# Fuzzy Decision Support System for Battery Selection of Electric Vehicles

Gül Aysu ÇAKIR
*Gazi University*
*Faculty of Technology*
*Department of Electrical & Electronics Engineering*
Ankara, TÜRKİYE
0009-0004-6959-5396

Cansu HATUN
*Gazi University*
*Faculty of Technology*
*Department of Electrical & Electronics Engineering*
Ankara, TÜRKİYE
0009-0001-5911-9351

Meral ÖZARSLAN YATAK
*Gazi University*
*Faculty of Technology*
*Department of Electrical & Electronics Engineering*
Ankara, TÜRKİYE
0000-0002-1091-1647

2026 5th International Informatics and Software Engineering Conference (IISEC) | 979-8-3315-8031-5/26/$31.00 ©2026 IEEE | DOI: 10.1109/IISEC69317.2026.11418488

***Abstract*—Electric vehicles, one of the leading players in today's transportation sector, are environmentally friendly and energy efficient. The most critical factor enabling electric vehicles to offer these advantages is the battery system. Evaluating numerous criteria in battery selection, such as energy density, cycle life, cost, safety, and environmental impact, requires the use of multi-criteria decision-making (MCDM) approaches. In this study, the Fuzzy Analytic Hierarchy Process (AHP)–Multi-Objective Optimisation by Ratio Analysis (MOORA) and Fuzzy Step-wise Weight Assessment Ratio Analysis (SWARA)–Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) methods were used as a hybrid approach to compare the most suitable battery selection in electric vehicles. The Fuzzy AHP method was used to weight the criteria, and then the battery selection was evaluated using the Fuzzy MOORA method. The same decision problem was evaluated using the Fuzzy SWARA-TOPSIS method, and the model results were compared. In both models, the NMC (Lithium Nickel Manganese Cobalt Oxide) battery was determined to be the alternative closest to the ideal solution. The Consistency Ratio (CR) values obtained in the analyses confirmed the reliability of the criterion weights, while the Coincidence Coefficient (CC) values indicated that the TOPSIS results provided a stable ranking. This study demonstrated that the use of fuzzy logic-supported MCDM methods in engineering decisions involving uncertainty significantly increases consistency in the decision-making process. Furthermore, it is anticipated that the proposed integrated method can be applied to new-generation energy systems, such as the analysis of battery technologies.**

***Keywords—battery selection, multi-criteria decision making, fuzzy AHP–MOORA, fuzzy SWARA–TOPSIS.***

## I. INTRODUCTION

The need for cleaner and more sustainable energy in the transportation sector has brought electric vehicles (EVs) to the forefront as an alternative to internal combustion engines. Battery technology is one of the most crucial components that affect the efficiency and performance of EVs. By 2025, the global electric vehicle battery market is expected to reach approximately $100 billion in size and to record a compound annual growth rate of 15-20% over recent years [1].

The battery system is the factor that most significantly influences EV performance. A vehicle's range, acceleration, charging time, and overall energy efficiency are determined by the battery's characteristics. Therefore, selecting the appropriate battery for electric vehicles is an important decision from both an engineering and economic perspective.

Battery systems are highly effective and important for capacity, energy, power density, and thermal management. In terms of safety and service life, the thermal management system is crucial. Advanced cooling systems should be used to ensure that vehicles operate smoothly under high thermal loads. Research on this topic indicates that liquid-based or hybrid cooling methods should be preferred for electric vehicles [2]. With all these results in mind, battery selection is both an engineering-based optimization problem and a multi-criteria, multidisciplinary decision-making process.

Multi-Criteria Decision Making (MCDM) approaches offer holistic solutions that consider both quantitative and qualitative data in uncertain situations by evaluating different criteria simultaneously, thereby enabling the selection of the most ideal option.

The Analytic Hierarchy Process (AHP), developed by Saaty (1987), is an MCDM method that enables the hierarchical ranking of decision problems to determine the relative importance of criteria [3]. However, the Multi-Objective Optimisation by Ratio Analysis (MOORA) decision-making model balances utility and cost by using normalized decision matrices. It offers high applicability and statistical consistency in decision-making processes [4]. The Stepwise Weighted Assessment Ratio Analysis (SWARA) method compares decision-makers' criteria, assigns weightings to their importance levels, and enables their evaluation in a ranked manner. This approach enables a more flexible assessment of the importance levels of criteria in energy systems [5]. The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method ranks alternatives based on the distances of each alternative from the positive and negative ideal solutions. This approach is particularly favored in multi-criteria problems such as battery performance analysis, energy density, cost, and environmental impacts [6].

Incorporating Fuzzy Logic (FL) into these traditional MCDM techniques enables the consistent representation of uncertainties in real-world decision-making. FL is an approach that makes classical logic's definitive ‘true’ and ‘false’ judgments more flexible, enabling human judgment to be incorporated into decision-making processes [7]. Since problems encountered in daily life are not usually defined by clear boundaries, FL is used to model situations that are “partially correct” or “appropriate to a certain degree.” This feature enables a more realistic assessment of expert opinions and uncertain data in multi-criteria decision-making methods.

979-8-3315-8031-5/26/$31.00 ©2026 IEEE

Authorized licensed use limited to: ULAKBIM UASL - GAZI UNIVERSITESI. Downloaded on April 17,2026 at 13:02:32 UTC from IEEE Xplore. Restrictions apply.

Ankar and Pinkymol developed an integrated optimization framework for hybrid energy storage systems for electric vehicles. They combined NSGA-III sizing with an FL-based energy management plan. The results showed significant improvements in battery life, system weight, and life cycle costs compared to independent high-power battery systems, and demonstrated the effect of FL-supported instantaneous power sharing in HESS (Hybrid Energy Storage System) structures [8].

Lithium-ion batteries are widely used in electric vehicles due to their many advantages; however, critical issues such as safety, cost, and durability arise in high-capacity batteries. This situation highlights the importance of battery management systems (BMS) with functions such as balancing and fault diagnosis. Lu et al. [9] clarified various criteria for battery technology selection by examining technical constraints and the BMS's function in detail, and established a structure that highlights multi-criteria decision-making approaches. Ren et al. [10] determined that the combination of attribute determination processes based on sensitivity with MCDM methods effectively defined the important criteria in electric vehicle selection and highlighted the importance of systematic multi-criteria approaches for evaluating electric vehicle technologies. Wang et al. [11] developed a fuzzy-rough MCDM method encompassing the SWARA and MARCOS methods for electric vehicles in urban logistics and found that price and range are the most important criteria in expert evaluations. As a result of the research, they emphasized the importance of using the fuzzy MCDM method to analyze electric vehicle options and make environmentally sensitive decisions. Loganathan et al. demonstrated the accuracy of the fuzzy MCDM method by evaluating Li-ion, NiMH, and Pb-acid batteries, considering criteria such as cost, environmental impact, and energy density [12].

In the first part of this work, the fuzzy AHP and MOORA methods were employed to select batteries for electric vehicles. First, the criteria weights were obtained using the Fuzzy AHP method. These weights were integrated into the Fuzzy MOORA method and assessed against the energy density, charging time, cycle life, environmental impact, safety, cost, and weight criteria for seven battery alternatives ($LiCoO_2$, $LiMn_2O_4$, $LiFePO_4$, NMC, LTO, NCA, LMO). In the second part, the hybrid Fuzzy SWARA and TOPSIS method was used to select the battery. The fuzzy SWARA method utilized linguistic data from decision mechanisms to determine the relative importance of criteria, while the Fuzzy TOPSIS method ranked alternatives based on their proximity to the ideal solution. These two methods were used in conjunction to reduce uncertainties when selecting batteries for electric vehicles. These models have created hybrid systems that make complex decision-making processes more stable and easier to manage.

This study contributes to a comprehensive analysis of batteries in electric vehicles by employing two hybrid fuzzy MCDM methods in conjunction, evaluating environmental, technical, and economic criteria, and incorporating verbal and uncertainty-laden expert evaluations.

## II. BATTERY SELECTION FOR ELECTRIC VEHICLES

The battery selection stage in EVs encompasses several key criteria, including cost analysis, performance optimization, sustainability, and safety considerations. At the same time, these assessments include uncertainty such as 'high reliability', 'medium energy density', or 'low cost', and are often based on linguistic phrases. For this reason, the decision-making process is handled using FL-based methods.

The choice of battery technology plays a decisive role in factors such as cost, charging time, safety, range, and vehicle performance. Accordingly, Table I presents a comparison of the technical characteristics of seven different types of batteries based on research in the academic literature [13, 14]. These technical characteristics of NMC and NCA batteries include higher specific energy and higher energy density, while LTO and $LiFePO_4$ (LFP) batteries offer longer cycle life. LTO stands out for its low-voltage rating and superior cycle life, while LMO and LCO batteries offer a more stable structure. Table II presents the decision criteria, labels, and features used in this study [15].

## III. BATTERY SELECTION WITH FUZZY AHP-FUZZY MOORA HYBRID APPROACH

FL is a versatile tool widely used across many disciplines. MCDM and FL have gained increased importance due to their sensitivity to uncertainties in multifaceted decision-making problems. The rapid development of energy storage systems and EV technologies has presented both technical and strategic challenges for decision-making in this field.

TABLE I. TECHNICAL COMPARISON OF BATTERY TYPES

| Features | $LiCoO_2$ (LCO) | $LiMn_2O_4$ (LMO) | $LiFePO_4$ (LFP) | NMC | LTO | NMC | LTO |
|---|---|---|---|---|---|---|---|
| **Specific Energy (Wh/kg)** | 175 | 125 | 130 | 180 | 90 | 220 | 110 |
| **Energy Density (Wh/l)** | 500 | 400 | 300 | 600 | 200 | 650 | 380 |
| **Electrical Efficiency (%)** | 88 | 92 | 93 | 94 | 95 | 92 | 91 |
| **Self-Discharge Rate (%/month)** | 4 | 3 | 2 | 3 | 1 | 3 | 2 |
| **Nominal Voltage (V)** | 3.7 | 4.0 | 3.2 | 3.6 | 2.4 | 3.6 | 3.9 |
| **Energy per Cycle (Wh)** | 8.6 | 7.5 | 7.0 | 8.0 | 6.0 | 8.5 | 7.2 |
| **Cycle Life (cycles)** | 800 | 1000 | 4000 | 1500 | 7000 | 1200 | 1200 |

TABLE II. DECISION CRITERIA FOR THE BATTERY SELECTION

| Label | Decision Criteria | Property |
|---|---|---|
| C1 | Energy Density | Determines range and affects capacity |
| C2 | Cycle Life | Defines lifespan and impacts cost. |
| C3 | Charging Time | Influences usability and operation. |
| C4 | Safety | Indicates durability and ensures safety. |
| C5 | Cost | Determines affordability and adoption. |
| C6 | Environmental Impact | Represents ecological burden. |
| C7 | Weight | Affects consumption and performance. |

Authorized licensed use limited to: ULAKBIM UASL - GAZI UNIVERSITESI. Downloaded on January 17,2026 at 13:02:32 UTC from IEEE Xplore. Restrictions apply.

### A. Weighting of Decision Criteria with the Fuzzy AHP

In this study, the Fuzzy AHP and Fuzzy MOORA methods were integrated to determine the most suitable battery type for EVs. In the first step, the criteria weights were calculated using the Fuzzy AHP method. In the second step, these weights were examined using the Fuzzy MOORA method.

Fuzzy AHP is an MCDM method developed to better represent the decision maker's uncertain judgments by assigning weights to them. In particular, it ensures realistic results in decision-making problems that require intensive qualitative assessment. While binary comparisons are made using clear numbers in the classical AHP method, the Fuzzy AHP method expresses these evaluations using fuzzy triangular numbers (FTN) with $(l, m, u)$ format. Here, $l$ represents the lowest value, $m$ the most probable value, and $u$ the highest value. The membership function of this number is defined as follows:

$$\mu_{\tilde{A}}(x) = \begin{cases} x - l/m - l\,, & if\ l \le x \le m \\ u - x/u - m, & if\ m < x \le u \\ 0, & otherwise \end{cases} \quad (1)$$

In this study, the Chang's Expansion Analysis Method was applied to determine the criterion weights in the fuzzy AHP. The steps are given below:

Step 1: Pairwise comparisons are performed for each criterion pair, and the obtained values are expressed in TFN format.

Step 2: Fuzzy expansion values are calculated for each criterion: $S_i = \widetilde{M}_i \times \left(\sum_{j=1}^{n} \widetilde{M}_j\right)^{-1}$

Step 3: The comparison probability between two fuzzy numbers is calculated:

$$V(M_1 \ge M_2) = sup_{x \ge y}[\min\left(\mu_{M_1}(x), \mu_{M_2}(y)\right)] \quad (2)$$

Step 4: The relative superiority of each criterion is determined to obtain the weight vector: $d'(X_i) = minV\left(S_i \ge S_j\right),\ i \ne j$

Step 5: The final criterion weights are calculated by normalizing: $W = (d'(X_1), d'(X_2), \dots, d'(X_n))^T$

Based on a literature review of the seven criteria used in battery selection, a pairwise comparison matrix was created using TFN, and the example matrix is as follows:

$$[C1 \quad vs \quad C2] = (3,5,7)$$

$$[C1 \quad vs \quad C3] = (2,3,4) \quad (3)$$

Synthetic values ($S$) were calculated for each criterion using Chang's method. The minimum process was applied for each $S$, and the minimum values ($d$) were determined. The $d$ values found for all criteria were normalized to a total of 1, and the weight vector was obtained. The normalized criterion weights are as follows: The $d$ values found for all criteria were normalized to a total of 1, and the weight vector was obtained. The normalized criterion weights are as follows:

$$W = \begin{bmatrix} 0.22\ (C1), 0.18\ (C2), 0.14\ (C3), 0.12\ (C4), \\ 0.11\ (C5), 0.13\ (C6), 0.10\ (C7) \end{bmatrix} \quad (4)$$

### B. Fuzzy MOORA

The MOORA method is an effective MCDM approach that enables the evaluation of alternatives based on benefit and cost criteria. The fuzzy nature of this method increases the proximity of the decision to the ideal, while accounting for the decision maker's ambiguous verbal statements. In this study, the criteria weights obtained via the Fuzzy AHP were applied to the Fuzzy MOORA method, and the battery types were ranked according to the defined performance criteria to determine the most suitable battery option. The decision matrix displays the values each alternative possesses in relation to the specified criteria.

The criterion weights obtained from the Fuzzy AHP method are shown in Table III.

TABLE III. CRITERION WEIGHTS (BASED ON FUZZY AHP RESULTS)

| Criterion | Weight (w) |
|---|---|
| C1 – Energy Density | 0.2948 |
| C2 – Cycle Life | 0.1990 |
| C3 – Charging Time | 0.1354 |
| C4 – Safety | 0.1021 |
| C5 – Cost | 0.0861 |
| C6 – Environmental Impact | 0.1093 |
| C7 – Weight | 0.0733 |

In the fuzzy MOORA method, the TFNs in the decision matrix are first converted to crisp values. After this conversion, the evaluation value of each alternative for each criterion is normalized as in the classical MOORA method. The normalization process is as follows:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{ij}^{m} x_{ij}^2}} \quad (5)$$

where $x_{ij}$: is the crisp value of criterion $j$ for alternative $i$ and $r_{ij}$ is the normalized decision matrix value. The normalized matrix obtained from this process is ready for the application of criterion weights. Table IV shows the normalized values for alternative battery types.

TABLE IV. NORMALISED VALUES OF ALTERNATIVE BATTERY TYPES

| Alterntive | C1 | C2 | C3 | C4 | C5 | C6 | C7 |
|---|---|---|---|---|---|---|---|
| $LiCoO_2$ | 0.1400 | 0.0632 | 0.018 | 0.032 | 0.067 | 0.0258 | 0.0232 |
| $LiMn_2O_4$ | 0.0934 | 0.0722 | 0.057 | 0.047 | 0.035 | 0.0429 | 0.0325 |
| $LiFePO_4$ | 0.0934 | 0.0812 | 0.079 | 0.021 | 0.035 | 0.0601 | 0.0325 |
| NMC | 0.1245 | 0.0812 | 0.027 | 0.047 | 0.035 | 0.0515 | 0.0232 |
| LTO | 0.0778 | 0.0812 | 0.027 | 0.021 | 0.091 | 0.0258 | 0.0186 |
| NCA | 0.1400 | 0.0812 | 0.018 | 0.080 | 0.035 | 0.0258 | 0.0325 |
| LMO | 0.0934 | 0.0632 | 0.057 | 0.047 | 0.035 | 0.0429 | 0.0279 |

The normalized decision matrix is multiplied by the criterion weights to obtain the weighted normalized matrix. This process reflects the contribution of each alternative to the criteria, taking into account the relative importance of each criterion. The weighted normalized values is calculated as follows:

$$v_{ij} = w_j . r_{ij} \quad (6)$$

where $v_{ij}$ is the weighted normalized value of criterion j of ith alternative and $w_j$ is the jth weight obtained for the criterion using Fuzzy AHP. Table V shows the weighted normalized decision matrix.

Authorized licensed use limited to: ULAKBIM UASL - GAZI UNIVERSITESI. Downloaded on February 17,2026 at 13:02:32 UTC from IEEE Xplore. Restrictions apply.

TABLE V. WEIGHTED NORMALIZED DECISION MATRIX

| Alterntive | C1 | C2 | C3 | C4 | C5 | C6 | C7 |
|---|---|---|---|---|---|---|---|
| $LiCoO_2$ | 0.0413 | 0.0126 | 0.0057 | 0.0024 | 0.0014 | 0.0028 | 0.0017 |
| $LiMn_2O_4$ | 0.0275 | 0.0144 | 0.0075 | 0.0035 | 0.0029 | 0.0047 | 0.0024 |
| $LiFePO_4$ | 0.0275 | 0.0161 | 0.0038 | 0.0053 | 0.0029 | 0.0066 | 0.0024 |
| NMC | 0.0367 | 0.0161 | 0.085 | 0.0035 | 0.0029 | 0.0056 | 0.0017 |
| LTO | 0.0229 | 0.0161 | 0.0085 | 0.0053 | 0.0034 | 0.0028 | 0.0014 |
| NCA | 0.0413 | 0.0161 | 0.0057 | 0.0032 | 0.0029 | 0.0028 | 0.0024 |
| LMO | 0.0275 | 0.0126 | 0.0075 | 0.0035 | 0.0029 | 0.0047 | 0.0021 |

The Fuzzy MOORA method evaluates alternatives by separating the criteria into benefit and cost groups, where higher values are preferred for benefit criteria and lower values are advantageous for cost criteria. For each alternative, the aggregated benefit and cost scores are computed, and their difference yields the net performance score used for ranking (Table VI). The net score is calculated as follows:

$$Net\ Score_i = \sum_{j \in Benefit} w_j \,.\, x_{ij} - \sum_{j \in Cost} w_j \,.\, x_{ij} \quad (7)$$

The consistency of the Fuzzy AHP-based weighting was verified by calculating the Consistency Ratio (CR) for the comparison matrix. The obtained CR value was below the critical threshold of 0.1, confirming the logical stability of the expert judgments and allowing proceeding with the MOORA analysis. Figure 1 shows the final results for the battery types.

TABLE VI. BATTERY RANKING BY BENEFIT-COST AND NET SCORE

| Alternative | Benefit Score | Cost Score | Net Score | Ranking |
|---|---|---|---|---|
| NMC | 0.2709 | 0.0560 | 0.2149 | 1 |
| NCA | 0.2599 | 0.0530 | 0.2069 | 2 |
| LTO | 0.2513 | 0.0525 | 0.1988 | 3 |
| $LiCoO_2$ | 0.2346 | 0.0560 | 0.1786 | 4 |
| $LiMn_2O_4$ | 0.2295 | 0.0722 | 0.1573 | 5 |
| LMO | 0.2248 | 0.0700 | 0.1548 | 6 |
| $LiFePO_4$ | 0.2222 | 0.0728 | 0.1494 | 7 |

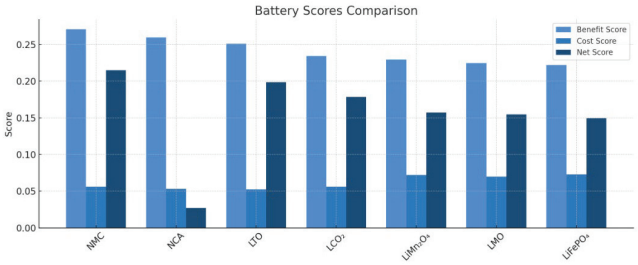



Figure 1. Comparison of benefits, costs, and net scores by battery type

## IV. BATTERY SELECTION WITH FUZZY SWARA-FUZZY TOPSIS HYBRID APPROACH

### A. Weighting of Decision Criteria with the Fuzzy SWARA

The integration of the SWARA method with FL significantly enhances SWARA's flexibility and applicability in decision-making environments with uncertainty. In the SWARA method, decision-makers rank the criteria according to their importance levels [15]. The SWARA method begins by determining the direction of each criterion. While positive high values are preferred for benefit criteria (+1 for Energy Density, Cycle Life, Charging Time, Safety), negative values are preferred for cost criteria (-1 for Cost, Environmental Impact, Weight). In this method, experts verbally indicate the relative importance of the criteria to one another (e.g., "very important," "moderately important"). These statements are then converted into triangular fuzzy numbers, enabling mathematical calculations. The linguistic terms and TFN equivalent are shown in Table VII. This conversion table enables decision-makers to make intuitive assessments and convert them into a mathematical model. The Energy Density criterion has been taken as the reference criterion, and no *"s"* coefficient has been assigned to it. All other criteria have been evaluated relative to the previous criterion, and the evaluation has been conducted using qualitative statements. These qualitative statements are converted into TFN values, which form the basis for subsequent calculations. Thanks to this structure, the degrees of importance that decision-makers cannot express clearly but know intuitively can be modelled numerically, establishing a more realistic weighting structure. Figure 2 illustrates the weight coefficients for an example battery, specifically an NMC battery.

TABLE VII. DETERMINATION OF THE COEFFICIENT *"S"*

| Criterion | Priority Rank | Linguistic Assessment | TFN (s_j) |
|---|---|---|---|
| Energy Density | 1 | - (reference criterion) | – |
| Cycle Life | 2 | Important | (0.5, 0.7, 0.9) |
| Charging Rate | 3 | Moderately Important | (0.3, 0.5, 0.7) |
| Safety | 4 | Slightly Important | (0.1, 0.3, 0.5) |
| Cost | 5 | Slightly Important | (0.1, 0.3, 0.5) |
| Env.Impact | 6 | Very Slightly Important | (0.0, 0.1, 0.3) |
| Weight | 7 | Slightly Important | (0.1, 0.3, 0.5) |

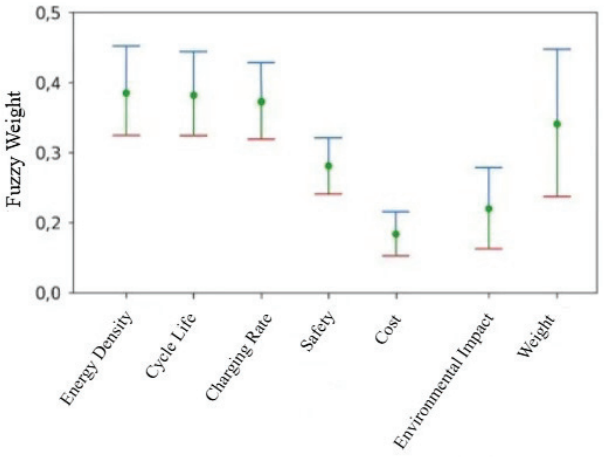



**Figure 2**. Criterion weights with TFN values (NMC battery)

In the Fuzzy SWARA method, the $k$ coefficient is determined after the $s$ coefficient is calculated for each criterion. This coefficient represents the relative importance compared to the previous criterion and is calculated as:

$$\tilde{k}_j = \check{s}_j + (1,1,1) \quad (8)$$

where $\check{s}_j$ is a triangular fuzzy number indicating the relative importance of the j[th] criterion compared to the previous criterion.

The $q$ coefficient represents the cumulative effect of each criterion's weight ratio. This process ensures that the worst-case-to-best-case relationship is evaluated.

$$\tilde{q}_1 = (1,1,1)\ ; \quad \check{q}_j = \frac{\check{q}_{j-1}}{\check{k}_j} \quad (9)$$

The weight of each criterion is normalized by dividing it by the sum of the $\check{q}_j$ values and calculated as

$$\sum \check{q}_j = (L, M, U) \quad (10)$$

Authorized licensed use limited to: ULAKBIM UASL - GAZI UNIVERSITESI. Downloaded on January 17,2026 at 13:02:32 UTC from IEEE Xplore. Restrictions apply.

$$\widetilde{w_j} = \frac{q_j}{\sum \widetilde{q_j}} \tag{11}$$

In this way, the relative importance of all criteria is represented by fuzzy numbers. To obtain crisp values from the fuzzy weights for the subsequent TOPSIS analysis, the Center of Area (CoA) method was applied. Table VIII shows the SWARA weight calculations using these coefficients. The resulting net weights indicate that Energy Density (30.9%) and Cycle Life (18.7%) are the primary drivers in the decision-making process.

TABLE VIII. SWARA RESULTS TABLE

| Criterion | Direction | *s* Coef (TFN) | *k* Coefficient (TFN) | *q* Coefficient (TFN) | Normalized Weight (TFN) | Net Weight ($w_j$) |
|---|---|---|---|---|---|---|
| Energy Density | +1 | – | (1.0, 1.0, 1.0) | (1.000, 1.000, 1.000) | (0.226, 0.310, 0.392) | 0.309 |
| Cycle Life | +1 | (0.5, 0.7, 0.9) | (1.5, 1.7, 1.9) | (0.526, 0.588, 0.667) | (0.119, 0.182, 0.261) | 0.187 |
| Charging Rate | +1 | (0.3, 0.5, 0.7) | (1.3, 1.5, 1.7) | (0.309, 0.392, 0.513) | (0.070, 0.121, 0.201) | 0.131 |
| Safety | +1 | (0.1, 0.3, 0.5) | (1.1, 1.3, 1.5) | (0.206, 0.302, 0.466) | (0.047, 0.094, 0.183) | 0.108 |
| Cost | –1 | (0.1, 0.3, 0.5) | (1.1, 1.3, 1.5) | (0.137, 0.232, 0.424) | (0.031, 0.072, 0.166) | 0.090 |
| Environmental Impact | –1 | (0.0, 0.1, 0.3) | (1.0, 1.1, 1.3) | (0.124, 0.211, 0.424) | (0.028, 0.065, 0.166) | 0.086 |
| Weight | –1 | (0.1, 0.3, 0.5) | (1.1, 1.3, 1.5) | (0.082, 0.162, 0.386) | (0.019, 0.050, 0.151) | 0.073 |

*B. Fuzzy TOPSIS*

The Fuzzy TOPSIS method is a powerful analytical tool that ranks alternatives based on their relative proximity to the ideal solution in MCDM problems. In this method, evaluations of criteria are expressed using fuzzy numbers, thereby directly incorporating uncertainties in the decision environment into the modelling. The performance of each alternative according to each criterion is defined using triangular fuzzy numbers; then, using fuzzy distance measures, the distances to the positive-ideal and negative-ideal solutions are calculated. This process enables the analysis of alternatives based on their relative proximity coefficients.

Using the weights obtained by the SWARA method, a normalized and weighted decision matrix of alternatives is created as:

$$\begin{bmatrix} x_{11} & x_{12} \dots & x_{1n} \\ x_{21} & \ddots & \vdots \\ \vdots & & \\ x_{m1} & x_{m2} \dots & x_{mn} \end{bmatrix} \tag{12}$$

Each criterion is normalized according to its direction: The formula used for benefit criteria is as follows:

$$r_{ij} = \frac{x_{ij}}{\max(x_{ij})} \tag{13}$$

The formula used for cost criteria is as follows:

$$r_{ij} = \frac{\min(x_j)}{x_{ij}} \tag{14}$$

$$\begin{bmatrix} r_{11} & r_{12} \dots & r_{1n} \\ r_{21} & \ddots & \vdots \\ \vdots & & \\ r_{m1} & r_{m2} \dots & r_{mn} \end{bmatrix} \tag{15}$$

The normalized decision matrix is multiplied by the criterion weights $(w_j)$ to obtain the weighted normalized decision matrix $(v_{ij})$:

$$v_{ij} = w_j \,.\, r_{ij} = \begin{bmatrix} v_{11} & v_{12} \dots & v_{1n} \\ v_{21} & \ddots & \vdots \\ \vdots & & \\ v_{m1} & v_{m2} \dots & v_{mn} \end{bmatrix} \tag{16}$$

The Fuzzy Positive Ideal Solution (PIS) and Fuzzy Negative Ideal Solution (NIS) vectors are defined as the best and worst values for each criterion. The distances of the alternatives from these ideal solutions are calculated using the Euclidean distance. In the final step, the closeness coefficient ($CC_i$) is calculated for each alternative, and the alternatives are ranked according to this coefficient: The following formulas are used for each alternative:

$$D_i^+ = \sqrt{\sum_{j=1}^{n} (v_{ij} - FPIS_j)^2}$$

$$D_i^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - FNIS_j)^2}$$

$$CC_i = \frac{D_i^-}{D_i^+ + D_i^-} \tag{17}$$

This coefficient takes a value between 0 and 1. The closer the value is to 1, the better the alternative is.

The calculated distances to the fuzzy PIS and NIS, along with the resulting closeness coefficients ($CC_i$) for each battery alternative, are presented in Table IX. This table provides the numerical basis for the final ranking, where the primary metric for determining the proximity of each alternative to the ideal performance characteristics.

As seen in the results, the NMC battery achieves the highest $CC_i$ value, reinforcing its selection as the optimal solution across the weighted criteria.

A sensitivity analysis was conducted to address the inherent trade-offs between battery characteristics and to thoroughly validate the robustness of the proposed hybrid MCDM model. In this scenario, the weight of the 'Cycle Life' criterion was increased to 0.28 from 0.187, making it the most significant factor, while 'Energy Density' was set to 0.22 (its original value was 0.309). The results of this redistribution are summarized in Table X.

TABLE IX. BATTERY RANKING RESULTS FOR HYBRID APPROACH

| Alternative | $D_i^+$ | $D_i^-$ | $CC_i$ | Ranking |
|---|---|---|---|---|
| NMC | 0.0066252 | 0.05228 | 0.88753 | 1 |
| NCA | 0.0072911 | 0.049493 | 0.8716 | 2 |
| $LiFePO_4$ | 0.018892 | 0.03694 | 0.66163 | 3 |
| LTO | 0.024292 | 0.038195 | 0.61125 | 4 |
| $LiMn_2O_4$ | 0.039706 | 0.015709 | 0.28348 | 5 |
| LMO | 0.040789 | 0.014529 | 0.26264 | 6 |
| $LiCoO_2$ | 0.045541 | 0.010305 | 0.18452 | 7 |

Authorized licensed use limited to: ULAKBIM UASL - [illegible]. Downloaded on February 17,2026 at 13:02:32 UTC from IEEE Xplore. Restrictions apply.

TABLE X. SENSITIVITY ANALYSIS (CYCLE LIFE PRIORITIZED)

| Alternative | $D_i^+$ | $D_i^-$ | $CC_i$ | Ranking |
|---|---|---|---|---|
| NMC | 0.0058472 | 0.055042 | 0.90397 | 1 |
| NCA | 0.0069898 | 0.051989 | 0.88149 | 2 |
| LiFePO4 | 0.019304 | 0.038873 | 0.66818 | 3 |
| LTO | 0.024653 | 0.040695 | 0.62274 | 4 |
| LiMn2O4 | 0.041182 | 0.016592 | 0.28718 | 5 |
| LMO | 0.042342 | 0.015351 | 0.26608 | 6 |
| LiCoO2 | 0.047167 | 0.010936 | 0.18822 | 7 |

Despite the focus on longevity, the NMC battery's $CC_i$ value improved to 0.90397, maintaining its first-place position. This proves that the proposed model is robust and that NMC remains the most balanced choice even when longevity is prioritized.

## V. CONCLUSION

In this study, the Fuzzy AHP and Fuzzy SWARA methods were employed to determine the criteria weights, while the Fuzzy MOORA and Fuzzy TOPSIS methods were utilized to rank the batteries. This multi-structure is preferred because the determination of weights and the alternative battery evaluation stages occur as separate parts within the MCDM. Fuzzy AHP and Fuzzy SWARA methods are highly effective for making consistent decisions on problems involving ambiguous linguistic expressions, while Fuzzy MOORA and Fuzzy TOPSIS provide a very good tool for evaluating and sorting alternatives using blurred weight criteria. The use of fuzzy structures in both stages provides consistency in assessing the ambiguous linguistic expressions of expert opinions, thereby increasing the consistency and reliability of the results. The results of both models indicated that the NMC battery is the option closest to the ideal solution. When the weights obtained using the Fuzzy AHP-MOORA method were compared with those from the Fuzzy SWARA-TOPSIS model, they showed strong consistency. The CR value, which implies the consistency of the decisions made in the decision matrix, is specific to the AHP method. Comparisons with a CR value below 0.10 indicate consistent acceptance. The resulting CR was found to be within the acceptable limit (CR $< 0.10$), confirming that the criteria weights are reliable and the expert judgments are consistent with the objective requirements of battery selection. In the TOPSIS method, CC is calculated as the ratio of the distance of each alternative to the ideal solution ($D^+$) and the negative ideal solution ($D^-$). The CC value indicates how close each alternative is to the ideal solution and how far it is from it. It is used as a decision method when sorting alternatives.

To assess the stability and reliability of the battery selection results, a sensitivity analysis was performed. This analysis specifically examined the impact of varying criterion weights, focusing on the Cycle Life parameter. By strategically increasing Cycle Life's weight to 0.28—making it the most dominant factor—the model's response was monitored. The results indicated that the NMC battery consistently maintained its first-place ranking. This stability demonstrates that the proposed hybrid Fuzzy SWARA-TOPSIS and Fuzzy AHP-MOORA frameworks are not overly sensitive to minor fluctuations in subjective weighting. Furthermore, the convergence of results from two different hybrid methodologies confirms that NMC offers the most balanced performance-to-cost ratio, making it the most robust choice for EVs, regardless of whether the focus is on longevity or energy density.

In the future, it is recommended that this model be applied to next-generation energy storage systems, such as hybrid or solid-state batteries, and that it be examined by comparing it with different weighting methods. Furthermore, combining multi-criteria decision-making techniques with artificial intelligence-based optimization algorithms could help develop more comprehensive decision models for sustainable transport systems.

## REFERENCES


[1] *Electric Vehicle Battery Market (2025 - 2030)*. Size, Share & Trends Analysis Report By Battery Type (Lithium-Ion Battery, Lead-Acid Battery), By Propulsion Type (BEV, PHEV), By Vehicle Type (Two-Wheeler, Passenger Cars, Buses), By Region, And Segment Forecasts [cited 2025 27.11.2025]; Available from: https://www.grandviewresearch.com/industry-analysis/electric-vehicle-battery-market

[2] M. Y. Kaba, O. Kalkan, and A. Celen, "Elektrikli araçlarda kullanilan bataryalar ve termal yönetim sistemlerinin incelenmesi," Konya Journal of Engineering Sciences, vol. 9, no. 4, pp. 1119-1136, 2021.

[3] R. W. Saaty, "The analytic hierarchy process—what it is and how it is used". Mathematical modelling, vol. 9, no. 3-5, pp. 161-176, 1987.

[4] W. K. M Brauers, E. K. Zavadskas, F. Peldschus, Z. Turskis, "Multi-objective decision-making for road design," Transport, vol. 23, no. 3, pp. 183-193, 2008.

[5] S. H. Zolfani, and J. Saparauskas, "New application of SWARA method in prioritizing sustainability assessment indicators of energy system," Engineering economics, vol. 24, no. 5, pp. 408-414, 2013.

[6] C.-L. Hwang, and K. Yoon, "Multiple attribute decision making: methods and applications: a state-of-the-art survey,". 1981.

[7] L.A. Zadeh, "Fuzzy sets," Information and control, vol. 8, no. 3, pp. 338-353.1965.

[8] S. J. Ankar, and K.P. Pinkymol, "Optimal Sizing and Energy Management of Electric Vehicle Hybrid Energy Storage Systems With Multi-Objective Optimization Criterion," IEEE Transactions on Vehicular Technology, vol. 73, no. 8, pp. 11082-11096, 2024.

[9] L. Lu, X. Han, J. Li, J. Hua, M. Ouyang, "A review on the key issues for lithium-ion battery management in electric vehicles,". Journal of power sources, vol. 226: pp. 272-288, 2013.

[10] X. Ren, S. Sun, and R. Yuan, "A Study on Selection Strategies for Battery Electric Vehicles Based on Sentiments, Analysis, and the MCDM Model," Mathematical Problems in Engineering, Vol. 2021, pp. 1-23, 2021.

[11] N. Wang, Y. Xu, A. Puška, Ž. Stević, A. F. Alrasheedi, "Multi-Criteria Selection of Electric Delivery Vehicles Using Fuzzy–Rough Methods," Sustainability, vol. 15, no. 21, pp. 1554, 2023.

[12] M. Loganathan, B. Mishra, C. M. Tan, T. Kongsvik, RN Rai, "Multi-Criteria decision making (MCDM) for the selection of Li-Ion batteries used in electric vehicles (EVs)," Materials Today: Proceedings, vol. 41, pp. 1073-1077, 2021.

[13] G. Zubi, R. Dufo-López, M. Carvalho, G. Pasaoglu, "The lithium-ion battery: State of the art and future perspectives," Renewable and sustainable energy reviews, vol. 89: pp. 292-308, 2018.

[14] S.S. Zhang, "A review on the separators of liquid electrolyte Li-ion batteries," Journal of Power Sources, vol. 164, no. 1, pp.351-364, 2007.

[15] M. Hamurcu, E. Çakır, and T. Eren, "Kullanıcı perspektifli çok kriterli karar verme ile elektrikli araçlarda batarya seçimi," International Journal of Engineering Research and Development, vol. 13, no. 2, pp. 733-749, 2021.


Authorized licensed use limited to: ULAKBIM UASL - [illegible] Downloaded on February 17,2026 at 13:02:32 UTC from IEEE Xplore. Restrictions apply.