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An Integrated Hybrid MCDM Framework for Renewable Energy Prioritization in Sustainable Development

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ABSTRACT

Switching to renewable energy is essential for reducing carbon emissions, enhancing energy security, and promoting sustainability. However, the decision-making process is complex, influenced by conflicting factors, uncertainties in expert judgments, and data variability. Existing methodologies often struggle to manage these uncertainties, leading to inconsistent outcomes. This study presents a decision-support framework that employs Linear Diophantine Fuzzy Sets (LiDFS) to more accurately model uncertainty and address these challenges. The Ranking Comparison (RANCOM) method is used to calculate subjective weights, offering a structured, expert-driven approach. In contrast, the Method based on the Removal Effects of Criteria (MEREC) determines objective weights, reducing bias and enhancing reliability. The Multi-Attribute Utility Theory (MAUT) method is then applied to systematically rank available options based on their overall utility. Sensitivity analysis evaluates the impact of weight variations on decision outcomes, while comparative analysis confirms the robustness of the proposed approach. This integrated framework provides a transparent and scientifically grounded methodology to support decision-makers in selecting optimal solutions within the renewable energy sector, effectively addressing uncertainty and conflicting priorities.

1. Introduction

Energy production constitutes a significant challenge for human societies and is crucial for the advancement of sustainable communities. The rising standards of living have led to an increased demand for alternative energy sources, while the depletion of fossil fuels necessitates the adoption of

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renewable energy. Fossil fuels, nuclear energy, and alternative energy sources represent the primary global energy resources, with carbon dioxide recognized as the main greenhouse gas contributing to global warming [1]. Bojic et al. [2] formulated a mathematical model to tackle the location–allocation problem for solid fuel power plants in a region defined by particular biomass supplies and power potential. The primary factors affecting the sites and amounts of biomass conversion facilities include the operational capacities of the plants and the geographical distribution of available biomass [4]. Jameel et al. [3] introduced a novel decision-making framework that integrates entropy-SWARA with the CoCoSo method for evaluating sustainable renewable energy systems.
The MCDM approach and sustainability variables make biomass for bioenergy a practical and strategic choice [5]. Fuzzy set theory provides a solid mathematical foundation for studying fuzzy conceptual processes. Some systems with fuzzy couplings, parameters, and events are called "modelling languages." According to Zhang et al. [6], a new method for Pythagorean fuzzy MCDM uses similarity measurements. Ren et al. [7] studied the Pythagorean fuzzy approach for MCDM. According to Moradi-Aliabadi and Huang [8], this strategy assumes a high score for the preferred alternative and a slight deviation from the ideal situation. This paper proposes the hybrid SECA and PRSRV approach for sustainable biomass resource selection and shows its excellent performance in fuzzy multidimensional scenarios. Because PRSRV involves experts or individuals rating criteria and alternatives subjectively, personal biases may skew results. Due to its complexity and expert judgement, the approach may take time and resources, especially for large-scale decision issues. PRSRV may also struggle to handle partial or ambiguous data, limiting its use in uncertain or unreliable situations. MCDM has many drawbacks, including bias, resource constraints, and uncertainty limits. Economic factors are often considered when selecting biomass for bioenergy, but sustainable production also involves social and environmental factors [9, 10].
Although considerable research has been conducted on the evaluation of renewable energy sources (RES), current methodologies frequently face challenges in adequately addressing uncertainty and imprecision in expert assessments. Many traditional MCDM methods do not incorporate subjective and objective perspectives in decision making, leading to inconsistent results. The interdependencies among criteria, fluctuations in the dynamic energy market, and regional disparities in resource availability complicate decision-making. A comprehensive and adaptable decision-support model is essential for systematically and accurately ranking renewable energy alternatives in addressing these challenges. This study introduces a novel hybrid decision-making framework integrating LiDFS, RANCOM for subjective weight evaluation, MEREC for objective weight calculation, and MAUT for the ultimate ranking procedure. The LiDFS approach effectively mitigates uncertainty and vagueness in expert judgements, while the RANCOM and MEREC methods provide a balanced weighting mechanism through the integration of subjective expert opinions and objective data-driven criteria. MAUT classifies renewable energy options based on their overall utility values. Additionally, sensitivity and comparative analyses are conducted to evaluate the resilience and durability of the proposed framework.

Objectives of the Study

This research seeks to develop a thorough, uncertainty-informed, and multi-criteria decision-making framework for the optimal selection of renewable energy sources. This study seeks to achieve the following main objectives:

- This method represents uncertainty in decision-making by employing LiDFS, thereby enabling a more flexible and precise representation of ambiguous and imprecise expert judgements.
- To establish a balanced weighting mechanism that integrates RANCOM for subjective weight

determination and MEREC for objective weight computation, thus facilitating a comprehensive evaluation of criteria.

- Utilize MAUT to rank renewable energy alternatives, facilitating a systematic and rational decision-making process.
- Perform sensitivity analysis to evaluate the robustness of ranking outcomes under different scenarios and variations in criteria weights.
- Conduct a comparative study with existing MCDM techniques to validate the superiority and efficacy of the proposed framework.
- To provide decision-makers, policymakers, and energy planners with a dependable and adaptable decision support system for the selection of sustainable renewable energy sources.

1.1 *Literature review*

Zadeh's "fuzzy sets" (FS) [11] changed decision-making in ambiguous situations. His mathematical framework can absorb and communicate obscure and murky information, making it valuable for decision-making. Zadeh's simple framework is comprehensive and easy to use for characterizing and regulating imprecision. This is because decision-making often involves uncertainty. The "intuitionistic fuzzy sets" (IFS) developed by Atanassov [12] provide an additional step to this foundation. Use these sets to merge membership and non-membership attributes. This invention makes fuzzy sets more flexible and better at handling decision-making complexity. When quality absence is as significant as quality presence, IFS non-membership criteria are even more crucial for decision-making.
LiDFSs have gained prominence in MCDM for effectively handling uncertainty and vagueness beyond traditional FSs. Introduced by Riaz and Hashmi [13], LiDFSs generalize IFSs, PFSs, and q-ROFSs, offering enhanced modeling through reference parameters. LiDFSs support real-world applications, uncertainty analysis, and computational efficiency. Pamucar [14] proposed the NWGDBM operator with interval grey numbers, while Jankovic and Pamucar [15] developed the HIRWPH operator, both contributing to advanced aggregation techniques in MCDM. Al-Quran et al. [16] explored the application of cubic picture fuzzy aggregation operators for enhancing tropical artificial forests.
Riaz et al. [17] introduced new aggregation operators within the LiDFS framework to enhance decision-making in uncertain contexts. The study demonstrated LiDFS's effectiveness in complex decision scenarios, providing a superior approach compared to traditional fuzzy logic methods. Vimala et al. [18] enhanced the PROMETHEE method by integrating (p, q)-rung linear Diophantine fuzzy sets for robot selection issues. This study demonstrated that the approach enhanced decision accuracy by integrating membership and non-membership degrees within a linear Diophantine framework. Surya et al. [19] proposed an entropy-based method for q-rung linear Diophantine fuzzy hypersoft sets, utilised in multi-attribute decision-making (MADM). The methodology improved judgement reliability and consistency in uncertain situations by systematically setting criteria weights. Using an alternative method for linear Diophantine fuzzy rough sets in two universes. Jeevitha et al. [20] studied digital transformation using linear Diophantine multi-fuzzy aggregation operators. LiDFS improves data fusion and decision-making in digital environments, especially Industry 4.0 applications, according to the study. Kamacı [21] created cosine similarity metrics for several applications using complex linear Diophantine fuzzy sets. Pattern recognition, image processing, and medical diagnosis were studied to demonstrate LiDFS adaptability. The studies demonstrate the effectiveness of linear Diophantine fuzzy sets in complex decision-making. The integration of LiDFS with entropy methods, aggregation operators, and similarity measures has improved decision accuracy, proving valuable across domains such

as robotics, digital transformation, and medical applications. Future research may investigate hybrid models that integrate LiDFS with other advanced computational techniques to enhance applicability.

1.2 A Review of MEREC, RANCOM, and MAUT Approaches

Saidin et al. [22] evaluate alternative performance using the fuzzy MEREC approach, which alters the normalising technique and improves the algorithm function in the weighting phase. Wang et al. proposed a methodology for optimising e-commerce platform selection through the root assessment method and MEREC weighting. The study incorporates MEREC to ensure decision-makers prioritise criteria according to their contribution to overall variability, thereby strengthening platform selection robustness. Divya et al. [23] presented a systematic method employing MEREC and CoCoSo to assess critical testing coverage metrics in software development. This study shows that integrating MEREC and CoCoSo enhances the accuracy of system reliability assessments by highlighting key software quality attributes. Kara et al. developed a hybrid MEREC-RBNAR framework to improve the financial performance evaluation of sustainability-indexed companies. The study demonstrated the effectiveness of integrating objective weighting MEREC with machine learning to develop predictive models for financial decision-making. Mastilo et al. [24] utilised MEREC alongside the MARCOS method to evaluate financial indicators in Bosnia and Herzegovina's banking sector. The study demonstrates MEREC's effectiveness in assigning objective weights to essential financial indicators, minimising evaluation subjectivity. Yadav et al. proposed an enhanced MEREC-TOPSIS method for optimal network selection in 5G heterogeneous networks for IoT applications. This study highlighted the necessity of a systematic method for selecting the optimal network according to diverse performance criteria. The integration of MEREC with TOPSIS facilitates a balanced and objective criterion weighting process, enhancing the efficiency and reliability of network selection in IoT-based 5G environments.

The RANCOM approach presented in this paper offers a novel strategy to address the limitations of expert judgements, frequently utilised in MCDM. This study identifies the evolutionary background, classification, verification, application, and comparative evaluation of RANCOM through existing academic literature. RANCOM, developed by Wieckowski et al. [25], compares criterion relevance and assesses the expert's error value impact. Inaccurate measurement modelling enhances decision-making processes, distinguishing it from traditional methods like AHP.

Wieckowski et al. [26] improved the proposed method by creating fuzzy RANCOM, which addresses model uncertainties using fuzzy theory. This singularity enhances flexibility and precision, which are essential in contexts characterised by limited or ambiguous data. The advancements have broadened the applicability of RANCOM, establishing it as a solution for diverse resource allocation challenges. This method has seen extensive application, particularly within the energy and sustainability sectors. Wieckowski et al. [27] utilised RANCOM in comparative analyses of COPRAS, PROMETHEE, and EDAS, specifically focused on sustainable energy development. The comparisons underscored RANCOM's ability to enhance understanding of criteria relevance and problem-solving associated with weight assignment. Kizielewicz et al. [28] improved the neutrosophic distance measure by utilizing RANCOM and the AROMAN model to examine sustainable human resource management in manufacturing firms. The examples illustrate the successful use of RANCOM in addressing organizational challenges related to subjective assessments and their associated risks. This study validates the RANCOM method as an innovative multi-criteria decision-making approach, distinguishing it from prior research that depended on expert estimates. Artificial neural networks (ANN) demonstrate significant compatibility with fuzzy logic, as supported by numerous studies that underscore their applicability in various business sectors. The implementation of energy systems, sustainability, and organizational management illustrates the effectiveness of the intervention, while comparisons with traditional methods reveal significant advantages. The complexity of management decision-making tasks requires the multi-

dimensional strategy provided by RANCOM, which is expected to yield improved and more transparent outcomes.
MAUT is a prevalent decision-making framework that enables the assessment of various alternatives through utility functions. The method has been utilised in multiple domains, such as employee selection, social welfare, business expansion, and infrastructure planning. This literature review examines recent studies that illustrate the versatility and effectiveness of the MAUT method. Setiawansyah et al. [29] examined the application of the Geometric G-MAUT in identifying the optimal honorary employees. The study demonstrated the efficacy of employing a geometric mean approach to enhance decision accuracy by considering multiple performance attributes.
Akpan and Morimoto [30] examined how MAUT can prioritise rural road development in Nigeria. Their study showed how MAUT might help policymakers prioritise infrastructure projects by socioeconomic effect, accessibility, and feasibility. Mahendra and Hartono [31] enhanced the application by combining AHP with MAUT for on-the-work training student placement, better aligning competencies with work requirements. MAUT is effective in structured decision-making across areas, as shown by the evaluated studies. MAU provides a flexible framework for complicated multi-criteria evaluations in employee selection, social welfare, corporate expansion, and infrastructure planning. Future research may investigate hybrid MAUT-machine learning models to improve DSS and predictive analytics.

1.3 Research gap

Despite the extensive research on RES selection using MCDM methods, several critical gaps remain unaddressed:

- Numerous studies utilize traditional fuzzy sets or crisp data, which inadequately address the uncertainty and vagueness present in expert evaluations. A more flexible and precise approach to handling uncertainty is necessary.
- Previous studies predominantly depend on subjective expert opinions or exclusively emphasize data-driven objective weighting methods. Limited research combines subjective and objective weight assignment methods to facilitate a balanced and impartial evaluation process.
- Numerous MCDM methods are available for RES evaluation; however, they are frequently utilised independently, neglecting the potential benefits of integrating various techniques. An integrated framework is required that incorporates uncertainty modelling, subjective-objective weighting mechanisms, and a robust ranking methodology.
- Numerous studies present a singular ranking outcome without evaluating its stability. Sensitivity analysis is frequently neglected, complicating the assessment of how ranking outcomes fluctuate with changes in criteria weights.
- Scalability and adaptability are critical factors in system design and implementation. Concerns: Current decision-support models are frequently tailored to particular case studies or regional contexts, which restricts their relevance across varied geographical, economic, and policy-driven settings. A more generalized and adaptable framework is required.

1.4 Motivation and contribution

The transition to RES is essential for meeting sustainability objectives, decreasing carbon emissions, and securing energy stability. The selection of the most suitable renewable energy sources involves a complex challenge characterized by multiple, often conflicting criteria, such as economic feasibility, environmental impact, technical performance, and social acceptance. The selection process encounters considerable difficulties stemming from the uncertainty associated with expert opinions and the variability of data. Traditional decision-making models do not sufficiently account for this ambiguity, leading to inconsistencies and biased results. Moreover, many contemporary studies rely solely on subjective expert-based weight assignment or entirely on objective statistical methods, resulting in an unbalanced approach that fails to integrate both perspectives. Moreover, many decision models exhibit insufficient validation via sensitivity and comparative analysis, complicating the evaluation of ranking stability in varying conditions. Due to the evolving characteristics of the energy sector, a robust and flexible DSS is essential for improving the reliability of decision-making. This study proposes a hybrid MCDM framework to address these challenges, incorporating LiDFS for uncertainty modelling, RANCOM for subjective weight determination, MEREC for objective weight calculation, and MAUT for ranking RES alternatives. The analysis includes sensitivity and comparative assessments to validate the model's robustness. This research integrates advanced methodologies to offer decision-makers, policymakers, and energy planners a reliable, data-driven, and adaptable decision-support system for renewable energy investments.

Contribution of the paper

The key contributions of this paper are as follows:

- Introduces LiDFS for the effective management of uncertainty and imprecise information in decision-making processes.
- Employs RANCOM for the determination of subjective weights and MEREC for the computation of objective weights, thereby ensuring a balanced and reliable assessment of the importance of criteria.
- Implements MAUT to rank alternatives, providing a structured, preference-based decision-making framework.
- Evaluates the influence of weight variations on ranking results, thereby ensuring the stability and robustness of the proposed model.
- Evaluates the proposed framework's effectiveness through a comparative analysis with alternative decision-making methods to underscore its advantages.
- Offers a scientifically validated methodology for policymakers and energy planners to select the most appropriate RES.

1.5 Structure of the paper

The study is organised systematically, beginning in Section 2 with a comprehensive analysis of the fundamental concepts and principles of LiDFS. This section systematically establishes the foundation by elucidating the fundamental concepts, mathematical expressions, and key characteristics of LiDFs. Building on this foundation, Section 3 introduces the proposed MEREC and RANCOM-MAUT technique, which effectively integrates the MAUT approach for alternative ranking with the MEREC method for determining criterion weights. A comprehensive analysis of the methodological complexity is presented. Section 4 presents a real-world scenario that demonstrates the practical applicability of MEREC and RANCOM-MAUT in the context of WMS software selection. Section 5 presents a summary of the findings, an analysis, and recommendations for further research on environmentally sustainable industrial practices.

2. Preliminaries

Definition 2.1. *[13]*A LiDFS $\aleph$ in χ is defined as

$$\aleph = \{(E, \langle \varpi_{\P}(E), \varepsilon_{\P}(E)\rangle, \langle \varrho_{\P}(E), \psi_{\P}(E)\rangle) : E \in \chi\},$$

where $\varpi_{\P}(E), \varepsilon_{\P}(E), \varrho_{\P}(E), \psi_{\P}(E) \in [0,1]$ are the MD, the NMD and the corresponding "reference parameters (RPs)", respectively. Moreover,

$$0 \le \varrho_{\P}(E) + \psi_{\P}(E) \le 1,$$

and

$$0 \le \varrho_{\P}(E)\varpi_{\P}(E) + \psi_{\P}(E)\varepsilon_{\P}(E) \le 1$$

for all $E \in \chi$. The LiDFS

$$\aleph_{\chi} = \{(E, \langle 1,0\rangle, \langle 1,0\rangle) : E \in \chi\}$$

is known the absolute LiDFS in χ. The LiDFS

$$\aleph_{\phi} = \{(E, \langle 0,1\rangle, \langle 0,1\rangle) : E \in \chi\}$$

is known the null LiDFS in χ.

The RPs can be applied to describe or classify certain structures. Sorting different systems can be achieved by changing the physical meaning of the reference parameters.

Definition 2.2. *[13]*A "linear Diophantine fuzzy number" (LiDFN) is a tuple $\ell = (\langle \varpi_\ell, \varepsilon_\ell\rangle, \langle \varrho_\ell, \psi_\ell\rangle)$ satisfying the following conditions:

(1) $0 \le \varpi_\ell, \varepsilon_\ell, \varrho_\ell, \psi_\ell \le 1$;

(2) $0 \le \varrho_\ell + \psi_\ell \le 1$;

(3) $0 \le \varrho_\ell \varpi_\ell + \psi_\ell \varepsilon_\ell \le 1$.

Definition 2.3. *[13]*Let $\ell = (\langle \varpi_\ell, \varepsilon_\ell\rangle, \langle \varrho_\ell, \psi_\ell\rangle)$ be a LiDFN, then score function $\wp(\ell)$ can be define by the mapping $\wp(\ell) : LiDFN(\chi) \to [-1,1]$ and given by

$$\wp(\ell) = \frac{1}{2}[(\varpi_\ell - \varepsilon_\ell) + (\varrho_\ell - \psi_\ell)] \tag{1}$$

where $LiDFN(\chi)$ is an assemblage of LiDFNs on χ.

Definition 2.4. *[13]*Let $\ell = (\langle \varpi_\ell, \varepsilon_\ell\rangle, \langle \varrho_\ell, \psi_\ell\rangle)$ be a LiDFN, then accuracy function can be defined by the mapping $\rho : LiDFN(\chi) \to [0,1]$ and given as

$$\rho(\ell) = \frac{1}{2}\left[\left(\frac{\varpi_\ell + \varepsilon_\ell}{2}\right) + (\varrho_\ell + \psi_\ell)\right]$$

Definition 2.5. *[13]*The accuracy and score functions may be used to produce the following, given two LiDFNs, ℓ_1 and ℓ_2:
(i): If $\wp(\ell_1) < \wp(\ell_2)$ then $\ell_1 < \ell_2$,
(ii): If $\wp(\ell_2) < \wp(\ell_1)$ then $\ell_2 < \ell_1$,
(iii): If $\wp(\ell_2) = \wp(\ell_1)$ then,
(a): If $\rho(\ell_1) < \rho(\ell_2)$ then $\ell_1 < \ell_2$,
(b): If $\rho(\ell_2) < \rho(\ell_1)$ then $\ell_2 < \ell_1$,
(c): If $\rho(\ell_1) = \rho(\ell_2)$ then $\ell_1 = \ell_2$.

Definition 2.6. *[13]*Let $\ell = (\langle \varrho_\ell, \psi_\ell \rangle), \varpi_\ell, \varepsilon_\ell \rangle) If$ is a LiDFN, then the expectation score function (ESF) on $LiDFN(\chi)$ with range $\mathscr{H} : LiDFN(\chi) \to [0,1]$ is another definition of a scoring function and specify as

$$\mathscr{H}(\ell) = \frac{1}{2}\left[\frac{(\varpi_\ell - \varepsilon_\ell + 1)}{2} + \frac{(\varrho_\ell - \psi_\ell + 1)}{2}\right]$$

Definition 2.7. *[13]*Let $\ell_i = (\langle \varpi_i, \varepsilon_i \rangle, \langle \varrho_i, \psi_i \rangle)$ be two LiDFNs with $i = 1,2$. Then

- $\ell_1 \subseteq \ell_2 \Leftrightarrow \varpi_1 \le \varpi_2, \varepsilon_2 \le \varepsilon_1, \varrho_1 \le \varrho_2, \psi_2 \le \psi_1$;
- $\ell_1 = \ell_2 \Leftrightarrow \varpi_1 = \varpi_2, \varepsilon_1 = \varepsilon_2, \varrho_1 = \varrho_2, \psi_1 = \psi_2$;
- $\ell_1 \oplus \ell_2 = \left(\langle \varpi_1 + \varpi_2 - \varpi_1\varpi_2, \varepsilon_1\varepsilon_2 \rangle, \langle \varrho_1 + \varrho_2 - \varrho_1\varrho_2, \psi_1\psi_2 \rangle\right)$;
- $\ell_1 \otimes \ell_2 = \left(\langle \varpi_1\varpi_2, \varepsilon_1 + \varepsilon_2 - \varepsilon_1\varepsilon_2 \rangle, \langle \varrho_1\varrho_2, \psi_1 + \psi_2 - \psi_1\psi_2 \rangle\right)$.
- $\ell_1^c = (\langle \varepsilon_1, \varpi_1 \rangle, \langle \psi_1, \varrho_1 \rangle)$;
- $\varepsilon\ell_1 = \left(\langle 1-(1-\varpi_1)^\omega, \varepsilon_1^\omega \rangle, \langle 1-(1-\varrho_1)^\omega, \psi_1^\omega \rangle\right)$;
- $\ell_1^\omega = \left(\langle \varpi_1^\omega, 1-(1-\varepsilon_1)^\omega \rangle, \langle \varrho_1^\omega, 1-(1-\psi_1)^\omega \rangle\right)$.

Definition 2.8. *[13]*Let $\hbar_i = \{((\varpi^\omega{}_i, \varepsilon^\omega{}_i), (\varrho_i^\omega, \psi_i)^\omega)) : i = 1,2,3,...,n\}$ be the collection of LDFNs and $w = ({}_1, {}_2, ..., {}_n)^T$ be the weight vector with $\sum_{i=1}^{n} {}_i = 1$, then the mapping $\mho : LDFN(X) \to LDFN(X)$ is called linear Diophantine fuzzy weighted geometric aggregation operator (LiDFWGAO) and defined as

$$LiDFWGA(\hbar_1, \hbar_2, \hbar_3, ..., \hbar_n) = \prod_{i=1}^{n} \hbar_{\mathscr{D}_i}^{i} = \left(\left(\prod_{i=1}^{n} \varpi^{\omega_i}{}_i, 1 - \prod_{i=1}^{n}(1-\varepsilon^\omega{}_i)^i\right), \left(\prod_{i=1}^{n} \varrho_i^{\omega_i}, 1 - \prod_{i=1}^{n}(1-\phi_i^\omega)^{w_i}\right)\right). \quad (2)$$

3. MEREC and RANCOM-MAUT Model based on LiDFSs

Assume that there is a set of m alternatives of the kind $D = \{S^v{}_1, \ldots, S^v{}_i, \ldots, S^v{}_m\}$, and that n is larger than or equal to 2. The value of C, which represents a finite collection of criteria, may be represented in the following manner: In the mathematical representation of G, the equation $G = \{C_1, \ldots, C_j, \ldots, C_n\} (n \ge 2)$ is used. D = $\{D_1, \ldots, D_e, \ldots, D_z\} (z \ge 2)$ is the definition of the set of decision-makers (DMs) that have been invited. It is possible to have a better understanding of the MEREC and RANCOM-MAUT method by going through the steps that are listed below.

Algorithm

Step 1: Generalized linguistic terms are used to describe each alternative, and these terms are provided in Table 1. In addition to providing more evidence for these beliefs, Table 2 also includes linguistic idioms that are associated with knowledge. Because there is such a wide variety of linguistic languages accessible, it is feasible to provide a full depiction of the process of information evaluation. Compare the data set that was entered by LiDFNs with the parameters that are pertinent to the situation. Consider the impact of many criteria on the value of $\mathrm{S}^v{}_\mathrm{p}; (p = 1,2,...,m)$, assuming that $C_q; (q = 1,2,...,n)$.

Table 1
Generalized linguistic terms and their corresponding LiDFNs

Linguistic term	Abbreviation	LiDFNs
Importance level$_1$	$M.V_1$	$(\langle 1-0.05\cdot 0,\ 0+0.05\cdot 0\rangle,\ \langle 0.9-\frac{0.05\cdot 0}{2},\ 0.1+\frac{0.05\cdot 0}{2}\rangle)$
Importance level$_2$	$M.V_2$	$(\langle 1-0.05\cdot 1,\ 0+0.05\cdot 1\rangle,\ \langle 0.9-\frac{0.05\cdot 1}{2},\ 0.1+\frac{0.05\cdot 1}{2}\rangle)$
$\vdots$	$\vdots$	$\vdots$
Importance level$_h$	$M.V_h$	$(\langle 1-0.05\cdot(h-1),\ 0+0.05\cdot(h-1)\rangle,\ \langle 0.9-\frac{0.05\cdot h}{2},\ 0.1+\frac{0.05\cdot h}{2}\rangle)$
$\vdots$	$\vdots$	$\vdots$
Importance level$_n$	$M.V_n$	$(\langle 1-0.05\cdot(n-1),\ 0+0.05\cdot(n-1)\rangle,\ \langle 0.9-\frac{0.05\cdot n}{2},\ 0.1+\frac{0.05\cdot n}{2}\rangle)$

Table 2
Decision Makers' Roles and Experience

Profession	**Role and Responsibilities**	**Experience**
Energy Policy Analyst	Evaluates energy policies, assesses regulatory frameworks, and ensures sustainability in renewable energy adoption.	15 years in energy policy development and regulatory analysis.
Renewable Energy Engineer	Designs and optimizes RES, assesses technical feasibility, and ensures efficiency in implementation.	12 years in RES design and project management.
Environmental Economist	Analyzes economic impacts of renewable energy, conducts cost-benefit analysis, and ensures financial viability of projects.	10 years in energy economics, sustainability analysis, and financial modeling.

Step 2: The DMs should be ranked according to the relevance of LiDFNs, assuming that Table 1 includes the LTs. The LiDFN for the importance of the k-th DM. This is the assumption that we are making. On account of this, the weight Φ_k of the k-th DM determined by employing the method that can be found in Equation 3:

$$\Phi_k = \frac{U_e}{\sum_{k=1}^{p} U_e}, k = 1,2,3,\dots z \tag{3}$$

where $U_e = \frac{\sum_{k=1}^{p}[(\varpi_\ell-\varepsilon_\ell)+(\varrho_\ell-\psi_\ell)]}{[\sum_{k=1}^{q}\sum_{k=1}^{p}(\varpi_\ell-\varepsilon_\ell)+(\varrho_\ell-\psi_\ell)]}$ and clearly $\sum_{k=1}^{p}\Phi_k = 1$.

Step 3: Utilizing Equation 2, compute the aggregated decision matrix $M = [M_{ij}]_{m\times n}$.

Weighting method MEREC

Step 4: Use Equation 1 to calculate the aggregated matrix score.
Step 5: Equation 4 is used to apply the normalization to the decision matrix, yielding the matrix α_{ij}.

$$\alpha_{ij} = \begin{cases} \dfrac{\wp(\ell)_{ij} - \min\limits_i(\wp(\ell)_{ij})}{\max\limits_i(\wp(\ell)_{ij}) - \min\limits_i(\wp(\ell)_{ij})}, \ for\ benefical\ criteria \\ \dfrac{\max\limits_i(\wp(\ell)_{ij}) - \wp(\ell)_{ij}}{\max\limits_i(\wp(\ell)_{ij}) - \min\limits_i(\wp(\ell)_{ij})}, \ for\ cost\ criteria \end{cases} \tag{4}$$

Step 6: Before calculating the overall performance values of the alternatives, we have to deal with $ln(\alpha_{ij})$ for $\alpha_{ij} = 0$ and its undefined value. Therefore, a standardization step is introduced via expression 5.

$$\eta_{ij} = \frac{\alpha_{ij} + \tau}{\sum\limits_{i=1}^{m}(\alpha_{ij} + \tau)} \tag{5}$$

where, $\alpha_{ij} + \tau > 0$.
Step 7: In this stage, the total performance of the alternatives is calculated using equation 6 since it is crucial to know how well each option performs in determining the weights of the criteria.

$$\gamma_i = ln\left(1 + \left(\theta \sum_j ln|\eta_{ij}|\right)\right), \quad \theta = \frac{1}{m} \tag{6}$$

Step 8: By subtracting each criterion from the total performance amounts, γ_{ij}^p in Equation 7 represents the partially achieved performance levels associated with the ith alternatives, by the approach's specificity, which is based on the impact caused by eliminating jth criteria.

$$\gamma_{ij}^p = ln\left(1 + \left(\frac{1}{m} \sum_{k,k\neq j} |ln(\eta_{ij})|\right)\right) \tag{7}$$

Step 9: The sum of all the variations After the jth criteria are removed, the value V_j is calculated using the values from the previous steps, as Equation 8 below illustrates:

$$V_j = \sum_i |\gamma_{ij}^p - \gamma_i|, \ \ \forall j \tag{8}$$

Step 10: The weights of each criterion are determined in this stage by computing the elimination impact of consequences V_j. The notation $\Re(\xi)_j$ denotes the weight of the jth criteria. Weights are computed using the following formula 9.:

$$\Re(\xi)_j = \frac{V_j}{\sum\limits_j V_j}, \ \ \forall j \tag{9}$$

RANCOM

Step 11: The ranking comparison matrix (π) was constructed by calculating the relative locations of each criterion.

$$H = \begin{array}{c c} & \begin{bmatrix} \Re(\xi)_1 & \Re(\xi)_2 & \cdots & \Re(\xi)_n \end{bmatrix} \\ \begin{array}{c} \Re(\xi)_1 \\ \Re(\xi)_2 \\ \vdots \\ \Re(\xi)_n \end{array} & \begin{bmatrix} \pi_{11} & \pi_{12} & \cdots & \pi_{1n} \\ \pi_{21} & \pi_{22} & \cdots & \pi_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \pi_{n1} & \pi_{n2} & \cdots & \pi_{nn} \end{bmatrix} \\ & [\qquad\qquad\qquad\qquad\qquad\qquad] \end{array}$$

Where,

$$\mathfrak{K}_{ij} = \begin{cases} 1, & \Re(\xi)_i) < (\Re(\xi)_j) \\ 0, & \Re(\xi)_i) > (\Re(\xi)_j) \\ 0.5, & \Re(\xi)_i) = (\Re(\xi)_j) \end{cases} \tag{10}$$

and $\S(\Re(\xi)_j)$ is the significance function of jth criteria.
Step 12: Using Equation (11), the weights of the summand criterion (ρ) are established.

$$\varphi_j = \sum_{t=1}^{n} \pi_{jt}, j = 1, 2, \ldots, b \tag{11}$$

Step 13: To evaluate the criterion's weight subjectively, solve the formula (12).

$$\varphi_j{}^A = \frac{\rho}{\sum_{j=1}^{n} \rho} j = 1, 2, \ldots, n \tag{12}$$

Step 14: Equation (13) uses the objective weighting technique MEREC and the RANCOM to calculate the criterion weights. Thus, the final criteria weights are determined as shown in Equation (14).

$$C^{\zeta}{}_j = \frac{(\lambda)\Re(\xi)_j + (1-\lambda)\varphi_j{}^A{}_j}{2}, \quad \lambda \in [0,1] \quad j = 1, 2, \ldots, n \tag{13}$$

$$\beth_j = \frac{C^{\zeta}{}_j}{\sum_{j=1}^{t} C^{\zeta}{}_j} j = 1, 2, \ldots, n \tag{14}$$

3.1 MAUT

Step 15: The values of the choice matrix are normalized under the type of qualities that are either positive or negative. The values of the positive attributes are normalized with the help of Equation (15), and those of the negative attributes are normalized with Equation (16).

$$Q^{y}_{ij} = \frac{\wp(\ell)ij - \min(\wp(\ell)ij)}{\max(\wp(\ell)ij) - \min(\wp(\ell)ij)} \tag{15}$$

$$Q^{y}_{ij} = 1 + \frac{\min(\wp(\ell)ij) - \wp(\ell)ij}{\max(\wp(\ell)ij) - \min(\wp(\ell)ij)} \tag{16}$$

Step 16: Determine the marginal utility score using the Equation (17).

$$\daleth_{ij} = \frac{e^{(Q^y)^2} - 1}{1.71} \tag{17}$$

Step 17: The ultimate utility score of each alternative is determined by applying Equation (18) to the data and ranking the alternative by using the utility score values.

$$\Xi_i = \sum_{j=1}^{m} \daleth_{ij} \cdot \beth_j \tag{18}$$

4. Statement of the Problem

The global energy environment is undergoing a significant transition driven by the rising need for sustainable, low-carbon energy alternatives. This transformation is propelled by multiple interconnected causes, including as climate change mitigation, the exhaustion of fossil fuel supplies, energy security issues, and the necessity for long-term economic stability. Various governments and companies worldwide are working to transition from traditional fossil fuel-based energy production to cleaner renewable energy sources. Technologies including solar, wind, hydro, biomass, and geothermal energy offer effective solutions for significantly reducing greenhouse gas emissions while maintaining a reliable and sustainable energy supply. Selecting the appropriate energy source for a given region or application, notwithstanding the considerable potential of renewable energy sources, constitutes a complex and multifaceted challenge. Decision-making entails a variety of frequently conflicting criteria, including economic, environmental, technical, and social factors. Each renewable energy option presents distinct advantages and disadvantages, with its efficacy influenced by contextual factors including local conditions, existing infrastructure, and regulatory frameworks. Investments in renewable energy necessitate significant capital expenditure, thus requiring a comprehensive evaluation to guarantee cost-effectiveness and long-term sustainability. A significant challenge in selecting renewable energy sources is balancing economic viability with environmental sustainability. Although certain renewable energy technologies present reduced operational costs, they often necessitate substantial initial investments or encounter challenges related to energy storage and grid integration. In contrast, many environmentally sustainable alternatives may encounter obstacles to commercial viability due to technological limitations or regulatory barriers. The complexities of energy security, especially the intermittent characteristics of solar and wind energy, present challenges for decision-making, requiring the adoption of hybrid solutions or advanced energy storage systems.

A notable concern is the unpredictability and inconsistency in the performance of renewable energy sources. Variable weather conditions, resource accessibility, and technical progress provide significant uncertainty in renewable energy source assessments. This unpredictability hinders the establishment of a universal strategy, requiring adaptable, data-informed techniques for decision-makers to respond to evolving conditions. The selection process is affected by stakeholder preferences and subjective evaluations, leading to inconsistencies and biases. Stakeholders, such as legislators, investors, local communities, and environmental organisations, have varied priorities and risk perceptions. Incorporating varied viewpoints into a systematic decision-making framework poses a considerable difficulty. An effective, open, and scientifically rigorous decision-support framework is crucial for the objective assessment of diverse renewable energy options, given the significant implications of these investments. A framework must accommodate extensive datasets, incorporate both quantitative and qualitative criteria, and mitigate biases in expert evaluations.

To address these complexities, this study proposes a novel MCDM approach that integrates:

- MEREC aims to ascertain the objective weights of evaluation criteria through the analysis of data-driven variability.
- RANCOM is designed to integrate subjective expert opinions in a structured and impartial way.

- MAUT is utilized to rank and choose the most appropriate renewable energy alternative based on a thorough utility-based decision model.

The proposed model integrates advanced MCDM techniques to address the challenges associated with renewable energy selection, providing a more effective, data-driven, and transparent DSS for policymakers and industry stakeholders.

4.1 Renewable Energy Alternatives

Floating Solar Photovoltaics (${S^v}_1$)

Solar panels are mounted on floating platforms over water features such as lakes, reservoirs, and coastlines. This technology is gaining popularity because of its capacity to overcome land constraints while improving energy efficiency by utilising the cooling impact of water. The floating structure is made up of buoyant supports, anchoring systems, and solar modules, which turn sunshine into electricity. These devices can be integrated into existing hydroelectric infrastructure to increase renewable energy generation.
Advantages:

- Water cooling improves the performance of photovoltaic cells by mitigating overheating and minimizing efficiency loss.
- Reduces the requirement for extensive land areas, rendering it appropriate for densely populated areas.
- Minimizes evaporation from aquatic environments, advantageous for regions with limited water resources.
- Restricts excessive sunlight penetration, thereby preventing harmful algal blooms that compromise water quality.

Disadvantages:

- Increases construction costs by necessitating specialized floating platforms and anchoring systems.
- May disrupt aquatic ecosystems and impact water oxygen levels.
- Exposure to water can result in biofouling and corrosion, which can increase maintenance requirements.

Tidal Energy (${S^v}_2$)

Tidal energy uses the kinetic and potential energy of the ocean tides to generate power. This is accomplished via tidal barrages, underwater turbines, and dynamic tidal power systems. Tidal barrages, like hydroelectric dams, use rising and falling water levels to power turbines. Like wind turbines, tidal stream generators employ underwater turbines to gather energy from ocean currents. This technique takes use of tide predictability to provide a dependable supply of renewable energy.
Advantages:

- Unlike solar and wind energy, tidal energy is unaffected by weather and has a predictable moon cycle.

- Tidal power stations can run for over 100 years with low fuel costs.
- Produces clean energy with no direct greenhouse gas emissions.

Disadvantages:

- The construction of tidal barrages and underwater turbines necessitates substantial expenditure.
- Exclusively appropriate for coastal areas exhibiting significant tidal activity.
- May interfere with marine ecosystems, impact ichthyological migration, and modify tidal dynamics.

Green Hydrogen Energy ($S^v{}_3$)

Green hydrogen is created by splitting water molecules into hydrogen and oxygen using renewable electricity via electrolysis. Unlike traditional hydrogen manufacturing methods that use fossil fuels, green hydrogen is a clean and sustainable energy carrier. It can be stored, transported, and used in fuel cells to generate power, conduct industrial processes, and carry goods. Green hydrogen is a viable solution for decarbonizing industries that are difficult to electrify, such as aviation and heavy manufacturing.
Advantages:

- Hydrogen combustion or fuel cell operation produces just water as a waste.
- It can be stored for extended periods and used as needed.
- Applications include power generation, transportation, and industrial heating.

Disadvantages:

- Electrolysis involves greater expenses compared to conventional hydrogen production techniques.
- The process requires high-pressure tanks or cryogenic conditions.
- Energy conversion from electricity to hydrogen and back to electricity demonstrates inefficiencies.

Algae Biofuel Energy ($S^v{}_4$)

Algae biofuels originate from microalgae that efficiently capture carbon dioxide and generate lipid-rich biomass, which can be transformed into biodiesel, bioethanol, or biogas. In contrast to traditional biofuels sourced from food crops, algae can be grown on non-arable land utilising wastewater, thereby minimising competition with food production. This renewable energy source has the potential to supplant fossil fuels in aviation, transportation, and power generation.
Advantages:

- Algae sequester carbon $C\gamma_2$ during their growth phase, mitigating emissions from fuel combustion.
- Algae exhibit a higher reproduction rate compared to terrestrial biofuel crops, ensuring a consistent supply.

- Can be grown on wastewater or saline land.

Disadvantages:

- Cultivation and extraction technologies remain costly.
- Large-scale commercial production is in the nascent phase.
- The conversion of algae into biofuels necessitates a significant energy investment.

Enhanced Geothermal Systems ($S^{v}{}_{5}$)

It uses hydraulic fracturing and sophisticated drilling methods to draw heat from subterranean reservoirs. EGS produces artificial reservoirs by injecting water into arid rock formations to produce steam, in contrast to conventional geothermal systems that depend on naturally existing hot water. Geothermal energy is now much more accessible in areas lacking natural geothermal hotspots because of this technology.
Advantages:

- Ensures a consistent and reliable source of power generation, unaffected by weather conditions.
- Demands a smaller footprint in comparison to solar and wind farms.
- It is capable of functioning for many years with minimal maintenance expenses.

Disadvantages:

- Deep drilling and hydraulic fracturing contribute to elevated development costs.
- Fluid injection has the potential to trigger minor seismic activity.
- It is essential to have particular geological conditions in place to ensure successful implementation.

Effective solutions for sustainable energy development are offered by the five cutting-edge renewable energy options covered in this study. Since every alternative has distinct advantages and disadvantages, it is essential to use an MCDM technique to assess each one's viability in light of technological, financial, and environmental considerations.

4.2 Evaluation criteria for alternatives

Economic Viability C_1

The overall cost-effectiveness of setting up and running a RES is called economic viability. This covers the levelized energy cost, capital expenditures, and operating and maintenance expenses.
Impact: A cost-effective renewable energy solution promotes long-term financial sustainability. Significant initial investment costs may present a barrier; however, reduced operational expenses and government incentives can enhance financial viability.

Energy Efficiency C_2

Energy efficiency assesses the efficacy of RES in transforming available resources into useful electricity or heat. It is articulated as the proportion of input energy transformed into beneficial output.
Impact: Enhanced efficiency results in increased energy production with reduced resource consumption, yielding superior cost savings and enhanced environmental performance. Inefficient systems may necessitate expanded infrastructure, hence escalating costs and land utilization.

Environmental Impact C_3

The environmental impact criterion evaluates the ecological footprint of energy production, encompassing greenhouse gas emissions, water usage, and ecosystem disruption.
Impact: Renewable energy must mitigate environmental harm. Technologies that produce significant emissions or adversely impact biodiversity may lack long-term sustainability. Minimally invasive solutions improve public approval and adherence to regulations.

Resource Availability C_4

This criterion assesses the availability and accessibility of natural resources necessary for energy production, such as sunlight, wind velocities, geothermal energy, or biomass supplies.
Impact: A reliable and sufficient resource supply guarantees stable energy production. Energy sources that depend on seasonal or geographical availability may necessitate backup systems or energy storage solutions, thereby increasing complexity.

Technological Maturity C_5

This applies to the degree of advancement and market readiness of a renewable energy technology, encompassing its reliability, scalability, and compatibility with current energy grids.
Impact: Technologies that are well-established and demonstrate proven performance present lower risks for investment and implementation. Emerging technologies have the potential to enhance efficiency; however, they necessitate additional research and infrastructure development.

Energy Storage and Grid Integration C_6

The capacity to store generated energy and incorporate it into the electricity grid is crucial for the effective provision of a stable and reliable power supply by RES.
Impact: Continuous energy sources such as solar and wind necessitate effective storage solutions, including batteries and pumped hydro, to guarantee consistent power availability. Inadequate grid integration can result in energy loss or instability.

Social Acceptance and Policy Support C_7

Social acceptance encompasses public perception, community engagement, and backing from policymakers, which includes government incentives, subsidies, and regulatory structures.
Impact: Robust policy backing and popular endorsement help to accelerate renewable energy deployment. Projects facing local opposition or insufficient legislative incentives may face delays, legal challenges, or funding issues.

Table 4
DMs weights for evaluation

DM	Role	Role	Key responsibilities	Weight
DM_1	$M.V_1$	$M.V_3$	$M.V_5$	0.4640
DM_2	$M.V_3$	$M.V_2$	$M.V_3$	0.3367
DM_3	$M.V_4$	$M.V_5$	$M.V_4$	0.1993

Scalability and Land Uses C_8

Scalability denotes the ease with which a RES can be augmented to accommodate increasing energy requirements. Land utilization assesses the geographic footprint necessary for installation. **Impact:** Scalable technologies enable long-term growth and energy security. Solar farms and biofuel plantations may conflict with agriculture or urban growth due to their land requirements.

4.3 Experimental Results

The procedure can be broken down into the following steps:
Step 1: For each alternative, the DMs employed the LiDFNs dataset along with other criteria (including language phrases from Table 1) given in Table 3.

Table 3
Evaluations of each alternative with extended criteria

DMs	Alternatives	Cr_1	Cr_2	Cr_3	Cr_4	Cr_5	Cr_6	Cr_7	Cr_8
DM_1	$S^v{}_1$	$M.V_3$	$M.V_5$	$M.V_7$	$M.V_{12}$	$M.V_9$	$M.V_{14}$	$M.V_6$	$M.V_8$
	$S^v{}_2$	$M.V_{11}$	$M.V_{14}$	$M.V_2$	$M.V_5$	$M.V_8$	$M.V_7$	$M.V_3$	$M.V_{12}$
	$S^v{}_3$	$M.V_9$	$M.V_6$	$M.V_{14}$	$M.V_3$	$M.V_{12}$	$M.V_8$	$M.V_{10}$	$M.V_1$
	$S^v{}_4$	$M.V_{10}$	$M.V_1$	$M.V_3$	$M.V_{13}$	$M.V_7$	$M.V_{11}$	$M.V_{12}$	$M.V_5$
	$S^v{}_5$	$M.V_7$	$M.V_8$	$M.V_4$	$M.V_6$	$M.V_{11}$	$M.V_3$	$M.V_9$	$M.V_{14}$
DM_2	$S^v{}_1$	$M.V_2$	$M.V_6$	$M.V_6$	$M.V_{11}$	$M.V_8$	$M.V_{13}$	$M.V_5$	$M.V_3$
	$S^v{}_2$	$M.V_{12}$	$M.V_{13}$	$M.V_1$	$M.V_6$	$M.V_7$	$M.V_6$	$M.V_4$	$M.V_{10}$
	$S^v{}_3$	$M.V_8$	$M.V_7$	$M.V_{13}$	$M.V_2$	$M.V_{11}$	$M.V_9$	$M.V_9$	$M.V_7$
	$S^v{}_4$	$M.V_9$	$M.V_2$	$M.V_2$	$M.V_{12}$	$M.V_6$	$M.V_{10}$	$M.V_{11}$	$M.V_4$
	$S^v{}_5$	$M.V_6$	$M.V_9$	$M.V_5$	$M.V_5$	$M.V_{10}$	$M.V_4$	$M.V_8$	$M.V_{13}$
DM_3	$S^v{}_1$	$M.V_5$	$M.V_3$	$M.V_9$	$M.V_5$	$M.V_{14}$	$M.V_3$	$M.V_7$	$M.V_{11}$
	$S^v{}_2$	$M.V_4$	$M.V_{11}$	$M.V_6$	$M.V_{13}$	$M.V_1$	$M.V_8$	$M.V_{10}$	$M.V_2$
	$S^v{}_3$	$M.V_{14}$	$M.V_5$	$M.V_3$	$M.V_7$	$M.V_9$	$M.V_{12}$	$M.V_2$	$M.V_6$
	$S^v{}_4$	$M.V_1$	$M.V_8$	$M.V_{13}$	$M.V_4$	$M.V_6$	$M.V_{11}$	$M.V_5$	$M.V_9$
	$S^v{}_5$	$M.V_7$	$M.V_3$	$M.V_{10}$	$M.V_2$	$M.V_{12}$	$M.V_9$	$M.V_{14}$	$M.V_1$

Step 2: Equation 3 was used to compute the weights of the DMs. The values obtained are shown in Table 4.
Step 3: The ADM $M = [M_{ij}]_{m\times n}$ may be built using Equation (2). Table 5 displays the outcomes.

Table 5
Aggregated decision matrix with randomized unique values

${S^v}_i$	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
${S^v}_1$	$(\langle 0.925,0.071\rangle\langle 0.648,0.083\rangle)$	$(\langle 0.937,0.057\rangle\langle 0.629,0.094\rangle)$	$(\langle 0.918,0.089\rangle\langle 0.681,0.067\rangle)$	$(\langle 0.912,0.068\rangle\langle 0.673,0.097\rangle)$	$(\langle 0.63,0.37\rangle,\langle 0.47,0.19\rangle)$	$(\langle 0.82,0.31\rangle,\langle 0.74,0.57\rangle)$	$(\langle 0.79,0.21\rangle,\langle 0.69,0.27\rangle)$	$(\langle 0.54,0.59\rangle,\langle 0.76,0.38\rangle)$
${S^v}_2$	$(\langle 0.847,0.088\rangle\langle 0.631,0.142\rangle)$	$(\langle 0.901,0.078\rangle\langle 0.679,0.124\rangle)$	$(\langle 0.902,0.092\rangle\langle 0.614,0.107\rangle)$	$(\langle 0.862,0.088\rangle\langle 0.598,0.076\rangle)$	$(\langle 0.31,0.46\rangle,\langle 0.43,0.36\rangle)$	$(\langle 0.65,0.42\rangle,\langle 0.67,0.26\rangle)$	$(\langle 0.85,0.27\rangle,\langle 0.57,0.39\rangle)$	$(\langle 0.81,0.33\rangle,\langle 0.72,0.46\rangle)$
${S^v}_3$	$(\langle 0.846,0.135\rangle\langle 0.621,0.123\rangle)$	$(\langle 0.839,0.146\rangle\langle 0.569,0.168\rangle)$	$(\langle 0.858,0.122\rangle\langle 0.589,0.134\rangle)$	$(\langle 0.851,0.139\rangle\langle 0.578,0.169\rangle)$	$(\langle 0.57,0.62\rangle,\langle 0.39,0.25\rangle)$	$(\langle 0.69,0.49\rangle,\langle 0.51,0.32\rangle)$	$(\langle 0.75,0.35\rangle,\langle 0.62,0.47\rangle)$	$(\langle 0.87,0.43\rangle,\langle 0.64,0.29\rangle)$
${S^v}_4$	$(\langle 0.836,0.152\rangle\langle 0.543,0.247\rangle)$	$(\langle 0.729,0.209\rangle\langle 0.527,0.316\rangle)$	$(\langle 0.742,0.238\rangle\langle 0.569,0.253\rangle)$	$(\langle 0.709,0.251\rangle\langle 0.738,0.274\rangle)$	$(\langle 0.49,0.58\rangle,\langle 0.41,0.49\rangle)$	$(\langle 0.81,0.53\rangle,\langle 0.37,0.31\rangle)$	$(\langle 0.87,0.38\rangle,\langle 0.49,0.39\rangle)$	$(\langle 0.92,0.35\rangle,\langle 0.69,0.57\rangle)$
${S^v}_5$	$(\langle 0.649,0.336\rangle\langle 0.542,0.414\rangle)$	$(\langle 0.709,0.275\rangle\langle 0.429,0.319\rangle)$	$(\langle 0.659,0.317\rangle\langle 0.517,0.371\rangle)$	$(\langle 0.729,0.247\rangle\langle 0.507,0.417\rangle)$	$(\langle 0.69,0.73\rangle,\langle 0.45,0.58\rangle)$	$(\langle 0.78,0.67\rangle,\langle 0.59,0.28\rangle)$	$(\langle 0.64,0.42\rangle,\langle 0.71,0.48\rangle)$	$(\langle 0.83,0.64\rangle,\langle 0.58,0.27\rangle)$

MEREC Method

Step 4: The formula from Equation 1 is used to declare the findings in the aggregated decision score matrix once the aggregated LiDFS score values have been formulated.

$$\begin{bmatrix} 0.7095 & 0.7075 & 0.7215 & 0.7100 & 0.2500 & 0.3500 & 0.5000 & 0.1950 \\ 0.6240 & 0.6890 & 0.6585 & 0.6480 & -0.0650 & 0.2850 & 0.3600 & 0.3650 \\ 0.6045 & 0.5470 & 0.5955 & 0.5605 & 0.0400 & 0.1950 & 0.2400 & 0.3600 \\ 0.4900 & 0.3655 & 0.4100 & 0.4610 & -0.1100 & 0.1650 & 0.3000 & 0.3150 \\ 0.2205 & 0.2720 & 0.2440 & 0.2860 & -0.1200 & 0.1650 & 0.1850 & 0.2000 \end{bmatrix}$$

Step 5: The normalized matrix η_{ij} may be produced by using Equation 4.

$$\eta_{ij} = \begin{bmatrix} 0.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 \\ 0.1748 & 0.9575 & 0.8681 & 0.8538 & 0.1486 & 0.6486 & 0.5556 & 0.0000 \\ 0.2147 & 0.6315 & 0.7361 & 0.6474 & 0.4324 & 0.1622 & 0.1746 & 0.0294 \\ 0.4489 & 0.2147 & 0.3476 & 0.4127 & 0.0270 & 0.0000 & 0.3651 & 0.2941 \\ 1.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0000 & 0.9706 \end{bmatrix}$$

Step 6: Before calculating the overall performance values of the alternatives, we have to deal with $ln(\alpha_{ij})$ for $\alpha_{ij} = 0$ and its undefined value. Therefore, a standardization step is introduced via expression 5.

$$\eta_{ij} = \begin{bmatrix} 0.2720 & 0.5350 & 0.5082 & 0.5148 & 0.9328 & 0.8284 & 0.7159 & 0.6538 \\ 0.3671 & 0.5199 & 0.4635 & 0.4646 & 0.4034 & 0.6343 & 0.5038 & 0.2179 \\ 0.3888 & 0.4036 & 0.4188 & 0.3938 & 0.5798 & 0.3657 & 0.3220 & 0.2308 \\ 0.5161 & 0.2549 & 0.2872 & 0.3132 & 0.3277 & 0.2761 & 0.4129 & 0.3462 \\ 0.8159 & 0.1783 & 0.1694 & 0.1716 & 0.3109 & 0.2761 & 0.2386 & 0.6410 \end{bmatrix}$$

Step 7: In this stage, the total performance of the alternatives is calculated using equation 6 since it is crucial to know how well each option performs in determining the weights of the criteria.

Table 6
$\mathbb{VRS}$ overall performance results

Alternatives	${S^v}_1$	${S^v}_2$	${S^v}_3$	${S^v}_4$	${S^v}_5$
γ_i	0.6892	0.5393	0.4828	0.4362	0.4449

Step 8: By subtracting each criterion from the total performance amounts, γ_{ij}^p in Equation 7 represents the partially achieved performance levels associated with the alternatives ith, by the specificity of the approach, which is based on the impact caused by eliminating the criteria jth.

$$\gamma_{ij}^p = \begin{bmatrix} 0.4679 & 0.5493 & 0.5433 & 0.5448 & 0.6115 & 0.5985 & 0.5824 & 0.5722 \\ 0.7666 & 0.7984 & 0.7880 & 0.7882 & 0.7753 & 0.8162 & 0.7956 & 0.7169 \\ 0.8638 & 0.8669 & 0.8700 & 0.8649 & 0.8969 & 0.8586 & 0.8478 & 0.8188 \\ 0.9650 & 0.9097 & 0.9192 & 0.9262 & 0.9297 & 0.9161 & 0.9478 & 0.9340 \\ 1.0712 & 0.9612 & 0.9573 & 0.9583 & 1.0028 & 0.9941 & 0.9832 & 1.0546 \end{bmatrix}$$

Step 9: Table 7 computes the absolute deviation, which is defined as the difference between the γ_{ij}^{p} and R_i matrices, and its sum, as provided by Equation 8.

Table 7
Sum of absolute deviation

Criteria	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
V_j	1.9845	1.7729	1.7771	1.7786	1.7792	1.7724	1.7779	1.7381

Step 10: Finally, weights $\Re(\xi)_j$ of criteria are computed and shown in Table 8 using the absolute deviation values as described in Equation 9.

Table 8
Weights of criteria

Criteria	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
$\Re(\xi)_j$	0.1813	0.1614	0.1437	0.1279	0.1138	0.1013	0.0902	0.0804

Step 11: As shown below, pairwise comparisons of the criterion locations were used to create the ranking comparison matrix.

$$\begin{bmatrix} \frac{1}{2} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & \frac{1}{2} & 1 & 1 & 1 & 0 & 1 & 0 \\ 1 & 0 & \frac{1}{2} & 1 & 1 & 0 & 1 & 0 \\ 1 & 0 & 0 & \frac{1}{2} & 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & \frac{1}{2} & 0 & 0 & 0 \\ 1 & 1 & 1 & 1 & 1 & \frac{1}{2} & 1 & 0 \\ 1 & 0 & 0 & 1 & 1 & 0 & \frac{1}{2} & 0 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & \frac{1}{2} \end{bmatrix}$$

Step 12: The equation given in Equation (11) was used to determine the summand criteria weights (ρ).

$$\begin{bmatrix} \frac{1}{2} & \frac{11}{2} & \frac{9}{2} & \frac{5}{2} & \frac{3}{2} & \frac{13}{2} & \frac{7}{2} & \frac{15}{2} \end{bmatrix}$$

Step 13: The formula shown in Equation (12) is used to calculate the weight of the criterion, which is based on subjective judgement.

$$\begin{bmatrix} \frac{1}{64} & \frac{11}{64} & \frac{9}{64} & \frac{5}{64} & \frac{3}{64} & \frac{13}{64} & \frac{7}{64} & \frac{15}{64} \end{bmatrix}$$

Step 14: The aggregated weights, derived from both subjective and objective methods, are calculated using Equation (13), with α established at 0.5.

Table 9
Values of F_i for different λ values

	λ values									
F_i	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
F_1	0.0279	0.0401	0.0523	0.0646	0.0768	0.0890	0.1013	0.1135	0.1258	0.1380
F_2	0.1670	0.1622	0.1573	0.1524	0.1476	0.1427	0.1379	0.1330	0.1281	0.1233
F_3	0.1389	0.1372	0.1355	0.1338	0.1321	0.1304	0.1287	0.1270	0.1253	0.1236
F_4	0.0827	0.0872	0.0918	0.0963	0.1009	0.1055	0.1100	0.1146	0.1191	0.1237
F_5	0.0546	0.0622	0.0699	0.0776	0.0853	0.0930	0.1007	0.1084	0.1160	0.1237
F_6	0.1951	0.1871	0.1792	0.1712	0.1632	0.1552	0.1472	0.1392	0.1312	0.1232
F_7	0.1108	0.1122	0.1137	0.1151	0.1165	0.1179	0.1194	0.1208	0.1222	0.1236
F_8	0.2230	0.2117	0.2003	0.1890	0.1776	0.1663	0.1549	0.1436	0.1322	0.1209

$$C^{\zeta}{}_j = \begin{bmatrix} 0.0829 & 0.1452 & 0.1312 & 0.1032 & 0.0891 & 0.1592 & 0.1172 & 0.1719 \end{bmatrix}$$

4.4 MAUT

Step 15: The values of the choice matrix are normalized under the type of qualities that are either positive or negative. The values of the positive attributes are normalized with the help of Equation (15), and those of the negative attributes are normalized with Equation (16).

$$Q^{y}_{ij} = \begin{bmatrix} 0 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 0.1748 & 0.9575 & 0.8681 & 0.8538 & 0.1486 & 0.6486 & 0.5556 & 0 \\ 0.2147 & 0.6315 & 0.7361 & 0.6474 & 0.4324 & 0.1622 & 0.1746 & 0.0294 \\ 0.4489 & 0.2147 & 0.3476 & 0.4127 & 0.0270 & 0 & 0.3651 & 0.2941 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0.9706 \end{bmatrix}$$

Step 16: Determine the marginal utility score using the Equation (17).

$$\daleth_{ij} = \begin{bmatrix} 0 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 \\ 0.0182 & 0.8780 & 0.6576 & 0.6274 & 0.0131 & 0.3059 & 0.2114 & 0 \\ 0.0276 & 0.2865 & 0.4206 & 0.3045 & 0.1202 & 0.0156 & 0.0181 & 0.0005 \\ 0.1305 & 0.0276 & 0.0751 & 0.1086 & 0.0004 & 0 & 0.0834 & 0.0528 \\ 1.0000 & 0 & 0 & 0 & 0 & 0 & 0 & 0.9153 \end{bmatrix}$$

Step 17: The ultimate utility score of each alternative is determined by applying Equation (18) to the data and ranking the alternative by using the utility score values is $S^{v}{}_1 > S^{v}{}_2 > S^{v}{}_5 > S^{v}{}_3 > S^{v}{}_4$.

$$\Xi = \begin{bmatrix} 0.9215 & 0.3546 & 0.1459 & 0.0548 & 0.2407 \end{bmatrix}$$

4.5 Sensitivity Analysis of Results

The sensitivity analysis in Table 10 shows how changing the parameter λ affects the ranking of five alternatives ($S^{v}{}_1$ to $S^{v}{}_5$) using MEREC-RANCOM-MAUT under various aggregation methods (LiDFWGA, LiDFWA, LiDFOWA, and LiDFOWG). All methods and λ values (0.1-0.9) rank alternatives in the same order: $S^{v}{}_1 > S^{v}{}_2 > S^{v}{}_5 > S^{v}{}_3 > S^{v}{}_4$. This consistency suggests that the ranking results are stable and less sensitive to changes in the λ parameter. As λ varies, utility values for each choice gradually increase or drop, but the preference order remains unchanged. The parameter λ affects assessment scores but not decision-making outcomes, proving the method's reliability and stability under variable risk or uncertainty levels.

Figure 1 presents parallel coordinates that illustrate the relationships among eight criteria within the dataset. The vertical axes denote distinct criteria, whereas each line represents a specific data instance, illustrating its values across all criteria. This plot type facilitates the identification of patterns, correlations, and anomalies within the data. This graph illustrates the transition of values between columns, facilitating the interpretation of each criterion's influence to others. This visualisation aids in identifying criteria with varying impacts on the ranking of alternatives, thereby facilitating more informed decision-making in feature selection. Figure 2 presents the outcomes of the sensitivity analysis. This figure presents a comparative analysis of the impact of parameter value variations on the ranking of alternatives, thereby confirming the robustness and reliability of the proposed decision-making framework.

Table 10
The impact of the parameters λ on the decision result by applying MEREC-RANCOM-MAUT with

Techniques	λ	$(S^{v}{}_{1})$	$(S^{v}{}_{2})$	$(S^{v}{}_{3})$	$(S^{v}{}_{4})$	$(S^{v}{}_{5})$	Ranking
LiDFWA	$\lambda = 0.1$	0.8321	0.3410	0.1012	-0.0243	0.2005	$S^{v}{}_{1} > S^{v}{}_{2} > S^{v}{}_{5} > S^{v}{}_{3} > S^{v}{}_{4}$
	$\lambda = 0.3$	0.9365	0.3236	0.1427	0.0553	0.2421	$S^{v}{}_{1} > S^{v}{}_{2} > S^{v}{}_{5} > S^{v}{}_{3} > S^{v}{}_{4}$
	$\lambda = 0.5$	0.8567	0.3301	0.1225	0.0417	0.2179	$S^{v}{}_{1} > S^{v}{}_{2} > S^{v}{}_{5} > S^{v}{}_{3} > S^{v}{}_{4}$
	$\lambda = 0.7$	0.7982	0.3108	0.1083	0.0356	0.2051	$S^{v}{}_{1} > S^{v}{}_{2} > S^{v}{}_{5} > S^{v}{}_{3} > S^{v}{}_{4}$
	$\lambda = 0.9$	0.7439	0.2956	0.0942	0.0291	0.1918	$S^{v}{}_{1} > S^{v}{}_{2} > S^{v}{}_{5} > S^{v}{}_{3} > S^{v}{}_{4}$
LiDFWGA	$\lambda = 0.1$	0.4412	0.2125	0.0821	-0.0527	0.1403	$S^{v}{}_{1} > S^{v}{}_{2} > S^{v}{}_{5} > S^{v}{}_{3} > S^{v}{}_{4}$
	$\lambda = 0.3$	0.4873	0.2302	0.0976	-0.0381	0.1632	$S^{v}{}_{1} > S^{v}{}_{2} > S^{v}{}_{5} > S^{v}{}_{3} > S^{v}{}_{4}$
	$\lambda = 0.5$	0.5381	0.2494	0.1115	-0.0237	0.1857	$S^{v}{}_{1} > S^{v}{}_{2} > S^{v}{}_{5} > S^{v}{}_{3} > S^{v}{}_{4}$
	$\lambda = 0.7$	0.5926	0.2712	0.1268	-0.0114	0.2089	$S^{v}{}_{1} > S^{v}{}_{2} > S^{v}{}_{5} > S^{v}{}_{3} > S^{v}{}_{4}$
	$\lambda = 0.9$	0.6417	0.2893	0.1397	0.0021	0.2292	$S^{v}{}_{1} > S^{v}{}_{2} > S^{v}{}_{5} > S^{v}{}_{3} > S^{v}{}_{4}$
LiDFOWA	$\lambda = 0.1$	0.6984	0.2982	0.1194	-0.0178	0.2032	$S^{v}{}_{1} > S^{v}{}_{2} > S^{v}{}_{5} > S^{v}{}_{3} > S^{v}{}_{4}$
	$\lambda = 0.3$	0.7216	0.3154	0.1311	-0.0082	0.2205	$S^{v}{}_{1} > S^{v}{}_{2} > S^{v}{}_{5} > S^{v}{}_{3} > S^{v}{}_{4}$
	$\lambda = 0.5$	0.7481	0.3341	0.1468	0.0054	0.2387	$S^{v}{}_{1} > S^{v}{}_{2} > S^{v}{}_{5} > S^{v}{}_{3} > S^{v}{}_{4}$
	$\lambda = 0.7$	0.7734	0.3519	0.1603	0.0182	0.2569	$S^{v}{}_{1} > S^{v}{}_{2} > S^{v}{}_{5} > S^{v}{}_{3} > S^{v}{}_{4}$
	$\lambda = 0.9$	0.7942	0.3671	0.1734	0.0314	0.2742	$S^{v}{}_{1} > S^{v}{}_{2} > S^{v}{}_{5} > S^{v}{}_{3} > S^{v}{}_{4}$
LiDFOWG	$\lambda = 0.1$	0.5431	0.2032	0.1381	0.0789	0.1795	$S^{v}{}_{1} > S^{v}{}_{2} > S^{v}{}_{5} > S^{v}{}_{3} > S^{v}{}_{4}$
	$\lambda = 0.3$	0.5782	0.2179	0.1517	0.0895	0.1923	$S^{v}{}_{1} > S^{v}{}_{2} > S^{v}{}_{5} > S^{v}{}_{3} > S^{v}{}_{4}$
	$\lambda = 0.5$	0.6095	0.2341	0.1654	0.1011	0.2065	$S^{v}{}_{1} > S^{v}{}_{2} > S^{v}{}_{5} > S^{v}{}_{3} > S^{v}{}_{4}$
	$\lambda = 0.7$	0.6374	0.2476	0.1782	0.1136	0.2194	$S^{v}{}_{1} > S^{v}{}_{2} > S^{v}{}_{5} > S^{v}{}_{3} > S^{v}{}_{4}$
	$\lambda = 0.9$	0.6625	0.2607	0.1912	0.1274	0.2325	$S^{v}{}_{1} > S^{v}{}_{2} > S^{v}{}_{5} > S^{v}{}_{3} > S^{v}{}_{4}$

criteria analysis.jpg

Fig. 1. Impact of each criterion on ranking

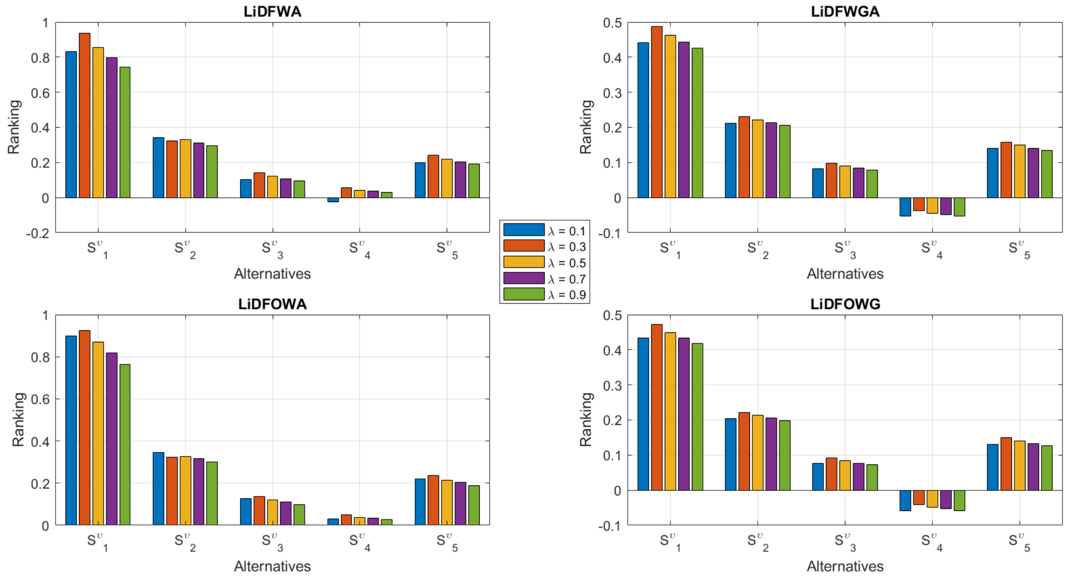

Fig. 2. Graphical representation of the results

4.6 Limitations of the Model

The suggested framework presents a comprehensive and systematic method for optimising RES; however, many limitations must be acknowledged.

- The RANCOM technique depends on expert judgements for the assignment of subjective weights, potentially leading to bias or inconsistency in the assessment of criteria. Divergences in expert perceptions can influence the ultimate outcome.
- The combination of LiDFS, RANCOM, MEREC, and MAUT increases the computing load, particularly when addressing extensive datasets or a substantial number of options and criteria.
- Despite the execution of a sensitivity analysis, the model's outcomes may still be affected by the selection of weighting methodologies. Diverse weight assignment methodologies may produce marginally distinct ranks, necessitating meticulous validation.
- The model assesses renewable energy options with fixed data. Nonetheless, elements such as technological progress, legislative modifications, and economic variations may influence the viability of energy sources over time, requiring regular revisions.
- Although LiDFS improves the management of uncertainty, qualitative factors necessitate subjective interpretation, potentially resulting in ambiguity in decision-making.

Addressing these constraints in forthcoming research will improve the adaptability, precision, and resilience of the proposed framework for renewable energy choices.

4.7 Discussion

The transition to renewable energy is crucial for addressing global challenges related to climate change, energy security, and sustainability. The selection of the most suitable renewable energy sources involves a complex decision-making process, marked by various conflicting criteria, uncertainty in expert evaluations, and variations in technological and economic conditions. Traditional

decision-making approaches often inadequately address these complexities, leading to inconsistent or biassed results. This research introduces a systematic decision-support framework that incorporates LiDFS, RANCOM, MEREC, and MAUT to overcome current limitations. A case study was performed to assess the validity of the proposed method for selecting renewable energy alternatives. The case study employed real-world data and multiple evaluation criteria, enabling a practical and realistic analysis of decision-making challenges. The integration of diverse criteria, such as economic feasibility, environmental impact, and technical efficiency, enabled a comprehensive evaluation of renewable energy sources (RES). The proposed decision model effectively integrates expert-driven and data-driven weighting methods. The RANCOM method was employed to obtain subjective weights based on expert preferences, thus incorporating human knowledge and experience into the decision-making process. The MEREC method was utilised for objective weight determination, reducing bias and improving evaluation reliability. The MAUT method was utilised to rank the alternatives, offering a structured approach for determining the most optimal renewable energy source.
The optimal alternative was identified through the analysis of the highest utility score obtained from the MAUT method, based on the computational results. The ranking process provided a systematic approach for selecting RES, enabling decision-makers to make informed, data-driven choices. The results demonstrate that the proposed framework successfully tackles multi-dimensional decision-making issues in the renewable energy sector. A sensitivity analysis was conducted to assess the robustness of the proposed model through the variation of criteria weights and the examination of ranking result stability. The findings revealed that the rankings remained consistent across different weighting scenarios, highlighting the robustness of the decision model. A comparative analysis was performed on existing decision-making methods to evaluate the efficiency and superiority of the proposed framework. The findings demonstrated that the integration of LiDFS, RANCOM, MEREC, and MAUT resulted in a more accurate and fair assessment compared to conventional models, highlighting their effectiveness in managing uncertainty, conflicting criteria, and complexities in decision-making. The proposed framework offers a systematic, transparent, and reliable approach for selecting the most suitable renewable energy sources. This study improves decision-support systems in energy planning by providing a scientifically validated methodology to aid policymakers and energy planners in making informed and sustainable decisions.

5. Conclusion

This research presents a decision-support framework for selecting RES, incorporating LiDFS, RANCOM, MEREC, and MAUT. The model successfully tackled the complexities inherent in multi-criteria decision-making by integrating both subjective and objective weighting methods while managing uncertainty in expert evaluations. The proposed methodology, through a real-world case study, effectively and systematically ranked renewable energy alternatives, facilitating a transparent and data-driven decision-making process. The study's results determined the optimal renewable energy alternative through a comprehensive assessment of economic, environmental, technical, and social factors. Sensitivity analysis demonstrated the stability and reliability of the rankings across various weighting scenarios, while comparative analysis affirmed the superiority of the proposed approach compared to traditional decision-making methods. The model presents several limitations, such as reliance on expert opinions, computational complexity, and difficulties in managing qualitative data. Future research may investigate the incorporation of dynamic criteria weighting, the interdependencies among criteria, and real-time data analysis to enhance decision-making accuracy. This study enhances decision-support systems in renewable energy planning by providing policymakers, energy planners, and stakeholders with a structured and robust method for selecting the most sustainable and efficient energy solutions.

6. Future Research Directions

The study offers a systematic method for assessing sustainable RES, however numerous aspects require additional investigation to improve their application and resilience. Subsequent research avenues may expand the scope and enhance the model's efficacy:

- Utilizing artificial intelligence and machine learning methodologies to examine historical data, forecast energy trends, and dynamically adjust criteria weights might enhance the model's precision and flexibility.
- This study centres on renewable energy choices; however, the proposed framework can be used to other fields, including smart transportation, sustainable manufacturing, and supply chain management, to improve decision-making in intricate systems.
- With the evolution of renewable energy laws and regulations, it is essential to create adaptive decision-support systems capable of dynamically responding to policy modifications, risk mitigation strategies, and emerging compliance obligations. This would enhance the long-term utility and adaptability of the decision-making mechanism.
- The model presupposes independence among criteria, which may not always be valid. Future studies may utilise fuzzy cognitive maps, Bayesian networks, or MCDM models with interdependencies to more accurately represent the intricacies of real-world decision-making.
- The existing approach assesses options using static data. Future research may integrate real-time data with adaptive criterion weighting to reflect evolving economic, environmental, and technological circumstances.

By following these guidelines, future research can enhance the scalability, adaptability, and empirical robustness of decision-making frameworks for renewable energy optimisation, hence ensuring their efficacy in tackling emerging sustainability concerns.

Conflicts of Interest

The authors declare no conflicts of interest.

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