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The Future of Energy Storage in Vietnam: A Fuzzy Multi-Criteria Decision-Making Approach to Metal-Ion Battery Assessments

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Abstract: Lithium-ion (Li-ion) batteries, despite their prevalence, face issues of resource scarcity and environmental concerns, prompting the search for alternative technologies. This study addresses the need to assess and identify viable metal-ion battery alternatives to Li-ion batteries, focusing on the rapidly industrializing context of Vietnam. It acknowledges the criticality of developing a sustainable, cost-effective, and resource-efficient energy storage solution that aligns with the country's growth trajectory. The primary objective is to evaluate the suitability of emerging metal-ion batteries—specifically sodium-ion (SIB), sodium-ion saltwater (SIB-S), magnesium-ion (MIB), and zinc-ion (ZIB)—for Vietnam's energy storage needs, guiding future investment and policy decisions. A Fuzzy Multiple-Criteria Decision-Making (MCDM) approach is employed, incorporating both quantitative and qualitative criteria. This study utilizes the Fuzzy Best-Worst Method (BWM) to determine the relative importance of various performance indicators and then applies the Bonferroni Fuzzy Combined Compromise Solution (Bonferroni FCoCoSo) method to rank the battery alternatives. The SIBs emerged as the most promising alternative, scoring the highest in the overall evaluation. The MIBs and SIB-saltwater batteries displayed competitive potential, while the ZIBs ranked the lowest among the considered options. This research provides a strategic framework for energy policy formulation and investment prioritization. It contributes to the field by applying a fuzzy-based MCDM approach in a novel context and offers a structured comparative analysis of metal-ion batteries, enhancing the body of knowledge on sustainable energy storage technologies.

Keywords: metal-ion batteries; fuzzy theory; multiple-criteria decision making; Best-Worst Method; Vietnam; technologies

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1. Introduction

The global energy sector is experiencing profound changes, necessitated by the urgent demand for sustainable and efficient energy storage technologies [1]. Leading this shift, lithium-ion batteries (LIBs) have been pivotal due to their remarkable energy capacity, durability, and adaptability, powering a wide array of devices and systems from handheld gadgets to electric vehicles and energy grids [2]. Yet, the widespread use of Li-ion batteries faces significant hurdles, including the scarcity of lithium, environmental concerns related to its extraction, safety risks, and high costs, prompting the exploration of alternative energy storage options [3,4]. Metal-ion batteries, such as sodium-ion (SIB), sodium-ion saltwater (SIB-S), magnesium-ion (MIB), and zinc-ion (ZIB) variants, emerge as viable contenders [1]. These alternatives boast advantages like resource abundance, cost-effectiveness, safer operation, and lower environmental impacts, making them appealing for addressing the increasing demand for energy storage solutions [4,5].

Vietnam's rapid industrialization journey is at a crossroads, faced with the pressing need to develop a secure, environmentally friendly, and self-reliant energy infrastructure [6]. This infrastructure is crucial to support the nation's expanding manufacturing and technological sectors [7]. As Vietnam strides forward, the exploration and adoption of innovative energy technologies become paramount. Among these technologies, metal-ion batteries stand out as a sustainable alternative, promising to catalyze industrial progress and fulfill sustainability aspirations [8]. This shift not only aims to reduce Vietnam's dependency on LIBs, but also sets the stage for a broader movement towards energy independence, aligning with global sustainability trends and local industrial demands.

Our research aims to rigorously identify and evaluate alternative metal-ion battery technologies beyond conventional Li-ion batteries with the goal of meeting the specific industrial needs of Vietnam in the near future. This task is encumbered by a wide range of factors, including economic viability, environmental implications, technological maturity, and societal acceptance, all of which are crucial in shaping the nation's energy direction. To adeptly maneuver through this multifaceted challenge, Multiple-Criteria Decision Making (MCDM) is employed as the analytical backbone. By using MCDM, a detailed evaluation of alternatives against a broad array of criteria is enabled, facilitating structured and insightful decision making in complex scenarios. At the core of our inquiry is the determination of how criteria that are critical for assessing the suitability of metal-ion batteries for Vietnam's industrial landscape can be effectively quantified and prioritized, while the congruence between Vietnam's current research and investment efforts and the potential of these burgeoning battery technologies is also gauged. In response to this inquiry, a cutting-edge fuzzy-based MCDM approach is proposed, designed to conduct an exhaustive analysis, comparison, and selection of the most viable metal-ion battery technologies for Vietnam. More than a mere search for a technological substitute, this methodology represents a strategic blueprint aiming to establish Vietnam as a frontrunner in the adoption of sustainable energy technologies by 2030.

This article is structured as follows: Section 1 introduces this study, setting the context and outlining the motivation behind exploring alternative metal-ion batteries for Vietnam. Section 2 provides a comprehensive literature review, examining the existing research on metal-ion batteries and their potential applications. Section 3 describes the methodology, detailing the fuzzy-based MCDM approach used for the evaluation. Section 4 presents the numerical results and discussion, interpreting the findings in the context of Vietnam's industrial and energy landscape. Section 5 provides the managerial implications of this study. Finally, Section 6 concludes this study, summarizing the key insights and suggesting directions for future research and policy-making.

2. Literature Review

2.1. Metal-Ion Battery Studies

Recent advancements in battery technology underscore the pivotal role of metal-ion batteries in the transition towards sustainable energy systems [9,10]. A synthesis of the literature reveals a dynamic field focused on addressing the limitations of lithium-ion (Li-ion) batteries and exploring alternative metal-ion technologies, such as sodium (Na), magnesium (Mg), and zinc (Zn)-based systems. The collective research efforts aim to enhance battery performance, safety, and sustainability, reflecting a concerted push towards more efficient and environmentally friendly energy storage solutions.

Zhan et al. (2018) and Chen et al. (2021) both emphasize the challenges and opportunities in developing cathode materials for Li-ion and multivalent metal-ion batteries, respectively [11,12]. Zhan et al. highlight the issues of capacity and power fading in TM-based cathodes due to the dissolution–migration–deposition (DMD) process, stressing the need for innovative solutions to prolong battery life [11]. Similarly, Chen et al. discuss the slow solid-state diffusion and desolvation processes at the cathode/electrolyte interface in multivalent metal-ion batteries, pointing out the necessity for advancements in cathode material development to unlock the full potential of these technologies for grid-scale energy storage [12].

Machine learning (ML) emerges as a transformative tool in accelerating material discovery for battery applications, as demonstrated by Joshi et al. [13]. Their work showcases the predictive capabilities of ML models in identifying candidate electrode materials, thereby facilitating a more efficient screening process. This computational approach complements the experimental strategies discussed by Liang et al. (2020) and Verma and Kumar (2021), who reviewed the strengths and limitations of multivalent metal-based batteries and assessed their suitability for electric vehicle (EV) applications [14,15]. The discussions around anode growth behavior, storage mechanisms, and comparative analyses of battery types underline the complexity and multidimensional nature of battery technology development. Furthermore, the exploration of sustainable materials, particularly carbon anodes derived from biomass, as reviewed by Soltani et al. in 2021, aligns with the broader goal of reducing the environmental footprint of battery systems [16]. This research direction not only addresses the scarcity of lithium but also opens up avenues for utilizing abundant materials like Na and K, offering a path towards more sustainable and ethically responsible battery technologies.

Additionally, the focus on production efficiency and environmental impact, as explored by Degen and Krätzig (2022) and Zhao et al. (2023), highlights the significance of manufacturing innovations and material engineering in enhancing battery performance [17,18]. The push towards dry coating technologies and the rational design of metal tellurides reflect an industry striving for cost reduction, energy savings, and improved electrochemical performance.

Despite the significant strides made in metal-ion battery research, a notable gap persists in the comprehensive evaluation of these batteries' suitability across different applications, particularly in emerging markets like Vietnam. While existing studies extensively cover material innovations, the adoption of machine learning for material discovery, and the exploration of sustainable and efficient production methods, there remains a scarcity of research focusing on integrating these advancements within specific industrial and environmental contexts of developing economies.

2.2. Multiple-Criteria Decision-Making Studies and Applications

MCDM is a vital approach employed in various fields to tackle complex decision-making scenarios characterized by the presence of multiple and often conflicting objectives or criteria [19]. It encompasses a diverse range of methodologies designed to aid decision makers in selecting the most suitable alternative from a set of available options. MCDM techniques enable decision makers to systematically evaluate and prioritize alternatives based on multiple criteria, taking into account various factors such as preferences, constraints, and uncertainties. By providing structured frameworks for decision analysis, MCDM facilitates informed and rational decision-making processes across diverse domains, including business, engineering, healthcare, and environmental management [20–23].

Over the past decade, a notable trend in research has been the integration of Multiple MCDM methods, capitalizing on their unique strengths [24]. This shift has led to the development of multi-stage/multi-layer MCDM approaches or frameworks, particularly in the domain of location selection problems. These comprehensive frameworks typically comprise various stages, including the primary phase, criteria weighting phase, and alternative prioritization phase, each serving distinct purposes [25]. In the primary phase, tasks often entail defining a group of decision makers, selecting relevant criteria, and systematically narrowing down the list of potential alternatives. As for the criteria weighting phase, traditional MCDM methods like the Analytic Hierarchy Process (AHP) have long been favored for analyzing the relative importance of criteria based on comparisons made by decision makers [26]. However, in 2015, the introduction of the Best-Worst Method (BWM) by Rezaei marked a significant advancement in this domain, offering enhanced convenience and effectiveness compared to the AHP [27]. The BWM's advantages lie in its reduced requirement for pairwise comparisons and its ability to provide optimal weights and consistency in comparisons due to its mathematical model foundation [28]. Furthermore, in 2017, H. Ashkan and H. Arian proposed a fuzzy extended version of BWM tailored for group decision-making problems, further expanding the method's applicability [29]. When it comes to prioritizing alternatives, distance-based MCDM methods such as Evaluation Based on Distance from Average Solution (EDAS), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), and Combinative Distance based Assessment (CODAS) have emerged as popular choices among analysts [30–34]. More recently, the Combined Compromise Solution (CoCoSo) method, rooted in compromise solutions principles, has emerged as a promising alternative for prioritization in MCDM problems [35]. Additionally, researchers have developed a hybrid approach known as Bonferroni FCoCoSo, combining the CoCoSo method with normalized weighted geometric Bonferroni mean functions to address fuzzy environments [28]. This combination not only reveals interrelationships between criteria but also provides compromise solutions for Fuzzy CoCoSo.

The application of MCDM techniques highlights a methodological framework for addressing complex decision-making scenarios that involve multiple and often conflicting objectives or criteria. Despite the development of sophisticated MCDM methodologies, including the integration of fuzzy logic and the BWM for enhanced decision-making accuracy and efficiency, the application of these advanced MCDM approaches to the specific context of metal-ion battery selection and implementation in developing countries like Vietnam has not been thoroughly investigated. This presents a critical research gap, underscoring the need for studies that not only apply MCDM techniques to evaluate the suitability of metal-ion batteries but also consider the unique industrial growth patterns, resource availability, and sustainability goals of such regions.

3. Methodology

In this section, as shown in Figure 1, the proposed methodology employs the fuzzy-based MCDM approach to systematically prioritize metal-ion battery technologies for the Vietnamese industry. The process initiates with the formulation of a problem statement that clearly defines the scope and objectives of the research. Following this, a comprehensive literature review is conducted to gather existing knowledge in the field, identify the state of the art, and discern the research gaps that the study aims to address.

Subsequently, experts from Vietnam's industry with relevant domain knowledge are identified to contribute to the study. Their insights are pivotal for the next step, which is the identification of criteria. These criteria, derived from the literature review and expert consultations, serve as the benchmarks against which metal-ion batteries will be evaluated. Interviews with the identified experts are then conducted to obtain qualitative insights and to validate the criteria, ensuring they are both comprehensive and pertinent to the context of the study. The process continues with a linguistic pairwise comparison of the criteria, employing the best-worst approach. This step allows for the assessment of the relative importance of each criterion as viewed by the experts. The Fuzzy Best-Worst Method (Fuzzy BWM) is then applied to determine the optimized weights for each criterion. This method uses fuzzy linguistic comparisons to derive a consistent and representative weighting scheme.

The data collection phase follows, gathering both quantitative and qualitative data relevant to the identified criteria. Depending on the nature of the collected data, two distinct conversion paths are taken. If the data are numerical, they are converted into Triangular Fuzzy Numbers (TriFN) based on their maximum and minimum values. This fuzzy conversion accommodates the uncertainty and imprecision inherent in real-world data. For non-numerical data, a similar conversion to TriFN is performed, but it is based on a predefined linguistic scale, as shown in Table 1. This allows for qualitative assessments to be quantitatively analyzed within the fuzzy framework.

Table 1. The Fuzzy BWM linguistic pairwise comparison and consistency indices (CIs).

Linguistic Pairwise Comparison	TriFNs	CIs
Equally significant (ES)	(1.00, 1.00, 1.00)	3.00
Slightly significant (SS)	(0.67, 1.00, 1.50)	3.80
Moderately significant (MS)	(1.50, 2.00, 2.50)	5.29
Highly significant (HS)	(2.50, 3.00, 3.50)	6.69
Very significant (VS)	(3.50, 4.00, 5.50)	8.04
Exceptionally significant (ES)	(4.50, 5.00, 5.50)	9.35

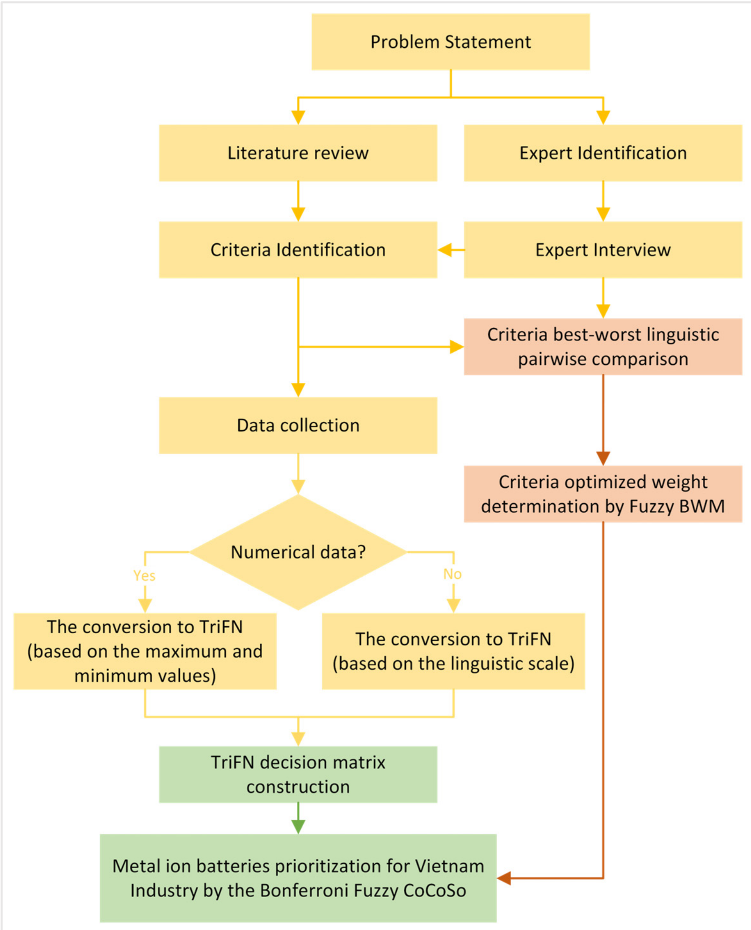

Figure 1. The proposed framework.

With the data converted into a fuzzy format, a TriFN decision matrix is constructed. This matrix is a fuzzy representation of the performance of each metal-ion battery alternative against the set criteria. Finally, this study utilizes the Bonferroni Fuzzy Combined Compromise Solution (Bonferroni Fuzzy CoCoSo) method to prioritize metal-ion battery alternatives for the Vietnamese industry. By integrating the fuzzy decision matrix with the derived criteria weights, the Bonferroni Fuzzy CoCoSo method systematically evaluates each alternative, leading to a prioritization that reflects the nuanced trade-offs and synergies among the criteria. The detailed procedures of the Fuzzy BWM and Bonferroni Fuzzy CoCoSo methods are presented in the sections below.

3.1. The Fuzzy Theory and Triangular Fuzzy Number

In order to enhance decision-making processes, particularly in contexts characterized by uncertainty, the integration of fuzzy numbers plays a pivotal role within MCDM methodologies. Fuzzy numbers are leveraged not only for the weighting of criteria but also for the prioritization of alternatives, offering a nuanced approach that accommodates imprecise or vague information that is inherent in complex decision scenarios. This utilization of fuzzy numbers facilitates a more comprehensive and flexible decision-making framework, allowing decision makers to account for uncertainty and ambiguity more effectively [36,37].

Definition 1. *A fuzzy number* $\widetilde{r}$ *is characterized as a function* $f(R)$*, where* $\widetilde{r}$ *is defined by* $\left[x, \xi_{\widetilde{r}_\mu}(x) \geq \alpha\right]$ *and constitutes a closed interval for any* $\alpha \in [0,1]$*; there must be an* $x_0 \in R$ *such that* $\xi_{\widetilde{r}}(x_0) = 1$*. Here,* $\xi_{\widetilde{r}}(x)$*,* R*, and* $f(R)$ *denote the fuzzy membership function, the set of real numbers, and the fuzzy set, respectively.*

Definition 2. *A triangular fuzzy number (TriFN) is indicated by* $\widetilde{r} = (x, y, z)$*, with* x, y*, and* z *being the lower, middle, and upper values of the TriFN* $\widetilde{r}$*, respectively. Consequently, the membership function of* $\widetilde{r}$ *can be expressed by Equation (1) [38].*

$$\xi_{\widetilde{r}}(t) = \begin{cases} \frac{t-x}{y-x}, & x \leq t < y \\ \frac{z-t}{z-y}, & y \leq t \leq z \\ 0, & otherwise \end{cases} \tag{1}$$

Definition 3. *Consider two TriFNs,* $\widetilde{r}_1 = (x_1, y_1, z_1)$ *and* $\widetilde{t}_2 = (x_2, y_2, z_2)$*, where the basic arithmetic operations with any real number* $\mu > 0$ *are defined by Equations (2)–(7) [39].*

$$\widetilde{r}_1 \oplus \widetilde{r}_2 = (x_1 + x_2, y_1 + y_2, z_1 + z_2) \tag{2}$$

$$\widetilde{r}_1 \otimes \widetilde{r}_2 = (x_1 \times x_2, y_1 \times y_2, z_1 \times z_2) \tag{3}$$

$$\widetilde{r}_1 \ominus \widetilde{r}_2 = (x_1 - z_2, y_1 - y_2, z_1 - x_2) \tag{4}$$

$$\widetilde{r}_1 \oslash \widetilde{r}_2 = (x_1 \div z_2, y_1 \div y_2, z_1 \div x_2) \tag{5}$$

$$\widetilde{r}_1^{\,-1} = \left(\frac{1}{z_1}, \frac{1}{y_1}, \frac{1}{x_1}\right) \tag{6}$$

$$\mu \widetilde{r}_1 = (\mu x_1, \mu y_1, \mu z_1) \tag{7}$$

Definition 4. *The process of converting TriFNs into a crisp value* $\left(CV\left(\widetilde{r}\right)\right)$ *is achieved through the graded mean as follows [40]:*

$$CV\left(\widetilde{r}\right) = \frac{x + 4y + z}{6} \tag{8}$$

3.2. The Fuzzy BWM

The Best-Worst Method (BWM) was initially established to ascertain the weights of criteria based on a non-linear mathematical model [27]. The BWM is indeed inspired by and built upon the foundational principles of decision-making frameworks, including the AHP developed by Thomas L. Saaty [41]. In 2017, S. Guo and H. Zhao advanced the BWM by incorporating a TriFN [42]. The enhanced version, termed the Fuzzy BWM, can be executed in a series of steps:

Step 1: Designate decision makers as DM_k, where k is from 1 to K.

Step 2: Pinpoint the criteria or indicators from the literature or through suggestions from decision makers, labeled as IN_j, where j is from 1 to J.

Step 3: Determine the worst criterion (C_q) and the best criterion (C_p) for each decision maker.

Step 4: Develop linguistic comparisons of C_p against all other criteria by each decision maker. Then, convert these linguistic assessments into TriFNs based on the relationships depicted in Table 1. This conversion creates the fuzzy preference vector for the kth decision maker, symbolized as $\overset{\sim k}{T}_p = \left(\overset{\sim k}{t}_{p1}, \overset{\sim k}{t}_{p2}, \ldots, \overset{\sim k}{t}_{pj}, \ldots, \overset{\sim k}{t}_{pJ}\right)$ with $\overset{\sim k}{t}_{pj} = \left(x^k_{pj}, y^k_{pj}, z^k_{pj}\right)$. It is clear that $\overset{\sim k}{t}_{pp} = (1,\ 1,\ 1)$.

Step 5: Analogous to step 4, the fuzzy anti-preference vector $\tilde{T}_q$ is formed to compare other criteria against the worst criterion (C_q). Thus, the fuzzy anti-preference vector for the kth decision maker can be articulated as $\overset{\sim k}{T}_q = \left(\overset{\sim k}{t}_{1q}, \overset{\sim k}{t}_{2q}, \ldots, \overset{\sim k}{t}_{jq}, \ldots, \overset{\sim k}{t}_{Jq}\right)$, with $\overset{\sim k}{t}_{jq} = \left(x^k_{jq}, y^k_{jq}, z^k_{jq}\right)$ and $\overset{\sim k}{t}_{qq} = (1,\ 1,\ 1)$.

Step 6: Assume that the optimal value γ^{k*} is represented by a TriFN, $\gamma^{k*} = \left(\sigma^{k*}, \sigma^{k*}, \sigma^{k*}\right)$ and $\gamma^k = \left(x^{k\gamma}, y^{k\gamma}, z^{k\gamma}\right)$, with the condition that $\sigma^{k*} \le x^{k\gamma}$. The fuzzy weights ($\overset{\sim k}{w}_j$) for the jth criterion according to the kth decision maker are calculated by solving the fuzzy non-linear programming model (9) to ascertain the optimal value of γ^{k*} [42].

$$
\begin{array}{ll}
 & subjectto: \\
Minimize\gamma^{k*} & \begin{array}{ll}
\left|\dfrac{\left(x^k_p, y^k_p, z^k_p\right)}{\left(x^k_j, y^k_j, z^k_j\right)} - \left(x^k_{pj}, y^k_{pj}, z^k_{pj}\right)\right| \le \left(\sigma^{k*}, \sigma^{k*}, \sigma^{k*}\right) & j = 1, 2, \ldots, J \\
\left|\dfrac{\left(x^k_j, y^k_j, z^k_j\right)}{\left(x^k_q, y^k_q, z^k_q\right)} - \left(x^k_{jq}, y^k_{jq}, z^k_{jq}\right)\right| \le \left(\sigma^{k*}, \sigma^{k*}, \sigma^{k*}\right) & j = 1, 2, \ldots, J \\
0 \le x^k_j \le y^k_j \le z^k_j & j = 1, 2, \ldots, J \\
0 \le x^k_p \le y^k_p \le z^k_p & \\
0 \le x^k_q \le y^k_q \le z^k_q &
\end{array}
\end{array}
\tag{9}
$$

where $\overset{\sim k}{w}_j = \left(x^k_j, y^k_j, z^k_j\right)$, $\overset{\sim k}{w}_p = \left(x^k_p, y^k_p, z^k_p\right)$, $\overset{\sim k}{w}_\beta = \left(x^k_q, y^k_q, z^k_q\right)$, $\overset{\sim k}{t}_{pj} = \left(x^k_{pj}, y^k_{pj}, z^k_{pj}\right)$, and $\overset{\sim k}{t}_{jq} = \left(x^k_{jq}, y^k_{jq}, z^k_{jq}\right)$.

Step 7: Check the consistency ratio (CRA^k) according to Equation (10) based on the given consistency index (CI) value, as shown in Table 1. The linguistic comparisons made by the kth decision maker are deemed consistent if the consistency ratio CRA^k is less than or equal to 0.1.

$$CRA^k = \frac{\gamma^{k*}}{CI} \tag{10}$$

Step 8: Compile the criteria weights from all decision makers using Equation (11).

$$\tilde{w}_j = \frac{1}{K}\sum_{k=1}^{K} \overset{\sim k}{w}_j \; j = 1, 2, \ldots, J \tag{11}$$

Step 9: Convert the fuzzy weights ($\tilde{w}_j$) into crisp weights (w_j) according to Equation (8).

3.3. The Bonferroni Fuzzy CoCoSo Approach

In a divergent approach, drawing inspiration from M. Yazdani's CoCoSo methodology, M. Yazdani et al. enhanced this approach by integrating geometric Bonferroni mean functions specifically tailored to fuzzy environments [35]. This innovative amalgamation expands the applicability and efficacy of the CoCoSo method, particularly in scenarios characterized by uncertainty and imprecision, thereby offering a more robust decision-making framework suited for complex and dynamic environments. The steps for the method are as follows:

Step 1: Pinpoint the criteria or indicators from the literature or through suggestions from decision makers, labeled as A_i, where i is from 1 to I.

Step 2: Collect the data of the alternatives for each indicator or criterion.

Step 2a: If the data are numeric with the value set $[f^-, f^+]$, transform them into TriFN numbers according to Equations (12) and (13).

$$\overset{\sim k}{f}_{ij} = \left(x_{ij}^{(f)k}, y_{ij}^{(f)k}, z_{ij}^{(f)k}\right) \; i = 1, 2, \ldots, I; j = 1, 2, \ldots, J \tag{12}$$

$$\text{where } y_{ij}^{(f)k} = \frac{x_{ij}^{(f)k} + z_{ij}^{(f)k}}{2},\; x_{ij}^{(f)k} = f^-,\; z_{ij}^{(f)k} = f^+ \; i = 1, 2, \ldots, I; j = 1, 2, \ldots, J \tag{13}$$

Step 2b: Otherwise, transform the linguistic evaluations into TriFNs as the relationships shown in Table 2.

Table 2. Bonferroni Fuzzy CoCoSo linguistics corresponding to TriFNs.

Linguistic Evaluations	TriFNs
Very low (VL)	(1, 1, 2)
Low (L)	(1, 2, 3)
Moderate (M)	(2, 3, 4)
High (H)	(3, 4, 5)
Very high (VH)	(4, 5, 5)

Step 3: Construct the individual fuzzy decision matrices $\left(\overset{\sim k}{F}\right)$ as the results, expressed as Equations (14) and (15).

$$\overset{\sim k}{F} = \left[\overset{\sim k}{f}_{ij}\right] \; i = 1, 2, \ldots, I; j = 1, 2, \ldots, J \tag{14}$$

$$\text{where } \overset{\sim k}{f}_{ij} = \left(x_{ij}^{(f)k}, y_{ij}^{(f)k}, z_{ij}^{(f)k}\right) \; i = 1, 2, \ldots, I; j = 1, 2, \ldots, J \tag{15}$$

Step 4: Aggregate the fuzzy decision matrix $(\widetilde{F})$ based on the individual fuzzy decision matrices of K decision makers as Equations (16)–(20).

$$\widetilde{F} = \left[\widetilde{F}_{ij}\right] \; i = 1, 2, \ldots, I; j = 1, 2, \ldots, J \tag{16}$$

$$\text{where } \widetilde{f}_{ij} = \left(x_{ij}^{(f)}, y_{ij}^{(f)}, z_{ij}^{(f)}\right) \; i = 1, 2, \ldots, I; j = 1, 2, \ldots, J \tag{17}$$

$$x_{ij}^{(f)} = \sum_{k=1}^{K} x_{ij}^{(f)k} \; i = 1, 2, \ldots, I; j = 1, 2, \ldots, J \tag{18}$$

$$y_{ij}^{(f)} = \sum_{k=1}^{K} y_{ij}^{(f)k} \; i = 1, 2, \ldots, I; j = 1, 2, \ldots, J \tag{19}$$

$$z_{ij}^{(f)} = \sum_{k=1}^{K} z_{ij}^{(f)k} \; i = 1, 2, \ldots, I; j = 1, 2, \ldots, J \tag{20}$$

Step 4: Construct the normalized fuzzy decision matrix $(\widetilde{Y})$ as Equations (21)–(24).

$$\widetilde{G} = \left[\widetilde{g}_{ij}\right] \; i = 1, 2, \ldots, I; j = 1, 2, \ldots, J \tag{21}$$

$$\text{where } \widetilde{g}_{ij} = \left(x_{ij}^{(g)}, y_{ij}^{(g)}, z_{ij}^{(g)}\right) \; i = 1, 2, \ldots, I; j = 1, 2, \ldots, J \tag{22}$$

$$\text{For a benefical criterion } j\left(x_{ij}^{(g)}, y_{ij}^{(g)}, z_{ij}^{(g)}\right) = \left(\frac{x_{ij}^{(f)}}{\max\limits_{i}\left(z_{ij}^{(f)}\right)}, \frac{y_{ij}^{(f)}}{\max\limits_{i}\left(z_{ij}^{(f)}\right)}, \frac{z_{ij}^{(f)}}{\max\limits_{i}\left(z_{ij}^{(f)}\right)}\right) \tag{23}$$

$$\text{For a non} - \text{benefical criterion } j\left(x_{ij}^{(g)}, y_{ij}^{(g)}, z_{ij}^{(g)}\right) = \left(\frac{\min\limits_{i} x_{ij}^{(f)}}{z_{ij}^{(f)}}, \frac{\min\limits_{i} x_{ij}^{(f)}}{y_{ij}^{(f)}}, \frac{\min\limits_{i} x_{ij}^{(f)}}{x_{ij}^{(f)}}\right) \tag{24}$$

Step 5: The process involves computing the fuzzy weighted normalized geometric mean sequence $\left(G\widetilde{S}M_i\right)$ and the fuzzy weighted normalized arithmetic mean sequence $\left(A\widetilde{S}M_i\right)$ for alternatives. Determine these sequences utilizing Equations (25) and (26), which employ the fuzzy normalized weighted geometric Bonferroni mean function and the fuzzy normalized weighted Bonferroni mean function, respectively. This computational step enables the derivation of comprehensive evaluations for each alternative, accounting for their respective fuzzy weights and normalized values within the decision-making framework.

$$G\widetilde{S}M_i = \begin{pmatrix} \frac{1}{\alpha+\beta} \prod\limits_{\substack{j_1, j_2 = 1 \\ j_1 \neq j_2}}^{J} \left(\alpha x_{ij_1}^{(g)} + \beta x_{ij_2}^{(g)}\right)^{\frac{w_{j_1} w_{j_2}}{1 - w_{j_1}}}, \\ \frac{1}{\alpha+\beta} \prod\limits_{\substack{j_1, j_2 = 1 \\ j_1 \neq j_2}}^{J} \left(\alpha y_{ij_1}^{(g)} + \beta y_{ij_2}^{(g)}\right)^{\frac{w_{j_1} w_{j_2}}{1 - w_{j_1}}} \\ \frac{1}{\alpha+\beta} \prod\limits_{\substack{j_1, j_2 = 1 \\ j_1 \neq j_2}}^{J} \left(\alpha z_{ij_1}^{(g)} + \beta z_{ij_2}^{(g)}\right)^{\frac{w_{j_1} w_{j_2}}{1 - w_{j_1}}} \end{pmatrix} i = 1, 2, \ldots, I; \alpha, \beta \geq 0 \tag{25}$$

$$A\widetilde{S}M_i = \begin{pmatrix} \left(\sum\limits_{\substack{j_1, j_2 = 1 \\ j_1 \neq j_2}}^{J} \frac{w_{j_1} w_{j_2}}{1 - w_{j_1}} x_{ij_1}^{(g)\alpha} x_{ij_2}^{(g)\beta}\right)^{\frac{1}{\alpha+\beta}}, \\ \left(\sum\limits_{\substack{j_1, j_2 = 1 \\ j_1 \neq j_2}}^{J} \frac{w_{j_1} w_{j_2}}{1 - w_{j_1}} y_{ij_1}^{(g)\alpha} y_{ij_2}^{(g)\beta}\right)^{\frac{1}{\alpha+\beta}}, \\ \left(\sum\limits_{\substack{j_1, j_2 = 1 \\ j_1 \neq j_2}}^{J} \frac{w_{j_1} w_{j_2}}{1 - w_{j_1}} z_{ij_1}^{(g)\alpha} z_{ij_2}^{(g)\beta}\right)^{\frac{1}{\alpha+\beta}} \end{pmatrix} i = 1, 2, \ldots, I; \alpha, \beta \geq 0 \tag{26}$$

where α and β represent the stabilization parameters. The overall result may be altered by the stabilization parameter changes. They are suggested with a value of 1 $(\alpha = \beta = 1)$ [43]. w_j represents the criteria weight.

Step 6: Defuzzy the fuzzy weighted geometric mean sequence $\left(G\widetilde{S}M_i\right)$ and the fuzzy arithmetic mean sequence $\left(A\widetilde{S}M_i\right)$ into the crisp weighted geometric mean sequence (GSM_i) and the crisp fuzzy arithmetic mean sequence (ASM_i) according to Equation (8).

Step 7: Determine the additive normalized importance (δ_i), the relative importance (ω_i), and the trade-off importance (ϑ_i) of both the fuzzy weighted normalized arithmetic mean and fuzzy weighted normalized geometric mean functions. Articulate these calculations through Equations (27)–(29), which enable the quantification of the significance and interplay of these metrics within the decision-making context.

$$\delta_i = \frac{GS_i + AS_i}{\sum\limits_{i=1}^{I} (GS_i + AS_i)} \; i = 1, 2, \ldots, I \tag{27}$$

$$\omega_i = \frac{AS_i}{\min\limits_i (AS_i)} + \frac{GS_i}{\min\limits_i (GS_i)} \; i = 1, 2, \ldots, I \tag{28}$$

$$\vartheta_i = \frac{\lambda AS_i + (1-\lambda) GS_i}{\lambda \max\limits_i (AS_i) + (1-\lambda) \max\limits_i (GS_i)} \; i = 1, 2, \ldots, I; 0 \leq \lambda \leq 1 \tag{29}$$

Step 8: Determine the overall score (φ_i) for each alternative using Equation (30). The alternative with a higher value of φ_i is deemed superior, signifying its better suitability or performance compared to the others in the set.

$$\varphi_i = \frac{(\delta_i + \omega_i + \vartheta_i)}{3} + \sqrt[3]{(\sigma_i \times \omega_i \times \vartheta_i)} \; i = 1, 2, \ldots, I \tag{30}$$

4. Numerical Results

4.1. Problems Description

The impetus for this study is rooted in the urgent need to identify sustainable and efficient energy storage solutions, as the global reliance on lithium-ion (Li-ion) batteries faces escalating challenges, including raw material scarcity and environmental concerns. This search for alternatives is not merely a response to Li-ion limitations but a strategic move towards diversifying energy resources and enhancing energy security, particularly for nations embarking on rapid industrialization and technological advancement. In this context, this study introduces a cadre of promising contenders: sodium-ion (SIB), sodium-ion saltwater (SIB-S), magnesium-ion (MIB), and zinc-ion (ZIB) batteries. These alternatives are gaining traction due to their potential benefits, which include greater material abundance, lower costs, and more favorable environmental profiles. SIBs and SIB-S batteries, leveraging the widespread availability of sodium, offer a promising avenue for large-scale and cost-effective energy storage. MIBs capitalize on magnesium's high volumetric capacity, which could lead to higher-energy-density storage systems. ZIBs, utilizing zinc's unique properties, present opportunities for safer and more robust battery chemistries. Together, these metal-ion batteries represent the next frontier in energy storage technologies, with the potential to transform the energy sector and provide a foundation for the sustainable growth of emerging economies. The problem at hand, therefore, is to systematically evaluate these alternatives and determine their suitability for Vietnam's burgeoning industry, with the broader goal of ensuring a sustainable, efficient, and secure energy future.

Therefore, to solve this MCDM problem, the alternatives being evaluated are SIB, SIB-S, MIB, and ZIB. These alternatives have been selected due to their potential to serve as viable and sustainable replacements for lithium-ion batteries, particularly considering their suitability for the industrial and energy storage needs of Vietnam. Each of these battery types offers unique advantages and has potential for innovation in the field of energy storage. Through the MCDM framework, this study will systematically assess and prioritize these alternatives based on a range of criteria.

The initial phase entailed the selection of a cohort of experts from industries closely affiliated with energy storage devices to engage in the research [44–46]. These experts were tasked with proposing evaluation criteria or indicators and conducting pairwise comparisons to gauge the importance of each criterion or indicator. The details regarding this group of experts are outlined in Table 3.

Table 3. Decision makers' expertise.

Decision Maker	Qualifications	Experience by Year	Industry
1	Ph.D.	10	Electronics
2	M.Eng.	12	Mining Industry
3	M.Eng.	12	Electronics
4	Ph.D.	8	Mining Industry
5	Ph.D.	15	Construction
6	M.Sc.	14	Electronics
7	M.Eng.	16	Mining Industry
8	Ph.D.	12	Electronics
9	M.Eng.	13	Construction
10	Ph.D.	10	Construction

Drawing from the input provided by decision makers and reference documents [3–5,12,14,18], this study delineates eight criteria and indicators aimed at assessing the suitability of metal-ion batteries for industrial development in Vietnam. Illustrated in Figure 2, these criteria and indicators are categorized into two types: numerical indicators and linguistic criteria. The numerical indicators demonstrate suitability and performance advantages, whereas the linguistic criteria reflect economic and social potential.

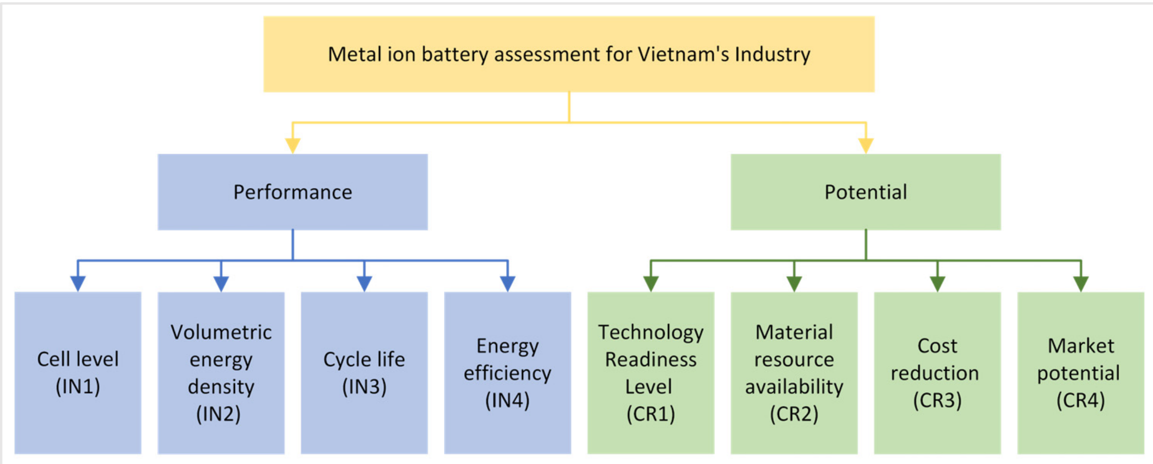

Figure 2. The assessment criteria and indicators.

Four numerical indicators provide objective data points for comparison. The cell-level energy density (IN1), measured in watt-hours per kilogram (Wh/kg), gauges how much energy can be stored for a given weight, which is a crucial factor for mobility and portability. The volumetric energy density (IN2), expressed in watt-hours per liter (Wh/l), assesses the energy storage per unit volume, reflecting the battery's fit in spatially constrained applications. The cycle life (IN3), quantified by the number of charge–discharge cycles a battery can sustain before its capacity significantly degrades, informs the battery's lifespan and operational cost over time. Energy efficiency (IN4), the percentage of energy retained and recoverable during use, signifies the operational economy and impact on long-term energy expenditure.

Complementing these are four linguistic criteria that capture the nuanced facets of technological viability and market readiness. The Technology Readiness Level or TRL (CR1) offers a qualitative scale of the technology's maturity, indicating its progression from conceptual stages to market readiness. Material resource availability (CR2) considers the accessibility and abundance of essential raw materials, a critical factor for scaling up production sustainably. The potential for cost reduction (CR3) encapsulates the technology's trajectory towards becoming more economically competitive as it matures and is subject to scaling and innovation. Lastly, market potential (CR4) captures the expected demand and integration capacity of the technology within the industry, an indicator of its commercial viability and long-term adoption.

4.2. Optimized Weighting by Fuzzy BWM

The aim of this section is to ascertain the weights of the criteria and indicators. Decision makers will undergo interviews to discern the best and worst criteria or indicators within each group. Subsequently, following the methodology outlined in Section 3.2, linguistic pairwise comparisons will be conducted for fuzzy preference vectors and fuzzy anti-preference vectors. These vectors are detailed in Tables A1–A3 in the Appendix A. By solving the non-linear programming model (9), the fuzzy local weights of factors, indicators, and criteria are determined. According to Equation (8), the defuzzification process is performed to obtain the crisp weights. The results of the Fuzzy BWM procedure, specifically the local fuzzy weights and the crisp weights, are presented in Tables A4–A6 in the Appendix A.

In the subsequent procedural phase, after determining the local weights for each criterion and indicator within the hierarchical structure, the process proceeds to establish the global weights. This involves the multiplication of the local weights, considering the hierarchical relationships established earlier. Subsequently, through a comprehensive aggregation of the results obtained from all decision makers involved in the assessment process, the final weight is precisely ascertained, as shown in Figure 3.

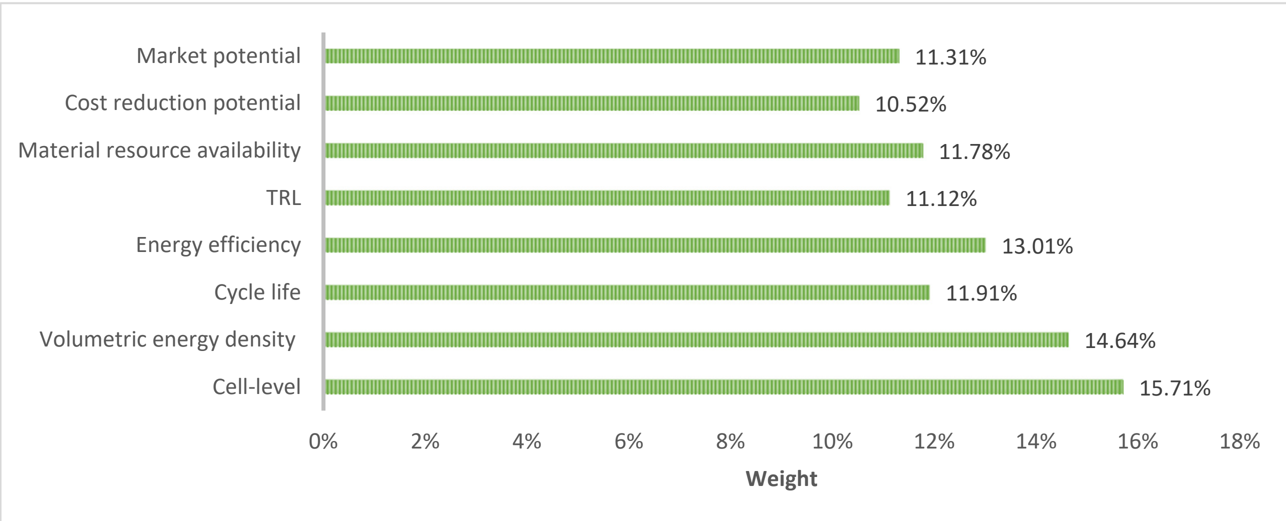

Figure 3. The optimized weights obtained using the Fuzzy Best-Worst Method.

The highest weight is attributed to the cell-level energy density (Wh/kg) of 15.7%, underscoring its significance in determining a battery's practicality for energy-intensive applications where weight is a critical factor. The volumetric energy density follows closely at 14.6%, reflecting the importance of space-efficient batteries in applications where the battery size is constrained. Cycle life and energy efficiency are given substantial importance with weights of 11.9% and 13.0%, respectively. These suggest a balanced concern for both the longevity and operational effectiveness of battery technologies, indicating that enduring performance and optimal energy utilization are vital for their long-term viability and cost-effectiveness. The Technology Readiness Level (TRL) at 11.1% and material resource availability at 11.8% reveal a keen awareness of the practical aspects of technology deployment and resource sustainability. The weights indicate a strategic consideration of not only the current state of technology development but also the importance of ensuring a stable and sustainable supply chain for battery production. Cost reduction potential, at a weight of 10.5%, highlights the economic considerations pivotal to the widespread adoption of new technologies, emphasizing the need for battery solutions that can become financially viable over time. Market potential, with a weight of 11.3%, reflects the importance of future demand and market growth for these technologies, suggesting that the potential market size and adoption rates are crucial factors in decision making.

The relatively close weight distribution suggests that no single criterion overwhelmingly dominates the decision-making process, indicating a complex interplay of factors that must be carefully managed to determine the most appropriate battery technology for Vietnam's needs.

4.3. Prioritization by the Bonferroni Fuzzy CoCoSo Method

In this section, the evaluation process commences with an extensive data collection endeavor focusing on metal-ion batteries, meticulously gathering pertinent information corresponding to each indicator and criterion. Data procurement primarily relies on a thorough review of published technical and economic studies concerning batteries, ensuring a robust foundation for the subsequent analysis. The culmination of this data aggregation effort is succinctly summarized and meticulously tabulated, providing a comprehensive overview of the collected data, as elucidated in Table 4. Subsequently, as delineated in Step 2 of Section 3.3, the acquired data undergo a transformation into TriFNs, facilitating the construction of a fuzzy decision matrix that is meticulously detailed in Table 5. Given the inherent inconsistency in the fuzzy scales of the indicators and criteria within the decision-making matrix, a normalization procedure is meticulously applied, adhering to Equations (21)–(24) to ensure uniformity and coherence in the subsequent analysis. This normalization process culminates in the establishment of a normalized fuzzy decision matrix, which is thoughtfully presented and meticulously structured in Table A7 in the Appendix A.

Table 4. The data summary.

Battery Type	Cell Level (Wh/Kg)	Volumetric Energy Density (Wh/l)	Cycle Life (Cycles)	Energy Efficiency (%)	TRL	Material Resource Availability	Cost Reduction Potential	Market Potential
SIBs	140–160 [47]	250–300 [47]	100–1000 [48,49]	90–95 [50]	VH [51,52]	VH [53]	VH [54]	M [52]
SIB-Salt	130–150 [55]	10–25 [55]	3000–4000 [56]	75–98 [57–59]	VH [55,57,60,61]	VH [62]	M [62]	M [55,62,63]
MIBs	50–150 [64]	150–300 [65]	150–750 [66,67]	90–94 [68]	M [69]	VH [69]	VH [70]	H [65]
ZIBs	30–60 [71]	40–100 [71]	600–800 [72]	80–90 [73]	M [74]	H [75]	H [75]	H [74]

Table 5. The fuzzy decision matrix.

Battery Type	IN1	IN2	IN3	IN4	CR1	CR2	CR3	CR4
SIBs	(140, 150, 160)	(250, 275, 300)	(100, 550, 1000)	(90, 92.5, 95)	(4, 5, 5)	(4, 5, 5)	(4, 5, 5)	(2, 3, 4)
SIB-Salt	(130, 140, 150)	(10, 17.5, 25)	(3000, 3500, 4000)	(75, 86.5, 98)	(4, 5, 5)	(4, 5, 5)	(2, 3, 4)	(2, 3, 4)
MIBs	(50, 100, 150)	(150, 225, 300)	(150, 450, 750)	(90, 92, 94)	(2, 3, 4)	(4, 5, 5)	(4, 5, 5)	(3, 4, 5)
ZIBs	(30, 45, 60)	(40, 70, 100)	(600, 700, 800)	(80, 85, 90)	(2, 3, 4)	(3, 4, 5)	(3, 4, 5)	(3, 4, 5)

Moving forward, the analytical framework transitions to the determination of critical metrics, namely the fuzzy weighted normalized geometric mean sequence $\left(G\tilde{S}M_i\right)$ and the fuzzy weighted normalized arithmetic mean sequence $\left(A\tilde{S}M_i\right)$, meticulously calculated in accordance with Equations (25) and (26). Subsequently, the crisp values derived from these sequences are meticulously computed utilizing Equation (8), offering a tangible representation of the analytical findings, which are succinctly summarized and methodically presented in Table 6. Finally, culminating in the conclusive phase of the evaluation, the significance and overall ranking of battery types are meticulously determined by employing a series of intricate computations detailed in Equations (27)–(30), which are meticulously tabulated and thoughtfully presented in Table 7, providing stakeholders with a comprehensive understanding of the relative performance and suitability of various battery types within the designated evaluation framework.

Table 6. The mean sequences obtained using the Bonferroni Fuzzy CoCoSo method.

Battery Type	$\tilde{ASM}_i$	$\tilde{GSM}_i$	ASM_i	GSM_i
SIBs	(0.236, 0.284, 0.304)	(0.518, 0.529, 0.534)	0.279	0.528
SIB-Salt	(0.194, 0.242, 0.269)	(0.506, 0.519, 0.526)	0.239	0.518
MIBs	(0.177, 0.243, 0.291)	(0.5, 0.519, 0.531)	0.240	0.518
ZIBs	(0.149, 0.196, 0.244)	(0.476, 0.494, 0.508)	0.196	0.494

Table 7. The Bonferroni Fuzzy CoCoSo method results with the trade-off coefficient, $\lambda = 0.5$.

The Battery Type	The Additive Normalized Importance (δ_i)	The Relative Importance (ω_i)	The Trade-Off Importance (ϑ_i)	The Overall Score (φ_i)
SIBs	0.268	2.494	1.000	2.128
SIB-Salt	0.251	2.265	0.937	1.962
MIBs	0.252	2.274	0.939	1.969
ZIBs	0.229	2.000	0.854	1.759

Based on the overall scores, the results of prioritizing battery types are illustrated in Figure 4. The results of the Bonferroni Fuzzy CoCoSo method reveal a clear ranking of the metal-ion battery alternatives under consideration for Vietnam's energy storage needs. Sodium-ion batteries (SIBs) emerge as the leading option with the highest overall score of 2.128, indicating their superior alignment with the evaluated criteria. This outcome suggests that, in the aggregate assessment of factors such as energy density, cycle life, efficiency, and market readiness, SIBs are likely to offer the most balanced performance. Magnesium-ion batteries (MIBs) follow closely, with an overall score of 1.969, positioning them as the second priority. Their score indicates that while they may not match SIBs in every aspect, they still represent a strong contender, potentially due to advantages in specific criteria like the volumetric energy density or material resource availability. Sodium-ion saltwater batteries (SIB-Salt) are ranked third with a score of 1.962. The proximity of their score to that of MIBs suggests a competitive offering, but they are perhaps slightly lacking in one or more critical areas that are important in the Vietnamese context. Zinc-ion batteries (ZIBs), with the lowest score of 1.759, are given the fourth priority. This indicates that while ZIBs may hold promise, they currently might not measure up as well against the selected criteria as the other battery types. This could be due to lower performance in key areas such as energy density or a lower readiness level compared to their counterparts.

This prioritization reflects a multifaceted assessment that incorporates both technical performance and broader strategic considerations. It is important to note that while the overall scores provide a clear rank order, the actual differences between the scores also matter. The relatively close scores between the SIB-salt and MIBs indicate tight competition, where small improvements or changes in market conditions could shift the ranking.

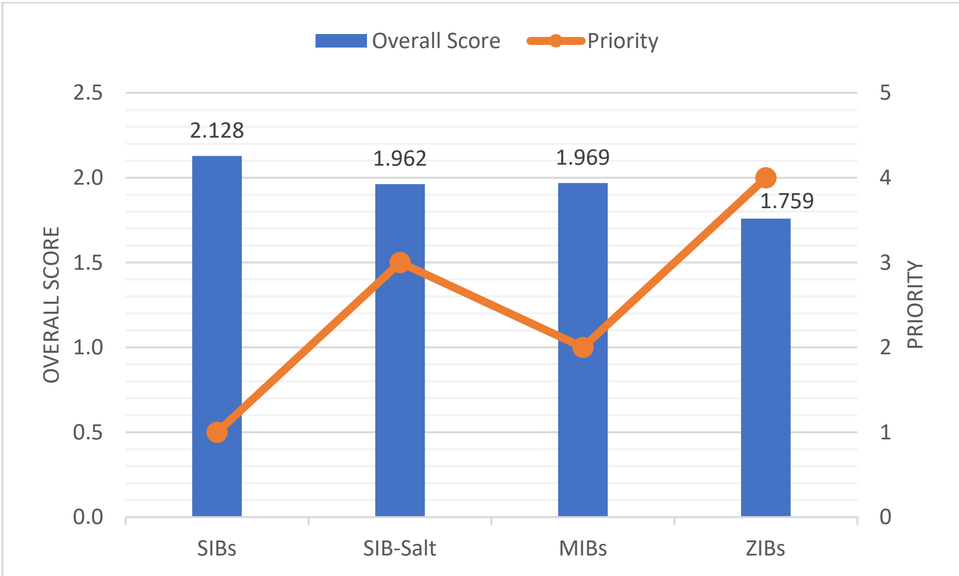

Figure 4. The prioritization of metal-ion batteries for Vietnam's industries.

5. Managerial Implications

The findings of this study offer significant managerial implications for stakeholders in Vietnam's energy sector, particularly those involved in policy formulation, technology investment, and research and development. The prioritization of SIBs suggests that managers should consider directing investment and support towards the development and scaling of SIB technology, which is likely to provide the most balanced return on investment considering the current criteria. This aligns with global trends in seeking alternatives to lithium-ion batteries and can place Vietnam at the forefront of adopting and possibly innovating within this emerging technology.

The close ranking between MIBs and SIB-salt indicates a competitive landscape where strategic investments could tip the scales in favor of one technology over the other. Managers should closely monitor advancements in these areas and be prepared to pivot resources in response to technological breakthroughs or shifts in market demand.

The relatively lower ranking of ZIBs suggests that, while not a priority, they should not be entirely discounted. Managers should maintain a portfolio approach, balancing investments in leading technologies while fostering research in areas like ZIBs that could capture future market niches or leapfrog in performance through innovation.

Furthermore, managers should leverage the insights obtained from the Fuzzy BWM to balance the trade-offs between different criteria. For instance, while the cell-level energy density and volumetric energy density are crucial, they should not completely overshadow considerations such as cycle life and energy efficiency, which contribute significantly to the total cost of ownership and sustainability.

6. Conclusions

This study embarked on a timely exploration against the backdrop of a global shift toward renewable energy sources and the concomitant need for robust and sustainable energy storage solutions. Driven by the necessity to circumvent the limitations of lithium-ion batteries and to fortify Vietnam's energy autonomy, our research sought to identify and evaluate alternative metal-ion battery technologies that are suitable for the nation's burgeoning energy needs.

Our methodology employed a rigorous MCDM approach, integrating both numerical data and qualitative expert judgments. The Fuzzy BWM was utilized to ascertain the weights of various criteria, which included cell-level energy density, volumetric energy density, cycle life, energy efficiency, Technology Readiness Level, material resource availability, cost reduction potential, and market potential. These criteria were carefully chosen to reflect the multifaceted nature of battery technology assessment, ensuring a comprehensive analysis that is both quantitatively robust and contextually nuanced.

The findings of this study, derived from the Bonferroni Fuzzy CoCoSo method, reveal a clear prioritization among the alternatives. Sodium-ion batteries emerged as the front runner, followed by magnesium-ion, sodium-ion saltwater, and zinc-ion batteries, in descending order of priority. These outcomes are indicative of the potential suitability of SIBs for Vietnam's specific industrial landscape, suggesting a strategic direction for future investments and policy-making.

The value of this research lies in its broad and impactful contributions. It delivers a sophisticated framework for decision making to those shaping policy and investing in the energy domain by utilizing a nuanced fuzzy-based MCDM methodology that was customized for the emerging context of Vietnam's energy technology sector. This work also advances academic discussions by methodically comparing metal-ion battery technologies, a sector that stands on the cusp of transformative potential for advancing sustainable energy storage options.

Nevertheless, this study acknowledges certain limitations that naturally pave the way for future scholarly inquiry. Given the reliance on the currently available data and expert insights, the fast-paced advancements in battery technology may alter the applicability of our findings over time. Prospective research endeavors could enhance this foundational work by assimilating up-to-the-minute market data, technological breakthroughs, and the shifting geopolitical context that influences the availability of material resources. Additionally, future research could take a more expansive look by incorporating lifecycle assessments and environmental impact studies of these battery technologies, thereby providing a more comprehensive perspective on their long-term sustainability.

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Appendix A

Table A1. The fuzzy preference vector and fuzzy anti-preference vector factors.

Decision Maker	Best Factor	Against Remaining Factors		Worst Factor	Remaining Factors Against	
		Performance	Potential		Performance	Potential
1	Performance	(1, 1, 1)	(1.5, 2, 2.5)	Potential	(1.5, 2, 2.5)	(1, 1, 1)
2	Performance	(1, 1, 1)	(2.5, 3, 3.5)	Potential	(2.5, 3, 3.5)	(1, 1, 1)
3	Performance	(1, 1, 1)	(1.5, 2, 2.5)	Potential	(1.5, 2, 2.5)	(1, 1, 1)
4	Potential	(1.5, 2, 2.5)	(1, 1, 1)	Performance	(1, 1, 1)	(1.5, 2, 2.5)
5	Performance	(1, 1, 1)	(2.5, 3, 3.5)	Potential	(2.5, 3, 3.5)	(1, 1, 1)
6	Potential	(1.5, 2, 2.5)	(1, 1, 1)	Performance	(1, 1, 1)	(1.5, 2, 2.5)
7	Potential	(1.5, 2, 2.5)	(1, 1, 1)	Performance	(1, 1, 1)	(1.5, 2, 2.5)
8	Performance	(1, 1, 1)	(1.5, 2, 2.5)	Potential	(1.5, 2, 2.5)	(1, 1, 1)
9	Performance	(1, 1, 1)	(1.5, 2, 2.5)	Potential	(1.5, 2, 2.5)	(1, 1, 1)
10	Potential	(1.5, 2, 2.5)	(1, 1, 1)	Performance	(1, 1, 1)	(1.5, 2, 2.5)

Table A2. The fuzzy preference vector and fuzzy anti-preference vector indicators.

Decision Maker	Best Indicator	Against Remaining Indicators				Worst Indicator	Remaining Indicators Against			
		IN1	IN2	IN3	IN4		IN1	IN2	IN3	IN4
1	IN3	(0.67, 1, 1.5)	(1.5, 2, 2.5)	(1, 1, 1)	(0.67, 1, 1.5)	IN1	(1, 1, 1)	(0.67, 1, 1.5)	(0.67, 1, 1.5)	(1.5, 2, 2.5)
2	IN1	(1, 1, 1)	(1.5, 2, 2.5)	(2.5, 3, 3.5)	(2.5, 3, 3.5)	IN2	(1.5, 2, 2.5)	(1, 1, 1)	(0.67, 1, 1.5)	(0.67, 1, 1.5)
3	IN4	(1.5, 2, 2.5)	(1.5, 2, 2.5)	(0.67, 1, 1.5)	(1, 1, 1)	IN1	(1, 1, 1)	(0.67, 1, 1.5)	(0.67, 1, 1.5)	(1.5, 2, 2.5)
4	IN1	(1, 1, 1)	(2.5, 3, 3.5)	(1.5, 2, 2.5)	(2.5, 3, 3.5)	IN2	(1.5, 2, 2.5)	(1, 1, 1)	(0.67, 1, 1.5)	(0.67, 1, 1.5)
5	IN3	(0.67, 1, 1.5)	(0.67, 1, 1.5)	(1, 1, 1)	(0.67, 1, 1.5)	IN4	(0.67, 1, 1.5)	(0.67, 1, 1.5)	(0.67, 1, 1.5)	(1, 1, 1)
6	IN3	(2.5, 3, 3.5)	(0.67, 1, 1.5)	(1, 1, 1)	(1.5, 2, 2.5)	IN2	(0.67, 1, 1.5)	(1, 1, 1)	(1.5, 2, 2.5)	(0.67, 1, 1.5)
7	IN1	(1, 1, 1)	(0.67, 1, 1.5)	(1.5, 2, 2.5)	(2.5, 3, 3.5)	IN4	(1.5, 2, 2.5)	(1.5, 2, 2.5)	(0.67, 1, 1.5)	(1, 1, 1)
8	IN2	(1.5, 2, 2.5)	(1, 1, 1)	(0.67, 1, 1.5)	(0.67, 1, 1.5)	IN1	(1, 1, 1)	(1.5, 2, 2.5)	(0.67, 1, 1.5)	(2.5, 3, 3.5)
9	IN1	(1, 1, 1)	(0.67, 1, 1.5)	(1.5, 2, 2.5)	(1.5, 2, 2.5)	IN3	(0.67, 1, 1.5)	(1.5, 2, 2.5)	(1, 1, 1)	(0.67, 1, 1.5)
10	IN2	(0.67, 1, 1.5)	(1, 1, 1)	(1.5, 2, 2.5)	(1.5, 2, 2.5)	IN3	(2.5, 3, 3.5)	(0.67, 1, 1.5)	(1, 1, 1)	(0.67, 1, 1.5)

Table A3. The fuzzy preference vector and fuzzy anti-preference vector criteria.

Decision Maker	Best Criterion	Against Remaining Criteria				Worst Criterion	Remaining Criteria Against			
		CR1	CR2	CR3	CR4		CR1	CR2	CR3	CR4
1	CR2	(0.67, 1, 1.5)	(1, 1, 1)	(0.67, 1, 1.5)	(0.67, 1, 1.5)	CR3	(0.67, 1, 1.5)	(0.67, 1, 1.5)	(1, 1, 1)	(1.5, 2, 2.5)
2	CR4	(0.67, 1, 1.5)	(2.5, 3, 3.5)	(2.5, 3, 3.5)	(1, 1, 1)	CR2	(0.67, 1, 1.5)	(1, 1, 1)	(0.67, 1, 1.5)	(1.5, 2, 2.5)
3	CR4	(1.5, 2, 2.5)	(0.67, 1, 1.5)	(1.5, 2, 2.5)	(1, 1, 1)	CR2	(0.67, 1, 1.5)	(1, 1, 1)	(0.67, 1, 1.5)	(0.67, 1, 1.5)
4	CR4	(0.67, 1, 1.5)	(0.67, 1, 1.5)	(0.67, 1, 1.5)	(1, 1, 1)	CR1	(1, 1, 1)	(0.67, 1, 1.5)	(0.67, 1, 1.5)	(0.67, 1, 1.5)
5	CR3	(1.5, 2, 2.5)	(1.5, 2, 2.5)	(1, 1, 1)	(0.67, 1, 1.5)	CR4	(1.5, 2, 2.5)	(0.67, 1, 1.5)	(0.67, 1, 1.5)	(1, 1, 1)
6	CR1	(1, 1, 1)	(1.5, 2, 2.5)	(1.5, 2, 2.5)	(1.5, 2, 2.5)	CR4	(2.5, 3, 3.5)	(0.67, 1, 1.5)	(0.67, 1, 1.5)	(1, 1, 1)
7	CR2	(1.5, 2, 2.5)	(1, 1, 1)	(1.5, 2, 2.5)	(1.5, 2, 2.5)	CR4	(0.67, 1, 1.5)	(1.5, 2, 2.5)	(0.67, 1, 1.5)	(1, 1, 1)
8	CR1	(1, 1, 1)	(1.5, 2, 2.5)	(0.67, 1, 1.5)	(0.67, 1, 1.5)	CR3	(0.67, 1, 1.5)	(0.67, 1, 1.5)	(1, 1, 1)	(2.5, 3, 3.5)
9	CR4	(1.5, 2, 2.5)	(0.67, 1, 1.5)	(0.67, 1, 1.5)	(1, 1, 1)	CR3	(0.67, 1, 1.5)	(1.5, 2, 2.5)	(1, 1, 1)	(0.67, 1, 1.5)
10	CR3	(0.67, 1, 1.5)	(0.67, 1, 1.5)	(1, 1, 1)	(1.5, 2, 2.5)	CR2	(0.67, 1, 1.5)	(1, 1, 1)	(0.67, 1, 1.5)	(0.67, 1, 1.5)

Table A4. The local fuzzy weight and crisp weight factors.

Decision Maker	Local Fuzzy Weight		Local Crisp Weight		CRA
	Performance	Potential	Performance	Potential	
1	(0.559, 0.708, 0.708)	(0.317, 0.317, 0.317)	0.683	0.317	5.02%
2	(0.750, 0.750, 0.750)	(0.250, 0.250, 0.250)	0.75	0.25	7.47%
3	(0.667, 0.667, 0.667)	(0.333, 0.333, 0.333)	0.667	0.333	9.45%
4	(0.314, 0.348, 0.348)	(0.559, 0.670, 0.708)	0.342	0.658	5.02%
5	(0.750, 0.750, 0.750)	(0.250, 0.250, 0.250)	0.75	0.25	7.47%
6	(0.294, 0.313, 0.357)	(0.559, 0.708, 0.708)	0.317	0.683	5.02%
7	(0.314, 0.348, 0.348)	(0.559, 0.670, 0.708)	0.342	0.658	5.02%
8	(0.667, 0.667, 0.667)	(0.333, 0.333, 0.333)	0.667	0.333	9.45%
9	(0.667, 0.667, 0.667)	(0.333, 0.333, 0.333)	0.667	0.333	9.45%
10	(0.314, 0.348, 0.348)	(0.559, 0.670, 0.708)	0.342	0.658	5.02%

Table A5. The local fuzzy weight and crisp weight indicators.

Decision Maker	Local Fuzzy Weight				Local Crisp Weight				CRA
	IN1	IN2	IN3	IN4	IN1	IN2	IN3	IN4	
1	(0.198, 0.215, 0.215)	(0.157, 0.157, 0.220)	(0.242, 0.242, 0.356)	(0.344, 0.344, 0.437)	0.212	0.167	0.261	0.359	5.85%
2	(0.438, 0.438, 0.497)	(0.213, 0.276, 0.276)	(0.123, 0.123, 0.224)	(0.134, 0.134, 0.209)	0.448	0.265	0.14	0.147	8.26%
3	(0.211, 0.211, 0.214)	(0.161, 0.161, 0.308)	(0.234, 0.234, 0.339)	(0.333, 0.333, 0.451)	0.211	0.185	0.251	0.352	8.11%
4	(0.350, 0.438, 0.525)	(0.175, 0.175, 0.175)	(0.213, 0.213, 0.213)	(0.175, 0.175, 0.175)	0.438	0.175	0.213	0.175	7.51%
5	(0.244, 0.326, 0.326)	(0.230, 0.230, 0.231)	(0.230, 0.230, 0.325)	(0.212, 0.212, 0.212)	0.313	0.23	0.245	0.212	7.88%
6	(0.131, 0.151, 0.187)	(0.200, 0.253, 0.322)	(0.396, 0.396, 0.413)	(0.192, 0.192, 0.192)	0.154	0.256	0.399	0.192	8.45%
7	(0.316, 0.316, 0.417)	(0.387, 0.387, 0.387)	(0.129, 0.129, 0.178)	(0.141, 0.141, 0.149)	0.333	0.387	0.137	0.142	9.33%
8	(0.118, 0.130, 0.130)	(0.221, 0.353, 0.379)	(0.205, 0.205, 0.205)	(0.332, 0.332, 0.332)	0.128	0.335	0.205	0.332	8.96%
9	(0.215, 0.250, 0.338)	(0.363, 0.411, 0.411)	(0.174, 0.174, 0.181)	(0.162, 0.162, 0.162)	0.259	0.403	0.175	0.162	8.52%
10	(0.329, 0.425, 0.514)	(0.240, 0.240, 0.348)	(0.149, 0.149, 0.227)	(0.156, 0.156, 0.156)	0.424	0.258	0.162	0.156	8.66%

Table A6. The local fuzzy weight and crisp weight criteria.

Decision Maker	Local Fuzzy Weight				Local Crisp Weight				CRA
	CR1	CR2	CR3	CR4	CR1	CR2	CR3	CR4	
1	(0.192, 0.192, 0.192)	(0.208, 0.268, 0.268)	(0.177, 0.218, 0.218)	(0.193, 0.369, 0.369)	0.192	0.258	0.211	0.340	6.23%
2	(0.239, 0.239, 0.239)	(0.176, 0.176, 0.176)	(0.175, 0.175, 0.175)	(0.317, 0.405, 0.525)	0.239	0.176	0.175	0.410	8.64%
3	(0.113, 0.163, 0.236)	(0.252, 0.252, 0.333)	(0.184, 0.231, 0.231)	(0.319, 0.35, 0.35)	0.167	0.265	0.223	0.344	8.99%
4	(0.261, 0.261, 0.261)	(0.209, 0.209, 0.332)	(0.226, 0.226, 0.226)	(0.283, 0.283, 0.283)	0.261	0.229	0.226	0.283	6.23%
5	(0.202, 0.27, 0.371)	(0.138, 0.138, 0.324)	(0.289, 0.359, 0.359)	(0.209, 0.209, 0.209)	0.275	0.169	0.347	0.209	8.96%
6	(0.37, 0.389, 0.466)	(0.182, 0.209, 0.209)	(0.211, 0.211, 0.366)	(0.155, 0.155, 0.185)	0.399	0.204	0.237	0.160	6.22%
7	(0.169, 0.169, 0.29)	(0.351, 0.397, 0.466)	(0.178, 0.241, 0.241)	(0.173, 0.173, 0.211)	0.189	0.401	0.230	0.179	6.57%
8	(0.213, 0.264, 0.344)	(0.145, 0.145, 0.221)	(0.165, 0.165, 0.165)	(0.392, 0.392, 0.491)	0.269	0.157	0.165	0.409	9.33%
9	(0.128, 0.128, 0.139)	(0.245, 0.528, 0.62)	(0.156, 0.156, 0.156)	(0.197, 0.197, 0.321)	0.130	0.496	0.156	0.218	9.37%
10	(0.252, 0.252, 0.252)	(0.209, 0.209, 0.32)	(0.253, 0.322, 0.39)	(0.200, 0.200, 0.200)	0.252	0.227	0.322	0.200	8.13%

Table A7. The normalized fuzzy decision matrix.

Battery Type	IN1	IN2	IN3	IN4	CR1	CR2	CR3	CR4
SIBs	(0.875, 0.938, 1)	(0.833, 0.917, 1)	(0.025, 0.138, 0.25)	(0.918, 0.944, 0.969)	(0.8, 1, 1)	(0.8, 1, 1)	(0.8, 1, 1)	(0.4, 0.6, 0.8)
SIB-Salt	(0.813, 0.875, 0.938)	(0.033, 0.058, 0.083)	(0.75, 0.875, 1)	(0.765, 0.883, 1)	(0.8, 1, 1)	(0.8, 1, 1)	(0.4, 0.6, 0.8)	(0.4, 0.6, 0.8)
MIBs	(0.313, 0.625, 0.938)	(0.5, 0.75, 1)	(0.038, 0.113, 0.188)	(0.918, 0.939, 0.959)	(0.4, 0.6, 0.8)	(0.8, 1, 1)	(0.8, 1, 1)	(0.6, 0.8, 1)
ZIBs	(0.188, 0.281, 0.375)	(0.133, 0.233, 0.333)	(0.15, 0.175, 0.2)	(0.816, 0.867, 0.918)	(0.4, 0.6, 0.8)	(0.6, 0.8, 1)	(0.6, 0.8, 1)	(0.6, 0.8, 1)

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