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Selection of Electric Vehicle Battery using Multi Attribute Decision Making Methods

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Abstract. An electric vehicle (EV) battery provides the energy required to power vehicles, ranging from passenger cars to buses. Among EV components, the battery is widely regarded as one of the most critical, as it directly supports vehicle operation. In parallel, the adoption of electric vehicles has increased, largely due to their potential to reduce carbon emissions and contribute to environmental protection initiatives. Consequently, selecting an appropriate battery for electric vehicles represents a significant decision-making challenge. To identify a suitable battery option, a multi-criteria decision-making (MCDM) approach is employed, taking into account several fundamental performance specifications. These criteria include battery lifespan, efficiency, durability, recharge time, temperature dependence, cost, and weight. The present work applies a structured framework for EV battery selection through the use of multiple decision-making techniques, namely the Analytic Hierarchy Process (AHP), the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), the Complex Proportional Assessment (COPRAS) method, and Multi-Objective Optimization on the basis of Ratio Analysis (MOORA). Collectively, these methods are used to evaluate and rank battery alternatives, thereby providing a systematic and comparative basis for informed decision-making.
Keywords: Selection of electric vehicle battery, Analytical hierarchy process, Technique for order performance by similarity to ideal solution, Complex Proportional Assessment, Multi-Objective Optimization on the basis of Ratio Analysis.

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1 Introduction

Electric vehicle (EV) batteries exhibit relatively high power-to-weight ratios, specific energies, and energy densities. As a result, smaller and lighter batteries are generally preferred, as they reduce vehicle mass and can enhance overall performance. Batteries function as the primary energy storage component in electric vehicles, and their type may vary depending on whether the vehicle is a fully electric vehicle (AEV) or a plug-in hybrid electric vehicle (PHEV). Contemporary battery technologies are typically designed to offer extended service life, commonly estimated at around eight years or 100,000 miles. Under moderate climatic conditions, certain battery types may operate for 12–15 years, whereas in harsher environments their lifespan is often reduced to approximately 8–12 years. The four principal battery technologies currently used in electric vehicles are lithium-ion, nickel–metal hydride, lead–acid, and nickel–cadmium.

In the present study, the challenge of selecting an appropriate battery for electric vehicles is framed as a multi-criteria decision-making problem. Five battery vendors are considered and evaluated against eight selection criteria, including lifespan (years), efficiency (%), cost, and other relevant attributes. The decision-making process is examined from problem definition through to solution implementation and evaluation, with particular attention paid to the role of multi-attribute decision-making (MADM) methods.

Luzon et al. [1] reported the application of the Analytic Hierarchy Process (AHP) for supplier evaluation in oil and gas projects in the UAE, considering ten attributes, namely quality, price, delivery, technical capability, production facilities, services, warranties and claims, performance history, financial position, and geographical location. Jianping et al. [2] proposed an improved

Complex Proportional Assessment (COPRAS) method for green supplier selection, based on four attributes: resource consumption, delivery cost, environmental protection capability, and eco-design.

The selection of suitable EV batteries represents a complex task for manufacturers; accordingly, MADM methods may be employed to identify appropriate alternatives among competing options. Techniques such as the Analytic Hierarchy Process (AHP), the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), Multi-Objective Optimization on the basis of Ratio Analysis (MOORA), and the Complex Proportional Assessment (COPRAS) method are commonly applied for this purpose. The MADM framework supports decision-making in contexts where a finite number of alternatives must be assessed against multiple criteria, specifying how attribute information should be processed and compared. These methods require explicit trade-offs, both within and across attributes.

Several studies have explored optimal decision-making strategies across different application domains. Tahriri et al. [3] presented an AHP-based approach for supplier selection in a steel manufacturing company using four attributes: cost, quality, facilities, and delivery. Xiang et al. [4] applied the VIKOR method to optimise black-start schemes using ten indicators, including voltage fluctuation, frequency fluctuation, recovery time, unit capacity, and load restoration. In the present work, an attempt is made to derive an optimal ranking of EV batteries using the proposed decision-making techniques, based on selected attributes and alternatives.

2 Literature Review

A substantial body of research addresses selection problems through the application of decision-making techniques. Numerous studies have examined how different MADM methods can be used to evaluate alternatives across multiple attributes. This section reviews representative works that apply such techniques to a variety of selection problems.

Dragincic et al. [5] employed an AHP-based group decision-making approach for selecting irrigation equipment, considering five attributes: product quality, price, payment terms, delivery time, and supplier reliability. Zolfani et al. [6] applied AHP and COPRAS methods to select a quality control manager in an iron production context, using seven attributes, including product knowledge, experience, administrative orientation, behavioural flexibility, and teamwork. Albayrak et al. [7] proposed the use of AHP to improve human performance, based on company culture, participation, human capability, and attitudes.

Yusuf Ersoy [8] applied the TOPSIS method to select environmentally friendly machinery in a manufacturing company, using six attributes such as price, lifting capacity, lifting height, and operational speed. Zhongyou et al. [9] used TOPSIS to select foreign players in professional basketball leagues based on twelve performance-related attributes. Pei et al. [10] applied TOPSIS to linguistic MADM problems, focusing on workstation design and operational characteristics. Jahanshahloo et al. [11] extended TOPSIS to decision-making problems involving fuzzy data.

Zavadskas et al. [12] proposed the COPRAS method for selecting road design solutions using attributes such as longevity, construction cost, environmental protection, economic feasibility, and construction duration. Liou et al. [13] applied COPRAS to green supply chain management selection problems, incorporating twelve environmental and organisational attributes. Krishankumar et al. [14] used COPRAS in a probabilistic hesitant fuzzy environment to support decision-making based on six service-related attributes. Organ et al. [15] applied COPRAS to evaluate the performance of research assistants using academic and professional indicators.

Zheng et al. [16] employed the VIKOR method to select renewable energy system schemes for tourist resorts, considering nine attributes, including investment cost, ecological impact, service life, and energy efficiency. Hashemi et al. [17] applied VIKOR to multi-target feature selection problems, while Hezer et al. [18] used VIKOR, TOPSIS, and COPRAS to evaluate regional safety during the COVID-19 pandemic. Kim et al. [19] applied VIKOR under conditions of incomplete criteria weights.

From the reviewed literature, it can be observed that MADM methods have been extensively applied across a wide range of selection problems. However, no prior study was identified that specifically addresses the selection of electric vehicle batteries using a combined application of AHP, TOPSIS, COPRAS, and MOORA methods. This gap provides the motivation for the present research, which focuses on ranking electric vehicle batteries based on eight key attributes: lifespan, efficiency, durability, warranty, recharge time, temperature dependence, cost, and weight.

3 MADM Methods

3.1 AHP Method

This method was introduced by Thomas L. Saaty in 1980, in collaboration with Ernest Foreman. It is designed to support the solution of complex decision-making problems by structuring and systematically analysing them. The Analytic Hierarchy Process (AHP) is among the most widely used methods within multi-attribute decision-making (MADM) and is generally regarded as capable of producing robust and reliable results. Within this approach, the decision maker evaluates each element independently, a feature that can enhance the consistency and transparency of the assessment process and may contribute to meaningful rankings of the alternatives under consideration.

Steps in the AHP method:
Step 1: Formation of a hierarchical structure, in which the overall goal is placed at the top level, the evaluation criteria (attributes) at the second level, and the alternatives at the third level.
Step 2: Determination of the relative importance of all attributes with respect to the overall goal through pairwise comparisons, followed by the calculation of attribute weights.

Table 1. Relative importance scale

Intensity of Importance	Definition	Explanation
1	Equal importance	Two activities contribute equally to the objective.
3	Weak importance of one over another	Experience and judgement slightly favour one activity over another.
5	Essential or strong importance	Experience and judgement strongly favour one activity over another.
7	Demonstrated Importance	An activity is strongly favoured and its dominance demonstrated in practice.
9	Absolute importance	The evidence favours one activity over another is of the highest order possible of affirmation.
2, 4, 6, 8	Intermediate values between two judgments	When compromise is needed.

To calculate the weights, a pairwise comparison matrix is constructed using the relative-importance scale defined in Table 1. The size of the pairwise comparison matrix depends on the number of attributes considered. When an attribute is compared with itself, the assigned value is 1; accordingly, all diagonal entries of the matrix are equal to 1. Based on the decision maker's judgements, each attribute is compared against the others, and the corresponding relative-importance values are assigned to the remaining entries of the matrix. The relative normalised weight vector for the attributes is then obtained by computing the geometric mean of each row and subsequently normalising these values so that their sum is equal to one. This procedure results in the attribute weights used in the subsequent analysis.

$$Wn = \frac{GM}{\sum GM_n} \quad \textbf{(1)}$$

Step 3 Checking the consistency.
Let us assume, M1 = pair wise matrix of comparison
M2 = weights of the attributes
Therefore, M3 = M1 x M2 and M4 = M3/M2
Then lambda max i.e. average of matrix M4 and M = size of matrix

$$\boldsymbol{\lambda}_{max}(Eigen\ value) = \frac{A4}{M} \quad \textbf{(2)}$$

$$CI = \frac{(\boldsymbol{\lambda}_{max} - M)}{(M\text{-}1)}, \qquad CR = \frac{CI}{RI} \quad \textbf{(3)}$$

For the value of the Random Index (RI), Table 2 is consulted, which reports RI values as a function of the number of attributes. The Consistency Ratio (CR) is generally required to be less than or equal to 0.1; when this condition is satisfied, the pairwise judgements are typically regarded as acceptably consistent. If the CR exceeds 0.1, the decision matrix should be revised and the procedure repeated from the relevant step.

Step 4: Compute the normalised matrix for each attribute considered.
Step 5: To obtain the overall performance score and ranking of alternatives, the relative weight vector (derived in Step 2) is multiplied by the corresponding normalised attribute values for each alternative (from Step 4). The resulting aggregated scores are then used to derive the ranking of alternatives.

This process allows for the application of MADM methods to support solution development and the ranking of alternatives.

Table 2. Random index on the basis on number of attributes taken.

Attribute	3	4	5	6	7	8	9	10
RI	0.52	0.89	1.11	1.25	1.35	1.4	1.45	1.49

3.2 TOPSIS Method

The method was developed by Ching-Lai Hwang and Yoon in the year 1981, this method totally focuses on the evaluation of all the attributes and criteria from the problem. This method is used to give ranking to the options which are compared and find out which is the optimal among them.
The steps for TOPSIS Method are as follows:
Step 1: Find Normalized decision matrix.

$$a_{ij} = \frac{y_{ij}}{(\sum y_{ij}^2)^{\frac{1}{2}}} \text{ for i=1…m; j=1…n} \quad \textbf{(4)}$$

Step 2: Find Weighted normalized matrix.

We have to multiply weights of for each criterion Wj for j= 1…n and each column of Normalized decision matrix is multiplied by the Weights which are related to it.

$$Z_{ij} = w_j * x_{ij} \quad \textbf{(5)}$$

Step 3: Positive Ideal and Negative

Positive Ideal (optimal)	Negative Ideal (inadequate)
Maximum value for beneficial and minimum for non-beneficial.	Maximum value for non-beneficial and Minimum beneficial.

Step 4: Separation measure.

$$Positive\ separation\ measures\ Si^{+} = \sqrt{[\sum(V_j^{+} - V_{ij})^2]} \quad \textbf{(6)}$$

$$Negative\ separation\ measures\ Si^{-} = \sqrt{[\sum(V_j^{-} - V_{ij})^2]} \quad \textbf{(7)}$$

Step 5 Finding out the relative closeness to the ideal solution.

$$Pi = \frac{S_i^{-}}{(S_i^{-} + S_i^{+})} \quad \textbf{(8)}$$

Step 6: Give Ranking to the Solution.

3.3 COPRAS Method

For the value of the Random Index (RI), Table 2 is consulted, which reports RI values as a function of the number of attributes.

The Consistency Ratio (CR) is generally expected to be less than or equal to 0.1; when this condition is satisfied, the pairwise judgements are typically regarded as acceptably consistent. If the CR exceeds 0.1, the decision matrix should be revised and the procedure repeated from the relevant step.

Step 4: Compute the normalised matrix for each attribute considered.
Step 5: To obtain the overall performance score and ranking of alternatives, the relative weight vector (derived in Step 2) is multiplied by the corresponding normalised attribute values for each alternative (from Step 4). The resulting aggregated scores are then used to determine the ranking of alternatives.

This process supports the application of MADM methods for solution development and the ranking of alternatives.

$$X = \left[X_{ij}\right]_{m\times n} = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \dots & \dots & \dots & \dots \\ x_{m1} & x_{m2} & \dots & x_{mn} \end{bmatrix}$$

Where Xij is the assessment value of i^{th} alternative with respect to j^{th} criterion m is number of alternatives and n is number of criteria.
Step 2: Do the normalization of above decision matrix with the help of equation (9).

$$R = [r_{ij}]_{\,m\times n} = x_{ij} / \textstyle\sum_{i=1}^{m} x_{ij} \tag{9}$$

Step 3: Find the weighted normalized decision matrix, D, using equation (10)

$$D = |y_{ij}|_{m\times n} = \text{i}r_{ij} \times w_j \tag{10}$$

Where r_{ij} is the normalized performance value of i^{th} alternative on j^{th} criterion and W_i is the weight of j^{th} criterion
The sum of weighted normalized values of each criterion = weight for that criterion

$$\sum_{i=1}^{m} y_{ij} = w_j \tag{11}$$

Step 4: Calculate the sums of weighted normalized values for beneficial as well as non-beneficial criteria by using equation (12)

$$S_{+i} = \textstyle\sum_{j=1}^{n} y_{+ij}, \qquad S_{-i} = \textstyle\sum_{j=1}^{n} y_{-ij} \tag{12}$$

Where y_{+ij} and y_{-ij} are weighted normalized values for the beneficial and non-beneficial criteria, respectively.
Step 5: Find the relative significance of the alternatives, Q_n by equation (13) below:

$$S_{+i} + \frac{S_{-min} \times \sum_{i=1}^{m} S_{-i}}{S_{-i} \times \sum_{i=1}^{m} (S_{-min/S_{-i}})} \tag{13}$$

Where S_{-min} is minimum value of S_{+i}
Step 6: Find quantitative utility, $U_i$for i^{th} alternative using equation (14) below:

$$U_i = \frac{Q_i}{Q_{max}} \times 100\% \quad (14)$$

Where Q_{max} is the maximum relative significance value.
Considering equation (6), utility value will range from 0% to 100%. As $U_i$value greater, higher is the priority. According to that, ranking will be calculated.

3.4 MOORA Method

This method is widely used because it typically requires fewer mathematical computations than alternative approaches and offers relatively rapid processing. The technique was introduced by Brauers in 2004 and is commonly characterised as an impartial approach. It is described as a corrective technique, in which desirable and undesirable criteria are considered simultaneously for ranking purposes. The method is applied exclusively to quantitative attributes.

The steps of this method are as follows:
Step 1: The first step involves the construction of a decision matrix. Within this matrix, preferences are expressed for m alternatives evaluated with respect to n attributes. The value y_{ij} is used to show how well the i^{th} alternative performs in relation to the j^{th} criteria.

$$Y_{ij} = \begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1n} \\ y_{21} & y_{22} & \cdots & y_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ y_{m1} & y_{m2} & \cdots & y_{mn} \end{bmatrix}$$

where i=1, 2, 3, …, m
j= 1, 2, 3…, n
m is use for number of alternatives
n is use for number of attributes.
Step 2. The values of every attribute in the decision-making matrix are normalized in the second stage. The qualities may or may not be advantageous. Yij* is a convenient way to express a normalized matrix. The formulas must be used to normalize the matrix**.**

$$Y_{ij}^{*} = \frac{Y_{ij}}{\sqrt{\sum Y_{ij}^{2}}} \quad (15)$$

Step 3. Evaluation value estimation Next, the weight criterion for all the choices must be multiplied by the normalized data. These normalized functions are added to the advantageous criteria for MOORA and subtracted from the non-beneficial criteria. Here, the AHP procedure can be used to calculate the weight criterion.

$$X_i = \sum_{j=1}^{g} w_{ij} \times Y_{ij} - \sum_{j=g+1}^{n} W_{ij} \times Y_{ij} \quad (16)$$

G= number of criteria must be maximized

Step 4. The appropriate option in the rank with the highest Xi value receives the top rank, while the appropriate alternative with the lowest Xi value receives the lowest rank, or the worst rank.

4 Problem Statement for selection of electric vehicle battery

In recent years, sales of electric vehicles have increased, and decision makers have increasingly recognised that selecting one or more suppliers from the available options is both important and challenging. In this paper, the selection of electric vehicle batteries for industrial applications is examined. The present study considers five commonly used electric vehicle battery types: lithium-ion, lead–acid, nickel–metal hydride, nickel–cadmium, and deep-cycle batteries. These alternatives are evaluated using eight attributes—lifespan, efficiency, durability, warranty, recharge time, temperature dependence, cost, and weight—as shown in Table 3. Temperature dependence, cost, and weight are treated as non-beneficial attributes, whereas lifespan, efficiency, durability, warranty, and recharge time are classified as beneficial attributes.

Table 3 Data for electric vehicle battery

Batteries	Life Span (Years)	Efficiency (%)	Durability (cycles)	Warranty (Years)	Recharge Time (Hours)	Temp. Dependence (ºC)	Cost (Rs)	Weight (Kg)
Lithium Ion	10	90	1200	5	3	300	20000	45
Lead Acid	5	85	1500	2	8	400	13300	32
Nickel Metal Hydride	5	92	2000	5	6	450	17500	40
Nickel Cadmium	15	85	2000	5	5	600	10800	11
Deep Cycles	6	80	3000	3	6	270	10500	32

5 Solution of MADM Method

5.1 Solution by AHP Method

Step 1 The Goal is to select the best battery for electric vehicle.

Step 2 Weightage calculation using pair wise comparison matrix and relative importance scale. Table 4 shows the pair wise comparison matrix.

Table 4 Pair wise comparison matrix for AHP method

Pair wise comparison matrix M1								
	Life Span (Years)	Efficiency (%)	Durability (cycles)	Warranty (Years)	Recharge Time (Hours)	Temp. Dependence (ºC)	Cost (Rs)	Weight (Kg)
Life span	1	1/3	3	3	5	3	5	3
Efficiency	3	1	5	3	3	5	7	7
Durability	1/3	1/5	1	1/3	2	3	5	3
Warranty	1/3	1/3	3	1	3	5	7	5
Recharge	1/5	1/3	1/2	1/3	1	3	5	3
Temp dependence	1/3	1/5	1/3	1/5	1/3	1	3	3
Cost	1/5	1/7	1/5	1/7	1/5	1/3	1	3

weight	1/3	1/7	1/3	1/3	1/3	1/3	1/3	1

Hence on calculation weightage we got is,
W1 = 0.2036, W2 = 0.3312, W3 = 0.0983, W4 = 0.1720, W5 = 0.08271, W6 = 0.0525, W7 = 0.0303, W8 = 0.0291.
Step 3 Checking the consistency.

Now lambda max that is Eigen value needs to be calculated by taking average of matrix 4.
Hence lambda max () = 8.9797.
Consistency Index (CI) = 0.1399.
Consistency Ratio (CR) = 0.0999.
For CI we use, For CR we use,

$$CI = \frac{(\lambda_{max} - M)}{(M\text{-}1)} \qquad CR = \frac{CI}{RI}$$

Here the value of CR ≤ 0.1, therefore the weights are accepted.

Table 5 Normalized Weighted Matrix for AHP

Normalization Matrix										
Batteries	Life Span (Years)	Efficiency (%)	Durability (cycles)	Warranty (Years)	Recharge time (hrs.)	Temp dependence (^{O}C)	Cost (Rs)	Weight (kg)	Performances Rate	Ranks
Lithium Ion	0.6666	0.9782	0.4	1	1	0.5	0.525	0.2444	0.8032	2
Lead Acid	0.3333	0.9239	0.5	0.4	0.3756	0.6666	0.7894	0.3437	0.5919	5
Nickel Cadmium hydride	0.3333	1	0.6666	1	0.5	0.75	0.6	0.2758	0.7437	3
Nickel cadmium	1	0.9239	0.6666	1	0.6	1	0.9722	1	0.9080	1
Deep cycles	0.4	0.8695	1	0.6	0.5	0.45	1	0.3437	0.6764	4

Step 4 involves the computation of the normalised weighted matrix. Based on this matrix, the overall performance indices and corresponding ranks are calculated and reported in Table 5. Finally, the ranks are determined by arranging the performance index values of the alternatives in descending order. Accordingly, the resulting ranking is as follows: Nickel–cadmium, lithium-ion, nickel–metal hydride, deep-cycle, and lead–acid batteries.

5.2 Solution for TOPSIS method

Step 1. Construct the decision matrix and determine the weight of criteria. Step 2. Calculate the normalized decision matrix. As shown in Table 6.

Table 6 Normalize matrix for TOPSIS method

Alternatives	Life Span (Year)	Efficiency (%)	Durability (cycles)	Warranty (Years)	Recharge time (hours)	Time Dependence (°c)	Cost (Rs)	Weight (kg)
1	0.4932	0.4652	0.2638	0.5330	0.2300	0.3188	0.6002	0.5911

2	0.3355	0.4394	0.3297	0.2132	0.6135	0.4250	0.3991	0.4203
3	0.2466	0.4756	0.4396	0.5330	0.4604	0.4782	0.5251	0.5254
4	0.7398	0.4394	0.4396	0.5330	0.3834	0.6376	0.3241	0.1445
5	0.2959	0.4135	0.6598	0.3198	0.4601	0.2869	0.3155	0.4203

Step 3. Calculate the weighted normalized decision matrix. As shown in Table 7

Table 7 Weighted normalize matrix for TOPSIS method

Alternatives	Life Span (Year)	Efficiency (%)	Durability (cycles)	Warranty (Years)	Recharge time (hours)	Time Dependence (°c)	Cost (Rs)	Weight (kg)
1	0.1004	0.1541	0.0259	0.0916	0.0190	0.0167	0.0181	0.0172
2	0.0683	0.1455	0.0324	0.0366	0.0507	0.0223	0.0120	0.0126
3	0.0502	0.1575	0.0432	0.0917	0.0380	0.0251	0.0159	0.0155
4	0.1506	0.1455	0.0432	0.0916	0.0317	0.0365	0.0098	0.0042
5	0.0602	0.1369	0.0648	0.0550	0.0380	0.0154	0.0095	0.0126

Step 4: Determine the positive ideal and negative ideal solutions.

The positive ideal alternative is defined as the option exhibiting extreme performance for each criterion, while the negative ideal alternative corresponds to the reverse extreme performance for each criterion. The positive ideal solution is characterised by the maximisation of benefit criteria and the minimisation of cost criteria, whereas the negative ideal solution reflects the maximisation of cost criteria and the minimisation of benefit criteria.

Step 5: Calculate the separation measures from the positive ideal solution and the negative ideal solution, as reported in Table 8.

Table 8 Positive ideal and negative ideal solution

Positive	0.1506	0.1575	0.0648	0.0916	0.0508	0.0156	0.0096	0.0042
Negative	0.0502	0.1369	0.0254	0.0365	0.0190	0.0334	0.0181	0.0172

Step 6. Calculate the relative closeness to the positive ideal solution Pi.
Step 7. Rank the preference order or select the alternative closest to 1. Following are the ranks of alternative
Nickel Cadmium- Lithium ion- Nickel Cadmium Hydride- Deep Cycles- Lead Acid.

5.3 Solution by COPRAS method

To solve the selection problem of electric vehicle batteries for industrial applications using the COPRAS method, the decision matrix is first normalised using Equation (9), as reported in Table 9. As indicated in this table, the decision matrix is normalised by applying Equation (10). The purpose of normalisation is to obtain dimensionless values for the different attributes, allowing them to be compared on a common scale. Subsequently, the weighted normalised decision matrix is constructed using Equation (11), with the results presented in Table 10. The sums of the weighted normalised values for both beneficial (S^{+}_{i}) and non-beneficial (S^{-}_{i}) attributes are then calculated using Equation (12), and these values are reported in Table 11. Finally, the relative importance or priority value (Q_i) and the quantitative utility degree (U_i) for each alternative are determined using Equations (13) and (14), as shown in Table 12.

Table 9 Normalized Decision Matrix for COPRAS method

Batteries	Life Span (Years)	Efficiency (%)	Durability (cycles)	Warranty (Years)	Recharge Time (Hours)	Temp. Dependence (°C)	Cost (Rs)	Weight (Kg)
Lithium Ion	0.2439	0.2083	0.1237	0.25	0.1071	0.1485	0.277	0.2812
Lead Acid	0.1218	0.1967	0.1545	0.1	0.2857	0.1985	0.1844	0.2
Nickel Metal Hydride	0.1219	0.2129	0.2061	0.25	0.2142	0.2222	0.2427	0.25
Nickel Cadmium	0.3658	0.1967	0.2061	0.25	0.1785	0.2970	0.1497	0.0685
Deep Cycles	0.1463	0.1851	0.3092	0.15	0.2142	0.1336	0.1456	0.2

Table 10 Weighted Normalized Matrix for COPRAS method

Batteries	Life Span (Years)	Efficiency (%)	Durability (cycles)	Warranty (Years)	Recharge Time (Hours)	Temp. Dependence (°C)	Cost (Rs)	Weight (Kg)
Lithium Ion	0.0496	0.0690	0.0121	0.0443	0.0088	0.0078	0.0084	0.0081
Lead Acid	0.0248	0.0651	0.0152	0.0177	0.0236	0.0104	0.0055	0.0058
Nickel Metal Hydride	0.0248	0.0705	0.0202	0.0443	0.0177	0.0117	0.0070	0.0072
Nickel Cadmium	0.0745	0.0651	0.0205	0.0443	0.0147	0.0156	0.0045	0.0020
Deep Cycles	0.0298	0.0613	0.0304	0.0265	0.0177	0.0070	0.0041	0.0058

Table 11 Sums of weighted normalized value

Batteries	$S_{+}i$	$S_{-}i$
Lithium Ion	0.1840	0.0609
Lead Acid	0.1465	0.0517
Nickel Metal Hydride	0.1776	0.0737
Nickel Cadmium	0.2190	0.0746
Deep Cycles	0.1658	0.0513

Table 12 Q_i and U_i values for alternative supplier

Batteries	Q_i	U_i	Ranking
Lithium Ion	0.2041	84.63	2
Lead Acid	0.1691	70.10	5
Nickel Metal Hydride	0.1963	81.39	3

Nickel Cadmium	0.2412	100	1
Deep Cycles	0.1943	80.56	4

5.4 Solution by MOORA Method

Step 1. The creation of a decision matrix is the first step. Weights must be taken from the AHP procedure and copied into the spreadsheet along with the attributes. Table 13 displays the attribute's maximum and minimum values.

Table 13 Decision matrix with maximum and minimum values of attributes

Batteries	Life Span (Years)	Efficiency (%)	Durability (Cycles)	Warranty (Years)	Recharge Time (Hours)	Temp Dependence	Cost (Rs)	Weight (Kg)
Lithium Ion	10	90	1200	5	3	300	20000	45
Lead Acid	5	85	1500	2	8	400	13300	32
Nickel Metal Hydride	5	92	2000	5	6	450	17500	40
Nickel Cadmium	15	85	2000	5	5	600	10800	11
Deep Cycles	6	80	3000	3	6	270	10500	32
Maximum	15	92	3000	5	8	600	20000	45
Minimum	5	80	1200	2	3	270	10500	11

Step 2. The values of all attributes in the decision-making matrix are in the second phase, as shown in Table 14. Take the square of each choice matrix value to obtain the value of Yij*. The value of Yij* is then obtained by taking the square root of the sum of the squared values.

Table 14 Normalized matrix for MOORA method

Normalizad matrix								
Lithium Ion	0.493	0.465	0.264	0.533	0.230	0.319	0.600	0.591
Lead Acid	0.247	0.439	0.330	0.213	0.614	0.425	0.399	0.420
Nickel Metal Hydride	0.247	0.476	0.440	0.533	0.460	0.478	0.525	0.525
Nickel Cadmium	0.740	0.439	0.440	0.533	0.383	0.638	0.324	0.145
Deep Cycles	0.296	0.414	0.660	0.320	0.460	0.287	0.315	0.420

Step 3. Estimate the assessment values using equation in the third stage (16). First, multiply Yij* by the weighted criterion, or Wij, to determine the value of Xi. Finally, as indicated in Table 15, add up all of the beneficial and non-beneficial criteria, and remove the value of the non-beneficial criteria from the beneficial criteria.

Table 15 Rank Table for MOORA method

Electric batteries	Xi	Rank
Lithium Ion	0.339	2
Lead Acid	0.269	5
Nickel Metal Hydride	0.324	3

Nickel Cadmium	0.415	1
Deep Cycles	0.318	4

Step 4. Give each choice a rank in this step based on its value. The appropriate option in the rank with the highest Xi value receives the top rank, while the appropriate alternative with the lowest Xi value receives the lowest rank, or the worst rank.

6 Results and Discussion

In the present work, four MADM methods—AHP, TOPSIS, COPRAS, and MOORA—are employed to support the selection of an electric vehicle battery. The analysis considers five alternatives evaluated with respect to eight battery-related attributes. The final ranking of the five alternatives is reported in Table 16. The results indicate that the nickel–cadmium battery attains the highest rank and is identified as the most suitable option among the considered alternatives. In contrast, the lead–acid battery ranks fifth and is found to be the least preferred option for electric vehicle applications based on the evaluated attributes.

Table 16 Combined Rank Table

Alternatives	AHP	TOPSIS	COPRAS	MOORA
Lithium Ion	2	2	2	2
Lead Acid	5	5	5	5
Nickel Cadmium hydride	3	3	3	3
Nickel cadmium	1	1	1	1
Deep cycles	4	4	4	4

The graphical representation of ranks with respect to the alternatives is shown in the Figure 1 that shows the rankings, in which Nickel cadmium Battery is the best option and Lead acid is worst to choose. The method used can be used to solve more such type of complex problems that improves the selection process.

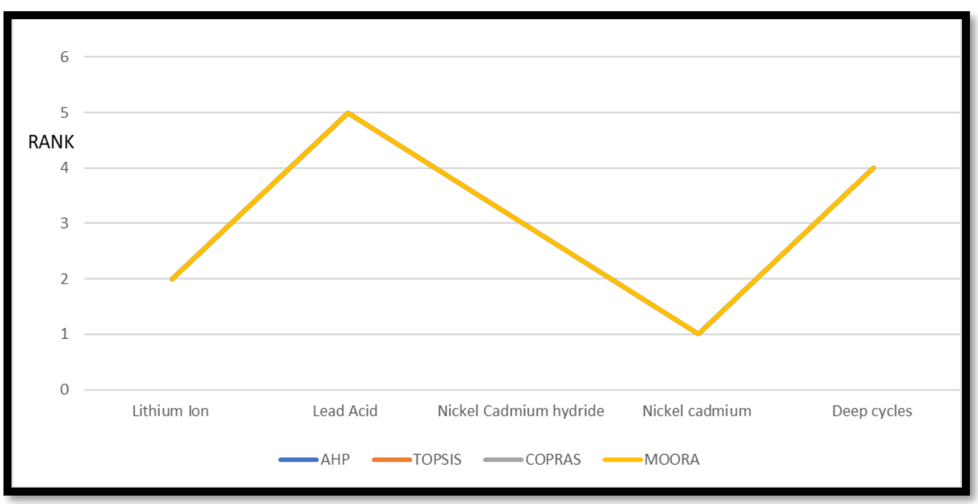

Fig.1 Comparison chart.

7 Conclusion

The aim of electric vehicle battery selection is to clarify and illustrate the process of multi-attribute decision-making. All battery alternatives are considered for evaluation, recognising that identifying the most suitable battery type for electric vehicles can represent a complex task due to the presence of multiple, and often conflicting, selection criteria. The present work proposes a structured and logically grounded methodological framework to support sound judgement in the selection of EV batteries. The adopted methodology is intended to assist decision-makers in reaching informed decisions in a systematic and scientific manner by considering both quantitative and qualitative selection criteria.

The four selected decision-making methods, namely AHP, TOPSIS, MOORA, and COPRAS, are applied to address the proposed selection problem. These methods are similarity-based and are utilised to support the evaluation and ranking of battery alternatives within the defined decision framework.

Although the present analysis focuses on these four MADM techniques, the problem may also be examined using alternative decision-making methods to enhance robustness and reliability. In addition, the selected methods may be extended to other engineering and management decision-making contexts.

Based on the application of the adopted methods, the results suggest that the nickel–cadmium battery emerges as the most suitable option for electric vehicle applications among the evaluated alternatives.

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