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Research Paper

A flexible tool for the multi-attribute evaluation of Lithium-ion batteries

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ABSTRACT

Lithium-ion batteries are among the most advanced electrochemical storage technologies and they are critical to the transition to sustainable energy systems. Despite their maturity, different chemistries are characterized by different technical, economic, environmental, and raw materials supply risks, highlighting the need for a comprehensive assessment. Seven lithium-ion battery chemistries were evaluated according to two domains: the techno-economic domain and the environmental and supply risk domain, and synthesized into an overall index called the Energy Storage Sustainability Index. A flexible multi-attribute evaluation tool, called Sustainable Technology Performance, has been developed based on the Multi-Attribute Value Theory model and the Analytic Hierarchy Process weighting method. The model's uncertainties are addressed by employing various marginal value functions and scenarios for the weights of the domains in the main simulations, and variation for the input data and a different weighting procedure for the attributes in the five sensitivity analyses conducted. The Lithium Iron Phosphate-Natural Graphite battery emerges as the preferred option, performing better in three out of five scenarios in *Simulation 1* and four out of five in *Simulation 2*, with high techno-economic scores (0.88 for *Simulation 1* and 0.93 for *Simulation 2*) and good environmental and supply risk scores (0.47 for *Simulation 1* and 0.6 for *Simulation 2*). Sensitivity analyses show that changing the weighting procedure from AHP to equal weights increases the contribution of attributes where the Lithium Iron Phosphate-Natural Graphite alternative underperforms, such as energy density and resource depletion. Overall, this alternative is preferred in most of the scenarios analyzed (twenty-six over fifty), highlighting its strengths in the techno-economic dimension.

1. Introduction

The increase in the share of renewable energy, especially that one coming from variable renewable energy sources (VRES), poses some issues for power systems [1]. In fact, the generation patterns of photovoltaic and wind are variable during the days, the weeks and the seasons, as they depend on the availability of sun and wind. The variability of renewable generation, especially in the case of high penetration of renewables in the electricity mix, can cause frequency, voltage and congestion issues [2]. In this sense, energy storage systems (ESSs) could act as a flexibility option able to mitigate the negative effects of VRES in power systems [3]. The role of ESSs as a source of flexibility to support transmission and distribution networks is recognized in the European Commission (EC) recommendation 2023/C 103/01 [4] and in the EC proposal for the revision of the electricity market design [5]. The inclusion of ESSs, such as batteries, raises new challenges related to their sustainability and the security of supply of raw material supply chains. The European Union (EU) has addressed these issues through the EU Directive 2006/66/EC, also known as the Battery Directive, which regulates the manufacturing and disposal stage of batteries [6]. In particular, Article 10 sets some quantitative collection targets for the EU Member States, while Article 12 sets the minimum recycling efficiency targets (50 % for all batteries except lead-acid and nickel–cadmium batteries). Due to the increasing role of batteries in the EU economy in recent years, the EC launched the European Battery Alliance (EBA) in 2017. The EBA aims "to develop an innovative, competitive and sustainable battery value chain in Europe" [7]. The 2006 Battery Directive has been replaced by the EU Directive 2018/849 [8], which introduces some minor changes (i.e., amendments) in the reporting and monitoring of collection and recycling targets. Furthermore, a proposal for a new EC Battery Regulation was made by the end of 2020, taking into account the changing socio-economic and environmental conditions of the EU, as well as the strong increase in demand for new batteries [9]. The proposal addressed arising issues such as sustainability, circularity, and security

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of supply of batteries. The EC proposal sets quantitative targets for both recycling efficiency (ratio between the mass of recycled output fractions and the mass of waste collected for recycling in input [10]) and the material recovery rates (ratio between the recycled material and the waste input material). Planned recycling efficiencies for Lithium-ion (Li-ion) batteries should reach 65 % by 2025 and 70 % by 2030. Material recovery rates for cobalt, nickel, lithium and copper are set at 95 %, 95 %, 70 % and 95 % respectively in 2030. The proposal also included a mandatory carbon footprint declaration for non-portable batteries. Finally, the EU reached an agreement on the 2020 Battery Regulation in 2022 [11]. The paramount role of the material supply chain security was also highlighted by the Critical Raw Materials Act [12], a proposal for a regulation made by the EC that identifies and sets targets for a selected list of strategic raw materials. The proposal included materials relevant for the manufacturing of Li-ion batteries, such as cobalt, copper, lithium (battery grade), manganese (battery grade), natural graphite (battery grade) and nickel (battery grade). The targets set out in this proposal include the domestic extraction of 10 % of the EU's annual consumption of strategic raw materials, the domestic sourcing of 40 % of intermediate stages of production and the domestic sourcing of 15 % of the EU's annual consumption of strategic raw materials by secondary raw materials (i.e., recycled within EU's borders). In addition, the share of supply from individual non-EU countries should not exceed 65 % "at any relevant stage of processing". The time horizon considered is analogous to the Battery Regulation. Since the previous regulatory framework, batteries have to be evaluated according to different domains, including the environmental, economic and the security of supply. In particular, for a comparative evaluation between several battery alternatives, which should include multiple criteria in the evaluation process (e.g., the carbon footprint, the security of supply), a multi-attribute decision making (MADM) model needs to be used to help decision-makers prioritize different battery technologies properly.

1.1. State-of-the-art

The evaluation of Li-ion batteries, as well as other Energy Storage Technologies (ESTs), requires an integrated and multi-domain approach, covering several aspects such as storage capacity, technological maturity, self-discharge, charge/discharge rates, investment costs, and many others, in order to have as holistic a view of the technologies under evaluation [13]. Several studies have been carried out in recent years in this context, particularly about the MADM applied to these batteries. Within these studies, the authors have compared different Li-ion batteries, as well as other ESTs with Li-ion batteries. An overview of selected articles within this field has been reported in Table 1, with some insights into the alternatives and the attributes used. Further details on the literature for MADM coupled to ESTs can be found in the Supplementary Material. The presence or absence of supply risk within the attributes selected for analysis has also been highlighted. It must be emphasized how limited efforts have been made to integrate the supply risk of materials into MADM models.

In [14], the author proposed a novel methodology for the comparative evaluation of four storage technologies, based on the interval Analytic Hierarchy Process for weighting the attributes and the Intuitionistic Fuzzy Combinative Distance-based Assessment Method for ranking the alternatives. However, a thorough analysis of the input data was missing.

In [15], the authors evaluated five ESTs, including Li-ion, using a Non-Linear Fuzzy Prioritization method to determine the weights, taking into account the uncertainties associated with the judgments. However, there may be some possible dependencies within attributes that should be investigated.

In [16], the authors proposed a methodology based on the Analytic Hierarchy Process (AHP) as a weighting procedure and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) for ranking the alternatives. Social aspects have been considered in the

Table 1
Review of MADM models applied to Li-ion batteries and other ESTs.

Energy Storage Technologies	Attributes	Materials Supply Risk	Reference
Pumped Hydro, Compressed Air, Flywheels, Li-ion	Energy Density, Energy Efficiency, Calendar Life, Technological Maturity, Investment Cost, O&M Cost, Cradle-to-Gate Greenhouse Gas (GHG) Emissions, Environmental Impact, Social Acceptance	No	[14]
Pumped Hydro, Compressed Air, Flywheels, Lead acid, Li-ion	Energy Density, Energy Efficiency, Calendar Life, Energy Intensity, Technological Maturity, Investment Cost, O&M Cost, Cradle-To-Gate GHG Emissions, Material Intensity, Environmental Impact	No	[15]
Liquid Air, Li-ion, Power to Gas, Sensible Heat Storage	Technological Maturity, Congestion Relief and Investment Deferral, Self-Consumption Increasing, Economic Benefits, Economic Viability, Environmental Benefits	No	[19]
Pumped Hydro, Compressed Air, Flywheels, Lead acid, Li-ion, Nickel cadmium, Sodium sulfur, Sodium nickel chloride, Vanadium Redox Flow, Zinc bromine, Power to Gas, Supercapacitors, Superconducting magnetic energy storage, Sensible Heat Storage	Power Size, Energy Density, Energy Efficiency, Cycle Life, Calendar Life, Self-Discharge, Discharge Rate, Response Time, Investment Costs, Environmental Impact	No	[20]
Lead acid, Li-ion NCA, Li-ion LFP, Lithium titanium oxide, Li-ion LMO, Li-ion NMC, Sodium nickel chloride, Vanadium Redox Flow	Technological Maturity, Technological Performance, Storage Flexibility, Investment Cost, Life Cycle Cost, Damage to Eco-Systems, Damage to Human Health, Damage to Resource Availability, Job Creation, Social Acceptance, Regulation and Policy	No	[16]
Pumped Hydro, Compressed Air, Lead acid, Li-ion NMC, Sodium ion, Vanadium Redox Flow battery, Hydrogen, Sensible Heat Storage	Power Size, Energy Density, Energy Efficiency, Cycle Life, Calendar Life, Self-Discharge, Discharge Rate, Response Time, Investment Cost, Lifecycle GHG Emissions, Material Intensity, Environmental Impact, Recyclability, Supply Chain	Yes (qualitative)	[17]

(continued on next page)

Table 1 (*continued*)

Energy Storage Technologies	Attributes	Materials Supply Risk	Reference
	Criticality, Human Rights, Health and Safety		
Li-ion NCA, Li-ion LFP, Li-ion LMO, Li-ion NMC, Li-ion LCO, Li-ion LNO	Power Size, Energy Density, Cycle Life, Stability, Cathode Theoretical Capacity, Investment Cost, Toxic Components, Health and Safety, Cell Voltage	No	[18]
Li-ion NCA, Li-ion LFP, Li-ion LMO, Li-ion NMC (various chemistries)	Energy Density, Manufacturing Cost, Cycle Life, Safety, Global Warming Potential, Resource Depletion, Supply Risk, Recycling Rate	Yes (quantitative)	This Study

analysis. However, the model lacks differentiating social features of the alternatives.

Balezentis et al. [17] adopted a TOPSIS-based methodology to rank several ESTs, including Li-ion Nickel Manganese Cobalt (NMC) batteries. However, the supply chain criticality attribute used for the storage materials was not detailed and was reported qualitatively on a 1–3 scale. In addition, a thorough analysis of the possible interdependencies of the attributes used was missing.

Tajik et al. [18] compared Li-ion batteries with different cathode materials using subjective and objective weighting methods. The Li-ion cathodes investigated were the Lithium Cobalt Oxide (LCO), the Lithium Nickel Oxide (LNO), Lithium Nickel Cobalt Aluminum Oxide (NCA), the NMC, the Lithium Manganese Oxide (LMO), and the Lithium Iron Phosphate (LFP). Despite the heterogeneous nature of the production of such batteries, environmental issues have been neglected, as well as the criticality of the materials used in the batteries.

1.2. Research goals and contributions

In order to try to overcome the limitations of the previous works regarding MADM and ESTs, especially for the lack of literature studies including the supply risk of storage materials, the authors propose the implementation of a new tool for the MADM analysis of Li-ion batteries. Furthermore, another aspect addressed in this study, and often neglected in the literature, is related to the investigation of possible interdependencies arising in the selected attributes. Therefore, the present study aims to integrate and extend the previous works reviewed in Section 1.1. According to the gap research highlighted above, the developed model is characterized by the following features:

- Multi-Attribute Value Method (MAVT) method, coupled with the Analytic Hierarchy Process (AHP), to rank Li-ion batteries according to user-specified attributes.
- Use of sub-indexes related to the specific domains to evaluate intermediate rankings of Li-ion batteries.
- Flexibility for users to modify the input parameters and the attribute weights.
- Integration of supply risk issues of critical and strategic raw materials in the MADM model through a quantitative indicator, which to the best of the authors' knowledge is the first of its kind for multi-attribute evaluation of Li-ion batteries.
- Investigation of possible correlations within the selected attributes through *ad hoc* Sensitivity Analyses.

2. Methods

This work proposes a model capable of performing a multi-attribute evaluation of ESTs. The choice of a MADM model rather than an optimization model is related to the ease of inclusion of non-numerical attributes, the reduced amount of data required, and the ability to easily modify the model by adding new attributes and/or alternatives without changing the mathematical formulation of the model itself [21]. The model relies on MAVT and, for the weighting procedure, on the AHP. The model is implemented in an original tool developed in MATLAB®, called Sustainable Technology Performance (STeP). The STeP tool is designed as an interactive tool to support decision-makers in handling complex decisions, such as evaluating several storage technologies on a set of attributes. The model allows the calculation of the sustainability of ESTs according to a synthetized indicator called the Energy Storage Sustainability Index (*ESSI*). The *ESSI* is obtained by weighting and merging two sub-indexes: the Techno-Economic sub-Index (*TEI*), and the Environmental and Supply Risk sub-Index (*ESRI*). Finally, a Case Study is investigated to test the developed model. A graphical workflow of the model is shown in Fig. 1. The novelties of the model are related to the creation of the original sub-indexes (*TEI* and *ESRI*), the original index *ESSI*, as well as the creation of a new flexible tool for decision-makers to evaluate energy storage technologies.

2.1. The Multi-Attribute Value Theory method

Among the available MADM methods, the MAVT method has been selected for the multi-attribute assessment [22].

The main reason for this choice is the high scalability of the method, which allows to obtain separate intermediate results for each of the previously mentioned sub-indexes (see Section 2). Starting from the evaluation matrix $\mathbf{X}$, which collects all the occurrences of the alternatives for the selected attributes, it is possible to assign a specific preference to the generic element x_{ij} of the matrix itself through the so-called marginal value function, denoted as $v_j(x_{ij})$. An overall score, for the i-th alternative a_i is obtained by weighting the generic marginal value function $v_j(x_{ij})$ with the corresponding weight for the j-th attribute b_j:

$$V(a_i) = \sum_{j=1}^{N} w_j \bullet v_j(x_{ij}) \tag{1}$$

where w_j is the weight, also called the scaling value function, for the j-th attribute and $V(a_i)$ is the canonical form of the additive value function for the alternative a_i considering the N attributes. The value function $V : \mathbb{A} \rightarrow \mathbb{R}$ represents a scale, such that:

$$\forall a_i, a_{i+1} \in \mathbb{A}, a_i \succ a_{i+1} \leftrightarrow V(a_i) > V(a_{i+1}) \tag{2}$$

In (2) it is stated that the preference statement of the alternative a_i, compared to a_{i+1}, is possible if and only if the real value $V(a_i)$ is higher than $V(a_{i+1})$. The binary relation between the two alternatives is settled by the operator $\succ$ (strict preference). The assessment of value functions is done by decomposed scaling [22], which consists in evaluating weights and marginal value functions separately. In particular, the next paragraph presents the adopted strategy for determining the corresponding weights.

2.2. Identification of weights

Assessment strategies for weight calculation include swing technique, rating, pairwise comparison, trade-off and qualitative translation [22]. The pairwise comparison (PC) approach was chosen because of its ease of use and the effectiveness of results. In fact, the PC enables the decision-maker to compare the relative importance of one attribute to another. This strategy simplifies the choice, as the difficulty of comparing attributes increases with the number of attributes evaluated. In this sense, Saaty's Analytic Hierarchy Process method is a well-known

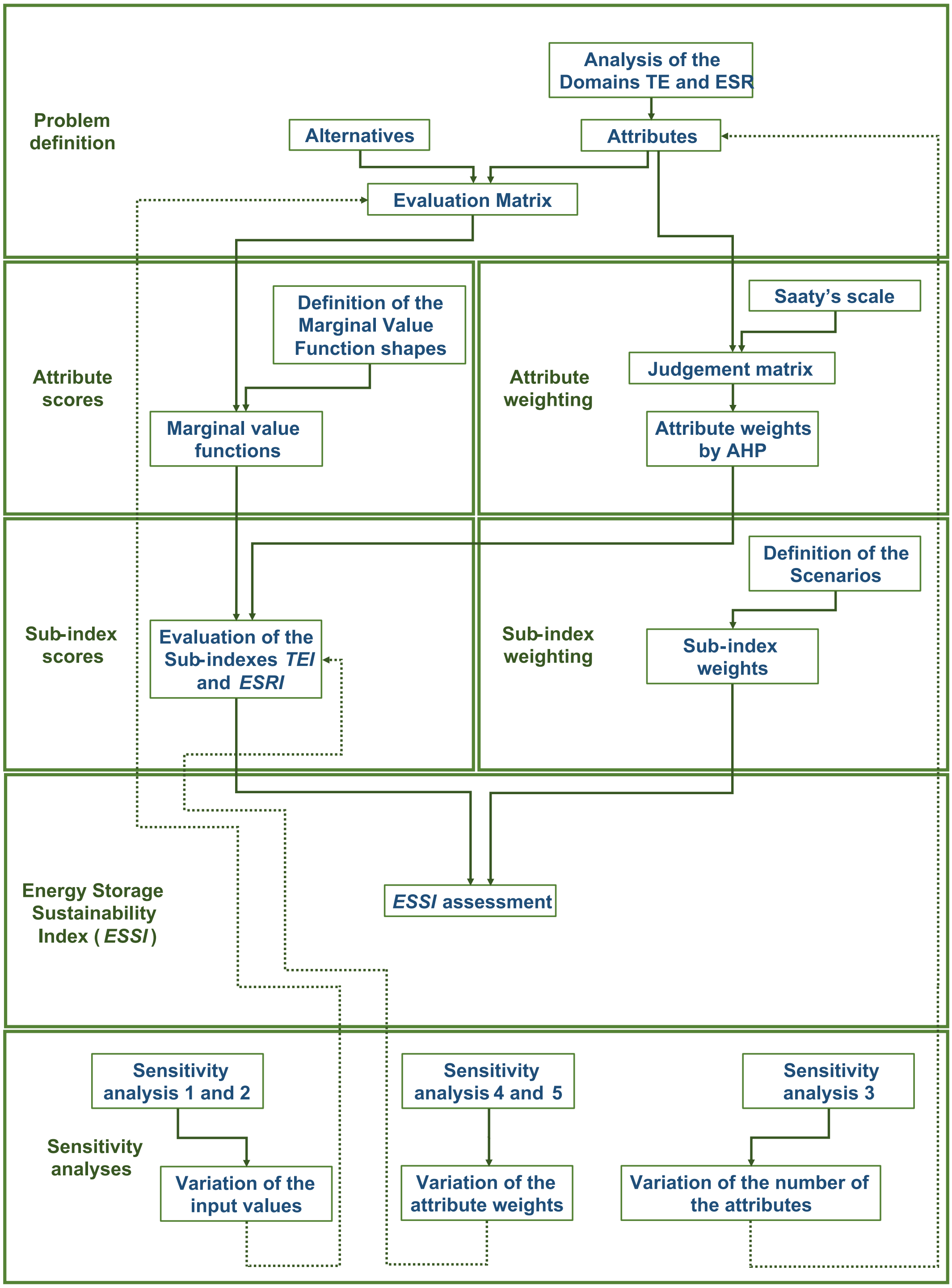

Fig. 1. Workflow of the MADM model implemented in the Sustainable Technology Performance (STeP) tool.

PC method that has been used in several MADM-based studies [13].

2.3. The Energy Storage Sustainability Index

The relative scores for the j-th attribute and the M alternatives are obtained by using the marginal value function v_j. The M relative scores for the j-th attribute depend on the choice of the shape of the marginal value function employed. Different shapes have been used in the literature, such as the linear and the quadratic shapes [22]. Finally, it is possible to assess the values of the sub-indexes by appropriate weights. The choice to compute separate sub-indexes is related to the difficulty for the user of the tool to handle too many attributes together, especially when estimating weights. In addition, the calculation of sub-indexes allows a preliminary evaluation of the partial scores of the alternatives in the domain of interest. The sub-indexes used are the Techno-Economic sub-Index (*TEI*) and the Environmental and Supply Risk sub-Index (*ESRI*):

$$TEI(a_i) = \sum_{t=1}^{N_{TEI}} w_t \bullet v_t(x_{it}) \tag{3}$$

$$ESRI(a_i) = \sum_{q=1}^{N_{ESRI}} w_q \bullet v_q(x_{iq}) \tag{4}$$

where: a_i represents the i-th alternative; $N_{TEI/ESRI}$ the number of *TEI/ESRI* attributes; $w_{t/q}$ the weights for *TEI/ESRI* attributes; $v_{t/q}(\bullet)$ the marginal value function for *TEI/ESRI* attributes; x_{it} the input value for the i-th alternative and the t-th *TEI* attribute; and x_{iq} the input value for the i-th alternative and the q-th *ESRI* attribute.

It is worth noting that $N = N_{TEI} + N_{ESRI}$ and, for sake of clarity, the attributes have been thought ranked as follows: the first N_{TEI} attributes falls under the *TEI* group, whereas the N_{ESRI} attributes lying between $N_{TEI}+1$ and $N_{TEI}+N_{ESRI}$ refer to the *ESRI* attribute group.

The Energy Storage Sustainability Index (*ESSI*) is finally computed through the additive aggregation of the two sub-indexes:

$$ESSI(a_i) = w_{TEI} \bullet TEI(a_i) + w_{ESRI} \bullet ESRI(a_i) \tag{5}$$

In (5), w_{TEI} and w_{ESRI} represent the weights for *TEI* and *ESRI* attribute groups, respectively. Finally, it should be noted that the choice of weights has a strong influence on the final result. To address this issue, different scenarios with different weights for the sub-indexes were considered. In addition, the variation in weights for the *TEI/ESRI* attributes was also taken into account through *ad hoc* sensitivity analyses.

2.4. Evaluation of parameter uncertainties: Sensitivity analysis

The shape of the value functions, the uncertainty of the input data, the number of attributes, and the weights assigned to the *TEI/ESRI* attributes play a central role in determining the *ESSI* for each alternative. Therefore, the MADM tool allows to vary the shape of the value function, the value of the input data, the number of attributes considered, and the weights assigned to the attributes, resulting in different uncertainty assessments:

- *Simulation 1* and *Simulation 2*. Two different shapes of the marginal value function, namely linear and quadratic, were considered to explore the effect of their variations on the *ESSI* results.
- *Sensitivity Analysis 1* and *Sensitivity Analysis 2*. About the input uncertainties, the effect of the input value x_{ij}, over a range of confidence on the *ESSI* results was investigated.
- *Sensitivity Analysis 3*. To account for the reduction in the number of attributes, a modified set of attributes $\mathbb{B}' = \{b'_\theta, \theta = 1, \cdots, \Theta\}$ is defined, with $\Theta \subset N$. The modified evaluation matrix and judgment matrix are $\mathbf{X}' \in \mathbb{R}^{M,\Theta}$ and $\mathbf{B}' \in \mathbb{R}^{\Theta,\Theta}$, respectively. The modified vector of absolute weights is $\boldsymbol{w}' = [w'_1, \cdots, w'_\Theta]$.
- *Sensitivity Analysis 4* and *Sensitivity Analysis 5*. Regarding the uncertainty associated with the weighting procedure, the effect of varying the weights for the *TEI/ESRI* attributes on the *ESSI* results was investigated. Specifically, equal weights for *TEI/ESRI* attributes were used, with a linear shape (*Sensitivity Analysis 4*) and a quadratic shape (*Sensitivity Analysis 5*) for the marginal value function.

2.5. Case study

The case study is related to a sustainable evaluation of different energy storage technologies. Table 2 shows the set of alternatives, the set of attributes, and the input values used in the MADM model. In particular, different chemistries of Li-ion batteries are selected as the alternatives of the MADM problem. They are characterized by different cathode active material and the same anode active material, namely natural graphite (NG).

The set of attributes is divided into the techno-economic (TE) and the environmental and supply risk (ESR) domains. Within the TE domain, the selected attributes are the battery energy density ε_{batt}, the manufacturing cost C_{man}, the cycle lifetime κ_c and the safety ς. Although the operation and maintenance (O&M) cost is an important attribute for the evaluation of ESTs, it has been neglected in this study because all alternatives differ only in the cathode materials and therefore have analogous O&M cost.

For the ESR domain the attributes are the global warming potential *GWP*, the resource depletion *RD*, the *HHI*-$\overline{WGI}$ composite indicator HHI_{WGI}, and the recycling rate η_R. In detail, the HHI_{WGI} attribute is used to assess the supply risk of the storage materials. It is obtained by weighting the Herfindahl-Hirschman Index (*HHI*) by the geopolitical stability of the supplying countries ($\overline{WGI}$). For both the *HHI*-$\overline{WGI}$ HHI_{WGI}

Table 2
Input values for the set of attributes selected.

Alternative	A_1	A_2	A_3	A_4	A_5	A_6	A_7
Chemistry	**LFP-NG**	**LMO-NG**	**NMC_{111}-NG**	**NMC_{532}-NG**	**NMC_{622}-NG**	**NMC_{811}-NG**	**NCA-NG**
Techno-economic attributes							
ε_{batt} [Wh/kg_{batt}]	79.2	85.5	104.9	114	114	109.7	116.6
C_{man} [€/kWh_{ec}]	93.4	90.5	107.9	100.2	100.9	97.7	100.8
κ_c [-]	6250	1500	4000	4000	4000	4000	3345
ς [-]	5	4	3	3	3	3	1
Environmental and Supply Risk attributes							
GWP [$kg_{CO2,eq}/kWh_{ec}$]	1.91E + 02	1.73E + 02	2.03E + 02	1.79E + 02	1.80E + 02	1.83E + 02	1.84E + 02
RD [$kg_{Sb,eq}/kWh_{ec}$]	1.97E-01	1.99E-01	1.68E-01	1.49E-01	1.51E-01	1.52E-01	1.44E-01
HHI_{WGI} [-]	1.36E-01	1.35E-01	1.85E-01	1.68E-01	1.67E-01	1.55E-01	1.54E-01
η_R [-]	2.18E-01	4.78E-01	3.83E-01	3.83E-01	3.85E-01	3.86E-01	4.19E-01

and the recycling rate η_R attributes, the aggregate values were obtained by a mass-based weighted average of the selected materials.

The meaning of the attributes used is briefly explained below. In particular, the (gravimetric) energy density ε_{batt} is defined as the ratio between the energy capacity of the battery and its mass [13]. The manufacturing cost C_{man} includes the cost of the materials and the costs associated with the manufacturing process and overhead [23]. The cycle lifetime κ_c is defined as the number of cycles that the energy storage system can achieve at certain operating parameters (e.g., the depth of discharge and the operating temperature), before reaching the end-of-service [24]. Safety ς is an attribute that accounts for the resilience of the battery to withstand to potential mechanical, electrical and thermal abuse [25]. The global warming potential GWP is used to assess the climate impact of the of greenhouse gas emissions, relative to an equivalent amount of carbon dioxide [26]. The resource depletion RD is used to assess the depletion of abiotic resources used as inputs in the system. The HHI_{WGI} is a concentration index of the supply of battery materials, weighted by the country governance of the producing countries, used as a proxy indicator for assessing the geopolitical stability of the supplying countries [27]. Finally, the recycling rate η_R is the ratio of the mass recovered from the recycling process of spent batteries, compared to the battery in input to the recycling process [28].

Furthermore, the methodological details on the aggregation procedure for obtaining HHI_{WGI} are reported in below:

$$HHI_{WGI} = \sum_{z=1}^{Z} HHI_{WGI,z} \bullet \frac{\Phi_z}{\Phi_{tot}} \tag{6}$$

In (6), $HHI_{WGI,z}$, Φ_z and Φ_{tot} represent the concentration index of the supply for the *z-th* battery material, the mass of the *z-th* battery material and the total mass of the battery materials, respectively. The procedure for estimating $HHI_{WGI,z}$ is reported in the Supplementary Material, and it follows the approach described in [29].

For the evaluation matrix shown in Table 2, several sources of data were collected. The manufacturing cost of the module for each alternative is taken from BatPac [23], converted to Euros and adjusted for taking into account the inflation. Cycle lifetime data sources are taken instead from [30–33]. Safety features are collected from [31,34]. The battery energy density was evaluated based on the cell energy density of each chemistry and the bill of materials used in the environmental impact assessment. The cell energy density for the alternatives was taken from [30,35–38]. For the Environmental and Supply Risk attributes, the method used to evaluate the GWP and the RD relies on the attributional LCA approach. The software used was SimaPro, while the background data were taken from Ecoinvent [39]. The data sources for the HHI_{WGI} are [40,41] for the HHI and [42] for the $\overline{WGI}$. Finally, the data source for the recycling rate η_R was taken from [43]. Further details can be found in the Supplementary Material.

The graphical representation of the input values of the set of attributes selected is shown in Fig. 2, where the reported values are the input values in Table 2 normalized according to the range $\left[x_j^{(min)}, x_j^{(max)}\right]$, where $x_j^{(min)} = \min_{i=1,\dots,M} x_{ij}$ and $x_j^{(max)} = \max_{i=1,\dots,M} x_{ij}$, are the minimum and maximum input values for the j-th attribute, considering the set of M alternatives. Intermediate values are obtained as: $\left(x_{ij} - x_j^{(min)}\right) / \left(x_j^{(max)} - x_j^{(min)}\right)$. From Fig. 2, it can be seen how the alternative A_7 has the highest energy density, the alternative A_3 has the highest manufacturing cost, while the alternative A_1 has the highest cycle lifetime and safety performances. Regarding the environmental parameters, the highest GWP is owned by the alternative A_3, whereas the highest score for RD is related to the alternative A_2. Finally, for the supply risk parameters, the highest relative score for HHI_{WGI} is linked to the alternative A_3, while for η_R the highest relative score is linked to the alternative A_2.

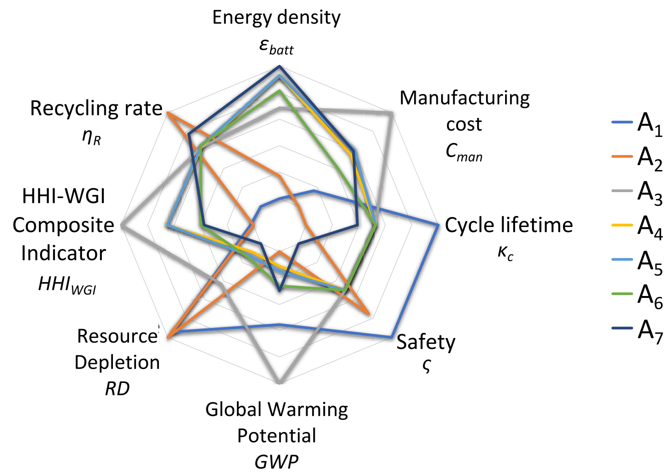

Fig. 2. Graphical representation of the input parameters of the MADM model.

2.5.1. Scenario Analysis

The developed tool is able to evaluate the relative scores, according to the user selection of the input data and the main assumptions of the MADM. In order to verify the flexibility of the model, two simulations were performed, namely *Simulation 1* and *Simulation 2*. The difference between the two is the shape of the marginal value function used for the analysis. Finally, for each simulation, several scenarios are examined that differ in the sub-index weights (imposed by the user).

The synthetic assumptions made for *Simulation 1* and the scenarios investigated are reported in Table 3. In detail, *Simulation 1* assumes a linear shape of the marginal value function. Furthermore, five scenarios are investigated, namely S_1, S_2, S_3, S_4 and S_5. Each scenario is characterized by different numerical values of the weights assigned to the sub-indexes.

Instead, the synthetic assumptions made for *Simulation 2* and the scenarios examined are reported in Table 4. A quadratic shape for the marginal value function is assumed in *Simulation 2*. As in *Simulation 1*, the weights for the two domains (i.e., TE and ESR) are imposed by the user, and five scenarios are investigated.

2.5.2. The attribute weights for Simulation 1 and Simulation 2

Once the relative importance between the two domains is imposed by the user (see Table 3 and Table 4, for *Simulation 1* and *Simulation 2*, respectively), it is necessary to define the relative importance among the attributes included in each domain. This is assessed using AHP, whose judgment matrices are provided in the Supplementary Material for both the TE (Table S.5) and ESR (Table S.6) domains.

The assessed weights are reported in Table 5 for each domain. It is worth noting that the values shown in Table 5 represent the attribute weights for the TE and ESR domains, formulated in (3) and (4) as w_t, w_q for the t-th attribute of the TE domain and the q-th attribute of the ESR domain, respectively. The cycle lifetime κ_c and the manufacturing cost C_{man} have the higher relative weights for the TE domain, while the global warming potential GWP and the HHI-$\overline{WGI}$ Composite Indicator

Table 3
Overview of the main assumptions for *Simulation 1* and the scenarios investigated.

Function shape	Scenario	Sub-index weights	
		w_{TEI} (%)	w_{ESRI} (%)
Linear	S_1	50	50
	S_2	60	40
	S_3	80	20
	S_4	40	60
	S_5	20	80

Table 4
Overview of the main assumptions for *Simulation 2* and the scenarios investigated.

Function shape	Scenario	Sub-indexes weight	
		w_{TEI}(%)	w_{ESRI}(%)
Quadratic	S_1	50	50
	S_2	60	40
	S_3	80	20
	S_4	40	60
	S_5	20	80

Table 5
Priority weights for TE and the ESR domains.

Attribute	Weight
Techno-economic	
ε_{batt}	6.6E-2
C_{man}	3.0E-1
κ_c	5.5E-1
ς	8.8E-2
Environmental and Supply Risk	
GWP	5.5E-1
RD	7.4E-2
HHI_{WGI}	2.5E-1
η_R	1.3E-1

HHI_{WGI} represent their counterparts in the ESR domain. A lower weight is assigned to the battery energy density, compared to the others TE attributes, because it is considered less relevant for stationary purposes.

3. Results

The graphical representation of the relative *ESSI* scores for *Simulation 1* and *Simulation 2* are shown in Fig. 3 and Fig. 4, respectively. It can be seen that the LFP-NG alternative (A_1) is the most preferred option in three out of five scenarios (i.e., namely Scenario S_1, Scenario S_2 and Scenario S_3), for *Simulation 1*, and in four out of five scenarios for *Simulation 2* (i.e., namely Scenario S_1, Scenario S_2, Scenario S_3 and Scenario S_4). This is mainly due to the high score of *TEI* (0.88 for *Simulation 1* and 0.93 for *Simulation 2*) and the relatively good score of *ESRI* (0.47 for *Simulation 1* and 0.6 for *Simulation 2*). The NMC_{811}-NG alternative (A_6) shows instead the second relatively higher scores in two out of five scenarios (i.e., namely Scenario S_2 and Scenario S_3) for *Simulation 1* and four scenarios for *Simulation 2* (i.e., namely Scenario S_1, Scenario S_2 and Scenario S_3 and Scenario S_5). The LMO-NG alternative (A_2) shows the highest *ESSI* in Scenario S_4 and Scenario S_5 for *Simulation 1* and only in Scenario S_5 for *Simulation 2*. The reasons for these high scores are related to the high value of *ESRI* (0.88 in *Simulation 1* and 0.93 in *Simulation 2*), that outweighs the relatively low score of *TEI* (0.38 in *Simulation 1* and 0.35 in *Simulation 2*) in case of preponderant weight assigned to *ESRI* (i.e., in Scenario S_5 w_{TEI} is 0.2 and w_{ESR} is 0.8). Finally, the NCM_{111}-NG alternative (A_3) shows the worst relative scores for all scenarios in both simulations performed.

3.1. Sensitivity analyses

Five different sensitivity analyses were performed, namely *Sensitivity Analysis 1*, *Sensitivity Analysis 2*, *Sensitivity Analysis 3*, *Sensitivity Analysis 4* and *Sensitivity Analysis 5*. The *Sensitivity Analysis 1* and the *Sensitivity Analysis 2* evaluate the influence of the variation of the Global Warming Potential *GWP* and of the cycle lifetime κ_c on the *ESSI* scores, respectively. The *Sensitivity Analysis 3* instead accounts for the variation of the number of input parameters assessed as attributes. In addition, the *Sensitivity Analysis 4* and the *Sensitivity Analysis 5* evaluate the impact of varying the weights of the *TEI/ESRI* attributes on the *ESSI* scores. Both the *Sensitivity Analysis 4* and the *Sensitivity Analysis 5* assume equal weights for the attributes, but differ in the shape of the marginal value function used.

3.1.1. Sensitivity Analysis 1

The *Sensitivity Analysis 1* accounted for the uncertainty of the numeric scores of the Global Warming Potential attribute for each alternative. Minimum and maximum values of *GWP* have been collected from literature sources [33,44–47]. The variation range for *GWP* is reported in Table 6, including the minimum values $GWP^{(min)}$, the maximum values $GWP^{(max)}$ and their absolute difference δ_{GWP}.

Furthermore, two cases have been carried for the *Sensitivity Analysis 1*, as shown in Table 7. *Case 1* exploit $GWP^{(min)}$ as the updated attribute, whilst *Case 2* $GWP^{(max)}$. The rest of the assumptions for the *Sensitivity Analysis 1* is coincident with those ones of the *Simulation 1*.

The results for the *Case 1* and *Case 2* of the *Sensitivity Analysis 1* are graphically reported in Fig. 5. It can be noticed how the alternative LFP-NG (A_1) remains the first in three out of five scenarios of the *Case 1* (Scenario S_1, Scenario S_2 and Scenario S_3), whilst for *Case 2* in Scenario S_1 (i.e., equal weights for the sub-indexes) the LMO-NG alternative (A_2) outperforms the LFP-NG alternative (A_1).

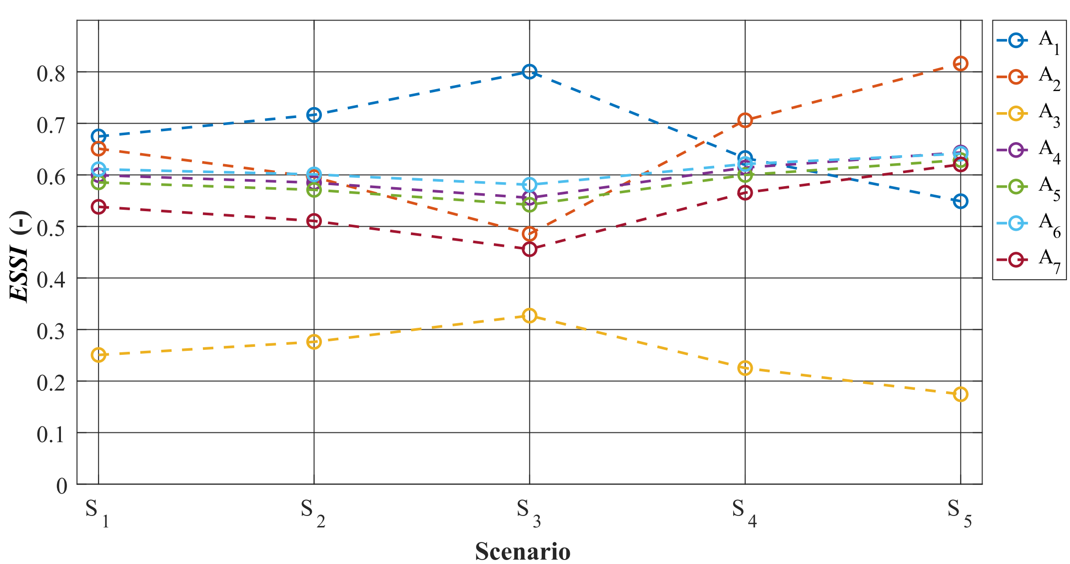

Fig. 3. Graphical representation of the *ESSI* scores for each alternative and scenario in *Simulation 1*.

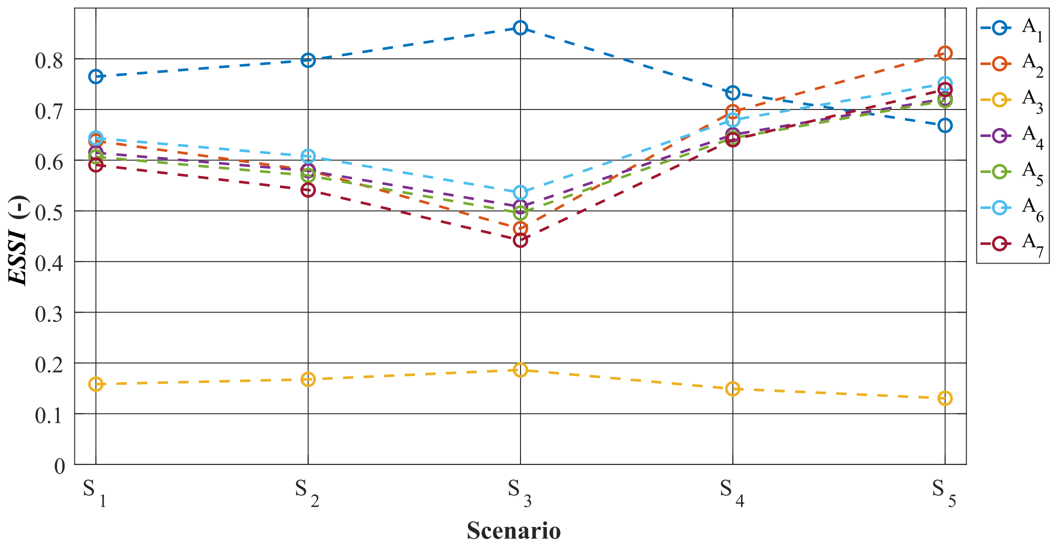

Fig. 4. Graphical representation of the *ESSI* scores for each alternative and scenario in *Simulation 2*.

Table 6
Overview of the variation range of *GWP* considered in the *Sensitivity Analysis 1*.

Alternative	$GWP^{(min)}$	$GWP^{(max)}$	δ_{GWP}
A_1	7.91E + 01	2.75E + 02	2.0E + 02
A_2	5.29E + 01	1.76E + 02	1.23E + 02
A_3	9.33E + 01	2.23E + 02	1.29E + 02
A_4	8.58E + 01	2.05E + 02	1.19E + 02
A_5	8.58E + 01	2.05E + 02	1.19E + 02
A_6	8.92E + 01	2.13E + 02	1.24E + 02
A_7	7.2E + 01	2.11E + 02	1.39E + 02

Table 7
Main assumptions for the *Case 1* and *Case 2* of the *Sensitivity Analysis 1*.

Case	Updated attribute	Function shape	Scenario	Sub-indexes weight	
				TEI (%)	*ESRI* (%)
1	$GWP^{(min)}$	Linear	S_1	50	50
			S_2	60	40
			S_3	80	20
			S_4	40	60
			S_5	20	80
2	$GWP^{(max)}$	Linear	S_1	50	50
			S_2	60	40
			S_3	80	20
			S_4	40	60
			S_5	20	80

3.1.2. *Sensitivity Analysis 2*

The *Sensitivity Analysis 2* accounted for the uncertainty of the numeric scores of the cycle lifetime attribute for each alternative. Minimum and maximum values of κ_c have been collected from literature sources [31–33,44]. The variation range for κ_c is reported in Table 8, including the minimum values $\kappa_c^{(min)}$, the maximum values $\kappa_c^{(max)}$ and their absolute difference $\delta_{\kappa c}$.

As in the *Sensitivity Analysis 1*, two cases have been investigated, as shown in Table 9. *Case 1* exploit $\kappa_c^{(min)}$ as the updated attribute, whilst *Case 2* $\kappa_c^{(max)}$. The rest of the assumptions for the *Sensitivity Analysis 2* is coincident with those ones of the *Simulation 1*.

The results for the *Case 1* and the *Case 2* of the *Sensitivity Analysis 2* are graphically reported in Fig. 6. It can be noticed how the alternative LFP-NG (A_1) remains the first in three out of five scenarios for both the cases (Scenario S_1, Scenario S_2 and Scenario S_3).

3.1.3. *Sensitivity Analysis 3*

The *Sensitivity Analysis 3* has been carried out to take into account a potential correlation between the energy density ε_{batt} and safety ς parameters. In fact, for the safety attribute, only the thermal runaway temperature was considered, which was used as a proxy parameter for safety. However, batteries with higher energy densities have lower thermal stability, which can lead to thermal runaway [48]. Moreover, potential correlations arise between the energy density ε_{batt} and the resource depletion *RD*, the *HHI-$\overline{WGI}$* Composite Indicator HHI_{WGI} and the manufacturing cost C_{man}, as well as between the cycle lifetime κ_c and the recycling rate η_R. The reduced statistical sample and the uncertainties in the input data led to the decision to keep all the attributes in the main case study and to assess the influence of potentially correlated attributes through a sensitivity analysis. Since the previous considerations, the *Sensitivity Analysis 3* consists in a reduction of the set of attributes and the subsequent evaluation of the possible effects on the final results. Between the energy density ε_{batt} and safety ς, the elimination choice has fallen on the first one. This is due to the fact that safety is considered as a more important attribute, compared to the energy density, for stationary purposes (see also Table 5). Furthermore, for the same considerations the recycling rate η_R and the *HHI-$\overline{WGI}$* Composite Indicator HHI_{WGI} have been removed as attributed in the *Sensitivity Analysis 3*. However, it has to be noted that, in case of evaluation of different battery applications, such as the mobility and the portable electronics, further assessments for the set of attributes and the priority of the weights have to be made. The modified comparison matrixes, for both the TE domain and the ESR domain, are reported in the Supplementary Materials (Table S.7 and Table S.8, respectively). The two cases considered in this analysis, namely *Case 1* and *Case 2*, differ from the *Simulation 1* and *Simulation 2* in terms of attributes and the priority weights obtained by applying the Saaty's scale. From the results, that are reported in Fig. 7 (*ESSI* scores in *Case 1*) and Fig. 8 (*ESSI* scores in *Case 2*), it can be noted how worst results appear to be the same as those computed in *Simulation 2*, whilst some differences can be underlined in the best alternatives. Indeed, in *Case 1* the alternative NMC_{532}-NG (A_4) outperforms the others in three out of five scenarios, reducing the number of scenarios in which alternative A_1 has the highest *ESSI* score (namely Scenario S_2 and S_3). Results for *Case 2* reward instead LFP-NG as the best alternative in Scenario S_1, S_2 and S_3, with the alternative A_4 with the higher *ESSI* score in the remaining scenarios (i.e., S_4 and S_5).

3.1.4. *Sensitivity Analysis 4 and Sensitivity Analysis 5*

The *Sensitivity Analysis 4* and the *Sensitivity Analysis 5* take into

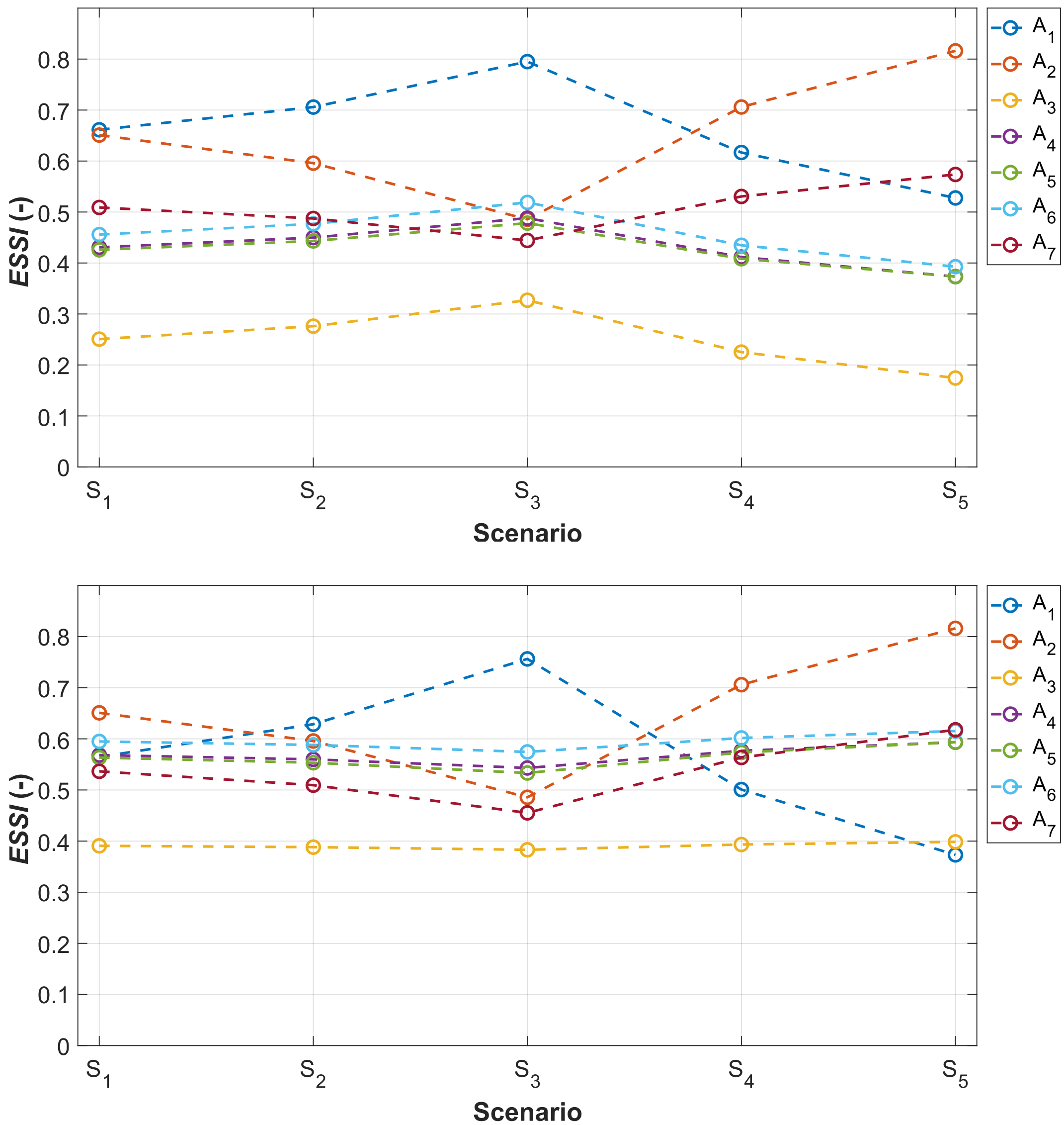

Fig. 5. Graphical representation of the *ESSI* scores for the *Case 1* (top figure) and *Case 2* (bottom figure) of the *Sensitivity Analysis 1*.

Table 8
Overview of the variation range of κ_c considered in the *Sensitivity analysis 2*.

Alternative	$\kappa_c^{(min)}$	$\kappa_c^{(max)}$	$\delta_{\kappa c}$
A_1	2.5E + 03	1.0E + 04	7.5E + 03
A_2	1.0E + 03	2.0E + 03	1.0E + 03
A_3	2.0E + 03	6.0E + 03	4.0E + 03
A_4	2.0E + 03	6.0E + 03	4.0E + 03
A_5	2.0E + 03	6.0E + 03	4.0E + 03
A_6	2.0E + 03	6.0E + 03	4.0E + 03
A_7	1.69E + 03	5.0E + 03	3.31E + 03

Table 9
Main assumptions for the *Case 1* and *Case 2* of the *Sensitivity analysis 2*.

Case	Updated attribute	Function shape	Scenario	Sub-indexes weight	
				TEI (%)	*ESRI* (%)
1	$\kappa_c^{(min)}$	Linear	S_1	50	50
			S_2	60	40
			S_3	80	20
			S_4	40	60
			S_5	20	80
2	$\kappa_c^{(max)}$	Linear	S_1	50	50
			S_2	60	40
			S_3	80	20
			S_4	40	60
			S_5	20	80

account the uncertainty of the *ESSI* results related to the selection of weights. An overview of the main assumptions is given in Table 10. It should be noted that both the *Sensitivity analysis 4* and the *Sensitivity Analysis 5* are characterized by equal weights for *TEI*/*ESRI* attributes and different shape of the marginal value function.

The results for both the *Sensitivity analysis 4* and the *Sensitivity Analysis 5* are shown in Fig. 9. It can be seen that the NMC_{811}-NG (A_6) alternative is the most preferred option in three out of five scenarios of the *Sensitivity Analysis 4* (Scenario S_1, Scenario S_2 and Scenario S_4). This is due to the shift from the priority weights for the TE and ESR domains identified by the AHP rating to the equal weights. This choice resulted in a 19 % reduction in the value of the *TEI* sub-index for the alternative A_1 compared to *Simulation 1*. For the alternative A_6, the value of *TEI* in the *Sensitivity Analysis 4* increases by 9 % compared to *Simulation 1*.

Finally, in the *Sensitivity Analysis 5*, the alternative LFP-NG (A_1) is the most preferred option only for technically oriented scenarios (i.e.,

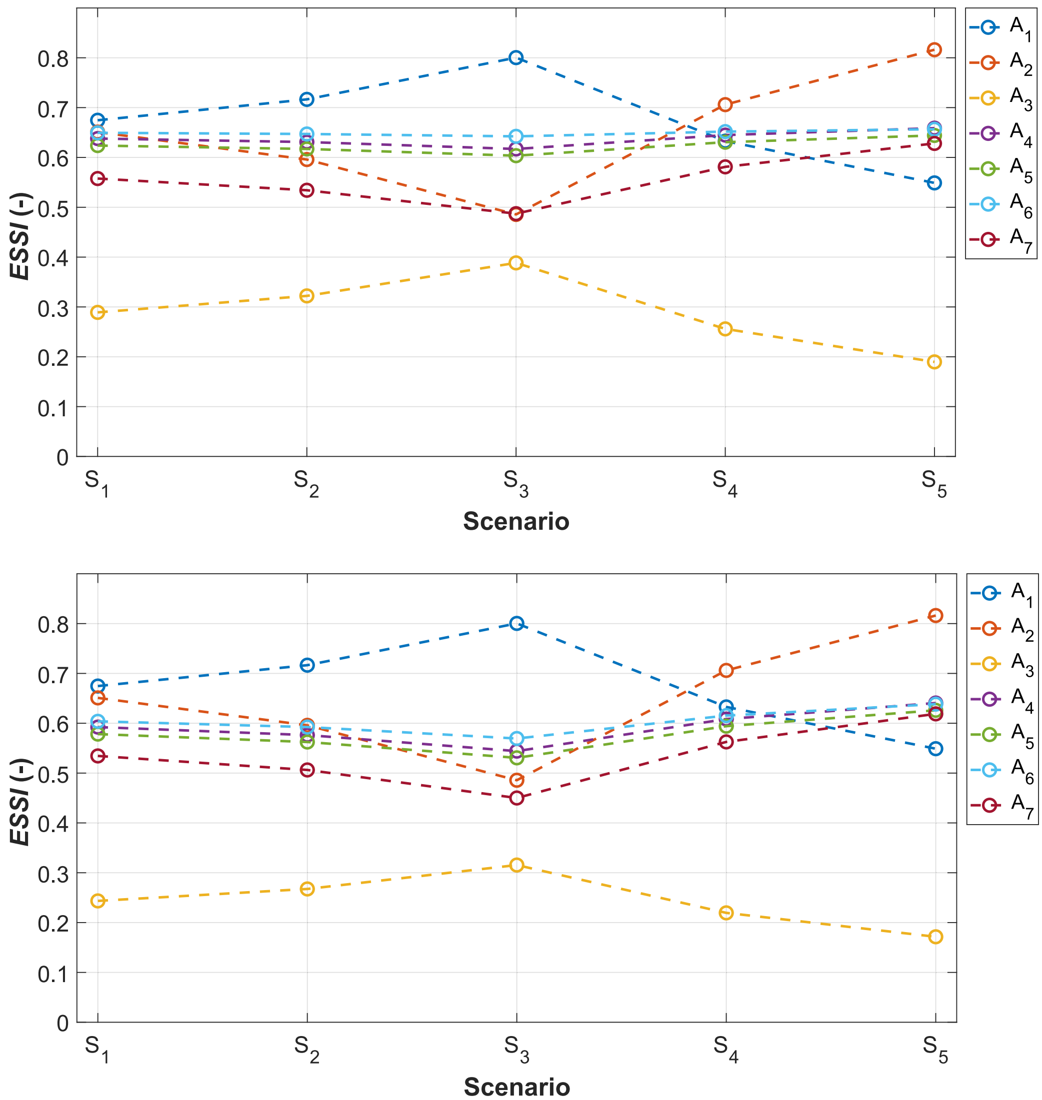

Fig. 6. Graphical representation of the *ESSI* scores for the *Case 1* (top figure) and *Case 2* (bottom figure) of the *Sensitivity Analysis 2.*

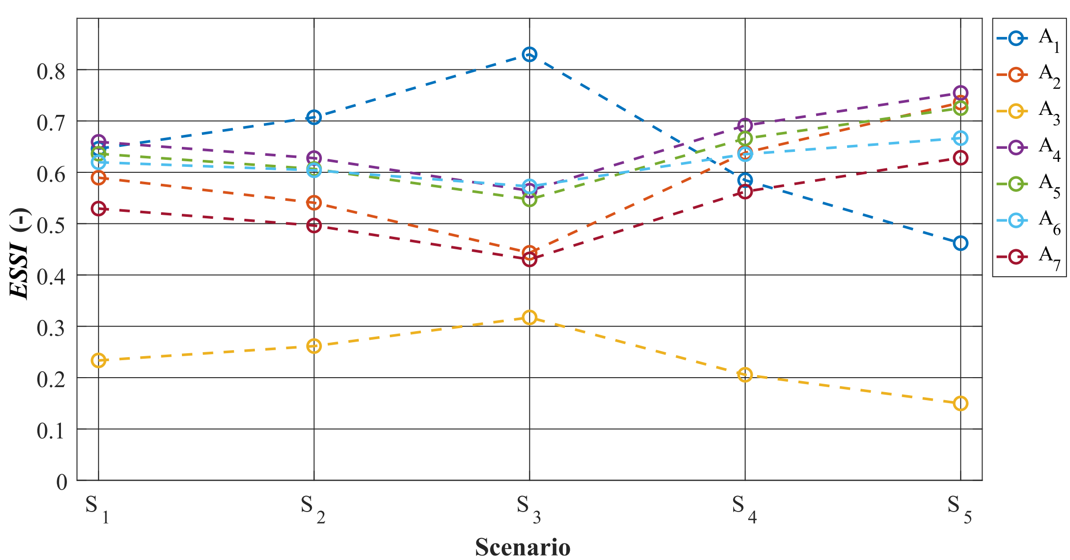

Fig. 7. Graphical representation of the *ESSI* scores for the *Case 1* of the *Sensitivity Analysis 3* (linear shape for the marginal value functions).

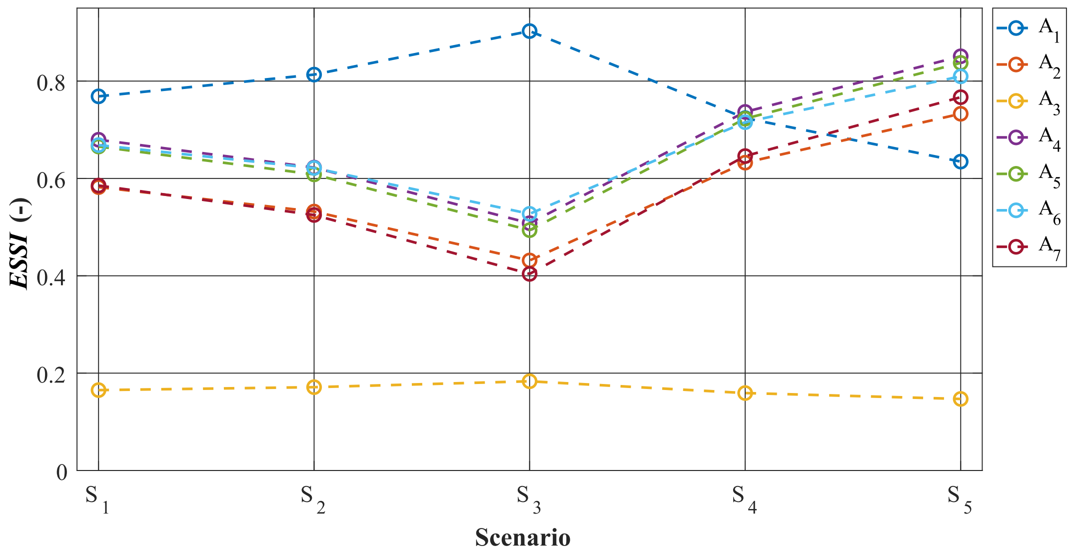

Fig. 8. Graphical representation of the *ESSI* scores for the *Case 2* of the *Sensitivity Analysis 3* (quadratic shape for the marginal value functions).

Table 10
Main assumptions for the *Sensitivity analysis 4* and the *Sensitivity Analysis 5*.

Sensitivity analysis	Updated parameters	Function shape	Scenario	Sub-indexes weight	
				TEI (%)	*ESRI* (%)
4	$w_t = \frac{1}{N_{TEI}} w_q = \frac{1}{N_{ESRI}}$	Linear	S_1	50	50
			S_2	60	40
			S_3	80	20
			S_4	40	60
			S_5	20	80
5	$w_t = \frac{1}{N_{TEI}} w_q = \frac{1}{N_{ESRI}}$	Quadratic	S_1	50	50
			S_2	60	40
			S_3	80	20
			S_4	40	60
			S_5	20	80

Scenario S_2 and Scenario S_3).

4. Discussion

The analysis of the results shows that LFP-NG (A_1) is the most preferred option, compared to the other Li-ion alternatives, for the majority of the scenarios analyzed. For the techno-economic domain, the most influential attributes are the cycle lifetime and the manufacturing cost, while for the environmental and supply risk domain the attributes with higher relevance are the Global Warming Potential *GWP* and the *HHI*-$\overline{WGI}$ Composite Indicator HHI_{WGI}. The preferred alternatives, in terms of the highest *ESSI* score for each scenario and simulation of the main results (i.e., *Simulation 1* and *Simulation 2*), are reported in Table 11. Table 11 also shows the results of the *Case 1* and *Case 2* of the *Sensitivity Analysis 1*, the *Sensitivity Analysis 2* and the *Sensitivity Analysis 3*, as well as the *Sensitivity Analysis 4* and the *Sensitivity Analysis 5*. It can be seen that the LFP-NG (A_1) alternative performs better than the other alternatives, in three out of five scenarios considered in *Simulation 1* and four out of five in *Simulation 2*. In the other scenarios (i.e., namely Scenario S_4 and Scenario S_5 in *Simulation 1*, Scenario S_5 in *Simulation 2*), the preferred alternative is represented by LMO-NG (A_2), which obtained the highest *ESSI* score. This is due to the higher weight given to the ESR domain (60 % in Scenario S_4 and 80 % in Scenario S_5), compared to the TE domain (40 % in Scenario S_4 and 20 % in Scenario S_5). The *Sensitivity Analysis 1* (*GWP* variation), the *Sensitivity Analysis 2* (κ_c variation) and the *Sensitivity Analysis 3* (reduced number of attributes) show an analogous trend, with the LFP-NG alternative (A_1) emerging as the most preferred option in the majority of the scenarios analyzed. A different trend is shown in the sensitivity analyses characterized by equal weights for the *TEI/ESRI* attributes, especially in the *Sensitivity Analysis 4*. In fact, in the latter, the most preferred option is the NMC_{811}-NG alternative (A_6), which obtained the highest *ESSI* score in three out of five scenarios. This is mainly due to the increase of the values of the weights for the energy density (from 6.6E-2 to 2.5E-1), and for the resource depletion (from 7.4E-2 to 2.5E-1) in the shift from AHP rating to the equal weights. It should be noted, however, that energy density is considered as less relevant than other attributes in the selection of Li-ion batteries for stationary applications.

5. Conclusions

This work provided a comprehensive assessment of seven Li-ion batteries, through an overall index called Energy Storage Sustainability Index (*ESSI*), which has been obtained by merging two domains, namely the techno-economic (TE) domain and the environmental and supply risk (ESR) domain. For the evaluation, a flexible tool called Sustainable Technology Performance (STeP) has been developed in MATLAB® environment for the multi-attribute decision-making (MADM) assessment of Li-ion batteries. The tool uses a model based on the Multi-Attribute Value Theory (MAVT) as ranking method, with the Analytic Hierarchy Process (AHP) as weighting method.

Two main simulations were analyzed, namely *Simulation 1* and *Simulation 2*, which differ in the shape of the marginal value function adopted. For each simulation, five different scenarios were run with different weights for the TE and ESR domains. The results show that the Lithium Iron Phosphate-Natural Graphite (LFP-NG) consistently emerges as the preferred option, in three out of five scenarios in *Simulation 1* and four out of five scenarios in *Simulation 2*. This is mainly due to the high scores of 0.88 and 0.93 achieved for the techno-economic sub-index in *Simulation 1* and in *Simulation 2*, respectively. However, this preference shifts in the remaining scenarios, emphasizing the ESR domains where the Lithium Manganese Oxide-Natural Graphite (LMO-NG) alternative ranks highest. In addition, five sensitivity analyses were performed to account for the uncertainties of the model. The results show that the LFP-NG alternative is the most preferred option in more than half of the scenarios analyzed (twenty-six over fifty).

Despite the robustness of the methodology, there are several weaknesses. In fact, the reliance on an AHP-based model may introduce potential subjectivity in weight assignment. This issue has been addressed

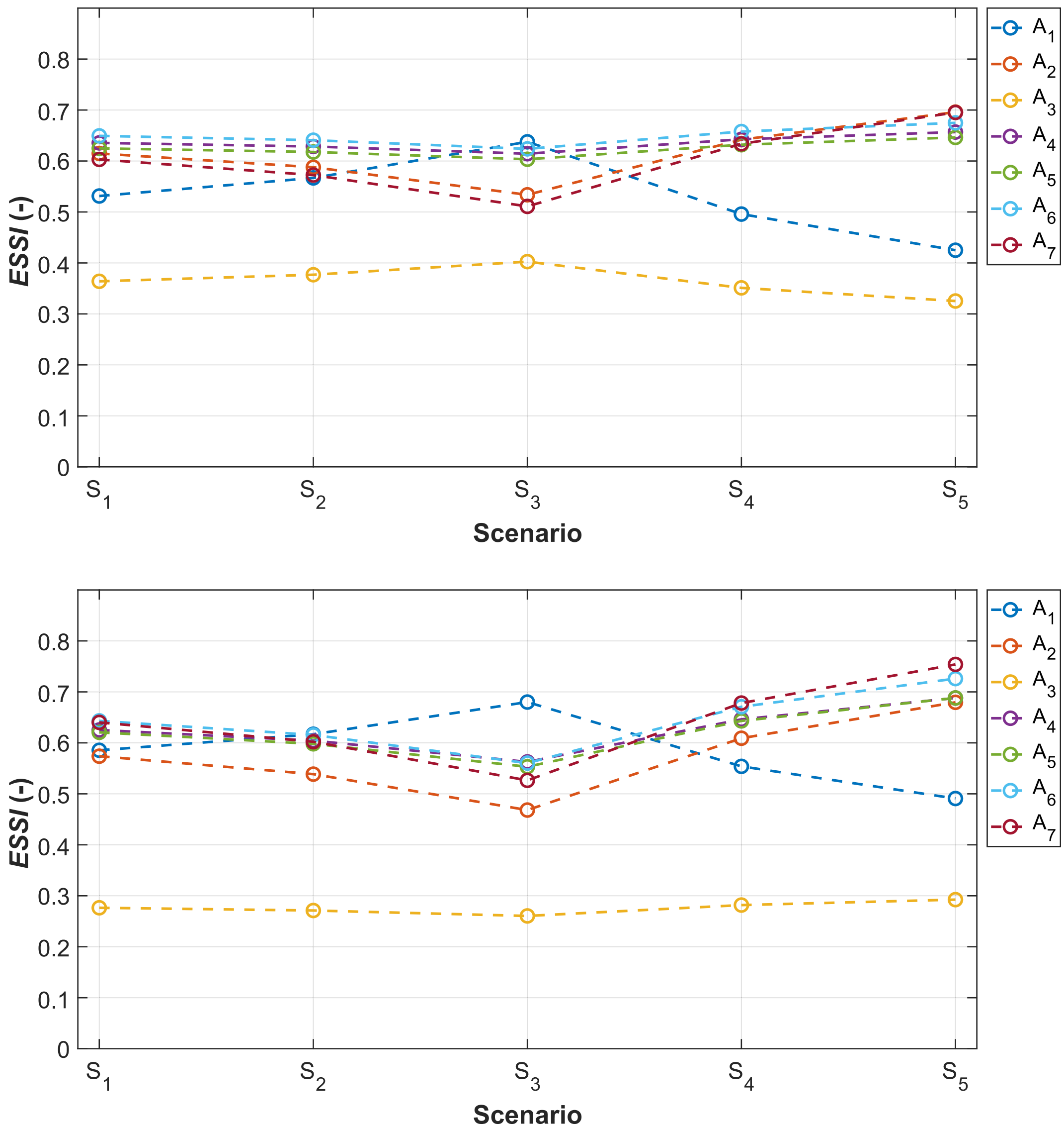

Fig. 9. Graphical representation of the *ESSI* scores for the *Sensitivity Analysis 4* (top figure) and the *Sensitivity Analysis 5* (bottom figure).

Table 11
Best alternative for each scenario considered of the main results and the sensitivity analyses.

Main results		**Scenario**				
		S_1	S_2	S_3	S_4	S_5
Simulation 1		A_1	A_1	A_1	A_2	A_2
Simulation 2		A_1	A_1	A_1	A_1	A_2
Sensitivity analysis	**Case**	**Scenario**				
		S_1	S_2	S_3	S_4	S_5
1	1	A_1	A_1	A_1	A_2	A_2
	2	A_2	A_1	A_1	A_2	A_2
2	1	A_1	A_1	A_1	A_2	A_2
	2	A_1	A_1	A_1	A_2	A_2
3	1	A_4	A_1	A_1	A_4	A_4
	2	A_1	A_1	A_1	A_4	A_4
4		A_6	A_6	A_1	A_6	A_2
5		A_6	A_1	A_1	A_7	A_7

through two *ad hoc* sensitivity analyses, namely the *Sensitivity Analysis 4* and the *Sensitivity Analysis 5*, which explored the influence of weight variation on the final results. The shift from the AHP rating to the equal weights increased the contribution of attributes where the LFP-NG alternative perform poorly, such as energy density and resource depletion.

Inaccuracies in the input data collected for the evaluation matrix could also play a large role in the final results. To address this issue, a variation range of the Global Warming Potential (*GWP*) and the Cycle Lifetime was evaluated in the *Sensitivity Analysis 1* and the *Sensitivity Analysis 2*. The results are analogous to those obtained in *Simulation 1* and *Simulation 2*, except for *Case 2* in the *Sensitivity Analysis 1*, where the highest upper *GWP* value assumed by the LFP-NG alternative, compared to the others, makes the LMO-NG alternative the most preferred option in an additional scenario (Scenario S_1).

From a commercial perspective, the study highlights limitations related to the availability and variability of input data for different battery chemistries, which may hinder the applicability of the results in other contexts. Furthermore, since the focus on stationary applications and Li-ion batteries, further evaluations should be carried out for implementation in different sectors and for different ESTs.

The lessons learned from the analysis, particularly the role of input data, the impact of weights, and the exploration of possible interdependencies among the selected attributes, may be transferred to other ESTs evaluations.

CRediT authorship contribution statement

Salvatore Cellura: Writing – review & editing, Writing – original draft, Visualization, Software, Investigation, Data curation. **Andrea Mazza:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Formal analysis, Conceptualization. **Ettore Bompard:** Resources, Funding acquisition. **Stefano Corgnati:** Resources, 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.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.enconman.2024.119312.

Data availability

Data will be made available on request.

References

[1] Salpakari J, Mikkola J, Lund PD. Improved flexibility with large-scale variable renewable power in cities through optimal demand side management and power-to-heat conversion. Energy Convers Manag 2016;126:649–61. https://doi.org/10.1016/j.enconman.2016.08.041.

[2] Impram S, Varbak Nese S, Oral B. Challenges of renewable energy penetration on power system flexibility: a survey. Energy Strateg Rev 2020;31:100539. https://doi.org/10.1016/j.esr.2020.100539.

[3] Tumminia G, Guarino F, Longo S, Aloisio D, Cellura S, Sergi F, et al. Grid interaction and environmental impact of a net zero energy building. Energy Convers Manag 2020;203. https://doi.org/10.1016/j.enconman.2019.112228.

[4] European Commission. COMMISSION RECOMMENDATION of 14 March 2023 on Energy Storage – Underpinning a decarbonised and secure EU energy system (2023/C 103/01); 2023.

[5] European Commission. Proposal for a REGULATION OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL amending Regulations (EU) 2019/943 and (EU) 2019/942 as well as Directives (EU) 2018/2001 and (EU) 2019/944 to improve the Union's electricity market design (COM/2023/148 final, 14.3.2023). Brussels; 2023.

[6] European Parliament, Council of the European Union. DIRECTIVE 2006/66/EC OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL of 6 September 2006 on batteries and accumulators and waste batteries and accumulators and repealing Directive 91/157/EEC; 2006.

[7] European Battery Alliance n.d. https://single-market-economy.ec.europa.eu/industry/strategy/industrial-alliances/european-battery-alliance_en (accessed January 29, 2023).

[8] European Parliament, Council of the European Union. DIRECTIVE (EU) 2018/849 OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL of 30 May 2018 amending Directives 2000/53/EC on end-of-life vehicles, 2006/66/EC on batteries and accumulators and waste batteries and accumulators, and 2012/19/EU on waste electrical; 2018.

[9] European Commission. Proposal for a REGULATION OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL concerning batteries and waste batteries, repealing Directive 2006/66/EC and amending Regulation (EU) No 2019/1020 (COM/2020/798, final, 10.12.2020). Brussels; 2020.

[10] Eurostat. Waste statistics - recycling of batteries and accumulators; 2023. https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Waste_statistics_-_recycling_of_batteries_and_accumulators#Recycling_efficiency_for_other_batteries (accessed July 26, 2023).

[11] European Commission. Green Deal: EU agrees new law on more sustainable and circular batteries to support EU's energy transition and competitive industry; 2022. https://ec.europa.eu/commission/presscorner/detail/en/ip_22_7588.

[12] European Commission. Proposal for a REGULATION OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL establishing a framework for ensuring a secure and sustainable supply of critical raw materials (COM(2023) 160 final, 16.3.2023). Brussels; 2023.

[13] Baumann M, Weil M, Peters JF, Chibeles-Martins N, Moniz AB. A review of multi-criteria decision making approaches for evaluating energy storage systems for grid applications. Renew Sustain Energy Rev 2019;107:516–34. https://doi.org/10.1016/j.rser.2019.02.016.

[14] Ren J. Sustainability prioritization of energy storage technologies for promoting the development of renewable energy: a novel intuitionistic fuzzy combinative distance-based assessment approach. Renew Energy 2018;121:666–76. https://doi.org/10.1016/j.renene.2018.01.087.

[15] Ren J, Ren X. Sustainability ranking of energy storage technologies under uncertainties. J Clean Prod 2018;170:1387–98. https://doi.org/10.1016/j.jclepro.2017.09.229.

[16] Baumann M, Peters J, Weil M. Exploratory multicriteria decision analysis of utility-scale battery storage technologies for multiple grid services based on life-cycle approaches. Energy Technol 2020;8:1901019. https://doi.org/10.1002/ente.201901019.

[17] Balezentis T, Streimikiene D, Siksnelyte-Butkiene I. Energy storage selection for sustainable energy development: the multi-criteria utility analysis based on the ideal solutions and integer geometric programming for coordination degree. Environ Impact Assess Rev 2021;91:106675. https://doi.org/10.1016/J.EIAR.2021.106675.

[18] Tajik M, Makui A, Tosarkani BM. Sustainable cathode material selection in lithium-ion batteries using a novel hybrid multi-criteria decision-making. J Energy Storage 2023;66:107089. https://doi.org/10.1016/j.est.2023.107089.

[19] Murrant D, Radcliffe J. Assessing energy storage technology options using a multi-criteria decision analysis-based framework. Appl Energy 2018;231:788–802. https://doi.org/10.1016/j.apenergy.2018.09.170.

[20] Zhang C, Chen C, Streimikiene D, Balezentis T. Intuitionistic fuzzy MULTIMOORA approach for multi-criteria assessment of the energy storage technologies. Appl Soft Comput J 2019;79:410–23. https://doi.org/10.1016/j.asoc.2019.04.008.

[21] Mazza A, Russo A, Chicco G, Di Martino A, Colombo CG, Longo M, et al. Categorization of attributes and features for the location of electric vehicle charging stations. Energies 2024;17. https://doi.org/10.3390/en17163920.

[22] Beinat E. Value Functions for Environmental Management. Springer Netherlands; 1997.

[23] Knehr KW, Kubal JJ, Nelson PA, Ahmed S. Battery Performance and Cost Modeling for Electric-Drive Vehicles: A Manual for BatPaC v5.0 2022. https://doi.org/10.2172/1877590.

[24] Cellura S, Mazza A, Bompard E, Corgnati S. An extended approach to the evaluation of energy storage systems: a case study of Li-ion batteries. Electronics 2023;12. https://doi.org/10.3390/electronics12112391.

[25] Chen Y, Kang Y, Zhao Y, Wang L, Liu J, Li Y, et al. A review of lithium-ion battery safety concerns: the issues, strategies, and testing standards. J Energy Chem 2021;59:83–99. https://doi.org/10.1016/j.jechem.2020.10.017.

[26] Masson-Delmotte VPZ, Pirani A, Connors SL, Péan C, Berger S, et al. IPCC, 2021: Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change; 2021.

[27] Blengini GA, et al. Assessment of the methodology for establishing the EU list of critical raw materials. JRC Tech Rep 2017. https://doi.org/10.2760/73303.

[28] Tercero Espinoza LA. Critical appraisal of recycling indicators used in European criticality exercises and circularity monitoring. Resour Policy 2021;73:102208. https://doi.org/10.1016/j.resourpol.2021.102208.

[29] Blengini GA, Nuss P, Dewulf J, Nita V, Peirò LT, Vidal-Legaz B, et al. EU methodology for critical raw materials assessment: policy needs and proposed solutions for incremental improvements. Resour Policy 2017;53:12–9. https://doi.org/10.1016/j.resourpol.2017.05.008.

[30] Carvalho ML, Temporelli A, Girardi P. Life cycle assessment of stationary storage systems within the Italian electric network. Energies 2021;14. https://doi.org/10.3390/en14082047.

[31] Porzio J, Scown CD. Life-cycle assessment considerations for batteries and battery materials. Adv Energy Mater 2021;11. https://doi.org/10.1002/aenm.202100771.

[32] Jasper FB, Späthe J, Baumann M, Peters JF, Ruhland J, Weil M. Life cycle assessment (LCA) of a battery home storage system based on primary data. J Clean Prod 2022;366:132899. https://doi.org/10.1016/j.jclepro.2022.132899.

[33] Peters JF, Baumann M, Zimmermann B, Braun J, Weil M. The environmental impact of Li-Ion batteries and the role of key parameters – A review. Renew Sustain Energy Rev 2017;67:491–506. https://doi.org/10.1016/j.rser.2016.08.039.

[34] Wang Q, Ping P, Zhao X, Chu G, Sun J, Chen C. Thermal runaway caused fire and explosion of lithium ion battery. J Power Sources 2012;208:210–24. https://doi.org/10.1016/J.JPOWSOUR.2012.02.038.

[35] Le Varlet T, Schmidt O, Gambhir A, Few S, Staffell I. Comparative life cycle assessment of lithium-ion battery chemistries for residential storage. J Energy Storage 2020;28:101230. https://doi.org/10.1016/j.est.2020.101230.

[36] Battery University. BU-205: Types of Lithium-ion n.d. https://batteryuniversity.com/article/bu-205-types-of-lithium-ion.

[37] Notter DA, Gauch M, Widmer R, Wäger P, Stamp A, Zah R, et al. Contribution of Li-ion batteries to the environmental impact of electric vehicles. Environ Sci Technol 2010;44:6550–6. https://doi.org/10.1021/es903729a.

[38] Dai Q, Kelly J, Dunn J, Benavides P. Update of bill-of-materials and cathode materials production for lithium-ion batteries in the GREET® model; 2018.

[39] ecoinvent Version 3 n.d. https://www.ecoinvent.org/database/database.html (accessed June 18, 2021).

[40] United States Geological Survey. Mineral Commodity Summaries; 2022. https://doi.org/10.3133/MCS2021.

[41] Austrian Federal Ministry of Finance (BMF). World Mining Data. 2022 n.d. https://www.world-mining-data.info/.

[42] Kaufmann D, Kraay A, Mastruzzi M. The Worldwide Governance Indicators: Methodology and Analytical Issues (September 2010). 2010.

[43] Mohr M, Peters JF, Baumann M, Weil M. Toward a cell-chemistry specific life cycle assessment of lithium-ion battery recycling processes. J Ind Ecol 2020;24:1310–22. https://doi.org/10.1111/jiec.13021.

[44] Baumann M, Peters JF, Weil M, Grunwald A. CO_2 Footprint and life-cycle costs of electrochemical energy storage for stationary grid applications. Energy Technol 2017;5:1071–83. https://doi.org/10.1002/ENTE.201600622.

[45] Peters JF, Weil M. Providing a common base for life cycle assessments of Li-Ion batteries. J Clean Prod 2018;171:704–13. https://doi.org/10.1016/J.JCLEPRO.2017.10.016.

[46] Thomas LV, Schmidt O, Gambhir A, Few S, Staffell I. Comparative life cycle assessment of lithium-ion battery chemistries for residential storage. J Energy Storage 2020;28:101230. https://doi.org/10.1016/J.EST.2020.101230.

[47] Yudhistira R, Khatiwada D, Sanchez F. A comparative life cycle assessment of lithium-ion and lead-acid batteries for grid energy storage. J Clean Prod 2022;358:131999. https://doi.org/10.1016/J.JCLEPRO.2022.131999.

[48] Shahid S, Agelin-Chaab M. A review of thermal runaway prevention and mitigation strategies for lithium-ion batteries. Energy Convers Manag X 2022;16:100310. https://doi.org/10.1016/J.ECMX.2022.100310.