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INTEGRATING FUZZY AHP AND GRA FOR STRATEGIC EVALUATION AND DECISION-MAKING IN RENEWABLE ENERGY TECHNOLOGIES

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ABSTRACT

Aim/Purpose	This paper presents a structured evaluation framework for renewable energy technologies (RETs) in project management, addressing the critical need to mitigate environmental impacts and reduce dependence on fossil fuels. By integrating decision-making techniques, the study aims to provide a systematic approach for selecting optimal RETs.
Background	Subjective judgments and uncertainties often complicate RET selection. To overcome these challenges, this study develops a dual-method framework using Fuzzy Analytic Hierarchy Process (F-AHP) and Grey Relational Analysis (GRA), applied within the Moroccan Agency for Sustainable Energy (MASEN) project. The framework enhances objectivity in RET decision-making.
Methodology	The research employs F-AHP to determine the relative importance of selection criteria, accounting for uncertainty in expert judgments. GRA then ranks RETs based on these weighted criteria. The methodology is applied to the MASEN project to validate its effectiveness empirically.
Contribution	This study introduces a novel integration of F-AHP and GRA in RET evaluation, bridging qualitative and quantitative decision-making approaches. By refining selection methodologies, it advances the practical application of systematic assessment tools in sustainable energy projects.

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Findings	The proposed F-AHP-GRA methodology demonstrates high effectiveness in RET evaluation. RET4, identified as the optimal choice, reflects the framework's ability to enhance decision-making transparency and accuracy. Detailed analysis of criteria weights provides deeper insights into RET prioritization.
Recommendations for Practitioners	Energy project managers can adopt this framework to make data-driven and objective decisions in RET selection, improving project sustainability and efficiency.
Recommendations for Researchers	Future studies should explore the adaptability of the F-AHP-GRA methodology across various energy project contexts, assessing its effectiveness in diverse geopolitical and technological settings. Additionally, refining selection criteria – such as socio-economic impacts and lifecycle costs – could enhance RET evaluation accuracy.
Impact on Society	By providing a structured framework for RET selection, this research supports sustainable energy advancements, reducing environmental degradation, and aiding the transition toward global sustainability goals. The methodology promotes data-driven decision-making, fostering more efficient and responsible energy management.
Future Research	Further investigation could focus on expanding the model to include dynamic, real-time data integration for improved responsiveness in RET evaluations. Additionally, exploring its applicability beyond RET selection, such as in broader sustainability initiatives, could unlock new opportunities for energy policy and project management.

Keywords	MASEN, renewable energy technologies, fuzzy analytic hierarchy process, grey relational analysis, sustainable decision-making

INTRODUCTION

The global transition toward sustainable development necessitates a shift from conventional fossil fuel-based energy systems to renewable energy technologies (RETs) (Hassan et al., 2024). Mounting environmental concerns – including climate change, air pollution, and resource depletion – underscore the urgency of this shift. RETs, encompassing solar, wind, hydro, and biomass energy, offer viable solutions that mitigate environmental degradation while enhancing energy security and economic resilience (Paraschiv & Paraschiv, 2023).

However, selecting the optimal RETs for implementation involves complex decision-making processes that require the evaluation of multiple criteria, such as economic feasibility, technological maturity, environmental sustainability, and social acceptance. Existing decision-making approaches often struggle to adequately address the inherent uncertainties and subjective judgments associated with RET selection, leading to inconsistencies and inefficiencies in project outcomes (Hernández-Torres et al., 2025). To overcome these limitations, advanced multi-criteria decision-making (MCDM) methodologies have gained prominence, particularly Fuzzy Analytic Hierarchy Process (F-AHP) and Grey Relational Analysis (GRA).

Although previous studies have explored these methodologies separately, a clear gap remains in their integrated application for RET evaluation, particularly in balancing uncertainty and expert-driven decision criteria. Conventional models typically focus on a singular methodological approach or lack systematic frameworks for handling ambiguity in RET prioritization (Mukelabai et al., 2024). This study seeks to bridge this gap by developing a hybrid decision-making framework that systematically evaluates RETs using F-AHP and GRA. The study specifically aims to assess the effectiveness of combining these techniques to enhance RET selection processes, identify the most suitable RET for the Moroccan Agency for Sustainable Energy (MASEN) project, and investigate the broader applicability of the framework in sustainable energy policy and project management.

By refining RET evaluation methodologies, this study contributes to the advancement of data-driven, transparent decision-making in energy project management. Furthermore, its findings offer policy implications, assisting stakeholders in optimizing sustainable energy investments and improving strategic resource allocation in large-scale RET initiatives.

Literature Review

Critical Success Factors (CSFs) for RETs Evaluation

RETs require a comprehensive analysis of various CSFs to ensure their effective implementation and sustainable operation. One of the foremost CSFs is economic feasibility, which encompasses the initial investment, operation, and maintenance costs associated with RETs. While traditional cost-benefit assessments provide financial insights, they often neglect long-term strategic sustainability concerns that influence RET adoption decisions (Olabi et al., 2023). Additionally, life cycle cost analysis is a crucial method used to evaluate the long-term financial implications of adopting RETs, providing a holistic view of their economic benefits and challenges (Vlad et al., 2023).

Another critical factor is technological maturity, referring to the readiness and reliability of the technology. Existing studies emphasize the significance of technology readiness levels (TRLs) in assessing RET viability; however, there is a lack of models integrating TRLs with policy-driven adoption mechanisms (Salvador-Carulla et al., 2024). The ongoing research and development activities play a significant role in advancing the technological readiness of emerging RETs, thereby enhancing their adoption potential.

Environmental impact is another essential CSF, as RETs are primarily adopted to mitigate adverse environmental effects such as greenhouse gas emissions and resource depletion. Despite the increasing focus on sustainability assessments, methodologies for quantifying the indirect environmental effects of RET implementation remain fragmented, requiring a more standardized approach (Sebestyén, 2021). Conducting life cycle assessments (LCA) allows stakeholders to evaluate the environmental footprint of RETs, ensuring that the chosen technologies contribute to sustainability goals.

Social acceptance is a crucial determinant of the successful deployment of RETs. Public perception and acceptance are influenced by various factors, including awareness, perceived benefits, and potential negative impacts (Hazrati, 2024). However, current frameworks assessing social acceptance often overlook dynamic factors such as evolving public sentiment and institutional trust, warranting a more adaptive evaluation model. Engaging stakeholders through participatory approaches and addressing their concerns can significantly enhance the social acceptance of RETs.

Policy and regulatory support also play a fundamental role in the proliferation of RETs. Although regulatory frameworks set the foundation for RET development, inconsistencies in incentive structures and policy implementation often hinder optimal technology adoption (Qadir et al., 2021). Government policies, incentives, and regulatory frameworks can either facilitate or hinder the adoption of renewable technologies. Policy stability and clarity are essential in providing a conducive environment for investment in RETs.

Finally, infrastructure and resource availability are vital for the successful implementation of RETs. The availability of necessary infrastructure, such as grid connections, storage facilities, and renewable resources (e.g., sunlight, wind), directly impacts the feasibility and efficiency of RETs (Nwagu et al., 2025). While extensive research exists on technical infrastructure, there remains a lack of comprehensive studies integrating spatial resource distribution with grid optimization strategies.

F-AHP AND GRA

F-AHP and GRA have seen widespread adoption across various fields due to their robustness in handling complex decision-making scenarios (Fan & Ma, 2024). Despite their established use, many applications remain largely descriptive without critically evaluating their limitations in capturing inter-dependencies among criteria in RET selection.

F-AHP, an extension of the classic AHP, utilizes fuzzy logic to capture the inherent uncertainties in the pairwise comparison process, making it a more reliable tool for deriving criteria weights in ambiguous environments. While F-AHP enhances reliability, it lacks standardized procedures for adapting fuzzy scaling across different sectors, leading to inconsistent outcomes in energy planning studies (Moreno Rocha, Daina, et al., 2025). For instance, F-AHP has been effectively employed to evaluate the sustainability of various projects by assessing environmental, economic, and social criteria. Similarly, in energy planning, F-AHP is used to prioritize renewable energy sources by considering factors such as economic feasibility, technological maturity, and environmental impact, providing a structured framework for policymakers to make informed decisions.

On the other hand, GRA is rooted in grey system theory and is particularly adept at handling systems with incomplete and uncertain information (Gerus-Gościewska & Gościewski, 2022). Its strength lies in ranking alternatives efficiently; however, its reliance on normalized values often results in oversimplifications that obscure subtle differences in RET performance. GRA complements F-AHP by ranking the alternatives based on their performance relative to multiple criteria, thus providing a comprehensive evaluation.

This dual approach of combining F-AHP and GRA is widely adopted in supply chain management to optimize supplier selection processes. Although widely implemented, limited research exists on adapting F-AHP-GRA for dynamic environments where RET performance evolves over time (Moreno Rocha, Buelvas, et al., 2025). By incorporating both qualitative and quantitative criteria, these methods ensure a holistic evaluation of supplier performance, logistics efficiency, and sustainability practices.

In technology evaluation, the F-AHP-GRA approach aids in assessing the adoption of new technologies by considering multiple performance indicators, such as cost, efficiency, and environmental impact, thereby facilitating the identification of the most suitable technologies for implementation (Parolin et al., 2024). Despite its advantages, integrating real-time adjustments into the framework remains an underexplored aspect of its application in RETs. Further refinements could enhance its responsiveness to shifting policy and market trends. Moreover, the methodological advancements in F-AHP and GRA have been leveraged in environmental impact assessments, where accurate weighting of criteria is critical for sustainable decision-making (Zaheb et al., 2024). For example, these methods have been used to evaluate the environmental impacts of industrial projects by considering factors such as emissions, resource consumption, and ecological disturbance, aiding in the formulation of mitigation strategies.

METHOD

This study employs a systematic approach to evaluating and prioritizing RETs using the F-AHP and GRA. The methodology is structured to ensure a transparent, reproducible MCDM framework for optimizing RET selection under uncertainty.

The evaluation process begins with problem definition, wherein RETs are assessed based on six primary criteria: economic feasibility, technological maturity, environmental impact, social acceptance, policy and regulatory support, and infrastructure availability. These criteria were selected through an extensive literature review, expert consultations, and alignment with the MASEN strategy to ensure validity and relevance. It is a pivotal organization in Morocco's renewable energy landscape, established in 2010 to spearhead the country's transition to sustainable energy sources. As the central entity responsible for managing and developing renewable energy projects, Masen has set ambitious targets, including generating an additional 6,000 MW of clean electricity by 2030 and ensuring that at least 52% of the nation's energy mix comes from renewable sources. The agency's integrated approach to project development, which emphasizes economic viability, technological innovation, and environmental sustainability, makes it an ideal candidate for applying the methodologies of F-AHP and GRA. By leveraging these advanced decision-making tools, Masen can enhance its project evaluation processes, optimize resource allocation, and ensure that its initiatives align with both national and global sustainability goals.

Data collection is conducted via structured expert surveys, supplemented by secondary data from government policy reports and technical documentation. The fuzzy pairwise comparison process utilizes MATLAB R2023a, which facilitates efficient computation of Triangular Fuzzy Numbers (TFNs) and consistency ratio validation. Pairwise comparison matrices are constructed, and defuzzification is performed using MATLAB's fuzzy logic toolbox. The Consistency Ratio (CR) is calculated via eigenvalue-based methods, ensuring that weight derivations remain statistically sound.

Normalization and grey relational grading are executed using Python 3.10, leveraging the NumPy and Pandas libraries for data processing and Scikit-learn for normalization procedures. The grey relational coefficients are computed using Python, with relational rankings determined through matrix-based evaluation techniques. Sensitivity analysis is implemented using IBM SPSS Statistics 29, wherein weight adjustments of ±10% and ±20% are applied to assess the robustness of RET rankings across varying criteria weight scenarios.

FINDINGS

The first step in the Fuzzy AHP-GRA approach is to clearly define the problem that needs to be addressed. In this case, the problem is to evaluate and prioritize various RETs for implementation in a specific region or organization. The objective is to identify the most suitable RET based on multiple criteria that reflect economic, technological, environmental, social, and policy considerations. We create a hierarchical structure with the main goal at the top, followed by the criteria and sub-criteria (Table 1).

Table 1. RETs hierarchical structure

Main goal	Criteria	Sub-criteria
Evaluate and Prioritize RETs	Economic Feasibility (C1)	Initial Investment (C1.1)
		Operational and Maintenance Costs (C1.2)
		Financial Returns (C1.3)
	Technological Maturity (C2)	Technology Readiness Level (C2.1)
		Performance Stability (C2.2)
		Development Status (C2.3)
	Environmental Impact (C3)	Greenhouse Gas Emissions (C3.1)
		Resource Use (C3.2)
		Ecological Impact (C3.3)
	Social Acceptance (C4)	Community Support (C4.1)
		Societal Benefits (C4.2)
		Social Challenges (C4.3)
	Policy and Regulatory Support (C5)	Government Policies (C5.1)
		Incentives (C5.2)
		Regulatory Frameworks (C5.3)
	Infrastructure and Resource Availability (C6)	Grid Connectivity (C6.1)
		Storage Facilities (C6.2)
		Renewable Resource Availability (C6.3)

A pairwis4e comparison matrix (Table 2) allows us to compare each criterion against every other criterion to determine their relative importance. The matrix is constructed as follows:

$$A = \begin{bmatrix} 1 & \cdots & A_{1n} \\ \vdots & \ddots & \vdots \\ \frac{1}{A_{1n}} & \cdots & 1 \end{bmatrix} \quad (1)$$

where A_{ij} represents the relative importance of criterion i compared to criterion j.

Table 2. The pairwise comparison matrix

	C1	C2	C3	C4	C5	C6
C1	1	3	1/2	2	4	3
C2	1/3	1	1/5	1	3	2
C3	2	5	1	3	5	4
C4	1/2	1	1/3	1	3	2
C5	1/4	1/3	1/5	1/3	1	1/2
C6	1/3	1/2	1/4	1/2	2	1

We use fuzzy numbers to represent the pairwise comparisons (Table 3), as they capture the uncertainty and vagueness in human judgment. TFN is commonly used and is represented as $\tilde{A} = (l, m, u)$ where l is the lower bound, m is the most likely value, and u is the upper bound.

Table 3. Fuzzy pairwise comparison matrix

	C1	C2	C3	C4	C5	C6
C1	(1, 1, 1)	(2, 3, 4)	(0.33, 0.5, 1)	(1, 2, 3)	(3, 4, 5)	(2, 3, 4)
C2	(0.25, 0.33, 0.5)	(1, 1, 1)	(0.2, 0.25, 0.33)	(0.5, 1, 2)	(2, 3, 4)	(1, 2, 3)
C3	(1, 2, 3)	(3, 4, 5)	(1, 1, 1)	(2, 3, 4)	(4, 5, 6)	(3, 4, 5)
C4	(0.33, 0.5, 1)	(0.5, 1, 2)	(0.25, 0.33, 0.5)	(1, 1, 1)	(2, 3, 4)	(1, 2, 3)
C5	(0.2, 0.25, 0.33)	(0.25, 0.33, 0.5)	(0.167, 0.2, 0.25)	(0.25, 0.33, 0.5)	(1, 1, 1)	(0.5, 1, 2)
C6	(0.25, 0.33, 0.5)	(0.33, 0.5, 1)	(0.2, 0.25, 0.33)	(0.33, 0.5, 1)	(0.5, 1, 2)	(1, 1, 1)

Using the fuzzy synthetic extent analysis method, we compute the weight vectors (Table 4). For each criterion C_i, the sum of the fuzzy comparisons is given by:

$$S_{C_i} = \left(\sum_{j=1}^{n} l_{ij}, \sum_{j=1}^{n} m_{ij}, \sum_{j=1}^{n} u_{ij}\right) \quad (2)$$

The inverse of the fuzzy sum S_{C_i} for each criterion is calculated as:

$$S_{C_i}^{-1} = \left(\frac{1}{u_{C_i}}, \frac{1}{m_{C_i}}, \frac{1}{l_{C_i}}\right) \quad (3)$$

The fuzzy synthetic extent $\widetilde{W_{C_i}}$ for each criterion Ci is given by:

$$\widetilde{W_{C_i}} = \frac{\sum_{j=1}^{n} S_{ij} \cdot S_{ij}^{-1}}{\sum_{i=1}^{m}\sum_{j=1}^{n} S_{ij} \cdot S_{ij}^{-1}} \quad (4)$$

The defuzzification of the fuzzy weights to crisp values is done using the centroid method (Table 4):

$$W = \frac{l+m+u}{3} \quad (5)$$

Table 4. Weight vectors of criteria

	l	m	u	W
C1	0.0556	0.0741	0.1072	0.079
C2	0.0231	0.0436	0.101	0.056
C3	0.0417	0.1052	0.2142	0.120
C4	0.0428	0.0979	0.1925	0.111
C5	0.0171	0.0321	0.0816	0.043
C6	0.0273	0.0557	0.1717	0.085

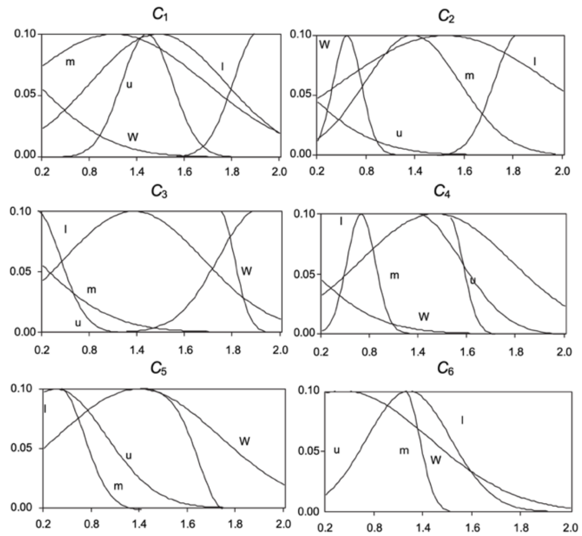

Figure 1. Defuzzified weights of criteria

As shown in Figure 1, the computed weight vectors reveal the relative significance of each evaluation criterion. C3 and C4 emerged as the most influential criteria, with defuzzified weights of 0.120 and 0.111, respectively. This suggests that sustainability considerations and community engagement play a primary role in RET selection. C1 and C6 demonstrated moderate importance, with respective weights of 0.079 and 0.085, reflecting their substantial but not dominant influence. C2 and C5 ranked lower, with weights of 0.056 and 0.043, indicating a secondary role in the overall decision-making process.

Normalization ensures that the sum of the weight vectors equals 1. This can be achieved using the following formula:

$$W_i' = \frac{W_i}{\sum_{i=1}^{n} W_i} \qquad (6)$$

where W_i is the weight of criterion i, and W_i' is the normalized weight.

To check the consistency of the pairwise comparison matrices, we use CR.

$$CR = \frac{CI}{RI} \qquad (7)$$

$$CI = \frac{\lambda_{max} - n}{n-1} \qquad (8)$$

where CI is the Consistency Index, λ_{max} is the maximum eigenvalue of the matrix, n is the number of criteria, and RI is the Random Index, which depends on n (Table 5).

Table 5. RI values

n	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

The CR is acceptable if it is below 0.1 (Table 6).

Table 6. Normalized weights and consistency check

	W	W'	λ_{max}
C1	0.079	0.193	1.155
C2	0.056	0.113	0.684
C3	0.120	0.243	1.462
C4	0.111	0.225	1.353
C5	0.043	0.087	0.528
C6	0.085	0.172	1.056

The CR is 0.038, which is below the acceptable threshold of 0.1, indicating that the pairwise comparison matrices are consistent. The reference sequence x_0 is constructed for each RET. It is the ideal value for each criterion (Table 7).

The grey relational coefficient (ξ) is calculated as:

$$\xi ij = \frac{+\zeta}{\Delta_{ij}+\zeta} \quad (9)$$

where $\Delta_{ij} = \left|x_{0j} - x_{ij}\right|$ and ζ is the distinguishing coefficient (ζ=0.5)

Table 7. Performance metrics, deviation analysis, and grey relational coefficients

	Actual value				Δ_{ij}				ξij			
	RET1	RET2	RET3	RET4	RET1	RET2	RET3	RET4	RET1	RET2	RET3	RET4
C1	0.8	0.9	0.7	0.6	0.2	0.1	0.3	0.4	0.636	0.778	0.538	0.467
C2	0.7	0.6	0.8	0.9	0.3	0.4	0.2	0.1	0.538	0.467	0.636	0.778
C3	0.9	0.8	0.7	0.6	0.1	0.2	0.3	0.4	0.778	0.636	0.538	0.467
C4	0.6	0.7	0.8	0.9	0.4	0.3	0.2	0.1	0.467	0.538	0.636	0.778
C5	0.5	0.6	0.7	0.8	0.5	0.4	0.3	0.2	0.412	0.467	0.538	0.636
C6	0.6	0.7	0.8	0.9	0.4	0.3	0.2	0.1	0.467	0.538	0.636	0.778

The grey relational grade (γ) for each RET (Table 8) is calculated by averaging ξij:

$$\gamma i = \frac{\sum_{j=1}^{n} \xi_{ij}}{n} \quad (10)$$

Table 8. Grey relational grades (γ)

	γ
RET1	0.55
RET2	0.57
RET3	0.59
RET4	0.65

The ranking of RETs is based on their Grey Relational Grades. The RET with the highest γ is considered the most suitable option (Table 9).

Table 9. Ranking of RETs

	γ	Rank
RET4	0.65	1
RET3	0.59	2
RET2	0.57	3
RET1	0.55	4

The grey relational coefficients were computed to derive relational grades and rank RET alternatives. RET4 achieved the highest grey relational grade (γ = 0.65), confirming its suitability for implementation, followed by RET3 (γ = 0.59), RET2 (γ = 0.57), and RET1 (γ = 0.55). This ranking demonstrates RET4's superior performance across all evaluation criteria, highlighting its strong environmental, economic, and social advantages compared to other alternatives.

Sensitivity analysis is a critical step in assessing the robustness of the results by varying the weights assigned to different criteria and observing how these changes affect the ranking of RETs. First, the weights of each criterion are adjusted by specified amounts (typically ±10% and ±20%) to account for potential variations in importance. Next, the grey relational grades are recalculated using these updated weights, ensuring the new calculations reflect the revised priorities. Finally, the changes in the rankings of the RETs are analyzed to determine if the initial rankings remain consistent or if there are significant shifts (Table 10).

Table 10. Weight adjustments, grey relational grades, and rankings of RETs

	-20%γ	-10%γ	Originally	+10%γ	+20%γ	Rank (original)	Rank (-20%)	Rank (-10%)	Rank (+10%)	Rank (+20%)
RET1	0.54	0.55	0.55	0.56	0.56	4	4	4	4	4
RET2	0.56	0.57	0.57	0.58	0.59	3	3	3	3	3
RET3	0.58	0.59	0.59	0.60	0.61	2	2	2	2	2
RET4	0.64	0.65	0.65	0.66	0.67	1	1	1	1	1

The sensitivity analysis shows that even with ±10% and ±20% variations in the weights, the rankings of the RETs remain consistent. RET4 consistently ranks as the most suitable option, followed by RET3, RET2, and RET1. This indicates that the initial ranking is robust and not significantly affected by minor changes in the weights of the criteria.

Based on the results of the ranking and sensitivity analysis, we can make a final decision on the most suitable RET for implementation. We check the average GRG values obtained from the ranking step and analyze how robust the rankings are to the changes in the weights. The RET with the highest average GRG across different weight scenarios is considered the most suitable option (Table 11).

Table 11. Average GRG

	Average GRG
RET1	0.552
RET2	0.574
RET3	0.594
RET4	0.654

The GRGs were calculated under various weight scenarios. The results are consistent, showing RET4 having the highest GRG in all scenarios, followed by RET3, RET2, and RET1. Then, the sensitivity analysis demonstrates that the rankings are robust to changes in the weights. RET4 consistently ranks first across all scenarios.

Based on the average GRG across different weight scenarios, we can conclude that RET4 is the most suitable option for implementation. RET4 has the highest average GRG of 0.654, indicating that it performs the best across all criteria, even when weights are varied (Table 12).

Table 12. Ranking of RETs based on average GRG

Rank	RET	Average GRG
1	RET4	0.654
2	RET3	0.594
3	RET2	0.574
4	RET1	0.552

The results of this study align with previous research on MCDM for renewable energy selection, particularly those emphasizing environmental impact and social acceptance as dominant factors. Similar studies have found that integrating sustainability metrics into RET selection leads to prioritization of technologies with lower emissions and high stakeholder acceptance. RET4's high ranking ($\gamma = 0.65$) corroborates these findings, indicating that its low greenhouse gas emissions and strong feasibility for integration into Morocco's energy landscape make it the optimal choice. The GRG consistently favors RET4 across sensitivity analyses, demonstrating stability even under varying weight assignments. This stability supports prior conclusions that methodologies incorporating fuzzy logic improve robustness in RET prioritization. The data sources, including structured expert surveys and policy documents, ensure alignment with national energy strategies, reducing biases that often emerge in subjective assessments. However, expert judgment remains a factor influencing weight assignments, reinforcing the need for sensitivity analysis to mitigate potential bias. The implications of these findings suggest that Morocco's renewable energy policy should emphasize technologies with strong environmental and social performance, ensuring long-term sustainability while maintaining stakeholder confidence.

DISCUSSION

The application of F-AHP enabled the systematic prioritization of evaluation criteria based on expert judgment and fuzzy logic integration. The ability of F-AHP to handle ambiguity and uncertainty in decision-making proved critical, ensuring that subjective preferences were appropriately modeled. The results indicated that Environmental Impact (C3) and Social Acceptance (C4) were the most significant factors influencing RET selection, aligning with sustainability-focused energy policy priorities. RET4 emerged as the most favorable option, demonstrating superior performance in these high-weighted criteria. The subsequent implementation of GRA reinforced these findings, providing a structured ranking of RETs based on their holistic performance across all criteria. The consistency observed between F-AHP and GRA results highlights the robustness and reliability of the combined methodological framework, validating the effectiveness of the integrated approach.

A comparison with prior studies reveals how the F-AHP-GRA framework enhances traditional methods such as AHP and TOPSIS. Moreno Rocha, Buelvas, et al. (2025) utilized AHP for RET selection in different urban environments, emphasizing the need for tailored energy strategies based on local conditions. While AHP provides structured pairwise comparisons, its inability to address uncertainty systematically limits its effectiveness in complex decision-making scenarios. By integrating fuzzy logic into AHP, this study improves methodological precision, mitigating the limitations of conventional weighting mechanisms. Furthermore, Haase et al. (2022) applied a comprehensive sustainability assessment model incorporating environmental, economic, and social factors. The GRA implementation in this study complements such approaches by offering quantitative ranking stability, ensuring that RET selection remains consistent across varying sensitivity scenarios.

The involvement of ten domain experts specializing in energy policy, environmental engineering, and project management further strengthens the reliability of the weighting process. Their assessments were critical in defining the relative importance of criteria, reducing the risk of bias in RET evaluation. However, expert subjectivity remains an inherent challenge in decision-making frameworks. To address this, a sensitivity analysis was conducted, varying weight assignments by ±10% and ±20%, demonstrating that RET4 consistently retained its leading position despite these adjustments. This resilience suggests that expert judgment biases did not significantly impact the final rankings, reinforcing the validity of the methodology.

The practical implications of identifying RET4 as the most suitable technology are substantial, particularly in the context of MASEN's renewable energy policies. RET4's low greenhouse gas emissions, high efficiency, and strong social acceptance position it as a viable candidate for Morocco's sustainable energy transition. Given that national energy policy prioritizes decarbonization and renewable energy integration, the findings suggest that MASEN should allocate investment and infrastructure support toward RET4 deployment. Additionally, the structured evaluation framework presented in this study can serve as a reference model for future RET selection projects, ensuring transparent, data-driven decision-making.

CONCLUSION

This study presented a structured multi-criteria decision-making approach, specifically integrating F-AHP and GRA, to evaluate and prioritize RETs. The methodology systematically addressed the complexity of RET selection by considering economic feasibility, technological maturity, environmental impact, social acceptance, policy support, and infrastructure availability. Through sensitivity analysis, RET4 consistently emerged as the most viable option, demonstrating robustness under varied weight conditions, confirming the reliability of the evaluation framework.

A key contribution of this research is the novel application of GRA in RET evaluation, offering a replicable methodology for assessing diverse energy technologies under uncertainty. By integrating fuzzy logic within the decision-making process, the study enhanced the precision of expert judgments, reducing the limitations associated with traditional deterministic approaches such as AHP and TOPSIS. Furthermore, the findings provide strategic policy insights, enabling organizations such as MASEN to optimize project implementation by aligning RET selection with sustainability and energy transition objectives.

Despite its methodological strengths, the study acknowledges limitations, including the subjectivity in expert weight assignments, which may introduce bias into ranking outcomes. Additionally, the restricted scope of evaluated criteria and technologies suggests the need for future research to expand the framework, incorporating real-time energy market dynamics, socio-economic impacts, and a broader range of RETs across multiple geographic regions. Such extensions would enhance the generalizability of the model and strengthen its applicability in global renewable energy strategies.

Looking ahead, further refinement of decision-support models integrating artificial intelligence and machine learning could improve dynamic RET assessment, ensuring adaptability to evolving technological and policy landscapes. By bridging theoretical decision-making models with practical implementation, this study contributes to both academic discourse and real-world energy planning, reinforcing the critical role of systematic evaluation in achieving global sustainability goals.

In summary, this study not only advances the methodological foundation for RET assessment but also provides a scalable decision-support framework with implications beyond MASEN, positioning it as a valuable tool for policymakers and stakeholders in the global renewable energy transition.

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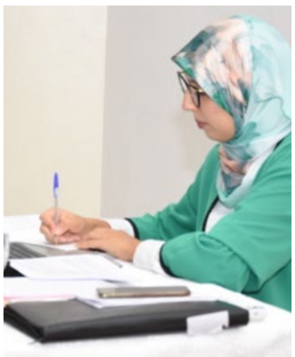

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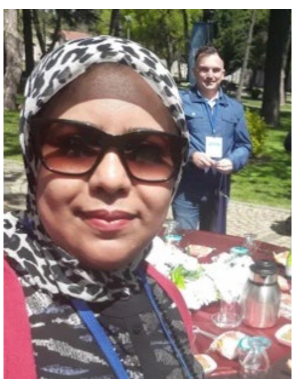

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