consider the normalised matrix  $N_{ij}$  and criteria weights vector  $w_j$ , the weighted normalized matrix  $WN_{ij} = (\mu_{ij}^{w_j}; v_{ij}^{w_j})$  can be found with Eq. (17).

$$WN_{ij} = w_j \otimes N_{ij} = \left( \sqrt[q]{1 - (1 - \mu_{ij}^q)^{w_j}}; v_{ij}^{w_j} \right) \quad (17)$$

**Step 5.** Estimate the values of BAA and the BAA matrix  $G = [g_j]_{l \times n}$

$$g_j = \left( \prod_{i=1}^m WN_{ij} \right)^{1/m} = \left\{ \left( \prod_{i=1}^m (\mu_{ij}^q) \right)^{1/m}; \sqrt[q]{1 - \prod_{j=1}^n (1 - v_{ij}^q)^{1/m}} \right\} \quad (18)$$

**Step 6.** Determine the distance  $D = [d_{ij}]_{m \times n}$  between alternatives and BAA by using Eq. (19).

$$d_{ij} = \begin{cases} d(WN_{ij}, g_j) \text{ if } WN_{ij} > g_j \\ 0, WN_{ij} = g_j \\ -d(WN_{ij}, g_j) \text{ if } WN_{ij} < g_j \end{cases} \quad (19)$$

where  $d(WN_{ij}, g_j)$  is the distance from  $WN_{ij}$  to  $g_j$ .  $d_{q-ROFNHD_{WN_{ij}, g_j}}$ , is calculated with q-Rung Orthopair fuzzy normalized Hamming distance measure. The formula is given in Eq. (20).

$$d_{q-ROFNHD_{WN_{ij}, g_j}} = \frac{1}{2} \left\{ |(\mu_{WN_{ij}})^q - (\mu_{g_j})^q| + |(v_{WN_{ij}})^q - (v_{g_j})^q| + |(\gamma_{WN_{ij}})^q - (\gamma_{g_j})^q| \right\} \quad (20)$$

Next, the indeterminacy degree  $\gamma_p(x)$  can be derived by Eq. (21).

$$\gamma_p(x) = \sqrt[q]{1 - ((\mu_p(x))^q + (v_p(x))^q)} \quad (21)$$

**Step 7.** Lastly, find the sum of distance values of alternatives,  $d_{ij}$ . As a result, the bigger the score, the better the choice.

$$S_i = \sum_{j=1}^n d_{ij} \quad (22)$$

## 4 Sustainable renewable energy source assessment in Türkiye

### 4.1 Application of q-ROFS CRITIC method

The evaluation criteria were established by a comprehensive literature review. Upon reviewing the criteria with the decision-makers, the evaluation criteria list was finalized. The experts contacted in this study mostly consist of senior managers and academics with extensive experience in the energy sector. The experts participating in this study were selected using a purposive sampling approach, a common method in decision-making and Delphi-based studies where participants are chosen based on their expertise, experience, and relevance to the research topic. The primary goal was to ensure that all experts possessed sufficient knowledge, professional experience, and decision-making authority in the renewable energy field. Also, All participants were asked to evaluate the criteria for all alternatives using Table 1. Table 11 presents a detailed enumeration of criteria, together with their definitions and citations.

**Table 5** The combined q-ROF decision matrix ( $r_{ij}$ )

	$\mu$	$\nu$	$\mu$	$\nu$	$\mu$	$\nu$	$\mu$	$\nu$	$\mu$	$\nu$	$\mu$	$\nu$	$\mu$	$\nu$	$\mu$	$\nu$	$\mu$	$\nu$
	<b>C1</b>		<b>C2</b>		<b>C3</b>		<b>C4</b>		<b>C5</b>		<b>C6</b>		<b>C7</b>		<b>C8</b>			
WI	0.43	0.70	0.73	0.40	0.66	0.49	0.63	0.49	0.41	0.72	0.70	0.41	0.70	0.41	0.60	0.50		
SE	0.46	0.67	0.61	0.50	0.53	0.59	0.60	0.54	0.41	0.72	0.68	0.43	0.66	0.45	0.56	0.55		
GE	0.53	0.58	0.55	0.56	0.63	0.49	0.56	0.56	0.61	0.53	0.64	0.47	0.68	0.43	0.58	0.53		
BI	0.71	0.43	0.56	0.59	0.73	0.40	0.59	0.53	0.67	0.46	0.66	0.45	0.70	0.41	0.60	0.50		
WA	0.44	0.67	0.57	0.57	0.57	0.57	0.55	0.56	0.48	0.66	0.75	0.37	0.76	0.36	0.64	0.47		
HC	0.68	0.47	0.65	0.49	0.75	0.37	0.57	0.57	0.61	0.53	0.70	0.41	0.72	0.39	0.64	0.47		
HN	0.59	0.52	0.48	0.63	0.48	0.63	0.53	0.58	0.59	0.53	0.70	0.41	0.70	0.41	0.62	0.50		
	<b>C9</b>		<b>C10</b>		<b>C11</b>		<b>C12</b>		<b>C13</b>		<b>C14</b>		<b>C15</b>					
WI	0.56	0.56	0.60	0.50	0.55	0.58	0.66	0.45	0.60	0.52	0.73	0.40	0.61	0.50				
SE	0.56	0.56	0.60	0.50	0.57	0.55	0.67	0.43	0.59	0.52	0.74	0.38	0.64	0.47				
GE	0.56	0.56	0.60	0.50	0.56	0.55	0.63	0.49	0.60	0.50	0.68	0.43	0.60	0.50				
BI	0.57	0.54	0.61	0.50	0.58	0.53	0.64	0.47	0.63	0.49	0.70	0.41	0.66	0.45				
WA	0.62	0.48	0.62	0.48	0.58	0.53	0.66	0.45	0.66	0.45	0.77	0.34	0.68	0.44				
HC	0.60	0.52	0.61	0.50	0.60	0.50	0.66	0.45	0.64	0.46	0.73	0.40	0.64	0.47				
HN	0.67	0.44	0.66	0.45	0.64	0.47	0.66	0.45	0.69	0.43	0.70	0.41	0.68	0.44				
	<b>C16</b>		<b>C17</b>		<b>C18</b>		<b>C19</b>		<b>C20</b>		<b>C21</b>		<b>C22</b>					
WI	0.63	0.49	0.60	0.50	0.59	0.52	0.61	0.50	0.63	0.49	0.59	0.52	0.56	0.56				
SE	0.63	0.49	0.60	0.50	0.60	0.50	0.61	0.50	0.64	0.47	0.61	0.50	0.52	0.61				
GE	0.57	0.54	0.58	0.53	0.58	0.53	0.62	0.48	0.66	0.45	0.62	0.48	0.57	0.54				
BI	0.64	0.47	0.56	0.55	0.58	0.53	0.67	0.43	0.66	0.45	0.67	0.43	0.64	0.47				
WA	0.70	0.41	0.62	0.50	0.58	0.53	0.60	0.50	0.60	0.52	0.55	0.55	0.56	0.55				
HC	0.66	0.45	0.66	0.45	0.64	0.47	0.62	0.48	0.59	0.52	0.60	0.50	0.66	0.46				
HN	0.70	0.41	0.66	0.45	0.67	0.45	0.67	0.43	0.66	0.45	0.57	0.54	0.58	0.53				

Table 6 The border approximation area (BAA)

	$\mu$	$\nu$	$\mu$	$\nu$	$\mu$	$\nu$	$\mu$	$\nu$	$\mu$	$\nu$	$\mu$	$\nu$	$\mu$	$\nu$
$s_j$	<b>C1</b>	0.30	0.98	<b>C2</b>	0.25	0.99	<b>C3</b>	0.25	0.99	<b>C4</b>	0.26	0.99	<b>C5</b>	0.31
$s_j$	<b>C9</b>	0.30	0.97	<b>C10</b>	0.34	0.96	<b>C11</b>	0.30	0.97	<b>C12</b>	0.34	0.97	<b>C13</b>	0.36
$s_j$	<b>C16</b>	0.36	0.96	<b>C17</b>	0.33	0.97	<b>C18</b>	0.33	0.97	<b>C19</b>	0.35	0.96	<b>C20</b>	0.35
													<b>C6</b>	0.23
													<b>C14</b>	0.39
													<b>C21</b>	0.33
													<b>C7</b>	0.22
													<b>C15</b>	0.36
													<b>C22</b>	0.33
													<b>C8</b>	0.28
														0.97

**Step 1.** To build the decision frame, we define the hierarchical structure that consists of four main criteria and 22 sub-criteria (see Fig. 4).

**Step 2–3.** The decision matrix  $N = (\xi_{ij}^{(k)})$ ,  $k = 1, \dots, 5$  of q-ROFNs is defined by each DM,  $DM_1, DM_2, \dots, DM_5$ , as in Appendix Table 12.

**Step 4.** The q-ROF decision matrix is  $N = (\xi_{ij})_{m \times n}$  provided in Table 2 with using Eq. (6) and Table 12. To derive the aggregated q-ROF decision matrix, we set  $q=3$ .

**Step 5–6.** The score matrix and standard decision matrix are calculated with Eq. (7) and Eq. (8).

**Step 7–8–9–10.** Next, using Eqs. (9)–(11), the standard deviation ( $\sigma_j$ ), correlation coefficient ( $C_j$ ) and amount of information of each criteria are estimated. Using Eq. (12) criteria weights ( $w_j$ ) are calculated and are shown in Table 3.

As illustrated in Table 3 and Fig. 5, economic risks (C9) are identified as the most significant factor, with a weight of 0.06. Conversely, land requirements (C2) are considered the least influential factor, Its weight is 0.024. The remaining criteria are ordered as follows:  $C9 > C11 > C13 > C16 > C10 > C8 > C22 > C6 > C19 > C20 > C15 > C7 > C18 > C21 > C1 > C17 > C5 > C14 > C12 > C3 > C4 > C2$ .

### 4.2 Application of q-ROFS MABAC method

Subsequently, the decision-makers evaluate the available alternatives in the context of a real-world case study. Following the determination of the q-ROFS weights during the preceding step, the ranking of the alternatives was conducted using q-ROFS MABAC. The individual ratings of five experts were collected in this study. The linguistic scale used is shown in Table 4.

Firstly, they were asked to select the most appropriate linguistic for evaluating each alternative based on each criterion. As shown in Table 4, these linguistic terms were mapped to the corresponding q-ROFS. The energy source options are listed as follows: (WI), (SE), (GE), (BI), (WA), (HC), and (HN).

**Step 1.** Construction of a q-ROF evaluation matrix for each decision maker. Firstly, subjective evaluations of experts on renewable energy alternatives are collected. The linguistic variable scores are converted into q-ROF scores using Table 4 and presented in Table 13.

**Step 2.** Creation of combined the decision matrix with the opinions of the experts. The combined q-ROF decision matrix in Table 5 is obtained by combining the opinions of five experts with the q-ROFWA operator presented in Eq. (14). This table presents the aggregated opinions of five experts on different renewable energy sources. It shows their evaluations for each criterion, using membership ( $\mu$ ) and non-membership ( $\nu$ ) values for each criterion (C1 to C22). The values represent how well each energy

**Table 7** Distances to the BAA

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
WI	0.041	0.018	0.004	0.008	0.043	0.002	0.001	0.001	0.012	0.004	0.014
SE	0.034	0.009	0.014	0.004	0.043	0.002	0.007	0.009	0.012	0.004	0.007
GE	0.017	0.011	0.002	0.004	0.024	0.009	0.003	0.006	0.012	0.004	0.009
BI	0.036	0.012	0.012	0.004	0.033	0.006	0.001	0.001	0.009	0.003	0.005
WA	0.036	0.010	0.010	0.005	0.027	0.009	0.007	0.006	0.011	0.004	0.005
HC	0.031	0.011	0.014	0.004	0.024	0.002	0.003	0.006	0.005	0.003	0.009
HN	0.020	0.020	0.022	0.007	0.022	0.002	0.001	0.002	0.019	0.012	0.015
	C12	C13	C14	C15	C16	C17	C18	C19	C20	C21	C22
WI	0.001	0.013	0.002	0.012	0.009	0.002	0.005	0.008	0.004	0.005	0.009
SE	0.005	0.015	0.005	0.006	0.009	0.002	0.002	0.008	0.004	0.003	0.018
GE	0.007	0.011	0.009	0.013	0.021	0.006	0.007	0.004	0.008	0.007	0.006
BI	0.002	0.006	0.005	0.008	0.004	0.010	0.007	0.014	0.008	0.018	0.018
WA	0.001	0.012	0.015	0.013	0.020	0.001	0.007	0.009	0.009	0.011	0.007
HC	0.001	0.010	0.002	0.004	0.008	0.010	0.009	0.004	0.011	0.002	0.022
HN	0.001	0.022	0.005	0.013	0.020	0.010	0.016	0.014	0.008	0.008	0.005

**Table 8**  $S_i$  values and ranking of decision alternatives

Alternative	$S_i$	Rank
Wind (WI)	0.218	5
Solar Energy (SE)	0.224	3
Geothermal (GE)	0.200	6
Biomass (BI)	0.223	4
Wave (WA)	0.237	2
Hydraulic (HC)	0.194	7
Hydrogen (HN)	0.264	1

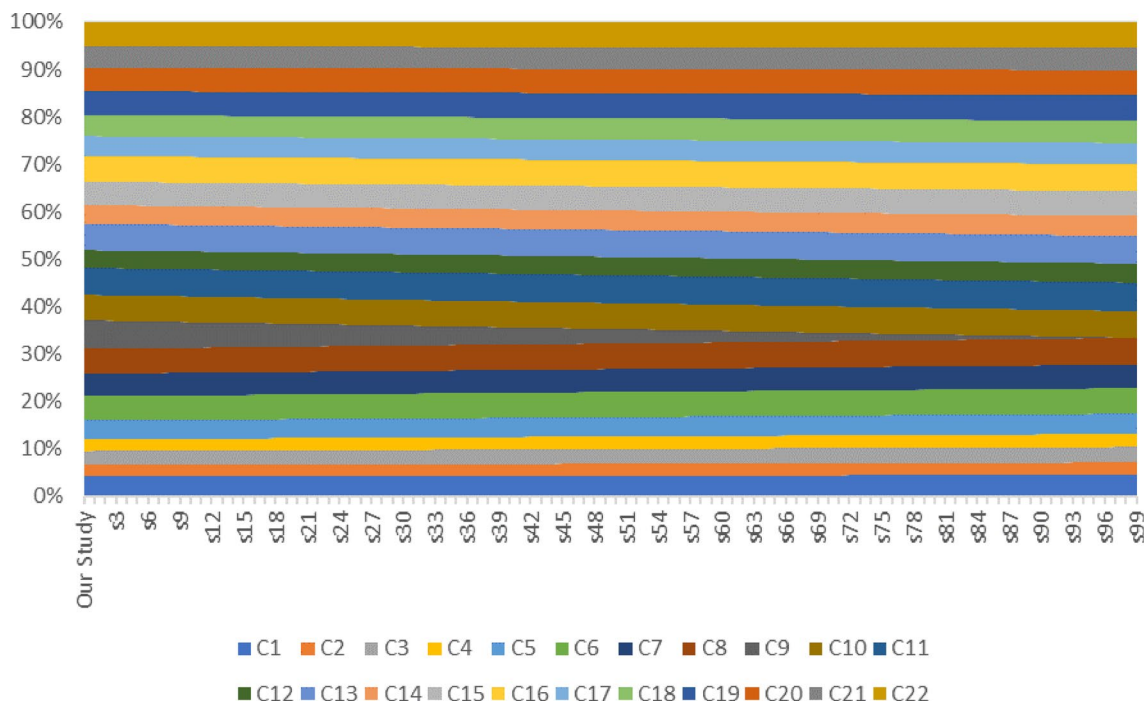
alternative meets each of the 22 criteria, where lower  $\nu$  and higher  $\mu$  are preferable. For example, the entry for Wind (WI) under Criterion C1 is  $\mu=0.43$ ,  $\nu=0.70$ , indicating

moderate membership and relatively high non-membership in satisfying C1.

**Step 3.** The aggregated decision matrix is normalized using the formulas specified in Eqs. (17) and (18), with adjustments made based on the type of each criterion. Table 14 shows the normalized decision matrix.

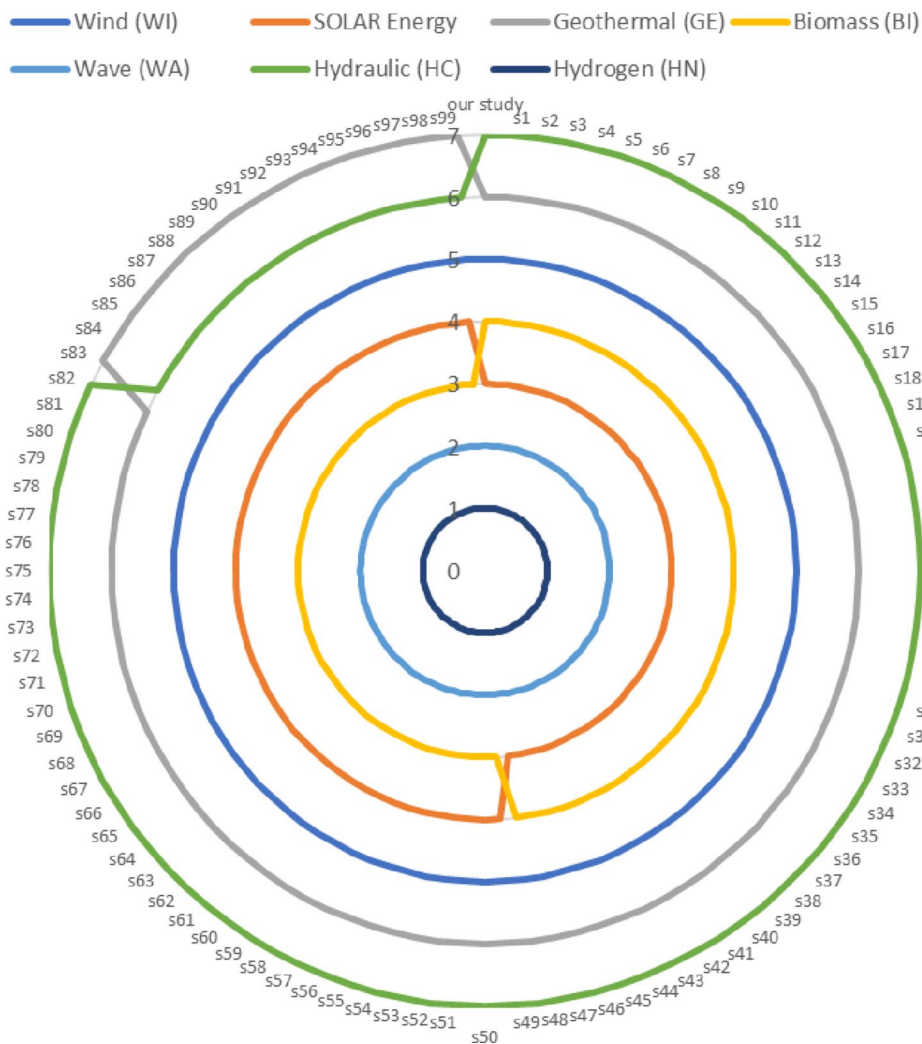
**Step 4:** Using the normalized values  $N_{ij}$  and the criterion weights,  $w_j$ , the elements of the weighted normalized matrix,  $WN_{ij}$ , are determined as Eq. (17). The outcomes are displayed in Table 15.

**Step 5.** Calculate the BAA. The Border Approximation Area (BAA) represents ideal values for comparison in



**Fig. 6** The simulated criteria importance scenarios

**Fig. 7** The result of the sensitivity analysis



decision-making. The  $\mu$  and  $\nu$  values for each criterion (C1 to C22) describe the boundary of the decision-making space. In this context, it provides the reference values against which the alternatives can be compared to determine their proximity to the ideal solution. The corresponding matrix is shown in Table 6.

**Step 6:** The distances between each alternative and the BAA are calculated using Eq. (21), with the results detailed in Table 7. This table displays the distance of each energy source alternative from the BAA across all criteria. A larger distance indicates a closer alignment with the ideal solution.

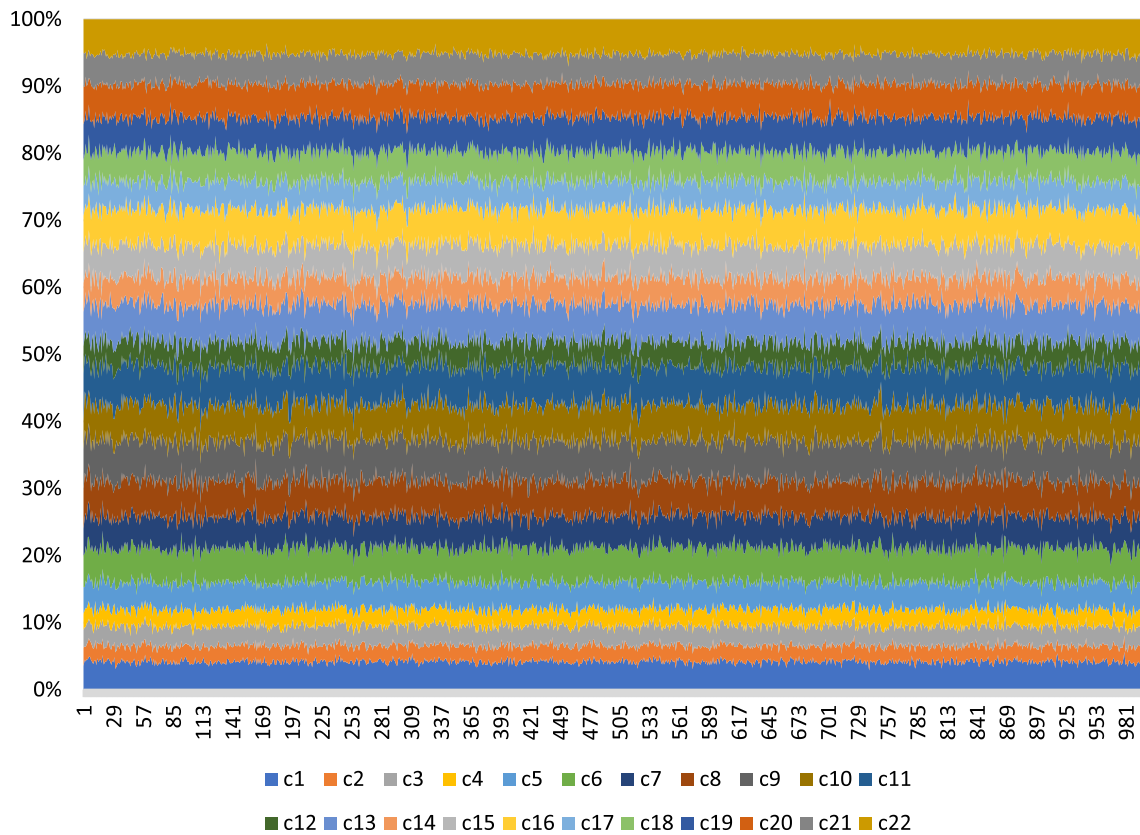
**Step 7:** Finally, the total distance for each alternative is computed using Eq. (22). The aggregated results are shown in Table 8, highlighting the overall distance ( $S_i$ ) of each energy source from the ideal solution by summing distances across all criteria. Among the evaluated options, hydrogen emerges as the top-performing energy alternative, whereas hydraulic scores the lowest.

A nomenclature table is added to the Appendix to increase the readability of mathematical formulations (See Table 16).

### 4.3 Sensitivity analysis

In this section of the study, two different sensitivity analyses were conducted with respect to criterion weights and the q-value. For the criterion weights, the sensitivity analysis was performed from two complementary perspectives: deterministic and probabilistic. The deterministic analysis assessed how controlled variations in the weights influence the ranking of alternatives, while the probabilistic analysis based on Monte Carlo simulations evaluated the robustness of the model under uncertainty by generating random weight distributions across multiple scenarios (Baležentis and Streimikiene 2017; Soltani and Imani 2024).

The deterministic sensitivity analysis examined an algorithm developed by Gorcun et al. (2021) that efficiently assesses the impact of adjusting each criterion’s weight individually. It considers all possible scenarios related to shifts in ranking results. This approach serves as a robust tool for testing the reliability of the decision-making method. In total, one hundred alternative scenarios were generated by



**Fig. 8** The criteria weighting scenarios for Monta Carlo analyses

reducing the weight of the most critical criterion (C9) by 1% and adjusting the weights of other criteria accordingly. The updated criterion values for each scenario are calculated using Eqs. (23) and (24).

$$w_{nv} = w_{pv} - (w_{pv} \cdot \% \alpha_v) \tag{23}$$

$$w_{nv}' = \frac{(1 - w_{nv})}{m - 1} + w_{pv}' \tag{24}$$

Here,  $w_{nv}$  represents the updated weight of the  $v^{th}$  factor, while  $w_{pv}$  denotes the prior value of the criterion, The percentage adjustment,  $\% \alpha_v$  is the modification degree. Additionally,  $w_{nv}'$  stands for the adjusted weights of the other factors, where  $m$  refers to the total number of factors,  $w_{pv}'$  is the previous values of the remaining criteria. We determined the respective ranking performances of the alternatives concerning the scenarios in Fig. 6.

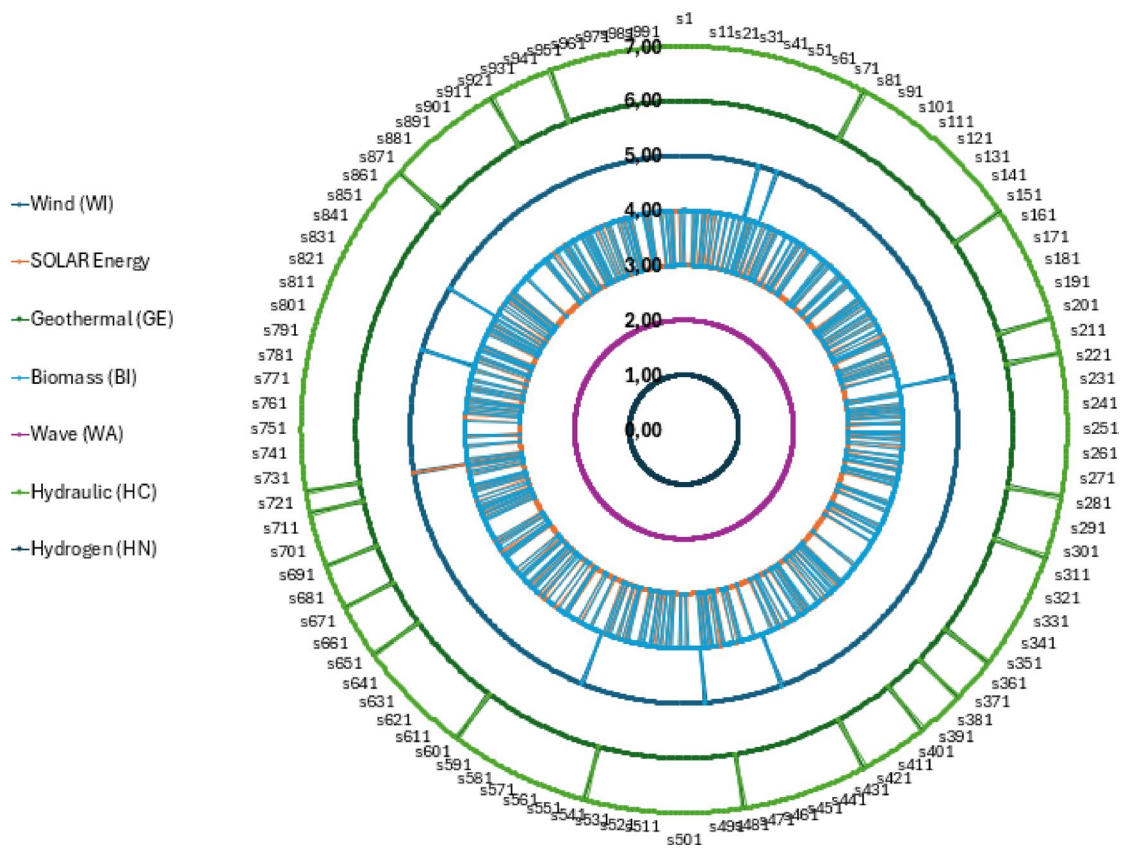
The new ranking results are shown in Fig. 7 that confirms hydrogen energy and wave energy are consistently ranked first and second across all scenarios. This result underscores the model’s reliability and robustness in handling variations in criteria weightings. Despite changes in the relative importance of different evaluation criteria, the ranking of these two energy sources remains unchanged. This indicates

that the q-ROFS CRITIC-MABAC model provides stable and robust results, offering decision-makers confidence in the reliability of the conclusions drawn from the analysis.

The minimal changes in the ranking of other energy sources, such as solar, wind, and biomass, further emphasize the model’s resilience to weight fluctuations. The outcomes are not overly sensitive to shifts in criteria importance, meaning that the model delivers consistent recommendations even when different decision-makers or experts prioritize criteria differently. This robustness ensures that the final decisions derived from this model are trustworthy and can withstand the subjective nature of weight assignment in multi-criteria decision-making processes.

For the probabilistic sensitivity analysis, to examine how uncertainty in the criteria weights could influence the ranking of renewable energy alternatives, a Monte Carlo simulation was performed. In each iteration, the criteria weights obtained by the q-ROFS CRITIC method were randomly perturbed within  $\pm 10\%$  of their nominal values, ensuring normalization to preserve the total weight sum (see Fig. 8).

The q-ROFS MABAC model was then recalculated for 1000 independent scenarios, and the rank of each renewable energy source was recorded in every run. The obtained frequency distributions clearly indicate that the proposed



**Fig. 9** The result of the Monte Carlo analysis

decision model demonstrates a remarkably robust ranking behavior under stochastic variations in the criteria weights.

As shown in Fig. 9, Hydrogen energy consistently occupied the first rank in all 1000 simulations (100%), which provides strong evidence of the model’s robustness and reliability. Wave energy predominantly appeared in the second position (100%), whereas solar energy was mainly ranked third (72.7%) or fourth (27.2%). Biomass showed a moderate level of sensitivity, mostly placed around the middle ranks (72% in fourth place). In contrast, geothermal and hydraulic energy alternatives were located at the lower end of the ranking spectrum, appearing in the sixth and seventh positions in approximately 97.9% of the cases.

Overall, the Monte Carlo results confirm that the proposed decision-making framework is probabilistically robust, and that minor random fluctuations in the weights do not alter the overall decision outcome. The fact that hydrogen energy maintained its top position across every simulated scenario provides compelling validation that it remains the most suitable renewable energy option, even under uncertainty in expert judgments and weighting schemes.

Consequently, both of deterministic sensitivity analysis and the probabilistic (the Monte Carlo) analysis provides convincing evidence that the model’s decision-making

process is resilient to subjective bias and random disturbances in the criteria weighting.

As the second sensitivity analysis, the q value was varied between 1–4. The binding restriction loosens as q grows, giving the decision maker the most freedom as q reaches infinite. However, with the same binding force, increasing q increases reluctance, which raises model uncertainty. To reduce uncertainty in a decision-making system, find the smallest q. The results obtained accordingly are shown in Table 9 and Fig. 8.

According to Fig. 10, hydrogen energy ranks first when q values are changed. Wave energy comes second. In general, there is no change in the rankings except for very small differences. Minimal changes in the ranking of energy sources indicate that the model is robust to changes in q values.

**Table 9** The result of the sensitivity analysis accordingly q values

	Q			
	1	2	3	4
Wind (WI)	5	5	5	5
Solar Energy (SE)	4	4	3	4
Geothermal (GE)	7	6	6	6
Biomass (BI)	3	3	4	3
Wave (WA)	2	2	2	2
Hydraulic (HC)	6	7	7	7
Hydrogen (HN)	1	1	1	1

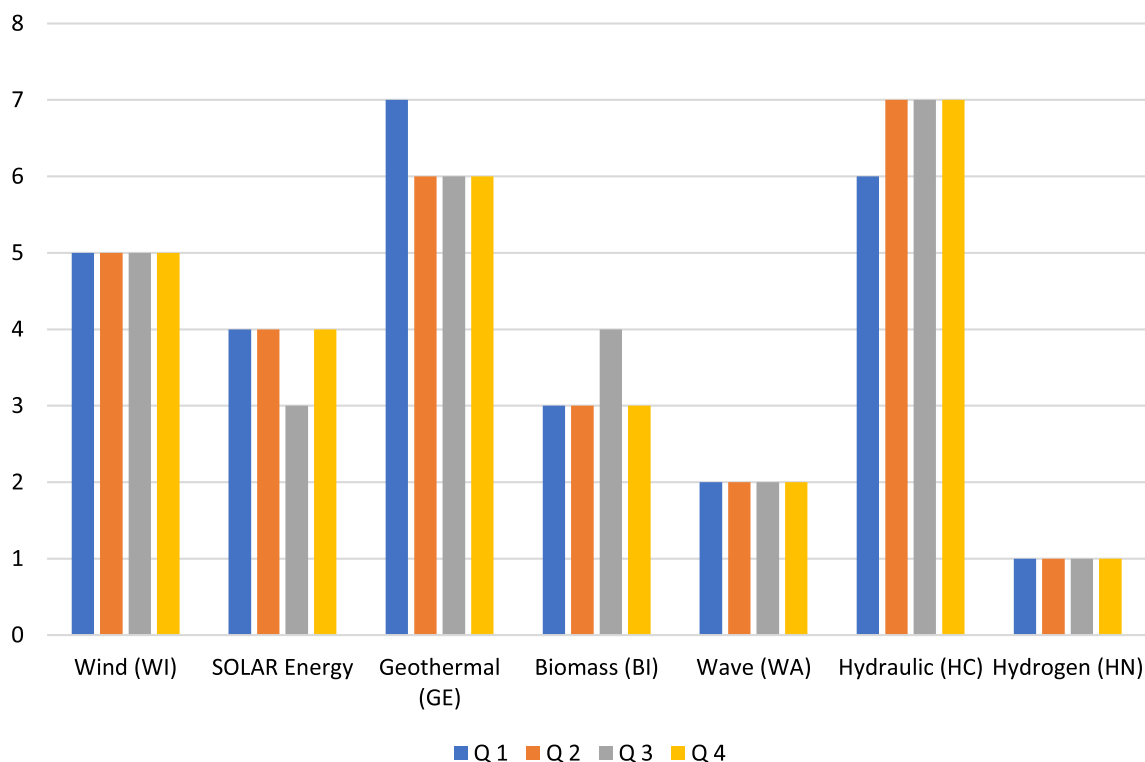


Fig. 10 The result of the sensitivity analysis accordingly q values

Table 10 Rankings with different ranking methods

Alternatives	q-Rung Orthopair Fuzzy CRITIC & MABAC	q-Rung Orthopair Fuzzy CRITIC & GRA	q-Rung Orthopair Fuzzy CRITIC & CODAS
	Rank	Rank	Rank
(WI)	5	4	2
(SE)	3	2	4
(GE)	6	6	5
(BI)	4	5	6
(WA)	2	3	3
(HC)	7	7	7
(HN)	1	1	1

### 4.4 Comparative analysis

In this section, a comparative evaluation is carried out to assess the validity, efficiency and robustness of the proposed q-Rung Orthopair Fuzzy CRITIC & MABAC framework. To this end, we applied the q-ROF Grey Relational Analysis (q-ROF GRA) and q-ROF CODAS. All these approaches were implemented on the same decision problem. As can be seen in Table 10, the rankings obtained by these three methods are slightly different. Using the presented q-Rung Orthopair Fuzzy CRITIC & MABAC, q-Rung Orthopair Fuzzy CRITIC & GRA, q-Rung Orthopair Fuzzy CRITIC & CODAS methods. The same result is visualised in Fig. 11.

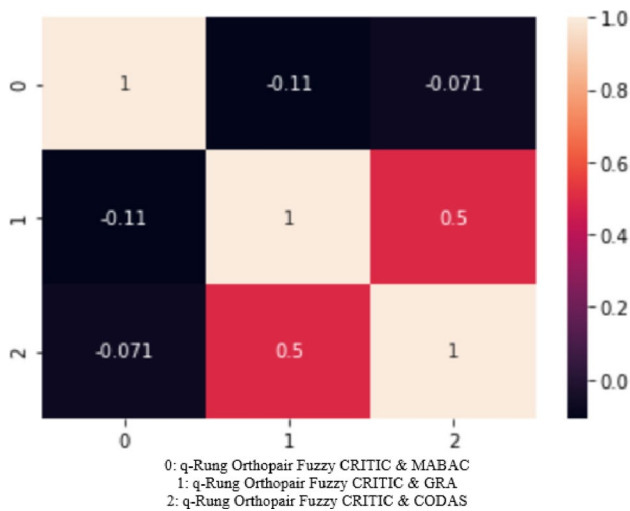
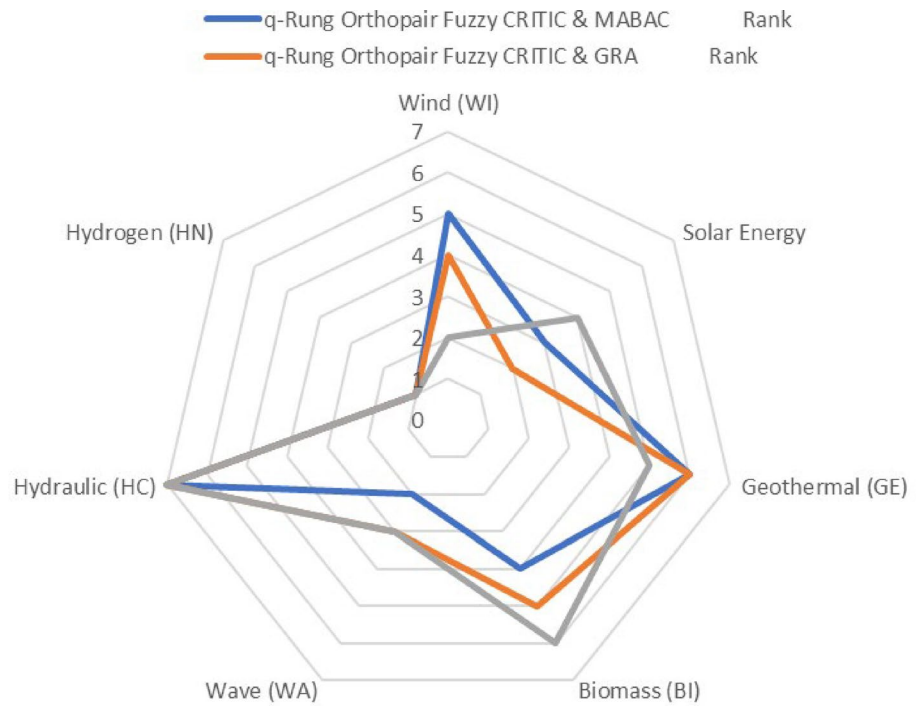
We also calculated Spearman’s correlation coefficients between the rankings obtained using the different methods.

Figure 12 is generated with Python and demonstrates the heat map of Spearman’s rank correlation coefficients.

### 5 Discussion and managerial implications

With its strategic geographic location and varied energy requirements, Türkiye faces a critical decision in selecting optimal energy resources to address its increasing demand while minimizing greenhouse gas emissions. However, the selection process is multifaceted. To make an informed decision, policymakers and stakeholders should draw on comprehensive feasibility studies, technological assessments, and energy modelling. A holistic approach, considering factors such as energy security, environmental impacts, and

**Fig. 11** The graphical depiction of the comparative analysis



**Fig. 12** The Spearman correlation coefficients between different methods

economic viability, will be essential in shaping Türkiye’s energy future. Diversifying energy sources is crucial for reaching these aims. Our study also found evidence supporting diversity, with renewable energy options like hydrogen, wave, biomass, and solar gaining prominence. The Ministry of Energy and Natural Resources of the Republic of Türkiye has published the Turkish national energy plan for the year 2022. The plan proposed "The Türkiye Energy Model".

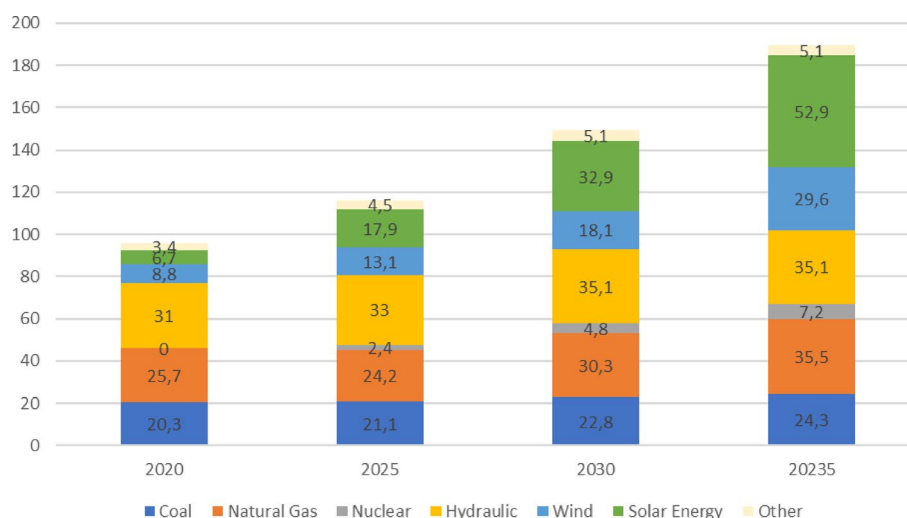
The country’s energy needs up to 2035 and the composition of alternative energy sources required to meet these needs have been determined (Ministry of energy and natural resources: Türkiye national energy plan 2022).

Upon detailed examination of Fig. 13, it can be observed that solar, wind, and nuclear energy will replace coal and natural gas. Similarly, a decrease is expected in the hydraulic energy source. Evaluating these figures reveals that Türkiye’s energy supply is expected to increasingly shift towards environmentally friendly sources like wind and solar. However, a major drawback of these resources is their vulnerability to seasonal changes and abrupt fluctuations in energy production (Karayel et al. 2022). This situation poses a serious obstacle to the establishment of a stable energy policy. Another significant issue here is the challenge of storing energy produced by wind and solar power on a large scale (Karayel et al. 2022).

Hydrogen is one of the most promising options for producing electrical energy directly and with higher efficiency using fuel cells without combustion (Uysal et al. 2021). Although hydrogen is primarily used in industrial sectors currently, it might also serve as a significant alternative for energy storage and transportation. "For this reason, the use of large areas and abundant solar energy can be a compensation for this lack of energy production (Karayel et al. 2022).The hydrogen injection into natural gas pipelines is a cost-effective solution for long-distance transmission due to the existing infrastructure and lower transportation costs compared to other methods (Karayel et al. 2022). Similarly, there are studies focusing on utilising surplus energy generated by wind turbines for hydrogen production (Li et al. 2019).

Studies have shown that Türkiye offers attractive opportunities for hydrogen production in terms of its solar energy potential. The cities of Van, Konya, Erzurum, Sivas and

**Fig. 13** Estimate of the installed power according to Türkiye's energy resources (GW)



were determined as the most suitable provinces in this regard (Karayel et al. 2022).

The study advocates for hydrogen energy as the most appropriate renewable resource due to its benefits, including geographical flexibility, storability, enhanced energy security, and environmental sustainability. Unlike other studies, hydrogen energy stands out as a strategic option for uninterrupted energy supply, zero emission targets and future technology investment. Hydrogen is a perfect solution for meeting future energy demand, because hydrogen is easily stored and transported, it reduces foreign dependency through local energy production and it has a minimal environmental impact. The growing interest in hydrogen in Türkiye is aligned with global trends. Hydrogen is a promising option for sustainable energy, particularly as a balance to the intermittent production of renewable energy sources such as wind and solar. While hydrogen has not been a dominant feature of renewable energy debates elsewhere, its potential role in energy storage, transport and industrial applications is being increasingly recognised. Particularly, recent studies are indicative of a trend focusing on the integration of hydrogen into natural gas pipelines or its use in fuel cells. The integration of hydrogen into natural gas transmission and distribution networks in Türkiye is currently under preliminary technical evaluation and regulatory consideration. From a technical point of view, the Turkish natural gas grid is largely composed of steel transmission pipelines and polyethylene distribution systems, which are generally compatible with blending ratios up to 10–20% hydrogen by volume, depending on material grade, pressure level, and end-user appliance tolerance. Studies indicate that pilot-scale testing of H<sub>2</sub>-NG blends is feasible under controlled conditions (Tetik and Kirkil 2024). From a regulatory point of view, Türkiye does not yet have a comprehensive legal framework that explicitly permits or defines standards for hydrogen blending. However, Hydrogen Technologies Roadmap (2023) outline progressive regulatory adaptation toward hydrogen integration

within the gas infrastructure by 2035. These documents foresee gradual amendments to gas quality standards and safety codes to enable partial hydrogen injection. In summary, while the full-scale implementation is not yet permitted under current legislation, both the technical infrastructure and policy direction in Turkey are evolving to make hydrogen blending technically and legally feasible in the medium term. While solar and wind energy are often prioritised in the broader literature, the Türkiye study positions hydrogen as a leading option. This is in line with both national energy needs and evolving global trends. This suggests a forward-looking approach to integrating hydrogen into Türkiye's renewable energy strategy.

## 6 Conclusions

In the quest for a sustainable and low carbon energy future, the assessment of renewable energy resources is of paramount importance. This study focused on the issue of selecting sustainable energy sources for Türkiye. The study introduced an innovative model that integrates q-ROFS CRITIC and q-ROFS MABAC. The study's key originality is in the approach that combines the q-ROFS versions of CRITIC and MABAC to include the subjectivity inherent in the rating process. The model's effectiveness was shown through a case study on Türkiye's energy sector. Academics, managers, and engineers with a wealth of expertise in their fields analyzed seven energy sources in the country. The findings show that hydrogen energy is the most suitable alternative energy source. This is followed by wave, solar, and wind energy. We have carried out a sensitivity analysis and a comparison study to assess the robustness of the decision to the model parameters and the reliability of the results. As a result, this work is one of the few attempts to develop a decision support tool using q-ROFS. In addition, the proposed model will provide a practical framework for use in the energy sector. In this way, the study can serve as a

reference for companies, researchers and decision-makers in the field, helping them to make more informed decisions. This will enhance the efficiency of renewable energy investments and help saving expenses.

Limitations of the study are that; there is a lack of standardized guidelines for the application of q-ROFS methods, leading to variability in implementation and interpretation across different studies and applications. The weighting of each decision expert is determined directly within the q-ROFS settings. This may introduce subjective variability. Therefore, deriving the decision expert's weight information poses a significant challenge in the process of MCDM. (Mishra & Rani 2023). Additionally, challenges associated with the existing regulatory framework, including inconsistent policies and bureaucratic barriers, may hinder the effective selection and integration

of renewable energy sources into the Turkish energy sector. Future research could analyze the impact of various policy shifts or reforms on the adoption of renewable energy technologies. This direction could enhance the decision-making process. It could provide a more resilient and adaptable energy framework for Türkiye and other countries transitioning to sustainable energy. Furthermore, the recent geo-political challenges, such wars in Ukraine and Palestine, pose additional risk on energy security and diversity. Subsequent research endeavours may explore these novel problem domains.

## Appendix

See Tables 11, 12, 13, 14, 15, 16

**Table 11** Evaluation criteria used in the study

Main Criteria	Sub-Criteria	Definition	Reference
<b>Environmental</b>	<b>Greenhouse Pollutant Emissions (C1)</b>	It is the amount of emission of gases such as CO2 and Nox etc. that cause global warming to the atmosphere	Büyüközkan and Güleriyüz (2016); Lee and Chang (2018); Alkan and Albayrak (2020)
	<b>Land requirements (C2)</b>	Refers to a appropriate land required for the establishment of a renewable energy plant	Kahraman et al. (2010); Ahmad and Tahar (2014); Büyüközkan and Güleriyüz (2016); Kumar and Samuel (2017); Mousavi et al. (2017); Büyüközkan et al. (2018); Lee and Chang (2018); Toklu and Taşkın (2018); Alkan and Albayrak (2020); Chen et al. (2020); Rani et al. (2020); Wang et al. (2020); Wang et al. (2021); Al-Barakati et al. (2022); Bilgili et al. (2022); Krishankumar et al. (2022); Sarkodie et al. (2022); Quteishat and Younis (2023)
	<b>Impact on environment (C3)</b>	Evaluates the damage of the renewable power plant to the environment and biodiversity	Ahmad and Tahar (2014); Wang et al. (2020); Almutairi et al. (2022); Ding et al. (2023)
	<b>Climate change (C4)</b>	Indicates climate change caused by greenhouse gas emissions	Büyüközkan et al. (2018)
	<b>Need of waste disposal (C5)</b>	Evaluates the negative effects of the wastes to be left by the renewable energy plant on the environmental quality	Kahraman et al. (2010); Mousavi et al. (2017); Rani et al. (2021); Al-Barakati et al. (2022); Quteishat and Younis (2023)
<b>Economical</b>	<b>Investment Cost (C6)</b>	Expenditures for the establishment and operation of a renewable energy plant (labor, equipment, technological investment and construction works, etc.)	Büyüközkan and Güleriyüz (2016); Çelikkbilek and Tüysüz (2016); Kumar and Samuel (2017); Mousavi et al. (2017); Büyüközkan et al. (2018); Lee and Chang (2018); Toklu and Taşkın (2018); Rani et al. (2020); Ecer et al. (2021); Al-Barakati et al. (2022)
	<b>Operation &amp; Maintenance Cost (C7)</b>	Refers to the expenditure required for operation and maintenance in the production of renewable energy (employee salaries, operating costs of the system, product and service costs)	Büyüközkan and Güleriyüz (2016); Samuel (2017); Büyüközkan et al. (2018); Kumar and Ishfaq et al. (2018); Lee and Chang (2018); Toklu and Taşkın (2018); Rani et al. (2020); Ecer et al. (2021); Bilgili et al. (2022); Sarkodie et al. (2022)
	<b>Payback Period (C8)</b>	Refers to the required period for the investment to become profitable	Alkan and Albayrak (2020); Chen et al. (2020); Bilgili et al. (2022); Ding et al. (2023)
	<b>Economic risks (C9)</b>	States the risk that the investment will be less profitable than expected	Mousavi et al. (2017); Al-Barakati et al. (2022)
	<b>Economic value (C10)</b>	Refers to the financial measurement of the benefit value provided by renewable energy production	Kahraman et al. (2010); Mousavi et al. (2017); Quteishat and Younis (2023); Alkan, (2024)
	<b>Electric cost (C11)</b>	Includes costs incurred in the electricity generation process (operating costs, fuel costs, depreciation expense, land cost, construction costs, etc.)	Lee and Chang (2018)

Table 11 (continued)

Main Criteria	Sub-Criteria	Definition	Reference
<b>Technical</b>	<b>Efficiency (C12)</b>	The ratio of energy to be produced to energy used	Ahmad and Tahar (2014); Büyüközkan and Güleriyüz (2016); Çelikbilek and Tüysüz (2016); Mousavi et al. (2017); Ishfaq et al. (2018); Lee and Chang (2018); Toklu and Taşkın (2018); Chen et al. (2020); Rani et al. (2020); Wang et al. (2020); Yazdani et al. (2020); Ecer et al. (2021); Wang et al. (2021); Almutairi et al. (2022); Bilgili et al. (2022); Ghose et al. (2022); Sarkodie et al. (2022)
	<b>Reliability &amp; Safety (C13)</b>	Refers to the capacity of the performance of the renewable energy system. Evaluates the ability of the system to perform its performance under the planned and designed conditions	Kahraman et al. (2010); Büyüközkan and Güleriyüz (2016); Mousavi et al. (2017); Toklu and Taşkın (2018); Ecer et al. (2021); Rani et al. (2021); Wang et al. (2021); Quteishat and Younis (2023)
	<b>Resource availability (C14)</b>	The amount of resources available to be used to produce renewable energy	Yazdani et al. (2020); Bilgili et al. (2022)
	<b>Technical Maturity (C15)</b>	Refers to an improved technology where faults are reduced. Measures the level of commercial reliability	Lee and Chang (2018); Wang et al. (2021)
	<b>Grid availability (C16)</b>	Indicates the renewable energy system has access to the on-grid	Wang et al. (2020); Wang et al. (2021)
	<b>Service Life (C17)</b>	Refers to the period (years) that the renewable energy plant can serve	Mousavi et al. (2017); Alkan and Albayrak (2020)
	<b>Capacity factor (C18)</b>	It is the ratio of the electricity produced by the power plant in a specific period to the electricity production of the power plant with uninterrupted full power capacity during the same period	Lee and Chang (2018); Yürek et al. (2021); Sarkodie et al. (2022)
	<b>Socio-Political</b>	<b>Compatibility with national energy policy objectives (C19)</b>	A measure of compliance with national energy policy
<b>Social Benefits (C20)</b>		Refers to the public benefits to be provided by the renewable energy plant	Büyüközkan and Güleriyüz (2016); Chen et al. (2020); Ecer et al. (2021); Wang et al. (2021); Bilgili et al. (2022)
<b>Social and political acceptability (C21)</b>		Refers to the learning, approval and acceptance of energy resources by stakeholders. The increase in acceptability is positive	Büyüközkan et al. (2018); Al-Barakati et al. (2022); Sarkodie et al. (2022)
<b>Job creation (C22)</b>		It means that the renewable power plant creates new job opportunities	Ahmad and Tahar (2014); Büyüközkan and Güleriyüz (2016); Lee and Chang (2018); Toklu and Taşkın (2018); Chen et al. (2020); Wang et al. (2020); Ecer et al. (2021); Rani et al. (2021); Wang et al. (2021); Bilgili et al. (2022); Krishankumar et al. (2022); Ding et al. (2023), Alkan, (2024)

**Table 12** Evaluation ratings of alternatives by five experts

		Wind (WI)		Solar Energy (SE)		Geothermal (GE)		Biomass (BI)		Wave (WA)		Hydraulic (HC)		Hydrogen (HN)	
		$\mu$	$\gamma$	$\mu$	$\gamma$	$\mu$	$\gamma$	$\mu$	$\gamma$	$\mu$	$\gamma$	$\mu$	$\gamma$	$\mu$	$\gamma$
C1	DM1	0.33	0.77	0.33	0.77	0.33	0.77	0.44	0.66	0.44	0.66	0.44	0.66	0.44	0.66
	DM2	0.44	0.66	0.55	0.55	0.55	0.55	0.55	0.55	0.44	0.66	0.44	0.66	0.55	0.55
	DM3	0.44	0.66	0.44	0.66	0.44	0.66	0.77	0.33	0.44	0.66	0.66	0.44	0.66	0.44
	DM4	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55
	DM5	0.22	0.88	0.22	0.88	0.66	0.44	0.88	0.22	0.22	0.88	0.88	0.22	0.66	0.44
C2	DM1	0.77	0.33	0.44	0.66	0.55	0.55	0.44	0.66	0.66	0.44	0.77	0.33	0.44	0.66
	DM2	0.55	0.55	0.55	0.55	0.55	0.55	0.44	0.66	0.55	0.55	0.55	0.55	0.55	0.55
	DM3	0.44	0.66	0.44	0.66	0.44	0.66	0.77	0.33	0.44	0.66	0.66	0.44	0.66	0.44
	DM4	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55
	DM5	0.22	0.88	0.22	0.88	0.66	0.44	0.88	0.22	0.22	0.88	0.88	0.22	0.66	0.44
C3	DM1	0.55	0.55	0.44	0.66	0.77	0.33	0.66	0.44	0.77	0.33	0.77	0.33	0.44	0.66
	DM2	0.44	0.66	0.44	0.66	0.55	0.55	0.55	0.55	0.44	0.66	0.55	0.55	0.44	0.66
	DM3	0.44	0.66	0.44	0.66	0.44	0.66	0.77	0.33	0.44	0.66	0.77	0.33	0.55	0.55
	DM4	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55
	DM5	0.88	0.22	0.66	0.44	0.66	0.44	0.88	0.22	0.33	0.77	0.88	0.22	0.33	0.77
C4	DM1	0.44	0.66	0.33	0.77	0.66	0.44	0.55	0.55	0.55	0.55	0.66	0.44	0.44	0.66
	DM2	0.55	0.55	0.33	0.77	0.44	0.66	0.44	0.66	0.55	0.55	0.55	0.55	0.55	0.55
	DM3	0.66	0.44	0.66	0.44	0.66	0.44	0.77	0.33	0.66	0.44	0.66	0.44	0.66	0.44
	DM4	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55
	DM5	0.77	0.33	0.77	0.33	0.33	0.77	0.44	0.66	0.66	0.44	0.99	0.99	0.33	0.77
C5	DM1	0.33	0.77	0.33	0.77	0.66	0.44	0.77	0.33	0.66	0.44	0.66	0.44	0.44	0.66
	DM2	0.44	0.66	0.44	0.66	0.55	0.55	0.66	0.44	0.44	0.66	0.44	0.66	0.44	0.66
	DM3	0.33	0.77	0.33	0.77	0.33	0.77	0.77	0.33	0.33	0.77	0.77	0.33	0.55	0.55
	DM4	0.55	0.55	0.55	0.55	0.44	0.66	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55
	DM5	0.22	0.88	0.22	0.88	0.77	0.33	0.77	0.33	0.22	0.88	0.77	0.33	0.77	0.33
C6	DM1	0.66	0.44	0.55	0.55	0.55	0.55	0.66	0.44	0.77	0.33	0.77	0.33	0.66	0.44
	DM2	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.44	0.66	0.55	0.55	0.55	0.55
	DM3	0.77	0.33	0.77	0.33	0.77	0.33	0.77	0.33	0.77	0.33	0.77	0.33	0.77	0.33
	DM4	0.66	0.44	0.66	0.44	0.66	0.44	0.66	0.44	0.66	0.44	0.66	0.44	0.66	0.44
	DM5	0.77	0.33	0.77	0.33	0.55	0.55	0.55	0.55	0.88	0.22	0.66	0.44	0.66	0.44
C7	DM1	0.66	0.44	0.55	0.55	0.55	0.55	0.66	0.44	0.77	0.33	0.77	0.33	0.66	0.44
	DM2	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55
	DM3	0.77	0.33	0.77	0.33	0.77	0.33	0.77	0.33	0.77	0.33	0.77	0.33	0.77	0.33
	DM4	0.66	0.44	0.66	0.44	0.66	0.44	0.66	0.44	0.66	0.44	0.66	0.44	0.66	0.44
	DM5	0.77	0.33	0.77	0.33	0.77	0.33	0.77	0.33	0.77	0.33	0.77	0.33	0.77	0.33

Table 12 (continued)

	Wind (WI)		Solar Energy (SE)		Geothermal (GE)		Biomass (BI)		Wave (WA)		Hydraulic (HC)		Hydrogen (HN)	
	μ	γ	μ	γ	μ	γ	μ	γ	μ	γ	μ	γ	μ	γ
C8	DM1	0.66	0.44	0.44	0.66	0.55	0.66	0.44	0.77	0.33	0.77	0.33	0.55	0.55
	DM2	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55
	DM3	0.66	0.44	0.66	0.44	0.66	0.44	0.66	0.44	0.44	0.66	0.44	0.77	0.33
	DM4	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55
	DM5	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55
C9	DM1	0.55	0.55	0.55	0.55	0.44	0.66	0.55	0.66	0.44	0.66	0.44	0.66	0.44
	DM2	0.44	0.66	0.44	0.66	0.55	0.55	0.44	0.55	0.55	0.44	0.66	0.44	0.66
	DM3	0.66	0.44	0.66	0.44	0.66	0.44	0.66	0.44	0.44	0.66	0.44	0.77	0.33
	DM4	0.66	0.44	0.66	0.44	0.66	0.44	0.66	0.44	0.44	0.66	0.44	0.77	0.33
	DM5	0.33	0.77	0.33	0.77	0.33	0.77	0.44	0.66	0.55	0.44	0.66	0.55	0.55
C10	DM1	0.55	0.55	0.55	0.55	0.55	0.66	0.44	0.66	0.44	0.66	0.44	0.66	0.44
	DM2	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55
	DM3	0.66	0.44	0.66	0.44	0.66	0.44	0.66	0.44	0.44	0.66	0.44	0.77	0.33
	DM4	0.66	0.44	0.66	0.44	0.66	0.44	0.66	0.44	0.44	0.66	0.44	0.66	0.44
	DM5	0.55	0.55	0.55	0.55	0.55	0.55	0.44	0.66	0.55	0.44	0.66	0.55	0.55
C11	DM1	0.55	0.55	0.66	0.44	0.44	0.66	0.55	0.55	0.55	0.66	0.44	0.55	0.55
	DM2	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55
	DM3	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.77	0.33
	DM4	0.66	0.44	0.66	0.44	0.66	0.44	0.66	0.44	0.44	0.66	0.44	0.66	0.44
	DM5	0.22	0.88	0.22	0.88	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55
C12	DM1	0.66	0.44	0.66	0.44	0.55	0.66	0.44	0.66	0.44	0.66	0.44	0.55	0.55
	DM2	0.55	0.55	0.66	0.44	0.44	0.66	0.55	0.55	0.55	0.66	0.44	0.55	0.55
	DM3	0.77	0.33	0.77	0.33	0.77	0.33	0.77	0.33	0.33	0.77	0.33	0.77	0.33
	DM4	0.66	0.44	0.66	0.44	0.66	0.44	0.66	0.44	0.44	0.66	0.44	0.66	0.44
	DM5	0.55	0.55	0.55	0.55	0.55	0.55	0.44	0.66	0.55	0.55	0.55	0.55	0.55
C13	DM1	0.66	0.44	0.55	0.55	0.55	0.66	0.44	0.77	0.33	0.66	0.44	0.77	0.33
	DM2	0.44	0.66	0.44	0.66	0.55	0.66	0.44	0.55	0.55	0.66	0.44	0.66	0.44
	DM3	0.66	0.44	0.66	0.44	0.66	0.44	0.66	0.44	0.44	0.66	0.44	0.77	0.33
	DM4	0.66	0.44	0.66	0.44	0.66	0.44	0.66	0.44	0.44	0.66	0.44	0.66	0.44
	DM5	0.44	0.66	0.55	0.55	0.55	0.55	0.44	0.66	0.55	0.55	0.55	0.55	0.55
C14	DM1	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.66	0.44	0.55	0.55	0.55	0.55
	DM2	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.66	0.44	0.55	0.55	0.55	0.55
	DM3	0.77	0.33	0.77	0.33	0.77	0.33	0.77	0.33	0.33	0.77	0.33	0.77	0.33
	DM4	0.66	0.44	0.55	0.55	0.66	0.44	0.66	0.44	0.33	0.66	0.44	0.66	0.44
	DM5	0.88	0.22	0.88	0.22	0.55	0.55	0.66	0.44	0.22	0.88	0.22	0.66	0.44

Table 12 (continued)

	Wind (WI)		Solar Energy (SE)		Geothermal (GE)		Biomass (BI)		Wave (WA)		Hydraulic (HC)		Hydrogen (HN)	
	$\mu$	$\gamma$	$\mu$	$\gamma$	$\mu$	$\gamma$	$\mu$	$\gamma$	$\mu$	$\gamma$	$\mu$	$\gamma$	$\mu$	$\gamma$
C15	DM1	0.44	0.66	0.55	0.55	0.55	0.44	0.66	0.66	0.66	0.44	0.55	0.66	0.44
	DM2	0.44	0.66	0.55	0.55	0.55	0.44	0.66	0.66	0.44	0.55	0.55	0.66	0.44
	DM3	0.66	0.44	0.66	0.44	0.66	0.66	0.44	0.66	0.66	0.44	0.66	0.77	0.33
	DM4	0.55	0.55	0.55	0.55	0.55	0.66	0.44	0.77	0.33	0.33	0.66	0.77	0.33
	DM5	0.55	0.55	0.55	0.55	0.55	0.66	0.44	0.33	0.77	0.44	0.66	0.33	0.77
C16	DM1	0.44	0.66	0.66	0.44	0.66	0.44	0.66	0.55	0.55	0.55	0.66	0.55	0.55
	DM2	0.44	0.66	0.66	0.44	0.66	0.44	0.66	0.55	0.55	0.66	0.66	0.55	0.55
	DM3	0.55	0.55	0.55	0.44	0.66	0.55	0.55	0.66	0.44	0.66	0.66	0.77	0.33
	DM4	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55
	DM5	0.66	0.44	0.66	0.44	0.66	0.77	0.33	0.66	0.66	0.44	0.77	0.33	0.66
C17	DM1	0.55	0.55	0.55	0.55	0.55	0.44	0.66	0.55	0.55	0.55	0.66	0.66	0.44
	DM2	0.55	0.55	0.55	0.55	0.55	0.44	0.66	0.55	0.55	0.66	0.66	0.66	0.44
	DM3	0.66	0.44	0.66	0.44	0.66	0.55	0.55	0.55	0.55	0.66	0.66	0.77	0.33
	DM4	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55
	DM5	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55
C18	DM1	0.44	0.66	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55
	DM2	0.44	0.66	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55
	DM3	0.66	0.44	0.66	0.44	0.66	0.66	0.44	0.55	0.55	0.66	0.66	0.77	0.33
	DM4	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55
	DM5	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55
C19	DM1	0.44	0.66	0.66	0.44	0.66	0.55	0.55	0.55	0.55	0.55	0.66	0.66	0.44
	DM2	0.66	0.44	0.66	0.44	0.66	0.66	0.44	0.55	0.55	0.66	0.66	0.55	0.55
	DM3	0.66	0.44	0.66	0.44	0.66	0.66	0.44	0.55	0.55	0.66	0.66	0.55	0.55
	DM4	0.55	0.55	0.55	0.55	0.55	0.66	0.44	0.55	0.55	0.55	0.55	0.55	0.55
	DM5	0.66	0.44	0.66	0.44	0.66	0.77	0.33	0.66	0.66	0.44	0.55	0.66	0.44
C20	DM1	0.44	0.66	0.66	0.44	0.66	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55
	DM2	0.66	0.44	0.66	0.44	0.66	0.66	0.44	0.55	0.55	0.66	0.66	0.55	0.55
	DM3	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55
	DM4	0.55	0.55	0.55	0.55	0.55	0.66	0.44	0.55	0.55	0.55	0.55	0.55	0.55
	DM5	0.66	0.44	0.66	0.44	0.66	0.77	0.33	0.66	0.66	0.44	0.55	0.66	0.44
C21	DM1	0.44	0.66	0.66	0.44	0.66	0.55	0.55	0.55	0.55	0.55	0.66	0.66	0.44
	DM2	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.66	0.66	0.44
	DM3	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.66	0.66	0.44
	DM4	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.66	0.66	0.44
	DM5	0.77	0.33	0.33	0.77	0.33	0.77	0.33	0.77	0.33	0.33	0.66	0.77	0.33
C21	DM1	0.44	0.66	0.66	0.44	0.66	0.55	0.55	0.55	0.55	0.55	0.66	0.66	0.44
	DM2	0.66	0.44	0.66	0.44	0.66	0.66	0.44	0.55	0.55	0.66	0.66	0.55	0.55
	DM3	0.55	0.55	0.55	0.55	0.55	0.66	0.44	0.55	0.55	0.55	0.66	0.66	0.44
	DM4	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55
	DM5	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55
C21	DM1	0.66	0.44	0.66	0.44	0.66	0.77	0.33	0.55	0.55	0.55	0.66	0.66	0.44
	DM2	0.66	0.44	0.66	0.44	0.66	0.77	0.33	0.55	0.55	0.66	0.66	0.66	0.44
	DM3	0.66	0.44	0.66	0.44	0.66	0.77	0.33	0.55	0.55	0.66	0.66	0.66	0.44
	DM4	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55
	DM5	0.66	0.44	0.66	0.44	0.66	0.77	0.33	0.55	0.55	0.66	0.66	0.66	0.44

Table 12 (continued)

	Wind (WI)		Solar Energy (SE)		Geothermal (GE)		Biomass (BI)		Wave (WA)		Hydraulic (HC)		Hydrogen (HN)	
	$\mu$	$\gamma$	$\mu$	$\gamma$	$\mu$	$\gamma$	$\mu$	$\gamma$	$\mu$	$\gamma$	$\mu$	$\gamma$	$\mu$	$\gamma$
C22	DM1	0.55	0.55	0.55	0.44	0.66	0.55	0.55	0.55	0.55	0.44	0.66	0.55	0.55
	DM2	0.66	0.44	0.66	0.44	0.66	0.66	0.44	0.55	0.55	0.66	0.44	0.55	0.55
	DM3	0.44	0.66	0.44	0.66	0.44	0.44	0.66	0.44	0.66	0.44	0.66	0.55	0.55
	DM4	0.44	0.66	0.44	0.66	0.44	0.44	0.66	0.44	0.66	0.44	0.66	0.55	0.55
	DM5	0.33	0.77	0.33	0.77	0.66	0.44	0.33	0.55	0.55	0.77	0.33	0.66	0.44









**Ethical approval** I testify on behalf of all co-authors that our article submitted to Journal of Soft Computing (SOCO). This research has not been published in whole or in part elsewhere; The manuscript is not currently being considered for publication in another journal; All authors have been personally and actively involved in substantive work leading to the manuscript and will hold themselves jointly and individually responsible for its content. This article does not contain any studies with human participants or animals performed by any of the authors.

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