

SCENARIO-BASED DYNAMIC EVALUATION OF LIFECYCLE ENVIRONMENTAL EFFICIENCY IN RENEWABLE ENERGY INFRASTRUCTURE USING A NOVEL HYBRID MULTI-FACET FUZZY DECISION-MAKING APPROACH

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Abstract. The efficiency of life cycle environmental impacts of renewable energy infrastructures is extremely important for ensuring sustainability and combating climate change effectively. Although prior studies have addressed various aspects of lifecycle environmental impacts in renewable energy systems, a limited number of studies have systematically identified and prioritized the most critical factors influencing lifecycle environmental efficiency. This limitation may lead to suboptimal allocation of improvement efforts and reduce the effectiveness of sustainability-oriented strategies. The main objective of this study is to determine the most effective strategies to increase environmental efficiency of economic life cycle of renewable energy infrastructures and to identify the most critical environmental impact factors in this process. For this purpose, an original decision-making model integrating dynamic multi-facet fuzzy sets, Bayesian networks and multi-objective optimization on the basis of ratio analysis (MOORA) techniques is developed. This study makes a significant contribution to the literature by presenting an innovative decision support model that systematically identifies the most critical factors for increasing life cycle environmental efficiency in renewable energy infrastructures. Considering multi-facet fuzzy sets allows dynamic redefinition of membership degrees for different scenarios (negative, positive, unstable, natural). This provides better modelling of uncertainty and variability of the decision environment.

Keywords: lifecycle environmental efficiency, renewable energy, energy infrastructure, circular economy, multi-facet fuzzy sets, uncertainty, MOORA.

JEL Classification: C02, C44, D81, O13, Q01, Q4.

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1. Introduction

Renewable energy infrastructures are generally associated with low emissions during the operational phase; however, significant environmental impacts may arise throughout their lifecycle, including raw material extraction, manufacturing, installation, maintenance, and

disposal stages. The raw material extraction and manufacturing process is one of the most critical stages in this context. Mining activities have been shown to contribute to deforestation and biodiversity loss, particularly in regions where regulatory frameworks are limited (Virah-Sawmy & Sturmberg, 2025). Installation and construction processes may also create environmental pressures due to extensive land use requirements, leading to habitat degradation. Operational activities generate additional environmental impacts, while maintenance and repair processes may also generate notable environmental impacts, particularly due to fossil fuel use and associated emissions. The use of fossil fuels in transportation and maintenance vehicles increases the carbon footprint, and dismantling processes may produce significant electronic and hazardous waste (Kou et al., 2025). Lifecycle environmental efficiency is influenced by several factors, including material selection, technological design, infrastructure requirements, and maintenance practices. Due to resource constraints, it is often not feasible to optimize all lifecycle stages simultaneously. Therefore, identifying and prioritizing the most critical factors is essential for improving environmental efficiency and guiding effective policy design. Although prior studies have addressed various aspects of lifecycle environmental impacts, a limited number of studies have systematically identified and prioritized the most critical factors affecting lifecycle environmental efficiency (Firoiu et al., 2026). This limitation may lead to suboptimal allocation of improvement efforts and reduce the effectiveness of climate change mitigation strategies.

In this study, lifecycle environmental efficiency refers to the extent to which renewable energy infrastructures minimize environmental impacts across all stages of their lifecycle, from raw material extraction to end-of-life disposal, while maintaining functional and economic performance. This concept encompasses multiple dimensions, including resource efficiency, emission reduction, waste management, and ecological sustainability. Within this context, the “most critical factors” denote the key criteria that have the greatest influence on improving lifecycle environmental efficiency (Rahadian et al., 2025). Based on the literature, these factors are identified as ecosystem disruption, habitat conversion, water footprint, use of recyclable materials, and ecological footprint efficiency. Although previous studies have examined these factors individually or within specific contexts, a systematic framework that simultaneously evaluates and prioritizes these factors within a unified decision-making model remains limited. Therefore, this study aims to address this gap by proposing an integrated and scenario-based evaluation approach.

To address this research gap in the literature, this study aims to find appropriate strategies to increase lifecycle environmental efficiency in renewable energy infrastructure. A novel decision-making model is constructed by integrating dynamic multi-facet fuzzy sets, Bayesian networks and multi-objective optimization on the basis of ratio analysis (MOORA) techniques. There is no consensus on which strategies are most effective for increasing life cycle environmental efficiency in renewable energy infrastructure. This creates a decision-making difficulty at both theoretical and practical levels. Moreover, this situation creates strategic uncertainty for the private sector and investors. If the right strategies are not determined, investments may be directed to the wrong areas. Establishing a new model to eliminate these deficiencies is also considered as an important motivation of the study. Hence, this study tries to find answers for the following research questions. (1) What are the most critical factors affecting

life cycle environmental efficiency in renewable energy infrastructure? (2) What are the most effective strategies to increase life cycle environmental efficiency? (3) How does the newly developed decision-making model contribute to increasing life cycle environmental efficiency in renewable energy infrastructures?

This study makes a significant contribution to the literature by presenting an innovative decision support model that systematically identifies the most critical factors for increasing life cycle environmental efficiency in renewable energy infrastructures. The superiorities of the proposed model can be explained as follows. (1) The developed multi-facet fuzzy sets concept provides a significant contribution to the literature and provides the model with significant advantages over other similar models. Traditional fuzzy set models are generally based on static parameters. However, multi-facet fuzzy sets allow dynamic redefinition of membership degrees for different scenarios (negative, positive, unstable, natural). This provides better modelling of uncertainty and variability of the decision environment. Dynamic determination of parameters with statistical methods increases objectivity and adaptation capacity in the decision-making model. Identification of different extreme cases and adjustment of parameters accordingly expands the application areas in complex and multi-dimensional decision problems. (2) The use of Bayesian networks technique in calculating the criteria weights contributes to the literature. This approach models the causal relationships and conditional probabilities between the criteria. Owing to this situation, the weights of the criteria are calculated not only based on their individual importance but also on their interdependence. This is a great advantage especially in systems with complex and interdependent criteria. Another advantage of this technique is the provision of dynamic updateability. Criteria weights can be updated as new information arrives, which ensures that the decision-making process remains adaptive and up to date.

The research gap in the literature is highlighted in the second section. The following section focuses on the proposed model constructed to satisfy this missing gap. The fourth section demonstrates the results of this model. In the next section, the findings are compared with the results of the similar studies. The sixth section identifies the main concluding remarks.

2. Literature review

The existing literature on lifecycle environmental impacts of renewable energy infrastructure has primarily focused on specific dimensions such as ecological footprint, resource consumption, and environmental governance. While these studies provide valuable insights into individual aspects of sustainability, they often adopt fragmented approaches that evaluate criteria in isolation. This limits the ability to develop a comprehensive understanding of lifecycle environmental efficiency, which inherently involves multiple interrelated factors. Moreover, prior research generally lacks an integrated decision-making framework that simultaneously identifies and prioritizes the most critical factors influencing environmental performance. As a result, there is still a need for a systematic and multi-dimensional approach that captures the complexity of lifecycle processes and supports more effective policy and investment decisions.

Ecosystem disruption is one of the effective criteria in improving the environmental performance of renewable energy infrastructure throughout its life cycle. Indeed, the transition to renewable energy sources can be expressed as one of the important steps in creating policy frameworks and encouraging international cooperation, reducing the risks of fossil fuel-related disasters and building a more sustainable future (Karmakar et al., 2024). Because the widespread use of fossil fuels causes serious environmental problems, while the intensive use of energy and natural resources can lead to ecosystem degradation by reducing biodiversity (Mukhtarov, 2024). Adopting the idea that renewable energy sources can stimulate the economy while also promoting environmental sustainability, Yang and Long (2024) examine the impact of renewable energy source development on natural resource extraction and the possibility of green economic recovery. With this review, the need for the state to establish strict environmental regulations on natural resource extraction comes to the fore. Khan et al. (2025) introduced the Bayesian Integrated Risk Mitigation Model, an adaptive decision support tool for socio-environmental risk assessment in large-scale infrastructure projects. This model is particularly useful for addressing high priority risks such as ecosystem degradation, socio-economic losses related to displacement, and long-term environmental degradation where early intervention is critical.

Habitat conversion is another effective criterion for improving the environmental performance of renewable energy infrastructure throughout its life cycle. Life cycle assessment is an approach that allows the assessment of multiple impacts resulting from various emissions and resource uses in different impact categories such as climate change, land use and resource depletion (Gilad et al., 2024). In other words, the habitat and ecology needs of the economy are an important issue to be taken into consideration in the development of renewable energy technologies (Arshed et al., 2024). Because projects such as solar or wind energy require a large area of land and can lead to habitat degradation (Tverijonaite & Sæþórsdóttir, 2024). Ramesh (2025), who wants to emphasize the critical transition from fossil fuels to renewable energy sources, examines the developments in hydro, solar, wind, geothermal and bioenergy technologies and addresses their roles in reducing greenhouse gas emissions and promoting energy security.

Water footprint can be expressed as one of the effective criteria in improving the environmental performance of renewable energy infrastructure throughout its life cycle. Indeed, optimizing the use of natural resources and using renewable energy resources can reduce the environmental footprint of a country and increase its load capacity (Lu et al., 2024). In other words, concentrating on separate network analyses of carbon or water footprints of energy systems also ignores the direct and indirect interdependencies between energy, water and carbon (Wang et al., 2025; Rehman et al., 2025). Clean renewable energy communities aim to reduce the energy carbon footprint, increase local energy resilience and improve the quality of life of individuals. In this context, Wehbi (2024) reviews criteria such as being able to evaluate the impact of energy transition plans and supporting decision-making to select technologies that create reliable and accessible energy systems. On the other hand, Idroes et al. (2024) investigates the dynamic impact of renewable and non-renewable energy, economic growth and capital formation on carbon dioxide emissions and ecological footprint in Indonesia.

The use of recyclable materials is another effective criterion for improving the environmental performance of renewable energy infrastructure throughout its life cycle. Promoting the use of recyclable materials in renewable energy infrastructure also supports the circular economy by reducing product complexity and ultimately extending the life cycle of renewable energy assets. In this way, environmental burdens such as carbon footprint or waste management are significantly reduced (Miller et al., 2025). In other words, renewable energy systems such as wind turbines and solar panels include various elements, including advanced insulation materials to improve energy capture, smart technologies to optimize energy consumption and water saving measures. In addition, they provide solutions that contribute to a more sustainable and environmentally friendly future, increase resource efficiency and reduce raw material dependency (Shafik, 2024). Crîstiu et al. (2025) aim to address the need to optimize the supply chain for the recycling of raw materials in Italy's green technology sector. In this direction, they focus on photovoltaic panels, battery electric vehicles and wind turbines. Ganda (2024) investigates the relationship between environmental governance, green goods, non-green goods and eco-innovation on material footprint and renewable energy for BRICS countries. The research reveals that eco-innovation and environmental governance produce a significant positive relationship with both material footprint and renewable energy consumption.

Ecological footprint efficiency is another effective criterion in improving the environmental performance of renewable energy infrastructure throughout its life cycle. Ecological footprint is one of the new measures that allows the assessment of human pressure on the environment according to the consumption volume of goods and services and is widely used to evaluate sustainability (Dembińska et al., 2022; Lin et al., 2024). As renewable energy initiatives gain momentum worldwide, understanding ecological footprints and life cycle impacts is becoming imperative for informed decision making. For this reason, Rahadian et al. (2025) establishes a theoretical framework to understand the impact of renewable energy on the ecological footprint and investigates the factors contributing to the development of renewable energy. Other researchers propose another innovative decision-making framework for assessment of energy-friendly and sustainable renovation solutions, together with the application of decision system tools (Velykorusova et al., 2023; Antohi et al., 2026). On the other hand, Sohag et al. (2024) aim to evaluate the effectiveness of environmental policy stringency in reducing the ecological footprint by controlling the impact of renewable energy and innovation in the example of OECD countries. Thus, the positive impact of renewable energy in reducing ecological footprints is considered and policies encourage the expansion of renewable energy sources.

The results of the literature review indicate that there are some important criteria for increasing the environmental performance of renewable energy infrastructure throughout its life cycle. In this context, there are five criteria addressed in this study. These criteria are ecosystem degradation, habitat transformation, water footprint, use of recyclable materials and ecological footprint efficiency. However, since it is not possible to develop more than one criterion at the same time, the aim of this study is to determine the most important criterion. In line with this purpose, a new decision-making model is used as an analysis method and the gap in the literature is tried to be filled.

3. Methodology

The proposed methodological framework offers several advantages for analyzing lifecycle environmental efficiency in renewable energy infrastructure. First, the use of dynamic multi-facet fuzzy sets enables a more flexible representation of uncertainty by incorporating multiple dimensions such as membership, non-membership, hesitation, engagement, and resistance. This allows the model to capture different decision-making scenarios more effectively compared to traditional fuzzy approaches. Second, the integration of Bayesian networks facilitates the identification of interdependencies among criteria, enabling a more realistic and data-driven weighting process. Finally, the MOORA method provides a robust and computationally efficient mechanism for ranking policy alternatives based on multiple criteria. The combination of these methods ensures a comprehensive, adaptive, and analytically rigorous decision-making framework.

However, it is important to note that the proposed dynamic multi-facet fuzzy framework is intentionally designed to incorporate decision-maker attitudes through its scenario-based parameters, rather than relying on a large panel of experts. By varying the parameters across four scenarios (negative, positive, unstable, natural), the model captures a wide range of possible cognitive and contextual biases that may affect the evaluation. This approach allows the internal consistency and sensitivity of the results to be tested using a single expert's judgments, which are systematically varied across scenarios.

For the research on determining the most suitable policy to increase the lifecycle environmental efficiency in renewable energy infrastructure, a scenario-based dynamic evaluation is performed using a novel hybrid multi-facet fuzzy decision-making approach. In this process, the assessment criteria for the lifecycle environmental impact of renewable energy infrastructure are weighted with Bayesian Networks. Using the criterion priorities obtained here, policy alternatives to increase the lifecycle environmental efficiency in renewable energy infrastructure are ranked with MOORA. In this process, uncertainty is measured with the novel developed Dynamic Multi-facet Fuzzy Sets. The flow of the process is presented in Figure 1.

3.1. Dynamic multi-facet fuzzy sets

The introduction of multi-facet fuzzy sets with additional functions such as engagement and resistance is motivated by the need to better capture behavioral and cognitive dimensions of decision-making under uncertainty (Liao et al., 2023). While traditional extensions such as intuitionistic, Pythagorean, and picture fuzzy sets incorporate hesitation and non-membership degrees, they primarily focus on static representations of uncertainty. However, decision-making processes in complex environments, such as renewable energy planning, often involve varying levels of expert involvement, confidence, and resistance to certain alternatives. In this context, the engagement function reflects the degree of active support or emphasis placed by decision-makers on specific criteria, which is conceptually related to attention-based and preference intensity models in behavioral decision theory (Liu et al., 2025). Similarly, the resistance function represents the reluctance or opposition to changes in membership evaluations, aligning with concepts such as loss aversion and cognitive resistance in behavioral economics. Therefore, these additional functions extend the traditional fuzzy framework by

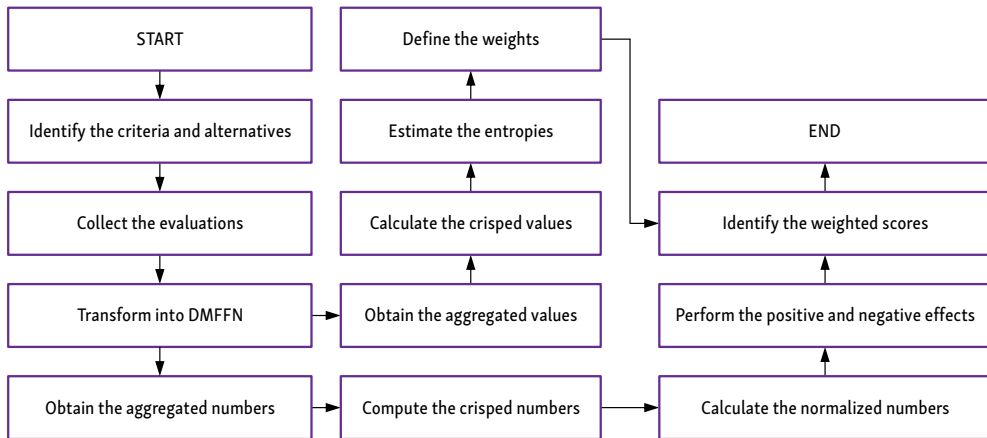


Figure 1. The flow of the process

incorporating dynamic and behaviorally informed dimensions, enabling a more realistic representation of expert judgments in complex decision environments.

Fuzzy sets are a theory developed to measure uncertainty. Traditional fuzzy sets have only the function of indicating the membership value of the element. However, Picture and Pythagorean fuzzy sets also include non-membership and hesitancy functions. On the other hand, more parameters are required to measure uncertainty. Various scenarios can be demonstrated in real-world situations with appropriate parameter settings. Thus, the constructed multi-way fuzzy sets contain five functions derived from the membership degree (Jovanovic et al., 2023). The proposed model, in addition to existing extensions of fuzzy sets, also defines functions of engagement and resistance functions.

It should be noted that this study does not aim to conduct a full life cycle assessment (LCA) in the conventional sense. Instead, the concept of lifecycle environmental efficiency is used as a conceptual framework to evaluate environmental performance across different stages of renewable energy infrastructure. While traditional LCA methodologies rely on detailed quantitative inventory data and standardized impact assessment procedures, the proposed approach adopts a multi-criteria decision-making perspective to assess and prioritize key environmental factors under uncertainty. Therefore, this study complements rather than replaces LCA by providing a decision-support framework that integrates lifecycle thinking with fuzzy-based evaluation techniques. This distinction clarifies the methodological positioning of the study and highlights its contribution as an alternative analytical approach.

The primary membership function (μ) is defined as the satisfactory value of the attributes or the base membership (MS) value and is between 0 and 1 (Amiri et al., 2022). The non-MS function is identified as the level of rejection to the attributes and defined as Eq. (1):

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

wherein $v(\mu)$ is the non-MS function of the multi-facet fuzzy sets and α refers to control parameter for the steepness of the transition between MS and non-MS degrees. Moreover,

choosing a high value of α is determined by taking a value around $\mu = 0.5$. The transition steepness is equal to the first derivative for the rate of change. That is, the derivative is calculated as in Eq. (2):

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

In this case the maximum slope is at the point where μ equals 0.5. At this point the slope is defined by Eqs. (3) and (4):

$$\left. \frac{dv}{d\mu} \right|_{\mu=0.5} = -\frac{\alpha}{4}; \quad (3)$$

$$\lim_{n \rightarrow \infty} v(\mu) = \begin{cases} 1 & \mu < 0.5 \\ 0.5 & \mu = 0.5 \\ 0 & \mu > 0.5 \end{cases}. \quad (4)$$

As can be seen from these equations, α directly controls the transition steepness. In other words, α approaches infinity, the non-MS function approaches a Heaviside step function. This situation satisfies boundary limits while providing adjustable transition areas. However, the boundedness of non-MS functions is proven in the logistic function in Eq. (5):

$$v(\mu) = \begin{cases} \frac{1}{1 + e^{\alpha(0.5-0.5)}} = \frac{1}{1 + e^0} = \frac{1}{2} = 0.5 & \text{for } \mu = 0.5 \\ \frac{1}{1 + e^{\alpha(1-0.5)}} = \frac{1}{1 + e^{\alpha/2}} \in (0, 1) & \text{for } \mu \rightarrow 1 \\ \frac{1}{1 + e^{\alpha(0-0.5)}} = \frac{1}{1 + e^{-\alpha/2}} \in (0, 1) & \text{for } \mu \rightarrow 0 \end{cases}. \quad (5)$$

$v(\mu)$ is a continuous and decreasing function and lies between 0 and 1 for every μ between 0 and 1. The uncertainty function is the third function of the multi-facet fuzzy sets and determined with Eq. (6):

$$\epsilon(\mu) = -a[\mu \ln \mu + (1-\mu) \ln (1-\mu)], \quad (6)$$

wherein the function is also the function of hesitation or doubt in the evaluation of the items and a amplifies uncertainty. In addition, the Shannon entropy satisfies the in Eq. (7):

$$H(\mu) = -\mu \ln \mu - (1-\mu) \ln (1-\mu), \quad (7)$$

wherein $H(\mu)$ is non-negative value for all value of μ and $H(0) = H(1) = 0$. The maximum value of $H(\mu)$ is defined at $\mu = 0.5$ and equals to $H(0.5) = \ln(2) \approx 0.693$. Then, the case in Eq. (8) is obtained:

$$\epsilon(\mu) = aH(\mu) \Rightarrow 0 \leq \epsilon(\mu) \leq a \ln(2). \quad (8)$$

So, if $a \leq \frac{1}{\ln(2)} \approx 1.442$, then $\epsilon(\mu) \leq 1$, for $a > \frac{1}{\ln(2)}$, $\epsilon(\mu) \in [0, 1]$. The maximum uncertainty at $\mu = 0.5$ is determined by the first and second derivatives as Eqs. (9)–(11):

$$\frac{d\epsilon}{d\mu} = -a[\ln \mu - \ln(1-\mu)]; \quad (9)$$

$$\ln \mu = \ln(1 - \mu) \Rightarrow \mu = 0.5; \quad (10)$$

$$\frac{d^2 \epsilon}{d\mu^2} = -a \left(\frac{1}{\mu} + \frac{1}{1 - \mu} \right) < 0. \quad (11)$$

The other function is engagement and reflects the experts' involvement and interest in the attributes. The function is named as the fourth function of multi-facet fuzzy sets and shown in Eq. (12):

$$n(\mu) = \mu^\delta, \quad (12)$$

wherein δ represents nonlinear engagement parameter. $\delta > 1$ rewards high the membership degrees while $\delta < 1$ suppresses μ . For $\delta > 1$, $n(0)$ is equal to 0, $n(1)$ is equal to 1 and $n(\mu)$ is between 0 and 1 for other values of μ . The impact and convexity of the δ are defined in Eqs. (13) and (14), respectively:

$$\frac{dn}{d\mu} = \delta \mu^{\delta-1}; \quad (13)$$

$$\frac{d^2 n}{d\mu^2} = \delta(\delta - 1) \mu^{\delta-2}. \quad (14)$$

The fifth function of the proposed fuzzy sets, the Resistance function, expresses information about the experts' cognitive or contextual resistance to the attributes and is calculated by Eq. (15):

$$\rho(\mu) = 1 - (1 - \mu)^\varphi, \quad (15)$$

wherein $\varphi > 0$, for $\varphi > 1$, resistance to MS loss increased. For $\varphi > 1$, $\rho(0) = 0$ and $\rho(1) = 1$. Behaviour analysis of resistance function is illustrated with the help of Eqs. (16) and (17):

$$\frac{d\rho}{d\mu} = \varphi(1 - \mu)^{\varphi-1}; \quad (16)$$

$$\frac{d^2 \rho}{d\mu^2} = -\varphi(\varphi - 1)(1 - \mu)^{\varphi-2}, \quad (17)$$

wherein if $\varphi > 1$, resistance increases near $\mu = 1$ and decreasing slope appears. If $\varphi < 1$, loss of MS degree accelerated with increasing slope.

Generalized presentation of the dynamic multi-facet fuzzy sets is identified using Eq. (18):

$$A = \left\{ \left(\begin{array}{c} x, \\ \mu(x), \\ v(\mu(x)), \\ \epsilon(\mu(x)), \\ n(\mu(x)), \\ \rho(\mu(x)) \end{array} \right) \middle| x \in X \right\} = \left\{ \left(\begin{array}{c} x, \\ \mu(x), \\ \frac{1}{1 + e^{\alpha(\mu-0.5)}}, \\ -a[\mu \ln \mu + (1 - \mu) \ln(1 - \mu)], \\ \mu^\delta, \\ 1 - (1 - \mu)^\varphi \end{array} \right) \middle| x \in X \right\}. \quad (18)$$

Some basic operations are summarized in Eqs. (19)–(22):

$$A \cup B = (\max(\mu_A, \mu_B), \min(v_A, v_B), \min(\epsilon_A, \epsilon_B), \max(n_A, n_B), \max(\rho_A, \rho_B)); \quad (19)$$

$$A \cap B = (\min(\mu_A, \mu_B), \max(v_A, v_B), \max(\epsilon_A, \epsilon_B), \min(n_A, n_B), \max(\rho_A, \rho_B)); \quad (20)$$

$$A + B = (\mu_A + \mu_B - \mu_A \mu_B, v_A v_B, \epsilon_A + \epsilon_B - \epsilon_A \epsilon_B, n_A + n_B - n_A n_B, \rho_A \rho_B); \quad (21)$$

$$A \times B = (\mu_A \mu_B, v_A + v_B - v_A v_B, \epsilon_A \epsilon_B, n_A n_B, \rho_A + \rho_B - \rho_A \rho_B). \quad (22)$$

These definitions are integrated with four different scenarios: negative, positive, unstable and natural. Negative case is scenario 1 and penalizes uncertainty and non-MS. Accordingly, parameter set as sharp non-MS transition ($\alpha:10$), high uncertainty penalty ($\alpha:10$), linear engagement ($\delta:10$), and baseline resistance ($\varphi:1$). Thus, the negative scenario of multi-facet fuzzy sets is defined in Eq. (23):

$$A_{negative} = \left\{ \left(x, \mu(x), \frac{1}{1 + e^{10(\mu-0.5)}}, -5[\mu \ln \mu + (1-\mu) \ln(1-\mu)], \mu^1, 1 - (1-\mu)^1 \right) \middle| x \in X \right\}. \quad (23)$$

Scenario 2 is called positive case and aims to provide high MS with reward engagement. So, parameters should be defined as gradual non-MS ($\alpha:1$), natural uncertainty ($\alpha:1$), nonlinear engagement boost ($\delta:5$), and baseline resistance ($\varphi:1$). The multi-facet fuzzy sets for positive scenario are determined in Eq. (24):

$$A_{positive} = \left\{ \left(x, \mu(x), \frac{1}{1 + e^{1(\mu-0.5)}}, -1[\mu \ln \mu + (1-\mu) \ln(1-\mu)], \mu^5, 1 - (1-\mu)^1 \right) \middle| x \in X \right\}. \quad (24)$$

The other scenario is unstable case with prioritized resistance and penalized low MS. Accordingly, the parameters of multi-facet fuzzy sets are assigned as gradual non-MS ($\alpha:1$), moderate uncertainty penalty ($\alpha:2$), linear engagement ($\delta:1$), and high resistance scaling ($\varphi:10$). The unstable case is illustrated in Eq. (25):

$$A_{unstable} = \left\{ \left(x, \mu(x), \frac{1}{1 + e^{1(\mu-0.5)}}, -2[\mu \ln \mu + (1-\mu) \ln(1-\mu)], \mu^1, 1 - (1-\mu)^{10} \right) \middle| x \in X \right\}. \quad (25)$$

Scenario 4 proposes natural case with neutral and balanced behaviour of the expert. According to this scenario, there are no environmental effects neither positive nor negative for providing the evaluations about the attributes from the expert. The limitations of the parameters are shown as smooth non-MS ($\alpha:1$), no uncertainty bias ($\alpha:1$), linear engagement ($\delta:1$), and baseline resistance ($\varphi:1$). The natural scenario is represented with Eq. (26):

$$A_{natural} = \left\{ \left(x, \mu(x), \frac{1}{1 + e^{1(\mu-0.5)}}, -1[\mu \ln \mu + (1-\mu) \ln(1-\mu)], \mu^1, 1 - (1-\mu)^1 \right) \middle| x \in X \right\}. \quad (26)$$

3.2. Dynamic multi-facet fuzzy Bayesian networks

This model, which calculates the weights of the criteria by evaluating the interdependencies between criteria, benefits from data science such as entropy, information gain, and conditional probability. Thus, the aim is to obtain more objective, accurate and realistic results. The steps of dynamic multi-facet fuzzy Bayesian networks-based weighting are shared below (Hu et al., 2025).

Firstly, evaluations about dependencies between the criteria are collected for creating the relation matrix. The evaluations are transformed into dynamic multi-facet fuzzy numbers and the dynamic multi-facet fuzzy relation matrix is shown in Eq. (27):

$$H_k = \begin{bmatrix} 0 & h_{12} & \cdots & \cdots & h_{1n} \\ h_{21} & 0 & \cdots & \cdots & h_{2n} \\ \vdots & \vdots & \ddots & \cdots & \vdots \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ h_{n1} & h_{n2} & \cdots & \cdots & 0 \end{bmatrix}. \quad (27)$$

wherein $H = [h_{ij}]_{n \times n}$ is the relationship degrees of criteria on the other criteria and $h_{ij} = (h_{\mu_{ij}}, h_{\nu_{ij}}, h_{\epsilon_{ij}}, h_{n_{ij}}, h_{p_{ij}})$ is about the influence degree of i^{th} criterion over j^{th} criterion. The k is the number of scenarios. Next, the aggregated values of k^{th} scenario are calculated using Eq. (28):

$$h = \left(x, \frac{1}{k} \sum_{i=1}^k h_{\mu_i}(x), \frac{1}{k} \sum_{i=1}^k h_{\nu_i}(x), \frac{1}{k} \sum_{i=1}^k h_{\epsilon_i}(x), \frac{1}{k} \sum_{i=1}^k h_{n_i}(x), \frac{1}{k} \sum_{i=1}^k h_{p_i}(x) \right). \quad (28)$$

Afterwards, the crisped values are obtained with the help of Eq. (29):

$$n_{ij} = \sum_{n=1}^5 w_1 \mu_{h_{ij}} + w_2 (1 - \nu_{h_{ij}}) + w_3 (1 - \epsilon_{h_{ij}}) + w_4 n_{h_{ij}} + w_5 p_{h_{ij}}, \quad (29)$$

wherein $w_1 = \frac{\beta}{S}$, $w_2 = \frac{\alpha}{S}$, $w_3 = \frac{a}{S}$, $w_4 = \frac{\delta}{S}$, $w_5 = \frac{\varphi}{S}$, the default value of β is 1 and $S = \beta + \alpha + a + \delta + \varphi$. Then, using the crisped values, the relation matrix shown in Eq. (30) is created:

$$D = \begin{bmatrix} 0 & n_{12} & \cdots & \cdots & n_{1n} \\ n_{21} & 0 & \cdots & \cdots & n_{2n} \\ \vdots & \vdots & \ddots & \cdots & \vdots \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ n_{n1} & n_{n2} & \cdots & \cdots & 0 \end{bmatrix}. \quad (30)$$

After creating the relation matrix, the entropies are computed using Eqs. (31) and (32):

$$E(C_i) = -\sum PR(C_i) \cdot \ln(PR(C_i)); \quad (31)$$

$$E(C_i | C_j) = -\sum PR(C_j) \cdot PR(C_i | C_j) \cdot \ln(PR(C_i | C_j)). \quad (32)$$

Finally, the weights are defined by Eq. (33):

$$w_i = \frac{E(C_i) - E(C_i | C_j)}{\sum_{i=1}^n (E(C_i) - E(C_i | C_j))}. \quad (33)$$

3.3. Dynamic multi-facet fuzzy MOORA

MOORA is a decision-making model developed for the evaluation of complex alternatives (Brauers & Zavadskas, 2006). The computation steps of the extended MOORA are detailed below (Wang & Li, 2025).

At the beginning, evaluations are collected and the decision matrix given in Eq. (34) is constructed (Chakraborty et al., 2023):

$$X_k = \begin{bmatrix} X_{11} & X_{12} & \cdots & \cdots & X_{1n} \\ X_{21} & X_{22} & \cdots & \cdots & X_{2n} \\ \vdots & \vdots & \ddots & \cdots & \vdots \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ X_{m1} & X_{m2} & \cdots & \cdots & X_{mn} \end{bmatrix}, \quad (34)$$

wherein X_{ij} presents the i^{th} alternative with respect to j^{th} criterion based on the Dynamic Multi-Facet fuzzy sets-based evaluations by k^{th} scenario. Later, the aggregated numbers are estimated using Equation (28) and the crisped numbers are computed with Eq. (29). Next, the normalized numbers are calculated by Eq. (35):

$$r_{ij} = \frac{n_{ij}}{\sqrt{\sum_{i=1}^m n_{ij}^2}}. \quad (35)$$

Afterwards, the positive and negative effects are performed using Eq. (36):

$$y_i = \sum_{j=1}^h r_{ij}^* - \sum_{j=h+1}^n r_{ij}^*. \quad (36)$$

Finally, the weighted ranking values are identified as Eq. (37):

$$y_i^* = \sum_{j=1}^h w_j r_{ij}^* - \sum_{j=h+1}^n w_j r_{ij}^*, \quad (37)$$

wherein h is the number of benefit criteria.

4. Analysis

The results of analysis for determining the most suitable policy alternative to increase lifecycle environmental efficiency in renewable energy infrastructure are presented with tables and figures in this section. Firstly, the assessment criteria for lifecycle environmental impact of renewable energy infrastructure are identified as ecosystem disruption (ED), habitat conversion (HC), water footprint (WF), recoverable material use (RMU), and ecological footprint efficiency (EFE). Similarly, policy alternatives to increase lifecycle environmental efficiency in renewable energy infrastructure are defined as building in low-sensitivity zones (BLD), investing in efficient technologies (ITECH), manufacturing with high-recovery designs (MNFD), partnership with high-footprint innovators (PRTN), and focusing on the multi-use infrastructure of renewable sources (FCS). After that, one expert evaluates the criteria and alternatives. The expert is an expert in the field of renewable energy and project management with 15-years' experience. The evaluations of the expert are shared in Table 1.

Table 1. Evaluations

	ED	HC	WF	RMU	EFE
ED		L	MH	H	EH
HC	EH		N	N	ML
WF	EL	H		L	ML
RMU	N	N	VH		EH
EFE	VH	VL	N	ML	
	ED	HC	WF	RMU	EFE
BLD	N	MH	VH	N	VH
ITECH	H	EH	EH	H	MH
MNFD	VH	H	H	H	H
PRTN	MH	MH	N	EH	N
FCS	VH	MH	H	EH	ML

4.1. Constructing the dynamic multi-facet fuzzy numbers by the scenarios

The linguistic evaluations to be used for the analysis, fuzzy MS and fuzzy numbers according to the scenario are summarized in Table 2. The scales are created using Eqs. (1)–(26).

Table 2. Scales

Scales	Linguistic Evaluations	Fuzzy MS	Dynamic Multi-Facet Fuzzy Numbers			
			Negative	Positive	Unstable	Natural
1	Extremely Low (EL)	0.1	(0.10, 0.98, 1.00, 0.10, 0.10)	(0.10, 0.60, 0.14, 0.00, 0.10)	(0.10, 0.60, 0.37, 0.10, 0.65)	(0.10, 0.60, 0.14, 0.10, 0.10)
2	Very Low (VL)	0.2	(0.20, 0.95, 1.00, 0.20, 0.20)	(0.20, 0.57, 0.14, 0.00, 0.20)	(0.20, 0.57, 0.47, 0.20, 0.89)	(0.20, 0.57, 0.14, 0.20, 0.20)
3	Low (L)	0.3	(0.30, 0.88, 1.00, 0.30, 0.30)	(0.30, 0.55, 0.11, 0.00, 0.30)	(0.30, 0.55, 0.47, 0.30, 0.97)	(0.30, 0.55, 0.11, 0.30, 0.30)
4	Moderately Low (ML)	0.4	(0.40, 0.73, 1.00, 0.40, 0.40)	(0.40, 0.52, 0.06, 0.01, 0.40)	(0.40, 0.52, 0.43, 0.40, 0.99)	(0.40, 0.52, 0.06, 0.40, 0.40)
5	Neutral (N)	0.5	(0.50, 0.50, 1.00, 0.50, 0.50)	(0.50, 0.50, 0.00, 0.03, 0.50)	(0.50, 0.50, 0.35, 0.50, 1.00)	(0.50, 0.50, 0.00, 0.50, 0.50)
6	Moderately High (MH)	0.6	(0.60, 0.27, 1.00, 0.60, 0.60)	(0.60, 0.48, 0.00, 0.08, 0.60)	(0.60, 0.48, 0.25, 0.60, 1.00)	(0.60, 0.48, 0.00, 0.60, 0.60)
7	High (H)	0.7	(0.70, 0.12, 0.89, 0.70, 0.70)	(0.70, 0.45, 0.00, 0.17, 0.70)	(0.70, 0.45, 0.14, 0.70, 1.00)	(0.70, 0.45, 0.00, 0.70, 0.70)
8	Very High (VH)	0.8	(0.80, 0.05, 0.57, 0.80, 0.80)	(0.80, 0.43, 0.00, 0.33, 0.80)	(0.80, 0.43, 0.04, 0.80, 1.00)	(0.80, 0.43, 0.00, 0.80, 0.80)
9	Extremely High (EH)	0.9	(0.90, 0.02, 0.24, 0.90, 0.90)	(0.90, 0.40, 0.00, 0.59, 0.90)	(0.90, 0.40, 0.00, 0.90, 1.00)	(0.90, 0.40, 0.00, 0.90, 0.90)

The evaluations of this expert are transformed into to fuzzy numbers regarding to values in Table 2. The dynamic multi-facet fuzzy evaluations are displayed in Table 3.

Table 3. The dynamic multi-facet fuzzy evaluations by scenarios

NEGATIVE	ED	HC	WF	RMU	EFE
ED		(0.30, 0.88, 1.00, 0.30, 0.30)	(0.60, 0.27, 1.00, 0.60, 0.60)	(0.70, 0.12, 0.89, 0.70, 0.70)	(0.90, 0.02, 0.24, 0.90, 0.90)
HC	(0.90, 0.02, 0.24, 0.90, 0.90)		(0.50, 0.50, 1.00, 0.50, 0.50)	(0.50, 0.50, 1.00, 0.50, 0.50)	(0.40, 0.73, 1.00, 0.40, 0.40)
WF	(0.10, 0.98, 1.00, 0.10, 0.10)	(0.70, 0.12, 0.89, 0.70, 0.70)		(0.30, 0.88, 1.00, 0.30, 0.30)	(0.40, 0.73, 1.00, 0.40, 0.40)
RMU	(0.50, 0.50, 1.00, 0.50, 0.50)	(0.50, 0.50, 1.00, 0.50, 0.50)	(0.80, 0.05, 0.57, 0.80, 0.80)		(0.90, 0.02, 0.24, 0.90, 0.90)
EFE	(0.80, 0.05, 0.57, 0.80, 0.80)	(0.20, 0.95, 1.00, 0.20, 0.20)	(0.50, 0.50, 1.00, 0.50, 0.50)	(0.40, 0.73, 1.00, 0.40, 0.40)	
POSITIVE	ED	HC	WF	RMU	EFE
ED		(0.30, 0.55, 0.11, 0.00, 0.30)	(0.60, 0.48, 0.00, 0.08, 0.60)	(0.70, 0.45, 0.00, 0.17, 0.70)	(0.90, 0.40, 0.00, 0.59, 0.90)
HC	(0.90, 0.40, 0.00, 0.59, 0.90)		(0.50, 0.50, 0.00, 0.03, 0.50)	(0.50, 0.50, 0.00, 0.03, 0.50)	(0.40, 0.52, 0.06, 0.01, 0.40)
WF	(0.10, 0.60, 0.14, 0.00, 0.10)	(0.70, 0.45, 0.00, 0.17, 0.70)		(0.30, 0.55, 0.11, 0.00, 0.30)	(0.40, 0.52, 0.06, 0.01, 0.40)
RMU	(0.50, 0.50, 0.00, 0.03, 0.50)	(0.50, 0.50, 0.00, 0.03, 0.50)	(0.80, 0.43, 0.00, 0.33, 0.80)		(0.90, 0.40, 0.00, 0.59, 0.90)
EFE	(0.80, 0.43, 0.00, 0.33, 0.80)	(0.20, 0.57, 0.14, 0.00, 0.20)	(0.50, 0.50, 0.00, 0.03, 0.50)	(0.40, 0.52, 0.06, 0.01, 0.40)	
UNSTABLE	ED	HC	WF	RMU	EFE
ED		(0.30, 0.55, 0.47, 0.30, 0.97)	(0.60, 0.48, 0.25, 0.60, 1.00)	(0.70, 0.45, 0.14, 0.70, 1.00)	(0.90, 0.40, 0.00, 0.90, 1.00)
HC	(0.90, 0.40, 0.00, 0.90, 1.00)		(0.50, 0.50, 0.35, 0.50, 1.00)	(0.50, 0.50, 0.35, 0.50, 1.00)	(0.40, 0.52, 0.43, 0.40, 0.99)
WF	(0.10, 0.60, 0.37, 0.10, 0.65)	(0.70, 0.45, 0.14, 0.70, 1.00)		(0.30, 0.55, 0.47, 0.30, 0.97)	(0.40, 0.52, 0.43, 0.40, 0.99)
RMU	(0.50, 0.50, 0.35, 0.50, 1.00)	(0.50, 0.50, 0.35, 0.50, 1.00)	(0.80, 0.43, 0.04, 0.80, 1.00)		(0.90, 0.40, 0.00, 0.90, 1.00)
EFE	(0.80, 0.43, 0.04, 0.80, 1.00)	(0.20, 0.57, 0.47, 0.20, 0.89)	(0.50, 0.50, 0.35, 0.50, 1.00)	(0.40, 0.52, 0.43, 0.40, 0.99)	
NATURAL	ED	HC	WF	RMU	EFE
ED		(0.30, 0.55, 0.11, 0.30, 0.30)	(0.60, 0.48, 0.00, 0.60, 0.60)	(0.70, 0.45, 0.00, 0.70, 0.70)	(0.90, 0.40, 0.00, 0.90, 0.90)
HC	(0.90, 0.40, 0.00, 0.90, 0.90)		(0.50, 0.50, 0.00, 0.50, 0.50)	(0.50, 0.50, 0.00, 0.50, 0.50)	(0.40, 0.52, 0.06, 0.40, 0.40)
WF	(0.10, 0.60, 0.14, 0.10, 0.10)	(0.70, 0.45, 0.00, 0.70, 0.70)		(0.30, 0.55, 0.11, 0.30, 0.30)	(0.40, 0.52, 0.06, 0.40, 0.40)
RMU	(0.50, 0.50, 0.00, 0.50, 0.50)	(0.50, 0.50, 0.00, 0.50, 0.50)	(0.80, 0.43, 0.00, 0.80, 0.80)		(0.90, 0.40, 0.00, 0.90, 0.90)
EFE	(0.80, 0.43, 0.00, 0.80, 0.80)	(0.20, 0.57, 0.14, 0.20, 0.20)	(0.50, 0.50, 0.00, 0.50, 0.50)	(0.40, 0.52, 0.06, 0.40, 0.40)	

End of Table 3

NEGATIVE	ED	HC	WF	RMU	EFE
BLD	(0.50, 0.50, 1.00, 0.50, 0.50)	(0.60, 0.27, 1.00, 0.60, 0.60)	(0.80, 0.05, 0.57, 0.80, 0.80)	(0.50, 0.50, 1.00, 0.50, 0.50)	(0.80, 0.05, 0.57, 0.80, 0.80)
ITECH	(0.70, 0.12, 0.89, 0.70, 0.70)	(0.90, 0.02, 0.24, 0.90, 0.90)	(0.90, 0.02, 0.24, 0.90, 0.90)	(0.70, 0.12, 0.89, 0.70, 0.70)	(0.60, 0.27, 1.00, 0.60, 0.60)
MNFD	(0.80, 0.05, 0.57, 0.80, 0.80)	(0.70, 0.12, 0.89, 0.70, 0.70)	(0.70, 0.12, 0.89, 0.70, 0.70)	(0.70, 0.12, 0.89, 0.70, 0.70)	(0.70, 0.12, 0.89, 0.70, 0.70)
PRTN	(0.60, 0.27, 1.00, 0.60, 0.60)	(0.60, 0.27, 1.00, 0.60, 0.60)	(0.50, 0.50, 1.00, 0.50, 0.50)	(0.90, 0.02, 0.24, 0.90, 0.90)	(0.50, 0.50, 1.00, 0.50, 0.50)
FCS	(0.80, 0.05, 0.57, 0.80, 0.80)	(0.60, 0.27, 1.00, 0.60, 0.60)	(0.70, 0.12, 0.89, 0.70, 0.70)	(0.90, 0.02, 0.24, 0.90, 0.90)	(0.40, 0.73, 1.00, 0.40, 0.40)
POSITIVE	ED	HC	WF	RMU	EFE
BLD	(0.50, 0.50, 0.00, 0.03, 0.50)	(0.60, 0.48, 0.00, 0.08, 0.60)	(0.80, 0.43, 0.00, 0.33, 0.80)	(0.50, 0.50, 0.00, 0.03, 0.50)	(0.80, 0.43, 0.00, 0.33, 0.80)
ITECH	(0.70, 0.45, 0.00, 0.17, 0.70)	(0.90, 0.40, 0.00, 0.59, 0.90)	(0.90, 0.40, 0.00, 0.59, 0.90)	(0.70, 0.45, 0.00, 0.17, 0.70)	(0.60, 0.48, 0.00, 0.08, 0.60)
MNFD	(0.80, 0.43, 0.00, 0.33, 0.80)	(0.70, 0.45, 0.00, 0.17, 0.70)	(0.70, 0.45, 0.00, 0.17, 0.70)	(0.70, 0.45, 0.00, 0.17, 0.70)	(0.70, 0.45, 0.00, 0.17, 0.70)
PRTN	(0.60, 0.48, 0.00, 0.08, 0.60)	(0.60, 0.48, 0.00, 0.08, 0.60)	(0.50, 0.50, 0.00, 0.03, 0.50)	(0.90, 0.40, 0.00, 0.59, 0.90)	(0.50, 0.50, 0.00, 0.03, 0.50)
FCS	(0.80, 0.43, 0.00, 0.33, 0.80)	(0.60, 0.48, 0.00, 0.08, 0.60)	(0.70, 0.45, 0.00, 0.17, 0.70)	(0.90, 0.40, 0.00, 0.59, 0.90)	(0.40, 0.52, 0.06, 0.01, 0.40)
UNSTABLE	ED	HC	WF	RMU	EFE
BLD	(0.50, 0.50, 0.35, 0.50, 1.00)	(0.60, 0.48, 0.25, 0.60, 1.00)	(0.80, 0.43, 0.04, 0.80, 1.00)	(0.50, 0.50, 0.35, 0.50, 1.00)	(0.80, 0.43, 0.04, 0.80, 1.00)
ITECH	(0.70, 0.45, 0.14, 0.70, 1.00)	(0.90, 0.40, 0.00, 0.90, 1.00)	(0.90, 0.40, 0.00, 0.90, 1.00)	(0.70, 0.45, 0.14, 0.70, 1.00)	(0.60, 0.48, 0.25, 0.60, 1.00)
MNFD	(0.80, 0.43, 0.04, 0.80, 1.00)	(0.70, 0.45, 0.14, 0.70, 1.00)	(0.70, 0.45, 0.14, 0.70, 1.00)	(0.70, 0.45, 0.14, 0.70, 1.00)	(0.70, 0.45, 0.14, 0.70, 1.00)
PRTN	(0.60, 0.48, 0.25, 0.60, 1.00)	(0.60, 0.48, 0.25, 0.60, 1.00)	(0.50, 0.50, 0.35, 0.50, 1.00)	(0.90, 0.40, 0.00, 0.90, 1.00)	(0.50, 0.50, 0.35, 0.50, 1.00)
FCS	(0.80, 0.43, 0.04, 0.80, 1.00)	(0.60, 0.48, 0.25, 0.60, 1.00)	(0.70, 0.45, 0.14, 0.70, 1.00)	(0.90, 0.40, 0.00, 0.90, 1.00)	(0.40, 0.52, 0.43, 0.40, 0.99)
NATURAL	ED	HC	WF	RMU	EFE
BLD	(0.50, 0.50, 0.00, 0.50, 0.50)	(0.60, 0.48, 0.00, 0.60, 0.60)	(0.80, 0.43, 0.00, 0.80, 0.80)	(0.50, 0.50, 0.00, 0.50, 0.50)	(0.80, 0.43, 0.00, 0.80, 0.80)
ITECH	(0.70, 0.45, 0.00, 0.70, 0.70)	(0.90, 0.40, 0.00, 0.90, 0.90)	(0.90, 0.40, 0.00, 0.90, 0.90)	(0.70, 0.45, 0.00, 0.70, 0.70)	(0.60, 0.48, 0.00, 0.60, 0.60)
MNFD	(0.80, 0.43, 0.00, 0.80, 0.80)	(0.70, 0.45, 0.00, 0.70, 0.70)	(0.70, 0.45, 0.00, 0.70, 0.70)	(0.70, 0.45, 0.00, 0.70, 0.70)	(0.70, 0.45, 0.00, 0.70, 0.70)
PRTN	(0.60, 0.48, 0.00, 0.60, 0.60)	(0.60, 0.48, 0.00, 0.60, 0.60)	(0.50, 0.50, 0.00, 0.50, 0.50)	(0.90, 0.40, 0.00, 0.90, 0.90)	(0.50, 0.50, 0.00, 0.50, 0.50)
FCS	(0.80, 0.43, 0.00, 0.80, 0.80)	(0.60, 0.48, 0.00, 0.60, 0.60)	(0.70, 0.45, 0.00, 0.70, 0.70)	(0.90, 0.40, 0.00, 0.90, 0.90)	(0.40, 0.52, 0.06, 0.40, 0.40)

4.2. Weighting the assessment criteria

Using Eqs. (27) and (28), the aggregated values are computed. The aggregated values are expressed in Table 4.

Table 4. Aggregated values

	ED	HC	WF	RMU	EFE
ED	(0.00, 0.00, 0.00, 0.00, 0.00)	(0.30, 0.63, 0.42, 0.23, 0.47)	(0.60, 0.42, 0.31, 0.47, 0.70)	(0.70, 0.37, 0.26, 0.57, 0.77)	(0.90, 0.31, 0.06, 0.82, 0.92)
HC	(0.90, 0.31, 0.06, 0.82, 0.92)	(0.00, 0.00, 0.00, 0.00, 0.00)	(0.50, 0.50, 0.34, 0.38, 0.62)	(0.50, 0.50, 0.34, 0.38, 0.62)	(0.40, 0.58, 0.39, 0.30, 0.55)
WF	(0.10, 0.69, 0.41, 0.08, 0.24)	(0.70, 0.37, 0.26, 0.57, 0.77)	(0.00, 0.00, 0.00, 0.00, 0.00)	(0.30, 0.63, 0.42, 0.23, 0.47)	(0.40, 0.58, 0.39, 0.30, 0.55)
RMU	(0.50, 0.50, 0.34, 0.38, 0.62)	(0.50, 0.50, 0.34, 0.38, 0.62)	(0.80, 0.33, 0.15, 0.68, 0.85)	(0.00, 0.00, 0.00, 0.00, 0.00)	(0.90, 0.31, 0.06, 0.82, 0.92)
EFE	(0.80, 0.33, 0.15, 0.68, 0.85)	(0.20, 0.67, 0.44, 0.15, 0.37)	(0.50, 0.50, 0.34, 0.38, 0.62)	(0.40, 0.58, 0.39, 0.30, 0.55)	(0.00, 0.00, 0.00, 0.00, 0.00)

Afterwards, the crisped values of relation matrix by the scenarios are obtained with the help of Eqs. (29) and (30) and shown in Table 5.

Table 5. Crisped values according to various scenarios

NEGATIVE	ED	HC	WF	RMU	EFE
ED	0.000	0.116	0.506	0.637	0.906
HC	0.906	0.000	0.361	0.361	0.216
WF	0.027	0.637	0.000	0.116	0.216
RMU	0.361	0.361	0.782	0.000	0.906
EFE	0.782	0.060	0.361	0.216	0.000
POSITIVE	ED	HC	WF	RMU	EFE
ED	0.000	0.217	0.346	0.421	0.706
HC	0.706	0.000	0.295	0.295	0.252
WF	0.163	0.421	0.000	0.217	0.252
RMU	0.295	0.295	0.535	0.000	0.706
EFE	0.535	0.187	0.295	0.252	0.000
UNSTABLE	ED	HC	WF	RMU	EFE
ED	0.000	0.788	0.882	0.912	0.960
HC	0.960	0.000	0.853	0.853	0.824
WF	0.559	0.912	0.000	0.788	0.824
RMU	0.853	0.853	0.940	0.000	0.960
EFE	0.940	0.721	0.853	0.824	0.000
NATURAL	ED	HC	WF	RMU	EFE
ED	0.000	0.448	0.665	0.730	0.860
HC	0.860	0.000	0.600	0.600	0.523
WF	0.313	0.730	0.000	0.448	0.523
RMU	0.600	0.600	0.795	0.000	0.860
EFE	0.795	0.376	0.600	0.523	0.000

After creating the relation matrix, the entropies are computed using Eqs. (31) and (32). The entropies and conditional entropies are given in Table 6.

Table 6. Entropies and conditional entropies

NEGATIVE	$E(C_i)$	$E(C_i C_j)$
ED	1.609	.972
HC		1.156
WF		.965
RMU		1.018
EFE		1.060
POSITIVE	$E(C_i)$	$E(C_i C_j)$
ED	1.609	1.309
HC		1.314
WF		1.338
RMU		1.301
EFE		1.356
UNSTABLE	$E(C_i)$	$E(C_i C_j)$
ED	1.609	.422
HC		.470
WF		.757
RMU		.368
EFE		.588
NATURAL	$E(C_i)$	$E(C_i C_j)$
ED	1.609	.991
HC		1.082
WF		1.292
RMU		.925
EFE		1.196
OVERALL	$E(C_i)$	$E(C_i C_j)$
ED	1.609	1.070
HC		1.165
WF		1.337
RMU		1.013
EFE		1.262

Finally, the weights are defined by Eq. (33). The weights of the assessment criteria for lifecycle environmental impact of renewable energy infrastructure are visualized in Figure 2.

The overall weight values are calculated by using the aggregated values of all scenarios. According to the four weight sets in Figure 2, the water footprint (WF) is the most effective assessment criterion in three out of four scenarios (negative, positive, and unstable) and is ranked second in the natural scenario. The overall aggregated weights also identify water footprint as the most important criterion. The consistency of this result across most scenarios and with the comparative validation supports the validity and robustness of the finding.

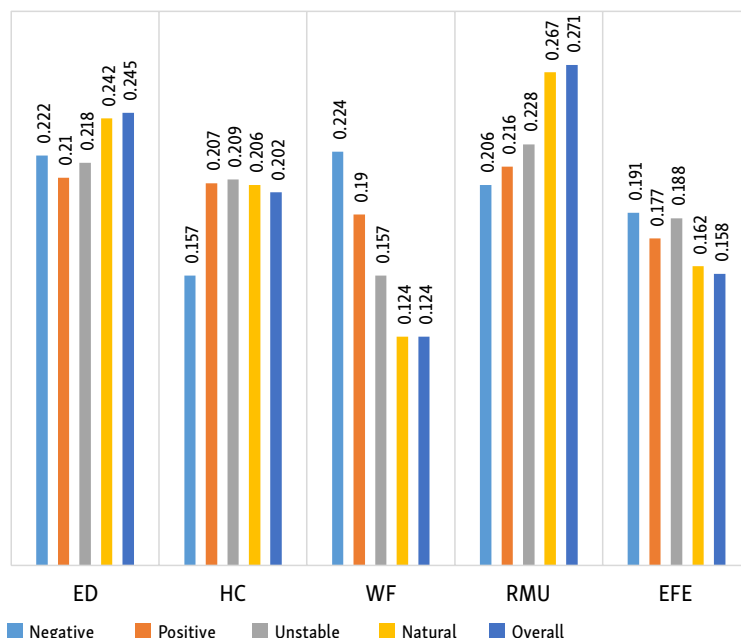


Figure 2. Weights according to various scenarios

4.3. Ranking of policy alternatives

At the beginning, the decision matrix given in Eq. (34) is constructed using Eq. (28). The decision matrix is illustrated in Table 7.

Table 7. Decision matrix

	ED	HC	WF	RMU	EFE
BLD	(0.50, 0.50, 0.34, 0.38, 0.62)	(0.60, 0.42, 0.31, 0.47, 0.70)	(0.80, 0.33, 0.15, 0.68, 0.85)	(0.50, 0.50, 0.34, 0.38, 0.62)	(0.80, 0.33, 0.15, 0.68, 0.85)
ITECH	(0.70, 0.37, 0.26, 0.57, 0.77)	(0.90, 0.31, 0.06, 0.82, 0.92)	(0.90, 0.31, 0.06, 0.82, 0.92)	(0.70, 0.37, 0.26, 0.57, 0.77)	(0.60, 0.42, 0.31, 0.47, 0.70)
MNFD	(0.80, 0.33, 0.15, 0.68, 0.85)	(0.70, 0.37, 0.26, 0.57, 0.77)	(0.70, 0.37, 0.26, 0.57, 0.77)	(0.70, 0.37, 0.26, 0.57, 0.77)	(0.70, 0.37, 0.26, 0.57, 0.77)
PRTN	(0.60, 0.42, 0.31, 0.47, 0.70)	(0.60, 0.42, 0.31, 0.47, 0.70)	(0.50, 0.50, 0.34, 0.38, 0.62)	(0.90, 0.31, 0.06, 0.82, 0.92)	(0.50, 0.50, 0.34, 0.38, 0.62)
FCS	(0.80, 0.33, 0.15, 0.68, 0.85)	(0.60, 0.42, 0.31, 0.47, 0.70)	(0.70, 0.37, 0.26, 0.57, 0.77)	(0.90, 0.31, 0.06, 0.82, 0.92)	(0.40, 0.58, 0.39, 0.30, 0.55)

Afterwards, the crisped numbers of decision matrix regarding various scenarios are estimated with the help of Eqs. (29) and (30) and shown in Table 8.

Table 8. Crisped numbers regarding various scenarios

NEGATIVE	ED	HC	WF	RMU	EFE
BLD	0.361	0.506	0.782	0.361	0.782
ITECH	0.637	0.906	0.906	0.637	0.506
MNFD	0.782	0.637	0.637	0.637	0.637
PRTN	0.506	0.506	0.361	0.906	0.361
FCS	0.782	0.506	0.637	0.906	0.216
POSITIVE	ED	HC	WF	RMU	EFE
BLD	0.295	0.346	0.535	0.295	0.535
ITECH	0.421	0.706	0.706	0.421	0.346
MNFD	0.535	0.421	0.421	0.421	0.421
PRTN	0.346	0.346	0.295	0.706	0.295
FCS	0.535	0.346	0.421	0.706	0.252
UNSTABLE	ED	HC	WF	RMU	EFE
BLD	0.853	0.882	0.940	0.853	0.940
ITECH	0.912	0.960	0.960	0.912	0.882
MNFD	0.940	0.912	0.912	0.912	0.912
PRTN	0.882	0.882	0.853	0.960	0.853
FCS	0.940	0.882	0.912	0.960	0.824
NATURAL	ED	HC	WF	RMU	EFE
BLD	0.600	0.665	0.795	0.600	0.795
ITECH	0.730	0.860	0.860	0.730	0.665
MNFD	0.795	0.730	0.730	0.730	0.730
PRTN	0.665	0.665	0.600	0.860	0.600
FCS	0.795	0.665	0.730	0.860	0.523

Afterwards, the normalized numbers are calculated by using Eq. (35). The normalized numbers are shared in Table 9.

To assess the robustness of the ranking obtained with the proposed Bayesian-network-based weighting method, a comparative analysis was performed using equal weights for all five criteria. The same normalized decision matrix (Table 9) was used, and the overall scores for the policy alternatives were recomputed with equal weights. The resulting ranking was compared with the original ranking using Spearman's rank correlation coefficient. The equal-weights ranking placed PRTN first, ITECH second, BLD third, MNFD fourth, and FCS fifth, identical to the original ranking. The Spearman correlation coefficient is 1.00 ($p < 0.01$) for the ranking order and 0.90 ($p < 0.05$) for the overall scores, indicating a very high degree of consistency. This demonstrates that the prioritization of policy alternatives is not an artifact of the novel weighting procedure and remains stable even under a simpler, widely accepted weighting scheme. The criteria weighting and alternative ranking results are summarized in Table 11.

Table 9. Normalized numbers

NEGATIVE	ED	HC	WF	RMU	EFE
BLD	0.254	0.358	0.507	0.225	0.649
ITECH	0.449	0.641	0.588	0.397	0.420
MNFD	0.551	0.451	0.414	0.397	0.529
PRTN	0.357	0.358	0.234	0.563	0.300
FCS	0.551	0.358	0.414	0.563	0.179
POSITIVE	ED	HC	WF	RMU	EFE
BLD	0.302	0.340	0.483	0.246	0.624
ITECH	0.431	0.694	0.637	0.351	0.404
MNFD	0.547	0.414	0.380	0.351	0.492
PRTN	0.354	0.340	0.267	0.589	0.345
FCS	0.547	0.340	0.380	0.589	0.294
UNSTABLE	ED	HC	WF	RMU	EFE
BLD	0.421	0.436	0.459	0.415	0.476
ITECH	0.450	0.475	0.469	0.443	0.447
MNFD	0.464	0.451	0.445	0.443	0.462
PRTN	0.435	0.436	0.417	0.467	0.432
FCS	0.464	0.436	0.445	0.467	0.417
NATURAL	ED	HC	WF	RMU	EFE
BLD	0.372	0.413	0.475	0.352	0.531
ITECH	0.453	0.533	0.514	0.428	0.444
MNFD	0.493	0.453	0.436	0.428	0.488
PRTN	0.413	0.413	0.359	0.505	0.401
FCS	0.493	0.413	0.436	0.505	0.349

Afterwards, the positive and negative effects are performed using Eq. (36). Finally, the weighted ranking values are identified as Eq. (37). The benefit, cost and weighted score values are summarized in Table 10.

Table 10. Benefit, cost and weighted scores

NEGATIVE	Benefit Values	Cost Values	Weighted Scores
BLD	0.227	0.170	0.057
ITECH	0.263	0.231	0.032
MNFD	0.254	0.215	0.039
PRTN	0.230	0.132	0.098
FCS	0.207	0.215	0.008
POSITIVE	Benefit Values	Cost Values	Weighted Scores
BLD	0.224	0.175	0.048
ITECH	0.259	0.238	0.020
MNFD	0.231	0.206	0.025
PRTN	0.240	0.138	0.102
FCS	0.231	0.206	0.024

End of Table 10

UNSTABLE	Benefit Values	Cost Values	Weighted Scores
BLD	0.245	0.196	0.049
ITECH	0.251	0.205	0.047
MNFD	0.250	0.203	0.048
PRTN	0.247	0.190	0.057
FCS	0.244	0.203	0.042
NATURAL	Benefit Values	Cost Values	Weighted Scores
BLD	0.239	0.189	0.050
ITECH	0.257	0.216	0.041
MNFD	0.253	0.207	0.045
PRTN	0.245	0.172	0.073
FCS	0.235	0.207	0.028
OVERALL	Benefit Values	Cost Values	Weighted Scores
BLD	0.257	0.146	0.111
ITECH	0.296	0.177	0.119
MNFD	0.282	0.177	0.105
PRTN	0.283	0.140	0.143
FCS	0.275	0.177	0.098

Table 11. Summary of criteria weights and alternative rankings

Criteria	Overall Weight	Rank
RMU	0.271	1
ED	0.245	2
HC	0.202	3
EFE	0.158	4
WF	0.124	5
Alternatives	Overall Score	Rank
PRTN	0.143	1
ITECH	0.119	2
BLD	0.111	3
MNFD	0.105	4
FCS	0.098	5

Using weighted scores, Figure 3 is created to show the ranking of policy alternatives to increase lifecycle environmental efficiency in renewable energy infrastructure.

As can be seen from Figure 3, the ranking of the policy alternatives is similar across all scenarios and in the overall situation. The most suitable policy alternative is partnership with high-footprint innovators (PRTN), which ranks first in all four scenarios and in the overall aggregation. The stability of this result across different parameter settings and the strong correlation with the equal-weights benchmark confirm that the ranking is robust and not dependent on the specific weighting method or scenario assumptions.

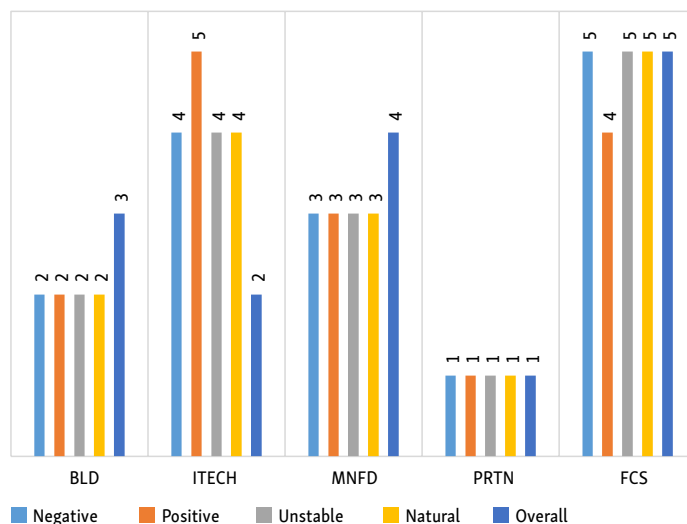


Figure 3. Ranking of policy alternatives regarding all scenarios

The results provide several important insights regarding lifecycle environmental efficiency in renewable energy infrastructure. First, the consistent identification of water footprint as the most critical criterion across all scenarios indicates that water resource management plays a central role in determining overall environmental performance. This finding suggests that renewable energy investments, while reducing carbon emissions, may still impose significant pressure on water resources, particularly in water-scarce regions. Second, the stability of the ranking results across different scenarios demonstrates the robustness of the proposed model. Despite variations in scenario assumptions, the prioritization of criteria and alternatives remains largely unchanged, indicating that the model produces reliable and consistent outcomes. Third, the identification of partnership with high-footprint innovators as the most effective policy alternative highlights the importance of collaborative approaches in improving environmental efficiency. This suggests that engaging with technologically advanced partners may accelerate the adoption of sustainable practices and enhance lifecycle performance. These findings contribute to the existing literature by providing a more integrated perspective on lifecycle environmental efficiency and by offering practical implications for policymakers and investors. Specifically, the results emphasize the need to consider not only carbon emissions but also resource-related impacts such as water use when designing renewable energy strategies.

The identification of “partnership with high-footprint innovators” as the most effective policy alternative can be explained by its strong alignment with the most influential criteria identified in the analysis. This strategy enables the adoption of advanced technologies and innovative practices that directly contribute to improving resource efficiency, especially in terms of water footprint and ecological performance. High-footprint innovators are typically characterized by their capacity to develop and implement cutting-edge solutions aimed at reducing environmental impacts across multiple lifecycle stages. Therefore, collaboration with

such actors facilitates knowledge transfer, accelerates technological adaptation, and enhances the overall environmental efficiency of renewable energy infrastructures. This explains why this alternative consistently achieves the highest ranking across different scenarios.

5. Discussion

Water footprint is the most important criterion in improving the environmental performance of renewable energy infrastructure throughout its life cycle. Indeed, the overall water impact of energy component data use can be significantly reduced by switching to renewable energy. For example, among renewable energy, solar and wind photovoltaics have the lowest water footprint, while reservoir-based hydroelectricity has the highest water footprint (Farfan & Lohrmann, 2023). In short, water footprint is one of the critical metrics for assessing the sustainability of energy resources, and evaluating the environmental impact of energy systems is of vital importance in this context (Fardnia et al., 2025). Wang et al. (2024) uses a multi-region input-output model to analyze changes in water withdrawal in China's energy sectors and conducts a scenario analysis to investigate the potential impacts of energy transition on regional water use and regional water stress. In addition, the increased deployment of renewable energy infrastructure alleviates the outflow of water resources from arid regions rather than radically changing the situation. Olaitan et al. (2024) follows the interests of governments and organizations to include hydrogen in the energy mix, considers the water footprint of primary energy used in the production process, infrastructure and feedstock water requirements, and measures the water footprint of different hydrogen production routes.

Ecosystem disruption is expressed as another effective criterion in improving the environmental performance of renewable energy infrastructure throughout its life cycle. In other words, energy transformation can include decentralized energy production that allows communities to generate power through renewable resources. In addition, energy transformation helps reduce ecosystem degradation and habitat destruction associated with resource extraction for fossil fuels (Tiwari et al., 2024). Ecosystem degradation brings definitional clarity to ecosystem studies by focusing on the fact that it can affect not only the residents in the focus but also any ecosystem actor and the value-creating relationships of the actors (Cozzolino & Geiger, 2024). Al Mubarak et al. (2024) analyze and compare the impacts of the main energy sources currently operated or under development on society, including geothermal, biomass, fossil fuels, hydroelectric, solar, nuclear, ocean and wind energies. For this purpose, it is essential to consider how high energy demand affects labor, energy prices and the environment, and thus to evaluate the advantages and disadvantages of each energy source. On the other hand, Arshed et al. (2024) stated that while international organizations care about establishing a balance between developing renewable energy infrastructure and protecting biodiversity, this requires non-linear effects analysis. For this reason, the results-oriented recommendations of the study can help countries find balance in developing energy infrastructure and ensuring biodiversity.

The findings of this study provide several important theoretical and practical implications. From a theoretical perspective, this study extends the existing literature by offering an integrated and scenario-based evaluation framework for lifecycle environmental efficiency.

Unlike prior studies that tend to focus on single dimensions such as carbon emissions or ecological footprint, this study demonstrates that lifecycle environmental efficiency is a multi-dimensional construct shaped by interrelated factors. The identification of water footprint as the most critical criterion supports recent studies emphasizing the growing importance of resource-based constraints in sustainable energy systems. However, this study goes beyond previous research by systematically prioritizing these factors within a unified decision-making framework.

From a practical perspective, the results provide actionable insights for policymakers and investors. The prominence of water footprint highlights the need for more comprehensive environmental assessment frameworks that incorporate water resource management into renewable energy planning. In addition, the identification of partnership with high-footprint innovators as the most effective strategy suggests that collaboration and technology transfer play a crucial role in improving lifecycle environmental performance. This finding implies that policy mechanisms encouraging strategic partnerships and innovation diffusion may significantly enhance sustainability outcomes.

The consistency of the ranking across four distinct scenarios and the strong correlation with a conventional equal-weights approach demonstrate the robustness of the proposed model. This indicates that the identification of water footprint as the most critical criterion and partnership with high-footprint innovators as the most effective strategy are not sensitive to the specific parameterization of the fuzzy framework or the weighting method.

6. Conclusions

6.1. General conclusions

This study tries to define the most appropriate strategies to improve life cycle environmental efficiency in renewable energy infrastructures and to identify the most critical environmental impact factors in this process. To achieve this objective, a novel decision-making model integrating dynamic multi-facet fuzzy sets, Bayesian networks and MOORA techniques is created. It is concluded that the water footprint is the most effective assessment criterion for lifecycle environmental impact of renewable energy infrastructure. The most suitable policy alternative for all scenarios and overall situation is partnership with high-footprint innovators. This study contributes to the literature by generating an innovative decision support model to identify the most critical factors for increasing life cycle environmental efficiency in renewable energy infrastructures. Using multi-facet fuzzy sets helps to make dynamic redefinition of membership degrees for different scenarios. With the help of this situation, uncertainty can be managed more effectively.

6.2. Theoretical implications

This study offers several important theoretical implications for decision theory, fuzzy set theory, and sustainability science. From the perspective of fuzzy set theory, the proposed dynamic multi-facet fuzzy framework extends traditional models by incorporating additional behavioral dimensions such as engagement and resistance. Unlike classical extensions, which

primarily focus on uncertainty representation through membership and non-membership degrees, this approach introduces a more dynamic and behaviorally enriched structure that better captures the complexity of expert judgments. From a decision theory perspective, the integration of dynamic multi-facet fuzzy sets with Bayesian networks and the MOORA method provides a novel hybrid framework for multi-criteria decision-making under uncertainty. This integrated structure enhances the ability to model interdependencies among criteria while simultaneously addressing ambiguity and variability in expert evaluations. In terms of sustainability science, this study contributes by operationalizing the concept of lifecycle environmental efficiency within a multi-dimensional decision-making framework. Rather than focusing on single indicators, the proposed model enables the simultaneous evaluation and prioritization of multiple environmental factors, offering a more holistic perspective on sustainable energy planning.

6.3. Limitations and future research directions

The study is based on expert opinions in weighting the criteria and evaluating the strategies. This situation is considered as the most important limitation of the study. In future studies, an econometric analysis can be performed using variables with numerical data. The developed model may not be generalizable to certain types of renewable energy infrastructure. Each type of infrastructure may have different environmental impacts. In future studies, different renewable energy projects can be analyzed separately. This situation contributes to the development of strategic suggestions on a sectoral basis. Another limitation of this model is that it could not be developed with data specific to a specific region or country. This situation may limit the validity of the model in different geographies. As a future research direction, a specific group of countries can be evaluated in this context. Similarly, future studies can provide more dynamic and instant solution suggestions to decision makers by automatically updating this model with artificial intelligence algorithms.

This study directly addresses its main objective of identifying the most critical factors and effective strategies for improving lifecycle environmental efficiency in renewable energy infrastructure. In this context, the study makes an original contribution by proposing an integrated and scenario-based decision-making framework that combines dynamic multi-facet fuzzy sets, Bayesian networks, and the MOORA method. This hybrid approach enables a more comprehensive evaluation of uncertainty, interdependencies, and multi-criteria decision processes compared to traditional models. From a policy perspective, the findings suggest that decision-makers should prioritize resource-related constraints, particularly water footprint, when designing renewable energy strategies. In addition, policies that promote collaboration with technologically advanced and high-impact innovators can enhance lifecycle environmental performance. Governments and regulatory bodies may also benefit from incorporating lifecycle-based assessment frameworks into energy planning processes to ensure more sustainable and efficient resource allocation.

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Author contributions

Conceptualization HD, SY, EE; methodology HD, SE; software SY, SE, HD; validation JA, DM; formal analysis HD, SY, SE, EE; investigation JA, DM; resources HD, SY, EE, SE, JA, DM; data curation HD, SY, SE; writing—original draft preparation HD, SY, EE, SE; writing—review and editing JA, DM; visualization HD, SY, SE; supervision JA. All authors have read and agreed to this version of the manuscript.

Disclosure statement

The authors declare no competing interests.

References

- Al Mubarak, F., Rezaee, R., & Wood, D. A. (2024). Economic, societal, and environmental impacts of available energy sources: A review. *Eng*, 5(3), 1232–1265. <https://doi.org/10.3390/eng5030067>
- Amiri, M., Hashemi-Tabatabaei, M., Keshavarz-Ghorabae, M., Kaklauskas, A., Zavadskas, E. K., & Antucheviciene, J. (2022). A fuzzy extension of simplified best-worst method (F-SBWM) and its applications to decision-making problems. *Symmetry*, 15(1), Article 81. <https://doi.org/10.3390/sym15010081>
- Antohi, V. M., Fortea, C., Zlati, M. L., & Balsalobre-Lorente, D. (2026). Impact of energy transition, digital integration, and financial inclusion on European Union sustainable growth. *Technological and Economic Development of Economy*. <https://doi.org/10.3846/tede.2026.26379>
- Arshed, N., Anwar, A., Abbas, M., & Mughal, W. (2024). Natural habitat vs human in competition for breathing space: need for restructuring clean energy infrastructure. *Ecological Economics*, 220, Article 108177. <https://doi.org/10.1016/j.ecolecon.2024.108177>
- Brauers, W. K., & Zavadskas, E. K. (2006). The MOORA Method and its application to privatization in a transition economy, *Control and Cybernetics*, 35(2), 443–468.
- Chakraborty, S., Datta, H. N., Kalita, K., & Chakraborty, S. (2023). A narrative review of multi-objective optimization on the basis of ratio analysis (MOORA) method in decision making. *Opsearch*, 60(4), 1844–1887. <https://doi.org/10.1007/s12597-023-00676-7>
- Cozzolino, A., & Geiger, S. (2024). Ecosystem disruption and regulatory positioning: Entry strategies of digital health startup orchestrators and complementors. *Research Policy*, 53(2), Article 104913. <https://doi.org/10.1016/j.respol.2023.104913>
- Crístiu, D., d'Amore, F., & Bezzo, F. (2025). Optimal design of sustainable supply chains for critical raw materials recycling in renewable energy technologies. *Resources, Conservation and Recycling*, 218, Article 108250. <https://doi.org/10.1016/j.resconrec.2025.108250>
- Dembińska, I., Kauf, S., Tłuczak, A., Szopik-Decpzyńska, K., Marzantowicz, Ł., & Ioppolo, G. (2022). The impact of space development structure on the level of ecological footprint-Shift share analysis for European Union countries. *Science of The Total Environment*, 851, Article 157936. <https://doi.org/10.1016/j.scitotenv.2022.157936>
- Fardnia, K., Yousefi, H., & Abdoos, M. (2025). A bibliometric analysis of carbon and water footprints in renewable energy: The post-COVID-19 landscape. *Green Technologies and Sustainability*, 3(3), Article 100162. <https://doi.org/10.1016/j.grets.2024.100162>
- Farfan, J., & Lohrmann, A. (2023). Gone with the clouds: Estimating the electricity and water footprint of digital data services in Europe. *Energy Conversion and Management*, 290, Article 117225. <https://doi.org/10.1016/j.enconman.2023.117225>

- Firoiu, D., Ionescu, G. H., Băndoi, A., Tănasie, A. V., & Tudor, S. (2026). Determinants of sustainable economic development in the EU: the role of innovation and infrastructure resilience. *Technological and Economic Development of Economy*, 32(2), 597–630. <https://doi.org/10.3846/tede.2026.25897>
- Ganda, F. (2024). Investigating the relationship and impact of environmental governance, green goods, non-green goods and eco-innovation on material footprint and renewable energy in the BRICS group. *Sustainability*, 16(4), Article 1602. <https://doi.org/10.3390/su16041602>
- Gilad, D., Borgelt, J., May, R., Dorber, M., & Verones, F. (2024). Biodiversity impacts of Norway's renewable electricity grid. *Journal of Cleaner Production*, 469, Article 143096. <https://doi.org/10.1016/j.jclepro.2024.143096>
- Hu, F., Peng, J., Wang, W., Shen, L., & Jia, M. (2025). Comparing the impact of various exercise modalities on old adults with Alzheimer's disease: a Bayesian network meta-analysis. *Complementary Therapies in Clinical Practice*, 59, Article 101968. <https://doi.org/10.1016/j.ctcp.2025.101968>
- Idroes, G. M., Hardi, I., Rahman, M. H., Afjal, M., Noviandy, T. R., & Idroes, R. (2024). The dynamic impact of non-renewable and renewable energy on carbon dioxide emissions and ecological footprint in Indonesia. *Carbon Research*, 3(1), Article 35. <https://doi.org/10.1007/s44246-024-00117-0>
- Jovanovic, S., Zavadskas, E. K., Stevic, Z., Marinkovic, M., Alrasheedi, A. F., & Badi, I. (2023). An intelligent fuzzy MCDM model based on D and Z numbers for paver selection: IMF D-SWARA-Fuzzy ARAS-Z model. *Axioms*, 12(6), Article 573. <https://doi.org/10.3390/axioms12060573>
- Karmakar, R., Tripathi, V., Kumar, P., Singh, N., & Kumar, R. (2024). The interplay of fossil fuels and natural disasters. In N. Singh & S. A. Babu (Eds.), *Climate crisis and sustainable solutions: Strategies for adaptation, mitigation and sustainable development* (pp. 91–106). Springer Nature Singapore. https://doi.org/10.1007/978-981-97-7110-3_6
- Khan, S. U., Zhao, Q., Wisal, M., Shah, K. A., & Shah, S. S. (2025). A data-driven Bayesian belief network influence diagram approach for socio-environmental risk assessment and mitigation in major ecosystem-and landscape-modifier projects. *Sustainability*, 17(8), Article 3537. <https://doi.org/10.3390/su17083537>
- Kou, G., Zavadskas, E. K., Ayata, A., Yüksel, S., Dinçer, H., & Eti, S. (2025). Addressing hidden challenges in urban renewable energy integration via a hybrid-decision model. *Technological and Economic Development of Economy*, 31(6), 2023–2044. <https://doi.org/10.3846/tede.2025.23903>
- Liao, H., Yang, S., Zavadskas, E. K., & Škare, M. (2023). An overview of fuzzy multi-criteria decisionmaking methods in hospitality and tourism industries: bibliometrics, methodologies, applications and future directions. *Economic Research-Ekonomska Istraživanja*, 36(3), Article 2150871. <https://doi.org/10.1080/1331677X.2022.2150871>
- Lin, Y., Mahmood, M. A., Meng, W., & Ali, Q. (2024). Green economy transition in Asia Pacific: A holistic assessment of renewable energy production. *Journal of Cleaner Production*, 437, Article 140648. <https://doi.org/10.1016/j.jclepro.2024.140648>
- Liu, Z., Zhu, S., Senapati, T., Deveci, M., Pamucar, D., & Yager, R. R. (2025). New distance measures of complex Fermatean fuzzy sets with applications in decision making and clustering problems. *Information Sciences*, 686, Article 121310. <https://doi.org/10.1016/j.ins.2024.121310>
- Lu, C., Hua, X., Peng, Y., Tian, J., & Tian, G. (2024). Achieving ecological sustainability in OECD countries: The role of fiscal decentralization and green energy. *Journal of Cleaner Production*, 466, Article 142814. <https://doi.org/10.1016/j.jclepro.2024.142814>
- Miller, T., Durlik, I., Kostecka, E., Kozłowska, P., Staude, M., & Sokołowska, S. (2025). The role of lightweight AI models in supporting a sustainable transition to renewable energy: A systematic review. *Energies*, 18(5), Article 1192. <https://doi.org/10.3390/en18051192>
- Mukhtarov, S. (2024). Oil prices and the renewable energy transition: Empirical evidence from China. *Utilities Policy*, 91, Article 101840. <https://doi.org/10.1016/j.jup.2024.101840>

- Olaitan, D., Bertagni, M., & Porporato, A. (2024). The water footprint of hydrogen production. *Science of the Total Environment*, 927, Article 172384. <https://doi.org/10.1016/j.scitotenv.2024.172384>
- Rahadian, D., Anggadwita, G., Firli, A., & Adibroto, A. (2025). Environmental impact of renewable energy projects: Life cycle assessment and ecological footprint. In H. Dinçer & S. Yüksel (Eds.), *Renewable energy projects and investments* (pp. 95–116). Elsevier. <https://doi.org/10.1016/B978-0-443-29869-1.00006-4>
- Ramesh, S. (2025). Renewable energy technologies. In *The political economy of contemporary human civilisation, volume II: From quantum computing and nuclear fusion to war and conflict* (pp. 183–218). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-84185-9_6
- Rehman, A., Ma, H., Ahmad, M. I., Batool, Z., Tillaguango, B., & Oláh, J. (2025). The technology innovation paradox in Asia's leading innovative economies: The importance of renewable energy and green financing. *Technological and Economic Development of Economy*, 31(6), 1953–1978. <https://doi.org/10.3846/tede.2025.23722>
- Shafik, W. (2024). Energy policies and infrastructure requirements for efficient green buildings. In C. S. Meena, A. Kumar, V. P. Singh, & A. Ghosh (Eds.), *Sustainable technologies for energy efficient buildings* (pp. 212–240). CRC Press. <https://doi.org/10.1201/9781003496656-10>
- Sohag, K., Husain, S., & Soytas, U. (2024). Environmental policy stringency and ecological footprint linkage: Mitigation measures of renewable energy and innovation. *Energy Economics*, 136, Article 107721. <https://doi.org/10.1016/j.eneco.2024.107721>
- Tiwari, S., Mentel, G., Mohammed, K. S., Rehman, M. Z., & Lewandowska, A. (2024). Unveiling the role of natural resources, energy transition and environmental policy stringency for sustainable environmental development: Evidence from BRIC + 1. *Resources Policy*, 96, Article 105204. <https://doi.org/10.1016/j.resourpol.2024.105204>
- Tverijonaite, E., & Sæþórsdóttir, A. D. (2024). Hydro, wind, and geothermal: navigating the compatibility of renewable energy infrastructure with tourism. *Tourism and Hospitality*, 5(1), 16–31. <https://doi.org/10.3390/tourhosp5010002>
- Velykorusova, A., Zavadskas, E. K., Tupenaite, L., Kanapeckiene, L., Migilinskas, D., Kutut, V., Ubarte, I., Abaravicius, Z., & Kaklauskas, A. (2023). Intelligent multi-criteria decision support for renovation solutions for a building based on emotion recognition by applying the COPRAS method and BIM integration. *Applied Sciences*, 13, Article 5453. <https://doi.org/10.3390/app13095453>
- Virah-Sawmy, D., & Sturmberg, B. (2025). Socio-economic and environmental impacts of renewable energy deployments: A review. *Renewable and Sustainable Energy Reviews*, 207, Article 114956. <https://doi.org/10.1016/j.rser.2024.114956>
- Wang, F., Ge, Z., Yan, X., Zhang, W., Jiang, K., & Cai, B. (2024). The impact of low-carbon transition of energy sectors on regional water use in China. *Sustainable Production and Consumption*, 49, 560–570. <https://doi.org/10.1016/j.spc.2024.07.009>
- Wang, S., Ding, X., Chen, J., Zhong, H., Liu, J., & Su, W. (2025). Virtual water-embodied carbon nexus in the new energy system: A case study of solar photovoltaic in China. *Energy*, 323, Article 135815. <https://doi.org/10.1016/j.energy.2025.135815>
- Wang, Y., & Li, J. (2025). Multi-criteria decision-making for green maritime transportation: A hybrid Fuzzy AHP-MOORA approach to reduce marine pollution. *Marine Pollution Bulletin*, 216, Article 118023. <https://doi.org/10.1016/j.marpolbul.2025.118023>
- Wehbi, H. (2024). Powering the future: An integrated framework for clean renewable energy transition. *Sustainability*, 16(13), Article 5594. <https://doi.org/10.3390/su16135594>
- Yang, X., & Long, L. (2024). Renewable energy transition and its implication on natural resource management for green and sustainable economic recovery. *Resources Policy*, 89, Article 104624. <https://doi.org/10.1016/j.resourpol.2023.104624>