



OPEN Optimizing renewable energy investments using artificial intelligence-based multi-facet fuzzy decision models

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Improving the performance of renewable energy projects is significant in the global energy transformation process. However, there is no consensus in the literature on which technical indicators are more determinant in these projects, making it difficult for investors and policy makers to make accurate and reliable decisions. To address this research gap, this study aims to optimize renewable energy investment strategies by identifying technical indicators as performance improvement criteria. The novelty of this study lies in the development of an integrated artificial intelligence-based decision-making framework that simultaneously incorporates parameter-driven artificial expert evaluations, dynamic multi-facet fuzzy sets, fuzzy cognitive maps, and principal component ranking optimization. Unlike existing studies, the proposed approach enables dynamic scenario-based adjustment of fuzzy membership parameters, allowing uncertainty to be modeled more realistically under negative, positive, unstable, and natural conditions. This integrated structure provides a more adaptive and data-driven prioritization of technical indicators compared to conventional fuzzy or multi-criteria models. The findings reveal that scalability and ease of maintenance are the most critical factors for enhancing technical performance in renewable energy projects. Accordingly, focusing on easy-to-service microgrids and maximizing lifecycle performance emerge as the most effective investment strategies.

Keywords Dynamic multi facet fuzzy sets, Parameter-driven artificial expert evaluations, Principal component ranking optimization, Renewable energy projects, Energy investments, Technical indicators

Technical indicators are very important in increasing the performance of renewable energy projects. These indicators are technical parameters that directly affect the efficiency of the projects. Therefore, these issues should be taken into consideration to make the right investment decisions. Efficiency is one of the most important technical indicators in increasing the performance of renewable energy projects. High efficiency allows more energy to be produced with the same source. Owing to this situation, the payback periods of investments are significantly reduced. Increasing efficiency reduces the cost per unit of energy¹. This situation contributes significantly to increasing the financial performance of the projects. Scalability is another factor that should be considered in this process. Renewable energy projects should be able to easily increase their capacity as energy demand increases. This situation allows for sustainable performance increase in the long term. Scalability allows the expansion of support systems such as energy storage and grid integration. This situation helps to ensure supply security by preventing energy outages². Reliability plays a very important role in increasing the performance of renewable energy projects. More reliable equipment and systems cause fewer failures and reduce the need for maintenance. This reduces replacement and renewal costs and increases long-term performance.

It is necessary to determine which of these technical indicators is the most important. This is primarily important for the efficient use of resources. In renewable energy projects, technical equipment, labour and budget are limited. Focusing on the essential technical factor ensures that investments are made in the area that will provide the greatest efficiency increase. Determining the most successful factors also supports being goal-oriented for performance increase³. It should be determined which technical factor is more important to maximize the performance of the business. Moreover, to manage risks more effectively, the variables that are most important should be determined. By determining these factors, possible problems can be detected at an early

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level⁴. This allows the necessary precautions to be taken on time. In summary, although each technical factor is important, it should be determined which of them is the most critical for the success of the project. The limited number of studies in the literature determining the most important technical indicators in renewable energy projects emerges as a significant research gap. This deficiency can cause a series of problems and uncertainties at both academic and applied levels. Existing studies usually focus on specific energy types or technologies. This makes it difficult to reach comprehensive and generalizable results.

Recent advances in renewable energy investment research increasingly emphasize the use of advanced decision-support systems to manage growing technical complexity, uncertainty, and interdependencies among performance indicators. State-of-the-art studies predominantly employ multi-criteria decision-making methods, fuzzy logic extensions, and hybrid optimization techniques to evaluate renewable energy technologies and investment strategies. In parallel, artificial intelligence-based approaches, including machine learning, expert systems, and cognitive modeling, have gained prominence in recent years for enhancing objectivity and adaptability in energy-related decision processes. Contemporary research highlights the importance of integrating uncertainty modeling with scenario-based analysis, particularly under volatile policy, market, and technological conditions. However, despite these advancements, most existing frameworks remain limited by static parameter structures, fixed expert weighting schemes, or insufficient consideration of causal relationships among technical criteria. Moreover, current state-of-the-art models rarely provide a fully integrated structure that simultaneously captures dynamic uncertainty, expert heterogeneity, inter-criterion dependencies, and dimensionality reduction in ranking processes. These limitations indicate the need for more adaptive, AI-supported, and holistic decision-making frameworks capable of operating at the current frontier of renewable energy investment research.

Despite the rapid growth of renewable energy investments, the existing literature reveals a clear research gap in identifying and prioritizing the most critical technical performance indicators and investment strategies under dynamic and uncertain conditions. Current studies predominantly focus on specific technologies or apply static multi-criteria decision-making approaches that do not adequately capture scenario-based uncertainty, expert heterogeneity, or interdependencies among technical indicators. Moreover, there is a lack of integrated frameworks that simultaneously determine expert importance, model causal relationships among criteria, and rank investment strategies in a data-driven and adaptive manner. To address this gap, this study aims to optimize renewable energy investment strategies by developing a novel artificial intelligence-based decision-making framework. The proposed model integrates parameter-driven artificial expert evaluations, dynamic multi-facet fuzzy sets, fuzzy cognitive maps, and principal component ranking optimization to provide a holistic and flexible prioritization structure. By explicitly linking methodological innovations to the identified gap, the study offers a more robust basis for investor and policy-maker decision-making, reduces the risk of misallocation of resources, and supports more effective design of renewable energy incentive and investment policies under uncertainty.

This study makes several original contributions to the renewable energy investment and decision-making literature. First, it introduces a novel artificial intelligence-based decision-making framework that integrates parameter-driven artificial expert evaluations, dynamic multi-facet fuzzy sets, fuzzy cognitive maps, and principal component ranking optimization within a unified structure. The primary methodological innovation lies in the development and application of dynamic multi-facet fuzzy sets, in which membership degree parameters are adaptively adjusted under different scenarios such as negative, positive, unstable, and natural conditions. This dynamic structure enables a more realistic representation of uncertainty and decision-maker behavior compared to conventional fuzzy models that rely on fixed parameters. Second, the proposed framework incorporates data-driven and AI-supported expert weighting, allowing expert importance levels to be determined dynamically based on knowledge-related and demographic characteristics rather than predefined coefficients. This approach enhances objectivity and reliability in expert-based evaluations. Third, the study advances the ranking process by employing principal component ranking optimization, which effectively reduces dimensionality while preserving critical information and accounting for interdependencies among criteria. By integrating these methodological innovations, the study provides a more adaptive, robust, and analytically rigorous framework for identifying critical technical indicators and optimal investment strategies in renewable energy projects.

The missing part in the literature is explained in the second section. The proposed model is created to address this missing part. The details of this novel model are denoted in the third section. The fourth section includes the main results of this model. The results are discussed with the similar studies in the fifth section. The main concluding remarks are given in the sixth section.

Literature review

Efficiency is a very important technical factor in determining the right renewable energy investment strategies. This is primarily necessary for ensuring energy conversion efficiency. A low-efficiency system produces less energy with more resources⁵. This negatively affects the performance of the projects. High efficiency shortens the payback period of the investment. Moreover, increasing efficiency also reduces the cost per unit of energy. This also contributes to the development of financial performance⁶. Providing high-efficiency systems also supports the production of more energy in less space. With the help of this issue, land areas can be used more efficiently⁷. This provides a strategic advantage especially for those investing in limited areas. Furthermore, Li et al.⁸ underlined that efficient systems provide more predictable and stable production. As a result of this issue, energy storage systems can be used more effectively. Similarly, according to von Rüden et al.⁹, this also allows projects to adapt to the grid more successfully. Ensuring efficiency also has important effects on achieving sustainability goals. A low-efficiency system produces by using more raw materials. It causes natural resources to be consumed more unconsciously.

Scalability is also an important technical factor in determining the right renewable energy investment strategies. It plays a critical role especially in long-term investment plans and system expansion capabilities.

The fact that the invested system can be easily expanded according to the growing energy demand increases the sustainability of the system in the long term¹⁰. With the increase in the population worldwide, the demand for energy is increasing significantly. This issue also leads to an increase in the need for modular growth¹¹. Scalable systems make it easier to integrate with new technologies that will emerge in the future. This condition provides a significant competitive advantage to projects¹². Owing to this condition, new generation battery systems can be adapted to projects more easily. Asaleye and Ncanywa¹³ discussed that expanding the project according to success reduces the financial risk of the investor. It also contributes to the reduction of possible financial losses. Chen et al.¹⁴ defined that scalable systems also help to adapt more easily to political and legal changes. With the help of this factor, the possibility of encountering legal penalties is significantly reduced.

Reliability is a very important technical factor in determining the right renewable energy investment strategies. Reliability refers to the ability of an energy system to operate stably. This feature is critical in terms of both technical performance and economic sustainability¹⁵. Renewable energy systems can cause grid imbalances when they are not reliable. This causes the balance of energy supply and demand to be disrupted. Highly reliable projects mean lower operational risks for investors¹⁶. This allows for increased financial profitability of projects. As a result of this condition, businesses can access the financial resources they need more easily¹⁷. Another advantage of this situation is that reliable systems have fewer failures. This allows for lower maintenance costs. Amin et al.¹⁸ concluded that the energy buyer prefers systems that guarantee the continuity of energy. Therefore, reliable systems are more advantageous in long-term energy sales contracts. Bashir et al.¹⁹ identified projects with low reliability require additional systems. This increases the cost and system complexity. In other words, it is possible to reduce costs by ensuring reliability.

Maintainability is an important technical factor in determining the right renewable energy investment strategies. Effective and easy-to-manage maintenance processes are essential for the longevity of projects. Downtime is shortened in systems that can be easily maintained²⁰. This contributes to the continuity of energy production. Disruptions in the production process cause a decrease in the revenues obtained from projects. On the other hand, modern energy systems usually include artificial intelligence-supported monitoring systems²¹. Systems with high maintainability are better integrated with these technologies. This supports projects in gaining a competitive advantage. Babaei et al.²² underlined that renewable energy projects are usually long-term investments. Therefore, maintainability is a vital variable in this process. Operating efficiency decreases significantly in systems that are difficult to maintain. He et al.²³ showed that this negatively affects the financial performance of projects. In other words, systems that can be easily maintained provide investors with a great advantage both technically and economically.

As a result of the literature review, it is determined that the main technical indicators to be considered in renewable energy projects are efficiency, scalability, reliability, maintainability and safety. Each of these factors plays a critical role in terms of project performance, sustainability and investment success. However, although there are many studies in the literature where these factors are addressed separately, it is observed that there are very limited comprehensive and comparative analyses on which factors are more prioritized or more decisive. This deficiency creates an important missing gap for the renewable energy literature. This situation creates uncertainty in the process of determining the right investment strategies and makes it difficult for decision makers to make effective choices. Therefore, this study aims to contribute to the elimination of this important gap in the literature by addressing these technical indicators with both a holistic and comparative approach.

Although the existing literature on renewable energy investments provides a broad application of multi-criteria decision-making methods, a comparative synthesis reveals several persistent methodological limitations. Classical MCDM approaches such as AHP, TOPSIS, VIKOR, and their fuzzy extensions are widely employed to rank renewable energy technologies and investment alternatives. However, these models typically rely on static weighting structures and predefined membership functions, which restrict their ability to capture dynamic uncertainty and evolving decision-maker preferences. Moreover, most studies treat evaluation criteria as independent, overlooking causal interdependencies and feedback mechanisms that characterize complex energy systems. Recent hybrid models partially address uncertainty by integrating fuzzy logic or interval-based representations, yet they often maintain fixed expert importance levels and do not systematically incorporate expert heterogeneity. In addition, conventional ranking techniques frequently suffer from information loss when handling high-dimensional datasets and correlated criteria. These methodological gaps indicate that existing MCDM frameworks remain largely descriptive and static, limiting their adaptability to rapidly changing technological, regulatory, and market environments. By synthesizing these limitations, it becomes evident that there is a need for advanced decision-making models that simultaneously address dynamic uncertainty, expert weighting, causal relationships among criteria, and dimensionality reduction within a unified analytical structure. This comparative assessment directly motivates the methodological design of the proposed framework in this study.

Proposed methodology

A novel model is generated to identify key technical performance indicators and determine the prior renewable energy investment strategies. To create a qualified model, firstly, it is aimed to satisfy the current criticisms regarding the existing models in the literature. In most of the models, the weights of the experts are not computed. However, these people can have different demographical factors, such as education and working experience. Thus, in this model, artificial intelligence methodology is used to calculate the expert weights. Another important criticism related to the existing models is that causal relationship between the criteria is not considered. To handle this problem, cognitive maps technique is used in this proposed model. Finally, there are also some criticisms related to the existing ranking techniques mainly due to the calculation process. In this proposed model, a novel ranking technique named as principal component ranking optimization is generated to

solve this problem. Additionally, dynamic multi facet fuzzy sets are also introduced to handle the uncertainties more successfully.

To improve clarity and accessibility, the cognitive interpretation of the proposed fuzzy functions is further clarified in this study. The engagement function is conceptually defined as the degree to which a decision maker actively supports or prioritizes a given criterion based on perceived relevance and confidence under a specific scenario. Higher engagement values indicate stronger alignment between the criterion and the decision maker's strategic intent. In contrast, the resistance function represents the cognitive or contextual hesitation of the decision maker toward a criterion, capturing behavioral inertia, perceived implementation difficulty, or risk aversion. Elevated resistance values imply a greater tendency to delay or oppose prioritization despite potential performance benefits.

Within the proposed framework, these functions jointly reflect the behavioral dimension of decision-making by distinguishing between technical suitability and cognitive acceptance. The integration of engagement and resistance functions enables the model to move beyond purely numerical aggregation and to incorporate human-centric reasoning into the optimization process. To enhance readability for non-specialist audiences, the mathematical formulations in Sections "Parameter-driven artificial expert evaluations with multi-facet fuzzy sets"–"Dynamic Multi-Facet Fuzzy Principal Component Ranking Optimization" are complemented with concise conceptual explanations that link each function to its practical decision-making interpretation. This clarification ensures that the proposed methodology remains mathematically rigorous while being more intuitively understandable for readers from broader energy policy, investment, and management disciplines.

Parameter-driven artificial expert evaluations with multi-facet fuzzy sets

Multi-facet fuzzy sets are a new concept developed for decision-making processes. In this process, it is aimed to express environmental conditions in a more dynamic and comprehensive way. Today's decision-making problems are becoming quite complex²⁴. In this context, it is important to model uncertainty with more detailed and real-world scenarios. Multi-facet fuzzy sets can flexibly define different scenarios with parameter settings. In other words, human attitudes can be reflected more accurately. With these features, these sets allow complex problems to be solved more effectively²⁵. Theoretical background of the multi-facet fuzzy sets is detailed as follows. Primary membership degree μ is the satisfactory value that is defined in Eq. (1).

$$\mu \in [0,1] \quad (1)$$

Non-membership degree defines the level of rejection as given in Eq. (2).

$$v(\mu) = \frac{1}{1 + e^{\alpha(\mu-0.5)}} \quad (2)$$

$v(\mu)$ refers to the non-membership function and α indicates control parameter. The transition steepness can be proofed while taking the first derivative as in Eq. (3).

$$\frac{dv}{d\mu} = \frac{\alpha e^{\alpha(\mu-0.5)}}{[1 + e^{\alpha(\mu-0.5)}]^2} \quad (3)$$

The maximum slope can be determined at $\mu = 0.5$ as in Eqs. (4) and (5).

$$\left. \frac{dv}{d\mu} \right|_{\mu=0.5} = -\frac{\alpha}{4} \quad (4)$$

$$\lim_{n \rightarrow \infty} v(\mu) = \begin{cases} 1 & \mu < 0.5 \\ 0.5 & \mu = 0.5 \\ 0 & \mu > 0.5 \end{cases} \quad (5)$$

In these equations, α directly controls the transition steepness. The boundedness of non-membership degrees is proofed in the logistic function as detailed in Eqs. (6)–(8).

$$v(\mu) = \frac{1}{1 + e^{\alpha(0.5-0.5)}} = \frac{1}{1 + e^0} = \frac{1}{2} = 0.5 \text{ at } \mu = 0.5 \quad (6)$$

$$v(\mu) = \frac{1}{1 + e^{\alpha(1-0.5)}} = \frac{1}{1 + e^{\alpha/2}} \in (0,1) \text{ as } \mu \rightarrow 1 \quad (7)$$

$$v(\mu) = \frac{1}{1 + e^{\alpha(0-0.5)}} = \frac{1}{1 + e^{-\alpha/2}} \in (0,1) \text{ as } \mu \rightarrow 0 \quad (8)$$

The third function of the multi-facet fuzzy sets $\epsilon(\mu)$ can be presented as uncertainty degree as demonstrated in Eq. (9).

$$\epsilon(\mu) = -a [\mu \ln \mu + (1 - \mu) \ln (1 - \mu)] \quad (9)$$

In this process, a amplifies uncertainty. The Shannon entropy $H(\mu)$ satisfies the conditions detailed in Eqs. (10)–(14).

$$H(\mu) = -\mu \ln \mu - (1 - \mu) \ln(1 - \mu) \quad (10)$$

$$H(\mu) \geq 0 \text{ for } \mu \in [0,1] \quad (11)$$

$$H(0) = H(1) = 0 \quad (12)$$

$$H(0.5) = \ln(2) \approx 0.693 \text{ at } \mu = 0.5, H(\mu) \text{ is maximized.} \quad (13)$$

$$\varepsilon(\mu) = aH(\mu) \Rightarrow 0 \leq \varepsilon(\mu) \leq a \ln(2) \quad (14)$$

The maximum uncertainty at $\mu = 0.5$ can be shown via the first and second derivatives as given in Eqs. (15)-(17).

$$\frac{d\varepsilon}{d\mu} = -a [\ln \mu - \ln(1 - \mu)] \quad (15)$$

$$\ln \mu = \ln(1 - \mu) \Rightarrow \mu = 0.5 \quad (16)$$

$$\frac{d^2\varepsilon}{d\mu^2} = -a \left(\frac{1}{\mu} + \frac{1}{1 - \mu} \right) < 0 \quad (17)$$

The fourth function $n(\mu)$ can be identified as engagement degree as denoted in Eq. (18).

$$n(\mu) = \mu^\delta \quad (18)$$

For $\mu \in [0,1]$ and $\delta > 1$, Eqs. (19) and (20) should be taken into consideration.

$$\text{If } \mu = 0 : n(\mu) = 0^\delta = 0 \quad (19)$$

$$\text{If } \mu = 1 : n(\mu) = 1^\delta = 1 \quad (20)$$

For $0 < \mu < 1$ and $\delta > 1$, Eq. (21) should be satisfied.

$$\mu^\delta \leq \mu, n(\mu) \in [0,1] \quad (21)$$

δ parameter impact and convexity are demonstrated in Eqs. (22) and (23).

$$\frac{dn}{d\mu} = \delta \mu^{\delta-1} \quad (22)$$

$$\frac{d^2n}{d\mu^2} = \delta(\delta - 1) \mu^{\delta-2} \quad (23)$$

The final function gives information about the cognitive or contextual resistance of the decision maker to the attributes. Resistance function $\rho(\mu)$ is explained as in Eq. (24).

$$\rho(\mu) = 1 - (1 - \mu)^\varphi \quad (24)$$

For $\mu \in [0,1]$ and $\varphi > 1$, Eqs. (25) and (26) can be considered.

$$\text{If } \mu = 0 : \rho(\mu) = 1 - 1^\varphi = 0 \quad (25)$$

$$\text{If } \mu = 1 : \rho(\mu) = 1 - 0^\varphi = 1 \quad (26)$$

For $0 < \mu < 1$, Eq. (27) can be used.

$$0 < (1 - \mu)^\varphi < 1 \Rightarrow 0 < \rho(\mu) < 1, \rho(\mu) \in [0, 1] \quad (27)$$

Behaviour analysis of resistance function is denoted in Eqs. (28) and (29).

$$\frac{d\rho}{d\mu} = \varphi(1 - \mu)^{\varphi-1} \quad (28)$$

$$\frac{d^2\rho}{d\mu^2} = -\varphi(\varphi - 1)(1 - \mu)^{\varphi-2} \quad (29)$$

Generalized presentation of the dynamic multi-facet fuzzy sets is indicated in Eqs. (30) and (31).

$$A = \{(x, \mu(x), v(\mu(x)), \varepsilon(\mu(x)), n(\mu(x)), \rho(\mu(x))) | x \in X\} \quad (30)$$

$$A = \left\{ \left(x, \mu(x), \frac{1}{1 + e^{\alpha(\mu-0.5)}}, -a[\mu \ln \mu + (1 - \mu) \ln(1 - \mu)], \mu^\delta, 1 - (1 - \mu)^\varphi \right) | x \in X \right\} \quad (31)$$

where A refers to the dynamic multi-facet fuzzy set. The functions of these sets are $\mu(x)$, $v(\mu(x))$, $\epsilon(\mu(x))$, $n(\mu(x))$ and $\rho(\mu(x))$. General operation rules of these sets are detailed as in Eqs. (32)-(37) where A and B denote two different types of dynamic multi-facet fuzzy sets.

$$A = (\mu_A, v_A(\mu_A), \epsilon_A(\mu_A), n_A(\mu_A), \rho_A(\mu_A)) \tag{32}$$

$$B = (\mu_B, v_B(\mu_B), \epsilon_B(\mu_B), n_B(\mu_B), \rho_B(\mu_B)) \tag{33}$$

$$A \cup B = (\max(\mu_A, \mu_B), \min(v_A, v_B), \min(\epsilon_A, \epsilon_B), \max(n_A, n_B), \max(\rho_A, \rho_B)) \tag{34}$$

$$A \cap B = (\min(\mu_A, \mu_B), \max(v_A, v_B), \max(\epsilon_A, \epsilon_B), \min(n_A, n_B), \max(\rho_A, \rho_B)) \tag{35}$$

$$A \oplus B = (\mu_A + \mu_B - \mu_A\mu_B, v_A v_B, \epsilon_A + \epsilon_B - \epsilon_A\epsilon_B, n_A + n_B - n_A n_B, \rho_A \rho_B) \tag{36}$$

$$A \otimes B = (\mu_A \mu_B, v_A + v_B - v_A v_B, \epsilon_A \epsilon_B, n_A n_B, \rho_A + \rho_B - \rho_A \rho_B) \tag{37}$$

In this proposed model, 4 unique scenarios entitled “Negative”, “Positive”, “Unstable”, “Natural” are taken into consideration. Scenario 1 is called as “Negative Case”. This scenario $A_{negative}$ is illustrated in Eq. (38).

$$A_{negative} = \left\{ \left(x, \mu(x), \frac{1}{1 + e^{10(\mu-0.5)}}, -5 [\mu \ln \mu + (1 - \mu) \ln (1 - \mu)], \mu^1, 1 - (1 - \mu)^1 \right) \mid x \in X \right\} \tag{38}$$

Scenario 2 defines “Positive Case” that aims to provide high membership with reward engagement. The equation of this scenario $A_{positive}$ is denoted in Eq. (39).

$$A_{positive} = \left\{ \left(x, \mu(x), \frac{1}{1 + e^{1(\mu-0.5)}}, -1 [\mu \ln \mu + (1 - \mu) \ln (1 - \mu)], \mu^5, 1 - (1 - \mu)^1 \right) \mid x \in X \right\} \tag{39}$$

Scenario 3 proposes “Unstable Case” with prioritized resistance and penalized low membership. The details of this scenario $A_{unstable}$ are shown in Eq. (40).

$$A_{unstable} = \left\{ \left(x, \mu(x), \frac{1}{1 + e^{1(\mu-0.5)}}, -2 [\mu \ln \mu + (1 - \mu) \ln (1 - \mu)], \mu^1, 1 - (1 - \mu)^{10} \right) \mid x \in X \right\} \tag{40}$$

Scenario 4 explains “Natural Case”. The equation of this scenario $A_{natural}$ is identified in Eq. (41).

$$A_{natural} = \left\{ \left(x, \mu(x), \frac{1}{1 + e^{1(\mu-0.5)}}, -1 [\mu \ln \mu + (1 - \mu) \ln (1 - \mu)], \mu^1, 1 - (1 - \mu)^1 \right) \mid x \in X \right\} \tag{41}$$

Accordingly, 4 extreme conditions are defined to determine the dynamic parameters for the multi-facet fuzzy sets. Condition 1 considers the maximum variance, Condition 2 defines the maximum entropy H_i , Condition 3 is based on the maximum resistance potential $(1 - m_i)$ and Condition 4 is a balanced position giving the average parameter values of these 3 conditions. The computations of per-item statistics are given in Eqs. (42)-(44).

$$m_i = \frac{1}{n} \sum m_{ij} \tag{42}$$

$$\sigma_i^2 = \frac{1}{n} \sum (\mu_{ij} - m_i)^2 \tag{43}$$

$$H_i = - \sum \frac{\mu_{ij}}{\sum \mu} \ln \left(\frac{\mu_{ij}}{\sum \mu} \right) \tag{44}$$

The dynamic parameter settings can be defined via Eqs. (45)-(48).

$$\alpha_i = 1 + 9 \frac{\sigma_i}{\max_n \sigma_n} [1,10] \tag{45}$$

$$a_i = 1 + 4 \frac{H_i}{\max_n H_n} [1,5] \tag{46}$$

$$\delta_i = 1 + 4m_i [1,5] \tag{47}$$

$$\varphi_i = 1 + 9 \frac{(1 - m_i)}{\max_n (1 - m_n)} [1,10] \tag{48}$$

Dynamic multi-facet fuzzy cognitive maps

Fuzzy cognitive map is a graphical model in which the variables in the system and the cause-effect relationships between these concepts are represented by fuzzy logic. In this process, concepts are represented by nodes and relationships are represented by directional and weighted edges²⁶. Evaluations from the expert team are collected in the first stage. Dynamic multi-facet fuzzy relation matrix is created as detailed in Eq. (49).

$$\varsigma_k = \begin{bmatrix} 0 & \varsigma_{12} & \cdots & \cdots & \varsigma_{1n} \\ \varsigma_{21} & 0 & \cdots & \cdots & \varsigma_{2n} \\ \vdots & \vdots & \ddots & \cdots & \cdots \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \varsigma_{n1} & \varsigma_{n2} & \cdots & \cdots & 0 \end{bmatrix} \tag{49}$$

where ς defines the dynamic multi-facet fuzzy numbers. The aggregated values ς are calculated via Eq. (50). In this equation, k denotes the number of scenarios.

$$\begin{aligned} \varsigma &= \left(\bigcup_{i=1}^k \varsigma_i \right) \\ &= \left\{ \left(x, \frac{1}{k} \sum_{i=1}^k \mu_{\varsigma_i}(x), \frac{1}{k} \sum_{i=1}^k v_{\varsigma_i}(x), \frac{1}{k} \sum_{i=1}^k \epsilon_{\varsigma_i}(x), \frac{1}{k} \sum_{i=1}^k n_{\varsigma_i}(x), \frac{1}{k} \sum_{i=1}^k \rho_{\varsigma_i}(x) \right) \text{mid } x \in X \right\} \end{aligned} \tag{50}$$

Defuzzified values are defined by using Eqs. (51)-(54).

$$DR = \begin{bmatrix} 0 & N_{12} & \cdots & \cdots & N_{1n} \\ N_{21} & 0 & \cdots & \cdots & N_{2n} \\ \vdots & \vdots & \ddots & \cdots & \cdots \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ N_{n1} & N_{n2} & \cdots & \cdots & 0 \end{bmatrix} \tag{51}$$

$$N_{ij} = \sum_{n=1}^5 w_n \mu_{\varsigma_{ij}} + w_2 (1 - v_{\varsigma_{ij}}) + w_3 (1 - \epsilon_{\varsigma_{ij}}) + w_4 n_{\varsigma_{ij}} + w_5 \rho_{\varsigma_{ij}} \tag{52}$$

$$w_1 = \frac{\beta}{S}, w_2 = \frac{\alpha}{S}, w_3 = \frac{a}{S}, w_4 = \frac{\delta}{S}, w_5 = \frac{\varphi}{S} \tag{53}$$

$$S = \beta + \alpha + a + \delta + \varphi \tag{54}$$

where w_i defines proportional to their controlling parameters and β refers to the baseline membership. The values of the state vector are computed via Eq. (55)

$$A(t) = [a_1(t), a_2(t), \dots, a_n(t)] \tag{55}$$

Also, the state vectors are updated iteratively as detailed in Eqs. (56) and (57).

$$A(t+1) = f(A(t) \cdot NR) \tag{56}$$

$$f(x) = \frac{1}{1 + e^{-x}} \tag{57}$$

where $f(x)$ is the sigmoid function and x shows the multiplication of the matrix and state vector values. Finally, the weighting values (W_j) can be calculated as in Eq. (58).

$$W_j = \frac{fA(s)_j}{\sum_{j=1}^n fA(s)_j} \tag{58}$$

Dynamic multi-facet fuzzy principal component ranking optimization

Principal component ranking optimization is a novel optimization technique for ranking the alternatives from the decision matrix. In classic ranking methodologies, pairwise comparisons are performed with the fixed formulas. This novel optimization technique proposes a new approach to weight vectors by maximizing the overall discrimination among alternatives²⁷. Evaluations are collected in the first step. Next, by using Eq. (59), the decision matrix can be generated.

$$X_k = \begin{bmatrix} 0 & X_{12} & \cdots & \cdots & X_{1m} \\ X_{21} & 0 & \cdots & \cdots & X_{2m} \\ \vdots & \vdots & \ddots & \cdots & \cdots \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ X_{n1} & X_{n2} & \cdots & \cdots & 0 \end{bmatrix} \tag{59}$$

The values are weighted based on the Eq. (60).

$$v_{ij} = w_{ij} \times x_{ij} \quad (60)$$

In the following process, covariance matrix (S) is constructed by Eq. (61).

$$S_{jk} = \frac{1}{m} \sum_{i=1}^m \left(v_{ij} - \frac{1}{m} \sum_{i=1}^m v_{ij} \right) \left(v_{ik} - \frac{1}{m} \sum_{i=1}^m v_{ik} \right) \quad (61)$$

Principal eigenvector (p) is computed via Eqs. (62) and (63) where $p^{(0)}$ is a guess vector for the initial iteration and $p^{(k)}$ is the eigenvector value for the k th iteration.

$$p^{(0)} = [1, \dots, 1] \quad (62)$$

$$p^{(k)} = \frac{Sp^{(k-1)}}{\|Sp^{(k-1)}\|} \quad (63)$$

Weighted eigenvector wp_j and the associated eigenvector is approximated by Rayleigh Quotient for λ_{max} as in Eqs. (64) and (65).

$$wp_j = Sp^{(k)} \quad (64)$$

$$\lambda_{max} = p^{(T)} Sp^{(k)} \quad (65)$$

Normalized vector N_i is calculated with Eq. (66).

$$N_j = \frac{\max(p_1, 0)}{\sum_j \max(p_1, 0), j} \quad (66)$$

Global scores U_i are defined via Eq. (67).

$$U_i = \sum_{j=1}^n N_j x_{ij} \quad (67)$$

Finally, ranking scores Z_i are computed by Eq. (68).

$$Z_i = \frac{U_i - \frac{1}{m} \sum_{i=1}^m U_i}{\sqrt{\lambda_{max}}} \quad (68)$$

where Z_i is the ranking score of the alternatives. In this scope, the alternatives are ranked in descending order. Although the proposed framework is demonstrated through methodological construction and simulated expert-based evaluations, this design choice is consistent with the primary objective of the study, which is to develop and validate a novel decision-making methodology rather than to assess the performance of a specific renewable energy project. Recent decision science literature recognizes simulation-based and expert-driven modeling as a valid and widely adopted approach, particularly in contexts where project-level datasets are limited, heterogeneous, or not publicly accessible. In renewable energy investments, project-specific technical and financial data are often confidential, fragmented, or highly context-dependent, which constrains the feasibility of comprehensive empirical benchmarking. To enhance practical applicability, the model is constructed in a modular and operationally interpretable manner, allowing direct integration with real-world project data when such datasets become available. The use of scenario-based dynamic multi-facet fuzzy sets, AI-based expert weighting, and causal modeling ensures that the framework can be readily adapted to project-level evaluations without structural modification. Accordingly, the current study establishes a methodological foundation, while future research can extend the framework by applying it to specific renewable energy projects, regional datasets, or comparative empirical benchmarking exercises.

Analysis results

The proposed hybrid model is illustrated in Fig. 1 and the analysis process is summarized below.

Figure 1 presents a six-stage integrated decision-making framework that combines AI-assisted expert elicitation, dynamic multi-facet fuzzy modeling, causal weighting via fuzzy cognitive maps, and ranking optimization, producing robust and sensitivity-tested final rankings. The analysis details are given as follows.

Constructing the evaluations for the criteria and alternatives by the parameter-adjusted expert choices

Expert evaluations are obtained for the criteria and alternatives. In this process, the scales in Table 1 are taken into consideration.

One decision maker who is expert in the field of renewable energy with 18-year experience, is assigned for assessing items with linguistic evaluations. These evaluations are defined initial expert assessments and

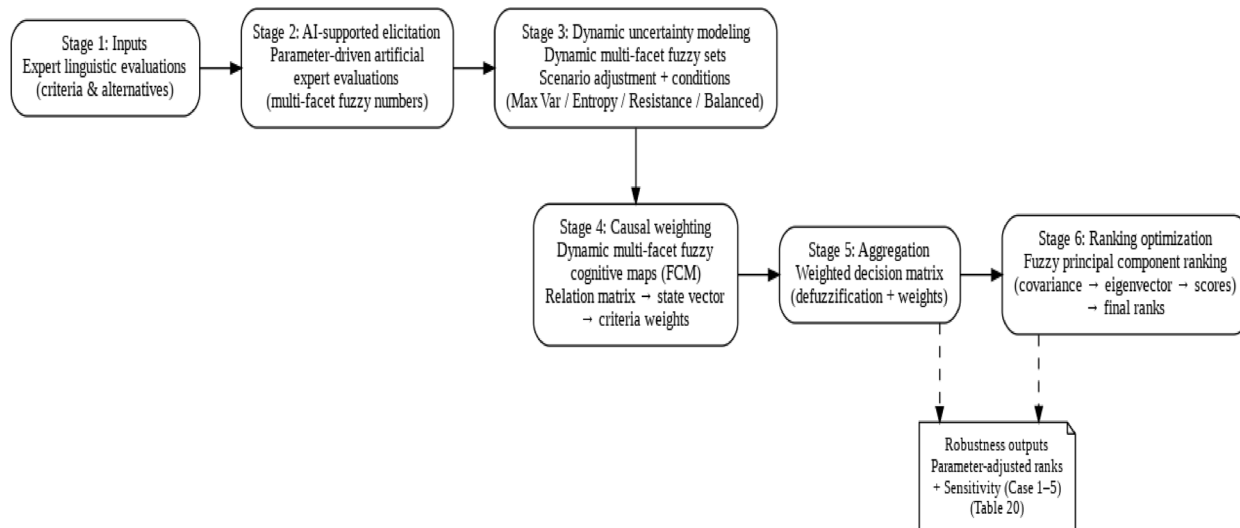


Fig. 1. Framework of the proposed hybrid model.

Scales	Linguistic evaluations	Fuzzy membership
1	Extremely low (EL)	0
2	Very low (VL)	0.2
3	Low (L)	0.3
4	Moderately low (ML)	0.4
5	Neutral (N)	0.5
6	Moderately high (MH)	0.6
7	High (H)	0.7
8	Very high (VH)	0.8
9	Extremely high (EH)	0.9

Table 1. Evaluation scales and fuzzy numbers.

Criteria	Efficiency	Scalability	Reliability	Maintainability	Safety
Efficiency		VH	H	VH	VH
Scalability	VH		H	EH	MH
Reliability	H	EH		EH	N
Maintainability	EH	EH	MH		H
Safety	MH	MH	VH	MH	

Table 2. Initial expert linguistic evaluations for the criteria.

then, they are converted to the multi-facet fuzzy numbers by initial and different scenarios. Selected technical indicators for renewable energy projects are efficiency, scalability, reliability, maintainability and safety (Table 2).

On the other side, investment strategies for renewable energy projects are selected as targeting high energy conversion technologies (Targeting), investing in stable and predictable systems (Predictable), focusing on easily serviced microgrids (Microgrids), combining multiple renewable sources (Combining) and maximizing lifecycle performance in renewable projects (Lifecycle). Table 3 gives information about the initial expert linguistic evaluations for the alternatives.

The per-item statistics for the parameter-adjusted multi-facet fuzzy sets of criteria are computed in Table 4.

These statistics for alternatives are denoted in Table 5.

The dynamic parameters by the conditions for the criteria are defined in Table 6.

Dynamic parameters by the conditions for the alternatives are demonstrated in Table 7.

The parameter-adjusted multi-facet fuzzy numbers by the conditions for the criteria are determined in Table 8.

These numbers by the conditions for the alternatives are defined in Table 9.

	Efficiency	Scalability	Reliability	Maintainability	Safety
Targeting	MH	H	H	VH	MH
Predictable	VH	VH	VH	VH	H
Microgrids	EH	MH	EH	H	VH
Combining	VH	H	MH	N	MH
Lifecycle	H	VH	EH	MH	VH

Table 3. Initial expert linguistic evaluations for the alternatives.

Criteria	m_i	σ_i^2	H_i
Efficiency	0.775	0.002	1.385
Scalability	0.750	0.013	1.375
Reliability	0.750	0.028	1.361
Maintainability	0.775	0.017	1.372
Safety	0.650	0.008	1.378

Table 4. Per-item statistics for the parameter-adjusted multi-facet fuzzy sets of criteria.

Alternatives	m_i	σ_i^2	H_i
Targeting	0.680	0.006	1.603
Predictable	0.780	0.002	1.608
Microgrids	0.780	0.014	1.598
Combining	0.640	0.010	1.597
Lifecycle	0.760	0.010	1.600

Table 5. Per-item statistics for the parameter-adjusted multi-facet fuzzy sets of alternatives.

Weighting the criteria with parameter-adjusted multi-facet fuzzy cognitive maps

Average fuzzy values for overall performance of relation matrix with parameter-adjusted assessments are generated in Table 10.

The defuzzified values of relation matrix by the parameter-adjusted assessments are constructed in Table 11.

The state vector and the function values are computed iteratively. The weights of the criteria by the parameter-adjusted assessments are shown in Table 12.

In 6th iteration, the function values $f(A(6))$ are the same with the values of 5th iteration $f(A(5))$. Hence, the final weighting priorities of the criteria can be defined in this step. Comparative weights of the criteria by the parameter-adjusted assessments are indicated in Table 13.

In Fig. 2, Dynamic multi-facet fuzzy cognitive map and the defuzzified causal influences are illustrated for the potential impacts of the criteria.

Table 12 denotes that scalability and maintainability are the most critical technical performance indicators to improve the effectiveness of the renewable energy projects. Efficiency, reliability and safety have lower weights comparing with these two indicators. Scalability is the ability of a renewable energy project to easily increase its capacity when demand increases. This feature shows the growth potential and flexibility of the project. Maintainability refers to the ease of regular maintenance and repair of the system. The ability to quickly fix technical problems reduces operating costs and ensures system continuity. In summary, it is understood that renewable energy projects must have the capacity to grow and have a structure that can be easily maintained to be more efficient and long-lasting. However, although the efficiency, reliability and safety criteria were given relatively lower weights, this does not mean that these criteria are unimportant. On the contrary, it is critical that efficiency, reliability and safety are meticulously considered for the long-term success and sustainability of the project. The results only show that in the current context, scalability and maintainability require higher prioritization compared to other criteria; therefore, all criteria should be evaluated with a holistic approach.

Ranking the alternatives with parameter-adjusted multi-facet fuzzy principal component ranking optimization

Average fuzzy values for overall performance of decision matrix are computed with parameter-adjusted assessments in Table 14.

The defuzzified values of decision matrix are calculated by the parameter-adjusted assessments in Table 15.

The weighted values of the decision matrix by the parameter-adjusted assessments are denoted in Table 16.

The covariance matrix by the parameter-adjusted assessments is created in Table 17.

The eigenvectors are computed iteratively by the parameter-adjusted assessments in Table 18.

	α_i	a_i	δ_i	φ_i
Maximum variance				
Efficiency	10.00	5.00	4.10	6.79
Scalability	10.00	4.97	4.00	7.43
Reliability	10.00	4.93	4.00	7.43
Maintainability	10.00	4.96	4.10	6.79
Safety	10.00	4.98	3.60	10.00
Maximum entropy				
Efficiency	1.61	5.00	4.10	6.79
Scalability	5.09	5.00	4.00	7.43
Reliability	10.00	5.00	4.00	7.43
Maintainability	6.52	5.00	4.10	6.79
Safety	3.45	5.00	3.60	10.00
Maximum resistance				
Efficiency	1.61	5.00	4.10	10.00
Scalability	5.09	4.97	4.00	10.00
Reliability	10.00	4.93	4.00	10.00
Maintainability	6.52	4.96	4.10	10.00
Safety	3.45	4.98	3.60	10.00
Balanced				
Efficiency	4.41	5.00	4.10	7.86
Scalability	6.73	4.98	4.00	8.29
Reliability	10.00	4.95	4.00	8.29
Maintainability	7.68	4.98	4.10	7.86
Safety	5.64	4.99	3.60	10.00

Table 6. Dynamic parameters by the conditions for the criteria.

	α_i	a_i	δ_i	φ_i
Maximum variance				
Targeting	10.00	4.99	3.72	9.00
Predictable	10.00	5.00	4.12	6.50
Microgrids	10.00	4.97	4.12	6.50
Combining	10.00	4.97	3.56	10.00
Lifecycle	10.00	4.98	4.04	7.00
Maximum entropy				
Targeting	4.71	5.00	3.72	9.00
Predictable	2.06	5.00	4.12	6.50
Microgrids	10.00	5.00	4.12	6.50
Combining	7.88	5.00	3.56	10.00
Lifecycle	7.88	5.00	4.04	7.00
Maximum resistance				
Targeting	4.71	4.99	3.72	10.00
Predictable	2.06	5.00	4.12	10.00
Microgrids	10.00	4.97	4.12	10.00
Combining	7.88	4.97	3.56	10.00
Lifecycle	7.88	4.98	4.04	10.00
Balanced				
Targeting	6.47	4.99	3.72	9.33
Predictable	4.71	5.00	4.12	7.67
Microgrids	10.00	4.98	4.12	7.67
Combining	8.59	4.98	3.56	10.00
Lifecycle	8.59	4.99	4.04	8.00

Table 7. Dynamic parameters by the conditions for the alternatives.

	Efficiency	Scalability	Reliability	Maintainability	Safety
Maximum variance					
Efficiency	(0.00, 0.00, 0.00, 0.00, 0.00)	(0.80, 0.05, 0.57, 0.40, 1.00)	(0.70, 0.12, 0.89, 0.23, 1.00)	(0.80, 0.05, 0.57, 0.40, 1.00)	(0.80, 0.05, 0.57, 0.40, 1.00)
Scalability	(0.80, 0.05, 0.57, 0.41, 1.00)	(0.00, 0.00, 0.00, 0.00, 0.00)	(0.70, 0.12, 0.88, 0.24, 1.00)	(0.90, 0.02, 0.24, 0.66, 1.00)	(0.60, 0.27, 1.00, 0.13, 1.00)
Reliability	(0.70, 0.12, 0.87, 0.24, 1.00)	(0.90, 0.02, 0.24, 0.66, 1.00)	(0.00, 0.00, 0.00, 0.00, 0.00)	(0.90, 0.02, 0.24, 0.66, 1.00)	(0.50, 0.50, 1.00, 0.06, 0.99)
Maintainability	(0.90, 0.02, 0.24, 0.65, 1.00)	(0.90, 0.02, 0.24, 0.65, 1.00)	(0.60, 0.27, 1.00, 0.12, 1.00)	(0.00, 0.00, 0.00, 0.00, 0.00)	(0.70, 0.12, 0.88, 0.23, 1.00)
Safety	(0.60, 0.27, 1.00, 0.16, 1.00)	(0.60, 0.27, 1.00, 0.16, 1.00)	(0.80, 0.05, 0.57, 0.45, 1.00)	(0.60, 0.27, 1.00, 0.16, 1.00)	(0.00, 0.00, 0.00, 0.00, 0.00)
Maximum entropy					
Efficiency	(0.00, 0.00, 0.00, 0.00, 0.00)	(0.80, 0.38, 0.57, 0.40, 1.00)	(0.70, 0.42, 0.89, 0.23, 1.00)	(0.80, 0.38, 0.57, 0.40, 1.00)	(0.80, 0.38, 0.57, 0.40, 1.00)
Scalability	(0.80, 0.18, 0.57, 0.41, 1.00)	(0.00, 0.00, 0.00, 0.00, 0.00)	(0.70, 0.27, 0.89, 0.24, 1.00)	(0.90, 0.12, 0.24, 0.66, 1.00)	(0.60, 0.38, 1.00, 0.13, 1.00)
Reliability	(0.70, 0.12, 0.89, 0.24, 1.00)	(0.90, 0.02, 0.24, 0.66, 1.00)	(0.00, 0.00, 0.00, 0.00, 0.00)	(0.90, 0.02, 0.24, 0.66, 1.00)	(0.50, 0.50, 1.00, 0.06, 0.99)
Maintainability	(0.90, 0.07, 0.24, 0.65, 1.00)	(0.90, 0.07, 0.24, 0.65, 1.00)	(0.60, 0.34, 1.00, 0.12, 1.00)	(0.00, 0.00, 0.00, 0.00, 0.00)	(0.70, 0.21, 0.89, 0.23, 1.00)
Safety	(0.60, 0.41, 1.00, 0.16, 1.00)	(0.60, 0.41, 1.00, 0.16, 1.00)	(0.80, 0.26, 0.57, 0.45, 1.00)	(0.60, 0.41, 1.00, 0.16, 1.00)	(0.00, 0.00, 0.00, 0.00, 0.00)
Maximum resistance					
Efficiency	(0.00, 0.00, 0.00, 0.00, 0.00)	(0.80, 0.38, 0.57, 0.40, 1.00)	(0.70, 0.42, 0.89, 0.23, 1.00)	(0.80, 0.38, 0.57, 0.40, 1.00)	(0.80, 0.38, 0.57, 0.40, 1.00)
Scalability	(0.80, 0.18, 0.57, 0.41, 1.00)	(0.00, 0.00, 0.00, 0.00, 0.00)	(0.70, 0.27, 0.88, 0.24, 1.00)	(0.90, 0.12, 0.24, 0.66, 1.00)	(0.60, 0.38, 1.00, 0.13, 1.00)
Reliability	(0.70, 0.12, 0.87, 0.24, 1.00)	(0.90, 0.02, 0.24, 0.66, 1.00)	(0.00, 0.00, 0.00, 0.00, 0.00)	(0.90, 0.02, 0.24, 0.66, 1.00)	(0.50, 0.50, 1.00, 0.06, 1.00)
Maintainability	(0.90, 0.07, 0.24, 0.65, 1.00)	(0.90, 0.07, 0.24, 0.65, 1.00)	(0.60, 0.34, 1.00, 0.12, 1.00)	(0.00, 0.00, 0.00, 0.00, 0.00)	(0.70, 0.21, 0.88, 0.23, 1.00)
Safety	(0.60, 0.41, 1.00, 0.16, 1.00)	(0.60, 0.41, 1.00, 0.16, 1.00)	(0.80, 0.26, 0.57, 0.45, 1.00)	(0.60, 0.41, 1.00, 0.16, 1.00)	(0.00, 0.00, 0.00, 0.00, 0.00)
Balanced					
Efficiency	(0.00, 0.00, 0.00, 0.00, 0.00)	(0.80, 0.21, 0.57, 0.40, 1.00)	(0.70, 0.29, 0.89, 0.23, 1.00)	(0.80, 0.21, 0.57, 0.40, 1.00)	(0.80, 0.21, 0.57, 0.40, 1.00)
Scalability	(0.80, 0.12, 0.57, 0.41, 1.00)	(0.00, 0.00, 0.00, 0.00, 0.00)	(0.70, 0.21, 0.88, 0.24, 1.00)	(0.90, 0.06, 0.24, 0.66, 1.00)	(0.60, 0.34, 1.00, 0.13, 1.00)
Reliability	(0.70, 0.12, 0.88, 0.24, 1.00)	(0.90, 0.02, 0.24, 0.66, 1.00)	(0.00, 0.00, 0.00, 0.00, 0.00)	(0.90, 0.02, 0.24, 0.66, 1.00)	(0.50, 0.50, 1.00, 0.06, 1.00)
Maintainability	(0.90, 0.04, 0.24, 0.65, 1.00)	(0.90, 0.04, 0.24, 0.65, 1.00)	(0.60, 0.32, 1.00, 0.12, 1.00)	(0.00, 0.00, 0.00, 0.00, 0.00)	(0.70, 0.18, 0.88, 0.23, 1.00)
Safety	(0.60, 0.36, 1.00, 0.16, 1.00)	(0.60, 0.36, 1.00, 0.16, 1.00)	(0.80, 0.16, 0.57, 0.45, 1.00)	(0.60, 0.36, 1.00, 0.16, 1.00)	(0.00, 0.00, 0.00, 0.00, 0.00)

Table 8. Parameter-adjusted multi-facet fuzzy numbers by the conditions for the criteria.

	Efficiency	Scalability	Reliability	Maintainability	Safety
Maximum variance					
Targeting	(0.60, 0.27, 1.00, 0.15, 1.00)	(0.70, 0.12, 0.88, 0.27, 1.00)	(0.70, 0.12, 0.88, 0.27, 1.00)	(0.80, 0.05, 0.57, 0.44, 1.00)	(0.60, 0.27, 1.00, 0.15, 1.00)
Predictable	(0.80, 0.05, 0.57, 0.40, 1.00)	(0.80, 0.05, 0.57, 0.40, 1.00)	(0.80, 0.05, 0.57, 0.40, 1.00)	(0.80, 0.05, 0.57, 0.40, 1.00)	(0.70, 0.12, 0.89, 0.23, 1.00)
Microgrids	(0.90, 0.02, 0.24, 0.65, 1.00)	(0.60, 0.27, 1.00, 0.12, 1.00)	(0.90, 0.02, 0.24, 0.65, 1.00)	(0.70, 0.12, 0.88, 0.23, 1.00)	(0.80, 0.05, 0.57, 0.40, 1.00)
Combining	(0.80, 0.05, 0.57, 0.45, 1.00)	(0.70, 0.12, 0.88, 0.28, 1.00)	(0.60, 0.27, 1.00, 0.16, 1.00)	(0.50, 0.50, 1.00, 0.08, 1.00)	(0.60, 0.27, 1.00, 0.16, 1.00)
Lifecycle	(0.70, 0.12, 0.88, 0.24, 1.00)	(0.80, 0.05, 0.57, 0.41, 1.00)	(0.90, 0.02, 0.24, 0.65, 1.00)	(0.60, 0.27, 1.00, 0.13, 1.00)	(0.80, 0.05, 0.57, 0.41, 1.00)
Maximum entropy					
Targeting	(0.60, 0.38, 1.00, 0.15, 1.00)	(0.70, 0.28, 0.89, 0.27, 1.00)	(0.70, 0.28, 0.89, 0.27, 1.00)	(0.80, 0.20, 0.57, 0.44, 1.00)	(0.60, 0.38, 1.00, 0.15, 1.00)
Predictable	(0.80, 0.35, 0.57, 0.40, 1.00)	(0.80, 0.35, 0.57, 0.40, 1.00)	(0.80, 0.35, 0.57, 0.40, 1.00)	(0.80, 0.35, 0.57, 0.40, 1.00)	(0.70, 0.40, 0.89, 0.23, 1.00)
Microgrids	(0.90, 0.02, 0.24, 0.65, 1.00)	(0.60, 0.27, 1.00, 0.12, 1.00)	(0.90, 0.02, 0.24, 0.65, 1.00)	(0.70, 0.12, 0.89, 0.23, 1.00)	(0.80, 0.05, 0.57, 0.40, 1.00)
Combining	(0.80, 0.09, 0.57, 0.45, 1.00)	(0.70, 0.17, 0.89, 0.28, 1.00)	(0.60, 0.31, 1.00, 0.16, 1.00)	(0.50, 0.50, 1.00, 0.08, 1.00)	(0.60, 0.31, 1.00, 0.16, 1.00)
Lifecycle	(0.70, 0.17, 0.89, 0.24, 1.00)	(0.80, 0.09, 0.57, 0.41, 1.00)	(0.90, 0.04, 0.24, 0.65, 1.00)	(0.60, 0.31, 1.00, 0.13, 1.00)	(0.80, 0.09, 0.57, 0.41, 1.00)
Maximum resistance					
Targeting	(0.60, 0.38, 1.00, 0.15, 1.00)	(0.70, 0.28, 0.88, 0.27, 1.00)	(0.70, 0.28, 0.88, 0.27, 1.00)	(0.80, 0.20, 0.57, 0.44, 1.00)	(0.60, 0.38, 1.00, 0.15, 1.00)
Predictable	(0.80, 0.35, 0.57, 0.40, 1.00)	(0.80, 0.35, 0.57, 0.40, 1.00)	(0.80, 0.35, 0.57, 0.40, 1.00)	(0.80, 0.35, 0.57, 0.40, 1.00)	(0.70, 0.40, 0.89, 0.23, 1.00)
Microgrids	(0.90, 0.02, 0.24, 0.65, 1.00)	(0.60, 0.27, 1.00, 0.12, 1.00)	(0.90, 0.02, 0.24, 0.65, 1.00)	(0.70, 0.12, 0.88, 0.23, 1.00)	(0.80, 0.05, 0.57, 0.40, 1.00)
Combining	(0.80, 0.09, 0.57, 0.45, 1.00)	(0.70, 0.17, 0.88, 0.28, 1.00)	(0.60, 0.31, 1.00, 0.16, 1.00)	(0.50, 0.50, 1.00, 0.08, 1.00)	(0.60, 0.31, 1.00, 0.16, 1.00)
Lifecycle	(0.70, 0.17, 0.88, 0.24, 1.00)	(0.80, 0.09, 0.57, 0.41, 1.00)	(0.90, 0.04, 0.24, 0.65, 1.00)	(0.60, 0.31, 1.00, 0.13, 1.00)	(0.80, 0.09, 0.57, 0.41, 1.00)
Balanced					
Targeting	(0.60, 0.34, 1.00, 0.15, 1.00)	(0.70, 0.22, 0.89, 0.27, 1.00)	(0.70, 0.22, 0.89, 0.27, 1.00)	(0.80, 0.13, 0.57, 0.44, 1.00)	(0.60, 0.34, 1.00, 0.15, 1.00)
Predictable	(0.80, 0.20, 0.57, 0.40, 1.00)	(0.80, 0.20, 0.57, 0.40, 1.00)	(0.80, 0.20, 0.57, 0.40, 1.00)	(0.80, 0.20, 0.57, 0.40, 1.00)	(0.70, 0.28, 0.89, 0.23, 1.00)
Microgrids	(0.90, 0.02, 0.24, 0.65, 1.00)	(0.60, 0.27, 1.00, 0.12, 1.00)	(0.90, 0.02, 0.24, 0.65, 1.00)	(0.70, 0.12, 0.88, 0.23, 1.00)	(0.80, 0.05, 0.57, 0.40, 1.00)
Combining	(0.80, 0.07, 0.57, 0.45, 1.00)	(0.70, 0.15, 0.88, 0.28, 1.00)	(0.60, 0.30, 1.00, 0.16, 1.00)	(0.50, 0.50, 1.00, 0.08, 1.00)	(0.60, 0.30, 1.00, 0.16, 1.00)
Lifecycle	(0.70, 0.15, 0.88, 0.24, 1.00)	(0.80, 0.07, 0.57, 0.41, 1.00)	(0.90, 0.03, 0.24, 0.65, 1.00)	(0.60, 0.30, 1.00, 0.13, 1.00)	(0.80, 0.07, 0.57, 0.41, 1.00)

Table 9. Parameter-adjusted multi-facet fuzzy numbers by the conditions for the alternatives.

Criteria	Efficiency	Scalability	Reliability	Maintainability	Safety
Efficiency	(0.00, 0.00, 0.00, 0.00, 0.00)	(0.80, 0.26, 0.57, 0.40, 1.00)	(0.70, 0.31, 0.89, 0.23, 1.00)	(0.80, 0.26, 0.57, 0.40, 1.00)	(0.80, 0.26, 0.57, 0.40, 1.00)
Scalability	(0.80, 0.13, 0.57, 0.41, 1.00)	(0.00, 0.00, 0.00, 0.00, 0.00)	(0.70, 0.21, 0.88, 0.24, 1.00)	(0.90, 0.08, 0.24, 0.66, 1.00)	(0.60, 0.34, 1.00, 0.13, 1.00)
Reliability	(0.70, 0.12, 0.88, 0.24, 1.00)	(0.90, 0.02, 0.24, 0.66, 1.00)	(0.00, 0.00, 0.00, 0.00, 0.00)	(0.90, 0.02, 0.24, 0.66, 1.00)	(0.50, 0.50, 1.00, 0.06, 1.00)
Maintainability	(0.90, 0.05, 0.24, 0.65, 1.00)	(0.90, 0.05, 0.24, 0.65, 1.00)	(0.60, 0.32, 1.00, 0.12, 1.00)	(0.00, 0.00, 0.00, 0.00, 0.00)	(0.70, 0.18, 0.88, 0.23, 1.00)
Safety	(0.60, 0.37, 1.00, 0.16, 1.00)	(0.60, 0.37, 1.00, 0.16, 1.00)	(0.80, 0.18, 0.57, 0.45, 1.00)	(0.60, 0.37, 1.00, 0.16, 1.00)	(0.00, 0.00, 0.00, 0.00, 0.00)

Table 10. Averaged fuzzy numbers for overall performance of relation matrix with parameter-adjusted assessments.

	Efficiency	Scalability	Reliability	Maintainability	Safety
Maximum variance					
Efficiency	0.000	0.777	0.662	0.777	0.777
Scalability	0.787	0.000	0.675	0.896	0.578
Reliability	0.678	0.897	0.000	0.897	0.480
Maintainability	0.892	0.892	0.566	0.000	0.665
Safety	0.625	0.625	0.815	0.625	0.000
Maximum entropy					
Efficiency	0.000	0.669	0.537	0.669	0.669
Scalability	0.719	0.000	0.595	0.854	0.520
Reliability	0.673	0.895	0.000	0.895	0.479
Maintainability	0.863	0.863	0.520	0.000	0.604
Safety	0.572	0.572	0.742	0.572	0.000
Maximum resistance					
Efficiency	0.000	0.718	0.606	0.718	0.718
Scalability	0.749	0.000	0.638	0.870	0.570
Reliability	0.705	0.906	0.000	0.906	0.526
Maintainability	0.880	0.880	0.579	0.000	0.654
Safety	0.573	0.573	0.743	0.573	0.000
Balanced					
Efficiency	0.000	0.712	0.590	0.712	0.712
Scalability	0.753	0.000	0.635	0.876	0.554
Reliability	0.686	0.899	0.000	0.899	0.496
Maintainability	0.880	0.880	0.555	0.000	0.641
Safety	0.585	0.585	0.766	0.585	0.000

Table 11. Defuzzified relation matrix by the parameter-adjusted assessments.

In the 6th iteration, the values of $p^{(6)}$ are stable with the previous iteration. As a result, $p^{(6)}$ can be taken into consideration to compute the values of wp_j and ranking scores. The values of wp_j , N_j , U_i , Z_i are demonstrated in Table 19.

The alternatives are ranked by the parameter-adjusted assessments and the comparative analysis results with the sensitivity analysis are given in Table 20.

Table 20 gives the information about the ranking results of the alternatives based on the different parameter adjustments and the cases into the sensitivity analysis. The sensitivity analysis is applied by changing the weights of the criteria consecutively into the weighted decision matrix. 5 cases are defined with 5 criteria, and their results are almost same for the parameter-adjusted scenarios. It demonstrates that our proposed methodology is comprehensive and applicable for the further extensions of the hybrid decision making methodologies. Also, ranking stability across the different weighting scenarios is given in Fig. 3.

However, the results denote that focusing on easily serviced microgrids is the most significant investment strategy for renewable energy projects. Maximizing lifecycle performance in renewable projects is another important strategy in this framework. On the other side, investing in stable and predictable systems, combining multiple renewable sources and targeting high energy conversion technologies have lower importance. This situation indicates that it is critical for the technical infrastructure of microgrids to be designed in accordance with maintenance and service processes for energy systems to operate efficiently and uninterruptedly. Since microgrids provide energy production and management at a local level, the fact that these systems are easily intervened and sustainable reduces operational costs for investors and increases system reliability. Therefore, investing in microgrids with easy serviceability both produces more efficient results in terms of economy and significantly increases the success of energy projects in the long term. On the other hand, maximizing life cycle

	Efficiency	Scalability	Reliability	Maintainability	Safety
Maximum variance					
$A(0)$	1	1	1	1	1
$A(1)$	2.981	3.190	2.717	3.195	2.501
$f(A(1))$	0.952	0.960	0.938	0.961	0.924
$A(2)$	2.825	3.015	2.575	3.019	2.384
$f(A(2))$	0.944	0.953	0.929	0.953	0.916
$A(3)$	2.802	2.989	2.554	2.993	2.365
$f(A(3))$	0.943	0.952	0.928	0.952	0.914
$A(4)$	2.798	2.985	2.550	2.989	2.362
$f(A(4))$	0.943	0.952	0.928	0.952	0.914
$A(5)$	2.797	2.984	2.550	2.988	2.362
$f(A(5))$	0.943	0.952	0.928	0.952	0.914
$A(6)$	2.797	2.984	2.549	2.988	2.361
$f(A(6))$	0.943	0.952	0.928	0.952	0.914
Weights	0.2011	0.2031	0.1979	0.2031	0.1949
Maximum entropy					
$A(0)$	1	1	1	1	1
$A(1)$	2.828	2.999	2.393	2.991	2.272
$f(A(1))$	0.944	0.953	0.916	0.952	0.907
$A(2)$	2.642	2.792	2.241	2.784	2.141
$f(A(2))$	0.934	0.942	0.904	0.942	0.895
$A(3)$	2.611	2.758	2.215	2.751	2.116
$f(A(3))$	0.932	0.940	0.902	0.940	0.892
$A(4)$	2.605	2.752	2.210	2.744	2.112
$f(A(4))$	0.931	0.940	0.901	0.940	0.892
$A(5)$	2.604	2.751	2.209	2.743	2.111
$f(A(5))$	0.931	0.940	0.901	0.940	0.892
$A(6)$	2.604	2.751	2.209	2.743	2.110
$f(A(6))$	0.931	0.940	0.901	0.940	0.892
Weights	0.2023	0.2042	0.1957	0.2041	0.1937
Maximum resistance					
$A(0)$	1	1	1	1	1
$A(1)$	2.908	3.077	2.566	3.066	2.468
$f(A(1))$	0.948	0.956	0.929	0.955	0.922
$A(2)$	2.741	2.891	2.423	2.881	2.339
$f(A(2))$	0.939	0.947	0.919	0.947	0.912
$A(3)$	2.714	2.862	2.400	2.853	2.317
$f(A(3))$	0.938	0.946	0.917	0.945	0.910
$A(4)$	2.709	2.857	2.396	2.848	2.313
$f(A(4))$	0.938	0.946	0.916	0.945	0.910
$A(5)$	2.708	2.856	2.395	2.847	2.313
$f(A(5))$	0.938	0.946	0.916	0.945	0.910
$A(6)$	2.708	2.856	2.395	2.847	2.312
$f(A(6))$	0.938	0.946	0.916	0.945	0.910
Weights	0.2014	0.2032	0.1969	0.2031	0.1955
Balanced					
$A(0)$	1	1	1	1	1
Continued					

	Efficiency	Scalability	Reliability	Maintainability	Safety
A (1)	2.904	3.077	2.545	3.072	2.404
f (A (1))	0.948	0.956	0.927	0.956	0.917
A (2)	2.733	2.887	2.398	2.883	2.278
f (A (2))	0.939	0.947	0.917	0.947	0.907
A (3)	2.706	2.857	2.375	2.853	2.256
f (A (3))	0.937	0.946	0.915	0.945	0.905
A (4)	2.701	2.852	2.371	2.848	2.252
f (A (4))	0.937	0.945	0.915	0.945	0.905
A (5)	2.700	2.851	2.370	2.847	2.251
f (A (5))	0.937	0.945	0.915	0.945	0.905
A (6)	2.700	2.851	2.370	2.847	2.251
f (A (6))	0.937	0.945	0.915	0.945	0.905
Weights	0.2017	0.2034	0.1968	0.2034	0.1947

Table 12. Iterative state vector, the function values and the weights for the parameter-adjusted assessments.

Criteria	Maximum variance	Maximum entropy	Maximum resistance	Balanced	Overall
Efficiency	3	3	3	3	3
Scalability	2	1	1	1	1
Reliability	4	4	4	4	4
Maintainability	1	2	2	2	2
Safety	5	5	5	5	5

Table 13. Comparative weights of the criteria by the parameter-adjusted assessments.

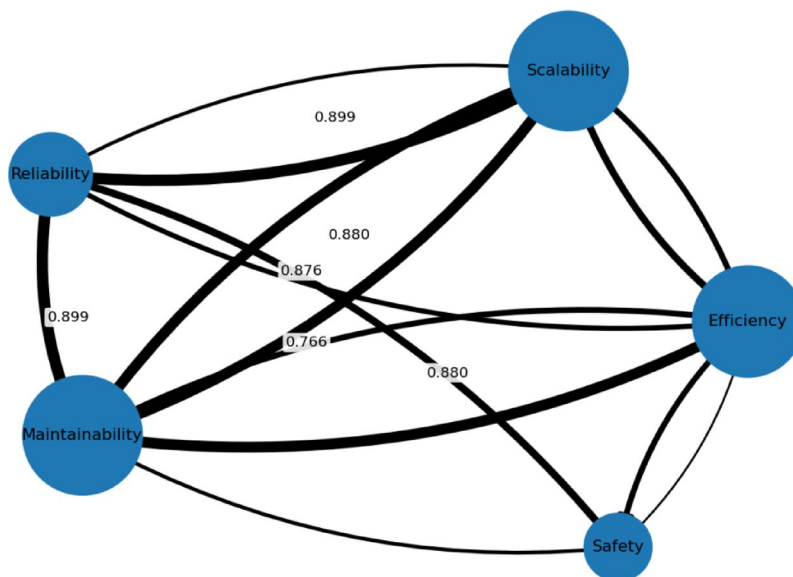


Fig. 2. Dynamic multi-facet fuzzy cognitive map.

performance in renewable energy projects is one of the important strategies highlighted by this study. This strategy aims to provide high efficiency and sustainability in all processes starting from the installation of an energy system to the operation, maintenance and final disposal stages. Maximizing life cycle performance requires focusing not only on the initial investment cost but also on the factors that will emerge throughout the life of the system. This approach provides long-term cost efficiency while also contributing to environmental

	Efficiency	Scalability	Reliability	Maintainability	Safety
Targeting	(0.60, 0.35, 1.00, 0.15, 1.00)	(0.70, 0.22, 0.89, 0.27, 1.00)	(0.70, 0.22, 0.89, 0.27, 1.00)	(0.80, 0.14, 0.57, 0.44, 1.00)	(0.60, 0.35, 1.00, 0.15, 1.00)
Predictable	(0.80, 0.24, 0.57, 0.40, 1.00)	(0.80, 0.24, 0.57, 0.40, 1.00)	(0.80, 0.24, 0.57, 0.40, 1.00)	(0.80, 0.24, 0.57, 0.40, 1.00)	(0.70, 0.30, 0.89, 0.23, 1.00)
Microgrids	(0.90, 0.02, 0.24, 0.65, 1.00)	(0.60, 0.27, 1.00, 0.12, 1.00)	(0.90, 0.02, 0.24, 0.65, 1.00)	(0.70, 0.12, 0.88, 0.23, 1.00)	(0.80, 0.05, 0.57, 0.40, 1.00)
Combining	(0.80, 0.07, 0.57, 0.45, 1.00)	(0.70, 0.15, 0.88, 0.28, 1.00)	(0.60, 0.30, 1.00, 0.16, 1.00)	(0.50, 0.50, 1.00, 0.08, 1.00)	(0.60, 0.30, 1.00, 0.16, 1.00)
Lifecycle	(0.70, 0.15, 0.88, 0.24, 1.00)	(0.80, 0.07, 0.57, 0.41, 1.00)	(0.90, 0.03, 0.24, 0.65, 1.00)	(0.60, 0.30, 1.00, 0.13, 1.00)	(0.80, 0.07, 0.57, 0.41, 1.00)

Table 14. Averaged fuzzy numbers for overall performance of decision matrix with parameter-adjusted assessments.

	Efficiency	Scalability	Reliability	Maintainability	Safety
Maximum variance					
Targeting	0.608	0.699	0.699	0.805	0.608
Predictable	0.774	0.774	0.774	0.774	0.658
Microgrids	0.890	0.560	0.890	0.660	0.776
Combining	0.816	0.715	0.626	0.535	0.626
Lifecycle	0.668	0.782	0.893	0.570	0.782
Maximum entropy					
Targeting	0.557	0.625	0.625	0.741	0.557
Predictable	0.665	0.665	0.665	0.665	0.533
Microgrids	0.889	0.560	0.889	0.658	0.774
Combining	0.793	0.685	0.605	0.537	0.605
Lifecycle	0.632	0.754	0.878	0.542	0.754
Maximum resistance					
Targeting	0.576	0.641	0.641	0.752	0.576
Predictable	0.718	0.718	0.718	0.718	0.606
Microgrids	0.903	0.612	0.903	0.699	0.802
Combining	0.794	0.687	0.605	0.537	0.605
Lifecycle	0.673	0.781	0.891	0.592	0.781
Balanced					
Targeting	0.577	0.653	0.653	0.767	0.577
Predictable	0.713	0.713	0.713	0.713	0.590
Microgrids	0.894	0.579	0.894	0.674	0.785
Combining	0.801	0.696	0.612	0.536	0.612
Lifecycle	0.658	0.773	0.888	0.569	0.773

Table 15. Defuzzified decision matrix by the parameter-adjusted assessments.

sustainability. Therefore, performance strategies that focus on the life cycle are increasingly critical for both investors and policy makers.

While the results section presents detailed fuzzy and defuzzified values across multiple scenarios, a deeper interpretation of the intermediate outputs provides important additional insights. The scenario-based analysis reveals that variations in parameter configurations meaningfully affect the relative influence of technical criteria, particularly under conditions of heightened uncertainty. For instance, scenarios emphasizing maximum entropy or resistance amplify the role of adaptability-oriented criteria, indicating that decision-maker behavior and risk perception significantly shape prioritization outcomes. These differences highlight that technical performance is not evaluated in isolation but is strongly mediated by contextual and cognitive factors embedded in the decision environment.

Moreover, the consistency of scalability and maintainability as dominant criteria across scenarios demonstrates the robustness of these indicators, suggesting that their importance is not sensitive to specific uncertainty assumptions. In contrast, the fluctuating relative positions of efficiency, reliability, and safety across scenarios reflect their dependence on external conditions and stakeholder attitudes. From an operational perspective, these intermediate results indicate that scenario-based fuzzy modeling enables decision makers to identify not only the most critical criteria but also the conditions under which certain factors gain or lose strategic relevance. Consequently, the proposed framework supports more nuanced and resilient investment planning by allowing practitioners to anticipate how technical priorities may shift under alternative future scenarios rather than relying on a single static ranking.

	Efficiency	Scalability	Reliability	Maintainability	Safety
Maximum variance					
Targeting	0.122	0.135	0.143	0.157	0.126
Predictable	0.156	0.150	0.159	0.151	0.136
Microgrids	0.179	0.108	0.182	0.128	0.160
Combining	0.164	0.138	0.128	0.104	0.129
Lifecycle	0.134	0.151	0.183	0.111	0.161
Maximum entropy					
Targeting	0.107	0.119	0.134	0.145	0.115
Predictable	0.128	0.127	0.143	0.130	0.110
Microgrids	0.171	0.107	0.191	0.129	0.160
Combining	0.152	0.131	0.130	0.105	0.125
Lifecycle	0.121	0.144	0.189	0.106	0.156
Maximum resistance					
Targeting	0.113	0.124	0.136	0.149	0.115
Predictable	0.141	0.139	0.152	0.142	0.121
Microgrids	0.177	0.118	0.192	0.138	0.160
Combining	0.156	0.133	0.129	0.106	0.121
Lifecycle	0.132	0.151	0.189	0.117	0.156
Balanced					
Targeting	0.113	0.126	0.138	0.151	0.118
Predictable	0.139	0.138	0.151	0.140	0.120
Microgrids	0.175	0.112	0.189	0.132	0.160
Combining	0.157	0.134	0.129	0.105	0.125
Lifecycle	0.129	0.149	0.188	0.112	0.158

Table 16. Weighted decision matrix by the parameter-adjusted assessments.

	Efficiency	Scalability	Reliability	Maintainability	Safety
Maximum variance					
Targeting	0.0004	-0.0002	0.0001	-0.0001	0.0001
Predictable	-0.0002	0.0002	-0.0001	0.0000	-0.0001
Microgrids	0.0001	-0.0001	0.0005	0.0000	0.0003
Combining	-0.0001	0.0000	0.0000	0.0004	-0.0001
Lifecycle	0.0001	-0.0001	0.0003	-0.0001	0.0002
Maximum entropy					
Targeting	0.0005	-0.0001	0.0002	-0.0001	0.0002
Predictable	-0.0001	0.0002	0.0000	-0.0001	0.0000
Microgrids	0.0002	0.0000	0.0007	-0.0001	0.0005
Combining	-0.0001	-0.0001	-0.0001	0.0002	-0.0001
Lifecycle	0.0002	0.0000	0.0005	-0.0001	0.0004
Maximum resistance					
Targeting	0.0005	-0.0001	0.0002	-0.0001	0.0002
Predictable	-0.0001	0.0001	0.0000	-0.0001	0.0000
Microgrids	0.0002	0.0000	0.0007	0.0000	0.0005
Combining	-0.0001	-0.0001	0.0000	0.0003	-0.0001
Lifecycle	0.0002	0.0000	0.0005	-0.0001	0.0004
Balanced					
Targeting	0.0005	-0.0001	0.0002	-0.0001	0.0002
Predictable	-0.0001	0.0002	0.0000	-0.0001	0.0000
Microgrids	0.0002	0.0000	0.0006	0.0000	0.0004
Combining	-0.0001	-0.0001	0.0000	0.0003	-0.0001
Lifecycle	0.0002	0.0000	0.0004	-0.0001	0.0004

Table 17. Covariance matrix by the parameter-adjusted assessments.

	$p^{(0)}$	$p^{(1)}$	$p^{(2)}$	$p^{(3)}$	$p^{(4)}$	$p^{(5)}$	$p^{(6)}$
Maximum variance							
Targeting	1	0.2614	0.2767	0.3360	0.3805	0.4090	0.4267
Predictable	1	-0.0895	-0.2186	-0.2409	-0.2478	-0.2519	-0.2548
Microgrids	1	0.8128	0.7668	0.7119	0.6683	0.6381	0.6184
Combining	1	0.1441	-0.0799	-0.2057	-0.2768	-0.3171	-0.3401
Lifecycle	1	0.4922	0.5304	0.5292	0.5201	0.5114	0.5049
Maximum entropy							
Targeting	1	0.3876	0.3969	0.3993	0.4000	0.4002	0.4002
Predictable	1	-0.0714	-0.0498	-0.0444	-0.0431	-0.0428	-0.0427
Microgrids	1	0.7197	0.7063	0.7031	0.7023	0.7021	0.7021
Combining	1	-0.1176	-0.1537	-0.1624	-0.1646	-0.1651	-0.1652
Lifecycle	1	0.5593	0.5635	0.5637	0.5638	0.5638	0.5638
Maximum resistance							
Targeting	1	0.3721	0.3852	0.3931	0.3962	0.3973	0.3977
Predictable	1	0.0129	0.0135	0.0166	0.0172	0.0173	0.0173
Microgrids	1	0.7559	0.7390	0.7336	0.7317	0.7310	0.7308
Combining	1	0.0207	-0.0382	-0.0529	-0.0571	-0.0583	-0.0587
Lifecycle	1	0.5382	0.5512	0.5516	0.5515	0.5514	0.5514
Balanced							
Targeting	1	0.3495	0.3771	0.3926	0.3992	0.4020	0.4032
Predictable	1	-0.0837	-0.0795	-0.0743	-0.0731	-0.0729	-0.0730
Microgrids	1	0.7558	0.7199	0.7072	0.7021	0.7001	0.6993
Combining	1	-0.0694	-0.1493	-0.1735	-0.1817	-0.1845	-0.1854
Lifecycle	1	0.5430	0.5576	0.5569	0.5562	0.5558	0.5556

Table 18. Eigenvectors iteratively by the parameter-adjusted assessments.

Discussion

Scalability stands out as the most critical technical performance indicator in increasing the effectiveness of renewable energy projects. Thanks to this feature, projects can be established on a small scale at the beginning and transformed into larger and more comprehensive systems over time. The demand for energy in today's world is increasing. Consequently, the system invested in must be expandable in the future. With the help of this situation, it is possible to ensure the long-term success and sustainability of projects. In addition, Park et al.²⁸ determined that scalability facilitates the integration of technological developments. This contributes to the reduction of investment risks. According to the findings in the literature, systems with this feature play a more effective role in increasing the performance of projects compared to other technical indicators. David et al.²⁹ highlighted that projects need to be designed in a modular structure. Owing to this condition, the system can be expanded with low additional cost in the face of increasing demand. It is also very critical for projects to be compatible with smart grid technologies. It supports the projects to adapt to production and demand levels at different scales. Increasing the energy storage capacity also helps to achieve this goal. This condition allows projects to support increasing energy loads more safely.

Maintainability stands out as another technical performance indicator in increasing the effectiveness of renewable energy projects. Renewable energy systems are generally long-lasting investments. This increases the possibility of failures in operational processes. Therefore, the effectiveness of maintenance processes must be ensured for these systems to operate with continuous performance. Habibzadeh et al.³⁰ discussed that easy and fast maintenance reduces operating costs and ensures uninterrupted operation of the system. This allows both operational and financial performance of projects to be increased. In addition, integrating maintenance processes with digital tools allows early detection of failures. With the help of this issue, preventive interventions can be made more possible. Movsessian et al.³¹ identified that the use of standardized parts and equipment allows projects to achieve their maintainability targets more easily. Therefore, easily available and widely used spare parts should be preferred. This supports the minimization of supply chain problems. As a result, it is possible to reduce system outages. In the analyses, efficiency, reliability and safety indicators are determined to have lower weights compared to technical performance indicators such as scalability and maintainability. However, this does not mean that these factors are unimportant. All three of these elements play a fundamental role in the success, sustainability and longevity of renewable energy projects. If these factors are not optimized, the overall project performance may be compromised, even if the systems have high scalability or ease of maintenance.

Focusing on easily serviced microgrids stands out as one of the most important investment strategies for renewable energy projects. Microgrids are small-scale energy systems that can manage electricity production and consumption in an integrated manner in a limited area. These structures offer great advantages in terms of ensuring energy security, especially in places where the grid connection is weak. Bampaou and Panopoulos³² denoted that fast and low-cost maintenance processes are essential for these systems to operate uninterruptedly.

	wp_j	N_j	U_i	Z_i
Maximum variance				
Targeting	0.0004	0.275	0.645	-3.396
Predictable	-0.0002	0.000	0.737	-0.170
Microgrids	0.0005	0.399	0.853	3.902
Combining	-0.0003	0.000	0.678	-2.214
Lifecycle	0.0004	0.326	0.795	1.878
Maximum entropy				
Targeting	0.0005	0.240	0.586	-3.101
Predictable	-0.0001	0.000	0.620	-2.130
Microgrids	0.0009	0.421	0.850	4.293
Combining	-0.0002	0.000	0.650	-1.304
Lifecycle	0.0007	0.338	0.777	2.242
Maximum resistance				
Targeting	0.0005	0.234	0.604	-3.403
Predictable	0.0000	0.010	0.682	-1.150
Microgrids	0.0009	0.431	0.867	4.232
Combining	-0.0001	0.000	0.650	-2.063
Lifecycle	0.0007	0.325	0.803	2.384
Balanced				
Targeting	0.0004	0.243	0.609	-3.311
Predictable	-0.0001	0.000	0.672	-1.412
Microgrids	0.0008	0.422	0.857	4.253
Combining	-0.0002	0.000	0.658	-1.834
Lifecycle	0.0006	0.335	0.794	2.304
Overall				
Targeting	0.0004	0.242	0.608	-3.264
Predictable	-0.0001	0.000	0.665	-1.556
Microgrids	0.0008	0.424	0.858	4.269
Combining	-0.0002	0.000	0.657	-1.783
Lifecycle	0.0006	0.335	0.793	2.333

Table 19. wp_j , N_j , U_i , Z_i values by the parameter-adjusted assessments.

Investing in microgrid systems that provide ease of maintenance reduces operating costs. In parallel, this also accelerates the continuity of the system and the return on investment. Yin et al.³³ showed that maximizing lifecycle performance in renewable energy projects is another critical strategy in terms of sustainability and efficiency of investments in this area. Thanks to this approach, not only the initial investment costs but also the total cost of ownership of the system can be taken into consideration. Increasing the performance of the system throughout the lifecycle reduces resource waste. This situation also contributes significantly to the development of the financial performance of the projects.

Despite the growing adoption of advanced decision-support frameworks in renewable energy investments, several challenges continue to limit their effective implementation. One major challenge concerns the availability and quality of expert knowledge and data inputs, as renewable energy projects often involve heterogeneous stakeholders with differing levels of technical expertise and risk perception. Recent studies emphasize that insufficient or biased expert input may lead to suboptimal investment prioritization and increased uncertainty in decision outcomes. Another critical challenge relates to the computational and practical complexity of advanced AI-supported and fuzzy-based models, which may hinder their adoption by practitioners lacking specialized analytical capabilities. In addition, regulatory uncertainty and rapidly evolving policy environments remain significant barriers, particularly for long-term infrastructure investments such as microgrids and decentralized energy systems. To address these challenges, recent research highlights several practical implementation solutions. The use of data-driven and adaptive expert weighting mechanisms, as adopted in this study, has been shown to reduce subjectivity and improve the robustness of expert-based evaluations. Furthermore, scenario-based fuzzy modeling frameworks enable decision makers to systematically assess investment strategies under alternative regulatory, technological, and market conditions, thereby enhancing resilience to uncertainty. From an operational standpoint, the modular design of renewable energy systems, particularly microgrids, has been widely recommended as an effective solution to scalability and maintenance challenges, as it allows incremental capacity expansion and simplifies system servicing. Policy-oriented studies further suggest that clear technical standards, stable incentive schemes, and targeted financial instruments such as low-interest loans and tax incentives are essential for facilitating the practical deployment of scalable and maintainable renewable energy technologies. By integrating these solution-oriented insights, the proposed framework aligns with contemporary

Alternatives	Maximum variance	Maximum entropy	Maximum resistance	Balanced	Overall
Case 1					
Targeting	5	5	5	5	5
Predictable	3	4	3	3	3
Microgrids	1	1	1	1	1
Combining	4	3	4	4	4
Lifecycle	2	2	2	2	2
Case 2					
Targeting	5	5	5	5	5
Predictable	3	4	3	3	3
Microgrids	1	1	1	1	1
Combining	4	3	4	4	4
Lifecycle	2	2	2	2	2
Case 3					
Targeting	5	5	4	5	4
Predictable	3	4	3	3	3
Microgrids	1	1	1	1	1
Combining	4	2	5	4	5
Lifecycle	2	3	2	2	2
Case 4					
Targeting	5	5	4	5	4
Predictable	3	4	3	3	3
Microgrids	1	1	1	1	1
Combining	4	2	5	4	5
Lifecycle	2	3	2	2	2
Case 5					
Targeting	5	5	5	5	5
Predictable	3	4	3	3	3
Microgrids	1	1	1	1	1
Combining	4	3	4	4	4
Lifecycle	2	2	2	2	2

Table 20. Comparative ranking results of the alternatives by the parameter-adjusted assessments and sensitivity analysis.

empirical findings and provides a viable pathway for translating advanced decision models into real-world renewable energy investment practices.

Conclusion

Main concluding issues

The purpose of this study is to optimize renewable energy investment strategies by considering technical performance indicators. A novel model has been created that integrates parameter-driven artificial expert evaluations, cognitive maps and principal component ranking optimization. Moreover, dynamic multi-facet fuzzy sets are taken into consideration to manage uncertainties in the decision process. This study contributes to the literature by proposing an innovative decision-making model supported by artificial intelligence to determine the most important technical indicators that provide performance increase in renewable energy projects. In this study, the dynamic multi-facet fuzzy sets are introduced. With the help of these new sets, the parameters of membership degrees can be dynamically adopted based on different scenarios that are negative, positive, unstable and natural. It is identified that scalability and ease of maintenance are the most essential factors that increase technical performance in renewable energy projects. On the other side, focusing on easy-to-service microgrids and maximizing lifecycle performance are identified as the most important investment strategies.

Limitations and future research directions

Despite its contributions, this study has several limitations that should be acknowledged and addressed in future research. First, the expert evaluations employed in the proposed framework are based on a limited number of domain specialists, which may restrict the generalizability of the findings. Although the artificial intelligence-based expert weighting mechanism enhances objectivity, future studies could benefit from larger and more diverse expert panels, including cross-country or cross-sector participation. Second, the model evaluates renewable energy investments within a general technical framework. However, technical priorities and operational constraints may differ significantly across renewable energy types such as solar, wind, hydro, or biomass. Future research could extend the proposed framework by conducting technology-specific analyses to

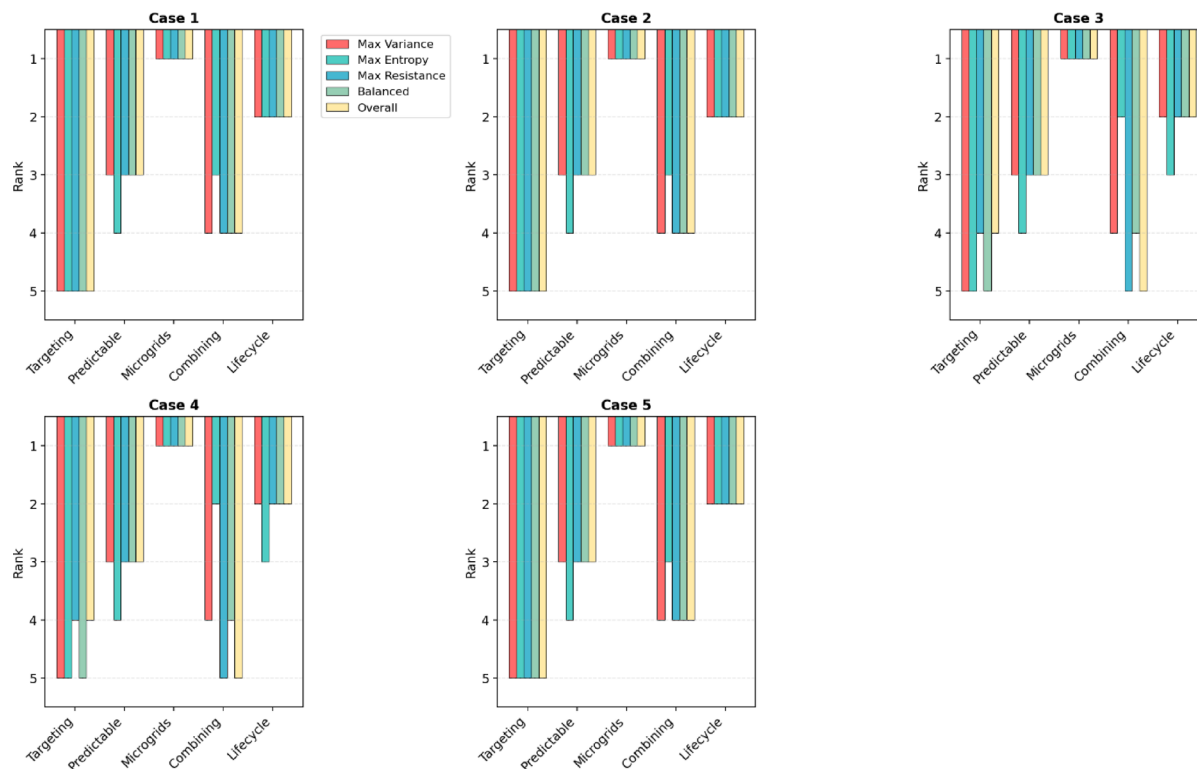


Fig. 3. Sensitivity analysis for ranking stability across different weighting scenarios.

capture these variations more precisely. Third, while the dynamic multi-facet fuzzy structure allows scenario-based uncertainty modeling, the results remain sensitive to parameter configuration and scenario design. Further studies may explore automated or learning-based parameter optimization techniques to further reduce user dependence and enhance model robustness. Finally, future research could integrate additional dimensions such as environmental, social, or geopolitical factors into the framework, enabling a more comprehensive assessment of renewable energy investment strategies under complex real-world conditions.

Policy implications

The findings of this study provide important theoretical and operational implications for renewable energy investments. From an operational perspective, the prioritization of scalability and ease of maintenance indicates that renewable energy systems should be designed with modular and adaptable technical architectures to respond effectively to rapidly growing and uncertain energy demand. Such designs support long-term sustainability objectives by enabling capacity expansion without significant efficiency losses or cost escalation. In addition, the emphasis on maintainability highlights the importance of selecting technologies characterized by low maintenance requirements, standardized components, and easily accessible spare parts, which collectively reduce operational costs and enhance system reliability. From a policy perspective, these results suggest that public support mechanisms should be aligned with technologies that demonstrate high scalability and maintainability performance. Policy instruments such as tax incentives, low-interest financing, and targeted subsidies can play a critical role in encouraging investments in systems with lower lifecycle costs and higher operational resilience. Furthermore, the strong performance of microgrid-based strategies underscores the growing relevance of decentralized energy structures in enhancing supply security and system flexibility. Promoting microgrids through regulatory frameworks and technical standards can improve energy continuity in both urban and rural contexts while supporting the transition toward more resilient and locally optimized energy systems. Overall, the study translates its theoretical contributions into actionable guidance for investors and policy makers, bridging the gap between advanced decision-making models and real-world renewable energy planning and implementation.

Data availability

The data used in the analysis is given in the manuscript.

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Competing interests

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Additional information

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