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Assessment of Battery Energy Storage Systems Using the Intuitionistic Fuzzy Removal Effects of Criteria and the Measurement of Alternatives and Ranking Based on Compromise Solution Method

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Abstract: The energy storage is an important character for sustainable energy structures and the prospective future economy. This paper aims to propose a multi-attribute decision analysis (MADA) approach to prioritize and choose the energy storage system (ESS) alternatives in terms of the different technical, economic, environmental and social aspects of them. In this line, an integrated approach is developed with the combination of intuitionistic fuzzy sets (IFSs), a method using the removal effects of criteria (MEREC), rank sum (RS) and the measurement of the alternatives and ranking based on compromise solution (MARCOS) methods for prioritizing the ESSs. The IF-MEREC-RS was used to find the integrated weight by combining the objective and subjective weights of the different indicators for prioritizing the ESSs. The MARCOS method was implemented to rank the various ESSs over several crucial indicators of sustainability. The practical outcome illustrates that the Li-ion battery (LIB) is the best ESS among all of the options, and this is followed by NaSB and NiMHB. A sensitivity investigation with the diverse weights of the indicators shows the impact of the risk preferences on an alternative prioritization. A comparison is discussed with the outcomes of the different presented, extant approaches to certify the superiority of the presented approach.

Keywords: intuitionistic fuzzy sets; energy storage; sustainability; MEREC; rank sum; MARCOS; multi-attribute decision analysis

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1. Introduction

Energy storage describes the capture of energy for the purpose of its consumption at a later time, and the key reason for this is to ensure long-term and seasonal energy storage. The issue of energy storage has risen in its importance from the perspective of the accelerating growth of renewable energy and the decreasing of amount of non-fluctuating sources of electricity such as coal-fired and nuclear power plants. Because of the intermittence and instability of renewable energy sources, large-capacity ESSs can absorb the excess energy during a power surplus and release the energy in case of a power shortage occurring. Some of the ESSs, such as super capacitor energy storage (SCES) and superconducting magnetic energy storage (SMES) have extensively been studied to improve the power quality [1]. Battery energy storage (BES) can compensate for instantaneous power shortages, smoothen the output power of the generators, and they are suitable for solving power flow problems [2]. The flywheel ESS has the advantages of having a high energy density, being environmentally friendly and low maintenance, and having a long life and a fast response time [3]. Thermal and mechanical ESSs have automatic load transfer switches and advanced thermal energy storage systems with long life cycles [4]. The underground storage of hydrogen and the utilization of the power that converts from this gas and the business connections in this process are also significant aspects for the decarbonization of the economy and the lessening of greenhouse gas emissions [5]. The ESS has been considered as the optimal choice to provide the motivation for the RES development and confirm the steadiness of electricity provision [6].

In general, the ESS can be categorized into mechanical storage (MS) types, chemical storage (CS) types and electro-magnetic storage (EMS) types [7]. For the MS type, it largely comprises the pumped hydro ESS, the compressed air ESS and the flywheel ESS [8–10]. For the CS type, it mainly comprises the Lead-acid battery (LAB), the Lithium-ion battery (LIB), the Sodium-sulfur battery (NaSB), the Nickel-metal Hydride battery (NiMHB), the Vanadium Redox Flow Battery (VRFB) and the Zinc Bromine flow battery (ZnBrFB) [11,12]. For the EMS type, it represents the super capacitors and the superconducting magnetic ESS [13,14]. The MS construction has a demanding requirement in terms of its geographical site. In addition, the cost of the products for the EMS system is comparatively high [15,16]. Thus, in the future structure of a smart grid and a micro-grid, the CS system will be broadly utilized because of the economic, safe and environmentally friendly features that it has. Though, several types of "battery energy storage systems (BESS)" have diverse performances, technological maturity levels, and costs. Hence, it is tough for "decision experts (DEs)" to choose the suitable choice the different BESSs because of there being several conflicting indicators. Therefore, it is crucial to introduce an ample assessment framework for selecting the best BESS.

Numerous researchers have concentrated on the optimization and the mechanism of the ESS. Nojavan et al. [17] presented a cost-reliability optimization model to form a multi-objective framework for a suitable site evaluation of the ESS. Zhang et al. [18] presented improved forms of the "simulated annealing algorithm (SAA)" for the optimal sizing of the "wind and solar energy systems" comprising the hydrogen and battery storage systems. Li et al. [19] discussed a droop control for energy sharing in the BESS, and they reckoned the extension of the battery's lifetime. Guney and Tepe [20] familiarized their readers with a broad explanation of the ESS with a thorough classification of them, their environmental impacts, and their employment potentials. Gumus et al. [21] discussed a decision-making approach using an "analytic hierarchy process (AHP)" and a "grey relational analysis (GRA)" with "fuzzy sets (FSs)" to select the optimal hydrogen ESS in Turkey. Özkan et al. [22] presented an integrated model with the AHP and the "technique for order of preference by similarity to ideal solution (TOPSIS)" methods using "type-2 fuzzy sets (T2FSs)" to choose the optimal ESS under various scenarios based on the DEs scoring. Recently, Zhang et al. [23] discussed a "multi-attribute decision analysis (MADA)" approach using a "multi-objective optimization on the basis of a ratio analysis plus the full multiplicative form (MULTIMOORA)" tool that was used for ranking the ESSs with the IFSs. Pózna et al. [24] addressed the parameter estimation of electrical vehicle batteries in the presence of a temperature effect. Further, the authors have analyzed the proposed parameter estimation method by running simulation experiments. Zhao et al. [25] discussed the fuzzy-MADA model using the "fuzzy-Delphi approach (FDA)", the "best-worst method (BWM)", and a "cumulative prospect theory (CPT)" for assessing the BESSs. Pamucar et al. [26] ranked the ESSs over the considered technical, cost-related, and environmental and social aspects. They presented a model using the Dombi operators and a "multi-attributive ideal-real comparative analysis (MAIRCA)" using "trapezoidal neutrosophic fuzzy numbers (TNFN)". The present study has made some contribution for the ranking of the ESS using diverse indicators. Károlyi et al. [27] established a new genetic algorithm-based optimization of a fuzzy controlled charging system for the LIBs. Their introduced fuzzy controller was used for controlling the charging current as a function of the temperature.

To deal with uncertainty of real-life situations, Atanassov [28] extended the fuzzy set to be the "intuitionistic fuzzy set (IFS)", which is characterized by the degrees of membership and non-membership. In the IFS, the sum of the degrees of membership and non-membership are restricted to one. The theory of the IFSs can be used to describe more complex fuzzy information. Thus, this study aims to propose an intuitionistic fuzzy information-based method that is used to more thoroughly deal with the vagueness and impreciseness of the information of real decision-making problems. To adapt the utility of the IFSs, we introduce an integrated approach for solving the MADA problem of the IFSs. The presented approach utilizes the weighting technique, combining the MEREC and RS methods to compute the indicators' weights of the IFSs. The MARCOS approach is a new elegant tool that is used to treat the MADA problems. Thus, in this study, we have implemented the IF-MEREC-RS-MARCOS framework for prioritizing the BESSs. The main motivations and contributions of the present study are presented as:

➢ The present study analyzes the limitations of the existing literature on BESSs from uncertain and sustainability perspectives.
➢ The determination of the criteria weights is an important task for decision makers. However, existing studies on the intuitionistic fuzzy "measurement of alternatives and ranking based on compromise solution (MARCOS)" method [29–32] have ignored the criteria weight determination process. To overcome the limitation of the existing MARCOS approaches [29–32], this study introduces an improved intuitionistic fuzzy MARCOS method with a new criteria weight-determining model.
➢ To derive the criteria weights, we propose an integrated weighting model by combining the objective weights based on the method using the removal effects of criteria (MEREC) and the subjective weights that are based on the "rank sum (RS)" model with the intuitionistic fuzzy information. A combined technique that is based on the integration of the objective and subjective weighting methods can overcome the insufficiencies which arise either in an objective weighting model or a subjective weighting model.
➢ Some authors [17,25] have evaluated the BESSs, however, these studies have limitations in dealing with the complex BESS selection problem in an intuitionistic fuzzy environment. However, the assessment of the BESSs can be considered as a MADA problem due to the existence of numerous sustainability aspects. To handle this issue, we implemented the proposed MARCOS method to solve a case study of BESSs from an intuitionistic fuzzy perspective.

The rest of paper is organized as follows: the literatures about the IFSs and MADA methods are given in Section 2. In Section 3, the preliminaries and the proposed IF-MEREC-RS-MARCOS approach is discussed. Section 4 provides the experimental findings and the comparative and sensitivity analyses results. Section 5 concludes the study with further recommendations.

2. Literature Review of IFSs and MADA Methods

Over two decades, numerous models and theories for treating ambiguous and uncertain information have been developed. Afterward, various generalizations of the FSs [33] have been discussed. In the FSs, the "membership function (MF)" is described in the range of interval [0, 1] and the "non-membership function (NF)" represents its complement. In reality, this assumption does not meet with the human perception. To elude the flaws of the FSs, the concept of the IFSs [28] is used by defining the three aspects: the MF, the NF and the "indeterminacy function (IF)" with the sum of MF and NF being ≤ 1 [32,34,35]. Recently, Mishra and Rani [36] presented the divergence measures-based MADA model to choose a "cloud service provider (CSP)" of the IFSs. Tao et al. [37] studied a hybrid framework by combining an IFS and an alternative queuing method for dynamic MCDM applications. Kumari and Mishra [38] presented a "complex proportional assessment (COPRAS)" model to treat the "green supplier selection (GSS)" problem of the IFSs setting. Rani et al. [39] studied an MADA framework with GRA of IFSs to solve the "telecom service providers (TSPs)" selection problem in Madhya Pradesh, India. Gohain et al. [40] proposed a novel intuitionistic fuzzy distance measure with applications in decision-making, pattern recognition and clustering problems.

Traditional MADA methods have been introduced for the DEs to make the accurate decisions. Though, in various MADA processes, the opinions and knowledge of the DEs should also be taken into consideration. In the presented MADA approach, the "method based on the removal effects of criteria (MEREC)" was utilized to find the objective weights. The MEREC that was pioneered by Ghorabaee et al. [41] was used to find the deviations in the diverse option performances that are associated with each criterion by removing their effects. Rani et al. [42] presented the "Fermatean fuzzy information (FFI)"-MEREC-ARAS model to treat a "food waste treatment technology (FWTT)" assessment problem. Mishra et al. [43] used a MEREC-MULTIMOORA model to select a "low carbon tourism strategy (LCTSs)" on a "single-valued neutrosophic sets (SVNSs)" setting. Further, Ul Haq et al. [44] introduced an innovative hybridized MEREC-MARCOS framework under the SVNS context. They applied their proposed method for the material selection of lightweight aircraft wing spars from a sustainable perspective. An incorporated MEREC model has been developed to derive the sustainable criteria weights for an offshore wind farm site selection [45]. The "rank sum (RS)" method was applied to find the subjective weights. The RS that was introduced by Stillwell et al. [46] was used to find the ranks of the considered criteria with the help of the DE opinions. Recently, Narayanamoorthy et al. [47] discussed a model using a "hesitant fuzzy subjective and objective weight integrated approach (HF-SOWIA)" and a "hesitant fuzzy multi-objective optimization based on simple ratio analysis (HF-MOOSRA)" to choose the appropriate "bio-medical waste disposal (BMWD)" method in the medical sector. Hezam et al. [48] introduced a hybrid MADA model with the MEREC-RS-"double normalization-based multiple aggregation (DNMA)" approach with IFSs, and they applied this to evaluate the "alternative fuel vehicles (AFVs)" problem. Until now, no one has proposed the combination of IF-MEREC-RS with the IF-MARCOS methods under an uncertain setting for the purpose of prioritizing the BESSs.

The "measurement alternatives and ranking based on compromise solution (MARCOS)" is an MADA tool that was pioneered by Stevic et al. [49]. Due to it taking a very short time to produce the results, this approach has been implemented for innumerous realistic problems, namely, an assessment of intermediate models of transport between the nations in the "Danube Region (DR)" [50], the handling of multi-objective problems to decrease the risks in road traffic [51], an assessment of the workers for a shipping firm [52], and a cost calculation in the construction industry [53]. Pamucar et al. [54] presented an MADA model using the FUCOM and MARCOS methods to rank the AFVs for sustainable transportation. Ul Haq et al. [44] combined the MARCOS method with MEREC model from a single-valued neutrosophic perspective. They employed their method for solving the material selection problem from sustainability perspectives. Though, this study has been conducted to apply the MARCOS tool for a MADA to treat the BESS assessment problem.

Obviously, previous scholars have addressed several concerns about the BESS assessment. The assessment indicators in the extant models are often datasets that are not considered to be crisp values. Through the "linguistic variables (LVs)", the IF-MEREC-RS procedure, which provides a combination of the objective and subjective weights, is a comparatively appropriate way for finding the weights of the indicators. Alternatively, there is no commonly recognized tool that is used to generate a dependable ranking order with the BESS evaluation. The presented tool can assist the DE to obtain more confidence in prioritizing the BESS outcomes. Hence, the study objectives are to fill the aforementioned gap in the literature using the combination of two prominent tools namely, IF-MEREC-RS and IF-MARCOS, and to select the best BESS for providing the motivation to pursue the development of renewable energy and the ESSs.

3. Proposed Intuitionistic Fuzzy-Based MADA Method

3.1. Preliminaries

Here, we present some concept about the IFSs.

Definition 1 ([28]). *An IFS S on $T = \{t_1,\ t_2,\ \ldots,\ t_n\}$ is defined as*

$$S = \{(t_i,\ \mu_S(t_i),\ \nu_S(t_i))\ :\ t_i \in T\}, \tag{1}$$

where $\mu_S : Z \to [0,\ 1]$ and $\nu_S : Z \to [0,\ 1]$ show the MF and the NF of t_i to S in T, respectively, with the condition $0 \leq \mu_S(t_i) + \nu_S(t_i) \leq 1, \forall\ t_i \in T$. An "indeterminacy function (IF)" of an object $t_i \in T$ to S is defined as $\pi_S(t_i) = 1 - \mu_S(t_i) - \nu_S(t_i)$ and $0 \leq \pi_S(t_i) \leq 1,\ \forall\ t_i\ \in T$. Also, Xu [55] considered the "intuitionistic fuzzy number (IFN)" $\zeta = (\mu_\zeta,\ \nu_\zeta)$ with the constraint $\mu_\zeta,\ \nu_\zeta \in [0,\ 1]$ and $0 \leq \mu_\zeta + \nu_\zeta \leq 1$.

Definition 2 ([55,56]). *Considering that $\zeta_j = (\mu_j,\ \nu_j), j = 1(1)n$, is the IFNs, then*

$$\mathbb{S}(\zeta_j) = \frac{1}{2}\big((\mu_j - \nu_j) + 1\big) \text{ and } H(\zeta_j) = (\mu_j + \nu_j), \tag{2}$$

are called the score and accuracy values, respectively.

Assuming that $\zeta_1 = (\mu_1,\ \nu_1)$ and $\zeta_2 = (\mu_2,\ \nu_2)$ are two IFNs, then, the ordering scheme is given by:

If $\mathbb{S}(\zeta_1) > \mathbb{S}(\zeta_2)$, then $\zeta_1 \succ \zeta_2$,
If $\mathbb{S}(\zeta_1) = \mathbb{S}(\zeta_2)$, then
  If $H(\zeta_1) > H(\zeta_2)$, then $\zeta_1 \succ \zeta_2$,
  If $H(\zeta_1) = H(\zeta_2)$, then $\zeta_1 = \zeta_2$.

Definition 3 ([55]). *When we are letting $\zeta_j = (\mu_j,\ \nu_j), j = 1(1)n$ be the IFNs then, the "intuitionistic fuzzy weighted averaging (IFWA)" and "intuitionistic fuzzy weighted geometric (IFWG)" operators are defined as*

$$IFWA_w(\zeta_1, \zeta_2, \ldots, \zeta_n) = \bigoplus_{j=1}^{n} w_j\zeta_j = \left[1 - \prod_{j=1}^{n}(1-\mu_j)^{w_j},\ \prod_{j=1}^{n}\nu_j^{\,w_j}\right], \tag{3}$$

$$IFWG_w(\zeta_1, \zeta_2, \ldots, \zeta_n) = \bigotimes_{j=1}^{n} w_j\zeta_j = \left[\prod_{j=1}^{n}\mu_j^{\,w_j},\ 1 - \prod_{j=1}^{n}(1-\nu_j)^{w_j}\right], \tag{4}$$

respectively, where $w_j = (w_1, w_2, \ldots, w_n)^T$ is a weight vector of ζ_j, $j = 1, 2, \ldots, n$, with $\sum_{j=1}^{n} w_j = 1, w_j \in [0,\ 1]$.

3.2. Introducing the IF-MEREC-RS-MARCOS Approach

This section proposes an extended MADA methodology, which is called the IF-MEREC-RS-MARCOS. The MARCOS framework considers the advantages of diverse "reference points (RPs)" and "utility degrees (UDs)" in a suitable manner. The "combined utility function (CUF)" of the MARCOS approach widely considers the utility values and the reference points, and thus, the final ranking result has a high degree of reliability. The process of the IF-MEREC-RS-MARCOS approach is discussed as follows (Figure 1):

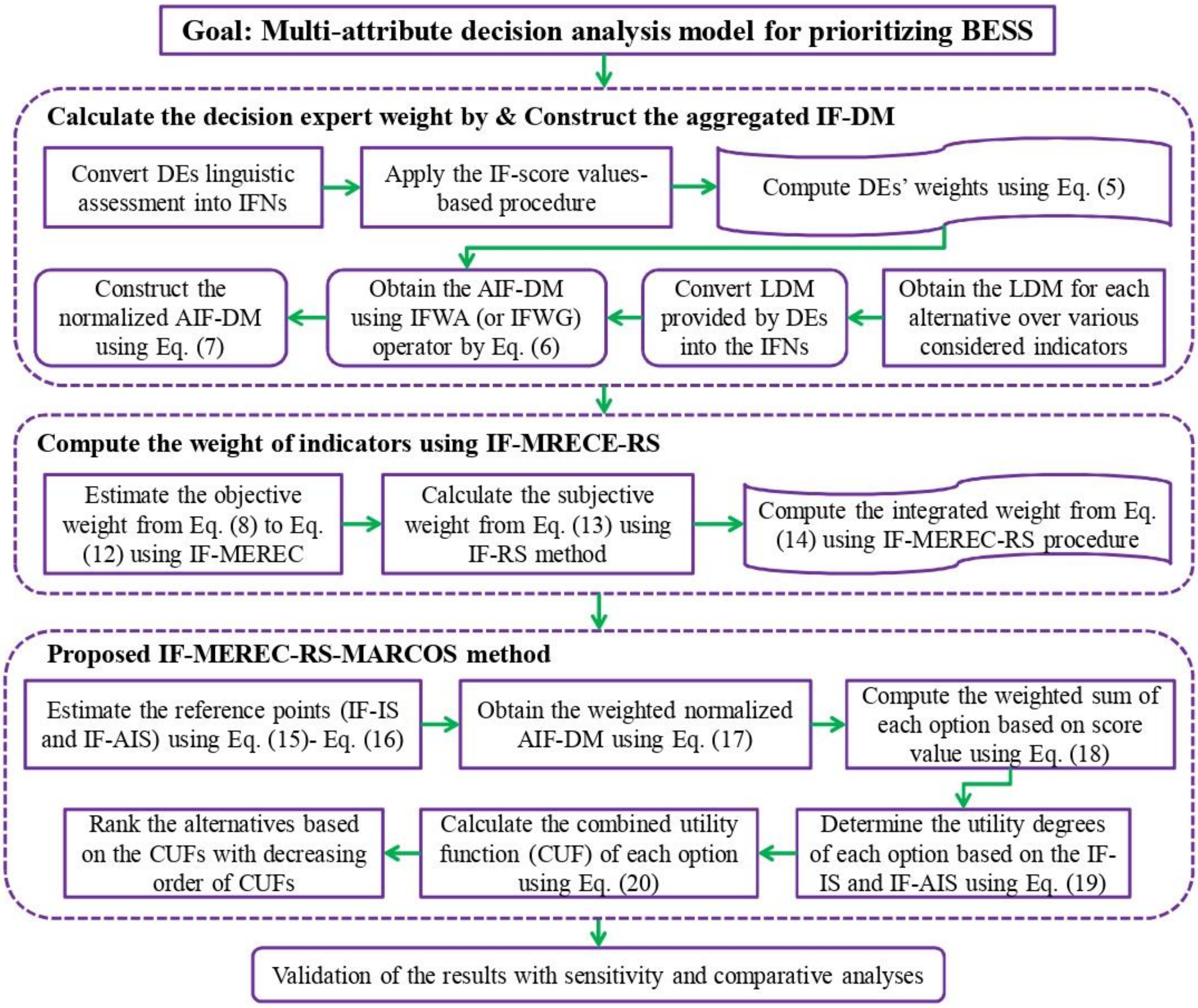

Figure 1. Flowchart of the proposed methodology.

Step 1: Form a "linguistic decision matrix (LDM)".

In the MCDM procedure, consider a set of m options $P = \{p_1, p_2, \ldots, p_m\}$ over a criterion set $Q = \{q_1, q_2, \ldots, q_n\}$. Form a committee of experts $D = \{d_1, d_2, \ldots, d_l\}$ to find the best choice(s). Let $T = \left(\xi_{ij}^{(k)}\right)_{m\times n}$ be the "linguistic decision matrix (LDM)" that is expressed by the "decision experts (DEs)", in which $\xi_{ij}^{(k)}$ entails the linguistic rating of an option p_i over a criterion q_j given by k^{th} expert, and further, convert this into the IF-DM.

Step 2: Find the weights (λ_k) of the Des.

To find the weight of the DE, firstly, the assessment ratings of the DEs are taken as the "linguistic variables (LVs)", and then, they are articulated by the IFNs. Let us suppose $d_k = (\mu_k, \nu_k)$ is an IFN, then the procedure for evaluating the kth DE weight is as

$$\lambda_k = \frac{\mu_k(2 - \mu_k - \nu_k)}{\sum\limits_{k=1}^{l}[\mu_k(2 - \mu_k - \nu_k)]}. \tag{5}$$

Clearly, $\lambda_k \geq 0$ and $\sum\limits_{k=1}^{l} \lambda_k = 1$.

Step 3: Determine the aggregated IF-DM (AIF-DM).

In this step, all of the individual decision matrices are required to be combined into the AIF-DM. For this perspective, the IFWA (or IFWG) operator that is applied to create the AIF-DM is $Z = \left(\xi_{ij}\right)_{m\times\, n}$, where

$$\xi_{ij} = \left(\mu_{ij}, \nu_{ij}\right) = IFWA_{\lambda_k}\left(\xi_{ij}^{(1)}, \xi_{ij}^{(2)}, \ldots, \xi_{ij}^{(l)}\right) \text{ or } IFWG_{\lambda_k}\left(\xi_{ij}^{(1)}, \xi_{ij}^{(2)}, \ldots, \xi_{ij}^{(l)}\right) \tag{6}$$

Step 4: Obtain the normalized AIF-DM.

The normalization is utilized to assess the values of the AIF-DM $Z = (\xi)_{m\,\times\,n}$ and create the normalized AIF-DM $\mathbb{N} = \left(\varsigma_{ij}\right)_{m\,\times\,n}$. Let q_b and q_n represent the benefit and cost-type attributes, then, the expression for the normalization is given by

$$\varsigma_{ij} = \left(\overline{\mu}_{ij}, \overline{\nu}_{ij}\right) = \begin{cases} \xi_{ij} = \left(\mu_{ij}, \nu_{ij}\right), & j \in q_b, \\ \left(\xi_{ij}\right)^c = \left(\nu_{ij}, \mu_{ij}\right), & j \in q_n. \end{cases} \tag{7}$$

Step 5: Obtain the indicator weight using IF-MEREC-RS.

Let $w = (w_1, w_2, \ldots, w_n)^T$ be the weight vector of the indicator with $\sum_{j=1}^{n} w_j = 1$ and $w_j \in [0,\ 1]$. The indicator weight is estimated by combining the objective and subjective assessments of the indicators.

Case I: The estimation of the objective weights using the IF-MEREC.

Now, to find the weight of the indicators, the classical MEREC is applied to the IFSs setting. In this line, the procedure of the IF-MEREC is given as follows.

Step 5a: Find the score values of the normalized AIF-DM.

From Equation (2), the score-matrix $\Omega = \left(\eta_{ij}\right)_{m\,\times\,n}$ of $\varsigma_{ij} = \left(\overline{\mu}_{ij}, \overline{\nu}_{ij}\right)$ is computed as

$$\eta_{ij} = \frac{1}{2}\left(\left(\overline{\mu}_{ij}\right) - \left(\overline{\nu}_{ij}\right) + 1\right). \tag{8}$$

Step 5b: Evaluate the overall performance of the options.

Corresponding to the normalized AIF-DM, we can certify that smaller rating of η_{ij} yields a greater performance rating. We apply the expression to estimate the performance of the options as follows:

$$S_i = \ ln\left(1 + \ \left(\frac{1}{n}\sum_j \left|ln\left(\eta_{ij}\right)\right|\right)\right). \tag{9}$$

Step 5c: Obtain the performance of options by removing each indicator.

We compute the alternatives' performances by eliminating each indicator separately. Thus, we find n sets of performances that are associated with n indicators. Let S_i' be the overall performance of ith option about the elimination of jth indicator. We use the following expression to implement this step as

$$S_{ij}' = ln\left(1 + \left(\frac{1}{n}\sum_{k,k\neq j} \left|ln\left(\eta_{ik}\right)\right|\right)\right). \tag{10}$$

Step 5d: Obtain the sum of absolute deviation.

We find the removal result of the jth indicator using the outcomes that were computed from Step 5b and Step 5c. Then, we compute the sum of the absolute deviation $\left(as_j\right)$ as follows:

$$as_j = \sum_i \left|S_{ij}' - S_i\right|, \ j = 1, 2, \ldots, n. \tag{11}$$

Step 5e: Assess the objective weight of indicator.

The weight of the indicator is computed by the removal effects $\left(as_j\right)$. Let w_j^o be the objective weight of the j^{th} indicator. The following expression is used for calculating w_j^o as

$$w_j^o = \frac{as_j}{\sum\limits_{j=1}^{n} as_j},\ j = 1, 2, \ldots, n. \tag{12}$$

Case II: The determination of the subjective weights using the IF-RS tool.

Here, the IF-RS tool assists the DEs to provide their rankings for the considered indicators. The expression of this process method is presented as

$$w_j^s = \frac{n - r_t + 1}{\sum\limits_{j=1}^{n} \left(n - r_j + 1\right)}, \tag{13}$$

where w_j^s signifies the objective weight of indicator, n symbolizes the total indicators and r_j means the rank of the indicator, $j = 1, 2, 3, \ldots, n$.

Case III: The calculation of the integrated weight of an indicator using the "IF-MEREC-RS" method.

To find the integrated weight indicator, the DEs need to utilize the both the subjective and objective weights of the indicators. The expression for the integrated weight is given by

$$w_j = \gamma w_j^o + (1 - \gamma) w_j^s,\ j = 1, 2, \ldots, n, \tag{14}$$

where $\gamma \in [0,\ 1]$ is a precision coefficient.

Step 6: Estimate the reference points.

We compute the "intuitionistic fuzzy-ideal solution (IF-IS)" and "intuitionistic fuzzy anti-ideal solution (IF-AIS)" with the use of following expressions:

$$\alpha_j^+ = \begin{cases} \left(\max\limits_i \mu_{ij}, \min\limits_i \nu_{ij}\right), & \text{for benefit criterion } q_b \\ \left(\min\limits_i \mu_{ij}, \max\limits_i \nu_{ij}\right), & \text{for cost criterion } q_n \end{cases} \quad \text{for } j = 1,\ 2, \ldots, n, \tag{15}$$

$$\alpha_j^- = \begin{cases} \left(\min\limits_i \mu_{ij}, \max\limits_i \nu_{ij}\right), & \text{for benefit criterion } q_b \\ \left(\max\limits_i \mu_{ij}, \min\limits_i \nu_{ij}\right), & \text{for cost criterion } q_n \end{cases} \quad \text{for } j = 1,\ 2, \ldots, n. \tag{16}$$

Step 7: Calculate the weighted normalized AIF-DM.

Here, the weighted normalized AIF-DM $\mathbb{N}_w = \left(\widehat{\varsigma}_{ij}\right)_{m \times n}$ is calculated, wherein

$$\widehat{\varsigma}_{ij} = \left(\widehat{\mu}_{ij},\ \widehat{\nu}_{ij}\right) = w_j\, \overline{\varsigma}_{ij} = \left(1 - \left(1 - \overline{\mu}_{ij}\right)^{w_j},\ \left(\overline{\nu}_{ij}\right)^{w_j}\right),\ j = 1, 2, \ldots, n. \tag{17}$$

Step 8: Evaluate the scare values of the weighted sum of each option

$$S_i = \sum_{j=1}^{n} \mathbb{S}\left(\widehat{\varsigma}_{ij}\right),\ i = 1, 2, \ldots, m, \tag{18}$$

where $\mathbb{S}\left(\widehat{\varsigma}_{ij}\right)$ represents the score values of each element of the weighted normalized IF-DM.

Step 9: Evaluate the UD of each option.

$$u_i^- = \frac{S_i}{S_{ais}} \text{ and } u_i^+ = \frac{S_i}{S_{is}}, \tag{19}$$

where S_{is} and S_{ais} signify the sum of score values of weighted values of α_{jw}^{+} and α_{jw}^{-}, respectively.

Step 10: Identify the CUF of each alternative.

The CUF is the compromise solution of the alternatives that are associated with the IF-IS and IF-AIS. Thus, the CUF of the alternatives are defined by

$$f(u_i) = \frac{u_i^{+} + u_i^{-}}{1 + \frac{1-f\left(u_i^{+}\right)}{f\left(u_i^{+}\right)} + \frac{1-f\left(u_i^{-}\right)}{f\left(u_i^{-}\right)}},$$
$$\text{where } f\left(u_i^{+}\right) = \frac{u_i^{-}}{u_i^{-}+u_i^{+}} \text{ and } f\left(u_i^{-}\right) = \frac{u_i^{+}}{u_i^{-}+u_i^{+}},\ i = 1, 2, \ldots, m. \tag{20}$$

Step 11: Rank the alternatives based on the CUFs. The appropriate option has the maximum CUF value.

4. Case Study: Assessment of BESS

Recently, the progress of the BESS has become increasingly important worldwide. The BESS is the most favorable ESS for the future creation of a smart grid, a micro-grid and a project incorporating the "renewable energy power generation (REPG)" models and the ESSs. The primary BESSs are expressed the LAB type, the NiMHB type, the LIB type, the NaSB type, the VRFB type, the NiCdB type, the $ZnMnO_2B$ type, and the ZnBrFB type. This paper considers the LAB type (G_1), the LIB type (G_2), the VRFB type (G_3), the NiMHB type (G_4), the and NaSB type (G_5) as the research objects/options. A systematic assessment using the presented IF-MEREC-RS-MARCOS method is discussed to rank the BESSs, and the references are provided for the DEs.

For the LAB type, it is the most widely used BESS with a combination of *PbO2*, *Pb* and sulfuric acid, respectively [57]. The benefits of the LAB type comprise a "short response time", a "small discharge rate", a "high cycle efficiency" and a "low cost" [58]. Nevertheless, the drawbacks of the LAB type comprise a "low cycling time" and "energy density" as well as a "bad manifestation in low temperature" [23]. The LAB type can be used in a "power management system (PMS)". It can also be utilized to supply power to "electric vehicles (EVs)".

For the LIB type, it is a combination of "graphitic carbon", "$LiCoO_2$ or $LiMO_2$", and "anhydrous organic liquid with lithium salts" [15]. The key advantages of the LIB type are its "short response time", "light equipment weights", and "high 97% cycle efficiency" [10]. The critical drawbacks are that the lifetime of it is effortlessly impacted by numerous natural aspects and "the operation cost is relatively high" [59].

For the VRF type, it is composition of "vanadium solution" in different oxidation statuses. The VRF type has a "short response time" and "a high efficiency achieving 85%" [60]. Nevertheless, it also contains a "low energy density" and it has a "high cost" [61]. The VRF type has the prospect of having an improved electricity quality and it highlights the alternating character of REPG.

For the NiMH type, it is a combination of "hydrogen-absorbing alloy", "nickel hydroxide", and "the aqueous alkali liquor" [62]. The NiMH type has a "high energy density" and it can be operated using portable apparatus and EVs. The critical weak point of it is that it has a "relatively high self-discharging rate reaching to 20%".

For the NaS type, it is a combination of "sulfur", "molten sodium", and "the "beta alumina". It needs a specific temperature which is essential to preserve its function within 574–624 K in order for the NaS type to operate normally. The features of the NaS type are that it has a "superior energy density" and an "inferior self-discharge rate" [23]. The NaS type is environmentally friendly because of its innocuous ingredients.

To better systematically prioritize the BESSs such as the LAB, LIB, NaS, NiMH, and VRF types, the assessment indicator procedure is of great importance over the economic, technological, environmental, social and performance aspects of the different BESSs. Referring the related literatures [23,25,26,59,60], thirteen assessment indicators are taken, which are comprise the abovementioned aspects to prioritize the BESSs. The detailed descriptions of criteria are presented in Table 1. To choose the key indicators and develop the systematic assessment indicator procedure, a collective questionnaire method with at least three questions which are used as comparative features for each indicator is considered based on the DEs' opinions. Four DEs are considered from various disciplines, comprising researchers of ESSs, stockholders, DEs and managers for micro-grid structures and prototypical project structures, combining REPG and ESS. To select the best BESS, a committee of four decision experts has been created. The procedure for the execution of the IF-MEREC-RS-MARCOS approach with the presented application is given as follows:

Table 1. Comprehensive assessment indicators for prioritizing BESSs.

Dimension	Criteria	Criteria Nature	Criteria Type
Economic (L_1)	Operation cost (q_1)	Quantitative	Min
	Capital intensity (q_2)	Quantitative	Min
	Energy storage system profit (q_3)	Quantitative	Max
Technology (L_2)	Cycle life (q_4)	Quantitative	Max
	Safety (q_5)	Qualitative	Max
	Specific energy (q_6)	Quantitative	Max
	Self-discharge rate (q_7)	Quantitative	Min
Environmental (L_3)	CO_2 intensity (q_8)	Quantitative	Min
	Environmental impact (q_9)	Qualitative	Min
Social (L_4)	Local development (q_{10})	Qualitative	Max
	Job creation (q_{11})	Quantitative	Max
Performance (L_5)	Energy efficiency (q_{12})	Quantitative	Max
	Energy intensity (q_{13})	Quantitative	Max

Steps 1–3: Table 2 is taken from [39,63,64] to show the LVs to evaluate the weight values of the DEs and the considered indicators to prioritize the BESSs, then, these were converted into the IFNs. From Table 2 and Equation (5), the DEs' weights were obtained, and they are given in Table 3. Table A1 (see Appendix A) signifies the LDM by the DEs as (d_1, d_2, d_3, d_4) for each alternative p_i concerning the considered criteria. From Equation (6) and Table A1, the AIF-DM was created and specified in Table A2 (see Appendix A).

Table 2. LVs for options for prioritizing BESSs.

LVs	IFNs
Absolutely high (AH)	(0.95, 0.05)
Very very high (VVH)	(0.85, 0.1)
Very high (VH)	(0.8, 0.15)
High (H)	(0.7, 0.2)
Slightly high (MH)	(0.6, 0.3)
Average (A)	(0.5, 0.4)
Slightly low (ML)	(0.4, 0.5)
Low (L)	(0.3,0.6)
Very very low (VL)	(0.2, 0.7)
Very low (VVL)	(0.1, 0.8)
Absolutely low (AL)	(0.05, 0.95)

Table 3. The DE's weight for prioritizing BESS.

DEs	d_1	d_2	d_3	d_4
Ratings	VVH (0.85, 0.1)	VH (0.8, 0.15)	EH (0.95, 0.05)	H (0.7, 0.2)
λ_k	0.2585	0.2433	0.2752	0.2230

Step 4: According to Equation (7) and Table A2 (see Appendix A), the normalized AIF-DMs of each option for prioritizing the BESSs are given in Table A3 (see Appendix A).

Step 5: To find the objective weight of the indicator by the IF-MEREC, we first find the score values of the normalized AIF-DM using Equation (8), then, we find the overall performance value of the option using Equation (9) with S_1= 0.374, S_2 = 0.302, S_3 = 0.402, S_4 = 0.365, and S_5 = 0.359. Next, using Equations (10) and (11), the overall performance $\left(S'_{ij}\right)$ options by removing each indicator and the sum of the absolute deviation (as_j) of each indicator are evaluated. From Equation (12), we compute the objective weight of each indicator to prioritize the BESS selection, and these are mentioned in Table A4 and Figure 2.

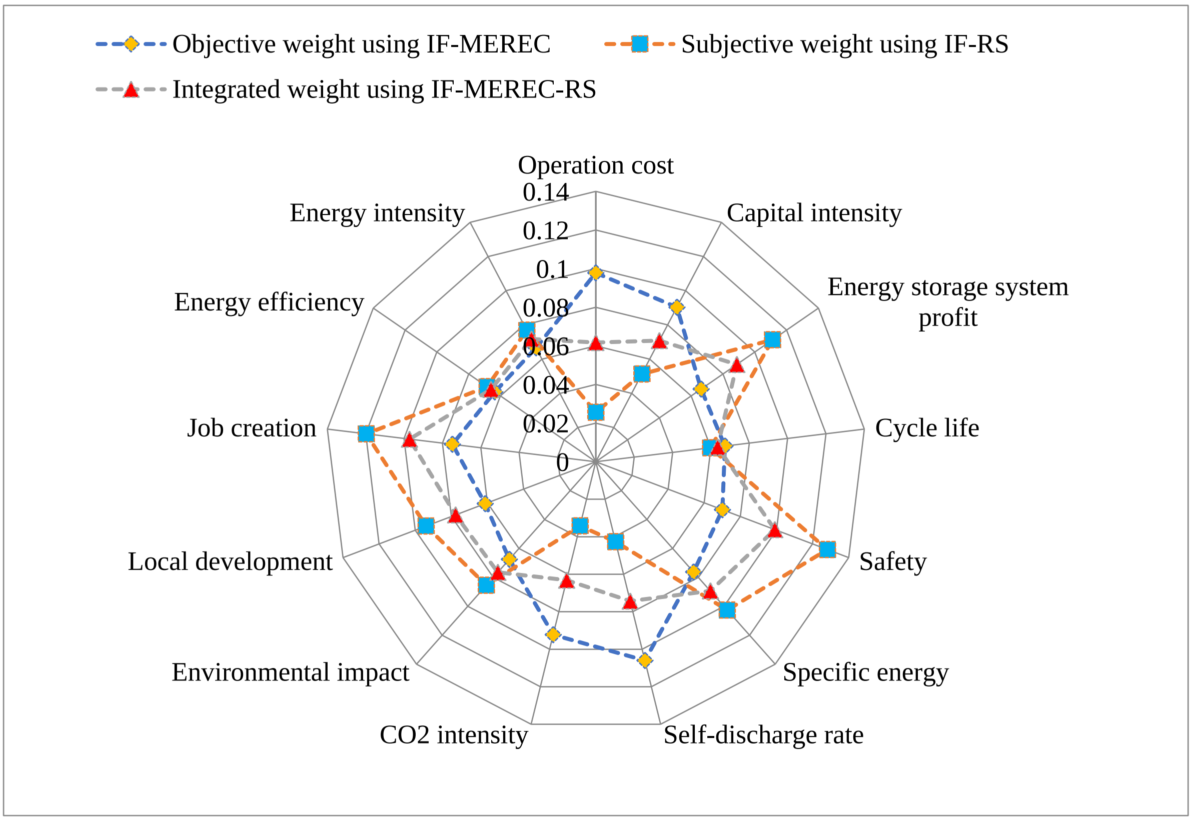

Figure 2. Weight of indicators for prioritizing BESS using the IF-MEREC-RS.

From Equation (13), the subjective weight of each indicator for prioritizing the BESS is obtained, and it is given in Table A5 and Figure 2.

Next, we combine the IF-MEREC and the IF-RS using Equation (14). The combined weight for $\tau = 0.5$ that is used to prioritize the BESSs is depicted in Figure 2, and it is given by

w_j = (0.0617, 0.0708, 0.0887, 0.0635, 0.0991, 0.0894, 0.0743, 0.0632, 0.0765, 0.0777, 0.0972, 0.0660, 0.0718).

Here, Figure 2 demonstrates the weights of the diverse indicators in the prioritization of the BESSs. The indicator safety (q_5) with a weight of 0.0991 has been demonstrated to be the most important indicator in the prioritization of the BESSs. Job creation (q_{11}) with a weight value of 0.0972 is the second most important indicator in the prioritization of the BESSs. Specific energy (q_{15}) with a significance value of 0.0894 is the third most important indicator in the prioritization of the BESSs, and the rest of indicators are taken to be crucial indicators in the prioritization of the BESSs.

Step 6: From Equations (15) and (16) and Table A2 (see Appendix A), the IF-IS and the IF-AIS that are used for prioritizing the BESSs are obtained as follows:

$\alpha_j^+ = \{(0.281, 0.618, 0.101), (0.274, 0.625, 0.101), (0.697, 0.217, 0.086), (0.793, 0.156, 0.051), (0.729, 0.200, 0.071), (0.666, 0.247, 0.087), (0.328, 0.569, 0.102), (0.300, 0.598, 0.101), (0.719, 0.195, 0.086), (0.736, 0.192, 0.072), (0.753, 0.204, 0.043), (0.739, 0.189, 0.071), (0.741, 0.189, 0.071)\}.$

$\alpha_j^+ = \{(0.468, 0.429, 0.103), (0.452, 0.447, 0.101), (0.598, 0.315, 0.087), (0.538, 0.361, 0.102), (0.528, 0.371, 0.102), (0.557, 0.339, 0.104), (0.435, 0.464, 0.101), (0.419, 0.476, 0.105), (0.598, 0.315, 0.087), (0.595, 0.317, 0.087), (0.461, 0.436, 0.103), (0.614, 0.301, 0.085), (0.531, 0.368, 0.102)\}.$

Step 7: According to Equation (17) and Table A3, the weighted normalized AIF-DMs of each option is used to prioritize the BESSs are given in Table A6 (see Appendix A).

Step 8: Using Equation (18) and Table A6, the score values of each alternative IF-IS and IF-AIS that are used to prioritize the BESSs are determined, and they are given in Table A7 (see Appendix A).

Steps 9–10: From Equations (19) and (20), we estimate the utility degrees, the CUFs, and the ranking order of the alternatives to prioritize the BESSs, and they are given in Table A8 (see Appendix A). Hence, the prioritization of the options that were obtained in the process of prioritizing the BESSs is $p_2 \succ p_5 \succ p_4 \succ p_1 \succ p_3$, and the LIB ($p_2$) is the best BESS with a maximum CUF.

4.1. Comparison Study

The comparison is performed with the results that were found using the IF-MEREC-RS-MARCOS method and different extant tools. To show the proficiency and show the irreplaceable merits of the IF-MEREC-RS-MARCOS method, the "intuitionistic fuzzy complex proportional assessment (IF-COPRAS) [65]" and "intuitionistic fuzzy weighted aggregated sum product assessment (IF-WASPAS) [64]" were used to handle the case.

4.1.1. IF-COPRAS Model

To facilitate the comparative study, we used the IF-COPRAS method with the assessment of the MADA problem, which are discussed in Section 4.1.

Steps 1–5: These steps are similar to proposed model.

Step 6: Calculate the sum of the ratings of the criteria for the benefit and cost.

Let α_i be the aggregated ratings of each option according to the benefit type, and β_i be the aggregated ratings of each option according to the benefit type, respectively. Then, utilize the following expressions to find the respective values of α_i and β_i, as

$$\alpha_i = \overset{l}{\underset{j=1}{\oplus}} w_j\, \xi_{ij},\ i = 1(1)m. \tag{21}$$

$$\beta_i = \overset{n}{\underset{j=l+1}{\oplus}} w_j\, \xi_{ij},\ i = 1(1)m. \tag{22}$$

Here, l is benefit type attribute, while n is the overall attribute.

Step 7: Find the "relative degree (RD)".

The RD γ_i of each option is described as follows:

$$\gamma_i = \vartheta \mathbb{S}(\alpha_i) + (1-\vartheta)\frac{\sum_{i=1}^{m} \mathbb{S}(\beta_i)}{\mathbb{S}(\beta_i)\sum_{i=1}^{m}\frac{1}{\mathbb{S}(\beta_i)}},\ i = 1(1)m, \tag{23}$$

where $\vartheta \in [0,1]$ is the strategic precision coefficient.

Step 8: Find the "utility degree (UD)".

The formula for the computation of the UD δ_i of each option is given as

$$\delta_i = \frac{\gamma_i}{\gamma_{\max}} \times 100\,\%,\ i = 1(1)m. \tag{24}$$

Here, γ_i and $\gamma_{\max}$ are the RDs that were obtained from Equation (23).

The whole computational results of the IF-COPRAS [65] model are presented in Table A9. From Table A2 and Equations (21)–(24), the RD and UD of the alternatives were obtained. Based on the UD (see Table A9), the LIB (p_2) was found to be the suitable BESS choice with a maximum RD (0.648) in the prioritization of the BESS.

4.1.2. IF-WASPAS Model

Steps 1–5: These steps are similar to developed model.

Step 6: Estimate the "weighted sum measure (WSM)" $\wp_i^{(1)}$ and the "weighted product measure (WPM)" $\wp_i^{(2)}$ using the following expressions:

$$\wp_i^{(1)} = \overset{n}{\underset{j=1}{\oplus}} w_j\, \varsigma_{ij}. \tag{25}$$

$$\wp_i^{(2)} = \overset{n}{\underset{j=1}{\otimes}} w_j \varsigma_{ij},\ i = 1, 2, \ldots, m. \tag{26}$$

Step 7: Find the "utility degree (UD)".

$$Q_i = \hbar\, \wp_i^{(1)} + (1 - \hbar)\, \wp_i^{(2)},\ i = 1, 2, \ldots, m, \tag{27}$$

where $\hbar \in [0,1]$ means the strategic coefficient.

Step 8: Prioritize the options with the score value of Q_i.

Using Equations (25)–(27), the WASPAS measures of the alternatives that were used to prioritize the BESSs are demonstrated in Table A10.

Therefore, the ranking order of the BESSs is $p_2 \succ p_5 \succ p_3 \succ p_1 \succ p_4$, and the alternative LIB (p_2) is the suitable choice with a maximum CUF when we were using different existing methods. Figure 3 presents the ranking orders that were obtained using different methods including IF-COPRAS, IF-WSM, IF-WPM, and IF-WASPAS and the proposed IF-MEREC-RS-MARCOS. In comparison with the existing methods such as IF-COPRAS, IF-WSM, IF-WPM, and IF-WASPAS, the advantages of the proposed method are listed as follows:

(a) The IF-WASPAS method computes only the objective weights of the criteria using a similarity measure, whereas the IF-COPRAS method considers the direct weights of the criteria. While the proposed approach computes the indicators' weights using a combined IF-MEREC-RS process, which is the combination of the objective and subjective weighting models. Thus, the proposed method considers the advantages of both the objective and subjective weighting models.

(b) When we were comparing it with other MADA models, we observed that the suitable choice with the use of all of the methodologies is the same, i.e., the alternative p_2 (LIB). The CUFs in the IF-MEREC-RS-MARCOS model have used IF-IS and IF-AIS, while the IF-COPRAS model used the averaging operator and the IF-WASPAS model utilized the averaging and geometric operators. So, the IF-MEREC-RS-MARCOS method is more general and more flexible than the IF-COPRAS, IF-WSM, IF-WPM and IF-WASPAS ones. Because of this characteristic, the presented IF-MEREC-RS and IF-MARCOS methods can be applied more widely in realistic decision-making situations.

(c) For the rational aggregation of the preferences, the MARCOS tool was pioneered by Stević et al. [49]. It gives a dynamic MADA model by (*i*) imposing the IF-IS and IF-AIS values, (*ii*) identifying the relations among the alternatives and the IS/AIS values, and (*iii*) characterizing the *UD* of each alternative that is associated with the IF-IS and the IF-AIS. According to Stević et al. [49], the outcomes that are acquired by the MARCOS method are more robust when they were compared to the other popular MCDM methods namely the VIKOR [36], TOPSIS [66], ARAS [67], COPRAS [68], and WASPAS [64] ones. Thus, the proposed hybrid MARCOS model handles the existing issues in the study of BESS assessments.

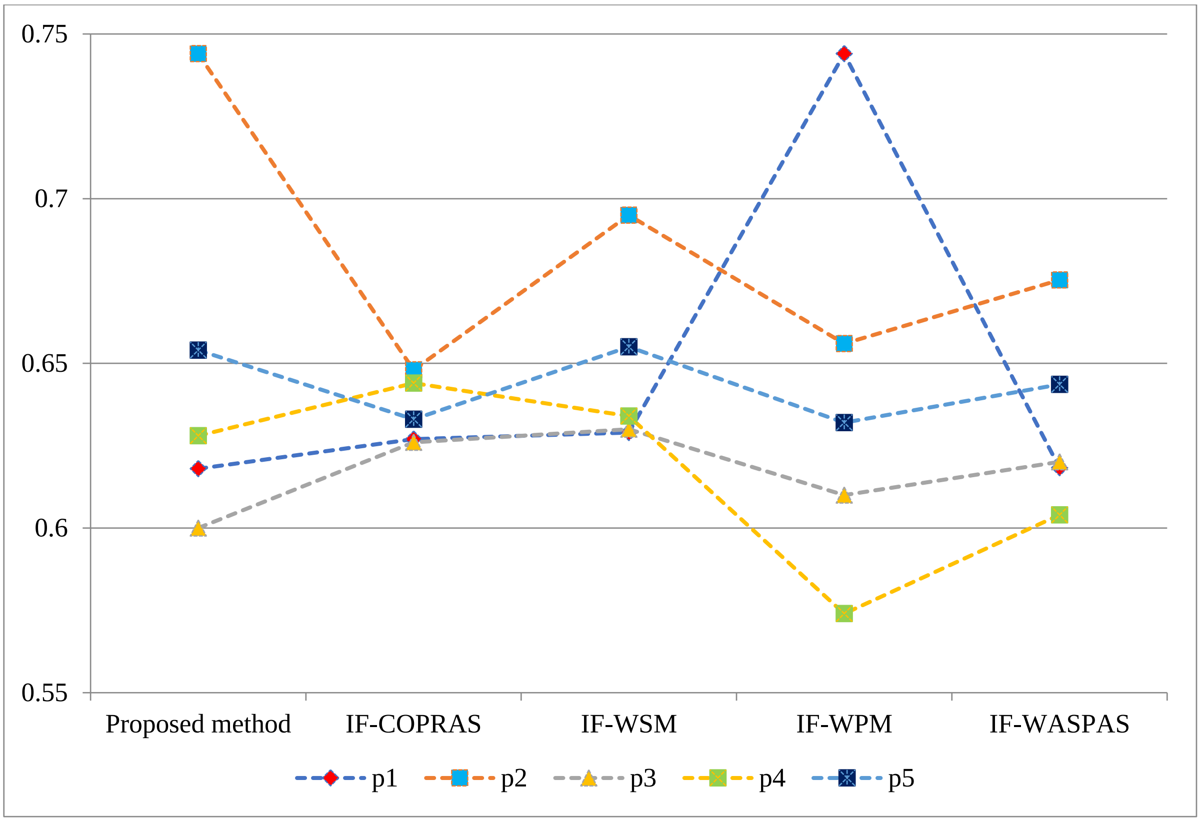

Figure 3. Ranking order when we were prioritizing the BESSs using different methods.

4.2. Sensitivity Assessment

In this portion, we discuss the variation between the weights of the indicators and the objective and subjective weights in the "IF-MEREC-RS method" for prioritizing the BESSs. In this line, the prioritizations of the BESSs have been obtained using the objective and subjective weights of the indicators in lieu of the IF-MEREC-RS model, and they are given in Table A11 and Figure 4. From the IF-MEREC method, the CUF values and the priority of the options are given as follows: the CUF values of the options are $p_1 = 0.625$, $p_2 = 0.749$, $p_3 = 0.590$, $p_4 = 0.633$ and $p_5 = 0.648$, and the prioritization of the BESSs is given as $p_2 \succ p_5 \succ p_4 \succ p_1 \succ p_3$. When applying the IF-RS method, the CUF values of the options and their priorities are discussed as follows: the CUF values of the options are $p_1 = 0.612$, $p_2 = 0.739$, $p_3 = 0.611$, $p_4 = 0.624$, and $p_5 = 0.660$, and the ranks of the BESSs are given as $p_2 \succ p_5 \succ p_4 \succ p_1 \succ p_3$. From the aforementioned investigation, it is concluded that the utilization of diverse values with a strategic coefficient will enhance the permanence of the IF-MEREC-RS-MARCOS method.

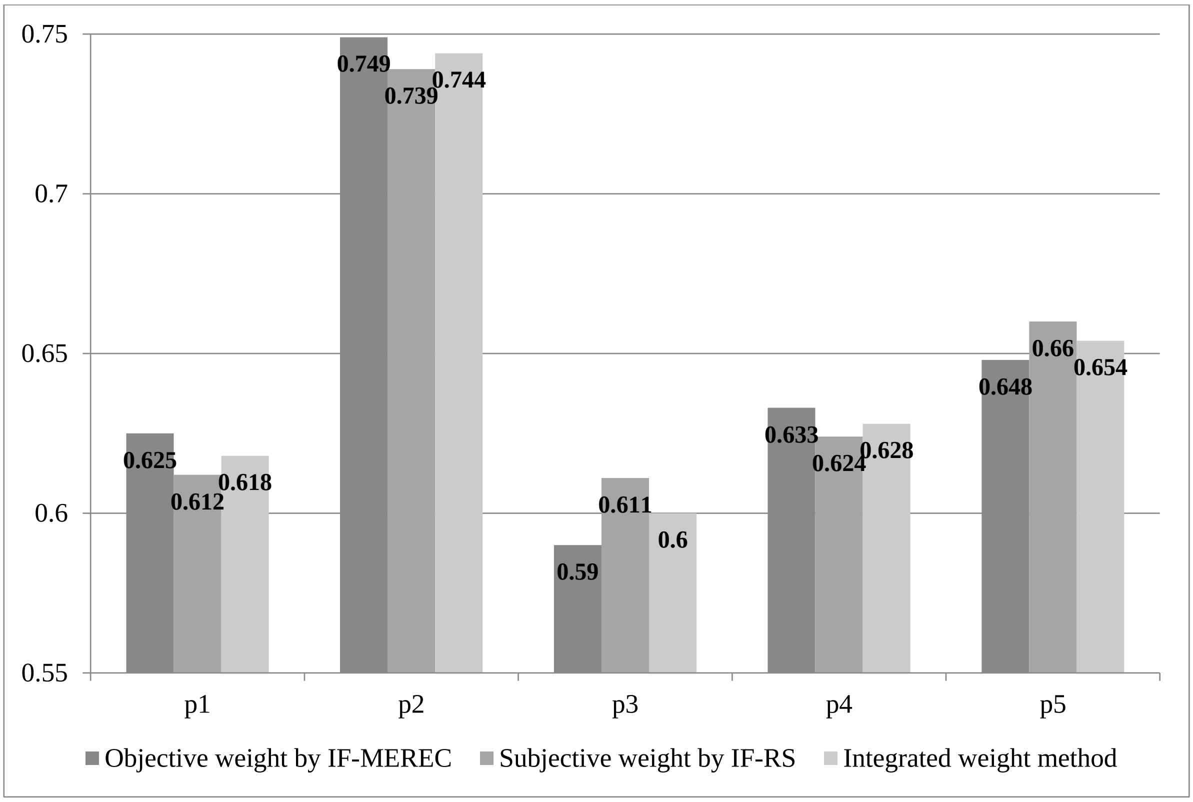

Figure 4. Sensitivity analysis for prioritizing the BESSs with different weighting procedures.

5. Conclusions

The objective of paper is to introduce an integrated approach with the use of the IF-MEREC-RS and IF-MARCOS ones with sustainability for prioritizing the BESSs. The proposed MADA approach provides an appropriate BESS assessment and selection framework to attract the interest of researchers, executives, and experts for them to take more efficient decisions. The presented model is implemented to prioritize the BESSs over various crucial economic, social, environmental, technological, and performance indicators. The presented method illustrates that the option LIB (G_2) is the optimal choice, while option VRF (G_3) was assessed to be the least appropriate ESS option.

Here, we notice that the following key contributions of the paper: (1) we propose a new integrated weighting method, which permits an objective weight to be determined with the IF-MEREC method and a subjective weight to be determined with the IF-RS approach; (2) the method that is discussed in the study offers a reliable MADA regarding the associations between the indicators for selecting the suitable alternatives using the IF-MARCOS method; (3) the developed approach facilitates the assessment of the options notwithstanding the problems that occur in the MADA procedure and a lack of quantifiable information.

Some limitations of the method can be found while we are inferring the outcomes: (i) In this study, we have chosen a very limited number of decision experts. (ii) This study ignores some important factors such as the application that the BESS is being used for (power/energy application), it's location in the grid (transmission/distribution/behind-the-meter), the system size, or the discharge duration.

Thus, a future study should be focused towards employing a broader number of worldwide DEs who will appraise the option, with a potential reduction in the number of considered indicators. It would be interesting to consider a large number of important factors in the prioritization of the BESSs. Furthermore, we can extend the presented approach with the diverse uncertainty disciplines, namely the "bipolar fuzzy sets (BFSs)", the "rough sets (RSs)", and the "grey sets (GSs)". The other path of future study is the investigation of the opportunity of the extension of the MARCOS and GLDS method, utilizing various weighting models, which would facilitate the removal of the impact of the extreme ratings from the biased DEs.

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Abbreviations

AFVs	Alternative fuel vehicles
AHP	Analytic hierarchy process
A-IF-DM	Aggregated intuitionistic fuzzy decision matrix
AOs	Aggregation operators
BESS	Battery energy storage systems
BMWD	Bio-medical waste disposal
BWM	Best worst method
COPRAS	Complex proportional assessment
CPT	Cumulative prospect theory
CRITIC	Criteria importance through intercriteria correlation
CS	Chemical storage
CSP	Cloud service provider
CUF	combined utility function
DEs	Decision experts
DNMA	Double normalization-based multiple aggregation
DR	Danube region
EMS	Electro-magnetic storage
EMS	Electro-magnetic storage
FDA	fuzzy-Delphi approach
FSs	Fuzzy sets
FWTT	Food waste treatment technology
GRA	Grey relational analysis
GSS	Green supplier selection
HF-MOOSRA	Hesitant fuzzy multi-objective optimization based on simple ratio analysis
HF-SOWIA	Hesitant fuzzy subjective and objective weight integrated approach
HLSS	Hydrogen large-scale seasonal storage
IF-AIS	intuitionistic fuzzy anti-ideal solution
IF-IS	intuitionistic fuzzy-ideal solution
IFSs	Intuitionistic fuzzy sets
IFWA	Intuitionistic fuzzy weighted averaging
IFWG	Intuitionistic fuzzy weighted geometric
IF-COPRAS	Intuitionistic fuzzy complex proportional assessment
IF-WASPAS	Intuitionistic fuzzy weighted aggregated sum product assessment
IFN	Intuitionistic fuzzy number
LAB	Lead-acid battery
LCTS	Low carbon tourism strategy

LDM	Linguistic decision matrix
LIB	Lithium-ion battery
LVs	Linguistic variables
MADA	Multi-attribute decision analysis
MAIRCA	Multi-attributive ideal-real comparative analysis
MARCOS	Measurement alternatives and ranking based on compromise solution
MEREC	Method based on the removal effects of criteria
MF	Membership function
MS	mechanical storage
MULTIMOORA	Multi-Objective Optimization on the basis of a Ratio Analysis plus the full multiplicative form
NaSB	Sodium-sulfur battery
NF	Non-membership function
NiMHB	Nickel-metal Hydride battery
q-ROFSs	q-rung orthopair fuzzy sets
RES	Renewable energy source
RP	Reference point
RS	Rank sum
SAA	Simulated annealing algorithm
SVNSs	Single-valued neutrosophic sets
SWM	Solid waste management
T2FSs	Type 2 fuzzy sets
TNFNs	Trapezoidal neutrosophic fuzzy numbers
TOPSIS	Technique for order of preference by similarity to ideal solution
TSPs	Telecom service providers
UDs	Utility degrees
VRFB	Vanadium Redox Flow Battery
ZnBrFB	Zinc Bromine flow battery

Appendix A

Table A1. The LDM for prioritizing the BESSs by DEs.

Parameters	p_1	p_2	p_3	p_4	p_5
q_1	(VL,VL,ML,ML)	(ML,L,VL,VL)	(MH, ML,A,L)	(L,ML,A,L)	(A,L,ML,ML)
q_2	(ML,ML,A,L)	(VL,L,VL,ML)	(A,A,ML,ML)	(VL,L,ML,L)	(VVL,L,ML,L)
q_3	(MH,ML,A,VH)	(A,VH,ML,MH)	(MH,A,VH,H)	(VH,H,A,MH)	(VVH,A,H,MH)
q_4	(A,MH,MH,H)	(H,AH,H,MH)	(MH,H,A,H)	(H,ML,MH,VH)	(MH,A,MH,ML)
q_5	(MH,H,A,MH)	(VH,H,VH,A)	(ML,MH,A,MH)	(VH,ML,A,MH)	(MH,MH,H,VH)
q_6	(A, MH,VH,A)	(ML,MH,A,H)	(H,VH,A,MH)	(A,MH,A,H)	(MH,A,H,A)
q_7	(L,L,L,VL)	(VL,ML,VL,A)	(A,L,A,ML)	(ML,L,A,A)	(A,ML,ML,L)
q_8	(VL,L,A,ML)	(A,VL,L,VL)	(A,MH,VL,L)	(VL,ML,VL,ML)	(A,L,ML,VL)
q_9	(A,H,MH,H)	(VVH,H,H,A)	(MH,H,A,H)	(MH,H,A,MH)	(ML,A,MH,VH)
q_{10}	(VVH,H,A,MH)	(MH,H,VH,H)	(ML,MH,A,VH)	(H,ML,A,H)	(MH,H,VH,VH)
q_{11}	(MH,A,L,ML)	(A,ML,AH,H)	(H,A,H,VVH)	(MH,ML,A,VH)	(A,A,MH,H)
q_{12}	(VVH,ML,A,MH)	(VH,MH,A,MH)	(VH,A,MH,ML)	(ML,MH,VH,H)	(VH,VH,H,MH)
q_{13}	(H,H,VH,A)	(H,VH,VH,MH)	(MH,ML,A,MH)	(MH,H,MH,H)	(A,ML,MH,VH)

Table A2. The AIF-DM for prioritizing the BESSs.

Parameters	p_1	p_2	p_3	p_4	p_5
q_1	(0.307, 0.592, 0.101)	(0.281, 0.618, 0.101)	(0.468, 0.429, 0.103)	(0.385, 0.513, 0.101)	(0.406, 0.493, 0.101)
q_2	(0.409, 0.490, 0.101)	(0.274, 0.625, 0.101)	(0.452, 0.447, 0.101)	(0.306, 0.594, 0.101)	(0.284, 0.615, 0.101)
q_3	(0.598, 0.315, 0.087)	(0.600, 0.314, 0.086)	(0.673, 0.243, 0.084)	(0.668, 0.246, 0.086)	(0.697, 0.217, 0.086)
q_4	(0.603, 0.295, 0.102)	(0.793, 0.156, 0.051)	(0.628, 0.269, 0.103)	(0.649, 0.262, 0.089)	(0.538, 0.361, 0.102)
q_5	(0.603, 0.294, 0.102)	(0.729, 0.200, 0.071)	(0.528, 0.371, 0.102)	(0.608, 0.307, 0.085)	(0.683, 0.230, 0.087)
q_6	(0.632, 0.285, 0.083)	(0.557, 0.339, 0.104)	(0.666, 0.247, 0.087)	(0.577, 0.320, 0.103)	(0.590, 0.307, 0.103)
q_7	(0.382, 0.513, 0.105)	(0.328, 0.569, 0.102)	(0.435, 0.464, 0.101)	(0.431, 0.468, 0.101)	(0.408, 0.492, 0.101)
q_8	(0.362, 0.536, 0.102)	(0.317, 0.581, 0.102)	(0.419, 0.476, 0.105)	(0.300, 0.598, 0.101)	(0.366, 0.532, 0.102)
q_9	(0.629, 0.267, 0.103)	(0.719, 0.195, 0.086)	(0.628, 0.269, 0.103)	(0.603, 0.294, 0.102)	(0.598, 0.315, 0.087)
q_{10}	(0.692, 0.221, 0.086)	(0.711, 0.205, 0.084)	(0.595, 0.317, 0.087)	(0.591, 0.302, 0.106)	(0.736, 0.192, 0.072)
q_{11}	(0.461, 0.436, 0.103)	(0.753, 0.204, 0.043)	(0.709, 0.203, 0.088)	(0.598, 0.315, 0.087)	(0.580, 0.317, 0.103)
q_{12}	(0.636, 0.277, 0.088)	(0.644, 0.271, 0.084)	(0.614, 0.301, 0.085)	(0.656, 0.258, 0.086)	(0.739, 0.189, 0.071)
q_{13}	(0.699, 0.216, 0.085)	(0.741, 0.189, 0.071)	(0.531, 0.368, 0.102)	(0.650, 0.248, 0.101)	(0.599, 0.314, 0.087)

Table A3. The normalized AIF-DM of each option for prioritizing the BESSs.

Parameters	p_1	p_2	p_3	p_4	p_5
q_1	(0.592, 0.307, 0.101)	(0.618, 0.281, 0.101)	(0.429, 0.468, 0.103)	(0.513, 0.385, 0.101)	(0.493, 0.406, 0.101)
q_2	(0.490, 0.409, 0.101)	(0.625, 0.274, 0.101)	(0.447, 0.452, 0.101)	(0.594, 0.306, 0.101)	(0.615, 0.284, 0.101)
q_3	(0.598, 0.315, 0.087)	(0.600, 0.314, 0.086)	(0.673, 0.243, 0.084)	(0.668, 0.246, 0.086)	(0.697, 0.217, 0.086)
q_4	(0.603, 0.295, 0.102)	(0.793, 0.156, 0.051)	(0.628, 0.269, 0.103)	(0.649, 0.262, 0.089)	(0.538, 0.361, 0.102)
q_5	(0.603, 0.294, 0.102)	(0.729, 0.200, 0.071)	(0.528, 0.371, 0.102)	(0.608, 0.307, 0.085)	(0.683, 0.230, 0.087)
q_6	(0.632, 0.285, 0.083)	(0.557, 0.339, 0.104)	(0.666, 0.247, 0.087)	(0.577, 0.320, 0.103)	(0.590, 0.307, 0.103)
q_7	(0.513, 0.382, 0.105)	(0.569, 0.328, 0.102)	(0.464, 0.435, 0.101)	(0.468, 0.431, 0.101)	(0.492, 0.408, 0.101)
q_8	(0.536, 0.362, 0.102)	(0.581, 0.317, 0.102)	(0.476, 0.419, 0.105)	(0.598, 0.300, 0.101)	(0.532, 0.366, 0.102)
q_9	(0.629, 0.267, 0.103)	(0.719, 0.195, 0.086)	(0.628, 0.269, 0.103)	(0.603, 0.294, 0.102)	(0.598, 0.315, 0.087)
q_{10}	(0.692, 0.221, 0.086)	(0.711, 0.205, 0.084)	(0.595, 0.317, 0.087)	(0.591, 0.302, 0.106)	(0.736, 0.192, 0.072)
q_{11}	(0.461, 0.436, 0.103)	(0.753, 0.204, 0.043)	(0.709, 0.203, 0.088)	(0.598, 0.315, 0.087)	(0.580, 0.317, 0.103)
q_{12}	(0.636, 0.277, 0.088)	(0.644, 0.271, 0.084)	(0.614, 0.301, 0.085)	(0.656, 0.258, 0.086)	(0.739, 0.189, 0.071)
q_{13}	(0.699, 0.216, 0.085)	(0.741, 0.189, 0.071)	(0.531, 0.368, 0.102)	(0.650, 0.248, 0.101)	(0.599, 0.314, 0.087)

Table A4. Objective weight of criteria using IF-MEREC for prioritizing the BESSs.

Parameters	S'_{ij}					as_j	w_j^o
	p_1	p_2	p_3	p_4	p_5		
q_1	0.350	0.279	0.363	0.334	0.326	0.150	0.0978
q_2	0.341	0.279	0.365	0.341	0.337	0.138	0.0903
q_3	0.350	0.276	0.384	0.347	0.343	0.101	0.0662
q_4	0.351	0.290	0.382	0.345	0.330	0.103	0.0673
q_5	0.351	0.286	0.373	0.342	0.342	0.107	0.0701
q_6	0.353	0.273	0.384	0.340	0.335	0.117	0.0763
q_7	0.343	0.274	0.367	0.329	0.326	0.162	0.1060

Table A4. *Cont.*

Parameters	S'_{ij}					as_j	w^o_j
	p_1	p_2	p_3	p_4	p_5		
q_8	0.345	0.275	0.368	0.342	0.330	0.141	0.0923
q_9	0.353	0.286	0.382	0.342	0.335	0.103	0.0675
q_{10}	0.357	0.285	0.378	0.341	0.345	0.094	0.0613
q_{11}	0.338	0.287	0.387	0.341	0.334	0.114	0.0748
q_{12}	0.353	0.280	0.380	0.346	0.346	0.097	0.0636
q_{13}	0.358	0.287	0.373	0.346	0.335	0.102	0.0666

Table A5. Subjective weight of indicator using RS method for prioritizing the BESSs.

Parameters	d_1	d_2	d_3	d_4	AIF-DM Values	$\mathbb{S}(\xi_{kj})$	r_j	w^s_j
q_1	H	A	ML	H	(0.589, 0.305, 0.106)	0.358	13	0.0256
q_2	MH	A	ML	ML	(0.483, 0.415, 0.102)	0.466	10	0.0513
q_3	H	MH	A	A	(0.585, 0.312, 0.103)	0.637	3	0.1111
q_4	MH	L	ML	A	(0.461, 0.436, 0.103)	0.513	9	0.0598
q_5	ML	MH	VH	ML	(0.598, 0.317, 0.085)	0.641	1	0.1282
q_6	A	H	MH	A	(0.585, 0.312, 0.103)	0.636	4	0.1026
q_7	ML	A	H	MH	(0.567, 0.328, 0.105)	0.381	11	0.0427
q_8	MH	A	L	VH	(0.578, 0.334, 0.088)	0.378	12	0.0342
q_9	A	ML	MH	H	(0.561, 0.334, 0.104)	0.614	6	0.0855
q_{10}	H	ML	A	MH	(0.564, 0.331, 0.105)	0.617	5	0.0940
q_{11}	VH	ML	MH	ML	(0.596, 0.318, 0.086)	0.639	2	0.1197
q_{12}	ML	MH	MH	A	(0.533, 0.365, 0.102)	0.584	8	0.0684
q_{13}	H	ML	ML	MH	(0.542, 0.352, 0.106)	0.595	7	0.0769

Table A6. The weighted normalized AIF-DM of each option for prioritizing the BESSs.

	p_1	p_2	p_3	p_4	p_5	α^+_{jw}	α^-_{jw}
q_1	(0.054, 0.930, 0.017)	(0.058, 0.925, 0.018)	(0.034, 0.954, 0.012)	(0.043, 0.943, 0.014)	(0.041, 0.946, 0.013)	(0.058, 0.925, 0.018)	(0.034, 0.954, 0.012)
q_2	(0.047, 0.939, 0.015)	(0.067, 0.912, 0.020)	(0.041, 0.945, 0.014)	(0.062, 0.919, 0.019)	(0.065, 0.915, 0.020)	(0.067, 0.912, 0.020)	(0.041, 0.945, 0.014)
q_3	(0.078, 0.903, 0.020)	(0.078, 0.902, 0.020)	(0.094, 0.882, 0.024)	(0.093, 0.883, 0.024)	(0.101, 0.873, 0.026)	(0.100, 0.873, 0.026)	(0.078, 0.903, 0.020)
q_4	(0.057, 0.925, 0.018)	(0.095, 0.889, 0.016)	(0.061, 0.920, 0.019)	(0.064, 0.918, 0.017)	(0.048, 0.937, 0.015)	(0.095, 0.889, 0.016)	(0.048, 0.937, 0.015)
q_5	(0.088, 0.886, 0.027)	(0.121, 0.853, 0.026)	(0.072, 0.906, 0.022)	(0.089, 0.890, 0.022)	(0.108, 0.864, 0.028)	(0.121, 0.853, 0.026)	(0.072, 0.906, 0.022)
q_6	(0.086, 0.894, 0.021)	(0.070, 0.908, 0.022)	(0.094, 0.882, 0.024)	(0.074, 0.903, 0.023)	(0.077, 0.900, 0.024)	(0.093, 0.882, 0.024)	(0.070, 0.908, 0.022)
q_7	(0.052, 0.931, 0.017)	(0.061, 0.921, 0.019)	(0.045, 0.940, 0.015)	(0.046, 0.939, 0.015)	(0.049, 0.935, 0.016)	(0.061, 0.920, 0.019)	(0.045, 0.940, 0.015)
q_8	(0.047, 0.938, 0.015)	(0.053, 0.930, 0.017)	(0.040, 0.946, 0.013)	(0.056, 0.927, 0.017)	(0.047, 0.938, 0.015)	(0.056, 0.927, 0.017)	(0.040, 0.946, 0.013)
q_9	(0.073, 0.904, 0.023)	(0.092, 0.883, 0.025)	(0.073, 0.904, 0.023)	(0.068, 0.911, 0.021)	(0.067, 0.915, 0.017)	(0.092, 0.882, 0.025)	(0.067, 0.915, 0.017)

Table A6. *Cont.*

	p_1	p_2	p_3	p_4	p_5	α_{jw}^{+}	α_{jw}^{-}
q_{10}	(0.087, 0.890, 0.023)	(0.092, 0.884, 0.024)	(0.068, 0.915, 0.017)	(0.067, 0.911, 0.022)	(0.098, 0.880, 0.022)	(0.098, 0.880, 0.022)	(0.068, 0.915, 0.018)
q_{11}	(0.058, 0.923, 0.019)	(0.127, 0.857, 0.016)	(0.113, 0.856, 0.031)	(0.085, 0.894, 0.021)	(0.081, 0.894, 0.025)	(0.127, 0.857, 0.016)	(0.058, 0.922, 0.019)
q_{12}	(0.064, 0.919, 0.017)	(0.066, 0.918, 0.016)	(0.061, 0.924, 0.015)	(0.068, 0.915, 0.017)	(0.085, 0.896, 0.019)	(0.085, 0.896, 0.019)	(0.061, 0.924, 0.015)
q_{13}	(0.083, 0.896, 0.022)	(0.092, 0.887, 0.020)	(0.053, 0.931, 0.016)	(0.073, 0.905, 0.023)	(0.064, 0.920, 0.016)	(0.092, 0.887, 0.020)	(0.053, 0.931, 0.016)

Table A7. Score values weighted normalized AIF-DM of each option for prioritizing the BESSs.

	p_1	p_2	p_3	p_4	p_5	α_{jw}^{+}	α_{jw}^{-}
q_1	0.062	0.067	0.040	0.050	0.048	0.067	0.040
q_2	0.054	0.077	0.048	0.071	0.075	0.077	0.048
q_3	0.087	0.088	0.106	0.105	0.114	0.114	0.087
q_4	0.066	0.103	0.071	0.073	0.055	0.103	0.055
q_5	0.101	0.134	0.083	0.099	0.122	0.134	0.083
q_6	0.096	0.081	0.106	0.086	0.088	0.105	0.081
q_7	0.061	0.070	0.053	0.053	0.057	0.070	0.053
q_8	0.055	0.062	0.047	0.065	0.054	0.065	0.047
q_9	0.085	0.105	0.084	0.079	0.076	0.105	0.076
q_{10}	0.099	0.104	0.077	0.078	0.109	0.109	0.077
q_{11}	0.068	0.135	0.128	0.095	0.093	0.135	0.068
q_{12}	0.073	0.074	0.068	0.077	0.094	0.094	0.069
q_{13}	0.093	0.103	0.061	0.084	0.072	0.103	0.061
S_i	0.999	1.203	0.971	1.015	1.058	1.282	0.844

Table A8. The utility degrees and CUF of each option for prioritizing the BESSs.

BESS	u_i^{+}	u_i^{-}	$f(u_i)$	Ranks
p_1	0.779	1.184	0.618	4
p_2	0.939	1.426	0.744	1
p_3	0.757	1.150	0.600	5
p_4	0.792	1.203	0.628	3
p_5	0.825	1.253	0.654	2

Table A9. The results for prioritizing BESSs using IF-COPRAS.

Options	α_i	$\mathbb{S}(\alpha_i)$	β_i	$\mathbb{S}(\beta_i)$	γ_i	δ_i	Ranking
p_1	(0.504, 0.404, 0.092)	0.550	(0.117, 0.842, 0.041)	0.137	0.627	96.71	4
p_2	(0.584, 0.338, 0.078)	0.623	(0.092, 0.870, 0.038)	0.111	0.648	100.00	1
p_3	(0.512, 0.395, 0.093)	0.558	(0.146, 0.808, 0.046)	0.169	0.626	96.65	5
p_4	(0.508, 0.400, 0.092)	0.554	(0.113, 0.846, 0.040)	0.134	0.644	99.49	2
p_5	(0.533, 0.378, 0.089)	0.577	(0.116, 0.843, 0.041)	0.137	0.633	97.68	3

Table A10. The IF-WASPAS method for prioritizing the BESSs.

Options	$\wp_i^{(1)}$	$\wp_i^{(2)}$	$\mathbb{S}(\wp_i^{(1)})$	$\mathbb{S}(\wp_i^{(2)})$	$Q_i(\hbar)$	Ranks
p_1	(0.580, 0.322, 0.097)	(0.558, 0.343, 0.099)	0.629	0.744	0.6183	4
p_2	(0.654, 0.264, 0.082)	(0.611, 0.300, 0.089)	0.695	0.656	0.6753	1
p_3	(0.581, 0.321, 0.097)	(0.561, 0.341, 0.098)	0.630	0.610	0.6201	3
p_4	(0.586, 0.317, 0.097)	(0.567, 0.420, 0.013)	0.634	0.574	0.6040	5
p_5	(0.609, 0.298, 0.093)	(0.584, 0.320, 0.095)	0.655	0.632	0.6436	2

Table A11. The CUF for prioritizing BESSs over different weighting procedures.

Weighting Model	CUFs for Prioritizing BESSs					Rank
	p_1	p_2	p_3	p_4	p_5	
IF-MEREC	0.625	0.749	0.590	0.633	0.648	$p_2 \succ p_5 \succ p_4 \succ p_1 \succ p_3$
IF-RS	0.612	0.739	0.611	0.624	0.660	$p_2 \succ p_5 \succ p_4 \succ p_1 \succ p_3$
Integrated method	0.618	0.744	0.600	0.628	0.654	$p_2 \succ p_5 \succ p_4 \succ p_1 \succ p_3$

References

1. Mitali, J.; Dhinakaran, S.; Mohamad, A.A. Energy storage systems: A review. *Energy Storage Sav.* **2022**, *1*, 166–216. [CrossRef]
2. Bizon, N. Effective mitigation of the load pulses by controlling the battery/SMES hybrid energy storage system. *Appl. Energy* **2018**, *229*, 459–473. [CrossRef]
3. Gao, H.; Li, W.; Cai, H. Distributed control of a flywheel energy storage system subject to unreliable communication network. *Energy Rep.* **2022**, *8*, 11729–11739. [CrossRef]
4. Behabtu, H.A.; Messagie, M.; Coosemans, T.; Berecibar, M.; Fante, K.A.; Kebede, A.A.; Mierlo, J.V. A Review of Energy Storage Technologies' Application Potentials in Renewable Energy Sources Grid Integration. *Sustainability* **2020**, *12*, 10511. [CrossRef]
5. Deveci, M. Site selection for hydrogen underground storage using interval type-2 hesitant fuzzy sets. *Int. J. Hydrogen Energy* **2018**, *43*, 9353–9368. [CrossRef]
6. Ren, J.; Ren, X. Sustainability ranking of energy storage technologies under uncertainties. *J. Clean. Prod.* **2018**, *170*, 1387–1398. [CrossRef]
7. Ashby, M.F.; Polyblank, J. *Materials for Energy Storage Systems—A White Paper*; University of Cambridge: Cambridge, UK, 2012.
8. Karellas, S.; Tzouganatos, N. Comparison of the performance of compressed-air and hydrogen energy storage systems: Karpathos island case study. *Renew. Sustain. Energy Rev.* **2014**, *29*, 865–882. [CrossRef]
9. Punys, P.; Baublys, R.; Kasiulis, E.; Vaisvila, A.; Pelikan, B.; Steller, J. Assessment of renewable electricity generation by pumped storage power plants in EU Member States. *Renew. Sustain. Energy Rev.* **2013**, *26*, 190–200. [CrossRef]
10. Sebastián, R.; Alzola, R.P. Flywheel energy storage systems: Review and simulation for an isolated wind power system. *Renew. Sustain. Energy Rev.* **2012**, *16*, 6803–6813. [CrossRef]
11. Alotto, P.; Guarnieri, M.; Moro, F. Redox flow batteries for the storage of renewable energy: A review. *Renew. Sustain. Energy Rev.* **2014**, *29*, 325–335. [CrossRef]
12. Dunn, B.; Kamath, H.; Tarascon, J.M. Electrical energy storage for the grid: A battery of choices. *Science* **2011**, *334*, 928–935. [CrossRef] [PubMed]
13. Ali, J. A q-rung orthopair fuzzy MARCOS method using novel score function and its application to solid waste management. *Appl. Intell.* **2022**, *52*, 8770–8792. [CrossRef]
14. Noriega, J.R.; Iyore, O.D.; Budime, C.; Gnade, B.; Vasselli, J. Characterization system for research on energy storage capacitors. *Rev. Sci. Instrum.* **2013**, *84*, 055109. [CrossRef]
15. Díaz-González, F.; Sumper, A.; Gomis-Bellmunt, O.; Villafafila-Robles, R. A review of energy storage technologies for wind power applications. *Renew. Sustain. Energy Rev.* **2012**, *16*, 2154–2171. [CrossRef]
16. Hall, P.J.; Bain, E.J. Energy-storage technologies and electricity generation. *Energy Policy* **2008**, *36*, 4352–4355. [CrossRef]
17. Nojavan, S.; Majidi, M.; Esfetanaj, N.N. An efficient cost-reliability optimization model for optimal siting and sizing of energy storage system in a microgrid in the presence of responsible load management. *Energy* **2017**, *139*, 89–97. [CrossRef]
18. Zhang, W.; Maleki, A.; Rosen, M.A.; Liu, J. Optimization with a simulated annealing algorithm of a hybrid system for renewable energy including battery and hydrogen storage. *Energy* **2018**, *163*, 191–207. [CrossRef]
19. Li, J.; Yang, Q.; Robinson, F.; Liang, F.; Zhang, M.; Yuan, W. Design and test of a new droop control algorithm for a SMES/battery hybrid energy storage system. *Energy* **2017**, *118*, 1110–1122. [CrossRef]
20. Guney, M.S.; Tepe, Y. Classification and assessment of energy storage systems. *Renew. Sustain. Energy Rev.* **2017**, *75*, 1187–1197. [CrossRef]

21. Gumus, A.T.; Yayla, A.Y.; Çelik, E.; Yildiz, A. A combined fuzzy-AHP and fuzzy-GRA methodology for hydrogen energy storage method selection in Turkey. *Energies* **2013**, *6*, 3017–3032. [CrossRef]
22. Özkan, B.; Kaya, İ.; Cebeci, U.; Başlıgil, H. A hybrid multicriteria decision making methodology based on type-2 fuzzy sets for selection among energy storage alternatives. *Int. J. Comput. Intell. Syst.* **2015**, *8*, 914–927. [CrossRef]
23. Zhang, C.; Chen, C.; Streimikiene, D.; Balezentis, T. Intuitionistic fuzzy MULTIMOORA approach for multi-criteria assessment of the energy storage technologies. *Appl. Soft Comput.* **2019**, *79*, 410–423. [CrossRef]
24. Pózna, A.I.; Hangos, K.M.; Magyar, A. Temperature dependent parameter estimation of electrical vehicle batteries. *Energies* **2019**, *12*, 3755. [CrossRef]
25. Zhao, H.; Guo, S.; Zhao, H. Comprehensive assessment for battery energy storage systems based on fuzzy-MCDM considering risk preferences. *Energy* **2019**, *168*, 450–461. [CrossRef]
26. Pamucar, D.; Deveci, M.; Schitea, D.; Erişkin, L.; Iordache, M.; Iordache, I. Developing a novel fuzzy neutrosophic numbers based decision making analysis for prioritizing the energy storage technologies. *Int. J. Hydrog. Energy* **2020**, *45*, 23027–23047. [CrossRef]
27. Károlyi, G.; Pózna, A.I.; Hangos, K.M.; Magyar, A. An Optimized Fuzzy Controlled Charging System for Lithium-Ion Batteries Using a Genetic Algorithm. *Energies* **2022**, *15*, 481. [CrossRef]
28. Atanassov, K.T. Intuitionistic fuzzy sets. *Fuzzy Sets Syst.* **1986**, *20*, 87–96. [CrossRef]
29. Chaurasiya, R.; Jain, D. Generalized Intuitionistic Fuzzy Entropy on IF-MARCOS Technique in Multi-criteria Decision Making. In *Advances in Computing and Data Sciences. ICACDS 2021. Communications in Computer and Information Science*; Singh, M., Tyagi, V., Gupta, P.K., Flusser, J., Ören, T., Sonawane, V.R., Eds.; Springer: Cham, Switzerland, 2021; Volume 1440. [CrossRef]
30. Rong, R.; Yu, L.; Niu, W.; Liu, Y.; Senapati, T.; Mishra, A.R. MARCOS approach based upon cubic Fermatean fuzzy set and its application in evaluation and selecting cold chain logistics distribution center. *Eng. Appl. Artif. Intell.* **2022**, *116*, 105401. [CrossRef]
31. Saha, A.; Pamucar, D.; Gorcun, O.F.; Mishra, A.R. Warehouse site selection for the automotive industry using a fermatean fuzzy-based decision-making approach. *Expert Syst. Appl.* **2023**, *211*, 118497. [CrossRef]
32. Ecer, F.; Pamucar, D. MARCOS technique under intuitionistic fuzzy environment for determining the COVID-19 pandemic performance of insurance companies in terms of healthcare services. *Appl. Soft Comput.* **2021**, *104*, 107199. [CrossRef]
33. Zadeh, L.A. Fuzzy sets. *Inf. Control.* **1965**, *8*, 338–353. [CrossRef]
34. Tripathi, D.K.; Nigam, S.K.; Rani, P.; Shah, A.R. New intuitionistic fuzzy parametric divergence measures and score function-based CoCoSo method for decision-making problems. *Decis. Mak. Appl. Manag. Eng.* 2022; *in press*. [CrossRef]
35. Tripathi, D.; Nigam, S.K.; Mishra, A.R.; Shah, A. A Novel Intuitionistic Fuzzy Distance Measure-SWARA-COPRAS Method for Multi-Criteria Food Waste Treatment Technology Selection. *Op. Res. Eng. Sci. Theory Appl.* 2022; *in press*. [CrossRef]
36. Mishra, A.R.; Rani, P. Shapley divergence measures with VIKOR method for multi-attribute decision making problems. *Neural Comput. Appl.* **2019**, *31*, 1299–1316. [CrossRef]
37. Tao, R.; Liu, Z.; Cai, R.; Cheong, K.H. A dynamic group MCDM model with intuitionistic fuzzy set: Perspective of alternative queuing method. *Inf. Sci.* **2021**, *555*, 85–103. [CrossRef]
38. Kumari, R.; Mishra, A.R. Multi-criteria COPRAS method based on parametric measures for intuitionistic fuzzy sets: Application of green supplier selection. *Iran. J. Sci. Technol Trans. Electr. Eng.* **2020**, *44*, 1645–1662. [CrossRef]
39. Rani, P.; Mishra, A.R.; Ansari, M.D.; Ali, J. Assessment of performance of telecom service providers using intuitionistic fuzzy grey relational analysis framework (IF-GRA). *Soft Comput.* **2021**, *25*, 1983–1993. [CrossRef]
40. Gohain, B.; Chutia, R.; Dutta, P. Distance measure on intuitionistic fuzzy sets and its application in decision-making, pattern recognition, and clustering problems. *Int. J. Intell. Syst.* **2022**, *37*, 2458–2501. [CrossRef]
41. Keshavarz-Ghorabaee, M.; Amiri, M.; Zavadskas, E.K.; Turskis, Z.; Antucheviciene, J. Determination of objective weights using a new method based on the removal effects of criteria (MEREC). *Symmetry* **2021**, *13*, 525. [CrossRef]
42. Rani, P.; Mishra, A.R.; Saha, A.; Hezam, I.M.; Pamucar, D. Fermatean Fuzzy Heronian Mean Operators and MEREC-Based Additive Ratio Assessment Method: An Application to Food Waste Treatment Technology Selection. *Int. J. Intell. Syst.* **2021**, *37*, 2612–2647. [CrossRef]
43. Mishra, A.R.; Saha, A.; Rani, P.; Hezam, I.M.; Shrivastava, R.; Smarandache, F. An Integrated Decision Support Framework Using Single-Valued-MEREC-MULTIMOORA for Low Carbon Tourism Strategy Assessment. *IEEE Access* **2022**, *10*, 24411–24432. [CrossRef]
44. Ul Haq, R.S.; Saeed, M.; Mateen, N.; Siddiqui, F.; Naqvi, M.; Yi, J.B.; Ahmed, S. Sustainable material selection with crisp and ambiguous data using single-valued neutrosophic-MEREC-MARCOS framework. *Appl. Soft Comput.* **2022**, *128*, 109546. [CrossRef]
45. Yu, Y.; Wu, S.; Yu, J.; Chen, H.; Zeng, Q.; Xu, Y.; Ding, H. An integrated MCDM framework based on interval 2-tuple linguistic: A case of offshore wind farm site selection in China. *Process Saf. Environ. Prot.* **2022**, *164*, 613–628. [CrossRef]
46. Stillwell, W.G.; Seaver, D.A.; Edwards, W. A comparison of weight approximation techniques in multiattribute utility decision making. *Organ Behav. Hum Perform.* **1981**, *28*, 62–77. [CrossRef]
47. Narayanamoorthy, S.; Annapoorani, V.; Kang, D.; Baleanu, D.; Jeon, J.; Kureethara, J.V.; Ramya, L. A novel assessment of biomedical waste disposal methods using integrating weighting approach and hesitant fuzzy MOOSRA. *J. Clean. Prod.* **2020**, *275*, 122587. [CrossRef]

48. Hezam, I.M.; Mishra, A.R.; Rani, P.; Cavallaro, F.; Saha, A.; Ali, J.; Strielkowski, W.; Štreimikienė, D. A Hybrid Intuitionistic Fuzzy-MEREC-RS-DNMA Method for Assessing the Alternative Fuel Vehicles with Sustainability Perspectives. *Sustainability* **2022**, *14*, 5463. [CrossRef]
49. Stević, Ž.; Pamučar, D.; Puška, A.; Chatterjee, P. Sustainable supplier selection in healthcare industries using a new MCDM method: Measurement Alternatives and Ranking according to COmpromise Solution (MARCOS). *Comput. Ind. Eng.* **2020**, *140*, 106231. [CrossRef]
50. Tadic, S.; Kilibarda, M.; Kovac, M.; Zecevic, S. The assessment of intermodal transport in countries of the Danube region. *Int. J. Traffic Transp. Eng.* **2021**, *11*, 375–391.
51. Miomir, S.; Stevic, Z.; Kumar, D.D.; Marko, S.; Pamucar, D. A New Fuzzy MARCOS Method for Road Traffic Risk Analysis. *Mathematics* **2020**, *8*, 457.
52. Stevic, Z.; Brkovic, N. A Novel Integrated FUCOM-MARCOS Model for Evaluation of Human Resources in a Transport Company. *Logistics* **2020**, *4*, 4. [CrossRef]
53. Anysz, H.; Nicał, A.; Stevic, Z.; Grzegorzewski, M.; Sikora, K. Pareto optimal decisions in multi-criteria decision making explained with construction cost cases. *Symmetry* **2021**, *13*, 46. [CrossRef]
54. Pamucar, D.; Ecer, F.; Deveci, M. Assessment of alternative fuel vehicles for sustainable road transportation of United States using integrated fuzzy FUCOM and neutrosophic fuzzy MARCOS methodology. *Sci. Total Environ.* **2021**, *788*, 147763. [CrossRef]
55. Xu, Z.S. Intuitionistic fuzzy aggregation operators. *IEEE Trans. Fuzzy Syst.* **2007**, *15*, 1179–1187.
56. Xu, G.L.; Wan, S.P.; Xie, X.L. A Selection Method Based on MAGDM with Interval-Valued Intuitionistic Fuzzy Sets. *Math. Probl. Eng.* **2015**, *2015*, 791204. [CrossRef]
57. Ibrahim, H.; Ilinca, A.; Perron, J. Energy storage systems—Characteristics and comparisons. *Renew. Sustain. Energy Rev.* **2008**, *12*, 1221–1250. [CrossRef]
58. Baker, J. New technology and possible advances in energy storage. *Energy Policy* **2008**, *36*, 4368–4373. [CrossRef]
59. Chen H, Cong T N, Yang W, Tan, C, Li, Y, Ding, Y, Progress in electrical energy storage system: A critical review. *Prog. Nat. Sci.* **2009**, *19*, 291–312. [CrossRef]
60. Yang, Z.; Zhang, J.; Kintner-Meyer, M.C.W.; Lu, X.; Choi, D.; Lemmon, J.P.; Liu, J. Electrochemical energy storage for green grid. *Chem. Rev.* **2011**, *111*, 3577–3613. [CrossRef] [PubMed]
61. Leung, P.; Li, X.; De León, C.P.; Berlouis, L.; Low, C.T.J.; Walsh, F.C. Progress in redox flow batteries, remaining challenges and their applications in energy storage. *RSC Adv.* **2012**, *2*, 10125–10156. [CrossRef]
62. Zhu, W.H.; Zhu, Y.; Davis, Z.; Tatarchuk, B.J. Energy efficiency and capacity retention of NiMH batteries for storage applications. *Appl. Energy* **2013**, *106*, 307–313. [CrossRef]
63. Mishra, A.R.; Rani, P.; Pardasani, K.R.; Mardani, A. A novel hesitant fuzzy WASPAS method for assessment of green supplier problem based on exponential information measures. *J. Clean. Prod.* **2019**, *238*, 117901. [CrossRef]
64. Mishra, A.R.; Singh, R.K.; Motwani, D. Multi-criteria assessment of cellular mobile telephone service providers using intuitionistic fuzzy WASPAS method with similarity measures. *Granul. Comput.* **2019**, *4*, 511–529. [CrossRef]
65. Gitinavard, H.; Shirazi, M.A. An extended intuitionistic fuzzy modified group complex proportional assessment approach. *J. Ind. Syst. Eng.* **2018**, *11*, 229–246.
66. Mishra, A.R. Intuitionistic fuzzy information with application in rating of township development. *Iranian J Fuzzy Syst.* **2016**, *13*, 49–70.
67. Mishra, A.R.; Sisodia, G.; Pardasani, K.R.; Sharma KMulticriteria, I.T. personnel selection on intuitionistic fuzzy information measures and ARAS methodology. *Iranian J Fuzzy Syst.* **2020**, *17*, 55–68. [CrossRef]
68. Mishra, A.R.; Rani, P.; Mardani, A.; Pardasani, K.R.; Govindan, K.; Alrasheedi, M. Healthcare evaluation in hazardous waste recycling using novel interval-valued intuitionistic fuzzy information based on complex proportional assessment method. *Comput Ind Eng.* **2020**, *139*, 106140. [CrossRef]