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Application of MCDM Techniques for Selection of Battery for Electric Vehicle

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Abstract

An electric vehicle (EV) operates using an electric motor, which differs from traditional vehicles powered by internal combustion enginesElectric motors are used to power EVs rather than gasoline and gasses. These motors are powered by fuel cells, solar panels, or battery packs that recharge. As a result, EVs are increasingly considered as potential replacements for conventional automobiles, aiming to combat issues such as pollution, global warming, and resource depletion. Electric cars are essentially the way of his future for transportation. In order to speed up battery selection, this work presents an integrated approach to multi-criteria decision-making (MCDM) which incorporates the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) ranking technique with the Probabilistic weight method. By employing the TOPSIS framework and Entropy Weight Method (EWM), we can assess various battery options based on their relevance to specific EV requirements. Both methodologies offer valuable insights into identifying the optimal battery technology for electric vehicles, considering a range of factors.

Keywords: Electric vehicle, Battery, MCDM, TOPSIS, EWM

INTRODUCTION

As society advances, the electric car industry is expanding rapidly in response to concerns about environmental pollution and escalating fuel pricesGovernments all throughout worldwide are encouraging the use of electric cars by providing subsidies to users and tax incentives to producers [1]. Choosing the right battery is an essential aspect of designing a car powered by electricity (EV).

Failure to match the battery pack with the drivetrain can lead to suboptimal performance, limited range, potential damage to drivetrain components, or battery malfunctions. Key considerations in battery selection include the required power, range, and physical size, as these factors dictate the design of the battery pack [2].

There is a growing demand for vehicles with extended range capabilities and fast charging capabilities, driving research into energy storage and charging systems. Automotive manufacturers must carefully choose the battery chemistry best suited for their vehicles. The popularity of electric vehicles has surged in recent years, leading to a decrease in the use of fossil-fuel vehicles and a corresponding increase in demand for electric alternatives. Consequently, every study conducted on electric vehicles holds significant importance [3].

The main elements of storage in electric cars are batteries, which store the chemical energy before converting it into electrical energy.

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Battery assemblies consisting of individual batteries are referred to as "battery packs" [4]. An evaluation was conducted to determine the energy storage system necessary for converting an internal combustion vehicle into an electric one. This evaluation aims to provide insights into the criteria for selecting the appropriate battery system for electric vehicles. Comparative discussions were held on various criteria, including price analysis, weight analysis, volume analysis, battery lifespan, and pros and cons [5].

Lithium Ion Battery Features

As the primary technology enabling energy storage systems and electric vehicles (EVs), lithium-ion batteries are at the very heart of the clean energy revolution. Graphite is used to make the anodes of the majority of lithium-ion batteries. Usually, the cathode's mineral makeup varies, resulting in discrepancies in battery chemistries. Lithium is usually included in the cathode material together with other minerals like iron, nickel, manganese, or cobalt. The battery's capacity, power, performance, cost, safety, and longevity are all influenced by its composition. Wider temperature operation range, quick charging, no memory effects, longer cycle life, and a lower rate of self-discharge are some benefits of batteries made from lithium ion.

Since carbon dioxide is used as the anode (negative electrode material) in most lithium-ion batteries and there can be appropriate material combinations for a variety of cathodes (positive electrode material), they are a suitable choice for applications in electric cars. Lithium-ion battery cathode materials fall into categories as follows:

Manganese Cobalt Oxide (NMC) Lithium Copper (A1): Large amounts of nickel are commonly found in NMC the cathodes which raises the energy density of the battery and enables EVs to go farther. Manganese and cobalt have been used to increase thermal stability and safety since a high nickel concentration might cause turbulence in the battery. A number of NMC combinations, such as NMC811 (80% nickel, 10% manganese, and 10% cobalt), NMC532, and NMC622, have achieved commercial viability.

Lithium Nickel Cobalt aluminum oxide (NCA) (A2): NCA packs have high specific power and energy density, two benefits of NMC that are based on nickel. For enhanced stability, NCA employs aluminum rather of manganese. But NCA cathodes are more costly, usually limited to high-performance EV vehicles, and comparatively less safe than other Li-ion methods.

Lithium Iron Phosphate (LFP) (A3): In comparison with nickel-based batteries, LFP batteries are less expensive to produce simply because they employ iron and phosphate rather than nickel and cobalt. They are more ideal for standard- or short-range EVs, though, since they deliver less specific energy. LFP may be used in energy storage systems since it is also regarded as one of the safest chemistries and has an extended lifetime.

Lithium Cobalt Oxide (LCO) (A4): Despite providing a high energy density, LCO batteries have a restricted specific power, a short lifetime, and poor thermal management. Because they can supply comparatively tiny quantities of power for extended periods of time, these batteries are a popular option for low-load applications like laptops and smartphones**.**

Lithium Manganese Oxide (LMO) (A5): LMO batteries, commonly referred to as manganese spinel batteries, provide improved safety along with quick charging and draining times. In EVs, LMO cathode material is frequently combined with NMC, allowing for longer driving ranges while the LMO component delivers a high current during speed.

Lithium Titanate (LTO)(A6): LTO batteries employ a special anode surface that includes lithium and titanium oxides, in contrast to the other chemistries mentioned above, where the cathode content makes a difference. The modest capacity and relatively high cost of these battery types restrict their widespread usage, despite their exceptional safety and performance in extremely hot and cold weather patterns.

LITERATURE SURVEY

Marzetti, S. et al. claim that increased awareness of the environment and the depletion of fossil fuels are the main causes of the interest in eco-friendly electric vehicles (EVs). In this study, six electric car batteries are evaluated using the TOPSIS technique with regards to of voltage, energy density, power density, temperature range, cycle life, and budget. According to the findings, Li-ion batteries perform the best [6]. According to research by M. Liaqat, Z. et al., EVs are becoming more and more popular since they are environmentally friendly, while traditional cars emit a lot of greenhouse gas emissions.

This study favors mixed sodium-nickel chloride batteries (SNCB) and super capacitors (SC) over lithium-ion batteries (LIB) and hydrogen fuel cells (HFC) as feasible EV storage options on account of their cost-effectiveness and technological advantages [7]. The fact that various battery types give the required energy for around ten years was taken into consideration while doing the techno-economic study of them. For comparison, seven distinct methods of battery storage were used: lead-acid, gel, Ni-Cd, Li-Ion, LiFePo4, LiPo, and Ni-MH. [8].

According to the investigated development trends of battery chemistry technologies, technologies related to batteries, and technologies that replace batteries. Evaluations were made about pre-lithium battery technologies, lithium-based technologies, and battery technologies beyond lithium [9]

MCDM is a mathematical process used to evaluate a set of alternatives regarding multiple criteria. Numerous disciplines, including engineering either operations research, management, and finance, might gain from this approach. Its frequent uses include construction [12], location selection [11], and vendor/supplier selection [10]. Furthermore, a number of established MCDM techniques have already been applied to identify the best production process and product.

This includes the compilation of a report on the materials selection of automobiles in full cycle against the background of green manufacturing [13] using various applications. These applications included PROMETHEE [14], gear materials selection [15], and turbine materials selection using PROMETHE-GAIA [16]. Polymer composite material was used for engineering applications through the AHP-MOORA method in [17], accompanied by the implementation of SAW, MOORA, TOPSIS, and VIKOR in [18]. Some of the technologies selected based on such methods were machined parts assembly [19] and sustainable disposal technology selection based on SBWM (stratified best-worst method) [20]. While an advanced manufacturing method emphasizes AHP and TOPSIS [22], other technologies are machining choice of parameters in milling epoxy granite composite with respect to simply AHP [21].

Pham and Nguyen [23] used adaptive fuzzy proportional integral sliding control for a two-tank interaction system.

METHODOLOGY

Entropy Weight Method (EWM)

One major weight model that has been thoroughly researched and used is the entropy weight method (EWM) [24]. This approach involves establishing m indicators and n samples for assessment, and recording the measured result of the indicator in the jth sample as xij.

Standardizing measurements is the initial step [25, 26]. The following formula is used to determine the standardized value of the ith index in the jth sample, which can be expressed as pij.

$$p_{ij} = \frac{x_{ij}}{\sum_{j=1}^{J} x_{ij}} \tag{1}$$

The entropy rating Ei of the ith index in the EWM has been defined as [27].

$$E_i = \frac{-\sum_{j=1}^{J} p_{ij} . \ln p_{ij}}{\ln n} \tag{2}$$

In the real assessment using the EWM, p_(ij).In order to make calculations easier, ln〖p_ij 〗 ie becomes zero when p_(ij)=0. The entropy value E_i falls between 0 and 1. More information may be obtained and the differentiation degree of index I goes with the size of E_iis. As a result, the index need to be given more weight. Consequently, the weight w_i estimation technique in the EWM is [24, 28].

$$w_i = \frac{1-E_i}{\sum_{i=1}^{m}(1-E_i)} \tag{3}$$

Technique for order preference by similarity to ideal solution (TOPSIS)

In order to solve multiple criteria decisions (MCDM) problems, Hwang and Yoon [29] developed the TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method. The approach is based on the idea that the alternative that is selected should have the shortest distance to the positive perfect answer (A*) and the longest distance from the negative ideal solution (A−). For example, whereas the negative ideal solution increases the cost and decreases the functionality, the positive ideal solution enhances the functionality and lowers the cost. The percentages of weight of the criterion and performance evaluations are provided as precise numbers during the TOPSIS action [30].

The TOPSIS approach has lately been the subject of a number of intriguing studies that have successfully applied it to a wide range of domains, such as rating the carrier choices, supplier selection, financial performance assessment site selection, firm evaluation, and tourism destination evaluation. The TOPSIS model's stages are as follows [31, 32]:

Step 1: The structure of the matrix

$$X = \begin{bmatrix} x_{12} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \tag{4}$$

Where xij is a crisp value indicating the performance rating of each alternative Ai about each criterion Cj.

***Step 2*:** Calculate the Normalized the matrix X by using the following formula:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{j=1}^{J} {x_{ij}}^2}} \tag{5}$$

Step 3: Construct the weighted normalized decision matrix by multiplying:

$$V_{ij} = w_{ij}.r_{ij} \tag{6}$$

***Step 4*:** Identify the positive ideal solution (A*) and negative ideal solution (A −)

$$A^* = \{(max\ v_{ij} |\ j\ \in J), (min\ v_{ij} \big| j\ \in J')\} \tag{7}$$

$$A^{-} = \{(min\ v_{ij} |\ j\ \in J), (max\ v_{ij} |j\ \in J')\} \tag{8}$$

Step 5: Calculate the separation measure

$$S_i^* = \sqrt{\sum_{j=1}^{n}(v_{ij} - v_j^*)^2} \tag{9}$$

$$S_i^- = \sqrt{\sum_{j=1}^{n}(v_{ij} - v_j^-)^2} \tag{10}$$

Step 6: Calculate the relative closeness to the ideal Solution

$$P_i^* = {S_i^-}\Big/{S_i^* + S_i^-}, 0 \le P_i^* \le 1 \tag{11}$$

Step 7: Calculate the total score and select the alternative closest to one.

ILLUSTRATIVE EXAMPLE

The goal of the presented Problems is to determine which battery is most suited for electric cars. There are six options (A1 to A6) and six selection criteria (C1 to C6). The six solutions are Lithium Iron Phosphate (LFP) (A3), Lithium Cobalt Oxide (LCO) (A4), Lithium Manganese Cobalt Oxide (LMO) (A5), Lithium Nickel Manganese Cobalt Oxide (NMC) (A1), Lithium Nickel Cobalt Metal Oxide (NCA) (A2), and Lithium Titanate (LTO) (A6).

The six criteria are Price/cost (C1), Specific energy (C2), Specific power (C3), Safety performance (C5), and Life span (C6) among which the cost of the battery is a non-beneficial attribute and other criteria are beneficial attributes, which is shown in Table 1.

Table 1. Initial data matrix.

	C1	**C2**	**C3**	**C4**	**C5**	**C6**
A1	5.000	4.000	4.000	4.000	4.000	4.000
A2	5.000	3.000	4.000	3.000	4.000	4.000
A3	3.000	4.000	5.000	5.000	4.000	5.000
A4	5.000	4.000	3.000	3.000	4.000	3.000
A5	4.000	4.000	4.000	4.000	3.000	3.000
A6	3.000	2.000	4.000	5.000	5.000	5.000

Calculation of the Entropy Weight

According to evaluation indexes which are the benefit indexes or the cost indexes, standardization of indexes is calculated by equations (1) ~ (3) and shown in Table 2.

Table 2. Weights of indexes

	C1	**C2**	**C3**	**C4**	**C5**	**C6**
A1	5.000	4.000	4.000	4.000	4.000	4.000
A2	5.000	3.000	4.000	3.000	4.000	4.000
A3	3.000	4.000	5.000	5.000	4.000	5.000
A4	5.000	4.000	3.000	3.000	4.000	3.000
A5	4.000	4.000	4.000	4.000	3.000	3.000
A6	3.000	2.000	4.000	5.000	5.000	5.000
SUM	25.000	21.000	24.000	24.000	24.000	24.000
Ej	0.987	0.985	0.994	0.988	0.994	0.988

Dj	0.013	0.015	0.006	0.012	0.006	0.012
Wj	0.211	0.233	0.093	0.185	0.093	0.185
Dj Total	0.063					
Sample Size	6					
K Factor	0.558					

Calculation of the TOPSIS Method

In this MCDM technique, we have used six criteria selected according to requirements. Also, we have used six alternatives that are currently presently available in the market. By the use of the decision matrix and putting it into equation (5), we will get the normalized matrix shown below in Table 3.

Table 3. Normalized matrix.

	C1	C2	C3	C4	C5	C6
A1	0.4789	0.3831	0.3831	0.3831	0.3831	0.3831
A2	0.4789	0.2873	0.3831	0.2873	0.3831	0.3831
A3	0.2873	0.3831	0.4789	0.4789	0.3831	0.4789
A4	0.4789	0.3831	0.2873	0.2873	0.3831	0.2873
A5	0.3831	0.3831	0.3831	0.3831	0.2873	0.2873
A6	0.2873	0.1916	0.3831	0.4789	0.4789	0.4789

Since all conditions are unequal and some of them compared to others are very important to the end user, they should provide a moderate weight which is calculated by the entropy weight method. Therefore, the weights of these methods are calculated and shown in Table 2, and these weights are multiplied by the correct column using equation (6), and shown in Table 4. Along with this, the best and worst values are also calculated.

Table 2. Weightage normalized matrix,

	C1	C2	C3	C4	C5	C6
A1	0.1013	0.0891	0.0355	0.0710	0.0355	0.0710
A2	0.1013	0.0668	0.0355	0.0533	0.0355	0.0710
A3	0.0608	0.0891	0.0444	0.0888	0.0355	0.0888
A4	0.1013	0.0891	0.0266	0.0533	0.0355	0.0533
A5	0.0810	0.0891	0.0355	0.0710	0.0266	0.0533
A6	0.0608	0.0445	0.0355	0.0888	0.0444	0.0888
V+	0.0608	0.0891	0.0444	0.0888	0.0444	0.0888
V-	0.1013	0.0445	0.0266	0.0533	0.0266	0.0533

Here equations (9) and (10) are in play to calculate the separation between the best and worst options and get an overall average of profitability by the method Table 5. For each associated case, the relative closeness of each location concerning the ideal solution is computed. The maximum value of relative closeness is the best.

Table 3. The relative closeness of each alternative & Ranking.

	Si+	Si-	Pi	Rank
A1	0.04928	0.05265	0.51656	4
A2	0.06221	0.03113	0.33349	6
A3	0.00888	0.08087	0.90110	1
A4	0.06749	0.04542	0.40228	5

A5	0.04878	0.05281	0.51981	3
A6	0.04542	0.06749	0.59772	2

RESULT

The application of the Algorithm for Order Preference by Similarity to Ideal Solution (TOPSIS) and Analytical Hierarchy Process (AHP) methodologies to assess how well and choose electric car batteries is the main topic of the present investigation.

An efficient framework for choosing the most appropriate battery for electric cars is offered by the TOPSIS approach in conjunction with the Entropy Weight approach (EWM). According to the findings, LFP (A3) is the ideal choice for normal or short-range EVs since it combines durability, affordability, and safety.With a relative closeness score of 0.90110, A3 (Lithium Iron Phosphate, or LFP) is placed first, meaning that, according to the factors taken into assessment, it is the best battery option. This is because of its extended lifespan, outstanding safety performance, and reasonably balanced power and cost capabilities.

CONCLUSION

Both AHP and TOPSIS methods effectively accounted for multiple criteria, offering a balanced assessment of each EV model's strengths and weaknesses. By combining these techniques, a thorough and impartial choice process was secured.

The consistency between the rankings obtained from AHP and TOPSIS highlights the reliability of these methods in multi-criteria decision-making scenarios. The alignment of results indicates that the selected criteria and their respective weights were appropriately chosen. Future studies could expand the criteria set and include additional factors such as user satisfaction, maintenance costs, and technological advancements. Continuous updates to the evaluation framework will ensure its relevance in the evolving landscape of electric mobility.However, results may vary if different criteria are used. As EV market is continuously evolving, new studies can be conducted using the modified parameters.

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