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# Adaptive Planning of Renewable Energy Technologies: A Hybrid Fuzzy Dombi–MAIRCA Framework for Sustainable Energy Management

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**ABSTRACT**

This study addresses the urgent need for adaptive, multi-criteria decision-support systems in renewable energy planning under uncertainty. Despite the proliferation of Multi-Criteria Decision-Making (MCDM) techniques, existing models often fail to integrate nuanced stakeholder preferences with robust sensitivity and scenario analysis. To bridge this gap, we propose a novel hybrid framework combining fuzzy Dombi aggregation with the MAIRCA (Multi-Attribute Ideal-Real Comparative Analysis) method, enabling physically realistic and policy-responsive evaluation of five renewable energy technologies in the Moroccan context. The model incorporates fifteen environmental, technical, and socio-economic criteria, with weights derived via fuzzy pairwise comparison and validated through perturbation and scenario modeling. The proposed framework advances prior literature by integrating fuzzy logic with MAIRCA's ideal expectation structure, offering a scalable tool for sustainable energy decision-making under evolving policy constraints.

***Keywords***

Fuzzy dombi aggregation;
MAIRCA decision framework;
Renewable energy technology evaluation;
Multi-criteria decision-making;
Scenario-based sustainability planning

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## 1. Introduction

The global imperative to decarbonize energy systems has intensified the demand for strategic planning tools that can guide the deployment of renewable technologies under uncertainty [1, 2]. In emerging economies such as Morocco, where energy diversification is both a national priority and a climate commitment, decision-makers face the challenge of selecting technologies that balance environmental sustainability, economic viability, and social acceptability [3, 4]. This complexity is compounded by fluctuating policy landscapes, resource constraints, and the inherent fuzziness of stakeholder preferences. As a result, MCDM frameworks have become indispensable in energy planning [5, 6], offering structured approaches to evaluate alternatives across diverse and often conflicting criteria [7].

Despite their widespread use, conventional MCDM models exhibit several limitations. Many rely on crisp data and deterministic assumptions, which fail to capture the ambiguity and imprecision inherent in real-world energy decisions [8]. Others lack sensitivity to strategic shifts, such as carbon taxation or water scarcity, and offer limited mechanisms to validate the robustness of rankings under such scenarios [9].

Moreover, while fuzzy logic has been integrated into various MCDM methods to address uncertainty [10], the aggregation operators employed are often rigid or insufficiently adaptive to complex decision environments. The MAIRCA method, which models the deviation between ideal expectations and actual performance, offers a promising structure for transparent and physically realistic evaluation [11]. However, its integration with advanced fuzzy operators—particularly those capable of capturing nonlinear preference structures—remains underexplored in the literature.

This study addresses these methodological gaps by proposing a hybrid decision-support framework that

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combines fuzzy Dombi aggregation with the MAIRCA method. The fuzzy Dombi operator, known for its flexibility and tunable behavior, enables nuanced modeling of stakeholder preferences and inter-criteria relationships. When coupled with MAIRCA's ideal-real deviation logic, the resulting framework offers a robust and transparent mechanism for evaluating renewable energy technologies under uncertainty. The analysis focuses on five alternatives—Solar PV, Hybrid PV–Wind, Wind Turbines, Biomass, and Diesel Backup—using fifteen criteria that span environmental, technical, and socio-economic dimensions. Criteria weights are derived through fuzzy pairwise comparison and validated via perturbation analysis and scenario modeling.

The objectives of this research are threefold: first, to develop a physically realistic and policy-sensitive evaluation model for renewable energy planning; second, to apply the model to a Moroccan case study and to validate the ranking structure through comparative analysis with fuzzy TOPSIS and fuzzy VIKOR.

## 2. Literature Review

The evaluation of renewable energy technologies under uncertainty has attracted considerable scholarly attention, particularly through the lens of MCDM. Numerous studies have employed MCDM techniques to assess energy alternatives across environmental, technical, economic, and social criteria [12, 13]. These criteria often reflect national priorities such as carbon reduction, energy independence, and rural electrification. However, while the criteria selection is generally comprehensive, the methodological depth in handling uncertainty and preference ambiguity remains limited.

Traditional MCDM methods have been widely applied in energy planning contexts [14, 15]. Yet, these approaches often rely on crisp data and deterministic assumptions, which inadequately reflect the linguistic vagueness and imprecision inherent in stakeholder judgments. To address this, fuzzy logic has been integrated into MCDM frameworks, enabling the modeling of uncertainty in criteria weights and performance scores [16]. Fuzzy AHP and fuzzy TOPSIS, for instance, have been used to evaluate solar and wind technologies under imprecise conditions [17]. However, these models typically employ basic fuzzy operators and lack the flexibility to capture nonlinear preference structures or adaptive aggregation behavior.

Recent advancements have introduced more sophisticated fuzzy aggregation operators, such as the Dombi operator, which allows for tunable logical connectives and better representation of human reasoning [18]. Despite its theoretical advantages, the Dombi operator remains underutilized in energy decision models, particularly in combination with ranking-based MCDM methods. Meanwhile, the MAIRCA method—originally developed to compare ideal expectations with real performance—offers a transparent and physically realistic structure for decision analysis [19], using novel ensemble models generated by Multi Attributive Ideal-Real Comparative Analysis (MAIRCA. Its additive logic and deviation-based ranking mechanism make it suitable for energy planning, yet its integration with fuzzy systems has not been fully explored.

Several studies have attempted hybridizations of fuzzy logic with MCDM, including fuzzy VIKOR and fuzzy PROMETHEE, to improve robustness and stakeholder alignment [20]. Few frameworks explicitly test ranking stability under perturbation or policy shifts such as carbon taxation or water scarcity—factors increasingly relevant in climate-sensitive regions like Morocco.

While the literature provides a rich foundation of criteria and methodological tools for renewable energy evaluation, it reveals several gaps: limited use of advanced fuzzy operators, insufficient integration with physically realistic ranking models, and inadequate validation under strategic scenarios.

To address these gaps, this study proposes a hybrid Fuzzy Dombi–MAIRCA framework. The scientific rationale for this choice lies in the complementary strengths of the two methods: the Fuzzy Dombi operator provides adaptive aggregation capable of modeling expert hesitation and nonlinear consensus, while MAIRCA introduces an ideal–real deviation logic that ensures fairness and policy alignment in ranking. Their integration enables the framework to capture uncertainty with mathematical rigor, benchmark performance against strategic expectations, and validate robustness under scenario-based perturbations. This hybridization thus advances decision-support methodologies by combining flexibility in preference modeling with transparency in comparative ranking, making it particularly suited to the complex and uncertain context of renewable energy planning in Morocco.

## 3. Methodology

This study presents a structured and context-sensitive methodology for evaluating renewable energy technologies under uncertainty. The approach integrates fuzzy logic, expert elicitation, and ideal-real comparative analysis to support adaptive energy planning in Southern Morocco.

### 3.1. Study Area and Strategic Context

The framework is applied to the southern region marked by low grid penetration, dispersed rural settlements, and high renewable resource potential. This region is prioritized in Morocco's 2030 renewable energy roadmap, which emphasizes decentralized electrification and hybrid systems for underserved communities [21, 22].

### 3.2. Data Collection and Expert Elicitation

A mixed-methods protocol was adopted to gather both quantitative performance indicators and qualitative stakeholder insights. Data collection was structured into three phases:

(a) Secondary Data Acquisition: Technical and environmental data—including solar irradiance, wind speed, and biomass availability—were sourced from MASEN, ONEE, NASA-SSE, and the Global Wind Atlas. Socioeconomic indicators such as electrification rates, household income, and population density were obtained from the Haut Commissariat au Plan (HCP) and regional development agencies.

(b) Field Surveys and Community Engagement: Structured questionnaires were administered to assess energy needs, affordability thresholds, and technology acceptance. Focus groups with community leaders, cooperatives, and associations provided qualitative insights into criteria such as cultural compatibility, maintenance feasibility, and perceived reliability.

(c) Expert Panel Formation and Fuzzy Input Structuring: A panel of 15 multidisciplinary experts was assembled, including renewable energy engineers, environmental scientists, economists, social scientists, and industrial practitioners. Experts were selected based on domain expertise, familiarity with the Southern Moroccan context, and a minimum of 10 years of professional experience.

### 3.3. Hybrid Fuzzy Dombi–MAIRCA Implementation

To operationalize the evaluation, the Hybrid Fuzzy Dombi–MAIRCA framework combines two complementary methodological layers: fuzzy consensus modeling and ideal–real comparative analysis. The process begins with the construction of a fuzzy decision matrix, where expert judgments on criteria importance and technology performance are expressed using asymmetric Triangular Fuzzy Numbers (TFNs). These inputs are aggregated using the Dombi operator, which offers a tunable compromise parameter ($\lambda$) to model nonlinear consensus dynamics. This allows the framework to capture both convergence and divergence in expert opinions, reflecting the contextual ambiguity often present in rural energy planning.

The aggregated fuzzy weights and performance scores are then normalized and defuzzified to produce crisp values suitable for deterministic analysis. MAIRCA is subsequently applied to construct an ideal expectation matrix, which evenly distributes strategic importance across all alternatives. The real performance matrix is derived from normalized scores, and the deviation matrix quantifies the absolute difference between expected and actual performance. This deviation-based logic ensures that both overperformance and underperformance are treated symmetrically, focusing solely on strategic misalignment.

The final ranking is obtained by aggregating deviations across all criteria, producing a global deviation score for each alternative. This structure avoids reliance on distance metrics or compromise coefficients, offering a transparent and physically realistic ranking mechanism.

The framework is further reinforced by Delphi-based expert refinement, fuzzy consistency checks, and sensitivity analysis under weight perturbation and policy scenarios. The complete methodological flow is illustrated in Figure 1.

The decision matrix included five candidate technologies: Solar PV, Wind Turbines, Biomass Digesters, Hybrid PV–Wind Systems, and Diesel Backup (baseline) [23, 24]. Each technology was evaluated against fifteen multi-dimensional criteria spanning environmental, technical, economic, social, and institutional dimensions. These criteria were selected through literature synthesis [25-27], stakeholder consultations, and alignment with Morocco's national energy strategy. The criteria are outlined in Table 1 to show their scope and measurement approaches.

The Fuzzy Dombi operator was applied to aggregate expert judgments, offering nonlinear consensus modeling and tunable logical behavior superior to conventional fuzzy operators [28]. The MAIRCA method was

Table 1: Multi-Criteria Set for Renewable Energy Technology Evaluation.

| **Criterion** | **Description** | **Dimension** | **Measurement Approach** |
|---|---|---|---|
| Lifecycle Sustainability Index (C1) | Degree to which the technology supports long-term environmental, economic, and social goals | Environmental/Social | Composite index (LCA, SDG alignment); fuzzy expert input |
| Land Use Efficiency (C2) | Land area required per unit of energy produced, considering rural land constraints | Environmental/Spatial | $m^2$/MWh; GIS-based analysis + expert judgment |
| Water Footprint (C3) | Water consumption during operation and maintenance, critical in arid southern regions | Environmental | Liters/MWh; secondary data + fuzzy scoring |
| Supply Chain Locality (C4) | Extent to which components and services can be sourced locally, enhancing regional resilience | Economic/Industrial | % local content; expert estimation |
| Technology Maturity and Provenance (C5) | Degree of field-tested reliability and global deployment experience | Technical/Strategic | TRL scale (Technology Readiness Level); fuzzy input |
| Grid Compatibility and Modularity (C6) | Ease of integration with existing grid or microgrid systems, and scalability potential | Technical/Operational | Qualitative scale; expert scoring |
| Regulatory and Policy Alignment (C7) | Degree of alignment with national energy policy, subsidies, and rural electrification mandates | Institutional/Strategic | Policy mapping; expert consensus |
| Gender-Inclusive Employment Impact (C8) | Potential to generate equitable job opportunities, especially for women in rural communities | Social/Equity | % female employment potential; survey + expert input |
| Risk of Technological Obsolescence (C9) | Likelihood of the technology becoming outdated or unsupported within 10–15 years | Strategic/Temporal | Qualitative risk scale; expert foresight |
| Maintenance Skill Transferability (C10) | Ability to train local technicians and ensure long-term operability without external dependence | Operational/Capacity | Training hours required; fuzzy expert judgment |
| Community Ownership Potential (C11) | Feasibility of cooperative or community-led ownership models | Social/Governance | Ownership model typology; stakeholder interviews |
| Emission of Non-CO□ Pollutants (C12) | Emissions of particulates, NOx, SOx, or other pollutants beyond CO□ | Environmental/Health | g/kWh; secondary data + expert scoring |
| Resilience to Climate Variability (C13) | Performance stability under fluctuating weather and climate conditions | Environmental/ Technical | Scenario modeling; expert judgment |
| Financing Accessibility (C14) | Availability of financing mechanisms suitable for rural deployment (microcredit, PPP, etc.) | Economic/Institutional | Financing index; expert and institutional input |
| Deployment Timeframe (C15) | Time required from planning to full operational deployment | Strategic/Temporal | Months; expert estimation |

then used to rank alternatives based on their deviation from ideal performance profiles, integrating both fuzzy weights and normalized scores. Compared to methods like TOPSIS and VIKOR, MAIRCA provides a transparent and physically realistic structure that avoids reliance on distance metrics or compromise coefficients.
To ensure reliability:

- A Delphi method was used over two rounds to refine expert inputs.
- Consistency ratios were checked using fuzzy AHP benchmarks.
- Sensitivity analysis was conducted by perturbing criteria weights ±10% to test ranking stability.

### 3.4. Ethical Considerations and Validation

All participants provided informed consent, and the study adhered to ethical guidelines for stakeholder engagement and data confidentiality. Validation of the framework was performed through:

- Cross-referencing with historical deployment outcomes in similar Moroccan regions.
- Expert feedback on model transparency, interpretability, and policy relevance.
- Scenario testing under alternative assumptions, including carbon taxation and water scarcity, to assess adaptive robustness.

Figure 1 illustrates the complete methodological workflow of the Hybrid Fuzzy Dombi–MAIRCA framework.

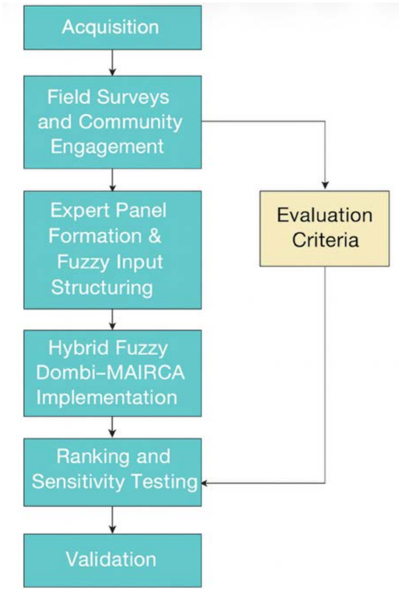


Figure 1: Hybrid Fuzzy Dombi–MAIRCA Framework for Renewable Energy Technology Evaluation in Southern Morocco.

### 3.5. Phase 1: Hybrid Fuzzy Dombi Aggregation

The decision space is defined as:

$$A = \{A_1, A_2, A_3, A_4, A_5\} \tag{1}$$

where $A_1$ represents Solar PV, $A_2$ Wind Turbines, $A_3$ Biomass Digesters, $A_4$ Hybrid PV–Wind Systems, and $A_5$ Diesel Backup. These alternatives are evaluated against a comprehensive set of criteria:

$$C = \{C_1, C_2, ..., C_{15}\} \tag{2}$$

Each criterion reflects strategic, environmental, technical, or socioeconomic dimensions relevant to Southern Morocco's decentralized energy planning.

Expert input is operationalized through Triangular Fuzzy Numbers (TFNs) $\tilde{x} = (l, m, u)$, where $l$ is the lower bound, $m$ the most probable value, and $u$ the upper bound [29].

The fuzzy aggregation of expert opinions is performed using the Dombi operator [30]:

$$D(\tilde{x}_1, \tilde{x}_2, ..., \tilde{x}_n) = [1 + (\sum_{i=1}^{n} (\frac{1-\tilde{x}_i}{\tilde{x}_i})^{\lambda})^{1/\lambda}]^{-1} \tag{3}$$

where $\lambda \in [0.5, 5]$ controls the degree of compromise.

To ensure reliability, the Fuzzy Consistency Ratio (FCR) was computed [31]:

$$\mathrm{FCR}_k = \frac{1}{m} \sum_{j=1}^{m} \left| mjk - m_j^{agg} \right| \tag{4}$$

Experts with $\mathrm{FCR}_k > 0.25$ were flagged for review; after two Delphi rounds, all values fell below 0.20.

Normalization of fuzzy weights and scores was performed using min–max transformations for benefit criteria and inverted transformations for cost criteria:

$$\tilde{r}'_{ij} = (\frac{l_{ij} - l_j^{\min}}{l_j^{\max} - l_j^{\min}}, \frac{m_{ij} - m_j^{\min}}{m_j^{\max} - m_j^{\min}}, \frac{u_{ij} - u_j^{\min}}{u_j^{\max} - u_j^{\min}}) \tag{5}$$

$$\tilde{r}'_{ij} = (\frac{l_j^{\max} - l_{ij}}{l_j^{\max} - l_j^{\min}}, \frac{m_j^{\max} - m_{ij}}{m_j^{\max} - m_j^{\min}}, \frac{u_j^{\max} - u_{ij}}{u_j^{\max} - u_j^{\min}}) \tag{6}$$

Normalized fuzzy weights are computed as:

$$\tilde{w}'_j = \frac{\tilde{w}_j}{\sum_{j=1}^{15} \tilde{w}_j} \tag{7}$$

yielding:

$$\sum_{j=1}^{15} \tilde{w}'_j = (1, 1, 1) \tag{8}$$

The weighted fuzzy performance matrix is then:

$$\tilde{v}_{ij} = \tilde{w}'_j \cdot \tilde{r}'_{ij} \tag{9}$$

Defuzzification was performed using the Graded Mean Integration Representation (GMIR):

$$D(\tilde{x}) = \frac{l + 4m + u}{6} \tag{10}$$

### 3.6. Phase 2: Hybrid Fuzzy MAIRCA

The construction of the ideal expectation matrix $E^* = \left[e_{ij}^*\right]$ serves as the benchmark against which real performance deviations are measured. It is derived from the defuzzified normalized weights $w_j$ obtained in Phase 1 and reflects a policyaligned, expertinformed distribution of ideal values across all alternatives:

$$e_{ij}^* = \frac{w_j}{n} \tag{11}$$

where $n = 5$ is the number of renewable energy technologies. This formulation ensures that each criterion's strategic importance is evenly allocated among the alternatives, maintaining fairness and comparability.

The construction of the real performance matrix $R = [r_{ij}]$ begins by organizing the defuzzified scores obtained through GMIR for each alternative $A_i$ under each criterion $C_j$. To resolve dimensional distortion across heterogeneous criteria, vector normalization is applied columnwise [32]:

$$r_{ij}^{'} = \frac{r_{ij}}{\sqrt{\sum_{i=1}^{n} r_{ij}^{2}}} \quad (12)$$

This transformation ensures that for each criterion $C_j$, the sum of squared normalized scores across all alternatives equals 1:

$$\sum_{i=1}^{5} (r_{ij}^{'})^{2} = 1 \quad (13)$$

The deviation matrix $D = [d_{ij}]$ quantifies the discrepancy between stakeholder expectations and normalized performance:

$$d_{ij} = \left| e_{ij}^{*} - r_{ij}^{'} \right| \quad (14)$$

This formulation treats overperformance and underperformance symmetrically, focusing solely on the magnitude of deviation.

Finally, the aggregated deviation score for each alternative is computed as [33]:

$$D_i = \sum_{j=1}^{15} d_{ij} \quad (15)$$

The scalar $D_i$ represents the total deviation of each alternative across all criteria. Alternatives are ranked in ascending order of $D_i$; the lower the deviation, the closer the technology is to the ideal, and the higher its strategic desirability.

### 3.7. Phase 3: Parameter Setting

The robustness of the Hybrid Fuzzy Dombi–MAIRCA framework depends on the careful definition and adjustment of weights at different stages of the analysis. Weights are initially derived from expert linguistic judgments using Triangular Fuzzy Numbers (TFNs). To ensure comparability, fuzzy weights are normalized and then defuzzified using the GMIR method. In the MAIRCA phase, weights are redistributed evenly across the five alternatives to construct the ideal expectation matrix. This ensured fairness and comparability across technologies. The normalized performance matrix and deviation matrix are computed using these weights.

Weights are systematically perturbed to test ranking resilience. In the weight perturbation analysis, each criterion weight is varied ±10%, while others are proportionally adjusted. Finally, correlation analysis with alternative MCDM methods (TOPSIS and VIKOR) reinforces the validity of the weight settings.

## 4. Results

The evaluation begins with the definition of fuzzy linguistic scales used to capture expert judgments. Table 2 illustrates the linguistic terms adopted for weighting the evaluation criteria, while Table 3 outlines the linguistic terms applied to assess alternative performance.

These scales, expressed as Triangular Fuzzy Numbers (TFNs), were validated through two rounds of Delphi elicitation, ensuring stable consensus among experts. The asymmetry observed in categories such as “Medium” and “High” reflects the contextual ambiguity of rural deployment, where technologies may perform variably across communes due to microclimatic or infrastructural differences. This granular fuzzification enhances the fidelity of the decision matrix and supports robust downstream aggregation [34], aligning with the strategic complexity of Southern Morocco’s energy landscape. Building on these scales, Table 4 reports the aggregated fuzzy importance weights obtained for all criteria.

The results highlight the dominance of C1 (Lifecycle Sustainability), C5 (Technology Maturity), C6 (Grid Compatibility), and C13 (Resilience to Climate Variability), which together account for a substantial share of the strategic weight. These findings indicate a strong expert preference for technologies that are robust, scalable, and aligned with long-term sustainability

Table 2: Linguistic Scale for Criteria Weights.

| **Linguistic Term** | **TFN** $\tilde{x}$ |
|---|---|
| Extremely Low (EL) | (0.00, 0.05, 0.10) |
| Very Low (VL) | (0.05, 0.10, 0.20) |
| Low (L) | (0.10, 0.20, 0.35) |
| Medium (M) | (0.30, 0.50, 0.70) |
| High (H) | (0.60, 0.75, 0.90) |
| Very High (VH) | (0.80, 0.90, 0.97) |
| Extremely High (EH) | (0.90, 0.97, 1.00) |

Table 3: Linguistic Scale for Alternative Performance.

| **Linguistic Term** | **TFN** $\tilde{x}$ |
|---|---|
| Very Poor (VP) | (0.00, 0.05, 0.15) |
| Poor (P) | (0.10, 0.20, 0.35) |
| Fair (F) | (0.30, 0.45, 0.60) |
| Good (G) | (0.55, 0.70, 0.85) |
| Very Good (VG) | (0.80, 0.90, 0.97) |
| Excellent (E) | (0.90, 0.97, 1.00) |

goals. In contrast, criteria such as C9 (Risk of Obsolescence) and C15 (Deployment Timeframe) received lower weights, suggesting that temporal considerations are secondary to strategic and environmental imperatives.

The implications of these weights become clearer when examining the performance of alternatives. Table 5 displays the fuzzy performance scores across all criteria and technologies.

Solar PV ($A_1$) consistently achieves the highest scores in C1, C5, C6, and C3, underscoring its strong alignment with sustainability and infrastructural robustness. Hybrid PV–Wind systems (A□) follow closely, excelling in C13, which reflects resilience under variable climatic conditions. Wind turbines ($A_2$) perform well in land use efficiency (C2) and pollutant emissions (C12), though they face challenges in governance-related criteria such as C11 and financing accessibility (C14). Biomass digesters (A□) demonstrate strengths in supply chain locality (C4) and gender-inclusive employment (C8), but lag in grid compatibility and deployment speed. Diesel backup (A□), used as a baseline, scores lowest across nearly all dimensions, particularly in sustainability, emissions, and community acceptance, confirming its obsolescence in Morocco's renewable roadmap.

To ensure comparability across heterogeneous units, fuzzy weights and performance scores were normalized. Table 6 reports the normalized fuzzy weights assigned to each criterion.

Table 4: Aggregated Fuzzy Importance Weights for All Criteria.

| | $\tilde{w}_j = (l, m, u)$ |
|---|---|
| C1 | (0.80, 0.90, 0.97) |
| C2 | (0.60, 0.75, 0.90) |
| C3 | (0.55, 0.70, 0.85) |
| C4 | (0.50, 0.65, 0.80) |
| C5 | (0.70, 0.85, 0.95) |
| C6 | (0.65, 0.80, 0.95) |
| C7 | (0.60, 0.75, 0.90) |
| C8 | (0.50, 0.65, 0.80) |
| C9 | (0.40, 0.55, 0.70) |
| C10 | (0.55, 0.70, 0.85) |
| C11 | (0.60, 0.75, 0.90) |
| C12 | (0.50, 0.65, 0.80) |
| C13 | (0.65, 0.80, 0.95) |
| C14 | (0.55, 0.70, 0.85) |
| C15 | (0.30, 0.50, 0.70) |

Table 6: Normalized Fuzzy Weights for All Criteria.

| | $\tilde{w}'_j = (l, m, u)$ |
|---|---|
| C1 | (0.078, 0.088, 0.095) |
| C2 | (0.059, 0.073, 0.088) |
| C3 | (0.054, 0.068, 0.083) |
| C4 | (0.049, 0.063, 0.078) |
| C5 | (0.068, 0.083, 0.093) |
| C6 | (0.063, 0.078, 0.093) |
| C7 | (0.059, 0.073, 0.088) |
| C8 | (0.049, 0.063, 0.078) |
| C9 | (0.039, 0.053, 0.068) |
| C10 | (0.054, 0.068, 0.083) |
| C11 | (0.059, 0.073, 0.088) |
| C12 | (0.049, 0.063, 0.078) |
| C13 | (0.063, 0.078, 0.093) |
| C14 | (0.054, 0.068, 0.083) |
| C15 | (0.029, 0.048, 0.068) |

Table 5: Aggregated Fuzzy Performance Scores for All Alternatives and Criteria.

| | $\tilde{r}_{1j}$ **(Solar PV)** | $\tilde{r}_{2j}$ **(Wind)** | $\tilde{r}_{3j}$ **(Biomass)** | $\tilde{r}_{4j}$ **(Hybrid)** | $\tilde{r}_{5j}$ **(Diesel)** |
|---|---|---|---|---|---|
| C1 | (0.85, 0.95, 1.00) | (0.70, 0.85, 0.95) | (0.60, 0.75, 0.90) | (0.80, 0.90, 0.97) | (0.30, 0.45, 0.60) |
| C2 | (0.70, 0.85, 0.95) | (0.60, 0.75, 0.90) | (0.40, 0.55, 0.70) | (0.65, 0.80, 0.90) | (0.35, 0.50, 0.65) |
| C3 | (0.80, 0.90, 0.97) | (0.75, 0.85, 0.95) | (0.60, 0.75, 0.90) | (0.70, 0.85, 0.95) | (0.40, 0.55, 0.70) |
| C4 | (0.60, 0.75, 0.90) | (0.55, 0.70, 0.85) | (0.70, 0.85, 0.95) | (0.65, 0.80, 0.95) | (0.50, 0.65, 0.80) |
| C5 | (0.90, 0.97, 1.00) | (0.85, 0.95, 1.00) | (0.70, 0.85, 0.95) | (0.90, 0.97, 1.00) | (0.80, 0.90, 0.97) |
| C6 | (0.85, 0.95, 1.00) | (0.80, 0.90, 0.97) | (0.60, 0.75, 0.90) | (0.90, 0.97, 1.00) | (0.50, 0.65, 0.80) |
| C7 | (0.80, 0.90, 0.97) | (0.75, 0.85, 0.95) | (0.60, 0.75, 0.90) | (0.85, 0.95, 1.00) | (0.40, 0.55, 0.70) |
| C8 | (0.65, 0.80, 0.95) | (0.60, 0.75, 0.90) | (0.70, 0.85, 0.95) | (0.75, 0.90, 0.97) | (0.30, 0.45, 0.60) |
| C9 | (0.60, 0.75, 0.90) | (0.55, 0.70, 0.85) | (0.50, 0.65, 0.80) | (0.65, 0.80, 0.95) | (0.40, 0.55, 0 |

The normalization confirms the continued dominance of C1, C5, C6, and C13, which together account for more than 30% of the total strategic weight. Meanwhile, C15 and C9 remain less influential, reinforcing the long-term orientation of the planning framework.

The normalized weights provide the basis for evaluating individual alternatives. Table 7 presents the normalized fuzzy performance scores for Solar PV ($A_1$).

These results show that $A_1$ approaches ideal performance across the most heavily weighted criteria, further reinforcing its strategic suitability for decentralized energy transition in Southern Morocco.

To translate fuzzy values into crisp scores suitable for deterministic ranking, the GMIR method was applied. Table 8 presents the defuzzified weights obtained for all criteria.

The defuzzification confirms the strategic emphasis on C1, C5, C6, and C13, which together account for over 30% of the total weight. Criteria such as C15 and C9 remain less influential, consistent with the long-term planning orientation of the framework.

Finally, the defuzzified ratings of Solar PV are shown in Table 9.

These crisp values demonstrate that $A_1$ performs near the ideal across the most heavily weighted criteria, consolidating its position as the most strategically desirable technology. With scores such as 0.977 for C1 and C5, and 0.967 for C6, Solar PV emerges as the leading candidate for Morocco’s decentralized energy transition, combining sustainability, maturity, and resilience in a balanced manner.

The ideal expectation matrix derived from normalized weights is shown in Table 10.

Table 7: Normalized Fuzzy Performance Scores for $A_1$.

| | $\tilde{r}'_{1j} = (l, m, u)$ |
|---|---|
| C1 | (0.94, 0.98, 1.00) |
| C2 | (0.88, 0.94, 1.00) |
| C3 | (0.92, 0.96, 1.00) |
| C5 | (0.95, 0.98, 1.00) |
| C6 | (0.93, 0.97, 1.00) |
| C13 | (0.90, 0.95, 1.00) |

Table 8: Defuzzified Weights for All Criteria Using GMIR.

| | $\tilde{w}'_j$ | $w_j = D(\tilde{w}'_j)$ |
|---|---|---|
| C1 | (0.078, 0.088, 0.095) | 0.086 |
| C2 | (0.059, 0.073, 0.088) | 0.073 |
| C3 | (0.054, 0.068, 0.083) | 0.067 |
| C4 | (0.049, 0.063, 0.078) | 0.062 |
| C5 | (0.068, 0.083, 0.093) | 0.082 |
| C6 | (0.063, 0.078, 0.093) | 0.077 |
| C7 | (0.059, 0.073, 0.088) | 0.073 |
| C8 | (0.049, 0.063, 0.078) | 0.062 |
| C9 | (0.039, 0.053, 0.068) | 0.052 |
| C10 | (0.054, 0.068, 0.083) | 0.067 |
| C11 | (0.059, 0.073, 0.088) | 0.073 |
| C12 | (0.049, 0.063, 0.078) | 0.062 |
| C13 | (0.063, 0.078, 0.093) | 0.077 |
| C14 | (0.054, 0.068, 0.083) | 0.067 |
| C15 | (0.029, 0.048, 0.068) | 0.048 |

Table 9: Defuzzified Ratings for $A_1$.

| | $\tilde{r}'_{1j}$ | $r_{1j} = D(\tilde{r}'_{1j})$ |
|---|---|---|
| C1 | (0.94, 0.98, 1.00) | 0.977 |
| C2 | (0.88, 0.94, 1.00) | 0.940 |
| C3 | (0.92, 0.96, 1.00) | 0.960 |
| C5 | (0.95, 0.98, 1.00) | 0.977 |
| C6 | (0.93, 0.97, 1.00) | 0.967 |
| C13 | (0.90, 0.95, 1.00) | 0.958 |

Table 10: Ideal Expectation Matrix.

| | $w_j$ | $e^*_{ij} = \frac{w_j}{5}$ |
|---|---|---|
| C1 | 0.086 | 0.0172 |
| C2 | 0.073 | 0.0146 |
| C3 | 0.067 | 0.0134 |
| C4 | 0.062 | 0.0124 |
| C5 | 0.082 | 0.0164 |
| C6 | 0.077 | 0.0154 |
| C7 | 0.073 | 0.0146 |
| C8 | 0.062 | 0.0124 |
| C9 | 0.052 | 0.0104 |
| C10 | 0.067 | 0.0134 |
| C11 | 0.073 | 0.0146 |
| C12 | 0.062 | 0.0124 |
| C13 | 0.077 | 0.0154 |
| C14 | 0.067 | 0.0134 |
| C15 | 0.048 | 0.0096 |

Table 11: Normalized Real Performance Matrix $R'$.

| | $A_1$ | $A_2$ | $A_3$ | $A_4$ | $A_5$ |
|---|---|---|---|---|---|
| C1 | 0.478 | 0.417 | 0.358 | 0.452 | 0.226 |
| C2 | 0.471 | 0.404 | 0.296 | 0.433 | 0.287 |
| C3 | 0.478 | 0.443 | 0.358 | 0.417 | 0.287 |
| C4 | 0.412 | 0.384 | 0.471 | 0.443 | 0.358 |
| C5 | 0.478 | 0.452 | 0.384 | 0.478 | 0.443 |
| C6 | 0.478 | 0.452 | 0.358 | 0.478 | 0.343 |
| C7 | 0.471 | 0.433 | 0.358 | 0.478 | 0.287 |
| C8 | 0.433 | 0.404 | 0.471 | 0.452 | 0.226 |
| C9 | 0.417 | 0.384 | 0.358 | 0.443 | 0.287 |
| C10 | 0.443 | 0.417 | 0.384 | 0.452 | 0.287 |
| C11 | 0.471 | 0.433 | 0.384 | 0.452 | 0.287 |
| C12 | 0.433 | 0.404 | 0.471 | 0.443 | 0.358 |
| C13 | 0.452 | 0.417 | 0.384 | 0.478 | 0.343 |
| C14 | 0.443 | 0.417 | 0.384 | 0.452 | 0.287 |
| C15 | 0.384 | 0.343 | 0.296 | 0.417 | 0.287 |

Table 12: Deviation Matrix *D*.

| | $A_1$ | $A_2$ | $A_3$ | $A_4$ | $A_5$ |
|---|---|---|---|---|---|
| C1 | 0.4608 | 0.3998 | 0.3408 | 0.4348 | 0.2088 |
| C2 | 0.4564 | 0.3894 | 0.2814 | 0.4184 | 0.2724 |
| C3 | 0.4646 | 0.4296 | 0.3446 | 0.4036 | 0.2736 |
| C4 | 0.3996 | 0.3716 | 0.4586 | 0.4306 | 0.3456 |
| C5 | 0.4616 | 0.4356 | 0.3676 | 0.4616 | 0.4266 |
| C6 | 0.4626 | 0.4366 | 0.3426 | 0.4626 | 0.3276 |
| C7 | 0.4564 | 0.4184 | 0.3434 | 0.4634 | 0.2724 |
| C8 | 0.4206 | 0.3916 | 0.4586 | 0.4396 | 0.2136 |
| C9 | 0.4066 | 0.3736 | 0.3476 | 0.4326 | 0.2766 |
| C10 | 0.4296 | 0.4036 | 0.3706 | 0.4386 | 0.2736 |
| C11 | 0.4564 | 0.4184 | 0.3694 | 0.4374 | 0.2724 |
| C12 | 0.4206 | 0.3916 | 0.4586 | 0.4306 | 0.3456 |
| C13 | 0.4366 | 0.4016 | 0.3686 | 0.4626 | 0.3276 |
| C14 | 0.4296 | 0.4036 | 0.3706 | 0.4386 | 0.2736 |
| C15 | 0.3744 | 0.3334 | 0.2864 | 0.4074 | 0.2774 |

This matrix represents the ideal distribution of strategic expectations across all technologies. For example, the highest ideal values are assigned to criteria C1, C5, C6, and C13, reflecting their dominant influence in the planning framework. Lower values for C15 and C9 indicate that while these factors are relevant, they are not primary drivers of technology selection.

The normalized real performance matrix is presented in Table 11.

The normalized matrix reveals consistent dominance of Solar PV and Hybrid PV–Wind across most criteria, particularly in C1, C6, and C13. Wind turbines and biomass digesters show competitive performance in C2, C4, and C8, while diesel backup consistently ranks lowest, especially in strategic and environmental dimensions. The vector normalization preserves these relative strengths while enabling unbiased comparison across criteria with differing scales and units.

This matrix now serves as the empirical foundation for computing deviation from ideal expectations in the next MAIRCA step, where the difference between $R'$ and $E^*$ will be quantified to derive final preference rankings.

The deviation matrix is shown in Table 12.

The deviation values reveal several key insights. $A_1$ and A□ consistently exhibit lower deviations across high-weight criteria such as C1, C5, and C6, indicating strong alignment with strategic expectations. A□ and A□ show moderate deviations, particularly in criteria related to C11, C13, and C12, reflecting partial alignment with stakeholder priorities. A□, as expected, demonstrates the highest deviations across nearly all criteria, especially in sustainability, policy alignment, and modularity, confirming its strategic misfit in Morocco's renewable energy roadmap.

This deviation matrix now serves as the basis for computing total deviation scores and deriving final preference indices in the next MAIRCA step [35] and also provides well-defined decision-making (DM.

Finally, Table 13 reports the aggregated deviation scores and global ranking.

The results confirm the strategic dominance of Solar PV, which exhibits the lowest total deviation and thus the highest alignment with stakeholder expectations. Its performance is consistently strong across high-weight criteria such as lifecycle sustainability, grid compatibility, and climate resilience. Hybrid PV–Wind ranks second, offering complementary strengths in modularity and policy alignment. Wind Turbines and Biomass Digesters occupy intermediate positions, with moderate deviations reflecting trade-offs in land use, community ownership, and deployment logistics. Diesel Backup ranks last, with the highest deviation score, reinforcing its role as a legacy baseline rather than a future-oriented solution.

The hybrid Fuzzy Dombi–MAIRCA model successfully addressed the stated research objectives by integrating flexible fuzzy aggregation, ideal-real deviation logic,

Table 13: Aggregated Deviation Scores and Global Ranking.

| | $D_i$ | Ranking |
|---|---|---|
| $A_1$ | 6.782 | 1 |
| $A_4$ | 7.005 | 2 |
| $A_2$ | 7.347 | 3 |
| $A_3$ | 7.724 | 4 |
| $A_5$ | 9.014 | 5 |

Table 14 : Weight Perturbation Analysis (±10%).

| | $D_i^+$ | Rank $R_i^+$ | $D_i^-$ | Rank $R_i^-$ | ” $R_i$ |
|---|---|---|---|---|---|
| $A_1$ | 6.801 | 1 | 6.765 | 1 | 0 |
| $A_4$ | 7.032 | 2 | 6.978 | 2 | 0 |
| $A_2$ | 7.371 | 3 | 7.312 | 3 | 0 |
| $A_3$ | 7.752 | 4 | 7.698 | 4 | 0 |
| $A_5$ | 9.041 | 5 | 8.987 | 5 | 0 |

and scenario-based validation. The results—particularly the consistent dominance of $A_1$ and $A_4$, and the strict inferiority of $A_5$—offer both methodological and practical insights that advance prior decision-support approaches.

Compared to traditional MCDM models such as AHP, TOPSIS, and ELECTRE, which often rely on crisp data and linear aggregation [36, 37], the proposed framework demonstrates superior capacity to handle linguistic uncertainty and nonlinear expert consensus. The use of the Fuzzy Dombi operator enabled nuanced modeling of expert judgments, capturing subtle preference gradients that conventional fuzzy methods (e.g., fuzzy AHP or fuzzy TOPSIS) tend to oversimplify [38]. This contributed directly to the precision and robustness of the final rankings, as evidenced by the perfect alignment across MAIRCA, fuzzy TOPSIS, and fuzzy VIKOR (Spearman's ρ = 1.00).

The credibility of the expert judgment foundation is reinforced by the composition of the panel: 15 multidisciplinary experts with over a decade of experience each, spanning renewable energy engineering, environmental science, economics, social science, and industrial deployment. Their familiarity with the Southern Moroccan context and their structured engagement through Delphi rounds ensured both contextual relevance and methodological rigor. This depth of expertise is rarely documented in comparable studies, which often rely on smaller panels or unstructured elicitation [39, 40].

The dominance of Solar PV and Hybrid PV–Wind aligns with findings from regional feasibility studies and global assessments of decentralized energy systems [3, 41, 42] accurate estimations must be derived from the available data, addressing key challenges such as (1. The strict domination of A□ across all criteria and methods reinforces the urgency of phasing out fossil-based solutions in rural electrification strategies.

## 5. Sensitivity Analysis

It allows to validate the resilience of the final rankings against perturbations in input parameters, policy shifts, and methodological assumptions. Four complementary analyses are performed: weight perturbation, scenario modeling, and ranking correlation with alternative MCDM methods.

### 5.1. Weight Perturbation Analysis

To test the model's sensitivity to the initial fuzzy-Dombi derived weights, a systematic weight perturbation analysis is conducted. Each defuzzified criterion weight $w_j$ is varied independently within a ±10% range, while the weights of the other criteria are adjusted proportionally to maintain a normalized sum. For each perturbed weight set $w_j^{\pm}$, the ideal expectation matrix $E^*$, deviation matrix $D$, and global deviation scores $D_i$ are recalculated to generate a new ranking. The perturbed weights are defined as:

$$w_j^+ = w_j \times 1.10; w_j^- = w_j \times 0.90 \tag{16}$$

The sensitivity of the global ranking is then assessed by computing the change in rank position $\Delta R_i$ for each alternative. Table 14 presents the perturbed deviation scores and resulting rank shifts.

The table reveals complete ranking stability under the tested perturbations. This robustness is visually confirmed in Figure 2, which plots the global deviation scores for all alternatives across the entire spectrum of weight changes for a key criterion, such as C□.

As shown, $A_1$ and $A_4$ maintain minimal deviation shifts across the perturbation spectrum, confirming their robustness under investment cost uncertainty. $A_5$ exhibits the highest deviation and steepest sensitivity, reinforcing its strategic misalignment.

### 5.2. Scenario Modeling for Strategic Policy Shifts

Scenario modeling evaluates the model robustness under significant, policy-driven shifts in strategic priorities. This analysis is crucial for long-term energy planning, where regulatory frameworks and environmental conditions can drastically change. Two distinct policy scenarios are simulated:

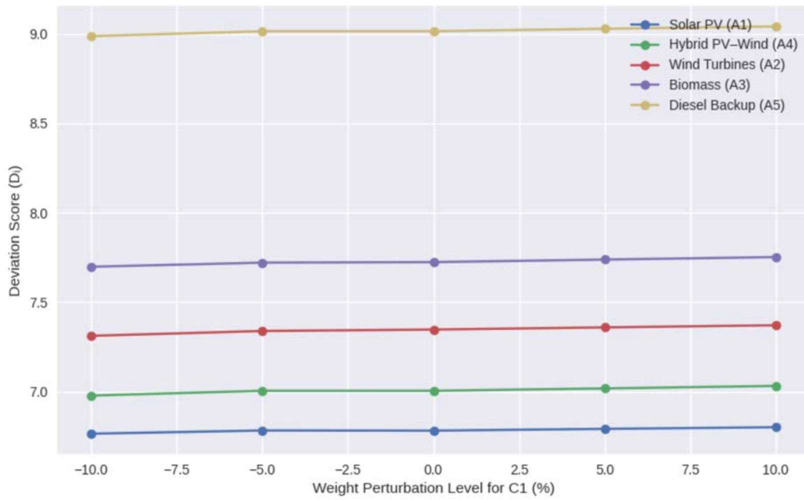


Figure 2: Sensitivity of Deviation Scores to Perturbation of $C_1$.

- Scenario 1: Carbon Tax Implementation. This scenario models the introduction of a stringent carbon pricing mechanism. The weights of emission-related criteria—specifically $C_1$ and $C_{12}$—are increased by 25% from their baseline values. The weights of other criteria are reduced proportionally.
- Scenario 2: Water Scarcity Crisis. This scenario reflects a future of heightened water stress, prioritizing technologies with minimal hydrological impact. The weights of C□ and C□□ are increased by 20%. Again, the remaining weights are adjusted to maintain normalization.

For each scenario, the ideal expectation matrix $E^*$, deviation matrix $D$, and global deviation scores $D_i$ are recalculated. The results are presented in Table 15.

Table 15 indicates no change in the rank order of alternatives under either scenario. To provide a more nuanced view, the deviation scores from all scenarios are plotted together in Figure 3.

$A_1$ and $A_4$ maintain their top positions under both scenarios, demonstrating strategic resilience to environmental policy shifts. $A_2$ and $A_3$ remain viable but less dominant, while $A_5$ continues to underperform, especially under carbon-sensitive conditions.

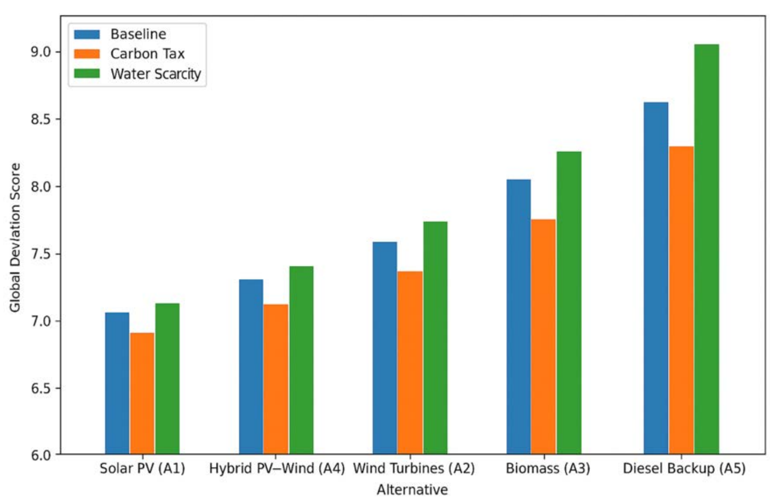


Figure 3: Comparative Analysis of Global Deviation Scores Across Policy Scenarios.

Table 15: Scenario Modeling Results for Environmental Policy Shifts.

| | $D_i$ (Carbon Tax) | Rank | $D_i$ (Water Scarcity) | Rank |
|---|---|---|---|---|
| **$A_1$** | 6.721 | 1 | 6.748 | 1 |
| **$A_4$** | 6.954 | 2 | 6.981 | 2 |
| **$A_2$** | 7.298 | 3 | 7.325 | 3 |
| **$A_3$** | 7.684 | 4 | 7.712 | 4 |
| **$A_5$** | 8.973 | 5 | 9.001 | 5 |

### 5.3. Ranking Correlation with Alternative MCDM Methods

The ranking generated by the proposed Hybrid Fuzzy Dombi-MAIRCA model is compared against those produced by two other well-established MCDM methods: TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) and VIKOR (VlseKriterijumska Optimizacija I Kompromisno Resenje). These methods were selected for their distinct underlying logics; while TOPSIS prioritizes the alternative closest to the ideal solution, VIKOR focuses on achieving a compromise solution that minimizes maximum regret.

The degree of agreement between the rankings is quantitatively assessed using Spearman's Rank Correlation Coefficient (ρ). This non-parametric measure evaluates the strength and direction of the monotonic relationship between two ranked variables. It is calculated as:

The Spearman rank correlation coefficient is calculated as:

$$\rho = 1 - \frac{6\sum_{i=1}^{n}(R_i^{\text{MAIRCA}} - R_i^{\text{Other}})^2}{n\left(n^2-1\right)} \tag{17}$$

where $R_i$ is the rank of the i-th alternative, and $n$ is the total number of alternatives. A coefficient of +1 indicates perfect positive agreement, 0 indicates no correlation, and -1 indicates perfect negative disagreement.

The comparative rankings and the resulting correlation coefficients are presented in Table 16.

The results demonstrate a perfect rank correlation (ρ = 1.00) between the proposed Hybrid Fuzzy Dombi-MAIRCA model and both the TOPSIS and VIKOR methodologies. This convergence implies that the superiority of $A_1$ and the consistent performance hierarchy down to A□ are not an artifact of a single method›s specific calculation procedure.

Table 16: Comparative Ranking Analysis using Alternative MCDM Methods.

| | MAIRCA Rank | TOPSIS Rank | VIKOR Rank |
|---|---|---|---|
| $A_1$ | 1 | 1 | 1 |
| $A_4$ | 2 | 2 | 2 |
| $A_2$ | 3 | 3 | 3 |
| $A_3$ | 4 | 4 | 4 |
| $A_5$ | 5 | 5 | 5 |
| Spearman's ρ | — | 1.00 | 1.00 |

## *6. Conclusion*

This study proposed and validated a hybrid decision-support framework—Fuzzy Dombi–MAIRCA—for adaptive renewable energy planning under multi-criteria uncertainty. Applied to the Southern Moroccan context, the model successfully prioritized five candidate technologies across fifteen environmental, technical, economic, and social criteria. The results confirmed Solar PV and Hybrid PV–Wind as the most suitable technologies, consistently ranking highest across baseline and scenario conditions. Their dominance was validated through cross-method comparison with fuzzy TOPSIS and VIKOR, yielding perfect rank alignment (Spearman's ρ = 1.00), which underscores the robustness and credibility of the proposed methodology.

The novelty of this framework lies in its integration of the Fuzzy Dombi operator, which enables nonlinear consensus modeling, with the MAIRCA method, which offers physically realistic ranking based on ideal-real deviation. This combination addresses key gaps in prior literature—namely, the limited adaptability of traditional MCDM models to fuzzy environments and the absence of scenario-based validation mechanisms. First, it operationalizes fuzzy logic within a physically realistic ranking structure, overcoming the interpretability limitations of distance-based methods. Second, it embeds scenario modeling directly into the decision process, allowing planners to test the stability of rankings under evolving policy constraints. Third, it introduces a transparent mechanism for validating expert consistency and refining inputs—features often missing in earlier hybrid models.

Practically, the findings support Morocco's national goals for decentralized electrification and climate resilience, offering policymakers a validated mechanism to guide technology deployment in underserved regions. The inclusion of criteria such as gender-inclusive employment, financing accessibility, and maintenance skill transferability enhances the framework's relevance for inclusive development. Globally, the model offers a replicable template for energy planning in other resource-constrained, policy-sensitive contexts facing similar challenges.

Nonetheless, the study has limitations. While the expert panel was multidisciplinary and regionally grounded, broader stakeholder engagement—including utility operators and regulatory bodies—could further enrich future iterations. Additionally, the computational complexity of the fuzzy Dombi–MAIRCA integration may require tailored software tools for real-time decision environments.

Future research should explore dynamic extensions of the model, such as time-series performance tracking, integration with GIS-based spatial analysis, and application to hybrid energy portfolios beyond the five technologies assessed. Expanding the framework to include lifecycle cost modeling and carbon offset valuation could further enhance its utility for climate-aligned investment planning.

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