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Optimal battery selection for electric vehicles: a comparative ranking approach

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ABSTRACT

Electric vehicles (EVs) have emerged as an eco-friendly alternative to traditional internal combustion engines, with battery technology playing a pivotal role in their success. Key factors like energy density, power output, charging speed, durability, cost, safety, and environmental impact hinge on the choice of battery. Various technologies in lithium-ion batteries are assessed for their suitability in EVs. The right battery is essential for optimal performance, extended range, and sustainability. This paper offers an in-depth look at battery selection in EVs, examining different types in lithium-ion and their pros and cons. Additionally, it explores into three prominent decision-making methods: fuzzy analytic hierarchy process (FAHP), evaluation based on distance from average solution (EDAS), and preference ranking organization method for enrichment evaluation-II (PROMETHEE II). FAHP ranks batteries based on their relevance to specific EV requirements, while EDAS and PROMETHEE II provide a multi-criteria framework. These methods offer valuable insights into choosing the most suitable lithium-ion battery for EVs. The study underscores the importance of meticulous battery selection and highlights the efficacy of decision-making approaches like FAHP, EDAS, and PROMETHEE II. As battery tech advances, future research on alternatives like solid-state and sodium-ion batteries could revolutionize the EV industry.

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1. INTRODUCTION

As the world transitions towards sustainable development, electric vehicles (EVs) stand out among cleaner mobility solutions. With the increased worry over climate change, the depletion of fossil fuels, and worsening air quality, the need to reduce greenhouse gas emissions from the transport sector has grown. Because traditional ICE emit a significant portion of carbon dioxide and other pollution emissions, as well as contribute to furthering existing environmental and public health risks, efforts to reduce ICE vehicles are increasing. EVs have zero tailpipe emissions therefore, they are recognized as more environmentally friendly alternatives [1], [2]. Switching from ICE vehicles to EVs greatly decreases urban pollutant emissions, together with emissions such as NOx and particulate matter, reduces respiratory diseases, and climate risks [3]. Overall, EVs help fulfill international and national climate objectives such as the Paris Agreement, reducing the use of fossil fuels, and increasing the integration of renewable energies into the transport sector [4]. EVs also provide energy security as the use of domestically generated electricity from a diverse range of sources, including: wind, solar, and hydropower, is less vulnerable to changes in global oil markets, thereby continuing to build resilience in the transportation system [5]. Moreover, the emerging EV industry is fostering development in sectors like: power electronics, smart grids, and energy storage; all of which are creating jobs and stimulating economic development [6], [7]. Batteries and the choice of battery chemistry, size, and configuration are critical components for electric vehicle performance, range, safety, cost, and sustainability properties. Battery chemistry plays an important role in the overall utility and sustainability of EVs [8]. Lithium-ion technology has emerged as the predominant energy storage technology for EVs, considering its high energy density, efficiency, and cycle life [9], [10]. Lithium-ion batteries use lithium-based chemistries such as: lithium cobalt oxide (LCO), lithium iron phosphate (LFP), and lithium nickel manganese cobalt oxide (NMC); enabling different trade-offs regarding cost, energy density, thermal stability, and cycle life [11].

For example, LCO batteries are often seen in portable electronics, having high energy density but thermal instability issues, limiting their usage in larger EV applications [12]. A hybrid FAHP-TOPSIS model for green material selection, offering a detailed explanation of fuzzy analytic hierarchy process (FAHP) steps including fuzzy comparison, aggregation, defuzzification, and consistency validation [13]. Additional lifecycle assessment and performance degradation studies reinforce how choosing the appropriate battery affects the overall environmental sustainability of electric mobility [14], [15]. Battery design may also impact consumers through charging times, weight, and energy efficiencies. Consequently, to choose the most appropriate battery technology, there are multiple technical, economic, and environmental criteria to consider at the same time. These different requirements create a complicated decision-making problem, where the trade-offs between criteria must be considered [16]. Multi-criteria decision-making (MCDM) methods have been applied in engineering, transportation, and environmental management to solve these complex problems [17]. MCDM techniques offer an approach to systematically reviewing and evaluating a number of alternatives across a defined number of conflicting criteria. In the case of selecting an EV battery, MCDM techniques allow decision-makers to compare and rank batteries based on different metrics, including cost, capacity, energy density, environmental impacts, battery lifespan and ease for charging [18]. FAHP, evaluation based on distance from average solution (EDAS), and preference ranking organization method for enrichment evaluation-II (PROMETHEE II) are just a few of the many MCDM techniques available, but they are very popular due to their flexibility and ease of use. Many researchers have successfully used these three methods in their own studies, such as battery selection, renewable energy planning, and infrastructure optimization [19].

The EDAS method evaluates alternatives from their positive and negative distances away from an average solution. EDAS provides a straightforward way to avoid some of the more complicated ranking problems. EDAS follows a logical computation process and can easily handle normalized data [20]. PROMETHEE II uses an outranking flow, which provides an overall ranking of alternatives by using preference functions to account for the intensity and direction of preference from one option to another to give meaning to all preferences [21]. While these MCDM methods effectively operate independently, they significantly strengthen decision-making outcomes when combined within a hybrid framework. Mishra *et al.* [22] provided an example using a hybrid FAHP and PROMETHEE II approach which consistently ranked potential renewable energy sites for projects and influenced to apply this to battery selection problems [23]. At present, there is little research that provides a combination of multiple MCDM methods to verify the rankings of EV batteries using cross-verification. Most previous studies and approaches utilized only one method of MCDM, resulting in variation possibly due to bias on selection of weightings or preference functions. To resolve this gap in research, this study provided a hybrid framework for the optimal selection of batteries for electric vehicles, integrating FAHP, EDAS, and PROMETHEE II.

This proposed processing begins with FAHP to calculate fuzzy weights for each criterion based on the opinions of experts. Then the fuzzy weights are utilized with EDAS and PROMETHEE II to rank a set of battery alternatives. The two rankings will be compared to choose the most reliable and consistent battery technology. The decision-making framework is shown in Figure 1. The battery technology selections are also aligned with emerging standards (IEEE 2993-2025) aimed at outlining best practices for second-life EV battery applications, and energy storage system design [24]. Including the standards into the MCDM framework guarantees the selected technology will be suitable for the future, sustainable, and consistent with global standards. In summary, the electric mobility transition depends on policy, infrastructure, but also, on selecting the best technologies [25]. Batteries are at the heart of the performance and sustainability EV. This research contributes to that transition by providing a validated hybrid MCDM approach to select suitable battery technologies to comply with regulations, operate efficiently, and be sustainable in the long-term.

2. METHODOLOGY

In MCDM problems, selecting the optimal alternative often involves evaluating conflicting criteria under uncertainty. To address this complexity, an integrated decision-making framework is essential. This study adopts a hybrid methodology that combines FAHP, EDAS, and PROMETHEE II. The integration of these techniques leverages the strengths of each: FAHP captures expert judgment in a fuzzy environment for determining criterion weights, EDAS emphasizes distance-based evaluation, and PROMETHEE II applies an outranking approach for preference analysis. This hybrid model ensures a more robust, transparent, and comprehensive ranking of alternatives. The methodology not only supports decision-making in complex environments but also enables comparison between different ranking approaches to validate the consistency and reliability of the outcomes. Figure 1 illustrates the battery selection roadmap.

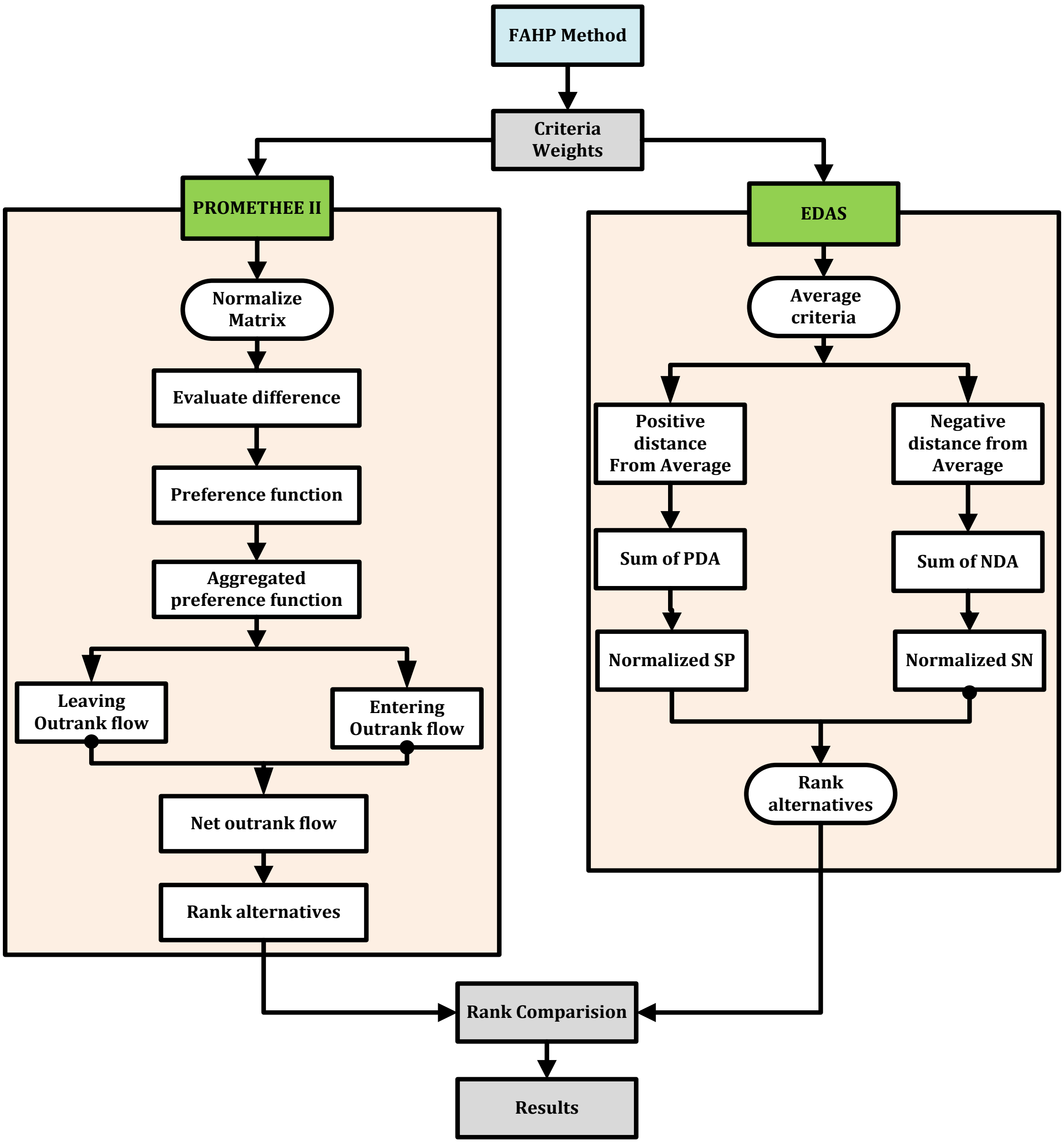

Figure 1. Battery selection roadmap

This study integrates FAHP, PROMETHEE II, and EDAS to assess and rank alternatives within an MCDM framework. FAHP is first applied to obtain the criteria weights by incorporating expert judgments expressed under uncertainty. These derived weights are then used as inputs for both PROMETHEE II and EDAS, enabling a comparative evaluation of rankings. In PROMETHEE II, a normalized decision matrix is developed, and pairwise differences between alternatives are computed. An appropriate preference function is assigned to each criterion to represent the intensity of preference. The aggregated results yield a global preference index, from which the leaving and entering flows are determined. The net flow value ultimately provides the ranking of alternatives. In contrast, EDAS begins by calculating the mean value of each criterion. For every alternative, the positive and negative distances from these averages are determined, aggregated, and normalized to obtain SP and SN scores. These are combined to generate an overall performance score, which forms the basis for ranking. The final step compares the rankings obtained from PROMETHEE II and EDAS to ensure consistency and robustness in the decision-making process. FAHP is selected for weight determination because it extends traditional AHP with fuzzy logic, enabling the use of linguistic terms and fuzzy numbers—an advantage when expert input is imprecise [13]. EDAS [5] and PROMETHEE II [6] are employed for evaluating and ranking the alternatives due to their strong capability in addressing conflicting criteria.

3. RESULTS

This section presents the findings obtained by applying the FAHP, EDAS, and PROMETHEE II methods for evaluating and ranking electric vehicle battery alternatives. Each method was implemented systematically using the weights derived from expert input and technical specifications. The FAHP technique was used to calculate the relative importance of the evaluation criteria, which were subsequently applied in both the EDAS and PROMETHEE II methods to generate alternative rankings. The purpose of this multi-method approach is to ensure robustness, validate consistency, and provide deeper insight into the decision-making process. The results are discussed method by method, followed by a comparison and correlation analysis to assess agreement across the rankings produced. Technical observations and interpretations accompany each method to clarify its performance and the rationale behind the rankings generated.

3.1. FAHP method

The pairwise comparison matrix for the chosen criteria has been established based on consumer preferences, following the steps outlined in the AHP method. The outcomes of this process are tabulated in Table 1. The FAHP method effectively captured expert uncertainties during the weighting process. The consistency ratio (CR = 0.02594) was well below the acceptable threshold (0.1), confirming that the judgments were reliable. The resulting weights emphasized the cost, cycle life, and weight as the most influential criteria, which aligns well with real-world EV battery selection requirements. Figure 2 illustrates the criteria weights.

Table 1. Fuzzy AHP pairwise comparison matrix

Criteria	Voltage drop (volts)	Cutoff voltage (volts)	100% of SOC voltage (volts)	Life cycles	Cost ($/kWh)	Shelf life (years)	Specific power (W/kg)	Maximum temperature (Celsius)	Weight (kg)	Normalized Weights w_i
Voltage drop (volts)	(1,1,1)	(1/6,1/5,1/4)	(1/7,1/6,1/5)	(1/8,1/7,1/6)	(9,9,9)	(1/3,1/2,1/1)	(1/5,1/4,1/3)	(1/4,1/3,1/2)	(1/9,1/8,1/7)	0.032
Cutoff voltage (volts)	(4,5,6)	(1,1,1)	(1/3,1/2,1/1)	(1/4,1/3,1/2)	(1/6,1/5,1/4)	(3,4,5)	(1,2,3)	(2,3,4)	(1/5,1/4,1/3)	0.071
100% of SOC voltage (volts)	(5,6,7)	(1,2,3)	(1,1,1)	(1/3,1/2,1/1)	(1/5,1/4,1/3)	(4,5,6)	(2,3,4)	(3,4,5)	(1/4,1/3,1/2)	0.104
Life cycles	(6,7,8)	(2,3,4)	(1,2,3)	(1,1,1)	(1/4,1/3,1/2)	(5,6,7)	(3,4,5)	(4,5,6)	(1/3,1/2,1/1)	0.151
Cost ($/kWh)	(9,9,9,)	(4,5,6)	(3,4,5)	(2,3,4)	(1,1,1)	(7,8,9)	(5,6,7)	(6,7,8)	(1,2,3)	0.315
Shelf life (years)	(1,2,3)	(1/5,1/4,1/3)	(1/6,1/5,1/4)	(1/7,1/6,1/5)	(1/9,1/8,1/7)	(1,1,1)	(1/4,1/3,1/2)	(1/3,1/2,1/1)	(1/8,1/7,1/6)	0.025
Specific power (W/kg)	(3,4,5)	(1/3,1/2,1/1)	(1/4,1/3,1/2)	(1/5,1/4,1/3)	(1/7,1/6,1/5)	(2,3,4)	(1,1,1)	(1,2,3)	(1/6,1/5,1/4)	0.049
Maximum temperature (Celsius)	(2,3,4)	(1/4,1/3,1/2)	(1/5,1/4,1/3)	(1/6,1/5,1/4)	(1/8,1/7,1/6)	(1,2,3)	(1/3,1/2,1/1)	(1,1,1)	(1/7,1/6,1/5)	0.034
Weight (kg)	(7,8,9)	(3,4,5)	(2,3,4)	(1,2,3)	(1/3,1/2,1/1)	(6,7,8)	(4,5,6)	(5,6,7)	(1,1,1)	0.219

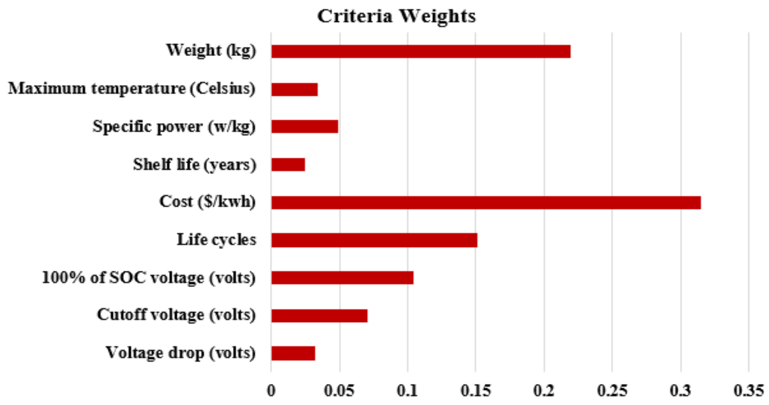

Figure 2. Criteria weights

3.2. EDAS method

One of the available MCDM approaches, the EDAS method uses two metrics; positive distance from average and negative distance from average, to evaluate the alternatives in relation to the average solution as shown in Table 2. It is fairly easy to get the average answer; all we have to do is take the arithmetic mean of the performance values of the various options on each criterion. In stochastic processes, the arithmetic mean is crucial. Because of this, using the EDAS approach to stochastic MCDM issues can be quite effect.

EDAS provided a straightforward, intuitive ranking mechanism based on normalized distances. Li-NCA emerged as the top performer with the highest ASi score. This validates the method’s effectiveness in identifying dominant options based on performance deviation from average values. However, the sensitivity to average values suggests results could shift with different data sets.

Table 2. EDAS rank preference

Alternatives	SP_i	SN_i	NSP_i	NSN_i	AS_i	Rank
Lithium cobalt oxide ($LiCoO_2$)	0.0556	0.2217	0.1997	0	0.0999	10
Lithium titanate (Li_2TiO_3)	0.2783	0.2056	1	0.0727	0.5364	4
Lithium iron phosphate ($LiFePO_4$)	0.1926	0.1999	0.692	0.0985	0.3953	6
Lithium manganese oxide ($LiMn_2O_4$)	0.075	0.123	0.2695	0.4453	0.3574	7
Lithium nickel cobalt aluminum oxide (Li-CA)	0.198	0.0652	0.7115	0.7059	0.7087	1
Lithium nickel manganese cobalt oxide (Li-MC)	0.0411	0.1316	0.1478	0.4065	0.2771	9
Lithium-Ion polymer (LiPo)	0.1485	0.1977	0.5337	0.1085	0.3211	8
Lithium-Ion manganese oxide (LMO)	0.169	0.0638	0.6071	0.7122	0.6596	2
Lithium silicon (Li-Si)	0.1432	0.0987	0.5146	0.5548	0.5347	5
Lithium Ion (Li-ion)	0.0802	0.0477	0.2882	0.7848	0.5365	3

3.3. PROMETHEE II method

The PROMETHEE II method commences by appraising alternatives concerning the criteria. This appraisal relies on numerical data and requires access to information regarding both the criteria's relative importance and the preference functions of the decision maker, the results of which are shown in Table 3. The PROMETHEE II method, which stands for the preference ranking organization method for enrichment of evaluations, along with its complementary geometrical analysis for interactive support, is commonly referred to as PROMETHEE II.

Table 3. PROMETHEE II preference ranking

Alternatives	Leaving flow α+(a)	Entering flow α-(a)	α(a)	Rank
$LiCoO_2$	0.11	0.23	-0.11	8
Li_2TiO_3	0.32	0.23	0.09	2
$LiFePO_4$	0.07	0.26	-0.19	10
$LiMn_2O_4$	0.08	0.24	-0.16	9
Li-CA	0.19	0.15	0.04	5
Li-MC	0.13	0.1	0.03	6
LiPo	0.24	0.16	0.08	3
LMO	0.17	0.1	0.07	4
Li-Si	0.15	0.17	-0.02	7
Li-ion	0.19	0.08	0.11	1

PROMETHEE II, initially formulated in the early 1980s, is rooted in mathematics and sociology. It has undergone extensive research and refinement over the years. This method finds widespread application in decision-making processes and is employed globally across a diverse range of decision scenarios. The final rankings obtained using the two methods and their comparison are shown in Table 4 and Figure 3, respectively.

PROMETHEE II offered a more nuanced evaluation through preference functions and net flows. Li-ion and Li_2TiO_3 consistently ranked high due to favorable entering and leaving flows, indicating strong dominance over other alternatives. The outranking approach enabled the identification of subtle strengths and weaknesses not captured by EDAS.

Table 4. Final ranking

MCDM method	EDAS		PROMITHEE 2	
alternatives	ASi	Rank	α(a)	Rank
$LiCoO_2$	0.0999	10	-0.11	8
Li_2TiO_3	0.5364	4	0.09	2
$LiFePO_4$	0.3953	6	-0.19	10
$LiMn_2O_4$	0.3574	7	-0.16	9
Li-CA	0.7087	1	0.04	5
Li-MC	0.2771	9	0.03	6
LiPo	0.3211	8	0.08	3
LMO	0.6596	2	0.07	4
Li-Si	0.5347	5	-0.02	7
Li-ion	0.5365	3	0.11	1

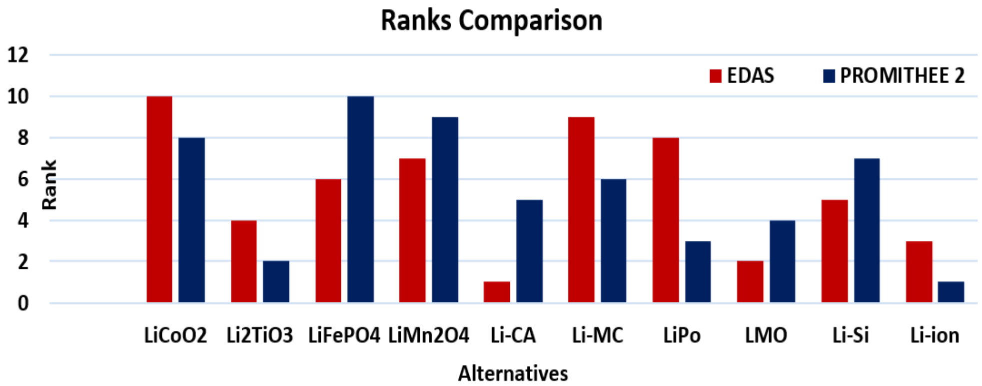

Figure 3. Comparison of ranking

4. CONCLUSION

The data derived from the comparative methods EDAS and PROMETHEE II show Li-NCA as the most strong and stable battery material. Li-NCA rated first in the EDAS framework using the ASi with a best ASi of 0.7087. Furthermore, in this PROMETHEE II framework, Li-NCA rated strongly with 5th place being the only consideration with a positive α(a) value of 0.04, indicating overall strength. Lithium-ion manganese oxide also rated highly, which is evidenced by a 2nd place ranking in EDAS with an ASi of 0.6596 and a 4th place rank in PROMETHEE II. This shows it is stable in both comparative systems. Li-ion rated moderately as it also places 3rd in EDAS ranking but rated 1st in PROMETHEE II. In the PROMETHEE II framework, Li-ion exceeded all alternatives with the best α(a) value of 0.11, indicating it is the most prepared for implementation. LTO clearly stands out from those above, where it ranked 4th in EDAS, but moved to 2nd place in PROMETHEE II. Furthermore, this would suggest that PROMETHEE II captures more of the additional strengths of LTO that may not be as clearly acknowledged in EDAS. This is a clear opportunity for the decision-maker to select a strong offering for a battery, and it has strong potential depending on the decision-maker's emphasis on batteries according to the different weighted criteria. Materials such as lithium silicon, lithium-ion polymer, and lithium nickel manganese cobalt oxide have a moderate impression as effective materials but varying ranks, implying their effectiveness will depend on the application, surrounding device, and environment, and the decision-maker's priorities in the key areas from the multiple criteria. LCO and LFP consistently rank lower in both decision-making methods, suggesting that they are potentially not as good as the alternatives reviewed in both methods. In conclusion, Li-NCA, Li-ion, and LTO materials stood out in the two decision-making models, and final material selection will need to be based on application requirements and decision-maker prioritisation of criteria.

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AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data supporting the findings of this study can be obtained from the corresponding author, [VM], upon reasonable request.

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