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AI Integrated Neutrosophic MCDM Framework for Promoting Carbon Neutrality through Li-Ion Battery Selection for Electric Vehicles

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Abstract

Battery Electric Vehicles (BEV) are anticipated to emerge as alternatives to fuel based vehicles in the coming decades to promote carbon neutrality. The compatibility and robustness of Li-ion based batteries make them more preferable in BEVs. A recent study has identified five different groups of Li- ion based batteries used in BEVs and applied a very simple multi–criteria decision making (MCDM) method of Weighted sum with equal criterion weights and linguistic matrix to rank the batteries. The present research work considers the same decision making problem and applies different MCDM methods to determine the criterion weights and ranking of the batteries with Triangular Neutrosophic matrix. The methodology proposed in this work works in five phases. The consistency of the neutrosophic ranking results is validated using Random forest technique, Feature importance analysis and SHAP explainability analysis. The comprehensive MCDM framework presented in this work will enable the decision makers of manufacturing company to make ideal selection of the electric vehicle batteries on comparing the ranking scores of the batteries using different methods with different criterion weights.

Keywords: MCDM Framework, Li-ion, Battery Electric Vehicles, Optimal Ranking, RFA, FIA, SHAP

Introduction

The automobile manufacturing industries are making several new attempts to produce more efficient battery electric vehicles. BEVs are suggested as substitute to conserve environment from vehicle emissions. The longevity of these BEVs are more dependent on the life span of batteries and moreover lithium (Li)-ion type of batteries are predominantly used. Abu et al [1] investigated on the state of health of Li-ion batteries. Zhou et al [2] framed estimation models to determine battery capacity. Tian et al [3] explored the state of health of Li-ion batteries using real time data. Wu et al [4] employed radial bases neural network in computing state of health of batteries. Chen et al [5] discoursed on state of charging of Li-ion based batteries. Yu et al [6] discussed on safety aspects of Li-ion batteries. Habib et al [7] elaborated on li- ion battery management. He et al [8] discoursed on the status of fast charging Li-ion batteries. Lin et al [9] applied multi feature optimization to make predictions on the state of health of the batteries. The recent studies on

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state of health and charging of Li-ion batteries clearly sketches the agility and durability of Li-ion batteries. Loganathan et al [10] explored different types of Li-ion batteries in specific. Some of the significant batteries are Lithium- Cobalt Oxide, Lithium- Manganese Oxide, Lithium-Nickel Manganese Cobalt Oxide, Lithium Iron Phosphate, Lithium-Titanate. A decision-making problem is formulated to make optimal ranking of these batteries based on the criteria of price, criteria, safety, specific power and specific energy density. The multi-criteria decision making method of weighted sum method is applied with equal criterion weights to the decision-making problem. Lithium Titanate occupies first and Lithium Cobalt Oxide occupies last position in ranking. On intense analysis of this research work, some of the limitations are identified as follows:

1. The MCDM method of WSM is very simple and fundamental ranking method.
2. The criterion weights are assumed to be equal.
3. The rating scale is crisp in nature.
4. The ranking results are not validated with any advanced techniques.

These limitations have motivated the authors to explore more on this ranking based decision making problem of Li-ion batteries. This research work applies different MCDM methods to determine the criterion weights. The same MCDM problem is subjected to the method of WSM and MAUT (Multi Attribute Utility Theory) with different criterion weights and triangular neutrosophic rating scale. The occurrences of uncertainty, impreciseness and indeterminacy in constructing decision matrix with linguistic values are very high and hence neutrosophic scales are used with triangular representations. This research work proposes a five phase decision making framework with three different criterion weight computing methods (AHP, CRITIC and Entropy) and two ranking methods (MAUT and WSM). The validity of neutrosophic ranking results is performed using artificial techniques such as Random Forest Algorithm, Feature Importance Analysis, SHAP Explainability Analysis.

The remaining contents of the paper are structured as follows: Section 2 presents the related works, section 3 sketches out the methodology, section 4 applies the proposed framework in decision making on Li-ion batteries, section 5 discusses the results with sensitivity analysis, section 6 briefs on industrial applications and the last section concludes the research work with future applications.

Related Works

Multi-criteria decision making (MCDM) methods refer to the Decision making methods applied in constructing ideal solutions to the problems involving several criteria. In general the decision making methods are applied either to calculate the criterion weights or to rank the alternatives. Some of the most commonly applied methods to calculate the criterion weights are Analytic Hierarchy Process, Entropy and CRiteria Importance Through Intercriteria Correlation (CRITIC). The methods that are generally preferred in ranking ranges from simple to complex. The ranking methods which are simple in computation are weighted sum method, weighted product method and the methods involving complex computations are TOPSIS, VIKOR and many other MCDM methods are widely applied to address wide range of intricate decision problems in the domain of electric vehicle, particularly in the site selection of electric vehicle charging stations, planning of charging infrastructure and battery management. The recent studies demonstrate a rigour integration of both conventional and advanced MCDM methods to handle multiple and interdependent criteria such as cost, energy efficiency, sustainability and performance. For instance, hybrid decision frameworks conflating methods like AHP, SAW, and WASPAS have been applied for prioritizing EV alternatives and selecting apt motor drives, with weights determined using the methods of CRITIC and entropy. In contrast, GIS based MCDM methods integrated with FAHP, CRITIC and metaheuristic algorithms are employed in studying EV charging infrastructure planning. Moreover, the competency of MCDM methods are further enhanced with the incorporation of fuzzy, spherical fuzzy, Fermatean fuzzy, and q-rung orthopair fuzzy sets. Emerging techniques such as machine learning blended MCDM are also applied to develop intelligent decision systems for EV selection and performance evaluation. Additionally, MCDM techniques are also used in determining optimal EV charging scheduling and battery management systems facilitating energy utilization and operational efficiency. Researchers have applied a varied range of MCDM decision frameworks in EV research. Some of the significant and recent applications of MCDM are presented in Table 1.

Table 1: MCDM Applications in Electric Vehicle Decision Making

Authors & Year	MCDM Method(s)	Area of Application
Loganathan et al. (2026) [11]	AHP–SAW	Motor drive selection for EV applications
Şimşek et al. (2025) [12]	CRITIC–LOPCOW + ML	Electric vehicle (EV) selection decision-support system
Grdinić-Rakonjac & Lučić (2025) [13]	Max–Min, Max–Max, SAW	EV selection using simple decision-making techniques
Li et al. (2025) [14]	GIS–MCDM	EV charging station site selection (bibliometric analysis)
Hisoğlu et al. (2025) [15]	AHP + GIS	Solar-assisted EV charging station site selection
Mandal & Mondal (2025) [16]	FAHP + GIS (Hybrid MCDM)	Urban–rural EV charging station site selection
Roy et al. (2025) [17]	CRITIC + Entropy + Metaheuristics + GIS	Optimal EV charging station placement with sustainability criteria
Seth & Kartheek (2024) [18]	AHP–WASPAS	EV selection in India
Gökler (2024) [19]	FUCOM + GIS	EV charging station site selection
Golui et al. (2024) [20]	Fermatean Fuzzy MCDM	EV selection under uncertainty
Yan et al. (2024) [21]	Spherical Fuzzy CoCoSo + CRITIC	EV charging station location selection
Parthasarathy et al. (2024) [22]	IVPF q-Rung Orthopair Fuzzy MCDM	EV battery charging technology selection
Mhana & Awad (2024) [23]	AHP + GIS	Optimal EV charging station location
Wei & Zhou (2023) [24]	MCDM Framework (unspecified hybrid)	EV supplier selection
Puška et al. (2023) [25]	MEREC–CRADIS	Electric car selection
Dwivedi & Sharma (2023) [26]	Entropy + TOPSIS	Ranking of battery electric vehicles
Zhang et al. (2023) [27]	Hesitant Fuzzy MCDM	EV charging station location
Aungkulanon et al. (2023) [28]	Fuzzy AHP	Strategic EV adoption decisions
Bošković et al. (2023) [29]	AROMAN	EV selection problem
Zhang & Wei (2023) [30]	CPT–CoCoSo + D-CRITIC	EV charging station site selection
Biswas et al. (2023) [31]	q-Rung Orthopair Fuzzy MCDM	EV comparison and evaluation
Gupta et al. (2023) [32]	Fuzzy AHP	Risk evaluation of EV charging infrastructure
Yagmahan & Yılmaz (2023) [33]	Group MCDM	Sustainable evaluation of EV charging stations

From the above Table 2 it is very evident that the MCDM methods are primarily applied to find optimal solutions to the selection based decision making problems of the following:

(i) Choice making on electric vehicles
(ii) Site selection of charging stations
(iii) Supplier selection

The literature of application of MCDM methods in making optimal decisions on battery selection is very limited and also the methods of AHP and TOPSIS are most repeatedly used. Also, AI integrated MCDM approach is not much explored to the best of our knowledge. This has motivated the authors to explore and extend the work of Loganathan et al [10] with different MCDM approaches.

Methods

This section, the steps involved in ranking the alternatives is presented in the flowchart with added description. The decision making framework comprises four phases. The steps followed in each phase are listed as follows.

Phase I: Initialization of Decision Problem

Under this phase, the first step is problem definition followed by construction of decision-making matrix with alternatives and criteria based on the decision experts. The initial decision-making matrix is framed with linguistic variables to stage a realistic kind of representations. Triangular neutrosophic scales are applied to quantify the linguistic variables to crisp values. The modified matrix is normalized to standardize the values of the matrix in the range [0,1].

The initial decision matrix is of the form

Alternatives ↓ / Criteria →	C_1	C_2	C_3	…	C_n
A_1	Lx_{11}	Lx_{12}	Lx_{13}	…	Lx_{1n}
A_2	Lx_{21}	Lx_{22}	Lx_{23}	…	Lx_{2n}
A_3	Lx_{31}	Lx_{32}	Lx_{33}	…	Lx_{3n}
…	…	…	…	…	…
A_m	Lx_{m1}	Lx_{m2}	Lx_{m3}	…	Lx_{mn}

Here each Lx_{ij} represents how the alternatives satisfy the criteria in linguistic sense. The criteria are classified as benefit and cost category. Each of the linguistic values is represented using triangular neutrosophic values. The modified values are normalized using equation (1) & (2).

For Benefit Criteria:

$$T_{ij} = \frac{r_{ij}-minr_j}{maxr_j-minr_j}, \quad I_{ij} = I_j, \quad F_{ij} = 1 - T_{ij} \quad (1)$$

For Cost Criteria:

$$T_{ij} = \frac{maxr_j - r_{ij}}{maxr_j - minr_j}, \quad I_{ij} = I_j, \quad F_{ij} = 1 - T_{ij} \quad (2)$$

Phase II: Computation of Criterion Weights

In this phase the criterion weights are determined using the methods of AHP, CRITIC and entropy. The core steps involved in the above said methods are presented briefly in the flow chart. For further comprehension, the readers shall refer [34-37].

Analytic Hierarchy Process (AHP)

- Pairwise comparison of the Alternatives and obtaining preferential scores a_{ij} based on Saaty rating scale
- Calculation of total weight
- Compute Consistency index CI
- Consistency ratio CR

$$CR = \frac{CI}{RI} \times 100$$

CRiteria Importance Through Intercriteria Correlation (CRITIC)

- Calculation of standard deviation vector of each criteria σ_j
- Compute criterion information C_j

$$C_j = \sigma_j \sum (1 - r_{jk})$$

- Obtain the criterion weights

$$w_j = \frac{C_j}{\sum C_j}$$

ENTROPY

- Calculation of the entropy of the criteria

$$E_j = -\frac{1}{ln\,(m)} \sum y_{ij} ln\,(y_{ij})$$

- Obtain the criterion weights

$$w_j = \frac{1 - E_j}{\sum (1 - E_j)}$$

Phase III: Computation of Alternative Scores & Ranking

In this phase the alternatives are ranked using MAUT MCDM method using the following steps.

- Computing Marginal Utility value

$$u_{ij} = \frac{x_{ij} - x_j^-}{x_j^+ - x_j^-}$$

- Calculating Final utility value

$$U_i = \sum u_{ij} w_j$$

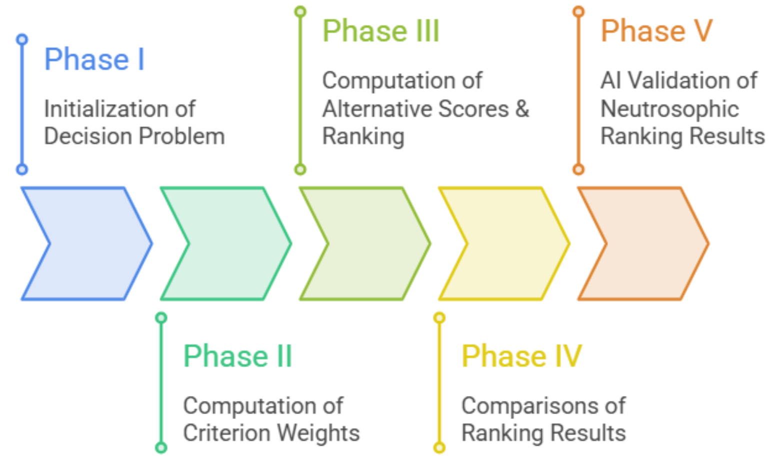
Phase IV: Comparisons of Ranking Results

In this phase, the ranking results are compared with the ranking results obtained using other methods. The optimal ranking results is determined from the feasible ranking patterns obtained in the previous phase.

Phase V: AI Validation of Neutrosophic Ranking Results

In addition to comparison of ranking results, AI driven techniques are applied to validate the ranking results of neutrosophic representations. The Random Forest Algorithm (RFA) is applied to train the data. This technique is employed to determined the consistency and reliability of neutrosophic rankings. Feature Importance Analysis is performed to determine the relative influence of each criterion of the decision making problem. SHAP Explainability analysis is leveraged to explore individual criterion contribution and to find the interpretability of the AI model. The overall framework of the proposed approach is presented in Figure 1.

Figure 1: Architecture of Five Phase Decision Framework



Application of MCDM Methods

This section presents the application of the MAUT method together with the criterion weight computing methods of AHP, CRITIC and Entropy in ranking the lithium ion batteries. The alternatives and the criteria with equal criterion weights are considered from the decision making problem constructed by Loganathan in ranking the best alternative of Li-ion batteries. The above considered decision making matrix with crisp scale (5 point scale) is modified using triangular neutrosophic scale as mentioned in Table 2.

Table 2: Triangular Neutrosophic Scale

Linguisticvariable	Triangular NeutrosophicScale	Equivalent Crisp value
Low (L)	$\langle(0.15,0.25,0.10),0.6,0.2,0.3\rangle$	0.36
Average (A)	$\langle(0.40,0.35,0.50),0.6,0.1,0.2\rangle$	0.64
High (H)	$\langle(0.70,0.65,0.80),0.9,0.2,0.1\rangle$	0.7
Very High (VH)	$\langle(0.90,0.85,0.90),0.7,0.2,0.2\rangle$	0.76
Exceptionally High (EH)	$\langle(0.95,0.9,0.95),0.9,0.1,0.1\rangle$	0.95

The alternatives and criteria considered are presented in Table 3.

Table 3: Alternatives & Criteria of Decision Making

Alternatives		Criteria	
B_1	Lithium-Cobalt Oxide Battery	C_1	Price
B_2	Lithium-Manganese Oxide Battery	C_2	Reliability
B_3	Lithium-Nickel ManganeseCobalt Oxide Battery	C_3	Safety
B_4	Lithium Iron Phosphate Battery	C_4	Specific power
B_5	Lithium-Titanate Battery	C_5	Specific Density energy

The criterion weights are obtained using the methods of AHP, CRITIC & Entropy based on the steps mentioned in section 3 as in Table 4.

Table 4: Criterion weights with Neutrosophic scales

Criteria	Methods		
	AHP	Entropy	CRITIC
C_1	0.324998277	0.469808276	0.156279389
C_2	0.362008648	0.156432	0.144750795
C_3	0.207207603	0.127865218	0.134537872
C_4	0.052892736	0.08946126	0.141675041
C_5	0.052892736	0.156432	0.422756903

The equivalence crisp based decision matrix is

	C_1	C_2	C_3	C_4	C_5
B_1	0.76	0.7	0.7	0.7	0.95
B_2	0.76	0.76	0.76	0.76	0.95
B_3	0.64	0.7	0.76	0.76	0.76
B_4	0.64	0.95	0.95	0.95	0.7
B_5	0.36	0.95	0.95	0.76	0.7

The modified decision making matrix with linguistic variable is

	C_1	C_2	C_3	C_4	C_5
B_1	VH	H	H	H	EH
B_2	VH	VH	VH	VH	EH
B_3	A	H	VH	VH	VH
B_4	A	EH	EH	EH	H
B_5	L	EH	EH	VH	H

Using the method of MAUT, the alternatives are ranked using the above criterion weights stated in table 5.

Table 5: MAUT Ranking results based on Neutrosophic scales

Alternatives	Methods		
	AHP	Entropy	CRITIC
B_1	4	4	4
B_2	3	2	3
B_3	5	5	5
B_4	2	3	2
B_5	1	1	1

The ranking results obtained using triangular neutrosophic scales are compared with the ranking results obtained crisp rating scale with the same criterion weights mentioned in table 6.

Table 6: MAUT Ranking results based on crisp rating scale

Alternatives	Methods		
	AHP	Entropy	CRITIC
B_1	5	4	5
B_2	4	1	3
B_3	3	5	4
B_4	2	2	2
B_5	1	3	1

Findings and Discussion

The ranking results presented in Table 5 & 6 is compared with the ranking results obtained using the method of weighted sum method with the same criterion weights as in Table 4. Table 7 and 8 presents the ranking results of the alternatives with WSM method using neutrosophic and crisp rating scales, respectively.

Table 7: WSM Ranking results based on Neutrosophic scales

Alternatives	Methods		
	AHP	Entropy	CRITIC
B_1	5	5	5
B_2	3	2	4
B_3	4	4	3
B_4	2	3	2
B_5	1	1	1

Table 8: WSM Ranking results based on crisp rating scales

Alternatives	Methods		
	AHP	Entropy	CRITIC
B_1	5	4	5
B_2	3	2	4
B_3	4	5	3
B_4	2	3	2
B_5	1	1	1

The ranking results obtained in Table 7 & 8 are compared with the ranking results obtained in the decision problem of Loganathan et al. The actual ranking results are presented in Table 9.

Table 9: Actual Ranking Results

B_1	B_2	B_3	B_4	B_5
5	3	4	2	1

By using Pearson's rank correlation coefficient, the competencies of the ranking results are determined as follows as in Table 10.

Table 10: Correlation comparison of the ranking results

	WSM with Triangular neutrosophicscale			WSM with crisp scale			MAUT with Triangular neutrosophicscale			MAUT with crisp scale		
	AHP	Entropy	CRITIC	AHP	Entropy	CRITIC	AHP	Entropy	CRITIC	AHP	Entropy	CRITIC
Actual Ranking results	1	0.9	0.9	1	0.8	0.9	0.9	0.8	0.9	0.9	0.5	1

The actual ranking results in Table 9 are perfectly correlated in three cases and in almost all the cases the ranking correlation coefficient appears to be very high. Also in comparison with the conventional crisp rating scale, the neutrosophic scales are yielding better results with different criterion weights. In almost all the ranking cases the alternative B_5, i.e Lithium-Titanate Battery occupies the first ranking position and in majority of the cases the alternative B_1. i.e Lithium-Cobalt Oxide Battery occupies the last position in ranking. The frequency of the different ranking positions obtained by other alternatives such as B_2, B_3 and B_4 shall be comprehended from the following Table 11.

Table 11: Frequency of Ranking Positions

Alternatives	Ranking Positions				
	I	II	III	IV	V
B_1	-	-	-	5	7
B_2	1	3	5	3	-
B_3	-	-	3	4	5
B_4	-	9	3	-	-
B_5	11	-	1	-	-

From the above table 11 the following ranking pattern $B_5 > B_4 > B_2 > B_3 > B_1$ is observed to be more optimal which is perfectly consistent with the actual ranking results. This observation is made from the comparison of overall ranking frameworks. But still, if the criterion weights are assumed to be distinct then the decision makers shall consider the criterion weights obtained using AHP with any of the rating scales, preferably the neutrosophic scales.

AI validation of Neutrosophic Ranking Results

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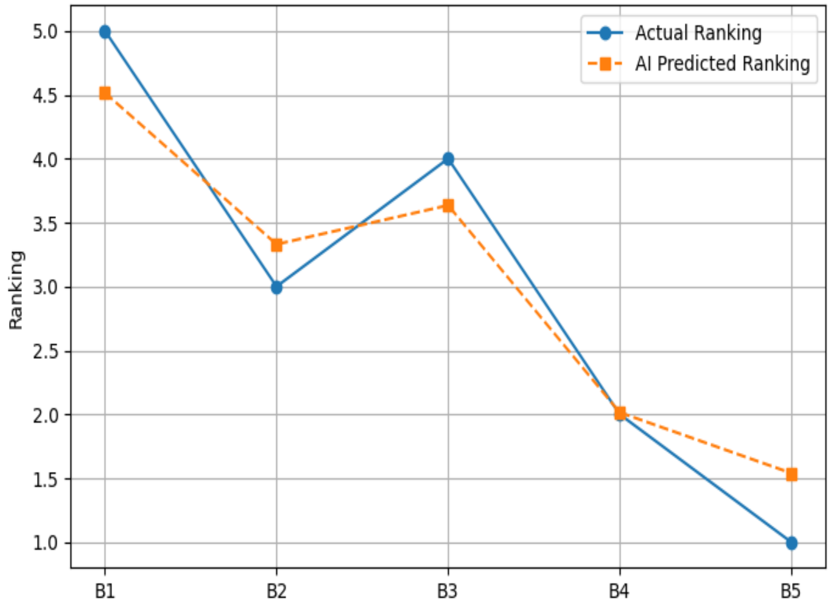
A Random Forest model is trained using the battery criteria and ranking data. The model verifies the consistency and reliability of the neutrosophic-MCDM rankings.

Figure 2: Actual Vs AI Predicted Rankings



The Figure 2 provides a visual comparison between the rankings obtained from the neutrosophic-MCDM framework and those predicted by the AI model. The Feature Importance Analysis is performed to ascertain the most influential criteria.

Figure 3: AI based Feature Importance

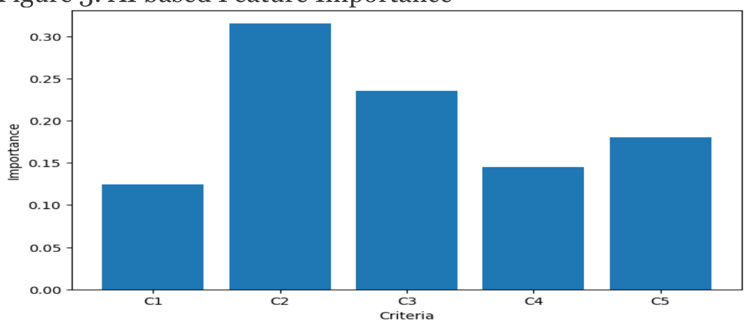
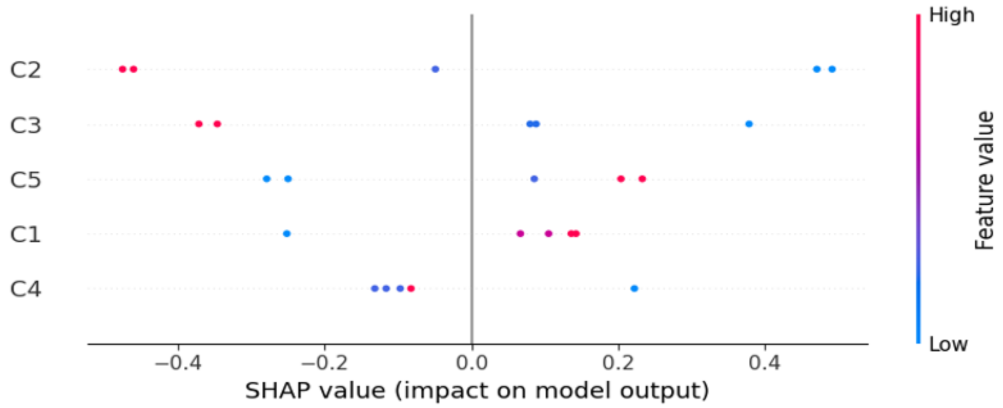


Figure 3 identifies the relative influence of each criterion on the battery ranking process and highlights the most significant decision-making factors. From the Fig. 3 it is evident that the criteria 2 i.e C_2 is relatively more significant in comparison with other criteria. The criterion weights obtained using different MCDM methods confirms the same. On other hand SHAP Explainability analysis is also performed to determine how each individual criteria contributes o the ranking.

Figure 4: SHAP Analysis



The ranking results of neutrosophic representations are confirmed with advanced AI techniques and it is evident that neutrosophic rankings are so convincing and promising as depicted in Figure 4.

Conclusion

The process of making decision is a part and parcel of every industrial activity. The managerial can design optimal solutions based only on the authentic and concrete information which requires purely insightful research. This research work based on Li-ion batteries decision making will surely take out the commotions on making choices of the batteries with and without considering the criterion weights. As a part of extension, the same techniques of decision making shall be applied in their decision making activities. This research work has presented the framework of making optimal decisions of Li-ion batteries with criterion weights. Three different methods of finding the criterion weights and two ranking methods are used in this work. The research work of Loganathan et al is considered as the grounds for this work. The case of ranking results with equal criterion weights is discussed under various instances in this paper. The sensitivity analysis on ranking results made facilitates the decision makers to draw more inferences. The validation of neutrosophic ranking results is performed using RFA, FIA and SHAP analysis.

This work shall be extended with other robust and viable decision making methods of criterion weight computation and ranking. As many MCDM methods are available in the literature, the same research problem shall be discussed under several scenarios. This research work has wide scope in the field of decision making and simultaneously the decision makers will receive various opportunities to make inferences on the ranking results.

Ethics approval

Not required.

Acknowledgments

Not Applicable.

Competing interests

All the authors declare that there are no conflicts of interest.

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Underlying data

Derived data supporting the findings of this study are available from the corresponding author on request.

Declaration of artificial intelligence use

Not Applicable.

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