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Research Paper

Comprehensive performance evaluation and sustainability ranking of battery technologies based on hesitant intuitionistic fuzzy linguistic decision-making

Sayan Das [a,*], Manuel Baumann [a], Marcel Weil [a,b]

[a] Institute for Technology Assessment and Systems Analysis (ITAS), Karlsruhe Institute of Technology (KIT), Karlsruhe, Germany
[b] Helmholtz-Institute Ulm - Electrochemical Energy Storage (HIU), Ulm, Germany

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ABSTRACT

Battery energy storage systems, in particular emerging systems based on abundant materials such as sodium and potassium are considered as sustainable alternatives to current lithium-based systems. However, sustainability assessment as well as the identification of potential improvement potentials require a complex assessment of multiple factors, including technical, economic, environmental and socio-political aspects. The interdependence and uncertainty of these criteria, particularly with qualitative data related to very different technology readiness levels (TRL), pose a significant challenge for robust assessments. The study proposes a new hesitant-intuitionistic framework for selecting energy storage technologies and to identify relevant improvement potentials, addressing all dimensions of sustainability under linguistic hesitancy and uncertainty. It uniquely incorporates detailed quantitative environmental impact data and raw material-based social sub-factors are also identified as the key factors that influence decision-making. The robustness of the results is validated with an additional fuzzy-decision making approach. Finally, the obstacle degree of each criterion and sub-criteria is conducted along with an uncertainty analysis to identify fields for improvement. The study exemplarily evaluates three different battery chemistries $LiFePO_4$ as state-of-the-art technology, and $KFeSO_4F$ and NaNMMT as emerging technologies. First results indicate that the NaNMMT battery is the most sustainable option followed by $LiFePO_4$ and $KFeSO_4F$ when socio-political factors are not considered. Whereas $LiFePO_4$ leads when this factor is included with other factors. The study identifies the environmental factor as the most influential in decision-making. Additionally, sub-factors such as cell voltage, energy density, cathode specific capacity, capital cost, price fluctuations, demand growth, and global warming also significantly impact the decision-making process.

1. Introduction

Energy storage technologies are highly important for a sustainable energy and mobility transition. In particular, electrochemical storage like lead-acid (LA) and lithium-ion batteries (LIB) are extensively used but face several technical and sustainability issues. Depending on the chemistry, challenges include specific energy, cycle lifetime, required periodic maintenance, and the use of hazardous or critical raw materials [1–3]. These concerns have spurred the demand for new electrochemical storage technologies based on more abundant materials – so-called post-lithium chemistries. Thus, current research entails technologies based on potassium, sodium, aluminum or calcium. Among these sodium-ion batteries (SIB) are currently strongly investigated and are starting to be utilized in different applications. Another prominent example are potassium-ion Batteries (PIB) which are close to application [1,4].

These battery technologies have different technology readiness levels (TRL) which inhibit different techno-economic and environmental performances. To provide decision-making support to select the most sustainable energy storage technologies as well as to identify potential hotspots that hinder further development, an evaluation of a range of factors is recommended. This includes factors such as energy density, longevity, environmental impact, economic feasibility and discharge rate, but is not limited to these [5]. The assessment should address both quantitative and qualitative criteria, recognizing that some of these criteria can be intangible and challenging to measure. Furthermore, socio-political factors are increasingly important [6], significantly

* Corresponding author.
E-mail address: sayan.das@kit.edu (S. Das).

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Nomenclature

List of Abbreviations

AHP	Analytic Hierarchy Process
CAES	Compressed Air Energy Storage
CI	Consistency Index
CR	Consistency Ratio
F	Fuzzy
FLTS	Fuzzy Linguistic Term Set
HES	Hybrid Energy System
HFL	Hesitant Fuzzy Logic
HFLTS	Hesitant Fuzzy Logic Term Set
KFeSo4F	Potassium iron sulphate fluoride
LA	Lead Acid
LAES	Liquid Air Energy Storage
LIB	Lithium-ion battery
LiFePO4	Lithium iron phosphate battery
MCDM	Multi-criteria decision making
NaNMMT	Sodium nickel manganese magnesium titanium oxide
NEAT-Fuzzy- PROMETHEE	New Easy Approach To Preference Ranking Organization method for Enrichment of Evaluations
NIS	Negative Ideal Solution
OWA	Ordered Weightage Average
PIB	Potassium-ion battery
PIS	Positive Ideal Solution
RCI	Relative Closeness Index
RI	Random Index
SIB	Sodium-ion battery
TFN	Triangular Fuzzy Number
TrFN	Trapezoidal Fuzzy Number
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
VIKOR	VlseKriterijumska Optimizacija i Kompromisno Resenje

Symbols

$\check{c}_i$	matrix
env (H_s)	HFLTS envelope
P	Subset within the range of
G_h	Grammar used in the linguistic term set (LTS) S
H_s	subset of S
$h_p(y)$	function
$\check{r}_i$	row number
S	$\{s_o, \ldots.., s_g\}$ is the set of linguistic terms
$S_{ll.}$	domain of the expressions generated by G_h
Y	Set

influencing overall sustainability. These factors must also be assessed in the evaluation process. However, the qualitative nature of the many socio-political factors adds complexity to the decision-making process, and signifies the requirement for a specific approach that can account for these difficulties. Consequently, it is difficult for decision-makers to decide the most sustainable storage system in a specific application scenario among different storage technologies due to various conflicting performance factors, application-specific requirements, different scales, qualitative criteria and cognitive limits [2]. Additionally, linguistic uncertainties associated with qualitative criteria further complicate the process, making it difficult for decision-makers to arrive at the most appropriate solution. Beyond that, decision makers must understand which factors influence the selection of a battery and how potential performance has to be enhanced to become competitive.

Therefore, an approach to support decision-making by considering the linguistic uncertainties of different criteria to evaluate application-specific scenarios among different storage systems is needed [7]. It seems suitable to apply an improved fuzzy theory along a multi-criteria decision-making (MCDM) approach because this adequately captures the imprecision of human evaluation during decision-making. Furthermore, the impact of input parameter variation can be thoroughly analyzed.

1.1. Research objectives and contribution

Addressing the identified research gaps, this paper recommends an advanced decision-making framework that integrates comprehensive sustainability factors to evaluate and select energy storage technologies in a linguistically hesitant, intuitionistic context. This study accounted for uncertainties associated with different technology TRLs, including potassium-ion batteries (PIBs) at TRL 5, SIBs at TRL 8, and market-proven LIBs with TRL of 9 [8]. Beyond that an overview of relevant criteria is provided, allowing us to identify the most influential criteria and to provide guidance of how to optimize the assessed systems. By analyzing holistic and quantitative data from more comprehensive life cycle assessment (LCA) the study reduces bias-prone judgment, enabling more reliable decision making. This study also analyzes the impact of critical raw material and socio-political dimensions obtained through the ESSENZ method to broaden the scope of sustainability considerations. The study focuses on emerging storage technologies, specifically PIB and SIB, with LIB serving as a benchmark.

To do so, this work introduces a hesitant intuitionistic decision-making methodology. It develops a hierarchical structure based on a hesitant fuzzy linguistic-analytic hierarchy process (HFL-AHP) and the New Easy Approach To-Fuzzy-PROMETHEE (NEAT-Fuzzy-PROMETHEE) method, which ensures that a wide spectrum of sustainability aspects can be considered. The HFL-AHP process is used to determine the local and global weights of the criteria, allowing for effective management of uncertainty, which in particular is evident in the early development phases of emerging batteries. An intuitionistic-based method, NEAT-Fuzzy-PROMETHEE, is used to rank the alternatives within this uncertain environment. Additionally, a novel obstacle degree model is introduced to identify and quantify the barriers presented by specific criteria that may hinder optimal storage technology selection and that can help to identify potential hotspots. This model enhances our understanding of factors that complicate sustainable technology adoption. To ensure robustness and validate the analysis, extensive sensitivity and comparative analyses are conducted. The shortcomings and problems of this kind of evaluation are also addressed, providing a balanced view for further development in a sustainable energy storage selection framework. Finally, a comprehensive framework combining hesitant-intuitionistic decision-making integrating LCA and critical raw material-based socio-political factors is presented to reduce bias and identify barriers to sustainable energy storage technology selection. Beyond that, the methodology supports technology development by identifying critical criteria (cell voltage, energy density, price fluctuation and capital cost) that strongly influence the ranking. Therefore, the study offers a base for a robust and comprehensive approach to sustainable decision-making for selecting energy storage technologies.

The paper is structured as follows: Section 2 reviews key literature on sustainable storage selection using the MCDM process, identifying research gaps and formulating research questions. Section 3 discusses storage technologies, research criteria and the working principle of the selected MCDM methods. Section 4 presents the results along with a detailed discussion of the analysis. Section 5 reflects on the study's limitations and Section 6 then concludes the paper by summarizing the study's contributions and offering recommendations for future research.

2. State of the art for sustainable storage evaluation using MCDM

In the following a brief overview of decision support for selecting sustainable storage technologies is presented. In this review, the scope is beyond chemical-ion batteries, because there are very few studies available explicitly targeting batteries. Thus, the review includes relevant methods and studies that deal with the storage selection process. The review was carried out via the use of Scopus, Wiley, Science Direct, Web-of-Science and Google Scholar with publication dates within 2013–2024. A comprehensive overview of MCDM methods can be found below. The published papers assessed the operational effect of storage technologies in specific scenarios and decided the optimal storage system. The reviewed work is summarized in Table 1.

2.1. Research gaps

The outcome of the literature review shows that when selecting suitable energy storage technologies through MCDM, several critical issues remain. Most previous studies primarily focused on techno-economic factors. Few studies have considered CO_2 intensity, and even fewer have focused on social factors. To the best of our knowledge, no previous MCDA studies significantly considered different TRLs with high uncertainty. Where social factors are considered, the data are often qualitative and lack comprehensiveness. As the data are largely linguistic, this introduces limits, bias the use of valuable data and affects the judgments [18]. This can lead to less meaningful decision-making, as these assessments do not comprehensively reflect the full characteristics of storage technologies, particularly in terms of detailed environmental and social considerations. This lack of depth also increases hesitation and uncertainty in decision-making, thus reducing the reliability of the outcomes. Additionally, much current research evaluates storage technologies in a specific application scenario. The reviewed studies did not consider the broader applicability of different storage technologies across various contexts and address the inherent MCDM problem. Emerging storage options, such as new ion-based batteries are often excluded from this literature. Furthermore, significant analysis to identify critical criteria and their impact level were not carried out in previous studies. This gap means potential decision-making factors were unexamined, potentially leading to suboptimal technology choice. Finally, comprehensive uncertainty assessments, which are crucial for identifying necessary improvements in recent technologies, remain unexplored in existing studies.

3. Materials and methods

The study proposes an integrated methodology to support the identification of the most promising sustainable storage technologies in terms of major sustainability factors. The study also identifies the relevance and impact of selected criteria on storage performance. However, the resulting rankings are not definitive, rather the methodology helps to determine sustainability hotspots that should be addressed to improve the performance of the assessed technologies. The most recent chemical storage technologies such as sodium and potassium are evaluated and compared with the widely used lithium-ion battery system to identify the most sustainable solution. The hesitant intuitionistic MCDM approach is used to overcome the limitations, hesitancy and uncertainty of decision-makers. Furthermore, the future direction of development is evaluated in this analysis through different approaches.

3.1. Introduction of storage technologies

To apply the proposed methodology for sustainable prioritization of storage technologies, this study considered the two most promising post-LIB technologies, i.e., sodium-ion (NaNMMT) and potassium-ion batteries ($KFeSO_4F$-graphite). These emerging technologies are benchmarked

Table 1
Summary of reviewed literature.

Authors and year	Objective of the work	Method	Outcome of the work
Gamal et al., (2024) [9]	To rank the energy storage technologies on the basis of techno-economic and carbon di-oxide (CO_2) intensity criteria	Fuzzy MCDM method	The study showed the pumped hydro energy storage is the promising solution
Lu et al., (2023), [7]	To rank the storage technologies on the basis of techno-economic, energy saving and emission reduction efficiency	Group MCDM	Pumped hydro ranked top in all cases
Shu et al., (2023) [10]	To compare hydrogen fuel cell, mechanical and chemical energy storage technologies in terms of techno-economic factors	VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR)-Entropy method	Study showed that the hydrogen fuel cell is the best solution among others
Pokhrel et al., (2022) [11]	To evaluate the techno-economic factors of solar borehole thermal energy storage system for renewable heating solution	Estimated payback period, heat loss, hot water demand	Solar borehole thermal storage outperforms the sewage heat recovery
Vichos et al., (2022) [12]	To evaluate the challenges of integrating hydrogen storage for zero energy ports	Cost of electricity, stored hydrogen volume analysis	The renewable energy supported by hydrogen storage was more environment-friendly than the grid option
Zubiria et al., (2022) [13]	To find the ranking of the storage technologies for grid system in terms of techno-economic and overall environmental impact	AHP-fuzzy Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) method	Study showed that the pumped hydro energy storage is the most suitable option for grid system
He et al., (2021) [14]	To compare battery, pumped hydro energy storage, thermal energy storage and hydrogen storage in terms of techno-economic factors	Developed multi-objective capacity optimization model	Study showed that the thermal storage system is the optimal solution
Alshafi and Bicer, (2021) [15]	To analyze the thermodynamic performances of pumped hydro, compressed air, thermal storage, lithium-ion, air storage, flow batteries, supercapacitors and fuel cells	First and second law of thermodynamics	Energy efficiency varies 10.9–74.6 % and exergy efficiency varies 23.1–71.9 %.
Li et al., (2020), [16]	To rank the different lead, vanadium redox and lithium-ion batteries in terms of economic factors	Bayesian best worst method-grey cumulative prospect theory	The result indicated that the 2 MW lithium battery is the optimal one
Yazdani et al., (2019), [17]	To explore economic efficiency, environmental impact of compressed air, liquid air and	Energy evaluation procedure	Liquid air energy storage had an energy sustainability index of 5.6, which is preferable

(*continued on next page*)

Table 1 (*continued*)

Authors and year	Objective of the work	Method	Outcome of the work
	hydrogen energy storage		compared to other technologies.
Zhao et al., (2019) [2]	To decide an optimal storage for micro-grid considering the techno-economic and CO_2 intensity	Fuzzy best worst method-cumulative prospect theory (CPT)	Study showed that the lithium battery is the most favorable option for micro-grid
Ren and Ren, (2018), [18]	To compare and select an optimal storage technology on the basis of techno-economic factors and CO_2 intensity	Fuzzy AHP- Interval multi attribute decision analysis	Pumped hydro energy storage technology is considered as an optimal solution
Guney and Tepe, (2017), [19]	To identify the strengths, weaknesses, opportunities and threats of different emerging storage technologies	Systematic review method	Study showed that energy storage is an important system for shifting towards sustainable economic development
Zamani et al., (2017), [20]	To investigate the impact of pumped hydro and compressed air energy storage on energy cost from a consumer's perspective	Optimization method	Compressed air reduced the energy cost more efficiently than other system
Ozkan et al., (2015) [21]	To rank the storage technologies on the basis of techno-economic, human health impact, toxic impact and ecological impact	Fuzzy AHP-TOPSIS	Study showed that the compressed air energy storage technology is the most promising alternative for grid system
Gim and Kim, (2014) [22]	To rank different hydrogen storage systems in terms of techno-economic factors for the automobile industry	Fuzzy AHP method	Study illustrated that the compressed gas hydrogen ranks top in the classification

against a state-of-the-art lithium-ion battery ($LiFePO_4$ -graphite). All three chemistries share the same electrochemical mechanism, called "rocking-chair". Within this mechanism, cathode and anode materials use topotactic intercalation chemistry for charge storage. All contain two current collectors, a separator and two electrodes with distinctive chemical potentials, and an ionically conductive electrolyte containing either a K-, Na- or Li-based salt [23]. However, the three technologies have very different TRLs, where LFP is a market-proven technology with a TRL of 9, and NaNMMT is only available in smaller quantities thus potentially with a TRL between 7–8. In sharp contrast, K-ion batteries have a TRL of 4–6, with little data available on their real-world performance. Details of these storage technologies are discussed in the following.

3.1.1. Lithium-ion ($LiFePO_4$) battery

In general, Li-based systems strongly dominate growing markets, with different chemistries being used for portable, mobility and stationary applications due to their e.g., high energy densities, cycle and calendric lifetimes and cost performance [24]. The most used chemistries, among others, are nickel manganese cobalt (NMC) followed by lithium iron phosphate batteries ($LiFePO_4$) [25] for automotive and stationary applications, whilst lithium cobalt oxide is mainly used for portable devices [26]. Like all lithium-ion batteries (LIB), $LiFePO_4$ is based on the exchange of lithium-ions ($Li+$) between anode and cathode. Typically, the anode is usually made of synthetic graphite in combination with a copper based current collector. $LiFePO_4$ represents the cathode material and plays a central role regarding e.g., cell voltage, energy density, operational safety and stability. Additionally, the electrodes are embedded in an electrolyte, usually a lithium salt (often LiPF6) dissolved in a liquid organic solvent [27]. Advantages of $LiFePO_4$ include long cycle lifetime, good safety properties, and the avoidance of most critical raw materials [28] for the cathode (e.g., no nickel or cobalt), as in other LIB types (e.g. NMC). One drawback is the comparably lower energy density in relation to other Li-based [1]. However, $LiFePO_4$ is widely applied for stationary applications [29] and is increasingly gaining momentum for electric mobility [30].

3.1.2. Sodium-ion (NaNMMT) battery

Sodium-ion batteries (SIB) are at present the most mature as well as the promising post-lithium technology due to their relatively good electrochemical performance and a lower demand for critical resources, leading also to potential cost advantages [31]. In addition, their environmental profile is also considered promising depending on the used chemistry [32]. Three types of cathode material are currently being considered for commercial applications: Prussian blue or Prussian white (analogues) type materials, polyanionic, and layered oxides materials [33,34]. As for LIB, several materials can be used on the cathode side including Prussian blue analogues, manganese, nickel or even cobalt. SIB shows comparable properties to LIB, in regard to efficiency and cycle lifetime but suffers from lower energy densities. In contrast to LIB, sodium is used instead of lithium for the electrode and electrolyte. In addition, no critical graphite is used in SIB, but hard carbons are used, which can be based on organic waste [35]. Even less costly and environmentally impactful aluminum can be used as a current collector, instead of copper. In this study, a layered oxide NaNMMT (Na1.1Ni0.3Mn0.5 Mg0.05Ti0.05O2) cell with a hard carbon anode from carbohydrate precursors (sugar) is considered as an example for the comparison, due to its promising performance in relation to LIB and other SIB [1].

3.1.3. Potassium-ion ($KFeSO_4F$) battery

Potassium-ion batteries (PIBs), follow comparable electrochemical processes to LIB and SIB. On the cathode side several materials can be combined including layered oxides, polyanionic or Prussian blue additives. As for LIB, graphite is used for the anode due to its good performance [36]. As for Na in SIB, K does not form alloys with aluminum in PIB, making it also possible to use aluminum foil as a current collector [23]. Potassium is a highly abundant resource in the Earth's crust and has a lower reduction potential than SIB, resulting in potential higher energy densities. As for LIB, graphite is used as anode material due to its good $K+$ intercalation capacity. Recently, other anode materials such as soft carbon are also discussed as alternatives to overcome sustainability and cost challenges related to graphite [37]. In this work, a $KFeSO_4F$-Graphite PIB type cell is used for comparison due to its promising results in terms of supply risk and environmental impact [4]. PIB have the lowest development level in relation to SIB and LIB, with comparably few data on their cycle lifetime or energy density.

3.2. Evaluation criteria

Four important dimensions of sustainability that have a direct impact on optimal storage selection in Europe have been considered. These are technology, economic, environmental and socio-political factors [9]. This study incorporates evaluation criteria based on quantitative data from existing literature relevant to chemical batteries, alongside criteria developed from manufacturers' reports and battery passports [2,4,7,9,10,13,18,21,38]. The study presented a more comprehensive decision-making approach that effectively handles greater linguistic uncertainty, hesitancy, and complex conditions. Furthermore, it provides a solution to the challenges related to the comparison of technologies with different TRLs. Typically, data availability related to low

TRLs is scarce and uncertain, while in contrast data for established technologies is usually available and validated.

Identified sub-factors are categorized under four major sustainability dimensions; technical, economic, social and environmental aspects. Technical aspects are not directly a sustainability dimension, but they have a strong impact on sustainability and are critical for evaluating energy storage technologies. An overview of all considered criteria is provided in the following.

The technical factor consists of seven important sub-factors; cell voltage, energy density, cycle lifetime, efficiency, cathode specific capacity, capacity retention and safety. Cell voltage is the potential difference between positive and negative electrodes of a single cell [39]. It is directly related to the thermodynamics of the cell reaction. Higher cell voltage often correlates with better efficiency because it influences the energy output per charge cycle. Energy density represents the capability of storing energy at per unit capacity. Energy density can be either volumetric (Wh/l) or gravimetric (Wh/kg). Battery efficiency demonstrates the ratio of the energy retrieved from the storage, to the energy provided to it. Cycle lifetime demonstrates the number of charge and discharge cycles [40]. Cathode specific capacity defines the total charge that can be delivered by per gram material of the cathode [41]. Capacity retention demonstrates the ability of a battery to deliver the same capacity after many cycles as compared to initial cycles [42]. The study considered a capacity retention value for 80 cycles across all alternatives. However, this value may vary with changes in cycle life. In this analysis, the criterion is accounted for within the framework of a generic methodology. Finally, one of the most important technical sub-factors is safety of the storage technology. This refers to the ability of battery systems to resist external effects and maintain stability to continue safe operation. This is the qualitative sub-factor [2].

The four economic sub-factors consist of capital cost, operational cost, economic suitability of recovery and price fluctuation. Capital cost is the cost of constructing the storage module [43]. The operational and maintenance (O&M) cost is the maintenance cost for the power unit energy storing cost [44]. The economic suitability for recovery or the profit from recycling and price fluctuation defines the product as economically sustainable for recycling and economic variation due to the different input parameters respectively [4,44].

In total, twelve environmental and four socio-political factors are derived from the work of Yokoi et al. [4], which considered the European database and evaluated the risk associated with the resources used for a product in terms of sustainability that includes environmental and socio-political dimensions.

Ideally, twelve sub-factors that are considered under environmental factor assess the environmental footprint of the battery across its entire lifecycle (extraction of raw materials, manufacturing, use and end of life) but are limited to a cradle-to-gate perspective in this work. A detailed evaluation of these factors ensures that the selected technology aligns with sustainability goals.

Including the socio-political dimension and related quantifiable indicators in sustainability assessments presents a significant challenge, as these indicators only capture a fraction of the potential socio-political impacts and implications. The four sub-factors drawn from Yokoi et al. [4], which are closely related to socio-political dimensions are included as socio-political sub-factors in this study, with their quantitative values incorporated into the decision-making analysis. In terms of evaluating the sustainability of storage technologies, the importance of considering different quantitative socio-political sub-factors, particularly related to the critical raw materials and their impacts on socio-political landscapes, are important. High demand growth of the storage systems indicates global market acceptance, suggesting the potential for widespread adoption of available systems, while supply risk highlights the challenges related to material availability, which could hinder the technology's growth [18]. Trade barriers refer to government-imposed restrictions on the free exchange of raw materials between countries. Finally, political stability defines the consistency and predictability of a political environment, which is crucial for the future development of society [4].

The detailed values of these criteria for each battery module are shown in Table 2.

3.3. Methods

In this section, the details of the proposed methods are discussed. The overall methodology is shown in Fig. 1. The proposed methodology presents a more robust sustainability framework that incorporates detailed LCA results, and raw material-based socio-political factors obtained through the ESSENZ method along with techno-economic aspects to select sustainable storage technologies. It also identifies the criteria that should be addressed to potentially alter the ranking of alternatives. This enables the possibility of improving the emerging technology to enhance its acceptability and adoption. The inclusion of additional sustainability parameters adds complexity and uncertainty to the process. HFL-AHP stands out from other MCDM methods by allowing decision-makers to express preferences through hesitant fuzzy linguistic terms, addressing uncertainty and hesitation in decision-making. NEAT-Fuzzy PROMETHEE enhances computational accuracy, handling uncertainty and imprecision in input data while maintaining low complexity and methodological consistency through improved fuzzy number mapping. The details of the work are shown below.

According to Fig. 1, the HFL-AHP with the NEAT-Fuzzy-PROMETHEE MCDM approach, combines the strengths of both methods to offer several key advantages [63,64]. Each method individually enhances decision-making, and together they form a more robust framework. This significantly improves the capacity to handle uncertainty and hesitancy, providing a closer representation of real-world decision-making scenarios. The integration of two methods improve the accuracy in weighting and ranking analysis by accommodating both qualitative and quantitative data. It reduces bias and enhances transparency in decision-making. The varying TRLs result in high data uncertainty, which the proposed method addresses through sensitivity analysis. The analysis involves varying the data by 30 %, 20 %, and 10 % for PIB, SIB, and LIB, respectively. This novel approach is specifically designed to manage the significant data uncertainty associated with different TRLs. According to the methodology, to determine the weights of the criteria, an accurate weight determination method, i.e., HFL-AHP method is introduced. Hesitant fuzzy theory is used to convert interval and crisp values to triangular fuzzy numbers for maximizing the objective data information [64]. The study considered detailed actual quantified and qualitative values to provide a robust ranking of the alternatives. Therefore, the study employed an improved NEAT-Fuzzy-PROMETHEE method to rank the alternatives [63]. The intuitionistic NEAT-Fuzzy-PROMETHEE method considered both the qualitative and quantitative data and complex linguistic uncertainty to prioritize the alternatives. The approach includes the Trapezoidal Fuzzy Number (TrFN) method and helps to improve the accuracy of the decision-making process. The obtained solution is validated by comparative analysis through the HFL-TOPSIS method. Additionally, an obstacle degree model was developed to find the obstacle levels of the indicators. As the study is focused on evaluating LIB, SIB and PIB which have different TRLs, it performs the uncertainty analysis with the 10 %, 20 % and 30 % variation of data respectively. The required improvement in design parameters are evaluated to develop the emerging battery technologies in a sustainable environment. As LIB is widely used the variation is considered to be low. The newest technology is PIB; therefore, uncertainty is considered maximum for this.

3.3.1. Weighting method

The study considered one of the most utilized methods, the modified AHP for weight determination [9]. To overcome the limitations of the traditional AHP method to deal with uncertainty, ambiguity and subjectivity, the AHP methods are modified by integrating a hesitant

Table 2
Sub-factors value of the corresponding battery technologies.

Criteria	Sub-criteria		$LiFePO_4$ (Market proven TRL of 9)	$KFeSO_4F$ (TRL 4–6)	$Na_{1.1}(Ni_{0.3}Mn_{0.5}Mg_{0.5}Ti_{0.05})O_2$ (TRL 7–8)
Technical (C1)	Cell voltage (C11)	Max	3.2 V [45]	3.6 V [46]	3.2 V [45]
	Energy density (C12)	Max	157.7 Wh/kg [4,47]	136.1 Wh/kg [48]	137.4 Wh/kg [4]
	Cycle lifetime (C13)	Max	3000 cycle [49]	2000–10000 cycle [48]	2000–6000 [49]
	Efficiency (C14)	Max	94 % [45]	>95 % [48]	94 % [45]
	Cathode specific capacity (C15)	Max	154 mAh/g [45]	128 mAh/g [50]	157 mAh/g [51]
	Capacity retention (for 80 cycle) (C16)	Max	88.88 % [52]	80.95 % [53]	86.9 % [54]
	Safety (C17)	Max	Moderate side reactions [55]	High side reactions [56]	moderately low reactions [55]
Economic (C2)	Capital cost of battery per year (C21)	Min	130 $/kWh [57]	157.02–168.5 $/kWh [58]	87 $/kWh [55,59,60]
	Operation cost per year (C22) [61]	Min	$3.68/kW	$1.57–1.68/kW	$0.87/kW
	Profit from recycling (C23) [62]	Max	$12–19/kWh	$18–22/kWh	$16–20/kWh
	Price fluctuation (C24)	Min	1.29	2.39	13.05
Environment (C3) [4]	Global warming intensity (kgCO2eq) (C31)	Min	74.4	83.37	72.41
	Ozone depletion (kgCFCeq) (C32)	Min	3.73	4.13	3.21
	Radiation (kgCOeq) (C33)	Min	12.55	11.76	13.13
	Ozone formation (kgNoxeq.) (C34)	Min	0.169	0.18	0.23
	Particulate matter (kgPM2.5 eq) (C35)	Min	0.12	0.11	0.16
	Toxicity (kg1.4DCBeq) (C36)	Min	309.3	230.3	249.9
	Water Use (C37)	Min	0.98	0.75	1.82
	Acidification ($kgSO_2eq$) (C38)	Min	0.29	0.272	0.42
	Eutrophication (kg Peq) (C39)	Min	0.052	0.048	0.047
	Land use (C39.1)	Min	2.505	1.97	2
	Mineral Resources (C39.2)	Min	2.48	0.92	2.86
	Fossil Resources (C39.3)	Min	20.78	23.2	22.5
Socio-political (C4) [4]	Demand growth (C41)	Max	537.3	59.9	36
	Supply risk (42)	Min	3333.3	1088.43	183.7
	Trade barriers (C43)	Min	246.38	323.8	68.21
	Political stability (C44)	Min	237.4	322.4	38.8

fuzzy linguistic term set with AHP. This method is considered to be a powerful approach to determine weights and is employed in this study. A detailed discussion of these methods is carried out in the following sections.

3.3.1.1. Preliminaries of hesitant fuzzy linguistic term set. Hesitancy and linguistic uncertainty are two major limitations of the real-life decision-making process. Due to this, the methods become more complex. Linguistic information is one option to manage the uncertainty. However, in some decision-making problems, certain linguistic information may not be able to express the linguistic opinions of the decision-makers under uncertainty. Using a complex linguistic expression is a precise solution to represent linguistic uncertainty. Therefore, using a hesitant fuzzy case is the potential solution to overcome this challenge, as linguistic information is considered as a form of comparative linguistic expression. The advantages of the hesitant fuzzy method are discussed by Buyukozkan et al. [64]. The hesitant fuzzy linguistic method is proposed by Torra [65]. In a hesitant fuzzy set (HFS), the degree of membership of an element may have several possible values between zero to one. This method is popular among researchers during evaluation as it is useful in expressing hesitation with high uncertainty levels. Liu and Rodriguez [66] presented an MCDM model where decision-makers express their valuation through linguistic expression using the HFL term set approach.

X is considered as a set. HFS is a function and subset of [0,1]. It is expressed as Eq. (1) [64].

$$E = \{ < x, h_E(x) > | x \in X\} \tag{1}$$

The steps to compute the fuzzy envelope of the HFL are shown in Fig. 2 [64].

Set of membership functions (n) are defined by M = {μ_1, μ_2, μ_3,…, μ_n}. The HFS includes M. The h_M is discussed as Eq. (2):

$$h_M : M \rightarrow [0, 1] \tag{2}$$

$$h_M(x) = \bigcup_{\mu \in M} \{\mu(x)\} \tag{3}$$

Set of linguistic terms are defined as S = {s_0, s_1, …, s_n}. The H_s is an ordered finite subset of S.

To turn the expressions in linguistic terms into H_s, a function is considered, i.e., E_{Gh}. The out of context grammar (G_h) is considered to utilize the LTS in S. The expression domain generated by G_h is generated by S_{ll}. It is expressed in Eq. (4).

$$E_{Gh} : S_{ll} \rightarrow H_s \tag{4}$$

Considering this approach, it is possible to change the comparative linguistic expressions into HFLTS. The steps of transforming the expressions are shown in Eqs. (5)–(10).

$$E_{Gh}(S_i) = \{s_i | s_i \in S\} \tag{5}$$

$$E_{Gh}(maximum S_i) = \{s_j | s_j \in S and s_j \leq s_i\} \tag{6}$$

$$E_{Gh}(< S_i) = \{s_j | s_j \in S and s_j < s_i\} \tag{7}$$

$$E_{Gh}(S_i at least) = \{s_j | s_j \in S and s_j \geq s_i\} \tag{8}$$

$$E_{Gh}(> S_i) = \{s_j | s_j \in S and s_j \geq s_i\} \tag{9}$$

$$E_{Gh}(in between S_i and s_j) = \{s_k | s_k \in S and s_j \leq s_k \leq s_i\} \tag{10}$$

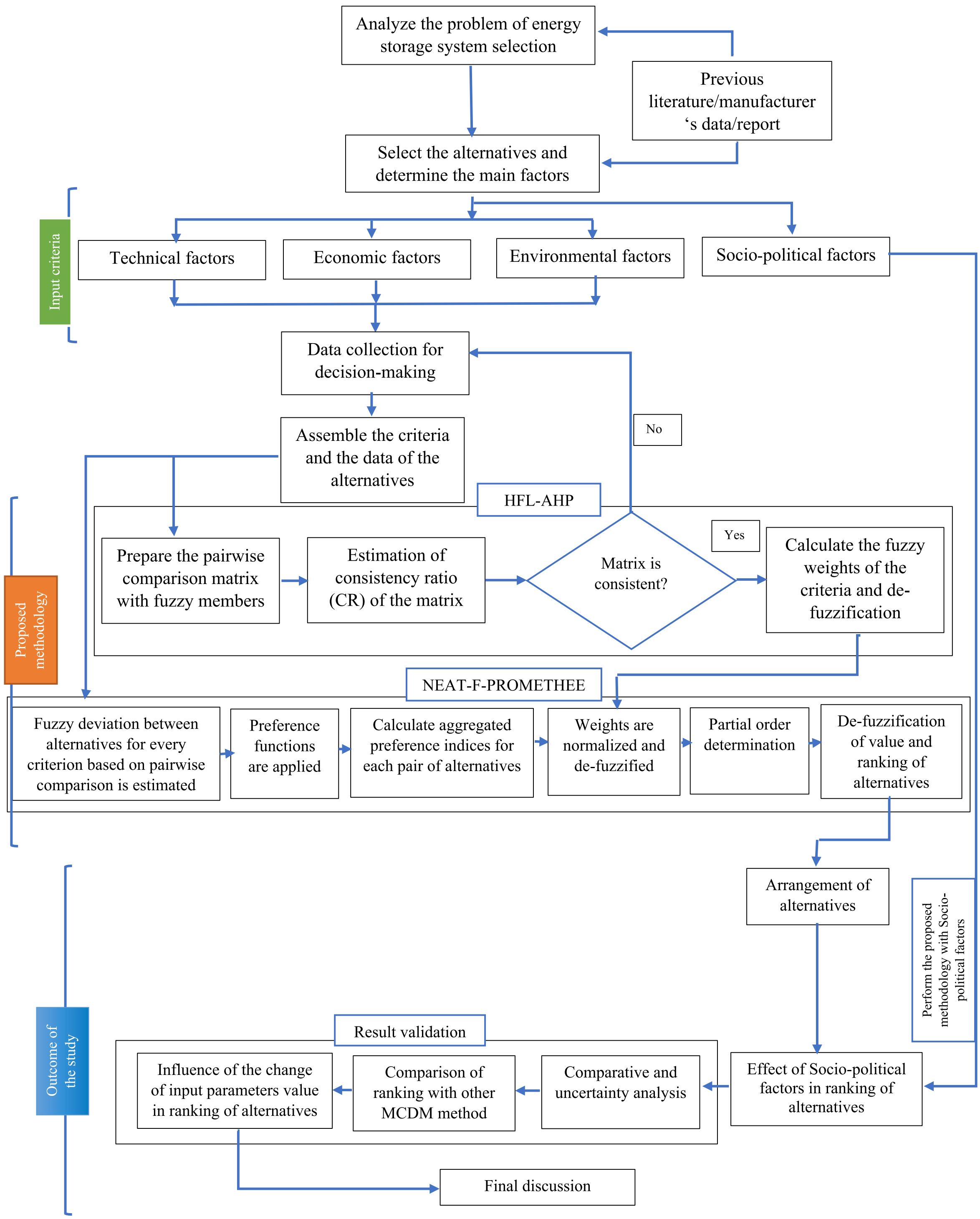


Fig. 1. Working principles of the proposed methodology.

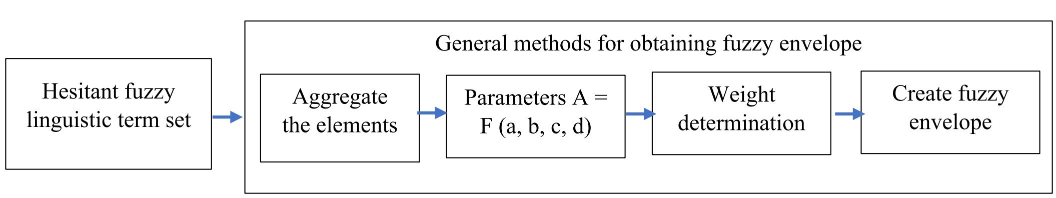


Fig. 2. General method for obtaining fuzzy envelope [64].

The envelope of the HFS, env (Hs) is a linguistic scale interval and includes upper bound (Hs_+) and lower bound (Hs_-) as shown in Eq. (11).

$$env(H_s) = [H_{s+}, H_{s-}] where H_s \leq H_{s+} \tag{11}$$

3.3.1.2. HFL-AHP method. Analytic hierarchy process (AHP) was first developed by Saaty [67]. This method is widely used in decision-making. It is a simple and strong decision-making method to prioritize various factors. Hesitancy is a common phenomenon in decision-making. In this study, the HFL-AHP method is used to decide the relative importance of the factors and the sub-factors. To overcome the challenge of linguistic hesitancy, the HFL method is included with the AHP method for an accurate solution. The judgments with several possible values are known as hesitant judgment [68]. In recent studies, this method is often used in different fields by Mi et al. and Buyukozkan et al. [69,70].

$A = \{a_1, a_2, \ldots, a_3]$ is the set of values that are to be aggregated. The ordered weighted average factor (OWA) is defined as F. The function is estimated as Eq. (12).

$$F(a_1, a_2, ..., a_n) = \sum_{i=1}^{n} w_i \times b_i \tag{12}$$

where W_i is the weight and b_i is the associated value vector. After this the HFL-AHP is used to generate the priorities by the following steps.

Step 1: Decision-makers construct the pairwise matrix and the evaluations are obtained with HFL by using the linguistic scale shown in Table S1 (Sec. A of SI).

Step 2: With OWA operator the fuzzy envelope for HFL is aggregated.

Step 3: The pairwise comparison matrix (C) is generated in the previous step where

$$\overline{\tilde{C}_{ij}} = (C_{ijl}, C_{ijm1}, C_{ijm2}, C_{iju}) \tag{13}$$

The reciprocal values are calculated by using Eq. (14).

$$\overline{\tilde{C}_{ij}} = (1/C_{iju}, 1/C_{ijm2}, 1/C_{ijm1}, 1/C_{ijl}) \tag{14}$$

Step 4: In this step, the consistency ratio of the pairwise matrix is evaluated. The fuzzy pairwise matrix is first de-fuzzified and then the consistency ratio is examined. In this analysis, TrFN, i.e., A = (l, m1, m2, u) is considered. The de-fuzzification is done by Eq. (15).

$$\mu_d = \frac{l + m_1 + m_2 + u}{6} \tag{15}$$

The consistency ratio is evaluated by Eqs. (16) and (17).

$$CI = \frac{\lambda_{max} - n}{n - 1} \tag{16}$$

$$CR = \frac{CI}{RI} \tag{17}$$

where CI is the consistency index, λ_{max} is the maximum eigenvector value of the matrix, n is the total criteria and RI is the random index.

If the consistency ratio of the pairwise matrix is not in the range, then the decision-makers need to re-evaluate this matrix.

Step 5: Fuzzy geometric mean is estimated for each row of the matrix by Eq. (18).

$$\overline{r_i} = (\overline{C_{i1}} \otimes \overline{C_{i2}} \otimes \cdots \otimes \overline{C_{in}})^{\frac{1}{n}} \tag{18}$$

Step 6: The fuzzy weight of each criterion is calculated by using Eq. (19).

$$\overline{W_i^{CR}} = \overline{r_i} \otimes \frac{1}{\overline{r_i}} \tag{19}$$

Step 7: In this step, the fuzzy global weights ($\overline{W_{ij}^G}$) are estimated by Eq. (20).

$$\overline{W_{ij}^G} = \overline{W_i^{CR}} \times \overline{W_j^{CR}} \tag{20}$$

Step 8: The fuzzy weights estimated by TrFN are de-fuzzified and normalized by Eq. (21) and (22) respectively.

$$W_{ij}^G = \frac{\alpha + 2\beta + 2\gamma + \delta}{6} \tag{21}$$

$$W_{ij}^N = \frac{W_{ij}^G}{\sum_i \sum_j W_{ij}^G} \tag{22}$$

3.3.2. Ranking of alternatives by NEAT-Fuzzy-PROMETHEE

The study considered the NEAT-Fuzzy-PROMETHEE method to rank the alternatives based on the calculated weights of the criteria. The advantages of this method over other methods is described by Ziemba [63]. This method is based on TrFN and allows the use of the natural fuzzy criteria values along with the linguistic scales (Table S2, Sec. A of SI) for assessing the alternative ranks based on the weights of the criteria. This NEAT-Fuzzy-PROMETHEE method includes two variants, NEAT-Fuzzy-PROMETHEE I that gives a partial order of alternatives, and the 2nd order NEAT-Fuzzy-PROMETHEE method which gives an aggregated order of the alternatives. Several steps are included in this method.

Step 1: The fuzzy deviation represented by $\tilde{d}$ for each pair of alternatives $\tilde{a}$ and $\tilde{b}$ is estimated using Eq. (23).

$$\tilde{d}_j\left(\tilde{a}, \tilde{b}\right) = C_j(\tilde{a}) \ominus C_j\left(\tilde{b}\right) \tag{23}$$

where $C_j(\tilde{a})$ and $C_j\left(\tilde{b}\right)$ are the fuzzy values of the alternatives $\tilde{a}$ and $\tilde{b}$ respectively for jth criterion.

Step 2: In this step, the value of $\tilde{d}_j\left(\tilde{a}, \tilde{b}\right)$ is mapped through selected preference functions f which belongs to the mapping function F.

$$\tilde{P}_j\left(\tilde{d}_j\right) = f_k\{\tilde{d}_j\left(\tilde{a}, \tilde{b}\right)\} \tag{24}$$

There are different preference functions which are described by Ziemba, which also discusses the working principles of these functions [71]. Depending on the selected preference functions, different thresholds can be considered, such as Gaussian, indifference and preference. In the NEAT-Fuzzy method the mapping analysis result is validated and the error due to approximation is corrected during this step.

Step 3: This method aggregates preference function values for each alternative by using Eq. (25).

$$\tilde{\pi}\left(\tilde{a}, \tilde{b}\right) = \sum_{j=1}^{n} w_j \otimes \tilde{P}_j\left(\tilde{d}_j\right) \tag{25}$$

where w is the weight of the criteria, the total number of criteria is n. The weights are classified as fuzzy numbers. Therefore, the de-fuzzifications and normalization of weights are performed.

Step 4: The positive (ϕ^+) and negative (ϕ^-) outranking flows are calculated, and based on that the net (ϕ^{net}) outranking flows are estimated. The positive outranking flow measures the extent to which an alternative outranks all other alternatives. Whereas, the negative outranking flow measures the extent to which an alternative is outranked by all other alternatives. The calculations are done on the basis of Eqs. (26)–(28) [72].

$$\tilde{\varphi}^+(\tilde{a}) = \frac{1}{m-1} \sum_{i=1}^{m} \tilde{\pi}\left(\tilde{a}, \tilde{b}_i\right) \tag{26}$$

$$\tilde{\varphi}^-(\tilde{a}) = \frac{1}{m-1} \sum_{i=1}^{m} \tilde{\pi}\left(\tilde{b}_i, \tilde{a}\right) \tag{27}$$

$$\tilde{\varphi}_{net} = \tilde{\varphi}^{+}(\tilde{a}) \ominus \tilde{\varphi}^{-}(\tilde{a}) \tag{28}$$

Step 5: In this final step, both the weights and the net outranking value are de-fuzzified. The de-fuzzification is done on the basis of the centroid method and the calculation used Eq. (29).

$$Df_c(\tilde{a}) = \frac{a_3^2 + a_4^2 + a_3a_4 - a_1^2 - a_3^2 - a_1a_2}{3(a_3 + a_4 - a_1 - a_2)} \tag{29}$$

3.3.3. Validation and sensitivity analysis

The robustness of the solution as well as the most influential criteria and the sub-criteria are assessed in this study. The details of these methods are discussed in sub-section 3.3.3.1.

3.3.3.1. Validation using HFL-TOPSIS method. In this study, the obtained solution is validated by using the HLF-TOPSIS MCDM method which was initially proposed by Hwang and Yoon [73]. This method also has the same characteristics as the proposed methodology. Thus, this HFL-TOPSIS method is used to validate the outcome of the study. This method is distance based MCDM and calculates the alternatives from the ideal solution. Firstly, the positive and negative ideal solution are estimated depending on the criterion type. Then, from the positive and negative ideal solutions, the distances of each alternative are measured. By using these values, the relative closeness is identified and with the highest closeness value, the ranking has been done. In this work, the TOPSIS method is integrated with HFLTS to overcome the limitations of linguistic uncertainties (scale shown in Table S3, Sec. A of SI). The steps of this method are as follows [74].

Step 1: The positive ideal solution (PIS) and negative ideal solution (NIS) are estimated by using Eqs. (30) and (31).

$$A^{*} = \left(h_1^{*}, h_2^{*}, \cdots, h_n^{*}\right), where h_j^{*} = \cup_{i=1}^{m} h_{ij} \tag{30}$$

$$A^{-} = \left(h_1^{-}, h_2^{-}, \cdots, h_n^{-}\right), where h_j^{-} = \sqcap_{i=1}^{m} h_{ij} \tag{31}$$

Step 2: The distance from the ideal solution of each value is estimated by using Eqs. (32) and (33). The hesitant normalized Euclidean distance is proposed for this purpose.

$$D_i^{*} = \sum_{j=1}^{n} \| h_{ij} - h_j^{*} \| {*} W_j \tag{32}$$

$$D_i^{-} = \sum_{j=1}^{n} \| h_{ij} - h_j^{-} \| {*} W_j \tag{33}$$

where W_j is the crisp value of the weights of the criterion. It is calculated by using the HFL-AHP method.

Step 3: the relative closeness index is calculated and the rank of the alternatives are determined. The highest relative closeness value is considered as the best alternative solution. To calculate the closeness index Eq. (34) is considered.

$$C_i = \frac{D_i^{-}}{D_i^{*} + D_i^{-}} \tag{34}$$

3.3.3.2. Modelling of obstacle degree. For the proposed two stage storage selection methodology, this study diagnoses the obstacle factors that affect the sustainability of energy storage selection approaches. This work developed an obstacle degree model to identify the obstacle degree factors for each alternative. The calculation of obstacle degree has been done using Eq. (35) [75].

$$\sigma_j = \frac{(1 - v_{ij}) \times w_{ij}}{\sum_{j=1}^{n} (1 - v_{ij}) \times w_{ij}} \tag{35}$$

where v_{ij} is the normalized value, w_{ij} is the weight of the contributing factor, 1-v_{ij} is the deviation and σ_j is the obstacle degree of the factors.

The sum of the obstacle degrees of all criteria is 1 [75].

3.3.3.3. Sensitivity analysis. A sensitivity analysis is carried out in this study to validate the obtained solution. It also indicates the robustness of the analysis. The LIB is already developed and the variation of the indices is limited. Therefore, the study considered minimum variation for LIB systems (±2-10 %). As the SIB is quite new and research is in progress to develop a more efficient battery module, this study considered the variation of the indices approximately (±4-20 %). Finally, the PIB is emerging and in the development phase, hence the study considered maximum variation of indices approximately (±6-30 %).

4. Results and discussion

The proposed methodology compares the sustainability of three different storage technologies: LIB, PIB and SIB. The objective is to determine which of these technologies is more sustainable for storage applications according to the proposed methodology. The analysis involves all four sustainability factors. The results provide an insight into the most sustainable option, involving balancing performance with minimal environmental and resource impact under the given assumptions of the sources used.

4.1. Sustainable storage selection considering techno-economic-environmental aspects

Techno-economic-environmental aspects are primarily considered in selecting storage technologies. The HFL-AHP method is employed to determine the local and global weights of various factors and sub-factors. These weights provide insight into the relevance of the selected criteria and are used to rank the alternative storage technologies. The weights are application-neutral; considering a specific application would result in a different ranking. Beyond that the weights provide insights into what to focus on during the development of low TRL technologies such as the K-ion battery.

4.1.1. Weight determination process

The first analysis using the HFL-AHP method was carried out to evaluate the weight of the three major categories, i.e., technical, economic and environmental factors. These weights are determined based on a priority matrix developed by the authors' group, comprising academics and experts specializing in sustainability assessment for emerging battery technologies. The result of this analysis is shown in Fig. 3. The detailed evaluation is discussed in Table S4 (Sec. B of SI).

Fig. 3 illustrates the influence of three major sustainability factors on

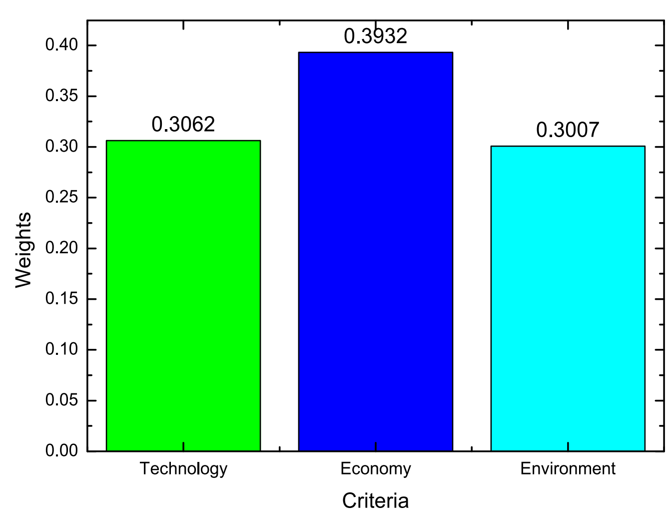


Fig. 3. Weights of techno-economic and environmental criteria.

the overall decision-making process. The result indicates that the economic factor emerging as the most significant factor, holds a weight of 0.3932. This factor contributes approximately 39.32 % of the total weight and it is 28.41 % and 30.76 % higher than those of the technical and environmental factors respectively. The technical factor carries a weight of 0.306, followed by the environmental factor at 30.06 % of the total weight. The assessment of the consistency of the priority matrix is critical to ensure that the weights are logically coherent. The calculated consistency ratio (CR) is 0.0784 lower than 0.1 (shown in Table S4 (Sec. B of SI)). It confirms the reliability of the determined weights and the developed priority matrix is justified. In addition, a similar picture of weights can be found in other works (Table 7 in Baumann et al. [76]), which further highlights the dominant role of economic factors in decision-making.

In the next phase, the proposed methodology is used to determine the weights of sub-factors within each major category. Fig. 4 shows the weights assigned to the seven technical sub-factors, highlighting which technical sub-factors are most critical within the category. A detailed breakdown of this weight analysis is provided in Table S5 (Sec. B of SI). This detailed evaluation offers granular data that contributes to the total evaluation.

The results highlight the relative importance of various attributes to the technical performance of the storage technologies. Fig. 4 identifies energy density as the most influential technical sub-factor, with a weight of 20.11 % of the total. The energy density of storage technology is defined as the ability to store energy in a compact form and according to the analysis it is highly important, a finding which aligns with previous research. Safety is the second most important sub-factor, following closely behind energy density with a weight of approximately 17 %. Efficiency is also a significant sub-factor with a weight of 0.1636, followed by cathode specific capacity (0.15). The least influential technical sub-factor is capacity retention with a weight of 0.074. Subsequently, in this study, the capacity retention factor is evaluated across all alternatives based on a lifetime of 80 cycles as these values are available for the three analyzed technologies. The CR value of this analysis is 0.0946 which is below the threshold level (shown in Table S5), confirming that the priority matrix used to establish technical sub-factor weights is both reliable and consistent, thereby justifying the solution.

After determining the weights of the technical sub-factors, the analysis proceeds to evaluate the weights of the four economic sub-factors. The results are depicted in Fig. 5.

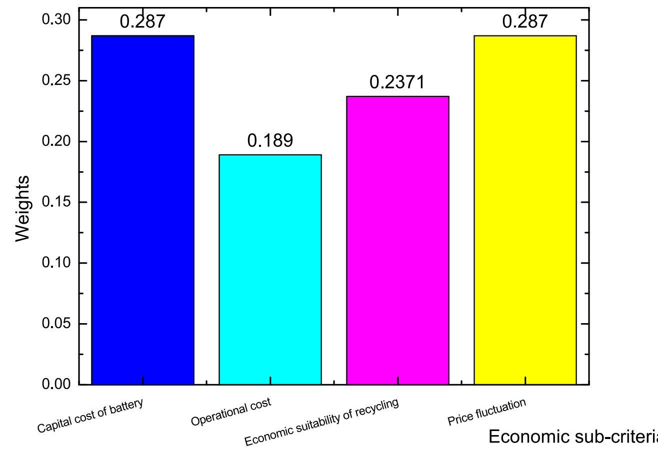


Fig. 5. Economic sub-factors.

The results highlight the impact of financial sub-factors in refining the sustainability assessment of storage technologies. Among the economic sub-factors, capital cost and price fluctuation are identified as the most critical, each holding an equal weight of 0.287. This indicates that initial investment cost and price variability over time are the most significant financial considerations for assessing the sustainability of these technologies. The importance of the economic suitability of the recycling sub-factor is moderately low, and the weight is 17.42 % less than those of these top factors. However, in terms of economic circularity and in the context of the long term, this sub-factor plays an important role. Operational cost is identified as the least significant sub-factor, with a weight of 0.189. The CR value of this economic sub-factor's assessment is below 0.1 (Table S6, Sec. B of SI). It confirms that the priority matrix used in this analysis is consistent and the solution is reliable.

Following the economic analysis, the priority and the weights of the twelve environmental sub-factors are analyzed and the outcome is shown in Fig. 6.

The study considered LCA results based on the Eco-invent database and the recipe method obtained from Yokoi et al. [4]. The analysis indicates that global warming potential has the highest weight at 0.1518,

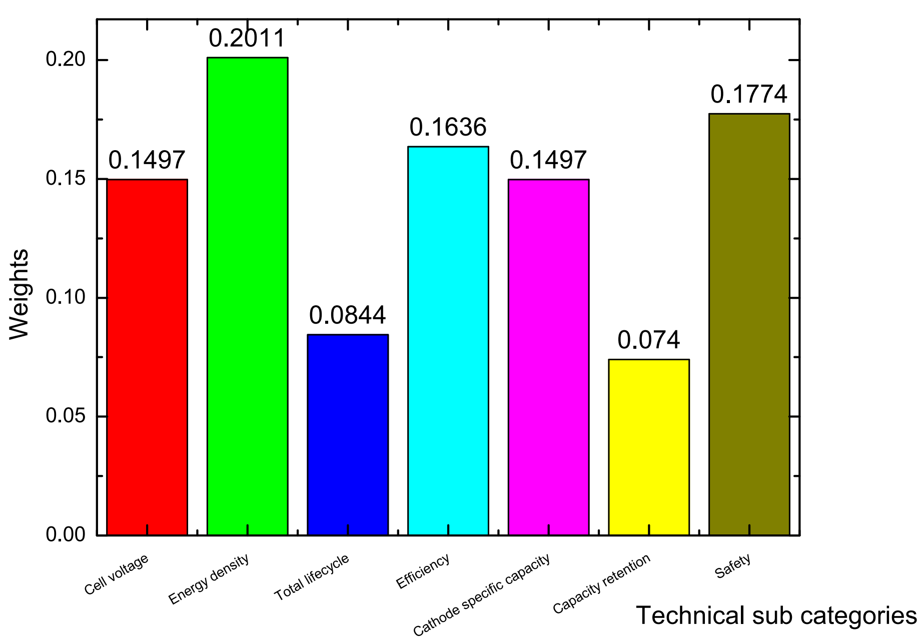


Fig. 4. Weights of Technical Sub-criteria.

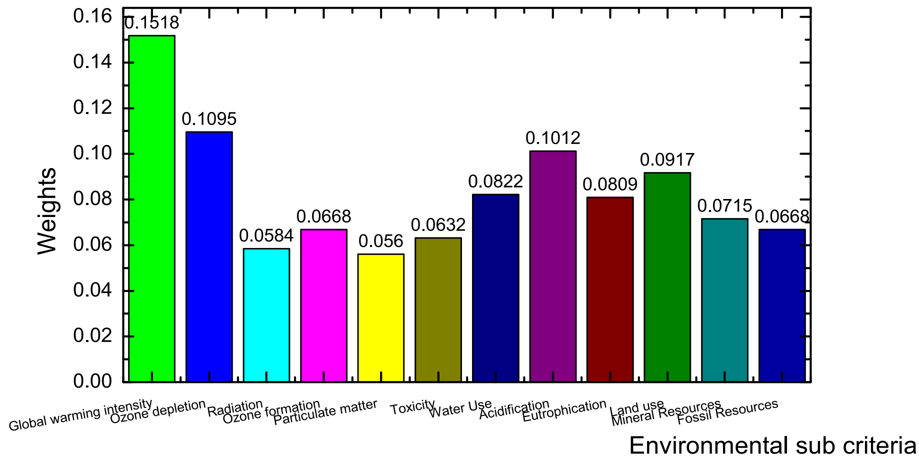


Fig. 6. Weights of environmental sub-factors.

which makes this sub-factor the most critical environmental aspect. The other environmental sub-factors are 27.8–63.1 % lower than that of global warming potential, meaning those factors are important but not as crucial as global warming. The second most important sub-factor is ozone depletion which represents 10.95 % of the total weight of the environmental sub-factors. The least influential sub-factor is particulate matter; it has a 5.6 % contribution to the environmental sub-factors. The CR value is 0.0989 for the weight analysis of the environmental sub-factors (Table S7, Sec. B of SI). This is less than the threshold level of 0.1. It confirms the reliability of the considered importance matrix and also that the obtained solution is consistent.

After determining the individual weights of the sub-factors, the next step involves estimating their global weights using the HFL-AHP method. The result of the analysis is shown in Fig. 7.

The global analysis integrates the weights of different techno-economic and environmental sub-factors, providing a comprehensive view of their relative importance. The overall weight analysis may alter the influence of sub-factors compared to their local weights. For instance, the impact of toxicity becomes significantly more pronounced in the global weight analysis than in the local environmental weight analysis. The analysis shows that the capital cost is the highest important sub-factor compared to the other techno-economic and environmental sub-factors. The weight of this sub-factor is 96.81 %-7.5 % higher than that of the other sub-factors. This factor shares 6.16 % of the total weight, followed by the global warming intensity sub-factor with 5.73 % of the total weight. The technical factors, such as energy density and cell voltage, also have high importance and the weight of these sub-factors are 5.41 % and 5.28 % of the total weight respectively. The minimum weight is obtained for the economic suitability of recycling sub-factor which shares 3.13 % of the total weight. The CR of this analysis is 0.0954 which is below the threshold level (Table S8, Sec. B of SI). It confirms the priority matrix is reliable and consistent.

Based on these global weights of the technical, economic and environmental sub-factors, the ranking of the three alternatives, i.e., $LiFePO_4$, $KFeSO_4F$ and $Na_{1.1}(Ni_{0.3}Mn_{0.5}Mg_{0.5}Ti_{0.05})O_2$ can be evaluated. The ranking demonstrates how each technology performs across the

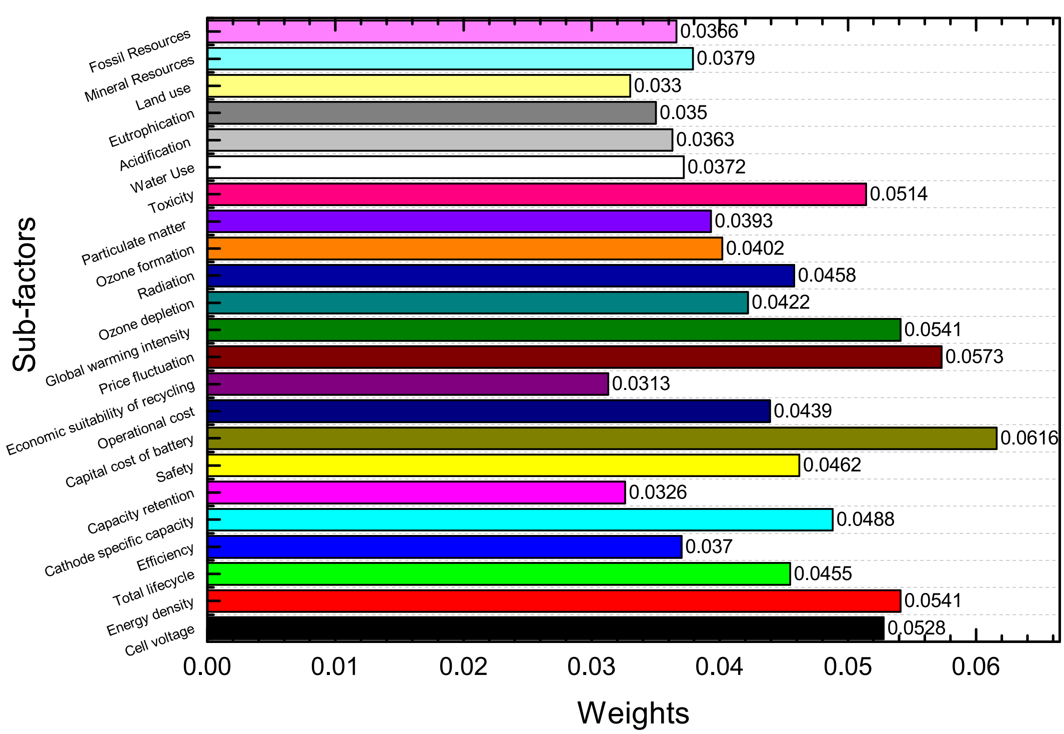
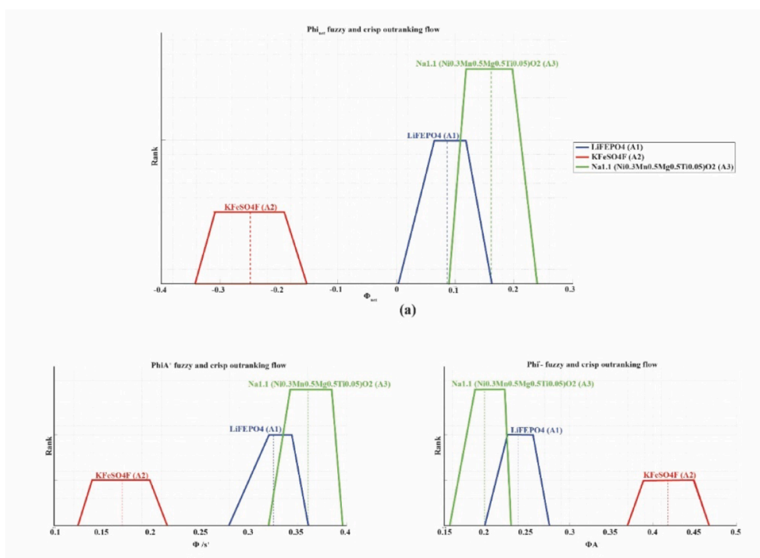


Fig. 7. Overall weights of technological, economic and environmental sub-factors.

different sub-factors, considering their relative weights.

4.1.2. Ranking analysis of alternatives

The ranking analysis of alternatives is conducted by evaluating the sub-factors within technical, economic, and environmental aspects. Both quantitative and qualitative values of these sub-factors, along with their calculated global weights, are considered to determine the solution. The considered alternatives are $LiFePO_4$ (A1), $KFeSO_4F$ (A2) and $Na_{1.1}(Ni_{0.3}Mn_{0.5}Mg_{0.5}Ti_{0.05})O_2$ (A3). The results are shown in Fig. 8a–c. Fig. 8 illustrates the fuzzy and crisp values of the alternatives, along with their respective rankings, for ϕ^{net}, ϕ^{+}, ϕ^{-} evaluation. In Fig. 8a, the ranking based on ϕ^{net} is analyzed, resulting in the following total order of alternatives, A3 > A1 > A2. Consequently, the analysis identifies that the solution to the decision problem is aligned with the ranking. Therefore, according to the solution the SIB, i.e., Na1.1 $(Ni_{0.3}Mn_{0.5}Mg_{0.5}Ti_{0.05})O_2$ (alternative-A3) is the most sustainable storage module, followed by A1 ($LiFePO_4$) and A2 ($KFeSO_4F$) when technical, economic and environmental aspects are considered. The overall order of alternatives is distinguished by a relatively low degree of uncertainty as demonstrated by the broad range of kernels and support associated with the obtained fuzzy numbers. This outcome is obtained by considering the global weights of the sub-factors of these three major factors. The crisp value of the rank of this SIB is 0.1616 which is 46.4–56.7 % higher than those of the alternatives. In Fig. 8b the positive outranking analysis (ϕ^{+}) reveals that the alternative with the highest outranking performance is A3. The alternative SIB outranked LIB and PIB by 4 % and 52.7 % respectively. On the other hand, in Fig. 8b, the negative outranking analysis ϕ^{-}, shows that the most outranked alternative is A2, followed by A1 and A3. However, the fuzzy number analysis identifies that the certain amount of A1 is outranked by A3. The NEAT Fuzzy PROMETHEE method utilizes convex and normal fuzzy sets, typically represented as triangular fuzzy numbers, trapezoidal fuzzy numbers, interval numbers, and crisp numbers. The method incorporates various preference functions, such as V-shape, U-shape, and Gaussian functions, each with different threshold values (indifference, preference, and Gaussian threshold) that can alter the visualization of trapezoid patterns. The different forms of trapezoid are also observed in [77]. The developed visualization is versatile and universal, enabling the representation of fuzzy numbers (FNs), interval numbers (INs), and crisp numbers (CNs). The study considered the preference functions along with their varying threshold values, as referenced in existing published works. The low capital cost, high cathode capacity retention, moderate cell voltage, global warming potential and safety are the key strengths of this technology. These techno-economic advantages help this technology to overcome the limitation of low energy density. According to the analysis the $LiFePO_4$ (A1) holds the second rank slightly



Φ_{net}		
Alternatives	Value	Rank
LiFePO4	0.0865	2
KFeSO4F	-0.2484	3
Na1.1(Ni0.3Mn0.5Mg0.5Ti0.05)O2	0.1616	1
Φplus		
Alternatives	Value	Rank
LiFePO4	0.3249	2
KFeSO4F	0.1695	3
Na1.1(Ni0.3Mn0.5Mg0.5Ti0.05)O2	0.3603	1
Φneg		
Alternatives	Value	Rank
LiFePO4	0.2385	2
KFeSO4F	0.4179	3
Na1.1(Ni0.3Mn0.5Mg0.5Ti0.05)O2	0.1986	1

(d)

Fig. 8. Ranking of alternatives: a) Net fuzzy and crisp outranking flow; b) Positive fuzzy and crisp outranking flow; c) Negative fuzzy and crisp outranking flow (without socio-political factors).

behind SIB, due to its better environmental impact. However, SIB outperformed this technology in terms of economic aspects. The $KFeSO_4F$ battery is ranked lowest among the considered alternatives, as it lags in several areas, including techno-economic aspects. Consequently, this technology becomes less sustainable compared to other alternatives, which to a certain degree may be due to its lower technology development status, even if optimistic values have been selected for the same.

4.2. Impact of socio-political sub-factors

The next phase of the study involves incorporating the socio-political impact of critical raw materials into the ranking analysis. The study highlights the dependence of technology on its TRL level. Local and global weights for these socio-political sub-factors are estimated alongside the other technical, economic, and environmental aspects and sub-factors. A detailed analysis is then conducted based on this expanded set of criteria.

4.2.1. Weight determination of all factors and sub-factors

First, the weight of the socio-political factor is compared with the previously considered factors. This phase is critical for a full evaluation, as it integrates the socio-political impacts of the storage technologies. The result of this analysis is shown in Fig. 9 (Table 7 in Baumann et al. [76]).

The integration of the socio-political factor into the sustainability assessment has led to a redistribution of the weights among the factors. Both economic and technical factors now hold equal importance in the overall sustainability assessment, each accounting for 26.4 % of the total weight. The newly introduced factor has a significant weight (approximately 25.88 % of the total). It shows that socio-political consideration is nearly as important as the top factors. The environmental factor's weight is now 0.2134. While it remains a critical factor, it has slightly lower influence than those of the other three factors after integrating the socio-political aspect. The CR is 35 % lower than the threshold value, which indicates that the solution is reliable. Subsequently, the weight of the four sub-factors of the socio-political factor are locally evaluated. The analysis result is shown in Fig. 10. The detailed analysis and the consistency ratio are provided in Table S10 (Sec. B of SI).

The local weight determination identifies the most influential aspects of this category in the context of sustainability for emerging storage technologies. The analysis shows that both the demand growth of the product and the supply risk of the material are the two most critical sub-factors. Each holds 28.7 % of the total weight within the socio-political category. These sub-factors are crucial because they directly impact the scalability and long-term viability of the technology. Political stability is also a significant sub-factor, although slightly less critical than the top two sub-factors. The weight of this factor is 25.45 % higher than that of the trade barriers sub-factor. The least important socio-political factor is trade barriers and the weight of this factor is 0.189. Table S10 shows that the CR is 0.0922 which is lower than threshold value. This justifies that the solution is accepted. After calculating the local weight of the socio-political sub-factors, the overall global weights of the total sub-factors are estimated as presented in Fig. 11. The detailed evaluation is shown in Table S11 (Sec. B of SI).

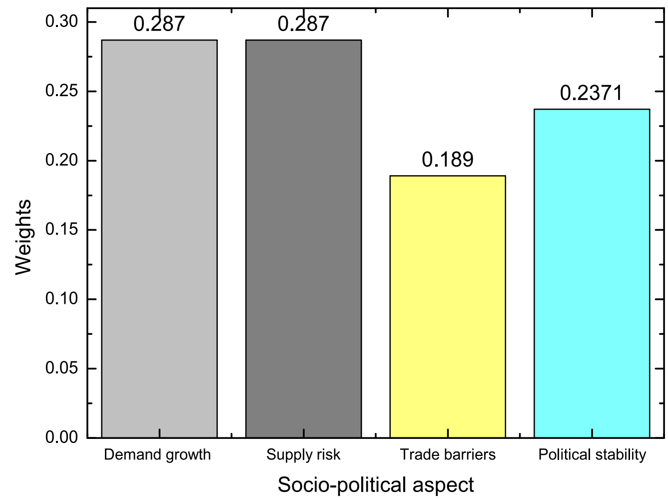


Fig. 10. Socio-political sub-factors weights.

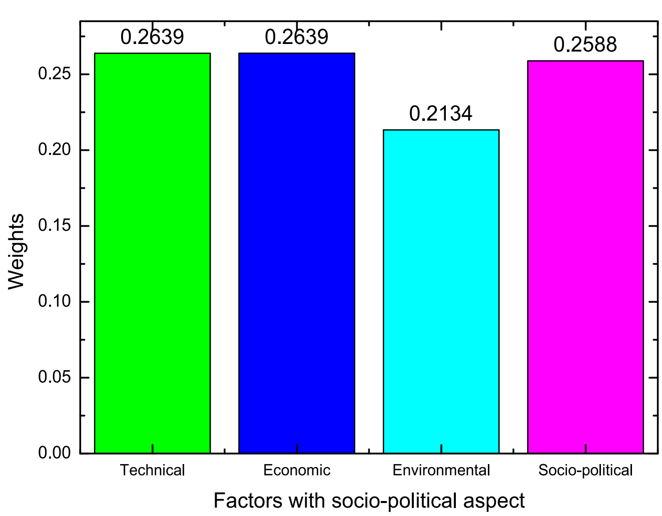


Fig. 9. Weights of the sustainability factors.

The global weight analysis has identified the most impactful sub-factors among all categories. It provides a comprehensive understanding of which aspects most significantly impact the sustainability of the storage technologies. According to the analysis, price fluctuation with a global weight of 0.05397 is the most influential sub-factor. This highlights the importance of economic stability and cost predictability in the sustainability assessment. Global warming intensity is close behind price fluctuation, with a weight of 0.05368. Its emphasis is the critical role of environmental impact in determining the sustainability of storage technologies. The third important sub-factor is cell voltage which shares 5.016 % of the total weight. This reflects the importance of technical performance in terms of energy efficiency and effectiveness. The sub-factors of energy density, cathode specific capacity, capital cost, safety and ozone depletion also show moderately high importance. The weights of these factors range between 4–4.6 %. These factors are also critical, but not as dominant as global warming potential and price fluctuation. The least important sub-factor is trade barriers, and the weight of this indicator is 2.352 %. According to the detailed evaluation shown in Table S11 the CR is less than 0.1. This analysis validates the considered priority matrix. Therefore, the obtained solution is acceptable.

4.2.2. Impact of socio-political sub-factors on ranking analysis

By using this global weight of different sustainability sub-factors that includes technical, economic, environmental and socio-political dimensions, the ranking of the alternatives is further evaluated and the result is shown in Fig. 12a–c.

The integration of socio-political factors into the sustainability assessment has significantly influenced the final ranking of the battery alternatives. The inclusion of the sub-factors of this criterion alongside other sub-factors leads to notable changes in the ranking analysis of the alternatives. According to the net outranking (ϕ^{net}) result as shown in Fig. 12a, the alternative A1, i.e., $LiFePO_4$ (LIB) now ranks as the most suitable sustainable option with a crisp value of 0.1277. This crisp value is 52.04 % higher than that of the SIB alternative. The demand growth is high for the $LiFePO_4$ battery. It indicates strong market acceptance and

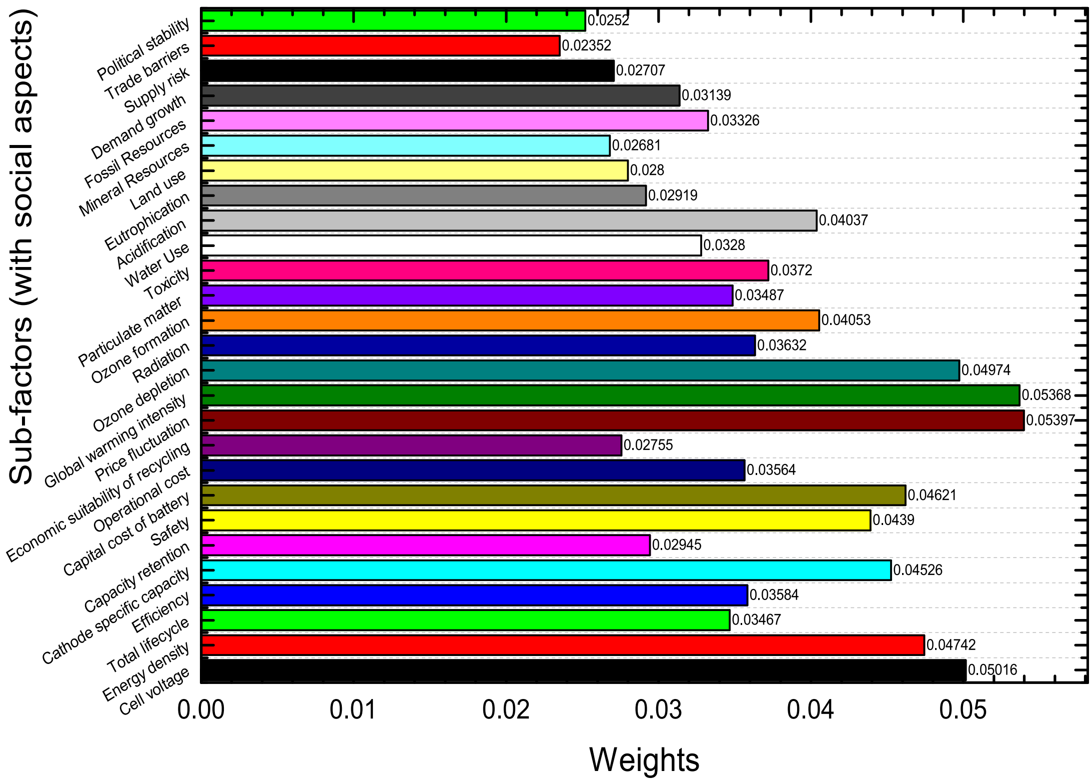


Fig. 11. Final global weights of all sub-factors.

potential for wide-scale adoption. The price fluctuation is also low, which makes it a more economically stable option. As the LIB battery is already commercially available, its high socio-political stability and favorable techno-economic characteristics make it a leading choice in the market. In Fig. 12b, the positive outranking flow ($\phi+$) shows that the $LiFePO_4$ battery outranks the A3-Na1.1(Ni0.3Mn0.5 Mg0.5Ti0.05)O2 (NaNMMT-SIB) and the A2-$KFeSO_4F$ (PIB) by 7.9 % and 44.7 % respectively. In Fig. 12.c the negative outranking flow (ϕ^-) shows that the LIB battery is outranked by SIB and the percentage of outrank is 3.8 %.

The SIB is the second most suitable alternative. It has the lowest capital cost and also performs better in socio-political aspects than the alternatives. The major limitation of this technique is low energy density and high price fluctuation, which affects its overall sustainability ranking. The PIB is the least sustainable option because of high political instability and moderate demand growth. Subsequently, the capital cost and socio-political factors are not suitable for the PIB. These limitations result in the PIB being the least favorable option despite some technical strengths.

Therefore, this emphasizes the importance of socio-political factors in ensuring the adoption and acceptance of emerging technologies. The study highlights the need for improvements in the SIB and PIB batteries, particularly in areas such as energy density, price stability, and socio-political stability, to make them more competitive and sustainable options in the future. The analysis results were validated using an alternative decision-making method, confirming the robustness and reliability of the findings.

4.3. Result validation

This section presents a result validation to confirm the validity, veracity of the solution obtained through the proposed methodology, and a comparative analysis has been performed in this sub-section. This comprehensive approach helps confirm that the findings are reliable and consistent, despite potential variation of data.

The same weights for the main factors and their sub-factors which are obtained through the HFL-AHP method are considered for this method. Fig. 13 shows the ranking of the alternatives obtained through this HFL-TOPSIS method.

According to the analysis LIB obtained the highest rank with a higher performance score. The performance score is 4.7 % and 15.82 % higher than the other two alternatives, i.e., SIB and PIB. The lowest score is obtained for the PIB. This approach also validates the output of the proposed methodology. Though the MCDM methods are focused on ranking the alternatives in accordance with a number of dimensions, they used a wide variety of normalization strategies and aggregation functions. These aggregation functions and normalization strategies provide their unique set of outcomes.

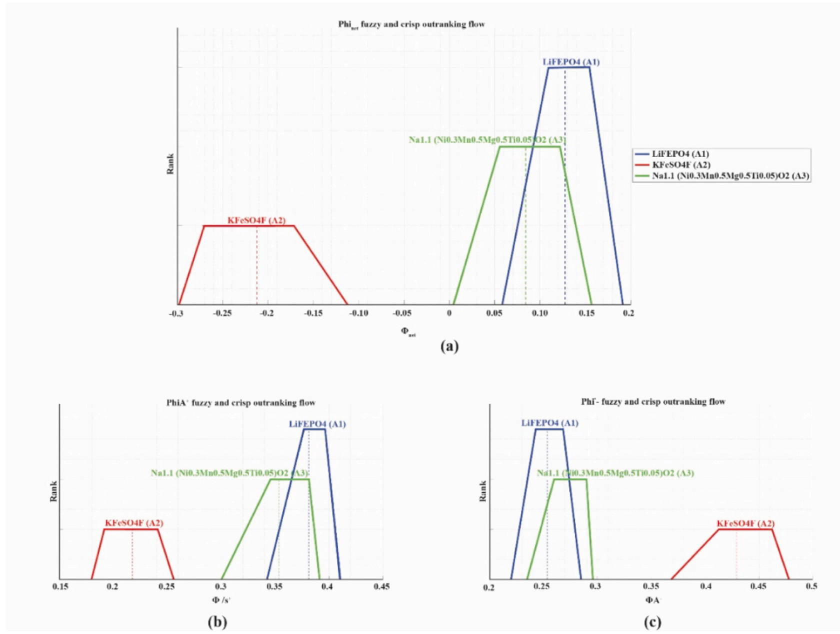
4.4. Obstacle degree analysis

An obstacle degree analysis of the factors and the sub-factors was undertaken. The obstacle degree analysis further identifies and quantifies the challenges posed by each factor and sub-factor. This provides more in-depth insights into the barriers to achieve optimal sustainability in the battery alternatives.

The study calculates the obstacle degree of the criteria and the sub-criteria by using Eq. (35). The detailed results of the obstacle degree analysis are shown in Table 3.

According to Table 3, the maximum obstacle degree is observed on the environmental side. On the environmental side the obstacle degree is 42.03 % followed by the obstacle degree of the technical factors (approximately 27.06 %). The minimum obstacle degree is for the socio-political factors which is approximately 12.59 %. The obstacle degree of the technical factors is moderate at about 18.32 %. The obstacle degree of the sub-factors is shown in Fig. 14.

According to Fig. 14, various sub-factors have been identified that play a crucial role in the decision-making process for selecting a sustainable energy storage solution. This includes cell voltage, energy density, cathode specific capacity, safety, capital cost, price fluctuation,



Φ_{net}		
Alternatives	Value	Rank
LiFEPO4	0.1277	1
KFeSO4F	-0.2122	3
Na1.1(Ni0.3Mn0.5Mg0.5Ti0.05)O2	0.0841	2
Φplus		
Alternatives	Value	Rank
LiFEPO4	0.3812	1
KFeSO4F	0.2175	3
Na1.1(Ni0.3Mn0.5Mg0.5Ti0.05)O2	0.3534	2
Φneg		
Alternatives	Value	Rank
LiFEPO4	0.2536	1
KFeSO4F	0.4295	3
Na1.1(Ni0.3Mn0.5Mg0.5Ti0.05)O2	0.2695	2

(d)

Fig. 12. Ranking of alternatives: a) Net fuzzy and crisp outranking flow; b) Positive fuzzy and crisp outranking flow; c) Negative fuzzy and crisp outranking flow with socio-political factors.

global warming intensity, ozone depletion and demand growth. The analysis reveals that the average obstacle levels of these sub-criteria are all above 4 %, specifically, 4.69 %, 4.03 %, 4.22 %, 4.19 %, 4.67 %, 7.1 %, 5.02 %, 4.03 %, 4.67 % and 4.05 % respectively.

The LiFePO4 battery has the distinct advantage of high energy density, cathode specific capacity and demand growth. It also experiences a lower price fluctuation than those of the alternatives. These factors are identified as influential criteria in determining a sustainable solution. The obstacle values for the LiFePO4 battery are significantly higher, approximately 25–32 % and 41–52 % more than SIB and PIB respectively. This highlights the areas where it outperforms the others.

Based on the obstacle degree analysis, the primary area needing improvement for emerging technologies, such as, SIB and PIB, is environmental factors. Specifically, improvement is needed in reducing global warming intensity and ozone depletion. Though SIB has the benefits of lower capital cost and higher safety, its lower energy density and high price fluctuation make it a second-best option. Furthermore, the PIB, being a more recent technology, requires significant technical development to mitigate the economic and environmental impacts. Additionally, demand growth, supply risk and trade barriers must be addressed to enhance the acceptability of these emerging technologies.

4.5. Sensitivity analysis

After exploring the obstacle degree of the factors and sub-factors, an uncertainty analysis is carried out. This analysis is critical as it provides deeper insights into how sensitive the solution is to changes in the underlying factors. This ensures the reliability and robustness of the alternative rankings, even when subjected to variations in key parameters.

As LIB is well established, the likelihood of significant variations in its input parameters is limited. In contrast, PIB, as a recent and developing technology, is subject to greater potential for variation in the input parameters. For SIB, which is relatively developed, a moderate variation is assumed. To account for these differences, the study varies the values of the sub-factors by +/-10 %, 20 % and 30 % for LIB, SIB and PIB respectively. Different scenarios are developed to evaluate these uncertainties that could impact the overall sustainability ranking of each battery technology. The decided sensitivity analysis scenario is provided in Table 4. The analysis result is shown in Fig. 15.

The advancement of sub-factors in a positive direction can significantly impact the ranking of battery alternatives. The uncertainty analysis reveals that as these sub-factors improve, the rankings of the alternatives also shift. According to the net outranking flow analysis, the

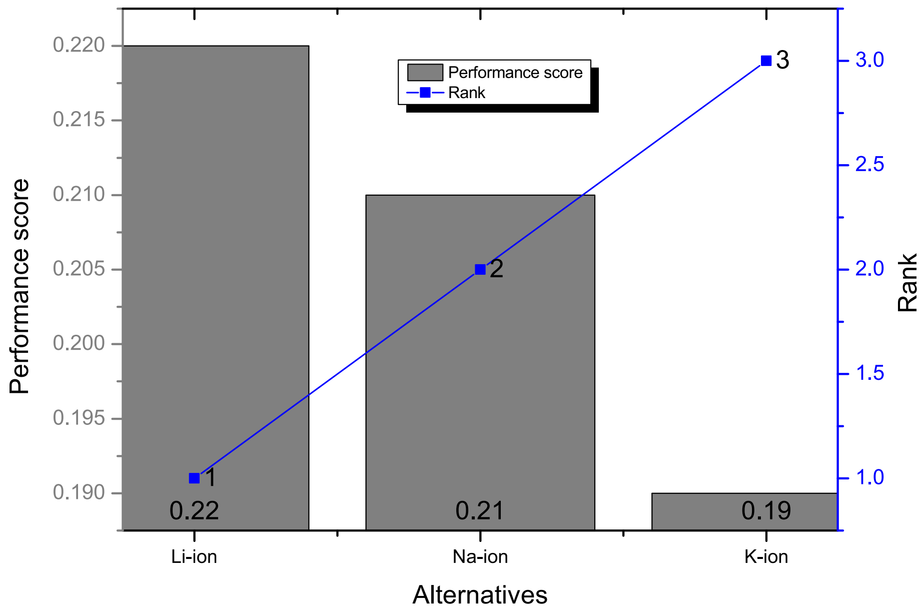


Fig. 13. Performance score and rank of the alternatives.

Table 3
Obstacle degree of factors and sub-factors.

	C11	C12	C13	C14	C15	C16	C17	C21	C22	C23	C24	C31	C32	C33	C34	C35	C36	C37	C38	C39	C39.1	C39.2	C39.3	C41	C42	C43	C44
LiFEPO4 (A1)	5.356847	4.180991	5.105778	3.639591	4.272568	3.007421	2.969243	4.395708	0.802217	3.299354	11.75895	5.663536	4.988245	3.647527	4.837506	3.954425	2.90779	4.347572	4.812716	2.707417	2.237588	2.329624	3.651773	0.062696	0.328151	2.265309	2.469452
$KFeSO_4F$ (A2)	3.913595	4.442202	1.661033	3.100945	4.649391	2.558384	5.820572	2.370789	4.429183	2.026905	9.362348	4.148407	3.671999	3.427247	3.90873	3.734227	3.83564	4.467463	4.42012	2.624554	2.757297	4.233027	2.723803	5.771155	3.86102	1.045928	1.034035
NaNMMT(A3)	4.815791	4.587027	3.635851	3.271982	3.726322	2.66286	3.797264	7.264677	6.567463	2.489316	0.197357	5.263963	5.349855	3.069839	2.773897	2.241437	3.647791	1.215029	2.375974	2.803269	2.81946	1.532166	2.962877	6.299359	5.514615	4.220006	4.894553
Sigma	4.695411	4.403407	3.467554	3.337506	4.216094	2.742888	4.195693	4.677058	3.932954	2.605191	7.10622	5.025302	4.670033	3.381538	3.840044	3.31003	3.46374	3.343355	3.869603	2.711747	2.604782	2.698273	3.112818	4.044403	3.234596	2.510414	2.799346
Sigma_Factor	27.05855253							18.32142351				42.0312642												12.58875975			
	Sigma (Technical)							Sigma (Economic)				Sigma (Env)												Sigma (Social)			

highest-ranked alternative is A1, which outranks both A2 and A3. As the input parameters vary in a positive direction, the outranking flow shifts, resulting in change of alternative's net ranking. This outcome is observed in cases 2, 3, 5, and 7. In these cases, when the sub-factors improve positively the PIB overtakes SIB to become the second most suitable option. The LIB remains the most suitable option. As positive changes continue in the sub-indicators, the crisp value of PIB gradually increases. Notably, in case 5 the value of PIB almost matches that of the LIB. In case 7, the fuzzy analysis indicates that alternative A2 surpasses A1 to a certain extent due to significant changes in the parameters. For the scenario 'a, c, e, g, i' the crisp value of PIB changes from −0.175–0.01, which indicates a significant improvement. If the parameters vary in a negative direction, there is no change in the ranking of the alternatives. However, very negligible variation is observed in the fuzzy outranking flow of this cases.

This highlights that even slight adjustments in sub-factor values can lead to considerable changes in the ranking and suitability of the alternatives. Therefore, the study recommends introducing some variation in all sub-factors to better accommodate and integrate new emerging battery technologies into society. Furthermore, this analysis demonstrates that the improved PIB battery may surpass the SIB battery in the future. This approach ensures that the sustainability assessment remains dynamic and responsive to technological advancements.

The assessment result is limited to selected battery chemistries and the assumptions made for LCA and social aspects in the used literature. The method of selecting sustainable storage modules using MCDM technology is generic and robust. The solution is also based on the obtained values through different literature. However, the ranking of the alternatives may change drastically with the change of materials and also due to the variation of input parameters.

5. Limitations

There are limitations associated not directly with the applied method, but rather from the used literature for the quantification of the selected criteria. Here it is challenging to gather comparable values, also as these are often interdependent. For example, the cell voltage impacts the specific energy, and the cycle lifetime and retention rate are strongly connected, making the criteria to a certain degree redundant. However, named criteria are important technical parameters which are assessed in corresponding testing campaigns of named cell types and are thus included as they provide important insights for technology developers. Consequently, a certain degree of double accounting is unavoidable, which in essence becomes true for all composite criteria, e.g. global

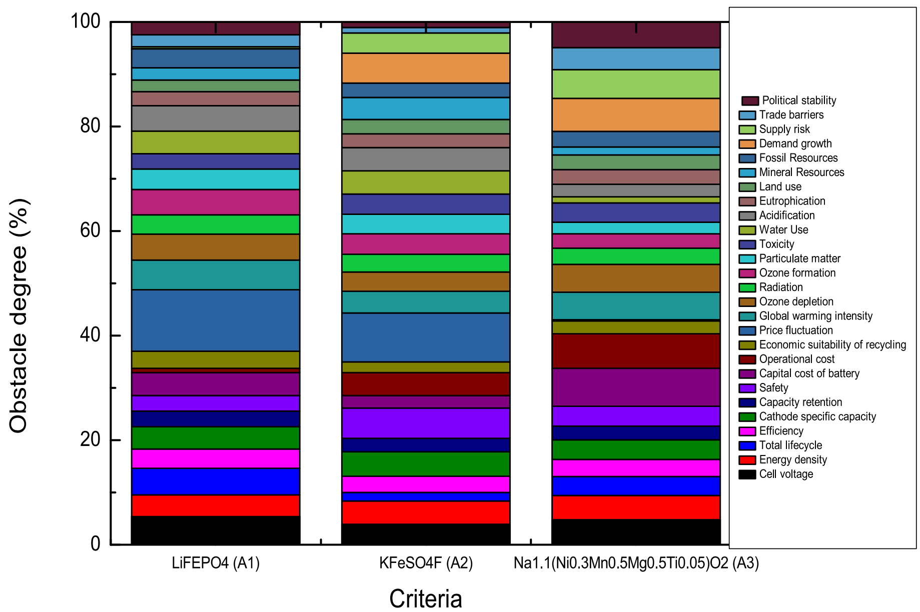


Fig. 14. Obstacle degree analysis for sub-factors.

Table 4
Scenario details (changes are carried out in %).

Scenario	Cases	
1	Case 1 (LIB: +2, PIB: +6, SIB: +4)	Case 2 (LIB: −2, PIB: −6, SIB: −4)
2	Case 3 (LIB: +4, PIB: +12, SIB: +8)	Case 4 (LIB: −4, PIB: −12, SIB: −8)
3	Case 5 (LIB: +6, PIB: +18, SIB: +12)	Case 6 (LIB: −6, PIB: −18, SIB: −12)
4	Case 7 (LIB: +8, PIB: +24, SIB: +16)	Case 8 (LIB: −8, PIB: −24, SIB: −16)
5	Case 9 (LIB: +10, PIB: +30, SIB: +20)	Case 4 (LIB: −10, PIB: −30, SIB: −20)

warming potential or capital cost which both depend on energy density, which vice versa depends on cell voltage etc. [76].

The TRL of the analyzed technologies is also very different, which leads to a potentially biased picture. LIB has undergone a strong learning curve for all named criteria which is not the case for PIB or SIB. Here it can make sense to e.g., select a reductionist approach where only one component is considered, e.g., the cathode as in [78] under the same boundary conditions (e.g., selecting only theoretical and very simplified performance values [79]). The deficit of different technology readiness levels (TRLs) was considered here in the sensitivity analysis as well as for the assessment containing the socio-political criteria. For example, there is barely any data available on real world performance of PIB batteries, which is also the case for SIB. In contrast, data for LIB is rather robust for most of the used criteria, thus the variation of performance was adjusted correspondingly for the three chemistries. Still, it is hard to predict how cell cost might look for PIB in the case of large-scale production volumes as in the case for LIB. The challenge lies in the cost disparity of LFP cells, with high-quality systems priced at approximately \$60/kWh and lower-quality LFP cells in China ranging between €40-45/kWh. This significant cost advantage could render the other two systems non-competitive.

The study considered the environmental impact of storage technologies only during the production process. However, the use phase and the end-of-life phase are also important as they can significantly influence environmental impacts. This is the case if advanced recycling routes are available, where chemistries containing valuable materials might have a better performance than those using abundant materials. In addition, batteries are optimized for a certain purpose, e.g., uninterruptible power supply (UPS) or ancillary services, which has to be considered. UPS typically does not require a high cycle lifetime, which is in contrast very relevant for ancillary services, making it necessary to distinguish the relevance of criteria related to the use of a battery. Therefore, considering the environmental impact of the battery for the full lifecycle of the storage technology is essential [1]. However, due to lack of data, in particular for PIB and the absence of a proven application field it is not possible to include them in the study without adding a higher degree of uncertainty.

Also, the social oriented aspects included here can easily be extended towards e.g., social life cycle assessment related impact categories such as human rights, or governance. In particular for batteries, there are concerns about the upstream processes for raw material mining and refining. Such factors should be considered when there is more data available for SIB and PIB.

However, the proposed integrated methodology has an added value for any cell developer or policymakers that must comply with current regulations. It allows us to gather information on the potential impact of different criteria on the overall performance of a battery cell and can accordingly help to optimize it.

6. Conclusion and future work

The aim of the study is to provide decision support and to identify improvement potential for three different battery storage chemistries: LiFePO4, (LFP) KFeSO4F (PiB) and a1.1(Ni0.3Mn0.5 Mg0.5Ti0.05)O2 (NaNMMT). To do so, the proposed methodology evaluates critical sustainability factors, including environmental impacts from LCA, and socio-political aspects of critical raw materials along with techno-economic factors to rank emerging battery storage technologies. The study simultaneously assesses the influence of socio-political factors on the decision-making process. It also addresses the challenges of missing data and data uncertainty associated with different technologies arising from varying TRLs. This proposed work primarily relies on quantitative data to minimize linguistic bias and uncertainty in decision-making. Given the complexity and interdependency of these sustainability factors, prioritizing alternatives becomes challenging, especially when accounting for linguistic uncertainties. To address these challenges, the study proposes an integrated, generic methodology combining hesitant intuitionistic fuzzy MCDM models. This approach uses more realistic, quantitative data to mitigate bias, hesitancy, and uncertainty. The methodology integrates HFL-AHP and NEAT-Fuzzy-PROMETHEE to

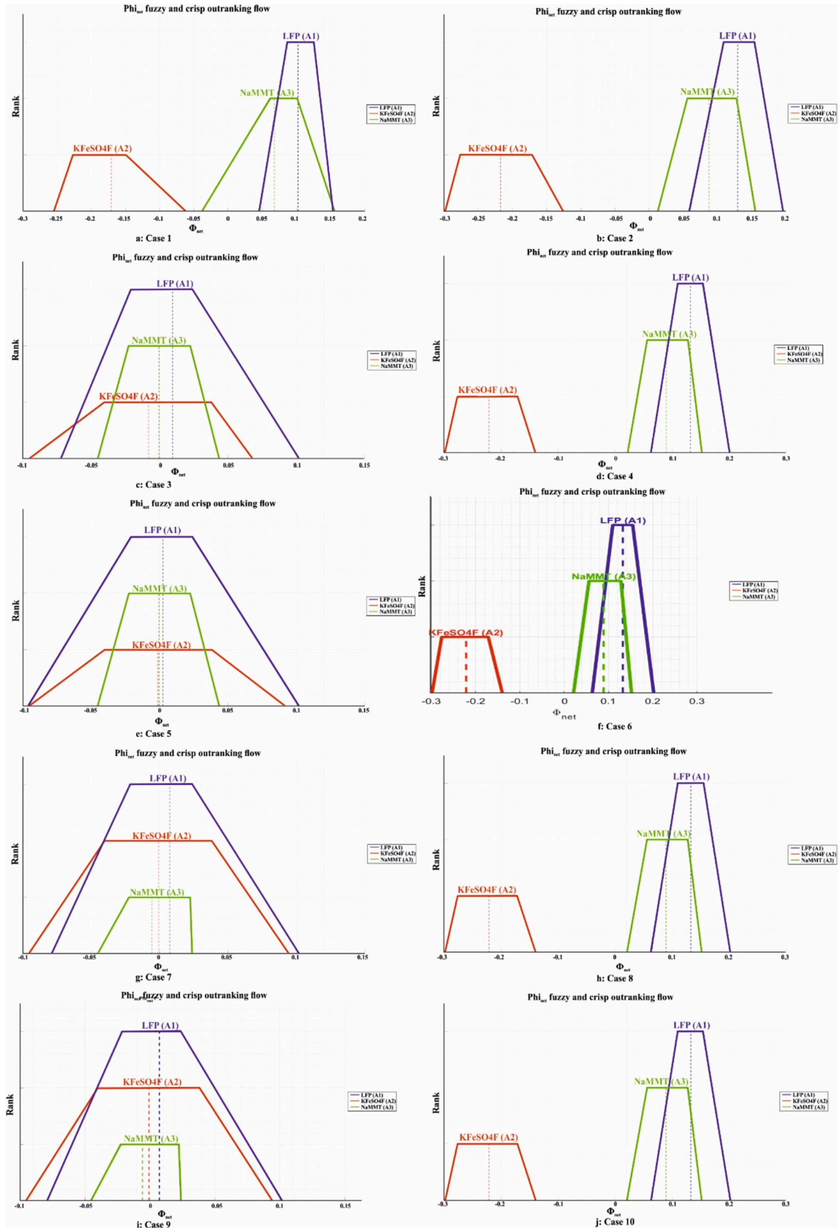


Fig. 15. Uncertainty analysis (Net outranking flow).

accurately estimate index weights and rank alternatives while managing bias and hesitancy. The HFL-TOPSIS method is employed to validate the results, ensuring robustness. Additionally, obstacle degree analysis evaluates the impact of each criterion on the decision-making process and identifies which criteria should be optimized to enhance the acceptability of emerging technologies. The uncertainty analysis is finally performed to examine how variations in indices influence the rankings. Given the significant variation in TRLs across the technologies, uncertainty analysis is conducted by varying the data by 30 %, 20 %, and 10 % for PIB, SIB, and LIB, respectively.

The analysis indicates that the SIB battery stands out as the most optimal solution, followed by the LIB battery, when considering technical, economic, and environmental factors. This is primarily due to its significant advantages across nearly all dimensions, making it a highly viable option. However, during the inclusion of socio-political factors the LIB became the highest priority solution due to its higher demand growth and less price fluctuation, followed by SIB. Thus, this outcome shows that in general any further inclusion of a new dimension or a new indicator for the evaluation process could or would change the results and ranking significantly. The findings are validated with the HFL-TOPSIS method, confirming the robustness of the solution. In both scenarios PIB ranks as the least favorable option, partially due to its moderate energy density which needs to be improved further, although it shows potential for improvement as it progresses beyond early development stages. Sensitivity analysis reveals that the shifts in particular values (energy density, cell voltage, capital cost, price fluctuation) may enhance the demand for emerging technologies. Additionally, obstacle degree analysis identifies environmental factors (42 %) and technology factors (27.1 %) as the primary challenges influencing sustainable prioritization. This study provides deeper insights into the most influential factors affecting sustainable prioritization. It highlights that the technological modifications such as increase of energy density and cell voltage with improved safety is required to establish emerging technologies in the future. Price fluctuations also need to be address for the emerging technologies as well as for established systems. Although the results may vary with the variation of the battery material, this proposed methodology remains generic and adaptable for decision-makers in selecting sustainable storage technologies under conditions of linguistic uncertainty. In an optimum case and for similar TRL, data should be provided by comparable testing procedures (regarding e.g., energy density, life cycle) and corresponding LCA and cost data from a Na-, K- and Li- battery production and test campaign from the same laboratory under equal conditions. Only in this case will the outcome of such an investigation be based on a robust, comparable and more reliable data. Since the authors' group are from academic backgrounds, there may be a possibility of limiting the applicability of the findings to industry-specific contexts. Therefore, with a different approach future research could involve stakeholders from industry to ensure that the selection of criteria reflects the interests and perspectives of the targeted community. This broader inclusion, which was beyond the scope of the present study, would enable a more comprehensive and balanced evaluation framework.

CRediT authorship contribution statement

Sayan Das: Writing – original draft, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Manuel Baumann:** Writing – review & editing, Validation, Supervision, Resources, Methodology, Data curation. **Marcel Weil:** Writing – review & editing, Validation, Supervision, Investigation, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.enconman.2025.119594.

Data availability

No data was used for the research described in the article.

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