Journal of Scientific & Industrial Research
Vol. 84, May 2025, pp. 567-574
DOI: 10.56042/jsir.v84i5.11859

Solar Site Selection: A Novel Normalized Expert Strictness for Tailored Evaluation in Decision-Making (NESTED) Approach

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Received 17 June 2024; revised 14 November 2024; accepted 21 February 2025

This paper introduces the NESTED methodology, addressing a critical gap in decision-making by normalizing variations in expert strictness during the criteria weighting phase. Traditional approaches assume uniformity in expert evaluations, often leading to inconsistent outcomes. In contrast, the approach systematically adjusts for individual variations in expert stringency, ensuring fairness and reliability. By integrating normalization techniques with subjective weighting methods, the framework enhances robustness and practicality. The methodology is validated through a solar energy site selection case study, showcasing its applicability in real-world scenarios. Sensitivity analysis underscores its reliability, particularly highlighting the influence of experienced experts on decision outcomes. Comparative analysis with established methods, such as Entropy and CIMAS, reveals the approach's distinct advantages in addressing expert biases, further solidifying its effectiveness. As a novel contribution, this method is the first to specifically tackle the normalization of expert strictness, an often-overlooked yet vital aspect of criteria weighting. The results demonstrate its potential to significantly enhance multi-criteria decision-making processes. By offering a practical solution to this longstanding challenge, the methodology lays the groundwork for future advancements in decision-making frameworks, promoting equitable and consistent evaluation practices.

Keyword: Criteria weighting, Decision-making, Multi-criteria decision-making, Renewable energy, Site selection

Introduction

Decision-making is a fundamental aspect of human endeavours across diverse domains, playing a pivotal role in shaping outcomes and steering the course of actions.[1] Whether in business, healthcare, politics, or everyday life, effective decision-making is essential for success and progress. In recognizing the complexity of decisions, it is common practice to engage experts who bring specialized knowledge, skills, and insights to the decision-making process.[2] Expert involvement enhances the quality of decisions by leveraging their domain-specific expertise, experience, and analytical capabilities.[3]

The incorporation of expert judgments into decision-making processes is not without its challenges, as it introduces a layer of subjectivity and potential biases stemming from variations in expert perspectives.[4] One significant challenge lies in the inherent subjectivity of expert opinions, as diverse professionals may interpret information differently based on their unique experiences, backgrounds, and expertise. These subjective interpretations can lead to divergent viewpoints, making consensus difficult to achieve. Additionally, biases may emerge due to personal beliefs, cultural influences, or even the context in which the decision is being made. Striking a balance and ensuring a fair representation of diverse expert opinions is crucial to mitigating these challenges.[5] Moreover, challenges may arise in managing conflicts between experts or addressing situations where certain individuals may dominate the decision-making process.

Criteria weighting is a fundamental and intricate aspect of the decision-making process, representing a methodical approach to evaluating options and making informed choices.[6] In this context, experts play a crucial role in assigning significance or weight to various criteria according to their judgment and expertise. The concept of criteria weighting recognizes that not all factors contributing to a decision hold equal importance. Instead, experts

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analyse the relevance of each criterion in the context of the decision at hand and assign appropriate weights to signify their relative importance.[7,8] This thoughtful evaluation ensures that critical aspects receive due consideration, guiding the decision-making process toward well-informed and balanced outcomes. Criteria weighting serves as a strategic tool to navigate complex decision landscapes, allowing for a nuanced approach that reflects the diverse expertise of involved professionals. By incorporating the insights and discernment of experts through criteria weighting, decision-makers enhance the precision and effectiveness of their decisions, leading to more robust and tailored solutions in various domains.

Two categories of approaches for criteria weighting are identified: Subjective Weighting Methods, which include Direct Rating (DR), Simple Multi-Attribute Rating Technique (SMART), Delphi, Full Consistency Method (FUCOM), Best-Worst Method (BWM), Analytic Hierarchy Process (AHP), Stepwise Weight Assessment Ratio Analysis (SWARA), among others; and Objective Weighting Methods, such as Entropy, CRITIC, Standard Deviation, etc. This study focuses on the subjective methods found in the existing literature. The primary information source for this investigation was the Web of Science database. The literature reveals a plethora of publications addressing criteria evaluation methods. Noteworthy contributions include Saaty's[9] introduction of the AHP method, Diakoulaki's development of the CRiteria Importance Through Intercriteria Correlation (CRITIC) method[7], Gabus and Fontela's creation of the Decision-making Trial and Evaluation Laboratory (DEMATEL) method[10], Rezaei's formulation of the BWM[11], Keršuliene *et al.*'s proposal of the SWARA method[12], and Pamučar *et al.*'s development of the Full Consistency Method (FUCOM).[8]

Each of these methods has been successfully applied across diverse fields. For instance, Joshi *et al.* [13] implemented Pythagorean Fuzzy DEMATEL approach in evaluation of factors influencing software quality. Ortega *et al*. employed the Best-Worst Method (BWM)[14] to identify an environmentally sustainable park-and-ride location. Wu *et al.* carried out Urban rail transit operation safety evaluation based on an improved CRITIC method and cloud model.[15] A study carried out by Zagonari[16], for the design of multi-purpose offshore platforms. Determination of objective characteristics of MCDM methods under uncertainty with financial data was also carried out.[17]

Contribution of the Work

The NESTED method represents a significant departure from existing MCDM approaches by introducing a systematic framework to address variations in expert strictness. While methods like TOPSIS and Entropy focus on weighting criteria based on predefined rules or mathematical models, they assume uniformity in expert evaluations. This assumption is often unrealistic, as experts bring diverse experiences, biases, and levels of stringency to the decision-making process. The NESTED method's novelty lies in its ability to normalize these variations, ensuring a more equitable and consistent evaluation framework.

Current approaches to handling variations in expert strictness during the evaluation of criteria weights exhibit notable limitations and shortcomings. Literature in this field often highlights the difficulty in achieving a consensus among experts, particularly when faced with ambiguous or complex decision scenarios.[18] Moreover, the influence of individual biases and personal inclinations can further complicate the process, introducing a degree of unpredictability.

The normalization of strictness in expert judgments is imperative in decision-making processes to ensure a more reliable, equitable, and transparent evaluation of criteria weights. When variations in expert strictness are left unaccounted for, the impact on decision outcomes can be substantial. Experts inherently possess diverse perspectives, experiences, and levels of stringency in their assessments. Normalizing strictness involves adjusting for these individual differences to create a standardized scale, allowing for fairer comparisons and more consistent weighting of criteria. Failing to normalize strictness can lead to biased decision results, where certain experts' more stringent or lenient evaluations disproportionately influence the overall outcome. This not only compromises the reliability of decisions but also raises concerns about equity and fairness in the process. By normalizing strictness, decision-makers can mitigate the influence of individual idiosyncrasies, fostering a more objective and uniform basis for assigning criteria weights. This approach not only enhances the accuracy of decision outcomes but also contributes to the transparency and credibility of the decision-making process, addressing the need for a standardized and equitable framework in handling variations in expert strictness.

A novel approach considering the normalization of strictness is warranted due to the existing gap in the literature regarding specific methodologies to handle variations in expert strictness during criteria weighting. Current research acknowledges the challenges posed by unaccounted variations in strictness but lacks a systematic and universally applicable framework to address this issue. Our proposed approach fills this gap by providing a structured methodology for normalizing strictness in expert judgments, offering a clear and standardized process for decision-makers.

The objectives of the study are mentioned as below:

1. To develop a novel methodology for normalizing expert strictness in criteria weighting.
2. To validate the proposed NESTED approach through a case study on solar energy site selection.
3. To demonstrate the method's robustness via sensitivity analysis and comparative evaluation with Entropy, CIMAS, and hybrid methods.

Normalized Expert Strictness for Tailored Evaluation in Decision-Making Approach

This paper introduces a novel methodology aimed at addressing variations in expert strictness during the criteria weighting phase of decision-making. Recognizing the significance of consistent and equitable decision outcomes, this methodology provides decision-makers with a systematic and standardized framework for normalizing expert strictness. By tailoring the evaluation process, it seeks to mitigate the impact of individual differences in expert judgments, ensuring a more reliable and fair criteria weighting system. This section outlines the key components and steps of the proposed approach, emphasizing its potential to enhance decision-making processes across diverse domains by offering a practical tool for tailored evaluation. A flowchart of the proposed methodology is depicted in Fig. 1.

The NESTED approach is elucidated by the subsequent stages:

Step 1. Identification of Experts:

This involves pinpointing individuals with the necessary knowledge and expertise for a specific decision-making context. Criteria for selection may include education, experience, and proficiency. This step sets the stage for involving qualified professionals in subsequent decision-making processes. Collect data regarding experts' experience in relevant field.

Step 2. Define a Set of Evaluation Criteria:

This entails a thorough examination of the factors that may influence decisions, outcomes, or assessments within a specific domain. The identification of factors can be achieved through various means, including literature review, data analysis, and expert consultation. This process ensures a nuanced understanding of the contextual elements that should be considered when making evaluations, leading to a more informed and comprehensive decision-making approach.

Step 3. Calculation of Experts' Importance

The significance of each expert's contribution is computed using the following methodology: let's consider "k" experts engaged in assessing criteria. If, for instance, Expert X possesses eight years of experience, Expert Y has five years, and Expert Z contributes ten years, their respective weights are determined as 8/23 for Expert X, 5/23 for Expert Y, and 10/23 for Expert Z. In a more general scenario, the importance of an expert's evaluation can be calculated using a formula analogous to Eq. (1). This systematic approach ensures that each expert's influence is proportionate to their experience, facilitating an equitable integration of their expertise into the overall decision-making process.

$$W^{E_i} = \frac{E_i}{\sum_{i=1}^{k} E_i}, i = 1,2, \ldots, k \quad \ldots (1)$$

This equation represents the weight W^{E_i} of Expert i in a set of k experts, where E_i denotes the experience or any other relevant factor of Expert i. The weights are calculated by dividing the individual expert's value by the sum of all experts' values.

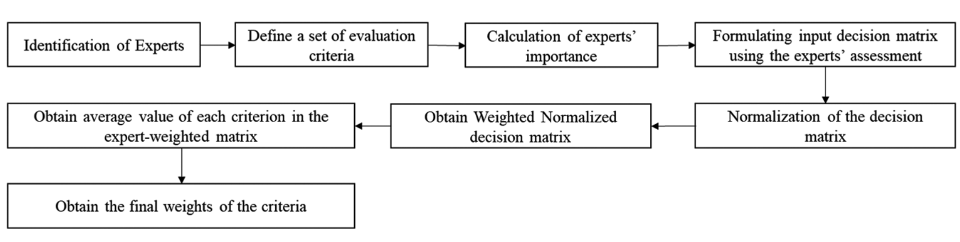

Fig. 1 — Proposed methodology

Step 4. Formulating Input Decision Matrix using the Experts' Assessment:

In this, the experts utilize a scale ranging from one to ten to construct an input decision matrix, with the highest significance for a criterion marked as 10 and the lowest as 1. The format of the input decision matrix is depicted in Table 1. Each Ei represents an expert among the k participants in the decision-making process, Cj denotes one of the p considered evaluation criteria, xij represents the assessment by expert i of the importance of criterion j (scaled from 1 to 10). Lastly, the values assigned from W_{E1} to W_{Eq} signify the respective weights of the experts.

Step 5. Normalization of the Decision Matrix

In this step, the strictness in the evaluation by the decision maker is considered.

$$x^*_{ji} = \frac{x_{ji}}{\sum_{i=1}^{k} x_{ji}}, i = 1,2, \dots, k; j = 1,2, \dots, \quad \dots (2)$$

Step 6. Obtain Weighted Normalized Decision Matrix

In this stage, the normalized input data undergo multiplication with the weights assigned to experts. This calculation is performed using Eq. (3).

$$\hat{x}_{ji} = x^*_{ji} \cdot W^{E_i}, i = 1,2, \dots k; j = 1,2, \dots, N \quad \dots (3)$$

Step 7. Obtain Average Value of Each Criterion in the Expert-Weighted Matrix

In this stage, the average values of each criterion within the columns are calculated using the Eq. (4).

$$A_j = \text{avg}_i \widehat{x^*}_{ij}, j = 1,2, \dots, N. \quad \dots (4)$$

Table 1 — Decision matrix

Factors / Experts	F_1	F_2	…	…	F_N
E_1	x_{11}	x_{12}	…	…	x_{1N}
E_2	x_{21}	x_{22}	…	…	x_{2N}
E_3	x_{31}	x_{32}	…	…	X_{3N}
…	…	…	…	…	…
E_k	x_{k1}	x_{k2}	…	…	x_{kN}

Step 8. Obtain the Final Weights of the Criteria

In this step, the significance of criteria (Wj) is determined by using Eq. (5).

$$W_j = \frac{A_j}{\sum_{j=1}^{q} A_j}, j = 1,2, \dots, N \quad \dots (5)$$

This method employs adaptations of commonly used formulations in MCDM methods like TOPSIS, specifically represented by Eqs (1) – (3). These include calculating expert weights based on their relative experience to ensure proportional influence in the decision-making process, normalizing the decision matrix, and computing the weighted normalized matrix. While foundational, these equations are uniquely applied within the framework to address variations in expert strictness. By embedding standard formulations into its innovative normalization methodology, the approach provides a fresh perspective on their application, enhancing consistency and fairness in multi-criteria decision-making.

Results & Discussion

In this section, the practical utility of the newly proposed NESTED method is illustrated within the context of evaluating criteria for optimal solar energy sites identification. Six criteria have been identified based on existing literature. Two factors each of environmental, Land related, and Operational viability. The criteria assessment problem is depicted in Fig. 2. The details of identified factors are given in Table 2.

Five experts specializing in solar panel installation participated in the assessment of criteria for identifying optimal solar energy sites. Table 3 provides an overview of these experts, all of whom possess varying years of experience in the solar energy field. Experts 1 and 2 serve as Chief Executive Officers (CEOs) of solar installation companies, while Experts 3, 4 and 5 hold the manager positions in medium-sized solar installation

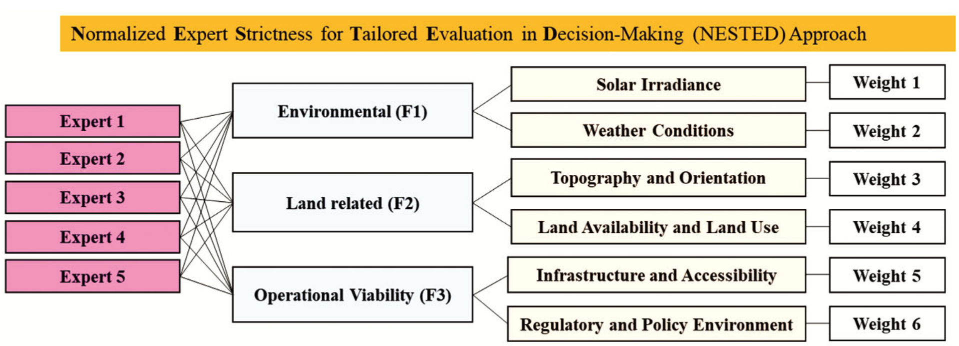

Fig. 2 — Case study illustration

Table 2 — Identification of factors

S. N	Category	Factor	Description
1	Environmental (F1)	Solar irradiance (F11)[19–21]	Assess the amount of sunlight received at a location. Higher solar irradiance indicates a greater potential for solar energy generation.
2		Weather conditions (F12)[22,23]	Consider the local climate, including cloud cover, rainfall, and temperature variations. Areas with consistent sunlight and favourable weather conditions are more suitable for solar energy projects.
3	Land related (F2)	Topography and orientation (F21)[24,25]	Analyse the terrain and slope of the land; Flat surfaces with a favourable orientation towards the sun can maximize sunlight exposure and energy capture.
4		Land availability and Land use (F22)[25,26]	Evaluate the availability of land and its current use; Unused or low-value land is preferable to minimize environmental impact and land use conflicts.
5	Operational Viability (F3)	Infrastructure and Accessibility (F31)[27]	Assess the proximity to existing power infrastructure and the ease of access for installation and maintenance; Access to transmission lines and roads can significantly impact the feasibility of a solar energy project.
6		Regulatory and policy environment (F32)[28]	Consider local regulations, incentives, and policies supporting solar energy; Favourable regulatory frameworks and financial incentives can enhance the viability of solar projects.

Table 3 — Details of experts' weight

Expert	Position	Years of experience	Expert-weights
Expert 1	Chief executive officers	2	2/29 = 0.1290
Expert 2	Chief executive officers	4	4/29 = 0.1290
Expert 3	Manager	8	8/29 = 0.2581
Expert 4	Manager	5	5/29 = 0.1613
Expert 5	Manager	10	10/29 = 0.3226
	Sum	29	

Table 4 — Initial decision matrix

Expert\Criteria	Solar irradiance	Weather conditions	Topography and orientation	Land availability and land use	Infrastructure and accessibility	Regulatory and policy environment
E1	9	8	8	7	7	6
E2	9	8	8	7	7	7
E3	8	7	7	7	6	7
E4	9	9	7	6	6	6
E5	10	9	6	6	5	5

Table 5 — Normalized decision matrix

Expert\Criteria	Solar irradiance	Weather conditions	Topography and orientation	Land availability and land use	Infrastructure and accessibility	Regulatory and policy environment
E1	0.2000	0.1778	0.1778	0.1556	0.1556	0.1333
E2	0.1957	0.1739	0.1739	0.1522	0.1522	0.1522
E3	0.1905	0.1667	0.1667	0.1667	0.1429	0.1667
E4	0.2093	0.2093	0.1628	0.1395	0.1395	0.1395
E5	0.2439	0.2195	0.1463	0.1463	0.1220	0.1220

Table 6 — Weighted normalized decision matrix

Expert\Criteria	Solar irradiance	Weather conditions	Topography and orientation	Land availability and land use	Infrastructure and accessibility	Regulatory and policy environment
E1	0.0138	0.0123	0.0123	0.0107	0.0107	0.0092
E2	0.0270	0.0240	0.0240	0.0210	0.0210	0.0210
E3	0.0525	0.0460	0.0460	0.0460	0.0394	0.0460
E4	0.0361	0.0361	0.0281	0.0241	0.0241	0.0241
E5	0.0841	0.0757	0.0505	0.0505	0.0421	0.0421
Average	0.0427	0.0388	0.0322	0.0304	0.0274	0.0285
Wj	**0.2135**	**0.1940**	**0.1608**	**0.1522**	**0.1372**	**0.1423**

firms in India. The names of individuals and companies are withheld to maintain privacy. Interviews with the experts were conducted through google meet. They were requested to assign importance to each criterion using a 10-point scale, where a rating of 10 indicated the highest priority, and 1 represented the lowest. Additionally, experts' weights were determined based on their experience in solar panel installation. The data generated from these criteria assessments form the foundation of this case study. The results of NESTED method application are presented in Table 4 – 6.

Sensitivity Analysis

A sensitivity analysis is conducted to assess variations in the NESTED method. The analysis involves excluding each of the experts from the model one at a time to observe the impact on the criteria ranking. Three scenarios were investigated: Scenario 1 involved excluding the highly experienced expert (Expert 5), followed by next experienced expert and so on. The findings of the sensitivity analysis are depicted in Fig. 3.

The sensitivity analysis was conducted to assess the impact of individual experts on the rankings of criteria for optimal solar energy site identification. In the original rankings, Solar Irradiance held the top position, followed by Weather conditions, while ‘Infrastructure and accessibility’ ranked lowest. Upon removing Expert 3, there were alterations in the rankings, particularly in ‘Regulatory and policy environment’ and ‘Infrastructure and accessibility’. The exclusion of Expert 3 resulted in changes, indicating their moderate influence. Removing Expert 5 did not alter the ranks but notably affected the weights. These variations underscore the importance of expert input and highlight potential areas of contention or consensus in the decision-making process. Removing inexperienced experts altered the weights negligibly. The sensitivity analysis offers valuable insights into the robustness of the decision model and the nuanced impact of individual experts on the prioritization of criteria for optimal solar site selection.

Comparative Analysis with Other Methods

In this sub-section, a comparison was made between the newly proposed NESTED method and the well-known Entropy method[29] introduced by Shannon in 1948. The Entropy method is classified as one of the objective techniques utilized for obtaining criteria weights. The same input data obtained from the five experts was employed by the authors of this paper, and the results of the comparative analysis are depicted in Fig. 4. The NESTED method was also compared with recently developed Criteria Importance Assessment (CIMAS) method[30], and hybrid method consisting of CIMAS and CRITIC methods.[7]

The comparison of rankings obtained by different methods for evaluating various factors influencing solar energy adoption provides valuable insights into the diversity of perspectives and methodologies employed in assessing renewable energy suitability. Notably, the NESTED, CIMAS, Hybrid Critic and CIMAS, and Entropy methods exhibit consistency in ranking ‘solar irradiance’ and ‘weather conditions’ as the top two influential factors. The NESTED and entropy method gives third preference to ‘Topography and orientation’. ‘Land availability and land use’ ranked fourth, ‘Infrastructure and accessibility’ ranked sixth by the methods namely, NESTED, CIMAS and hybrid CIMAS and CRTIIC method. However, variations emerge in the rankings of ‘topography and orientation’, ‘land availability and land use’, ‘infrastructure and accessibility’, and ‘regulatory and

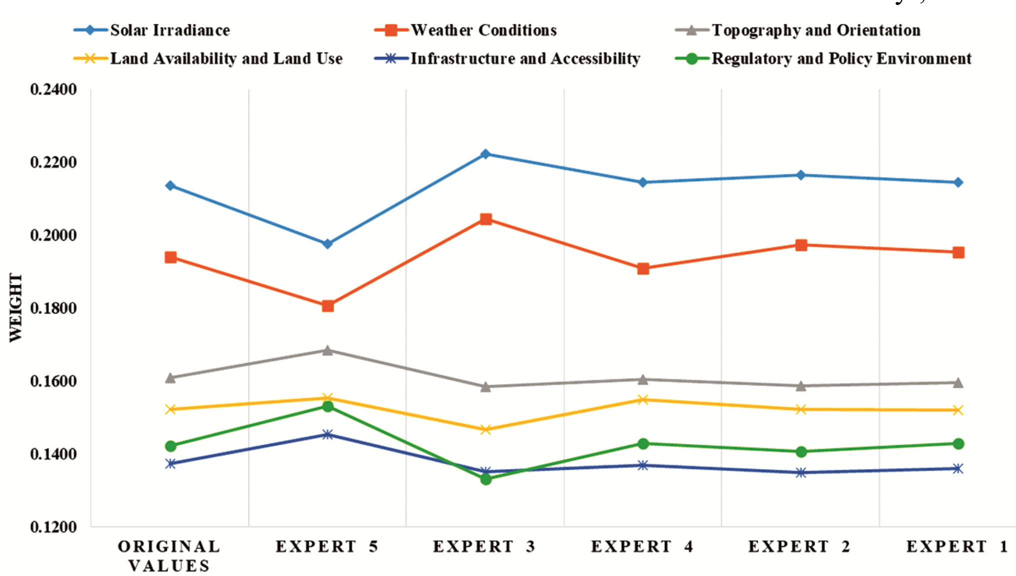

Fig. 3 – Sensitivity analysis

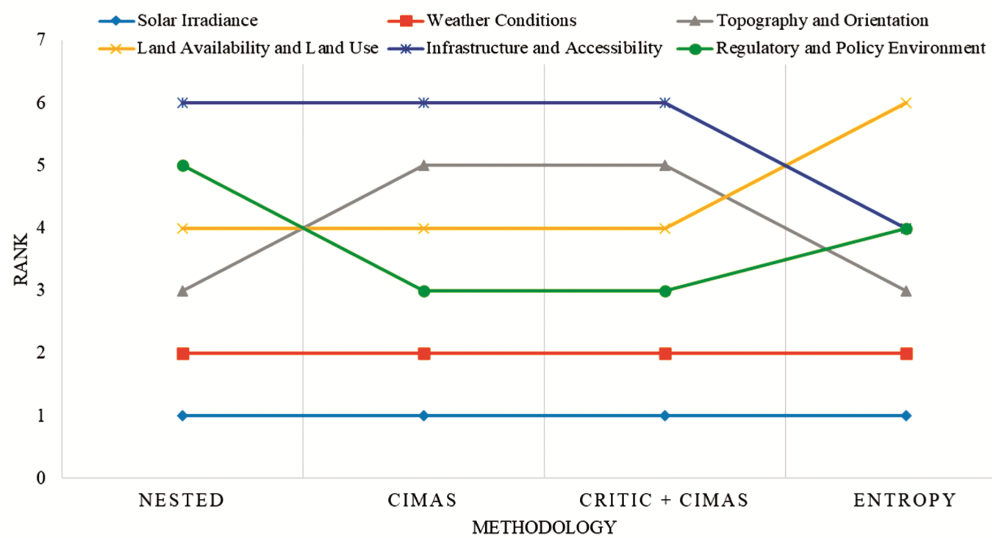

Fig. 4 — Comparative analysis between NESTED approach

policy environment'. These differences underscore the nuanced nature of decision-making in the renewable energy sector, where diverse considerations and weighting schemes can lead to distinct outcomes. Stakeholders must acknowledge and interpret these variations to enhance the robustness of solar energy planning and policy formulation.

Managerial Implications

The determination of criteria weights in the initial phase of selecting an optimal solar site is critical for all stakeholders involved in green renewable energy decisions. Given the various multi-criteria decision-making methods available, criteria weights may differ based on objective or subjective approaches. To enhance the precision of final ranking decisions and reduce uncertainty, we have devised a method that mitigates the rigidness imposed by expert evaluations. This method proves beneficial for managers seeking efficient and effective criteria assessment. The recommendation to managers is to adopt this approach due to its high level of robustness. Beyond the solar industry, this methodology is adaptable for assessing criteria in various sectors such as supply chain, medicine, education, automotive, construction, and more. The simplicity of implementation is a notable advantage, making it accessible for managers worldwide to apply and address their decision-making challenges.

Conclusions

This study introduced an innovative methodology designed to address variations in expert strictness during the criteria weighting phase of MCDM. The proposed approach offers a systematic framework to normalize expert evaluations, ensuring fairness and consistency. Its key strength lies in leveraging expert knowledge to prioritize criteria based on their relative importance, as demonstrated through a case study on solar energy site selection. Sensitivity analysis further validated the method's robustness, highlighting the critical role of experienced experts in shaping reliable decision outcomes. Despite its contributions, the study has notable limitations. The method's reliance on expert judgment poses a challenge, particularly when less experienced or biased experts are involved, potentially compromising the reliability of the results. The approach also lacks mechanisms to address conflicts or discrepancies among experts, which can affect the consistency of criteria weighting. Additionally, the validation of the methodology through a single case study limits its generalizability to other decision-making contexts. The absence of integration with advanced data-driven approaches, such as machine learning, further restricts its applicability in scenarios requiring a combination of subjective and objective inputs. Future research could address these limitations by incorporating hybrid models that combine expert input with data-driven techniques to enhance objectivity and robustness. Expanding the validation to diverse domains and decision-making contexts would help establish the method's adaptability and scalability. Additionally, introducing mechanisms for conflict resolution among experts and confidence-weighted scoring could further refine the approach. These enhancements would significantly broaden the scope and utility of the method in complex decision-making scenarios.

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