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A Synthetic Decision-Support System Based on Multi-Facet Fuzzy Sets with Dynamic Parameter Settings for Next-Gen Battery Technology Investments

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Abstract. New generation battery technology investments play a key role in the transition process from fossil fuels to renewable energy. The main problem related to the subject is that decision makers experience uncertainty about which of these numerous criteria affecting investment performance are prioritized. The lack of comprehensive models in the literature for systematically prioritizing these criteria creates a significant gap. The aim of this study is to determine the priority strategies to increase the performance of new generation battery technology investments. In this context, an innovative decision-making model is developed by integrating multi-facet fuzzy sets, logarithmic least-squares and WASPAS techniques. This study makes a significant contribution to the literature by prioritizing the performance indicators of new generation battery technology investments via an innovative decision-making model. The development of multi-facet fuzzy sets in this study provides an important contribution to the literature. Moreover, dynamic decision-making opportunity is provided by redefining membership degrees with different parameter sets for each scenario. This provides the opportunity to make clearer decisions based on scenarios and dynamic evaluations in complex decision-making processes. The main findings of the study indicate that circularity and compatibility with existing manufacturing infrastructure are priorities in improving the performance of these projects.

Key words: multi-facet fuzzy sets, dynamic parameter settings, synthetic evaluations, new generation battery technology, energy economics.

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1. Introduction

Next-generation battery technology investments refer to strategic research and development projects carried out to increase energy storage capacity and ensure environmental sustainability. These investments are of great importance, especially in the transition from fossil fuels to renewable energy (Maher and Boumaiza, 2024). In this process, alternative technologies such as solid-state batteries, lithium-sulfur, sodium-ion and flow battery systems come to the fore. New-generation battery technologies are also very effective in achieving sustainable development goals. Battery recycling processes and circular economy applications are being developed in an integrated manner with these investments. However, new-generation battery investments also bring some challenges. In this context, there are some technical and economic obstacles such as high research costs and security risks (Plante, 2025). In addition, dependence on critical raw materials is among the risks that need to be managed carefully. In this context, next-generation battery technology investments are considered one of the fundamental building blocks of the energy transformation. Due to this situation, these projects are considered a strategic priority by both the public and private sectors. In summary, to ensure the performance improvement of these projects, several measures must be implemented to manage these risks correctly.

Some criteria need to be improved systematically to increase the performance of next-generation battery technology investments. These criteria should be addressed at both technical and economic levels. Energy density is an issue that needs to be provided to achieve this goal. Increasing the amount of energy per battery is the most critical technical criterion. Cycle life and stability are also another important factors in this process. The number of charge-discharge cycles a battery can perform is directly related to the return on investment. Like this situation, charging time is also of critical importance in this process. Batteries that can be fully charged in a short time are of great importance in terms of user acceptance, especially in electric vehicles. This is necessary so that the batteries do not overheat and do not lose performance. Easy access to raw materials also increases the performance of these projects. In this context, battery production should be carried out with more sustainable and abundant materials instead of environmentally problematic metals. On the other hand, production and maintenance costs should be reduced for new technologies to be competitive. This situation contributes significantly to increasing the financial profitability of the projects. Furthermore, security risks such as fire and explosion should be minimized in new battery systems. The high security of investment projects allows more investors to focus on these projects.

It is necessary to determine the most important criteria in new generation battery technology investments. The fact that businesses do not have an unlimited budget when making investments forces them to make strategic decisions. Budget constraints make it impossible to improve all criteria at the same time at the highest level. Therefore, it is necessary to determine which criteria contribute more to investment performance. This helps to direct resources to the right areas (Moyo *et al.*, 2023). On the other hand, highlighting critical criteria allows businesses to develop priority strategies. This also plays an important role in preventing loss of time and waste of resources. Moreover, determining the most important variables reduces uncertainties and enables more effective decisions to be made.

Businesses design their strategic plans more soundly according to the determined priority criteria. In addition, the risk-benefit balance can be established more accurately. With the help of this issue, issues regarding which areas are riskier or more beneficial to invest in can be clarified. The fact that there are few studies in the literature that systematically determine the most effective criteria in new generation battery technology investments is considered a research gap. This deficiency leads to various problems and uncertainties at both academic and practical levels. Businesses lack models based on measurable and prioritized criteria that can guide their investment decisions. This deficiency increases the risk of errors in strategic planning.

To satisfy this deficiency, this study aims to determine the priority strategies to increase the performance of next-generation battery technology investments. In this process, a new decision-making model is developed to achieve this goal. In the first stage, the evaluations for the criteria and alternatives are constructed by the synthetic assessments. The second stage is related to the weighting the criteria with case and parameter-based multi-facet fuzzy logarithmic least-squares. Finally, the alternatives are ranked by considering fuzzy weighted aggregated sum product assessment (WASPAS). New generation battery technologies are of critical importance in many areas such as electric vehicles, renewable energy systems and portable devices. However, to increase the investment performance of these technologies, some technical and economic criteria need to be systematically improved. Many criteria have an impact on increasing the performance of these investments. However, there is a lack of systematic analysis in the literature on which of these criteria are more critical. This leads to decision uncertainty for investors. On the other hand, a new decision-making model is needed to solve this problem. Existing classical methods may be insufficient to solve these complex problems. The elimination of these deficiencies can be considered as the most important motivation of the study. In this context, this study aims to determine the answers to the following questions by establishing a new decision-making model.

(1) What are the technical and economic criteria that most affect performance in new generation battery technology investments?
(2) What strategies should be implemented as a priority in line with existing criteria and alternatives?
(3) How does the newly developed decision-making model contribute to strategic planning in investment decisions?

This study makes a significant contribution to the literature by systematically determining the technical and economic criteria affecting performance in new generation battery technology investments and presenting an innovative decision-making model that enables the development of priority strategies. The superiorities of the proposed model are demonstrated below. (1) The development of multi-facet fuzzy sets in this study provides an important contribution to the literature. These sets are introduced as a new type of fuzzy numbers that provide dynamic decision making. The dynamic feature is the redefinition of membership degrees with different parameter sets. Moreover, each scenario or fuzzy is created differently according to its evaluations. Scenario 1 is called the negative case. The priority of this scenario penalizes uncertainty and non-membership. Scenario 2 defines the positive case that aims to provide high membership with reward engagement. On the other side, Scenario 3 proposes an unstable case with prioritized resistance and penalized low membership. Moreover, scenario 4 defines the natural case with neutral and balanced behaviour of the decision maker. (2) In addition, dynamic evaluation can be done according to the conditions in this proposed model. Therefore, dynamic parameter sets are determined with various statistical calculations. The dynamic evaluations could also be considered by computing the parameters with per-item statistics. Accordingly, four extreme conditions are defined to determine the dynamic parameters for the multi-facet fuzzy sets. Condition 1 considers the maximum variance with the largest variance. Condition 2 defines the maximum entropy with the largest entropy measurement. Condition 3 is based on the maximum resistance potential. Condition 4 is a balanced position giving the average parameter values of these three conditions. This provides an opportunity to make clearer decisions based on scenarios and dynamic evaluations in complex decision-making processes.

The second section of the study examines the relevant literature and reveals current approaches and research gaps. The third section presents a detailed new decision-making model developed to make investment decisions more effective. The fourth section includes analysis results for the implementation of the proposed model. The fifth section discusses the findings and provides evaluations for literature and practitioners. Finally, the sixth section summarizes the general results of the study and provides suggestions for future research.

2. Literature Review

Circularity can significantly affect the performance of next-generation battery technology investments. New-generation batteries usually contain critical minerals. The circular economy approach ensures the recovery of these minerals. This contributes to the reduction of raw material dependency (Yang and Fulton, 2023). With the help of this condition, the costs of the projects are significantly reduced. As a result of this issue, the economic sustainability of the investments can be ensured (Suhail *et al.*, 2024). Circular applications are important in terms of reducing waste and reducing carbon emissions. In this way, investment projects can be evaluated as environmentally friendly. Environmentally friendly projects can also access the financing resources they need much faster (Wang *et al.*, 2023). On the other hand, this situation is also important in terms of providing innovation in production and design processes. Kim *et al.* (2024) denoted that if the battery is designed with circular economy principles, reuse can be ensured. This situation can significantly enable the cost effectiveness of the projects. According to Zhao *et al.* (2024), the image of companies that prioritize circularity is developing positively in the eyes of customers. Due to this situation, these products may be preferred more by investors with high social responsibility awareness.

The use of alternative materials contributes to the increase in the performance of next-generation battery technology investments. Critical minerals used in battery technologies are expensive and limited resources (Şensoy, 2023). On the other hand, alternative materials are cheaper and more abundant. This situation significantly reduces the cost of batteries. As a result of this situation, the investment payback period is significantly improved (Altiparmak *et al.*, 2025). The materials used in traditional batteries can be environmentally harmful. Alternative materials can have a lower carbon footprint. This situation allows the environmental pollution problem to be significantly reduced. The use of alternative materials is also necessary to reduce supply chain risk (Daniarta *et al.*, 2024). Most critical elements are produced in geopolitically sensitive regions. Pesaran (2023) identified that alternative materials allow this dependency to be reduced. This situation also contributes to the provision of supply chain security. Owing to this situation, the operational sustainability of investment projects can be increased. Furthermore, Mohseni *et al.* (2023) underlined that some alternative materials can provide certain advantages such as fast charging and increased energy density. This increases the competitiveness of battery systems.

Compatibility with existing manufacturing infrastructure significantly affects the performance of next-generation battery technology investments. The integration of a new battery technology into existing production lines significantly reduces the need for new equipment (Shaji *et al.*, 2023). Owing to this situation, capital expenditures of companies are significantly reduced. In the event of incompatibility, serious infrastructure transformation costs arise. This situation negatively affects the financial performance of projects (Watabe and Leaver, 2023). Compatible technologies can be quickly put into operation in existing production systems. As a result of this issue, the time to market of the product is shortened (Du, 2024). Thus, companies can gain a significant competitive advantage. Moreover, Vásquez *et al.* (2025) identified that this situation is also critical for ensuring operational efficiency. If existing automation systems can easily integrate with new technology, operational risks decrease and efficiency increases. Otherwise, new systems must be established to reach this objective. This situation causes significant increases in costs. Moreover, Zeng and Qu (2023) underlined that technologies that can be tested in existing production environments can go through processes such as error analysis at an early stage. This situation also significantly supports the reduction of uncertainties in the process.

The safety factor critically affects the performance of next-generation battery technology investments. It is important that new battery technologies are resistant to risks such as combustion and explosion. This situation supports the business from experiencing operational interruptions (Lyu *et al.*, 2023). Due to this situation, continuity of investment and operational efficiency can be ensured. Moreover, this situation also plays a critical role in reducing insurance costs (Bican *et al.*, 2023). Insurance premiums are lower in investments made in high-security technologies. Similarly, legal compliance can be achieved more easily, so legal costs can be reduced (Ajibade *et al.*, 2024). These issues also contribute significantly to strengthening financial sustainability. On the other hand, according to Dhairiyasamy *et al.* (2024), safety is a fundamental parameter that needs to be developed together with innovation in battery technologies. In other words, it is very necessary to bring the safety element to the forefront in research studies. Overbeck *et al.* (2023) concluded that although new technology develops, some problems occur because the safety factor is not taken into consideration. This situation also leads to an increase in financial costs.

The literature review results show that adopting circularity principles significantly increases the economic, environmental and operational sustainability of new generation battery technology investments. The use of alternative materials reduces costs and supports supply chain security. In addition, it is seen that technologies compatible with existing production infrastructures shorten investment payback periods and provide competitive advantage. The security factor directly affects not only operational continuity but also legal and insurance costs. However, some important deficiencies are striking in the literature. Studies on the evaluation of the interactions of these factors within a holistic model framework are limited. Moreover, there are not enough studies determining the most critical of these factors. This situation emerges as a significant deficiency in the literature on new generation battery technology investments. On the other side, while many previous studies focus on technical and economic performance indicators, they often rely on static decision-making approaches. However, these criteria are subject to high uncertainty and expert subjectivity. Therefore, a fuzzy dynamic modelling framework is essential to capture these complexities and provide more adaptable and realistic evaluations. This study addresses this gap by incorporating multi-facet fuzzy sets with dynamic membership functions.

3. Proposed Model

This proposed model integrates different techniques, such as synthetic evaluations, logarithmic least-squares weighting, multi-facet fuzzy sets and WASPAS. The details of these techniques are explained in the following parts.

3.1. *Synthetic Evaluations with Dynamic Multi-Facet Fuzzy Sets*

Multi-facet fuzzy sets refer to the new concept for presenting the environmental conditions of the decision making dynamically. These new sets define five functions generated from the membership degree. Primary membership degree (μ) defines the satisfactory value as in Eq. (1) (Rankin *et al.*, 2024).

$$\mu \in [0, 1]. \tag{1}$$

Non-membership degree identifies the level of rejection as explained in Eq. (2):

$$v(\mu) = \frac{1}{1 + e^{\alpha(\mu - .5)}}. \tag{2}$$

In this equation, α denotes control parameter. The transition steepness can be proofed by computing the first derivative in Eq. (3):

$$\frac{dv}{d\mu} = \frac{\alpha e^{\alpha(\mu - .5)}}{[1 + e^{\alpha(\mu - .5)}]^2}. \tag{3}$$

The maximum slope can be calculated at $\mu = .5$ as by using Eqs. (4) and (5).

$$\left.\frac{dv}{d\mu}\right|_{\mu=.5} = -\frac{\alpha}{4}, \tag{4}$$

$$\lim_{n\to\infty} v(\mu) = \begin{cases} 1, & \mu < .5, \\ .5, & \mu = .5, \\ 0, & \mu > .5. \end{cases} \tag{5}$$

In this scope, α controls the transition steepness. Equations (6)–(8) focus on the boundedness of non-membership degrees.

$$v(\mu) = \frac{1}{1+e^{\alpha(.5-.5)}} = \frac{1}{1+e^{0}} = \frac{1}{2} = .5 \quad \text{at } \mu = .5, \tag{6}$$

$$v(\mu) = \frac{1}{1+e^{\alpha(1-.5)}} = \frac{1}{1+e^{\alpha/2}} \in (0,1) \quad \text{as } \mu \to 1, \tag{7}$$

$$v(\mu) = \frac{1}{1+e^{\alpha(0-.5)}} = \frac{1}{1+e^{-\alpha/2}} \in (0,1) \quad \text{as } \mu \to 0. \tag{8}$$

The third function of multi-facet fuzzy sets $\epsilon(\mu)$ presents uncertainty degree as shown in Eq. (9).

$$\epsilon(\mu) = -a\big[\mu \ln \mu + (1-\mu)\ln(1-\mu)\big]. \tag{9}$$

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

$$H(\mu) = -\mu \ln \mu - (1-\mu)\ln(1-\mu), \tag{10}$$

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

$$H(0) = H(1) = 0, \tag{12}$$

$$H(.5) = \ln(2) \approx .693 \quad \text{at } \mu = .5,\ H(\mu) \text{ is maximized}, \tag{13}$$

$$\epsilon(\mu) = aH(\mu) \quad \Rightarrow \quad 0 \leqslant \epsilon(\mu) \leqslant a\ln(2). \tag{14}$$

Equations (15)–(17) define the maximum uncertainty at $\mu = .5$.

$$\frac{d\epsilon}{d\mu} = -a\big[\ln \mu - \ln(1-\mu)\big], \tag{15}$$

$$\ln \mu = \ln(1-\mu) \quad \Rightarrow \quad \mu = .5, \tag{16}$$

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

The fourth function of multi-facet fuzzy sets $n(\mu)$ can be defined in Eq. (18):

$$n(\mu) = \mu^{\delta}. \tag{18}$$

In this process, δ is a nonlinear engagement parameter. The calculation process of this parameter is indicated in Eqs. (19)–(21).

$$\text{For } \mu \in [0,1] \quad \text{and} \quad \delta > 1, \quad \text{If } \mu = 0\text{:} \quad n(\mu) = 0^{\delta} = 0, \tag{19}$$

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

$$\text{For } 0 < \mu < 1 \quad \text{and} \quad \delta > 1, \ \mu^{\delta} \leqslant \mu, \ n(\mu) \in [0,1]. \tag{21}$$

Equations (22) and (23) highlight δ parameter impact and convexity.

$$\frac{dn}{d\mu} = \delta \mu^{\delta-1}, \tag{22}$$

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

where if $\delta > 1$, it means the high membership and accelerating growth with convexity. If $\delta < 1$, membership degree has the low and decelerating growth with concave.

The final function of the proposed fuzzy sets shows information about the cognitive or contextual resistance. Resistance function $\rho(\mu)$ is indicated in Eqs. (24)–(27).

$$\rho(\mu) = 1 - (1-\mu)^{\varphi}, \tag{24}$$

$$\text{For } \mu \in [0,1] \quad \text{and} \quad \varphi > 1, \quad \text{If } \mu = 0\text{:} \quad \rho(\mu) = 1 - 1^{\varphi} = 0, \tag{25}$$

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

$$\text{For } 0 < \mu < 1, \ 0 < (1-\mu)^{\varphi} < 1 \quad \Rightarrow \quad 0 < \rho(\mu) < 1, \ \rho(\mu) \in [0,1]. \tag{27}$$

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

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

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

Generalized presentation of the dynamic multi-facet fuzzy sets is explained in Eqs. (A.1) and (A.2) where A refers to the dynamic multi-facet fuzzy set (DMFFS), the functions are indicated with $\mu(x)$, $v(\mu(x))$, $\epsilon(\mu(x))$, $n(\mu(x))$, $\rho(\mu(x))$. General operation rules of DMFFS are detailed in Eqs. (A.3)–(A.8). In this study, 4 unique scenarios are proposed named “Negative”, “Positive”, “Unstable”, “Natural”. Scenario 1 is called as “Negative Case”. The priority of this scenario penalizes uncertainty and non-membership as defined in Eq. (A.9). Scenario 2 defines “Positive Case”. It aims to provide high membership with reward engagement as shown in Eq. (A.10). Scenario 3 proposes “Unstable Case” with prioritized resistance and penalized low membership as in Eq. (A.11). Scenario 4 defines “Natural Case” with neutral and balanced behaviour of the decision maker. In this scenario, it is assumed that there are no environmental effects as indicated in Eq. (A.12). Condition 1 considers the maximum variance with the largest variance σ_i.

Condition 2 defines the maximum entropy H_i with the largest entropy measurement. Condition 3 is based on the maximum resistance potential $(1 - m_i)$. Condition 4 is a balanced position giving the average parameter values of these 3 conditions. The computations of per-item statistics are demonstrated in Eqs. (30)–(32).

$$m_i = \frac{1}{n} \sum m_{ij}, \tag{30}$$

$$\sigma_i^2 = \frac{1}{n} \sum (\mu_{ij} - m_i)^2, \tag{31}$$

$$H_i = -\sum \frac{\mu_{ij}}{\sum \mu} \ln\left(\frac{\mu_{ij}}{\sum \mu}\right). \tag{32}$$

The dynamic parameter settings are shown in Eqs. (A.13)–(A.16).

3.2. *Dynamic Multi-Facet Fuzzy Logarithmic Least-Squares Weighting*

Logarithmic least-squares weighting method is a mathematical method used to determine the weights of the criteria, especially in multi-criteria decision-making problems. In this process, based on the discrepancies obtained from the pairwise comparison matrix, the criteria weights are calculated by logarithmic regression (De Luca *et al.*, 2023). The first step focuses on the calculation of dependency degrees. Relation matrix (ς_k) is generated via Eq. (33).

$$\varsigma_k = \begin{bmatrix} 0 & \varsigma_{12} & \cdots & \cdots & \varsigma_{1n} \\ \varsigma_{21} & 0 & \cdots & \cdots & \varsigma_{2n} \\ \vdots & \vdots & \ddots & \cdots & \cdots \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \varsigma_{n1} & \varsigma_{n2} & \cdots & \cdots & 0 \end{bmatrix}. \tag{33}$$

The aggregated values ς are computed in the next step by Eq. (34).

$$\begin{aligned} \varsigma &= \left(\bigcup_{i=1}^{k} \varsigma_i\right) \\ &= \left\{\left(x, \frac{1}{k}\sum_{i=1}^{k}\mu_{\varsigma_i}(x), \frac{1}{k}\sum_{i=1}^{k}v_{\varsigma_i}(x), \frac{1}{k}\sum_{i=1}^{k}\epsilon_{\varsigma_i}(x), \frac{1}{k}\sum_{i=1}^{k}n_{\varsigma_i}(x), \frac{1}{k}\sum_{i=1}^{k}\rho_{\varsigma_i}(x)\right) \,\middle|\, x \in X\right\}. \end{aligned} \tag{34}$$

Defuzzified values (N_{ij}) are generated with Eqs. (36)–(38).

$$DR = \begin{bmatrix} 0 & N_{12} & \cdots & \cdots & N_{1n} \\ N_{21} & 0 & \cdots & \cdots & N_{2n} \\ \vdots & \vdots & \ddots & \cdots & \cdots \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ N_{n1} & N_{n2} & \cdots & \cdots & 0 \end{bmatrix}, \tag{35}$$

$$N_{ij} = \sum_{n=1}^{5} w_1 \mu_{\varsigma_{ij}} + w_2(1 - v_{\varsigma_{ij}}) + w_3(1 - \epsilon_{\varsigma_{ij}}) + w_4 n_{\varsigma_{ij}} + w_5 \rho_{\varsigma_{ij}}, \tag{36}$$

$$w_1 = \frac{\beta}{S}, \qquad w_2 = \frac{\alpha}{S}, \qquad w_3 = \frac{a}{S}, \qquad w_4 = \frac{\delta}{S}, \qquad w_5 = \frac{\varphi}{S}, \tag{37}$$

$$S = \beta + \alpha + a + \delta + \varphi, \tag{38}$$

where β is baseline membership. In the final part, equations (39)–(42) are considered to compute the criteria weights.

$$\Phi(w) = \sum_{i=1}^{n} \sum_{j=1}^{n} \bigl(\ln a_{ij} - (\ln w_i - \ln w_j)\bigr)^2, \quad \text{subject to } \sum_i w_i = 1, \tag{39}$$

$$x_k = \frac{1}{n} \sum_{i=1}^{n} b_{ki}, \tag{40}$$

$$b_{ki} = \frac{\ln a_{ki} - \ln a_{ik}}{2}, \tag{41}$$

$$W_k = \frac{e^{x_k}}{\sum_{l=1}^{n} e^{x_l}}. \tag{42}$$

3.3. *Dynamic Multi-Facet Fuzzy WASPAS*

WASPAS is a decision-making method used to solve multi-criteria decision-making problems (Chakraborty and Zavadskas, 2014; Kutlu Gundogdu and Kahraman, 2019). In this process, the aim is to rank the alternatives effectively (Deb *et al.*, 2023). Techniques such as simple additive weighting (SAW) and weighted product model (WPM) are integrated in the analysis stages (Zavadskas *et al.*, 2012; Yalcin Kavus *et al.*, 2023). This study integrates this technique with dynamic multi-facet fuzzy sets. The evaluations are obtained from the expert team in the first stage. After that, Eq. (43) is considered to create decision matrix.

$$X_k = \begin{bmatrix} 0 & X_{12} & \cdots & \cdots & X_{1m} \\ X_{21} & 0 & \cdots & \cdots & X_{2m} \\ \vdots & \vdots & \ddots & \cdots & \cdots \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ X_{n1} & X_{n2} & \cdots & \cdots & 0 \end{bmatrix}. \tag{43}$$

The normalized values are computed via Eq. (44):

$$r_{ij} = \frac{X_{ij}}{\max}(X_{ij}). \tag{44}$$

Equation (45) is used to generate weighted values.

$$v_{ij} = w_{ij} \times r_{ij}. \tag{45}$$

The values of SAW Q_i^{SAW} and WPM Q_i^{WPM} are computed with Eqs. (46) and (47).

$$Q_i^{SAW} = \sum_{j=1}^{m} v_{ij}, \tag{46}$$

$$Q_i^{WPM} = \prod_{j=1}^{m} r_{ij}^{w_{ij}}. \tag{47}$$

Equation (48) is taken into consideration to define the combining scores Q_i. These values are used for alternative ranking.

$$Q_i = \gamma Q_i^{SAW} + (1 - \gamma) Q_i^{WPM}. \tag{48}$$

4. Analysis Results

The proposed model has three different stages. The details of these stages are given in the following subsections. Briefly, to enhance readability, the intermediary computational results, including parameter-based multi-facet fuzzy numbers, per-item statistics, and normalized matrices, are presented in Appendix B (Tables A.1– A.25). This structure ensures that the main manuscript remains focused on key findings while preserving full transparency and reproducibility. Table 2 and 3 give information about the linguistic evaluations from the expert. Table 4 provides a comparison of the criteria weights obtained through both case-based assessments and parameter-based assessments. The similarity between these weighting results demonstrates the internal consistency and reliability of the proposed model. It is observed that circularity (CRCLT) and compatibility with existing manufacturing infrastructure (CWEMI) have the highest weights, indicating their critical role in next-generation battery technology investments. Table 5 presents the final rankings of the alternatives based on the aggregated multi-facet fuzzy WASPAS results. In this ranking process, both SAW (Simple Additive Weighting) and WASPAS components are integrated to provide a balanced evaluation of the alternatives. The aggregation is performed by combining the weighted normalized performance values obtained from the parameter-based assessments. The final ranking reflects the comprehensive performance of each alternative under dynamic conditions.

According to the final results, energy production in extreme weather conditions (EPEWC) is identified as the most critical investment alternative for next-generation battery technologies. This finding underscores the growing importance of resilient energy solutions in response to climate change and unpredictable environmental conditions. Early-stage biotech startups (ESBST) and electric vehicles with higher energy density (EVWHD) also emerge as significant alternatives, reflecting the technological advancements and strategic priorities within the sector.

Table 1
Evaluation scales and multi-facet fuzzy numbers by initial and case-based expert choices.

Scales	Linguistic evaluations	Fuzzy membership	Multi-facet fuzzy numbers			
			Negative	Positive	Unstable	Natural (Initial)
1	Extremely Low (EL)	.1	(.10, .98, 1.00, .10, .10)	(.10, .60, .14, .00, .10)	(.10, .60, .37, .10, .65)	(.10, .60, .14, .10, .10)
2	Very Low (VL)	.2	(.20, .95, 1.00, .20, .20)	(.20, .57, .14, .00, .20)	(.20, .57, .47, .20, .89)	(.20, .57, .14, .20, .20)
3	Low (L)	.3	(.30, .88, 1.00, .30, .30)	(.30, .55, .11, .00, .30)	(.30, .55, .47, .30, .97)	(.30, .55, .11, .30, .30)
4	Moderately Low (ML)	.4	(.40, .73, 1.00, .40, .40)	(.40, .52, .06, .01, .40)	(.40, .52, .43, .40, .99)	(.40, .52, .06, .40, .40)
5	Neutral (N)	.5	(.50, .50, 1.00, .50, .50)	(.50, .50, .00, .03, .50)	(.50, .50, .35, .50, 1.00)	(.50, .50, .00, .50, .50)
6	Moderately High (MH)	.6	(.60, .27, 1.00, .60, .60)	(.60, .48, .00, .08, .60)	(.60, .48, .25, .60, 1.00)	(.60, .48, .00, .60, .60)
7	High (H)	.7	(.70, .12, .89, .70, .70)	(.70, .45, .00, .17, .70)	(.70, .45, .14, .70, 1.00)	(.70, .45, .00, .70, .70)
8	Very High (VH)	.8	(.80, .05, .57, .80, .80)	(.80, .43, .00, .33, .80)	(.80, .43, .04, .80, 1.00)	(.80, .43, .00, .80, .80)
9	Extremely High (EH)	.9	(.90, .02, .24, .90, .90)	(.90, .40, .00, .59, .90)	(.90, .40, .00, .90, 1.00)	(.90, .40, .00, .90, .90)

4.1. *Constructing the Evaluations for the Criteria and Alternatives by the Synthetic Assessments*

In the first stage, the initial expert evaluations for the criteria and alternatives are collected. For this purpose, the scales in Table 1 are taken into consideration.

Table 1 shows the evaluation scales and multi-way fuzzy numbers. The scales include linguistic evaluations ranging from "Extremely Low" to "Extremely High". In this process, the fuzzy membership values and multi-way fuzzy numbers are shown for each scale. This table details the numerical values for different situations such as positive, negative, undecided and neutral. One decision maker who is an expert in the field of renewable energy and project management with 20-year experience is assigned for assessing the criteria and alternatives with linguistic evaluations. These evaluations are defined initial expert assessments and then they are converted to the multi-facet fuzzy numbers by initial and different scenarios. Criteria for assessing next-generation battery technology investments are defined as circularity (CRCLT), use of alternative materials (UAMTR), compatibility with existing manufacturing infrastructure (CWEMI), safety (SFETY), synergy with hybrid systems (SWHYS). These criteria are selected based on the literature review results. Table 2 gives information about the initial expert linguistic evaluations for the criteria.

In this study, expert evaluations were conducted to assess both the criteria and alternatives for next-generation battery technology investments. A domain expert with over 20 years of experience in renewable energy technologies and project management provided the linguistic assessments. This expert was selected based on their extensive professional background, ensuring informed and context-specific evaluations. To address potential concerns regarding subjectivity from using a single expert, the analysis incorporates multiple scenario-based assessments (Negative, Positive, Unstable, Natural) and dynamic parameter adjustments based on statistical indicators derived from the evaluation matrices. This approach increases the robustness of the results by considering different uncertainty conditions and testing the consistency of the findings across varied scenarios. While this study focuses on methodological development and applies an exploratory, expert-driven evaluation, future research is encouraged to involve larger expert groups and apply consensus-based fuzzy decision-making techniques to enhance generalizability.

Table 2
Initial expert linguistic evaluations for the criteria.

	CRCLT	UAMTR	CWEMI	SFETY	SWHYS
CRCLT		MH	EH	VH	N
UAMTR	ML		VH	H	MH
CWEMI	N	EH		N	EH
SFETY	H	N	ML		EH
SWHYS	EH	H	MH	N	

Table 3
Initial expert linguistic evaluations for the alternatives.

	CRCLT	UAMTR	CWEMI	SFETY	SWHYS
EVWHD	EH	H	MH	H	VH
GSWCL	VH	H	H	H	MH
LCESM	N	EH	VH	MH	N
EPEWC	H	VH	EH	EH	MH
ESBST	VH	MH	MH	VH	EH

Table 2 gives information about the initial expert linguistic evaluations. In this process, the questions are created by comparing criteria to each other. After that, the expert makes evaluations for these questions by using 9 different scales stated in Table 1. For example, to understand the impact of use of alternative materials on circularity, the expert says moderately low. However, this expert also thinks that the use of alternative materials has a very high impact on compatibility with existing manufacturing infrastructure. In the following process, the expert also provides opinions for the alternatives. Alternative investments for new generation battery technologies are identified as electric vehicles with higher energy density (EVWHD), grid storage with long cycle life (GSWCL), low-cost energy supply for manufacturers (LCESM), energy production in extreme weather conditions (EPEWC), early-stage biotech startups (ESBST). The initial expert linguistic evaluations for the alternatives are denoted in Table 3.

Table 3 indicates the evaluations of the expert for the alternatives by considering the criteria. For instance, according to the expert evaluation, grid storage with long cycle life is a very important investment alternative for new generation battery technologies by considering the criterion of circularity. Next, the multi-facet fuzzy numbers by initial and case-based assessments for the criteria are determined as in Table A.1. The multi-facet fuzzy numbers by initial and case-based assessments for the alternatives are also identified in Table A.2. In this process, the evaluations in Tables 2 and 3 are converted into the multi-facet fuzzy numbers by using the information stated in Table 1. The per-item statistics for the parameter-based multi-facet fuzzy sets of criteria and alternatives are computed in Table A.3. These values are also calculated for the alternatives in Table A.4. The dynamic parameters by the conditions for the criteria are determined in Table A.5. Table A.6 gives information about these values for the alternatives. The parameter-based multi-facet fuzzy numbers by the conditions for the criteria are defined in Table A.7. The parameter-based multi-facet fuzzy numbers by the conditions for the alternatives are defined in Table A.8.

Table 4
Comparative weights of the criteria by the case and parameter-based assessments.

Case-based assessments					
	Negative	Positive	Unstable	Natural	Overall
CRCLT	1	1	1	1	1
UAMTR	5	4	5	5	5
CWEMI	2	2	2	2	2
SFETY	4	3	3	3	3
SWHYS	3	5	4	4	4

Parameter-based assessments					
	Maximum variance	Maximum entropy	Maximum resistance	Balanced	Overall
CRCLT	1	2	1	1	1
UAMTR	4	4	4	4	4
CWEMI	3	3	2	2	2
SFETY	2	1	3	3	3
SWHYS	5	5	5	5	5

4.2. *Weighting the Criteria with Case and Parameter-Based Multi-Facet Fuzzy Logarithmic Least-Squares*

The average fuzzy values for overall performance of relation matrix with case and parameter-based assessments are shown in Tables A.9 and A.10. Defuzzified values of relation matrix by the case-based assessments are constructed in Table A.11. The defuzzified values of relation matrix by the parameter-based assessments are created in Table A.12. The values of b_{ki}, x_k, and the weights of the criteria by the case-based assessments are denoted in Table A.13. Table A.14 explains the values of b_{ki}, x_k, and the weights of the criteria by the parameter-based assessments. The comparative weights of the criteria by the case and parameter-based assessments are demonstrated in Table 4.

Table 4 denotes that the weighting results are similar for both case and parameter-based assessments. This situation gives information about the consistency of the analysis. Overall weighting results of the criteria are computed by using the aggregated values of the assessments. It is concluded that circularity (C1) and compatibility with existing manufacturing infrastructure (C3) have the greatest weights. Circularity is very important for the performance of investments in next-generation battery technologies. Circularity includes issues such as recycling and reuse. Waste reduction and secondary material use reduce production costs. This allows for increased profitability of projects. Some actions can be taken in the battery sector to ensure circularity. In this context, batteries that are easy to disassemble can be developed. This situation allows for more effective recycling. Compatibility with existing manufacturing infrastructure) is a critical factor that directly affects the performance of investments in next-generation battery technologies. Technologies compatible with existing lines significantly reduce the initial costs of projects. Compatible technologies provide a safer environment for investors. This situation significantly supports the increase in projects.

4.3. *Ranking the Alternatives with Case and Parameter-Based Multi-Facet Fuzzy WASPAS*

In investment evaluation processes, particularly those concerning next-generation battery technologies, uncertainty and inconsistency in expert judgments are inevitable due to market dynamics and incomplete information. To enhance the adaptability of the proposed model, dynamic parameter settings are applied to the multi-facet fuzzy numbers, as defined in equations (45) to (48).

The scaling factors in these equations are calculated using statistical measures derived from the expert evaluation matrices, including variance, entropy, and maximum range. These indicators capture uncertainty, inconsistency, and the level of disagreement among experts. When these statistical values are high, the model broadens the fuzzy membership functions to realistically reflect increased uncertainty. Conversely, when the variance and entropy are low, narrower membership functions are applied to represent higher consensus.

Incorporating such uncertainty-sensitive mechanisms is consistent with previous studies applying fuzzy WASPAS and advanced decision-making frameworks to problems involving incomplete or ambiguous information (Yalcin Kavus *et al.*, 2023; Deb *et al.*, 2023). Furthermore, our methodology builds on the foundation of WASPAS-based optimization for complex multi-criteria environments, as demonstrated by Zavadskas *et al.* (2012). By integrating these dynamic parameters, the model offers enhanced flexibility, robustness, and practical relevance, allowing for more realistic assessments under varying scenario conditions related to battery technology investments.

In the final stage, selected alternatives are ranked via multi-facet fuzzy WASPAS. The average fuzzy values for overall performance of decision matrix are computed. Table A.15 gives information about the averaged fuzzy numbers for overall performance of decision matrix with case-based assessments. On the other side, parameter-based assessments are demonstrated in Table A.16. The defuzzified values of decision matrix by the case-based assessments are constructed in Table A.17. The defuzzified values of decision matrix by the parameter-based assessments are created in Table A.18. Table A.19 indicates the normalized values of the decision matrix by the case-based assessments. Normalized decision matrix by the parameter-based assessments is demonstrated in Table A.20. Table A.21 shows the weighted decision matrix by the case-based assessments. Weighted decision matrix by the parameter-based assessments is given in Table A.22. The values of SAW, WPN and combining scores are computed in Table A.23. These values by the parameter-based assessments are defined in Table A.24. In the final step, alternatives are ranked by the case and the parameter-based assessments with the different combination parameters. Table A.25 explains the comparative ranking results of the alternatives by the case-based assessments with the different combination parameters. These ranking results by the parameter-based assessments are explained in Table 5.

Table 5 demonstrates that energy production in extreme weather conditions is the most critical investment alternative for new generation battery technologies. Moreover, early-stage biotech startups and electric vehicles with higher energy density are other significant alternatives for this situation. Energy production in extreme weather conditions can

Table 5
Comparative ranking results of the alternatives by the parameter-based assessments with the different combination parameters.

	$\gamma = 0$	$\gamma = 0.1$	$\gamma = 0.2$	$\gamma = 0.3$	$\gamma = 0.4$	$\gamma = 0.5$	$\gamma = 0.6$	$\gamma = 0.7$	$\gamma = 0.8$	$\gamma = 0.9$	$\gamma = 1$
Maximum variance											
EVWHD	3	3	3	3	3	3	3	3	3	3	3
GSWCL	4	4	4	4	4	4	4	4	4	4	4
LCESM	5	5	5	5	5	5	5	5	5	5	5
EPEWC	1	1	1	1	1	1	1	1	1	1	1
ESBST	2	2	2	2	2	2	2	2	2	2	2
Maximum entropy											
EVWHD	4	4	4	4	4	4	4	4	4	4	4
GSWCL	5	5	5	5	5	5	5	5	5	5	5
LCESM	3	3	3	3	3	3	3	3	3	3	3
EPEWC	1	1	1	1	1	1	1	1	1	1	1
ESBST	2	2	2	2	2	2	2	2	2	2	2
Maximum resistance											
EVWHD	3	3	3	3	3	3	3	3	3	3	3
GSWCL	5	5	5	5	5	5	5	5	5	5	5
LCESM	4	4	4	4	4	4	4	4	4	4	4
EPEWC	1	1	1	1	1	1	1	1	1	1	1
ESBST	2	2	2	2	2	2	2	2	2	2	2
Balanced											
EVWHD	3	3	3	3	3	3	3	3	3	3	3
GSWCL	5	5	5	5	5	5	5	5	5	5	5
LCESM	4	4	4	4	4	4	4	4	4	4	4
EPEWC	1	1	1	1	1	1	1	1	1	1	1
ESBST	2	2	2	2	2	2	2	2	2	2	2
Overall											
EVWHD	3	3	3	3	3	3	3	3	3	3	3
GSWCL	5	5	5	5	5	5	5	5	5	5	5
LCESM	4	4	4	4	4	4	4	4	4	4	4
EPEWC	1	1	1	1	1	1	1	1	1	1	1
ESBST	2	2	2	2	2	2	2	2	2	2	2

be considered as an important and strategic investment alternative. This situation is becoming increasingly critical especially in the context of climate change and sustainable development goals. Extreme weather events such as storms and droughts are increasing worldwide. These conditions can strain or disable traditional energy production infrastructures. Investing in energy production systems that are resistant to extreme conditions plays a key role in ensuring energy supply security.

However, the comparative ranking results of the extended TOPSIS are given with sensitivity analysis in Table 6. The weights of the criteria are changed consecutively and provided 5 scenarios for the sensitivity analysis. The comparative results with the sensitivity cases are illustrated as follows.

In Table 6, the comparative ranking results with extended TOPSIS are almost same for each case of sensitivity analysis. It demonstrates that our proposed methodology is coherent and applicable to the other extended methodologies for further studies.

Table 6
Comparative ranking results with sensitivity analysis.

	Extended WASPAS ($\gamma = 0.5$)					Extended TOPSIS				
	Case 1	Case 2	Case 3	Case 4	Case 5	Case 1	Case 2	Case 3	Case 4	Case 5
Max. var.										
EVWHD	3	3	3	3	3	3	3	3	3	3
GSWCL	4	4	5	5	4	4	4	5	4	4
LCESM	5	5	4	4	5	5	5	4	5	5
EPEWC	1	1	1	1	1	1	1	1	1	1
ESBST	2	2	2	2	2	2	2	2	2	2
Max. ent.										
EVWHD	4	4	4	4	4	4	4	4	4	4
GSWCL	5	5	5	5	5	5	5	5	5	5
LCESM	3	3	3	3	3	3	3	3	3	3
EPEWC	1	1	1	1	1	1	1	1	1	1
ESBST	2	2	2	2	2	2	2	2	2	2
Max. res.										
EVWHD	3	3	3	3	3	3	3	3	3	3
GSWCL	5	5	5	5	5	5	5	5	5	5
LCESM	4	4	4	4	4	4	4	4	4	4
EPEWC	1	1	1	1	1	1	1	1	1	1
ESBST	2	2	2	2	2	2	2	2	2	2
Balanced										
EVWHD	3	3	3	3	3	3	3	3	3	3
GSWCL	5	5	5	5	5	4	4	5	5	5
LCESM	4	4	4	4	4	5	5	4	4	4
EPEWC	1	1	1	1	1	1	1	1	1	1
ESBST	2	2	2	2	2	2	2	2	2	2
Overall										
EVWHD	3	3	3	3	3	3	3	3	3	3
GSWCL	5	5	5	5	5	4	5	5	5	5
LCESM	4	4	4	4	4	5	4	4	4	4
EPEWC	1	1	1	1	1	1	1	1	1	1
ESBST	2	2	2	2	2	2	2	2	2	2

5. Discussion

Circularity is an approach that prioritizes recycling and waste reduction throughout the life cycle of a product or technology. Battery designs that comply with circular economy principles can reduce environmental impacts while reducing costs. In the literature, it is emphasized that not only technological performance, but also material sustainability and recovery strategies are important in battery investments. With the provision of circularity, domestic production and resource independence can be achieved. Etxandi-Santolaya *et al.* (2023) mentioned that this situation contributes significantly to reducing the economic fragility of countries. In the literature, some studies underline the importance of energy density or cost efficiency for the performance improvements of the next-generation battery technology investments (Rizos and Urban, 2024). Unlike these traditional investment approaches, this study highlights the significance of the environmental issues in this process, such as resource efficiency and recyclability. Schulz-Mönninghoff *et al.* (2023) defined that future investment strategies should integrate circular design principles to these financial issues. Easier recovery of these batteries in a circular system also reduces external dependency on raw materials. Batteries with decomposable designs reduce recycling costs.

It is identified that compatibility with existing manufacturing infrastructure also plays a key role for the performance improvements of the next-generation battery technology investments. Integration with the existing manufacturing infrastructure supports the return on investment of these technologies. Fahma *et al.* (2024) demonstrated that establishing a new production line is quite costly in terms of both capital investment and time. It is vital that new battery technology is easily integrated into existing production lines. This allows for the reduction of restructuring costs. Denisart *et al.* (2024) identified that technologies compatible with the existing infrastructure shorten the time to production. With the help of these issues, these projects can become operational in the markets very quickly. This situation offers a significant competitive advantage to the enterprises. Moreover, according to Naseri *et al.* (2023), compatibility facilitates workforce adaptation, minimizes transition risks, and supports the integration with established supply chains. From a strategic investment perspective, infrastructure adaptability not only lowers operational risks but also enhances the attractiveness of such technologies for institutional investors and industry stakeholders.

In our proposed methodology, several scenarios and dynamic parameters are considered for solving the complex decision-making problems. Properly, we propose negative scenario to represent pessimistic market conditions, such as raw material shortages, regulatory restrictions, or major technological setbacks. For instance, lithium supply disruptions or unfavourable policies banning certain battery components lead to increased uncertainty and reduced stakeholder engagement. However, the positive scenario reflects highly favourable market dynamics, such as breakthrough research in solid-state battery technology, major cost reductions, or supportive government incentives like tax credits for green energy storage. Under these conditions, investor engagement is maximized, and technological optimism dominates. Unstable Case captures volatile and uncertain environments, characterized by fluctuating raw material prices, geopolitical tensions affecting supply chains, or rapid but uneven technological innovation. For example, sudden policy reversals on electric vehicle incentives or global supply chain disruptions due to pandemics are reflected by this scenario's prioritization of resistance and penalization of low membership. The natural scenario corresponds to stable, balanced market situations where neither major disruptions nor significant breakthroughs are expected. Typical examples include gradual, predictable improvements in battery technologies or steady policy environments without abrupt regulatory shifts.

Similarly, the dynamic parameter adjustments provide more satisfactory outcomes to discuss the performance metrics. Maximum variance condition reflects situations with highly inconsistent expert evaluations, signaling significant uncertainty or disagreement in market expectations. This often corresponds to unpredictable investment environments, such as emerging battery technologies facing technical feasibility debates or fragmented regulatory landscapes. Maximum entropy captures high system disorder, associated with rapidly evolving technologies, regulatory ambiguity, or unclear industry standards. For instance, shifting policy frameworks for battery recycling or evolving ESG (Environmental, Social, Governance) requirements increase decision complexity, justifying entropy-driven parameter adjustments. The condition of maximum resistance models contexts where stakeholders exhibit heightened resistance to adopting new battery technologies. Such scenarios may arise due to safety concerns (e.g. battery fires), public opposition to mining activities, or institutional inertia in established energy markets. Finally, balanced conditions represent moderate, predictable investment environments with average levels of uncertainty, risk, and stakeholder resistance. It applies to markets with incremental technological progress and stable policy frameworks.

The primary focus of this study is on technical and strategic criteria. However, it is also acknowledged that regulatory and policy mechanisms such as carbon pricing or mandatory recycling regulations can significantly influence the weight and relevance of certain investment indicators. Within this framework, the flexibility of the proposed multi-facet fuzzy model enables dynamic recalibration of membership functions based on policy-driven scenarios. For example, in a high carbon tax scenario, environmental compatibility and circularity-related criteria may gain greater importance. This adaptability enhances the practical value of the model by allowing stakeholders to test different regulatory environments. Owing to this issue, their potential impact on investment priorities can be observed.

6. Conclusion

This study tries to define the priority strategies to increase the performance of new generation battery technology investments. For this purpose, an innovative decision-making model is developed by integrating multi-facet fuzzy sets, logarithmic least-squares and WASPAS techniques. In the three-stage model proposed in the study, firstly the criteria and alternatives are defined by the synthetic evaluation method. In the second stage, the criteria weights are calculated by the multi-dimensional and situational fuzzy logarithmic least squares method. In the last stage, the alternatives are ranked by using the fuzzy WASPAS method. Circularity is found the most critical factor for the development of these projects. It is also identified that compatibility with existing manufacturing infrastructure also plays a key role for the performance improvements of the next-generation battery technology investments. It is concluded that energy production in extreme weather conditions is the most critical investment alternative for new generation battery technologies. Moreover, early-stage biotech startups and electric vehicles with higher energy density are other significant alternatives for this situation. Based on the prioritization of the circularity criterion, this study suggests several actionable strategies for investors. Adopting design-for-recycling principles in battery development can be very helpful to achieve this objective. Furthermore, using recyclable and low-impact materials can contribute significantly to improving the circular performance of battery technologies. These practices not only align with environmental goals but also help future-proof investments against tightening regulatory standards.

This study makes a significant contribution to the literature by prioritizing the performance indicators of new generation battery technology investments via an innovative decision-making model. This provides the opportunity to make clearer decisions based on scenarios and dynamic evaluations in complex decision-making processes. There are some important limitations of this study. The criteria and alternative evaluations used in the study are based on a limited number of expert opinions. This situation may create some limitations in terms of general validity and objectivity. In future studies, an analysis can be carried out with the participation of more experts. In this context, the generalizability of the model can be increased by obtaining the opinions of more experts working in different sectors. Weighting can be done according to the demographic and experience characteristics of the experts. Despite the use of a multiple scenario approach, all possible uncertainty situations are not fully covered. In this context, sensitivity analysis can be done according to different market conditions and technological development rates. This study relies on expert judgments that can introduce subjectivity and variability depending on the experts' background and consistency. Moreover, while the proposed model performs well for medium-scale problems, its computational complexity may increase significantly with a higher number of criteria and alternatives. Future research may address these constraints by integrating automated expert selection systems or developing scalable optimization-based fuzzy frameworks.

A. Appendix. Equations

$$A = \big\{\big(x, \mu(x), v\big(\mu(x)\big), \epsilon\big(\mu(x)\big), n\big(\mu(x)\big), \rho\big(\mu(x)\big)\big) \mid x \in X\big\}, \tag{A.1}$$

$$A = \left\{\left(x, \mu(x), \frac{1}{1 + e^{\alpha(\mu - .5)}}, -a\big[\mu \ln \mu + (1 - \mu)\ln(1 - \mu)\big], \mu^{\delta}, 1 - (1 - \mu)^{\varphi}\right) \middle| x \in X\right\}, \tag{A.2}$$

$$A = \big(\mu_A, v_A(\mu_A), \epsilon_A(\mu_A), n_A(\mu_A), \rho_A(\mu_A)\big), \tag{A.3}$$

$$B = \big(\mu_B, v_B(\mu_B), \epsilon_B(\mu_B), n_B(\mu_B), \rho_B(\mu_B)\big), \tag{A.4}$$

$$A \cup B = \big(\max(\mu_A, \mu_B), \min(v_A, v_B), \min(\epsilon_A, \epsilon_B), \max(n_A, n_B), \max(\rho_A, \rho_B)\big), \tag{A.5}$$

$$A \cap B = \big(\min(\mu_A, \mu_B), \max(v_A, v_B), \max(\epsilon_A, \epsilon_B), \min(n_A, n_B), \max(\rho_A, \rho_B)\big), \tag{A.6}$$

$$A \oplus B = (\mu_A + \mu_B - \mu_A\mu_B, v_Av_B, \epsilon_A + \epsilon_B - \epsilon_A\epsilon_B, n_A + n_B - n_An_B, \rho_A\rho_B), \tag{A.7}$$

$$A \otimes B = (\mu_A\mu_B, v_A + v_B - v_Av_B, v_Av_B, \epsilon_A\epsilon_B, n_An_B, \rho_A + \rho_B - \rho_A\rho_B), \tag{A.8}$$

$$A_{negative} = \left\{\left(x, \mu(x), \frac{1}{1 + e^{10(\mu - .5)}}, -5\big[\mu \ln \mu + (1 - \mu)\ln(1 - \mu)\big], \mu^{1}, 1 - (1 - \mu)^{1}\right) \middle| x \in X\right\}, \tag{A.9}$$

$$A_{positive} = \left\{ \left(x, \mu(x), \frac{1}{1+e^{1(\mu-.5)}}, -1\left[\mu \ln \mu + (1-\mu)\ln(1-\mu)\right], \mu^5, 1-(1-\mu)^1 \right) \Big| x \in X \right\}, \tag{A.10}$$

$$A_{unstable} = \left\{ \left(x, \mu(x), \frac{1}{1+e^{1(\mu-.5)}}, -2\left[\mu \ln \mu + (1-\mu)\ln(1-\mu)\right], \mu^1, 1-(1-\mu)^{10} \right) \Big| x \in X \right\}, \tag{A.11}$$

$$A_{natural} = \left\{ \left(x, \mu(x), \frac{1}{1+e^{1(\mu-.5)}}, -1\left[\mu \ln \mu + (1-\mu)\ln(1-\mu)\right], \mu^1, 1-(1-\mu)^1 \right) \mid x \in X \right\}, \tag{A.12}$$

$$\alpha_i = 1 + 9\frac{\sigma_i}{\max_n \sigma_n} \qquad [1, 10], \tag{A.13}$$

$$a_i = 1 + 4\frac{H_i}{\max_n H_n} \qquad [1, 5], \tag{A.14}$$

$$\delta_i = 1 + 4m_i \qquad [1, 5], \tag{A.15}$$

$$\varphi_i = 1 + 9\frac{(1-m_i)}{\max_n(1-m_n)} \qquad [1, 10]. \tag{A.16}$$

B. Appendix. Tables

Table A.1
Multi-facet fuzzy numbers by initial and case-based assessments for the criteria.

	CRCLT	UAMTR	CWEMI	SFETY	SWHYS
NEGATIVE					
CRCLT		(.60, .27, 1.00, .60, .60)	(.90, .02, .24, .90, .90)	(.80, .05, .57, .80, .80)	(.50, .50, 1.00, .50, .50)
UAMTR	(.40, .73, 1.00, .40, .40)		(.80, .05, .57, .80, .80)	(.70, .12, .89, .70, .70)	(.60, .27, 1.00, .60, .60)
CWEMI	(.50, .50, 1.00, .50, .50)	(.90, .02, .24, .90, .90)		(.50, .50, 1.00, .50, .50)	(.90, .02, .24, .90, .90)
SFETY	(.70, .12, .89, .70, .70)	(.50, .50, 1.00, .50, .50)	(.40, .73, 1.00, .40, .40)		(.90, .02, .24, .90, .90)
SWHYS	(.90, .02, .24, .90, .90)	(.70, .12, .89, .70, .70)	(.60, .27, 1.00, .60, .60)	(.50, .50, 1.00, .50, .50)	
POSITIVE					
CRCLT		(.60, .48, .00, .08, .60)	(.90, .40, .00, .59, .90)	(.80, .43, .00, .33, .80)	(.50, .50, .00, .03, .50)
UAMTR	(.40, .52, .06, .01, .40)		(.80, .43, .00, .33, .80)	(.70, .45, .00, .17, .70)	(.60, .48, .00, .08, .60)
CWEMI	(.50, .50, .00, .03, .50)	(.90, .40, .00, .59, .90)		(.50, .50, .00, .03, .50)	(.90, .40, .00, .59, .90)
SFETY	(.70, .45, .00, .17, .70)	(.50, .50, .00, .03, .50)	(.40, .52, .06, .01, .40)		(.90, .40, .00, .59, .90)
SWHYS	(.90, .40, .00, .59, .90)	(.70, .45, .00, .17, .70)	(.60, .48, .00, .08, .60)	(.50, .50, .00, .03, .50)	
UNSTABLE					
CRCLT		(.60, .48, .25, .60, 1.00)	(.90, .40, .00, .90, 1.00)	(.80, .43, .04, .80, 1.00)	(.50, .50, .35, .50, 1.00)
UAMTR	(.40, .52, .43, .40, .99)		(.80, .43, .04, .80, 1.00)	(.70, .45, .14, .70, 1.00)	(.60, .48, .25, .60, 1.00)
CWEMI	(.50, .50, .35, .50, 1.00)	(.90, .40, .00, .90, 1.00)		(.50, .50, .35, .50, 1.00)	(.90, .40, .00, .90, 1.00)
SFETY	(.70, .45, .14, .70, 1.00)	(.50, .50, .35, .50, 1.00)	(.40, .52, .43, .40, .99)		(.90, .40, .00, .90, 1.00)
SWHYS	(.90, .40, .00, .90, 1.00)	(.70, .45, .14, .70, 1.00)	(.60, .48, .25, .60, 1.00)	(.50, .50, .35, .50, 1.00)	
NATURAL					
CRCLT		(.60, .48, .00, .60, .60)	(.90, .40, .00, .90, .90)	(.80, .43, .00, .80, .80)	(.50, .50, .00, .50, .50)
UAMTR	(.40, .52, .06, .40, .40)		(.80, .43, .00, .80, .80)	(.70, .45, .00, .70, .70)	(.60, .48, .00, .60, .60)
CWEMI	(.50, .50, .00, .50, .50)	(.90, .40, .00, .90, .90)		(.50, .50, .00, .50, .50)	(.90, .40, .00, .90, .90)
SFETY	(.70, .45, .00, .70, .70)	(.50, .50, .00, .50, .50)	(.40, .52, .06, .40, .40)		(.90, .40, .00, .90, .90)
SWHYS	(.90, .40, .00, .90, .90)	(.70, .45, .00, .70, .70)	(.60, .48, .00, .60, .60)	(.50, .50, .00, .50, .50)	

Table A.2
Multi-facet fuzzy numbers by initial and case-based assessments for the alternatives.

	CRCLT	UAMTR	CWEMI	SFETY	SWHYS
NEGATIVE					
EVWHD	(.90, .02, .24, .90, .90)	(.70, .12, .89, .70, .70)	(.60, .27, 1.00, .60, .60)	(.70, .12, .89, .70, .70)	(.80, .05, .57, .80, .80)
GSWCL	(.80, .05, .57, .80, .80)	(.70, .12, .89, .70, .70)	(.70, .12, .89, .70, .70)	(.70, .12, .89, .70, .70)	(.60, .27, 1.00, .60, .60)
LCESM	(.50, .50, 1.00, .50, .50)	(.90, .02, .24, .90, .90)	(.80, .05, .57, .80, .80)	(.60, .27, 1.00, .60, .60)	(.50, .50, 1.00, .50, .50)
EPEWC	(.70, .12, .89, .70, .70)	(.80, .05, .57, .80, .80)	(.90, .02, .24, .90, .90)	(.90, .02, .24, .90, .90)	(.60, .27, 1.00, .60, .60)
ESBST	(.80, .05, .57, .80, .80)	(.60, .27, 1.00, .60, .60)	(.60, .27, 1.00, .60, .60)	(.80, .05, .57, .80, .80)	(.90, .02, .24, .90, .90)
POSITIVE					
EVWHD	(.90, .40, .00, .59, .90)	(.70, .45, .00, .17, .70)	(.60, .48, .00, .08, .60)	(.70, .45, .00, .17, .70)	(.80, .43, .00, .33, .80)
GSWCL	(.80, .43, .00, .33, .80)	(.70, .45, .00, .17, .70)	(.70, .45, .00, .17, .70)	(.70, .45, .00, .17, .70)	(.60, .48, .00, .08, .60)
LCESM	(.50, .50, .00, .03, .50)	(.90, .40, .00, .59, .90)	(.80, .43, .00, .33, .80)	(.60, .48, .00, .08, .60)	(.50, .50, .00, .03, .50)
EPEWC	(.70, .45, .00, .17, .70)	(.80, .43, .00, .33, .80)	(.90, .40, .00, .59, .90)	(.90, .40, .00, .59, .90)	(.60, .48, .00, .08, .60)
ESBST	(.80, .43, .00, .33, .80)	(.60, .48, .00, .08, .60)	(.60, .48, .00, .08, .60)	(.80, .43, .00, .33, .80)	(.90, .40, .00, .59, .90)
UNSTABLE					
EVWHD	(.90, .40, .00, .90, 1.00)	(.70, .45, .14, .70, 1.00)	(.60, .48, .25, .60, 1.00)	(.70, .45, .14, .70, 1.00)	(.80, .43, .04, .80, 1.00)
GSWCL	(.80, .43, .04, .80, 1.00)	(.70, .45, .14, .70, 1.00)	(.70, .45, .14, .70, 1.00)	(.70, .45, .14, .70, 1.00)	(.60, .48, .25, .60, 1.00)
LCESM	(.50, .50, .35, .50, 1.00)	(.90, .40, .00, .90, 1.00)	(.80, .43, .04, .80, 1.00)	(.60, .48, .25, .60, 1.00)	(.50, .50, .35, .50, 1.00)
EPEWC	(.70, .45, .14, .70, 1.00)	(.80, .43, .04, .80, 1.00)	(.90, .40, .00, .90, 1.00)	(.90, .40, .00, .90, 1.00)	(.60, .48, .25, .60, 1.00)
ESBST	(.80, .43, .04, .80, 1.00)	(.60, .48, .25, .60, 1.00)	(.60, .48, .25, .60, 1.00)	(.80, .43, .04, .80, 1.00)	(.90, .40, .00, .90, 1.00)
NATURAL					
EVWHD	(.90, .40, .00, .90, .90)	(.70, .45, .00, .70, .70)	(.60, .48, .00, .60, .60)	(.70, .45, .00, .70, .70)	(.80, .43, .00, .80, .80)
GSWCL	(.80, .43, .00, .80, .80)	(.70, .45, .00, .70, .70)	(.70, .45, .00, .70, .70)	(.70, .45, .00, .70, .70)	(.60, .48, .00, .60, .60)
LCESM	(.50, .50, .00, .50, .50)	(.90, .40, .00, .90, .90)	(.80, .43, .00, .80, .80)	(.60, .48, .00, .60, .60)	(.50, .50, .00, .50, .50)
EPEWC	(.70, .45, .00, .70, .70)	(.80, .43, .00, .80, .80)	(.90, .40, .00, .90, .90)	(.90, .40, .00, .90, .90)	(.60, .48, .00, .60, .60)
ESBST	(.80, .43, .00, .80, .80)	(.60, .48, .00, .60, .60)	(.60, .48, .00, .60, .60)	(.80, .43, .00, .80, .80)	(.90, .40, .00, .90, .90)

Table A.3
Per-item statistics for the parameter-based multi-facet fuzzy sets of criteria.

	m_i	σ_i^2	H_i
CRCLT	.700	.025	1.360
UAMTR	.625	.022	1.357
CWEMI	.700	.040	1.345
SFETY	.625	.037	1.339
SWHYS	.675	.022	1.363

Table A.4
Per-item statistics for the parameter-based multi-facet fuzzy sets of alternatives.

	m_i	σ_i^2	H_i
EVWHD	.740	.010	1.600
GSWCL	.700	.004	1.605
LCESM	.660	.026	1.580
EPEWC	.780	.014	1.598
ESBST	.740	.014	1.596

Table A.5
Dynamic parameters by the conditions for the criteria.

	α_i	a_i	δ_i	φ_i
Maximum variance				
CRCLT	1.00	4.99	3.80	8.20
UAMTR	1.00	4.98	3.50	1.00
CWEMI	1.00	4.95	3.80	8.20
SFETY	1.00	4.93	3.50	1.00
SWHYS	1.00	5.00	3.70	8.80
Maximum entropy				
CRCLT	6.63	5.00	3.80	8.20
UAMTR	5.92	5.00	3.50	1.00
CWEMI	1.00	5.00	3.80	8.20
SFETY	9.30	5.00	3.50	1.00
SWHYS	5.92	5.00	3.70	8.80
Maximum resistance				
CRCLT	6.63	4.99	3.80	1.00
UAMTR	5.92	4.98	3.50	1.00
CWEMI	1.00	4.95	3.80	1.00
SFETY	9.30	4.93	3.50	1.00
SWHYS	5.92	5.00	3.70	1.00
Balanced				
CRCLT	7.75	5.00	3.80	8.80
UAMTR	7.28	4.99	3.50	1.00
CWEMI	1.00	4.97	3.80	8.80
SFETY	9.53	4.95	3.50	1.00
SWHYS	7.28	5.00	3.70	9.20

Table A.6
Dynamic parameters by the conditions for the alternatives.

	α_i	a_i	δ_i	φ_i
Maximum variance				
EVWHD	1.00	4.99	3.96	7.88
GSWCL	1.00	5.00	3.80	8.94
LCESM	1.00	4.94	3.64	1.00
EPEWC	1.00	4.98	4.12	6.82
ESBST	1.00	4.98	3.96	7.88
Maximum entropy				
EVWHD	4.55	5.00	3.96	7.88
GSWCL	2.36	5.00	3.80	8.94
LCESM	1.00	5.00	3.64	1.00
EPEWC	5.64	5.00	4.12	6.82
ESBST	5.91	5.00	3.96	7.88
Maximum resistance				
EVWHD	4.55	4.99	3.96	1.00
GSWCL	2.36	5.00	3.80	1.00
LCESM	1.00	4.94	3.64	1.00
EPEWC	5.64	4.98	4.12	1.00
ESBST	5.91	4.98	3.96	1.00
Balanced				
EVWHD	6.36	4.99	3.96	8.59
GSWCL	4.91	5.00	3.80	9.29
LCESM	1.00	4.96	3.64	1.00
EPEWC	7.09	4.99	4.12	7.88
ESBST	7.27	4.98	3.96	8.59

Table A.7

Parameter-based multi-facet fuzzy numbers by the conditions for the criteria.

	CRCLT	UAMTR	CWEMI	SFETY	SWHYS
Maximum variance					
CRCLT		(.60, .27, 1.00, .14, 1.00)	(.90, .02, .24, .67, 1.00)	(.80, .05, .57, .43, 1.00)	(.50, .50, 1.00, .07, 1.00)
UAMTR	(.40, .73, 1.00, .04, .99)		(.80, .05, .57, .46, 1.00)	(.70, .12, .88, .29, 1.00)	(.60, .27, 1.00, .17, 1.00)
CWEMI	(.50, .50, 1.00, .07, 1.00)	(.90, .02, .24, .67, 1.00)		(.50, .50, 1.00, .07, 1.00)	(.90, .02, .24, .67, 1.00)
SFETY	(.70, .12, .87, .29, 1.00)	(.50, .50, 1.00, .09, 1.00)	(.40, .73, 1.00, .04, .99)		(.90, .02, .24, .69, 1.00)
SWHYS	(.90, .02, .24, .68, 1.00)	(.70, .12, .89, .27, 1.00)	(.60, .27, 1.00, .15, 1.00)	(.50, .50, 1.00, .08, 1.00)	
Maximum entropy					
CRCLT		(.60, .34, 1.00, .14, 1.00)	(.90, .07, .24, .67, 1.00)	(.80, .12, .57, .43, 1.00)	(.50, .50, 1.00, .07, 1.00)
UAMTR	(.40, .64, 1.00, .04, .99)		(.80, .14, .57, .46, 1.00)	(.70, .23, .89, .29, 1.00)	(.60, .36, 1.00, .17, 1.00)
CWEMI	(.50, .50, 1.00, .07, 1.00)	(.90, .02, .24, .67, 1.00)		(.50, .50, 1.00, .07, 1.00)	(.90, .02, .24, .67, 1.00)
SFETY	(.70, .13, .89, .29, 1.00)	(.50, .50, 1.00, .09, 1.00)	(.40, .72, 1.00, .04, .99)		(.90, .02, .24, .69, 1.00)
SWHYS	(.90, .09, .24, .68, 1.00)	(.70, .23, .89, .27, 1.00)	(.60, .36, 1.00, .15, 1.00)	(.50, .50, 1.00, .08, 1.00)	
Maximum resistance					
CRCLT		(.60, .34, 1.00, .14, 1.00)	(.90, .07, .24, .67, 1.00)	(.80, .12, .57, .43, 1.00)	(.50, .50, 1.00, .07, 1.00)
UAMTR	(.40, .64, 1.00, .04, .99)		(.80, .14, .57, .46, 1.00)	(.70, .23, .88, .29, 1.00)	(.60, .36, 1.00, .17, 1.00)
CWEMI	(.50, .50, 1.00, .07, 1.00)	(.90, .02, .24, .67, 1.00)		(.50, .50, 1.00, .07, 1.00)	(.90, .02, .24, .67, 1.00)
SFETY	(.70, .13, .87, .29, 1.00)	(.50, .50, 1.00, .09, 1.00)	(.40, .72, 1.00, .04, .99)		(.90, .02, .24, .69, 1.00)
SWHYS	(.90, .09, .24, .68, 1.00)	(.70, .23, .89, .27, 1.00)	(.60, .36, 1.00, .15, 1.00)	(.50, .50, 1.00, .08, 1.00)	
Balanced					
CRCLT		(.60, .32, 1.00, .14, 1.00)	(.90, .04, .24, .67, 1.00)	(.80, .09, .57, .43, 1.00)	(.50, .50, 1.00, .07, 1.00)
UAMTR	(.40, .67, 1.00, .04, .99)		(.80, .10, .57, .46, 1.00)	(.70, .19, .88, .29, 1.00)	(.60, .33, 1.00, .17, 1.00)
CWEMI	(.50, .50, 1.00, .07, 1.00)	(.90, .02, .24, .67, 1.00)		(.50, .50, 1.00, .07, 1.00)	(.90, .02, .24, .67, 1.00)
SFETY	(.70, .13, .88, .29, 1.00)	(.50, .50, 1.00, .09, 1.00)	(.40, .72, 1.00, .04, .99)		(.90, .02, .24, .69, 1.00)
SWHYS	(.90, .05, .24, .68, 1.00)	(.70, .19, .89, .27, 1.00)	(.60, .33, 1.00, .15, 1.00)	(.50, .50, 1.00, .08, 1.00)	

Table A.8

Parameter-based multi-facet fuzzy numbers by the conditions for the alternatives.

	CRCLT	UAMTR	CWEMI	SFETY	SWHYS
Maximum variance					
EVWHD	(.90, .02, .24, .66, 1.00)	(.70, .12, .88, .24, 1.00)	(.60, .27, 1.00, .13, 1.00)	(.70, .12, .88, .24, 1.00)	(.80, .05, .57, .41, 1.00)
GSWCL	(.80, .05, .57, .43, 1.00)	(.70, .12, .89, .26, 1.00)	(.70, .12, .89, .26, 1.00)	(.70, .12, .89, .26, 1.00)	(.60, .27, 1.00, .14, 1.00)
LCESM	(.50, .50, 1.00, .08, 1.00)	(.90, .02, .24, .68, 1.00)	(.80, .05, .56, .44, 1.00)	(.60, .27, 1.00, .16, 1.00)	(.50, .50, 1.00, .08, 1.00)
EPEWC	(.70, .12, .88, .23, 1.00)	(.80, .05, .57, .40, 1.00)	(.90, .02, .24, .65, 1.00)	(.90, .02, .24, .65, 1.00)	(.60, .27, 1.00, .12, 1.00)
ESBST	(.80, .05, .57, .41, 1.00)	(.60, .27, 1.00, .13, 1.00)	(.60, .27, 1.00, .13, 1.00)	(.80, .05, .57, .41, 1.00)	(.90, .02, .24, .66, 1.00)
Maximum entropy					
EVWHD	(.90, .14, .24, .66, 1.00)	(.70, .29, .89, .24, 1.00)	(.60, .39, 1.00, .13, 1.00)	(.70, .29, .89, .24, 1.00)	(.80, .20, .57, .41, 1.00)
GSWCL	(.80, .33, .57, .43, 1.00)	(.70, .38, .89, .26, 1.00)	(.70, .38, .89, .26, 1.00)	(.70, .38, .89, .26, 1.00)	(.60, .44, 1.00, .14, 1.00)
LCESM	(.50, .50, 1.00, .08, 1.00)	(.90, .02, .24, .68, 1.00)	(.80, .05, .57, .44, 1.00)	(.60, .27, 1.00, .16, 1.00)	(.50, .50, 1.00, .08, 1.00)
EPEWC	(.70, .24, .89, .23, 1.00)	(.80, .16, .57, .40, 1.00)	(.90, .09, .24, .65, 1.00)	(.90, .09, .24, .65, 1.00)	(.60, .36, 1.00, .12, 1.00)
ESBST	(.80, .15, .57, .41, 1.00)	(.60, .36, 1.00, .13, 1.00)	(.60, .36, 1.00, .13, 1.00)	(.80, .15, .57, .41, 1.00)	(.90, .09, .24, .66, 1.00)
Maximum resistance					
EVWHD	(.90, .14, .24, .66, 1.00)	(.70, .29, .88, .24, 1.00)	(.60, .39, 1.00, .13, 1.00)	(.70, .29, .88, .24, 1.00)	(.80, .20, .57, .41, 1.00)
GSWCL	(.80, .33, .57, .43, 1.00)	(.70, .38, .89, .26, 1.00)	(.70, .38, .89, .26, 1.00)	(.70, .38, .89, .26, 1.00)	(.60, .44, 1.00, .14, 1.00)
LCESM	(.50, .50, 1.00, .08, 1.00)	(.90, .02, .24, .68, 1.00)	(.80, .05, .56, .44, 1.00)	(.60, .27, 1.00, .16, 1.00)	(.50, .50, 1.00, .08, 1.00)
EPEWC	(.70, .24, .88, .23, 1.00)	(.80, .16, .57, .40, 1.00)	(.90, .09, .24, .65, 1.00)	(.90, .09, .24, .65, 1.00)	(.60, .36, 1.00, .12, 1.00)
ESBST	(.80, .15, .57, .41, 1.00)	(.60, .36, 1.00, .13, 1.00)	(.60, .36, 1.00, .13, 1.00)	(.80, .15, .57, .41, 1.00)	(.90, .09, .24, .66, 1.00)
Balanced					
EVWHD	(.90, .07, .24, .66, 1.00)	(.70, .22, .88, .24, 1.00)	(.60, .35, 1.00, .13, 1.00)	(.70, .22, .88, .24, 1.00)	(.80, .13, .57, .41, 1.00)
GSWCL	(.80, .19, .57, .43, 1.00)	(.70, .27, .89, .26, 1.00)	(.70, .27, .89, .26, 1.00)	(.70, .27, .89, .26, 1.00)	(.60, .38, 1.00, .14, 1.00)
LCESM	(.50, .50, 1.00, .08, 1.00)	(.90, .02, .24, .68, 1.00)	(.80, .05, .56, .44, 1.00)	(.60, .27, 1.00, .16, 1.00)	(.50, .50, 1.00, .08, 1.00)
EPEWC	(.70, .19, .88, .23, 1.00)	(.80, .11, .57, .40, 1.00)	(.90, .06, .24, .65, 1.00)	(.90, .06, .24, .65, 1.00)	(.60, .33, 1.00, .12, 1.00)
ESBST	(.80, .10, .57, .41, 1.00)	(.60, .33, 1.00, .13, 1.00)	(.60, .33, 1.00, .13, 1.00)	(.80, .10, .57, .41, 1.00)	(.90, .05, .24, .66, 1.00)

Table A.9
Averaged fuzzy numbers for overall performance of relation matrix with case-based assessments.

	CRCLT	UAMTR	CWEMI	SFETY	SWHYS
CRCLT	(.00, .00, .00, .00, .00)	(.60, .42, .31, .47, .70)	(.90, .31, .06, .82, .92)	(.80, .33, .15, .68, .85)	(.50, .50, .34, .38, .62)
UAMTR	(.40, .58, .39, .30, .55)	(.00, .00, .00, .00, .00)	(.80, .33, .15, .68, .85)	(.70, .37, .26, .57, .77)	(.60, .42, .31, .47, .70)
CWEMI	(.50, .50, .34, .38, .62)	(.90, .31, .06, .82, .92)	(.00, .00, .00, .00, .00)	(.50, .50, .34, .38, .62)	(.90, .31, .06, .82, .92)
SFETY	(.70, .37, .26, .57, .77)	(.50, .50, .34, .38, .62)	(.40, .58, .39, .30, .55)	(.00, .00, .00, .00, .00)	(.90, .31, .06, .82, .92)
SWHYS	(.90, .31, .06, .82, .92)	(.70, .37, .26, .57, .77)	(.60, .42, .31, .47, .70)	(.50, .50, .34, .38, .62)	(.00, .00, .00, .00, .00)

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

	CRCLT	UAMTR	CWEMI	SFETY	SWHYS
CRCLT	(.00, .00, .00, .00, .00)	(.60, .32, 1.00, .14, 1.00)	(.90, .05, .24, .67, 1.00)	(.80, .09, .57, .43, 1.00)	(.50, .50, 1.00, .07, 1.00)
UAMTR	(.40, .67, 1.00, .04, .99)	(.00, .00, .00, .00, .00)	(.80, .11, .57, .46, 1.00)	(.70, .19, .88, .29, 1.00)	(.60, .33, 1.00, .17, 1.00)
CWEMI	(.50, .50, 1.00, .07, 1.00)	(.90, .02, .24, .67, 1.00)	(.00, .00, .00, .00, .00)	(.50, .50, 1.00, .07, 1.00)	(.90, .02, .24, .67, 1.00)
SFETY	(.70, .13, .88, .29, 1.00)	(.50, .50, 1.00, .09, 1.00)	(.40, .72, 1.00, .04, .99)	(.00, .00, .00, .00, .00)	(.90, .02, .24, .69, 1.00)
SWHYS	(.90, .06, .24, .68, 1.00)	(.70, .19, .89, .27, 1.00)	(.60, .33, 1.00, .15, 1.00)	(.50, .50, 1.00, .08, 1.00)	(.00, .00, .00, .00, .00)

Table A.11
Defuzzified relation matrix by the case-based assessments.

	CRCLT	UAMTR	CWEMI	SFETY	SWHYS
NEGATIVE					
CRCLT	.000	.506	.906	.782	.361
UAMTR	.216	.000	.782	.637	.506
CWEMI	.361	.906	.000	.361	.906
SFETY	.637	.361	.216	.000	.906
SWHYS	.906	.637	.506	.361	.000
POSITIVE					
CRCLT	.000	.346	.706	.535	.295
UAMTR	.252	.000	.535	.421	.346
CWEMI	.295	.706	.000	.295	.706
SFETY	.421	.295	.252	.000	.706
SWHYS	.706	.421	.346	.295	.000
UNSTABLE					
CRCLT	.000	.882	.960	.940	.853
UAMTR	.824	.000	.940	.912	.882
CWEMI	.853	.960	.000	.853	.960
SFETY	.912	.853	.824	.000	.960
SWHYS	.960	.912	.882	.853	.000
NATURAL					
CRCLT	.000	.665	.860	.795	.600
UAMTR	.523	.000	.795	.730	.665
CWEMI	.600	.860	.000	.600	.860
SFETY	.730	.600	.523	.000	.860
SWHYS	.860	.730	.665	.600	.000

Table A.12
Defuzzified relation matrix by the parameter-based assessments.

	CRCLT	UAMTR	CWEMI	SFETY	SWHYS
Maximum variance					
CRCLT	.000	.595	.902	.797	.498
UAMTR	.447	.000	.817	.716	.627
CWEMI	.499	.903	.000	.499	.903
SFETY	.719	.537	.448	.000	.914
SWHYS	.905	.697	.606	.511	.000
Maximum entropy					
CRCLT	.000	.557	.878	.755	.498
UAMTR	.495	.000	.772	.661	.590
CWEMI	.498	.902	.000	.498	.902
SFETY	.705	.536	.455	.000	.909
SWHYS	.876	.638	.564	.513	.000
Maximum resistance					
CRCLT	.000	.587	.886	.772	.533
UAMTR	.496	.000	.772	.662	.590
CWEMI	.530	.909	.000	.530	.909
SFETY	.710	.538	.456	.000	.911
SWHYS	.882	.655	.584	.536	.000
Balanced					
CRCLT	.000	.579	.890	.776	.510
UAMTR	.480	.000	.788	.679	.601
CWEMI	.509	.904	.000	.509	.904
SFETY	.711	.537	.453	.000	.911
SWHYS	.890	.663	.583	.520	.000

Table A.13
Values of b_{ki}, x_k, and the weights of the criteria for the case-based assessments.

	b_{ki}					x_k	W_k
	CRCLT	UAMTR	CWEMI	SFETY	SWHYS		
Negative							
CRCLT	.000	.426	.460	.102	−.460	.106	.222
UAMTR	−.426	.000	−.074	.284	−.115	−.066	.187
CWEMI	−.460	.074	.000	.257	.291	.032	.206
SFETY	−.102	−.284	−.257	.000	.460	−.037	.192
SWHYS	.460	.115	−.291	−.460	.000	−.035	.193
Positive							
CRCLT	.000	.159	.436	.119	−.436	.056	.211
UAMTR	−.159	.000	−.139	.178	−.098	−.044	.191
CWEMI	−.436	.139	.000	.079	.356	.028	.205
SFETY	−.119	−.178	−.079	.000	.436	.012	.202
SWHYS	.436	.098	−.356	−.436	.000	−.052	.190
Unstable							
CRCLT	.000	.034	.059	.016	−.059	.010	.202
UAMTR	−.034	.000	−.010	.033	−.016	−.006	.199
CWEMI	−.059	.010	.000	.017	.042	.002	.200
SFETY	−.016	−.033	−.017	.000	.059	−.001	.200
SWHYS	.059	.016	−.042	−.059	.000	−.005	.199
Natural							
CRCLT	.000	.120	.180	.043	−.180	.033	.207
UAMTR	−.120	.000	−.039	.098	−.047	−.022	.196
CWEMI	−.180	.039	.000	.069	.128	.011	.202
SFETY	−.043	−.098	−.069	.000	.180	−.006	.199
SWHYS	.180	.047	−.128	−.180	.000	−.016	.197

Table A.14
Values of b_{ki}, x_k, and the weights of the criteria for the parameter-based assessments.

	b_{ki}					x_k	W_k
	CRCLT	UAMTR	CWEMI	SFETY	SWHYS		
Maximum variance							
CRCLT	.000	.143	.296	.052	−.299	.038	.208
UAMTR	−.143	.000	−.050	.144	−.053	−.020	.196
CWEMI	−.296	.050	.000	.054	.199	.002	.200
SFETY	−.052	−.144	−.054	.000	.291	.008	.202
SWHYS	.299	.053	−.199	−.291	.000	−.028	.194
Maximum entropy							
CRCLT	.000	.059	.283	.034	−.283	.019	.204
UAMTR	−.059	.000	−.078	.104	−.039	−.014	.197
CWEMI	−.283	.078	.000	.045	.235	.015	.203
SFETY	−.034	−.104	−.045	.000	.286	.021	.204
SWHYS	.283	.039	−.235	−.286	.000	−.040	.192
Maximum resistance							
CRCLT	.000	.085	.257	.042	−.252	.026	.205
UAMTR	−.085	.000	−.081	.104	−.052	−.023	.195
CWEMI	−.257	.081	.000	.075	.221	.024	.205
SFETY	−.042	−.104	−.075	.000	.265	.009	.202
SWHYS	.252	.052	−.221	−.265	.000	−.036	.193
Balanced							
CRCLT	.000	.093	.279	.043	−.279	.027	.206
UAMTR	−.093	.000	−.069	.118	−.049	−.019	.196
CWEMI	−.279	.069	.000	.059	.219	.014	.203
SFETY	−.043	−.118	−.059	.000	.281	.012	.202
SWHYS	.279	.049	−.219	−.281	.000	−.035	.193

Table A.15
Averaged fuzzy numbers for overall performance of decision matrix with case-based assessments.

	CRCLT	UAMTR	CWEMI	SFETY	SWHYS
EVWHD	(.90, .31, .06, .82, .92)	(.70, .37, .26, .57, .77)	(.60, .42, .31, .47, .70)	(.70, .37, .26, .57, .77)	(.80, .33, .15, .68, .85)
GSWCL	(.80, .33, .15, .68, .85)	(.70, .37, .26, .57, .77)	(.70, .37, .26, .57, .77)	(.70, .37, .26, .57, .77)	(.60, .42, .31, .47, .70)
LCESM	(.50, .50, .34, .38, .62)	(.90, .31, .06, .82, .92)	(.80, .33, .15, .68, .85)	(.60, .42, .31, .47, .70)	(.50, .50, .34, .38, .62)
EPEWC	(.70, .37, .26, .57, .77)	(.80, .33, .15, .68, .85)	(.90, .31, .06, .82, .92)	(.90, .31, .06, .82, .92)	(.60, .42, .31, .47, .70)
ESBST	(.80, .33, .15, .68, .85)	(.60, .42, .31, .47, .70)	(.60, .42, .31, .47, .70)	(.80, .33, .15, .68, .85)	(.90, .31, .06, .82, .92)

Table A.16
Averaged fuzzy numbers for overall performance of decision matrix with parameter-based assessments.

	CRCLT	UAMTR	CWEMI	SFETY	SWHYS
EVWHD	(.90, .09, .24, .66, 1.00)	(.70, .23, .88, .24, 1.00)	(.60, .35, 1.00, .13, 1.00)	(.70, .23, .88, .24, 1.00)	(.80, .15, .57, .41, 1.00)
GSWCL	(.80, .22, .57, .43, 1.00)	(.70, .29, .89, .26, 1.00)	(.70, .29, .89, .26, 1.00)	(.70, .29, .89, .26, 1.00)	(.60, .38, 1.00, .14, 1.00)
LCESM	(.50, .50, 1.00, .08, 1.00)	(.90, .02, .24, .68, 1.00)	(.80, .05, .56, .44, 1.00)	(.60, .27, 1.00, .16, 1.00)	(.50, .50, 1.00, .08, 1.00)
EPEWC	(.70, .20, .88, .23, 1.00)	(.80, .12, .57, .40, 1.00)	(.90, .07, .24, .65, 1.00)	(.90, .07, .24, .65, 1.00)	(.60, .33, 1.00, .12, 1.00)
ESBST	(.80, .11, .57, .41, 1.00)	(.60, .33, 1.00, .13, 1.00)	(.60, .33, 1.00, .13, 1.00)	(.80, .11, .57, .41, 1.00)	(.90, .06, .24, .66, 1.00)

Table A.17
Defuzzified decision matrix by the case-based assessments.

	CRCLT	UAMTR	CWEMI	SFETY	SWHYS
NEGATIVE					
EVWHD	.906	.637	.506	.637	.782
GSWCL	.782	.637	.637	.637	.506
LCESM	.361	.906	.782	.506	.361
EPEWC	.637	.782	.906	.906	.506
ESBST	.782	.506	.506	.782	.906
POSITIVE					
EVWHD	.706	.421	.346	.421	.535
GSWCL	.535	.421	.421	.421	.346
LCESM	.295	.706	.535	.346	.295
EPEWC	.421	.535	.706	.706	.346
ESBST	.535	.346	.346	.535	.706
UNSTABLE					
EVWHD	.960	.912	.882	.912	.940
GSWCL	.940	.912	.912	.912	.882
LCESM	.853	.960	.940	.882	.853
EPEWC	.912	.940	.960	.960	.882
ESBST	.940	.882	.882	.940	.960
NATURAL					
EVWHD	.860	.730	.665	.730	.795
GSWCL	.795	.730	.730	.730	.665
LCESM	.600	.860	.795	.665	.600
EPEWC	.730	.795	.860	.860	.665
ESBST	.795	.665	.665	.795	.860

Table A.18
Defuzzified decision matrix by the parameter-based assessments.

	CRCLT	UAMTR	CWEMI	SFETY	SWHYS
Maximum variance					
EVWHD	.898	.680	.586	.680	.790
GSWCL	.802	.696	.696	.696	.605
LCESM	.534	.912	.815	.625	.534
EPEWC	.663	.778	.891	.891	.565
ESBST	.791	.586	.586	.791	.898
Maximum entropy					
EVWHD	.852	.596	.526	.596	.718
GSWCL	.715	.599	.599	.599	.540
LCESM	.532	.910	.813	.623	.532
EPEWC	.589	.716	.854	.854	.510
ESBST	.737	.539	.539	.737	.866
Maximum resistance					
EVWHD	.865	.632	.568	.632	.743
GSWCL	.729	.618	.618	.618	.562
LCESM	.534	.912	.815	.625	.534
EPEWC	.641	.752	.872	.872	.571
ESBST	.760	.577	.577	.760	.878
Balanced					
EVWHD	.874	.634	.557	.634	.752
GSWCL	.744	.629	.629	.629	.562
LCESM	.533	.911	.815	.624	.533
EPEWC	.631	.750	.874	.874	.547
ESBST	.764	.566	.566	.764	.882

Table A.19
Normalized decision matrix by the case-based assessments.

	CRCLT	UAMTR	CWEMI	SFETY	SWHYS
NEGATIVE					
EVWHD	1.000	.704	.559	.704	.863
GSWCL	.863	.704	.704	.704	.559
LCESM	.399	1.000	.863	.559	.399
EPEWC	.704	.863	1.000	1.000	.559
ESBST	.863	.559	.559	.863	1.000
POSITIVE					
EVWHD	1.000	.597	.490	.597	.758
GSWCL	.758	.597	.597	.597	.490
LCESM	.418	1.000	.758	.490	.418
EPEWC	.597	.758	1.000	1.000	.490
ESBST	.758	.490	.490	.758	1.000
UNSTABLE					
EVWHD	1.000	.950	.919	.950	.980
GSWCL	.980	.950	.950	.950	.919
LCESM	.889	1.000	.980	.919	.889
EPEWC	.950	.980	1.000	1.000	.919
ESBST	.980	.919	.919	.980	1.000
NATURAL EVWHD	1.000	.849	.773	.849	.925
GSWCL	.925	.849	.849	.849	.773
LCESM	.698	1.000	.925	.773	.698
EPEWC	.849	.925	1.000	1.000	.773
ESBST	.925	.773	.773	.925	1.000

Table A.20
Normalized decision matrix by the parameter-based assessments.

	CRCLT	UAMTR	CWEMI	SFETY	SWHYS
Maximum variance					
EVWHD	1.000	.746	.658	.764	.880
GSWCL	.893	.763	.781	.781	.674
LCESM	.594	1.000	.915	.701	.594
EPEWC	.739	.853	1.000	1.000	.630
ESBST	.881	.643	.658	.888	1.000
Maximum entropy					
EVWHD	1.000	.655	.616	.699	.829
GSWCL	.839	.658	.702	.702	.624
LCESM	.625	1.000	.952	.730	.615
EPEWC	.691	.787	1.000	1.000	.588
ESBST	.865	.592	.631	.864	1.000
Maximum resistance					
EVWHD	1.000	.693	.651	.725	.847
GSWCL	.842	.678	.709	.709	.641
LCESM	.617	1.000	.935	.716	.608
EPEWC	.740	.825	1.000	1.000	.650
ESBST	.878	.633	.662	.872	1.000
Balanced					
EVWHD	1.000	.696	.637	.726	.852
GSWCL	.851	.691	.720	.720	.637
LCESM	.610	1.000	.932	.714	.604
EPEWC	.721	.823	1.000	1.000	.620
ESBST	.874	.621	.648	.874	1.000

Table A.21
Weighted decision matrix by the case-based assessments.

	CRCLT	UAMTR	CWEMI	SFETY	SWHYS
NEGATIVE					
EVWHD	.222	.132	.115	.135	.166
GSWCL	.192	.132	.145	.135	.108
LCESM	.088	.187	.178	.108	.077
EPEWC	.156	.161	.206	.192	.108
ESBST	.192	.104	.115	.166	.193
POSITIVE					
EVWHD	.211	.114	.101	.121	.144
GSWCL	.160	.114	.123	.121	.093
LCESM	.088	.191	.156	.099	.079
EPEWC	.126	.145	.205	.202	.093
ESBST	.160	.094	.101	.153	.190
UNSTABLE					
EVWHD	.202	.189	.184	.190	.195
GSWCL	.198	.189	.190	.190	.183
LCESM	.180	.199	.196	.184	.177
EPEWC	.192	.195	.200	.200	.183
ESBST	.198	.183	.184	.196	.199
NATURAL					
EVWHD	.207	.166	.156	.169	.182
GSWCL	.191	.166	.172	.169	.152
LCESM	.144	.196	.187	.154	.137
EPEWC	.175	.181	.202	.199	.152
ESBST	.191	.151	.156	.184	.197

Table A.22
Weighted decision matrix by the parameter-based assessments.

	CRCLT	UAMTR	CWEMI	SFETY	SWHYS
Maximum variance					
EVWHD	.208	.146	.132	.154	.171
GSWCL	.185	.149	.156	.157	.131
LCESM	.123	.196	.183	.141	.116
EPEWC	.154	.167	.200	.202	.122
ESBST	.183	.126	.132	.179	.194
Maximum entropy					
EVWHD	.204	.129	.125	.143	.159
GSWCL	.171	.130	.142	.143	.120
LCESM	.127	.197	.193	.149	.118
EPEWC	.141	.155	.203	.204	.113
ESBST	.176	.117	.128	.176	.192
Maximum resistance					
EVWHD	.205	.136	.133	.146	.163
GSWCL	.173	.133	.145	.143	.124
LCESM	.127	.195	.191	.144	.117
EPEWC	.152	.161	.205	.202	.125
ESBST	.180	.124	.136	.176	.193
Balanced					
EVWHD	.206	.137	.129	.147	.165
GSWCL	.175	.136	.146	.146	.123
LCESM	.125	.196	.189	.145	.117
EPEWC	.148	.162	.203	.202	.120
ESBST	.180	.122	.131	.177	.193

Table A.23
SAW, WPN, and combining scores by the case-based assessments.

	SAW	WPN	Combining scores ($\gamma = 0.5$)
NEGATIVE			
EVWHD	.770	.683	.727
GSWCL	.711	.638	.675
LCESM	.638	.537	.587
EPEWC	.824	.729	.776
ESBST	.770	.678	.724
POSITIVE			
EVWHD	.691	.472	.581
GSWCL	.611	.427	.519
LCESM	.614	.407	.510
EPEWC	.772	.524	.648
ESBST	.698	.474	.586
UNSTABLE			
EVWHD	.960	.921	.940
GSWCL	.950	.911	.930
LCESM	.935	.897	.916
EPEWC	.970	.930	.950
ESBST	.959	.920	.940
NATURAL			
EVWHD	.880	.753	.817
GSWCL	.850	.729	.790
LCESM	.818	.696	.757
EPEWC	.909	.778	.844
ESBST	.879	.752	.816
OVERALL			
EVWHD	.846	.713	.780
GSWCL	.807	.683	.745
LCESM	.775	.646	.710
EPEWC	.885	.745	.815
ESBST	.847	.712	.780

Table A.24
SAW, WPN, and combining scores by the parameter-based assessments.

	SAW	WPN	Combining scores ($\gamma = 0.5$)
Maximum variance			
EVWHD	.811	.720	.766
GSWCL	.780	.697	.739
LCESM	.760	.666	.713
EPEWC	.845	.747	.796
ESBST	.814	.720	.767
Maximum entropy			
EVWHD	.760	.648	.704
GSWCL	.706	.609	.658
LCESM	.785	.666	.725
EPEWC	.816	.692	.754
ESBST	.790	.671	.730
Maximum resistance			
EVWHD	.784	.681	.732
GSWCL	.717	.628	.672
LCESM	.775	.667	.721
EPEWC	.845	.733	.789
ESBST	.808	.700	.754

(*continued on next page*)

Table A.24
(*continued*)

	SAW	WPN	Combining scores ($\gamma = 0.5$)
Balanced			
EVWHD	.783	.682	.732
GSWCL	.725	.637	.681
LCESM	.772	.666	.719
EPEWC	.835	.725	.780
ESBST	.803	.697	.750
Overall			
EVWHD	.782	.679	.731
GSWCL	.723	.634	.678
LCESM	.774	.666	.720
EPEWC	.835	.723	.779
ESBST	.804	.696	.750

Table A.25
Comparative ranking results of the alternatives by the case-based assessments with the different combination parameters.

	$\gamma = 0$	$\gamma = 0.1$	$\gamma = 0.2$	$\gamma = 0.3$	$\gamma = 0.4$	$\gamma = 0.5$	$\gamma = 0.6$	$\gamma = 0.7$	$\gamma = 0.8$	$\gamma = 0.9$	$\gamma = 1$
Negative											
EVWHD	2	2	2	2	2	2	2	2	2	2	2
GSWCL	4	4	4	4	4	4	4	4	4	4	4
LCESM	5	5	5	5	5	5	5	5	5	5	5
EPEWC	1	1	1	1	1	1	1	1	1	1	1
ESBST	3	3	3	3	3	3	3	3	3	3	3
Positive											
EVWHD	3	3	3	3	3	3	3	3	3	3	3
GSWCL	4	4	4	4	4	4	4	4	4	4	4
LCESM	5	5	5	5	5	5	5	5	5	5	5
EPEWC	1	1	1	1	1	1	1	1	1	1	1
ESBST	2	2	2	2	2	2	2	2	2	2	2
Unstable											
EVWHD	2	2	2	2	2	2	2	2	2	2	2
GSWCL	4	4	4	4	4	4	4	4	4	4	4
LCESM	5	5	5	5	5	5	5	5	5	5	5
EPEWC	1	1	1	1	1	1	1	1	1	1	1
ESBST	3	3	3	3	3	3	3	3	3	3	3
Natural											
EVWHD	2	2	2	2	2	2	2	2	2	2	2
GSWCL	4	4	4	4	4	4	4	4	4	4	4
LCESM	5	5	5	5	5	5	5	5	5	5	5
EPEWC	1	1	1	1	1	1	1	1	1	1	1
ESBST	3	3	3	3	3	3	3	3	3	3	3
Overall											
EVWHD	3	3	3	3	3	3	3	3	3	3	3
GSWCL	4	4	4	4	4	4	4	4	4	4	4
LCESM	5	5	5	5	5	5	5	5	5	5	5
EPEWC	1	1	1	1	1	1	1	1	1	1	1
ESBST	2	2	2	2	2	2	2	2	2	2	2

References

Ajibade, H., Ujah, C.O., Nnakwo, K.C., Kallon, D.V. (2024). Improvement in battery technologies as panacea for renewable energy crisis. *Discover Applied Sciences*, 6(7), 374.

Altiparmak, S.O., Waters, K., Thies, C.G., Shutters, S.T. (2025). Cornering the market with foreign direct investments: China's cobalt politics. *Renewable and Sustainable Energy Transition*, 7, 100113.

Bican, P.M., Caspary, D., Guderian, C.C. (2023). Cross-border dynamics of IP modularity: international patenting in LEDs and lithium-ion secondary battery technology. *Management International Review*, 63(2), 347–376.

Chakraborty, S., Zavadskas, E.K. (2014). Applications of WASPAS method in manufacturing decision making. *Informatica*, 25(1), 1–20.

Daniarta, S., Kolasiński, P., Imre, A.R. (2024). Performance map and theoretical analysis of Carnot battery technology via novel reversible Rankine-based cycle. *Energy Reports*, 11, 4500–4514.

De Luca, G., Magnus, J.R., Peracchi, F. (2023). Weighted-average least squares (WALS): confidence and prediction intervals. *Computational Economics*, 61(4), 1637–1664.

Deb, P.P., Bhattacharya, D., Chatterjee, I., Chatterjee, P., Zavadskas, E.K. (2023). An intuitionistic fuzzy consensus WASPAS method for assessment of open-source software learning management systems. *Informatica*, 34(3), 529–556.

Denisart, L., Troncoso, J.F., Loup-Escande, E., Franco, A.A. (2024). Breaking down the barriers between the digital and the real: mixed reality applied to battery manufacturing R&D and training. *Batteries & Supercaps*, 7(7), e202400042.

Dhairiyasamy, R., Gabiriel, D., Bunpheng, W., Kit, C.C. (2024). A comprehensive analysis of India's electric vehicle battery supply chain: barriers and solutions. *Discover Sustainability*, 5(1), 361.

Du, R. (2024). Studying the impact of investments in critical minerals and energy transition in transportation sector in Asia. *Resources Policy*, 96, 105227.

Etxandi-Santolaya, M., Casals, L.C., Montes, T., Corchero, C. (2023). Are electric vehicle batteries being underused? A review of current practices and sources of circularity. *Journal of Environmental Management*, 338, 117814.

Fahma, F., Sutopo, W., Pujiyanto, E., Nizam, M. (2024). Dynamic open innovation to determine technology-based interoperability requirement for electric motorcycle swappable battery. *Journal of Open Innovation: Technology, Market, and Complexity*, 10(2), 100259.

Kim, J., Kim, Z., Lee, D.H. (2024). Prediction of the emergence of solid-state battery technology in the post-lithium ion battery era: a patent-based approach. *International Journal of Green Energy*, 21(6), 1210–1225.

Kutlu Gundogdu, F., Kahraman, C. (2019). Extension of WASPAS with spherical fuzzy sets. *Informatica*, 30(2), 269–292.

Lyu, R., Zhang, C., Li, Z., Zou, X. (2023). Impact of rexatory intervention on green technology and innovation investment of the NEV automaker. *Computers & Industrial Engineering*, 184, 109439.

Maher, K., Boumaiza, A. (2024). October. Qatar's energy future: challenges and opportunities in Lithium-Ion battery technology. In: *2024 12th International Conference on Smart Grid and Clean Energy Technologies (ICSGCE)*. IEEE, pp. 60–65.

Mohseni, P., Husev, O., Vinnikov, D., Strzelecki, R., Romero-Cadaval, E., Tokarski, I. (2023). Battery technologies in electric vehicles: improvements in electric battery packs. *IEEE Industrial Electronics Magazine*, 17(4), 55–65.

Moyo, T., Onososen, A.O., Musonda, I., Muzioreva, H. (2023). Advancements in E-mobility: a bibliometric literature review on battery technology, charging infrastructure, and energy management. In: *Smart and Resilient Infrastructure For Emerging Economies: Perspectives on Building Better*, pp. 82–89.

Naseri, F., Gil, S., Barbu, C., Cetkin, E., Yarimca, G., Jensen, A.C., Larsen, P.G., Gomes, C. (2023). Digital twin of electric vehicle battery systems: comprehensive review of the use cases, requirements, and platforms. *Renewable and Sustainable Energy Reviews*, 179, 11328.

Overbeck, L., Voigtländer, S., Lanza, G. (2023). Optimal line configurations for agile production systems for battery cell manufacturing. *Procedia CIRP*, 118, 976–981.

Pesaran, A.A. (2023). Lithium-ion battery technologies for electric vehicles: progress and challenges. *IEEE Electrification Magazine*, 11(2), 35–43.

Plante, M. (2025). Investing in the batteries and vehicles of the future: a view through the stock market. *Energy Economics*, 143, 108216.

Rankin, J., Bedrava, J., Covington, E., Johnson, J.L., Pollard-Larkin, J., Schipper, M.J., Castillo, R., Woodward, M., Xing, Paradis K. C, Y.-H. (2024). Women in the medical physics workforce: insights from membership trends of the American Association of Physicists in Medicine, 1993 to 2023. *International Journal of Radiation Oncology, Biology, Physics*, 119(5), 1336–1343.

Rizos, V., Urban, P. (2024). Barriers and policy challenges in developing circularity approaches in the EU battery sector: an assessment. *Resources, Conservation and Recycling*, 209, 107800.

Schulz-Mönninghoff, M., Neidhardt, M., Niero, M. (2023). What is the contribution of different business processes to material circularity at company-level? A case study for electric vehicle batteries. *Journal of Cleaner Production*, 382, 135232.

Şensoy, N. (2023). Determination of optimal battery and renewable capacity investment for hybrid energy storage systems. In: *2023 19th International Conference on the European Energy Market (EEM)*. IEEE, pp. 1–6.

Shaji, K.M., Dudhe, R., Alex, A.F. (2023). Neoteric innovations concerning battery technology and lubricants for electric vehicles. In: *2023 Advances in Science and Engineering Technology International Conferences (ASET)*. IEEE, pp. 1–6.

Suhail, A.H., Guangul, F.M., Nazeer, A. (2024). Pushing boundaries: advancements and challenges in electric vehicle battery technology. In: *Solving Fundamental Challenges of Electric Vehicles*. IGI Global, pp. 282–313.

Vásquez, L.O.P., Chavarría-Hernández, J.C., Trinidad, A.A., Ordóñez-López, L.C., Sosa, S.F., Pool, P.Y.C., Barrera-Cabrera, J.N. (2025). Life cycle assessment of electric and gasoline moto-taxis in Yucatán, México: impact of battery technology and social considerations. *Energy for Sustainable Development*, 85, 101614.

Wang, H., Dai, J., Wei, H., Lu, Q. (2023). Understanding technological innovation and evolution of energy storage in China: spatial differentiation of innovations in lithium-ion battery industry. *Journal of Energy Storage*, 66, 107307.

Watabe, A., Leaver, J. (2023). Transitioning to battery electric vehicles in Japan: impact of promotion policy, battery performance and carbon neutrality on greenhouse gas emissions reduction. *Journal of Cleaner Production*, 430, 13968.

Yalcin Kavus, B., Ayyildiz, E., Gulum Tas, P., Taskin, A. (2023). A hybrid Bayesian BWM and Pythagorean fuzzy WASPAS-based decision-making framework for parcel locker location selection problem. *Environmental Science and Pollution Research*, 30(39), 90006–90023.

Yang, H., Fulton, L. (2023). Decoding US investments for future battery and electric vehicle production. *Transportation Research Part D: Transport and Environment*, 118, 103693.

Zavadskas, E.K., Turskis, Z., Antucheviciene, J., Zakarevicius, A. (2012). Optimization of weighted aggregated sum product assessment. *Elektronika ir elektrotechnika*, 122(6), 3–6.

Zeng, Z., Qu, X. (2023). What's next for battery-electric bus charging systems. *Communications in Transportation Research*, 3, 100094.

Zhao, X., Wu, W., Wu, D. (2024). Technological trajectory analysis in lithium battery manufacturing: based on patent claims perspective. *Journal of Energy Storage*, 98, 112894.

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