



Evaluating the Performance of Battery Electric Vehicles using an Incorporated Decision Support Framework Based on Ranking Algorithms

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Abstract

The use of alternative energy sources rather than fossil fuels will be unavoidable in the nearish term due to rising levels of toxic residues that threaten natural life and human health. Furthermore, the use of fossil fuels puts subsequent generations in danger from environmental damage and climate change. Battery electric vehicles (BEVs), an environmentally friendly kind of vehicle, are important in light of transportation's significant contribution to the carbon footprint. In light of the recent fast growth of the BEV industry, it has become more important to consider all available BEV options from the perspective of the end-user. Each BEV's fundamental characteristics may be examined in order to make this evaluation. For the correct BEV buying choice, MCDM strategies are useful. As a result, eleven battery-electric vehicles (BEVs) are considered in this study. A variety of multi-criteria methodologies are used to rate these cars on the basis of their technical specifications, such as acceleration, pricing, battery life, and range. It is then used entropy weight and TOPSIS approaches to gather findings from different MCDM strategies. The entropy method is used to compute the weights of the criteria. Then the TOPSIS is used to rank the options. The 3 key considerations for BEV choosing are "price," "permitted load," and "energy usage," with Tesla Model S emphasized as the preferred route.

Keywords: Battery electric vehicles; MCDM; TOPSIS; Entropy; decision support

1. Introduction

In the latest days, rising green laws, sustainability practices, health concerns, and concern for the environment have all contributed to the dislocation of gas-powered cars by environmentally friendly technologies [1]. Regrettably, the overwhelming bulk of vehicles today are powered by fossil fuels and emit harmful gases into the atmosphere [2].

According to Kumar and Alok [3] the transportation sector is the primary source of emissions and ozone depletion, which leads to climate change caused by greenhouse gas (GHG) emissions such as CO, CH₄, N₂O, and CO₂; this has necessitated road transport electrification. In light of the above and technological advancements in this century, combustible automobiles have started to give way to automobiles that use solar and wind to improve the environment.

As a result of non-renewable-based technology like combustion engines, the globe is now at risk of climate change and environmental disruption as never before[4]. During the next generation, sustainable construction has great promise as a means of achieving growth that is positive for the ecosystem, people, and the economy. It is the goal of sustainable growth to preserve the natural

environment while also safeguarding the political and economic well-being of the people[5]. There are several ecological, political, and social benefits to sustainable transportation from the social viewpoint[6]. Many wealthy nations throughout the globe have turned toward electric vehicles (EVs) in an effort to combat environmental damage and promote sustainable development [7]. Electric vehicles have been seen as a handy way to reduce harmful gas emissions [8]. As a result, the mainstream adoption of electric vehicles (EVs) will be critical in addressing the industry's technical and energy challenges [9]. Nevertheless, several writers pointed out that the environmental benefits of clean cars and the EU's zero-emission transit aim can only be achieved if the power is provided from green energies like solar and wind [10]. Electric vehicles (EVs) only released 38 million metric tonnes of CO₂ equivalence from well to wheel in 2018, according to the International Energy Agency (IEA). This is the equivalent of 78 million metric tonnes of CO₂ emissions from a traditional fleet of the same size. Electric vehicles are predicted to cut oil use by 4.3 million barrels each day around the year 2030 [11].

There have been significant improvements in the design and performance of electric vehicles (EVs) over the last several years, making them one of the greatest alternatives to conventional vehicles [2]. Electric vehicles (EVs) may be divided into three categories: battery electric automobile (BEV), hybrid electric automobile (HEV), and plug-in hybrid electric automobile (PHEV). Zero-emission automobiles (BEVs), often known as electric vehicles (EVs), are cars that operate only on electricity. Because BEVs don't use any fossil fuels [12], they're a more environmentally friendly option for transportation [13]. A green power culture may be achieved via the use of BEVs [14]. Both environmental concern and the hope that BEVs may minimize environmental dangers are linked to the increased use of electric vehicles, according to Chen et al. [15]. As a result, the most potent solution for ecologically responsible transit systems is the dissemination of BEVs [16].

Users have just lately begun to accept EVs [6], and as a result, the quantity of EVs and e - mobility have grown tremendously [17]. More than half a million electric vehicles (5.1 million) were registered last year, an increase of almost 200,000 over 2017. Despite this, even if the quantity of BEVs has increased, industry predictions show that the dissemination of BEVs has not yet developed. Electric car sales and inventory are expected to almost treble by 2030, with early sales of 43 million and current value, excluding 2 and 3, exceeding 250 million, according to the International Energy Agency (IEA). Electric cars are expected to account for 30% of all automobiles on the road by 2030. In order to evaluate the available BEVs and make an informed conclusion, a decision methodology is clearly required. This research specifically provides a multi-criteria methodology that is thorough, dependable, and intelligible. Furthermore, deciding on the finest BEV is a difficult task complicated by a slew of competing considerations, such as cost, range, speed, battery life, and more. In this regard, MCDM may be a robust and successful strategy.

Standards weights play a significant part in MCDM as they have a direct impact on the final findings. Quantitative or emotional criterion weights may be calculated, evidently. The experts' opinions and experiences are used to establish subjective weights.

It is also feasible to account for the normality of the model and calculate the real weights of evaluation criteria, i.e., the independent weights of criteria, using the evaluation system To put it another way, the objective weights reveal the underlying structure of the data [18]. In order to get even more relevant ratings, objective weighting techniques must be used [19].

The rest of the research is outlined. A literature review of applied methodologies is conducted in Section 2 of this paper to identify the research gaps and explore the research purpose. The methodology used in this article is described in depth in Section 3. BEV evaluation findings are discussed in detail in Section 4. Managerial implications are discussed in Section 5. Ends with a review of findings, and concludes research in section 6.

2. Related Work

Electric cars are becoming a significant alternative fuel source due to the widespread availability of energy and the effects of global warming and climate change. Many research has been conducted in the last decade to explore electric vehicle buying choices [20], [21] due to the tight relationship between electric car purchasing and consumer adoption. These investigations are aimed at identifying the most significant motivators and impediments to widespread consumer adoption of BEVs. Customers who want to acquire clean car technology are more interested in performance qualities, even if the literature disagrees on the exact mix of vehicle attributes that consumers look for in a

vehicle purchase. The unique features that set BEVs apart from other electric vehicles are their pricing, range, battery capacity, and speed of charge.

Up to this point, a wide range of models and frameworks have been used to evaluate next generations of automobiles, such life cycle assessment, quantitative tools[22], [23], and MCDM methods[24], [25], among others. It has become more popular to use the MCDM concept as a grouping of methodologies. As a result, MCDM approaches were also used in this study.

MCDM techniques have been frequently used in the evaluation of clean cars, according to the existing research. Tzeng et al. [26] established an MCDM foundation for electric, fuel cell, and methanol-powered transit buses that includes AHP, TOPSIS, and VIKOR methods. The battery vehicles bus was known to be the optimum option after a situation analysis was used to create an evaluation model. To compare and evaluate alternative fuels from the perspectives of cost, efficiency, and environmental impact, Brey et al. [27] advocated using a multi-criteria assessment process. Their investigation used data envelopment analysis (DEA), which they decided was the most efficient method. Mohamadabadi et al. [27] proposed a multi-criteria system for selecting the best appropriate vehicle for the transportation system using the order of preference by similarity organization technique for enhancement and evaluations (PROMETHEE). There were a variety of factors that were taken into consideration, including car pricing, distance to filling stations, gasoline costs, greenhouse gases, and the variety of automobile options accessible to the customer. Vahdani et al. [28] used fuzzy TOPSIS and fuzzy preference choice index (PSI) methodologies to assess different fuel-based buses while taking into account many criteria such as ability, cost, and energy usage. Ultimately, the combination automobile was identified as the most viable choice. Traditional diesel engines, compressed natural gas (CNG), and liquefied petroleum gas (LPG) were shown to be the best choices. An AHP technique for evaluating new-generation automobiles was proposed by Tsita and Pilavachi [[29] in Greece, which included several policies and cost variables. As a result, Greece has chosen the first and second biofuels.

Yavuz et al. [20] proposed a fuzzy MCDM technique for the evaluation of a homecare service company's renewable energy automobiles. Electric vehicles were found to be the best option in their research.

Lanjewar et al. [30] demonstrated how graph theory and AHP approaches may be used to rank fuel-efficient automobiles. Several economic and environmental factors were considered while evaluating cars powered by regular diesel, traditional diesel, compressed natural gas (CNG), ethanol (E85), and hydrogen (H₂) fuels. CNG and E100 were the first and second options, respectively.

While taking into consideration environmental and economic factors, Maimoun et al. [31] used two MCDM approaches, TOPSIS and simple additive weighting (SAW), to evaluate alternative vehicles in the U.S. refuse collection industry. When monitoring the performance of alternative fuel-based cars, Onat et al. [32] suggested an intuitive TOPSIS technique that took into consideration three sustainability pillars. They concluded that hybrid electric cars were the best choice. As an example, Sehatpour et al. [24] used Iran as a case study and evaluated many alternative vehicles with both petroleum and greener bases, taking into account technical and economic, and social variables as well as political aspects. Light-duty cars are best served by biogas, according to this rating. According to Ullah et al. [33], using AHP, they evaluated the appropriateness of alternate transportation options for Pakistan, including CNG and LPG as well as liquefied natural gas (LNG). CNG was found to be a better alternative after conducting a thorough investigation. An examination of fuels to evaluate different vehicle technologies by Liang and colleagues [34] has just been published. The four elements that must be present (financial, social, ecological, and technical) were evaluated for fossil fuels, LPG, and biofuel automobiles. An MCDM algorithm to rate alternative vehicles was created by the researchers. The biodiesel car was ranked first, while CNG and LPG had ranked secondly and third, correspondingly, in the rankings of fuel efficiency.

Few studies have addressed the performance evaluation of electric hybrid cars, including customer adoption variables, in literature. Biswas and Das [35] used the combination of the fuzzy AHP and MABAC to rate different electric cars, which is even more closely connected to the current research. We looked at peak speed and range as well as time to accelerate and cost, as well as overall fuel efficiency. This resulted in an overwhelming preference for Hyundai's Ioniq Electric Vehicle. Fuzzy TOPSIS was used in another work by Khan et al. [2] to solve the hybrid vehicle choice issue for Pakistan. Seven distinct hybrid electric cars were evaluated, taking into account a wide range of factors, including ownership costs, greenhouse gas emissions, fuel efficiency, and more. The Toyota Aqua was found to be the greatest car.

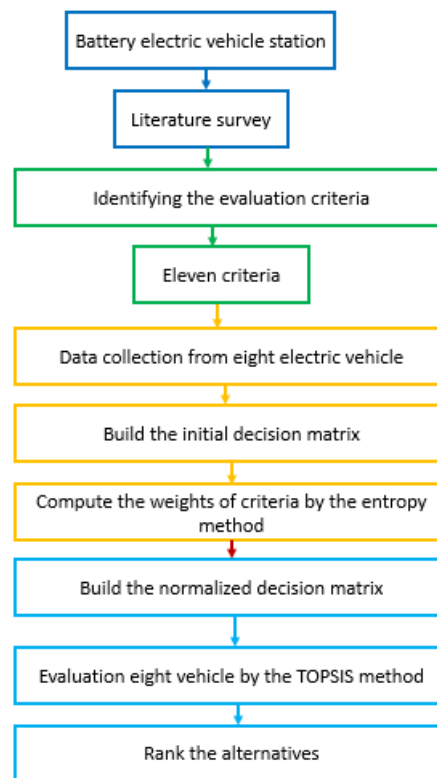


Figure 1. The decision-making process

3. Methodology

Figure 1 depicts the decision-making process. Using the TOPSIS technique, a preference/alternative must have the smallest deviation from the ideal satisfactory solution and the greatest geometric distance from the ideal bad result. The weights, normalization, geometric distance, and award recognition of each attribute are determined using this method. Since the variables or parameters in MCDM issues are usually of incompatible sizes, normalization is required. Trade-offs may be made between qualities using the TOPSIS approach, which provides compensating solutions. When one feature has a negative impact, the best outcome from another quality may make up for it.

The entropy weights approach is used to determine the criteria/attributes' goal weights. Imperfect information may be calculated using the principles of probability theory (Entropy). It does not take into account the decision-preferences maker's when determining the relevance of each answer parameter. It is generally accepted that higher weight index values are more useful than lower weight index values in the context of entropy-weighted measurements. An important part of this approach is going to decide on goals, which is done using a decision matrix, followed by computing a normalized decision model, entropy values for requirements and attributes (the average data embedded within every response), percentage points of deviation (the degree to which responses diverge), and entropy weight (the amount of information that every reaction contains).

For a decision-making issue, the full stages of the TOPSIS approach employing Entropy Weights may be carried out as follows:

The study's goals guide the development of potential alternatives and qualities. As shown in Equation (1), rows are given to options (Robotic) and every column to a single criteria (mechanics weight, reproducibility; payload; max range; and power usage). A number of options (n) and criteria (m) are inputs to the "DM" $i = 1, 2, \dots$, the number of options (n), and $j = 1, 2, \dots$, the amount of factors (m). According to this relation: $\sum_{j=1}^m w_j = 1$. . The weight of this criteria is w_j .

A. Entropy Method

Decision-making values dispersal may be measured using the entropy weights approach that Shannon and Weaver introduced in 1947. Imperfect information, such as entropy, may be calculated using this probability-based method. This approach is used to determine the real

weights of every factor since the relevance of every factor is reflected in its weight. A MCDM issue may be solved by using the entropy weights technique, which is as follows:

Step 1: Build the decision matrix between criteria and alternatives. Then aggregate the decision matrix.

$$DM = \begin{bmatrix} x_{11} & \cdots & x_{1m} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{mn} \end{bmatrix} \quad (1)$$

Step 2: Normalize the decision matrix as:

$$o_{ij} = \frac{x_{ij}}{\sum_{i=1}^n x_{ij}} \quad (2)$$

Where $j = 1, 2, 3 \dots m; i = 1, 2, 3 \dots n$

Step 2: Calculate the entropy

$$p_j = -\frac{1}{\log n} \sum_{i=1}^n o_{ij} \log(o_{ij}) \quad (3)$$

Where $j = 1, 2, 3 \dots m; i = 1, 2, 3 \dots n$

Where p_j refers to the amount of information included in the normalized decision matrix

Step 3: Compute the diversification degree as

$$d_j = 1 - p_j \quad (4)$$

Where $j = 1, 2, 3 \dots m$

Step 4: Compute the weights of the attributes as

$$w_j = \frac{d_j}{\sum_{j=1}^m d_j} \quad (5)$$

Where $j = 1, 2, 3 \dots m$

B. The TOPSIS Method

Step 5: Normalize the decision matrix by the TOPSIS method

$$Z_{ij} = \frac{x_{ij}}{\sum_{i=1}^n x_{ij}^2} \quad (6)$$

Where $j = 1, 2, 3 \dots m; i = 1, 2, 3 \dots n$

Step 6: Obtain the weighted normalized decision matrix as:

$$WZ_{ij} = [w_j \times Z_{ij}] \quad (7)$$

Step 7: By the beneficial criteria and non-beneficial criteria, the ideal best and worst are computed as:

$$B_j^+ = \{best(WZ_{ij})\}_{i=1}^n \quad (8)$$

$$B_j^+ = B_1^+, B_2^+, \dots, B_j^+ \dots B_m^+ \quad (9)$$

$$B_j^- = \{worst(WZ_{ij})\}_{i=1}^n \quad (10)$$

$$B_j^- = B_1^-, B_2^-, \dots, B_j^-, \dots, B_m^- \quad (11)$$

Where B_j^+ refers to beneficial criteria and B_j^- refers to non-beneficial criteria

Step 8: Compute the Euclidean distance to help the construct separation measurements

$$DIS_i^+ = \left\{ \sum_{j=1}^m (WZ_{ij} - B_j^+)^2 \right\}^{0.5} \quad (12)$$

$$DIS_i^- = \left\{ \sum_{j=1}^m (WZ_{ij} - B_j^-)^2 \right\}^{0.5} \quad (13)$$

Step 9: Compute the closeness of relatives as

$$CLO = \frac{DIS_i^-}{DIS_i^+ + DIS_i^-} \quad (14)$$

Step 10: Rank alternatives based on the highest value of CLO

4. MCDM Application and Results

An amalgamation of various MCDM methodologies into one may be significant in the suggested methodology's applicability for decision-making. Because the two MCDM approaches stated above were used, the findings were more accurate. First and foremost, thorough literature research is completed to identify the assessment criteria to properly pick BEV. These considerations include acceleration, rapid charge time, and battery capacity, as well as the cost of a vehicle and the weight of the vehicle's payload. A list of BEVs and their technical specifications are compiled in the second phase. In the third step, we construct a decision matrix, which contains the values of the options according to each assessment criteria in tables 1-3. We used three decision-makers. Next, weight coefficients are calculated using entropy. BEV options are examined and ranked according to each MCDM approach once the decision matrix is built (TOPSIS). The final ranks of alternatives are determined using entropy and the TOPSIS method. The criteria and alternatives are organized as:

Criteria	Vehicles
Quick charge time BEC1	Renault ZOE BEA1
Full charge time BEC2	Nissan Leaf e+ BEA2
Acceleration BEC3	Nissan Leaf e+ BEA3
Purchasing price BEC4	Chevrolet Bolt EV BEA4
Curb weight BEC5	KIA Soul EV BEA5
Energy consumption BEC6	BMW i3 BEA6
Battery capacity BEC7	Volkswagen e-Golf BEA7
Range BEC8	Hyundai Ioniq EV BEA8
Top speed BEC9	
Maximum power(performance) BEC10	
Permitted load (Hadith) BEC11	

The decision matrix for BEV choice, shown in table 3, was developed based on 11 acceptance variables (hereinafter termed criteria) gleaned from a thorough literature study and 8 BEV options examined in this work. Electric car manufacturers' websites were used to gather data for each BEV option. When it comes to weighting criteria and rating BEV choices.

Table 1. The opinions of the first expert

	B E C 1	B E C 2	B E C 3	B E C 4	B E C 5	B E C 6	B E C 7	B E C 8	B E C 9	B E C 10	B E C 11	B E C 11
B E A 1	6 8	5 0	3 8	6 8	6 8	8 3	5 0	6 8	5 0	5 0	6 8	6 8
B E A 2	8 3	8 3	6 8	5 0	6 8	8 3	3 8	6 8	6 8	5 0	8 3	8 3
B E A 3	6 8	3 8	8 3	6 8	5 0	8 3	3 8	8 3	6 8	6 8	8 3	6 8
B E A 4	3 8	6 8	8 3	3 8	6 8	6 8	1 6	8 3	8 3	8 3	8 3	3 8

B E A 5	6 8	8 3	3 8	6 8	3 8	6 8	6 8	6 8	8 3	8 3	6 8	6 8
B E A 6	8 3	6 8	3 8	3 8	3 8	5 0	3 8	3 8	6 8	6 8	3 8	8 3
B E A 7	8 3	8 3	1 6	6 8	8 3	6 8	1 6	8 3	3 8	8 3	1 6	8 3
B E A 8	8 3	3 8	6 8	3 8	8 3	3 8	6 8	6 8	6 8	3 8	3 8	8 3

Table 2. The opinions of experts by a second expert

	B E C 1	B E C 2	B E C 3	B E C 4	B E C 5	B E C 6	B E C 7	B E C 8	B E C 9	B E C 9	B E C 10	B E C 11
B E A 1	8 3	3 8	1 6	5 0	8 3	6 8	6 8	5 0	3 8	3 8	5 0	8 3
B E A 2	6 8	6 8	5 0	6 8	8 3	6 8	6 8	8 3	1 6	5 0	8 3	6 8
B E A 3	5 0	1 6	5 0	5 0	6 8	5 0	8 3	5 0	1 6	8 3	5 0	5 0
B E A 4	1 6	8 3	6 8	6 8	8 3	5 0	3 8	3 8	6 8	8 3	6 8	1 6
B E A 5	8 3	5 0	8 3	5 0	5 0	3 8	8 3	6 8	6 8	5 0	6 8	8 3
B E A 6	8 3	8 3	3 8	1 6	5 0	3 8	3 8	1 6	5 0	6 8	3 8	8 3

B E A 7	8 3	6 8	8 3	8 3	6 8	8 3	1 6	8 3	3 8	8 3	3 8	8 3
B E A 8	5 0	5 0	8 3	3 8	6 8	8 3	6 8	8 3	6 8	3 8	3 8	5 0

Table 3. The opinions of experts by second experts.

	B E C 1	B E C 2	B E C 3	B E C 4	B E C 5	B E C 6	B E C 7	B E C 8	B E C 9	B E C 9	B E C 10	B E C 11
B E A 1	5 0	5 0	3 8	8 3	5 0	1 6	8 3	6 8	5 0	1 6	6 8	5 0
B E A 2	8 3	8 3	3 8	8 3	6 8	3 8	8 3	6 8	3 8	5 0	6 8	8 3
B E A 3	3 8	6 8	1 6	5 0	6 8	6 8	6 8	3 8	3 8	8 3	3 8	3 8
B E A 4	3 8	8 3	8 3	3 8	6 8	8 3	5 0	1 6	5 0	6 8	1 6	3 8
B E A 5	8 3	5 0	6 8	1 6	5 0	3 8	6 8	1 6	6 8	3 8	1 6	8 3
B E A 6	5 0	5 0	1 6	1 6	8 3	5 0	5 0	1 6	5 0	8 3	5 0	5 0
B E A 7	8 3	6 8	6 8	6 8	6 8	6 8	5 0	3 8	6 8	6 8	3 8	8 3
B E A 8	5 0	3 8	8 3	3 8	6 8	5 0	6 8	8 3	8 3	3 8	5 0	5 0

Table 4. The combined opinions

	B E C 1	B E C 2	B E C 3	B E C 4	B E C 5	B E C 6	B E C 7	B E C 8	B E C 9	B E C 9	B E C 10	B E C 11
BEA ₁	6 7	4 6	3 0 . 6 6 6 6 7	6 7	6 7	5 5 . 6 6 6 6 7	6 7	6 2	4 6	3 4 . 6 6 6 6 7	6 2	6 7
BEA ₂	7 8	7 8	5 2	6 7	7 3	6 3	6 3	7 3	4 0 . 6 6 6 6 7	5 0	7 8	7 8
BEA ₃	5 2	4 0 . 6 6 6 6 7	4 9 . 6 6 6 6 7	5 6	6 2	6 7	6 3	5 7	4 0 . 6 6 6 6 7	7 8	5 7	5 2
BEA ₄	3 0 . 6 6 6 7	7 8	7 8	4 8	7 3	6 7	3 4 . 6 6 6 6 7	4 5 . 6 6 6 6 7	6 7	7 8	5 5 . 6 6 6 6 7	3 0 . 6 6 6 6 7
BEA ₅	7 8	6 1	6 3	4 4 . 6 6 6 6 7	4 6	4 8	7 3	5 0 . 6 6 6 6 7	7 3	5 7	5 0 . 6 6 6 6 7	7 8
BEA ₆	7 2	6 7	3 0 . 6 6 6 6 7	2 3 . 3 3 3 3 3	5 7	4 6	4 2	2 3 . 3 3 3 3 3	5 6	7 3	4 2	7 2
BEA ₇	8 3	7 3	5 5 . 6 6 6 6 7	7 3	7 3	7 3	2 7 . 3 3 3 3 3	6 8	4 8	7 8	3 0 . 6 6 6 6 7	8 3
BEA ₈	6 1	4 2	7 8	3 8	7 3	5 7	6 8	7 8	7 3	3 8	4 2	6 1

Based on criteria BEC₁, BEC₂, BEC₃..., and BEC₁₁, a ranking of BEVs (BEA₁, BEA₂, BEA₃..., BEA₈) is shown. BEC₁ through BEC₆ are cost factors (a lower value is better), whilst the rest criteria are benefit criteria (higher value is better). Eq. (2) is used to compute the normalized decision matrix by the entropy method in table 5. The amount of information is computed through entropy by Eq. (3).

Eq. (4) is used to compute the diversification value. Then the weights of the criteria are computed by using Eq. (5) in figure 2.

Table 5. The normalized matrix by entropy method

	B E C 1	B E C 2	B E C 3	B E C 4	B E C 5	B E C 6	B E C 7	B E C 8	B E C 9	B E C 9	B E C 10	B E C 11	
B E A 1	0 . 1 2 8 4 3 5	0 . 0 9 4 7 1 5	0 . 0 7 0 0 6 9	0 . 1 6 0 6 7 1	0 . 1 2 7 8 6 3	0 . 1 1 6 8 6 3	0 . 1 5 6 7 8 3	0 . 1 3 2 9 6 8	0 . 1 0 5 4 7 6	0 . 1 0 3 5 2 6	0 . 0 7 1 5 3 3	0 . 1 4 8 3 2 5	0 . 1 2 8 4 3 5
B E A 2	0 . 1 4 9 5 2 1	0 . 1 6 0 6 0 4	0 . 1 1 8 8 1 2	0 . 1 6 0 6 7 1	0 . 1 3 9 3 1 3	0 . 1 3 2 1 6 8	0 . 1 4 3 8 3 6	0 . 1 5 9 5 0 5	0 . 0 9 5 5 0 3	0 . 1 0 1 5 2 4	0 . 1 8 2 7 4 3	0 . 1 6 6 6 0 3	0 . 1 4 9 5 2 1
B E A 3	0 . 0 9 9 6 8 1	0 . 0 8 3 7 3 4	0 . 1 1 3 4 2 1	0 . 1 3 4 2 9 3	0 . 1 1 8 3 2 1	0 . 1 4 0 5 5 9	0 . 1 4 3 8 3 6	0 . 1 2 4 5 3 5	0 . 0 9 4 5 2 3	0 . 1 6 0 2 7 4	0 . 1 3 6 3 6 4	0 . 1 9 6 3 6 4	0 . 0 9 9 6 8 1
B E A 4	0 . 0 5 8 7 8 6	0 . 1 6 0 6 0 4	0 . 1 7 8 2 1 8	0 . 1 1 5 1 0 8	0 . 1 3 9 3 1 3	0 . 1 4 0 5 5 9	0 . 0 7 9 1 4 8	0 . 0 9 9 1 4 2	0 . 1 5 0 7 8 8	0 . 1 6 0 7 8 4	0 . 1 3 3 2 7 4	0 . 1 5 8 1 7 4	0 . 0 8 7 8 6
B E A 5	0 . 1 4 9 5 2 1	0 . 1 2 5 6 0 1	0 . 1 4 3 9 4 5	0 . 1 0 7 1 1 4	0 . 0 8 7 7 8 6	0 . 1 0 7 6 9 9	0 . 1 6 6 6 9 7	0 . 1 1 0 6 6 6	0 . 1 6 4 7 9 1	0 . 1 1 7 2 9 3	0 . 1 1 4 7 2 1	0 . 1 2 1 2 1 2	0 . 1 4 9 5 2 1
B E A 6	0 . 1 3 8 0 1 9	0 . 1 3 7 9 5 5	0 . 0 7 0 0 6 9	0 . 0 5 5 9 5 5	0 . 1 0 8 7 7 9	0 . 0 9 8 5 7 3	0 . 0 9 6 5 0 9	0 . 0 5 5 8 9 3	0 . 1 2 0 9 8 2	0 . 1 5 6 0 3 3	0 . 1 5 0 4 7 8	0 . 1 0 0 4 7 8	0 . 1 3 8 0 1 9

B E A 7	0	0	0	0	0	0	0	0	0	0	0	0	0

	1	1	1	1	1	1	0	1	1	1	0	1	1
	5	5	2	7	3	5	6	4	0	6	7	5	5
	9	0	7	5	9	3	2	8	8	0	3	9	1
	1	3	1	0	3	1	4	5	0	2	3	1	0
B E A 8	0	0	0	0	0	0	0	0	0	0	0	0	0

	1	0	1	0	1	1	1	1	1	0	1	1	1
	1	8	7	9	3	1	5	7	6	7	0	1	1
	6	6	8	1	9	9	5	0	4	8	0	6	6
	9	4	2	1	3	5	2	4	2	0	4	9	3
3	7	1	2	1	8	5	3	9	8	7	3	3	
3	9	8	7	3	1	1	3	1	2	8	3	3	

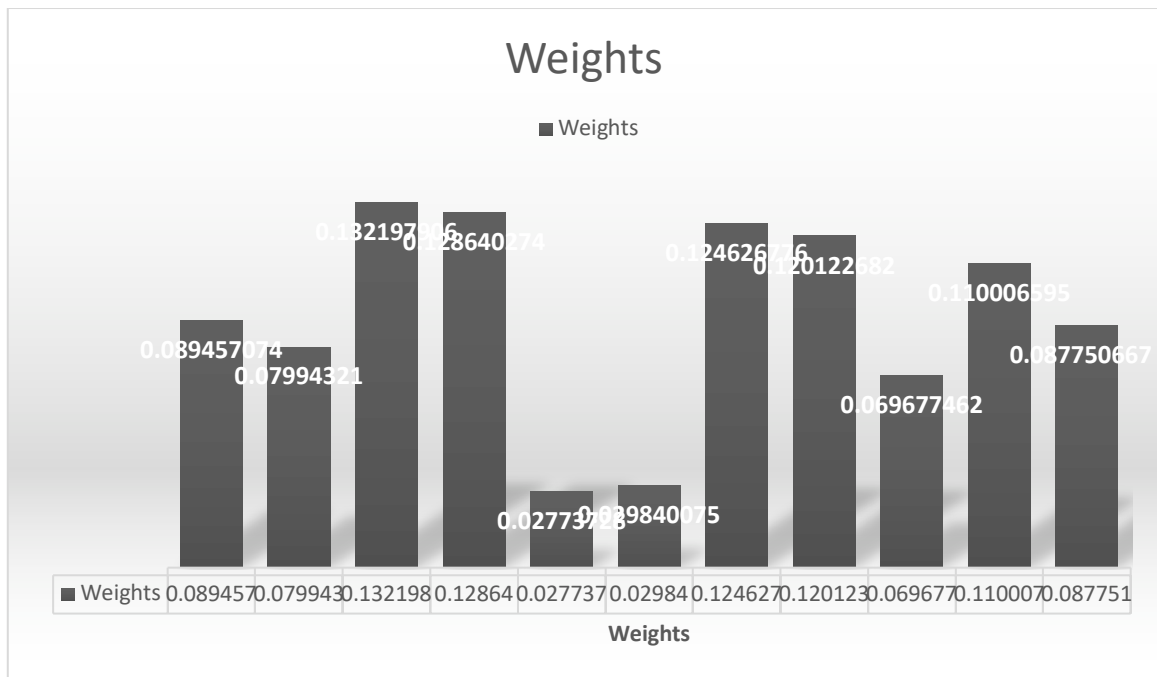


Figure 2. The weights of criteria.

Then apply the steps of the TOPSIS method to rank the alternatives and choose the best options. The normalized matrix is computed through Eq. (6) by the TOPSIS method in table 6. Then compute the weighted normalized decision matrix by multiplying the weights of criteria by the normalized decision matrix in table 7. By using Eqs. (8-11) the best and worst ideal solution is computed. Eqs. (12,13) are used to compute the distance from the cost and ideal solution in table 8. Then compute the closeness value by the positive and negative ideal solution in table 9. Then rank the alternatives according to the greatest value of closeness. Figure 3 shows the rank of alternatives. Form figure 3. The BEA₃ is the best alternative and the BEA₃ is the worst alternative.



Figure 3. The rank of alternatives by the TOPSIS method.

Table 6. The normalized matrix by the TOPSIS method

	B E C 1	B E C 2	B E C 3	B E C 4	B E C 5	B E C 6	B E C 7	B E C 8	B E C 9	B E C 9	B E C 10	B E C 11	
B E A 1	0 . 3 5 2 6 5 4	0 . 2 6 0 2 5 4	0 . 1 8 9 1 4 4	0 . 4 3 4 9 3 1	0 . 3 5 8 0 5 8	0 . 3 2 6 3 3 9	0 . 4 1 4 7 7 6	0 . 3 6 4 7 7 6	0 . 2 8 5 3 2 2	0 . 1 9 3 8 6 6	0 . 4 0 6 7 6 7	0 . 4 3 6 8 7 7	0 . 3 2 5 0 5 4
B E A 2	0 . 4 1 0 5 5 2	0 . 4 4 1 3 3 2	0 . 3 2 0 7 2 2	0 . 4 3 4 9 1 3	0 . 3 9 0 1 2 3	0 . 3 6 9 6 7 3	0 . 3 9 0 0 1 3	0 . 4 3 3 7 3 3	0 . 2 5 2 1 5 3	0 . 2 7 2 6 1 4	0 . 2 9 9 1 5 4	0 . 5 7 0 6 1 9	0 . 4 1 0 8 7 9
B E A 3	0 . 2 7 3 7 0 1	0 . 2 3 0 0 7 9	0 . 3 0 6 3 3 1	0 . 3 6 3 5 2 5	0 . 3 3 1 3 3 8	0 . 3 9 3 1 4 1	0 . 3 9 0 0 1 3	0 . 3 9 8 6 1 8	0 . 2 5 2 1 5 3	0 . 4 3 6 1 9 8	0 . 4 3 6 1 9 8	0 . 3 7 3 3 2 9	0 . 2 7 3 7 0 1

B E A 4	0	0	0	0	0	0	0	0	0	0	0	0

	1	4	4	3	3	3	2	2	4	4	3	1
	6	4	8	1	9	9	1	7	1	3	6	6
	1	1	1	1	0	3	4	1	5	6	4	1
B E A 5	4	3	3	2	2	2	4	3	4	3	3	4
	1	4	8	8	4	8	5	0	5	1	3	1
	0	5	8	9	5	1	1	1	2	8	1	0
	5	1	5	9	8	6	9	0	6	7	8	5
	5	1	6	5	3	5	2	3	3	6	4	5
B E A 6	2	9	7	4	1	3	9	5	9	5	8	2
	0	0	0	0	0	0	0	0	0	0	0	0

	3	3	1	1	3	2	2	1	3	4	2	3
	7	7	8	5	0	6	6	3	4	0	7	7
B E A 7	8	9	9	1	4	9	0	8	7	8	5	8
	9	0	1	4	6	9	0	6	2	2	0	9
	7	6	4	6	1	1	0	3	2	3	8	7
	1	5	4	9	7	8	9	6	7	7	4	1
	0	0	0	0	0	0	0	0	0	0	0	0
B E A 8
	4	4	3	4	3	4	1	4	2	4	2	4
	3	1	4	7	9	2	6	0	9	3	0	3
	6	3	3	3	0	8	9	4	7	6	0	6
	8	0	3	8	1	3	2	0	6	1	8	8
B E A 1	7	1	3	8	2	4	1	2	2	9	5	7
	1	1	7	1	3	8	2	5	3	8	5	7
	0	0	0	0	0	0	0	0	0	0	0	0

	3	2	4	2	3	3	4	4	4	2	2	3
B E A 1	2	3	8	4	9	3	2	6	5	1	7	2
	1	7	1	6	0	4	0	3	2	2	5	1
	0	6	0	6	1	4	9	4	6	5	0	0
	7	2	8	7	2	6	6	4	3	0	8	7
	3	3	3	8	3	3	7	1	5	7	4	3

Table 7. The weighted normalized matrix by the TOPSIS method

	B E C 1	B E C 2	B E C 3	B E C 4	B E C 5	B E C 6	B E C 7	B E C 8	B E C 9	B E C 9	B E C 10	B E C 11
B E A 1	0	0	0	0	0	0	0	0	0	0	0	0
.
0	0	0	0	0	0	0	0	0	0	0	0	0
3	2	2	5	0	9	9	1	4	9	1	3	3
1	0	5	5	9	7	6	2	8	3	6	5	1
5	8	0	9	9	4	9	5	7	2	3	4	5
4	0	0	5	3	4	9	5	7	2	3	4	7
7	6	4		2	7	2		4	7	4	7	

B E A 2	0	0	0	0	0	0	0	0	0	0	0	0

	0	0	0	0	0	0	0	0	0	0	0	0
	3	3	4	5	1	1	4	5	1	3	4	3
	6	5	2	5	0	1	8	2	7	0	4	6
	7	2	3	9	8	0	6	1	5	7	8	7
	2	7	9	5	2	3	0	0	6	5	2	2
7	9	9		1	1	6	1	9	9	9	7	
B E A 3	0	0	0	0	0	0	0	0	0	0	0	0

	0	0	0	0	0	0	0	0	0	0	0	0
	2	1	4	4	0	1	4	4	1	4	3	2
	4	8	0	6	9	1	8	0	7	7	2	4
	4	3	4	7	1	7	6	6	5	9	7	4
	8	9	9	6	9	3	0	8	6	8	6	8
5	3	6	4		1	6	2	9	5		5	
B E A 4	0	0	0	0	0	0	0	0	0	0	0	0

	0	0	0	0	0	0	0	0	0	0	0	0
	1	3	6	4	1	1	2	3	2	4	3	1
	4	5	3	0	0	1	6	2	8	7	1	4
	4	2	5	0	8	7	7	5	9	9	9	4
	4	7	9	8	2	3	4	9	4	8	9	4
9	9	8	3	1	1	6	3	6	5	4		
B E A 5	0	0	0	0	0	0	0	0	0	0	0	0

	0	0	0	0	0	0	0	0	0	0	0	0
	3	2	5	3	0	0	5	3	3	3	2	3
	6	7	1	7	6	8	6	6	1	5	9	6
	7	5	3	3	8	4	3	1	5	0	1	7
	2	9	6		1	0	2	6	3	6	2	2
7		8		9	5	1	2	8	6		7	
B E A 6	0	0	0	0	0	0	0	0	0	0	0	0

	0	0	0	0	0	0	0	0	0	0	0	0
	3	3	2	1	0	0	3	1	2	4	2	3
	3	0	5	9	8	8	2	6	4	4	4	3
	9	3	0	4	4	0	4	6	1	9	1	9
	0	0	0	8	4	5	0	5	9	0	3	0
2	4	4	5	9	4	4	3	4	9	9	2	
B E A 7	0	0	0	0	0	0	0	0	0	0	0	0

	0	0	0	0	0	0	0	0	0	0	0	0
	3	3	4	6	1	1	2	4	2	4	1	3
	9	3	5	0	0	2	1	8	0	7	7	9
	0	0	3	9	8	7	0	5	7	9	6	0
	8	1	8	6	2	8	8	3	3	8	2	8
1	7	8		1	2	8	3	8	5	5	1	

B	0	0	0	0	0	0	0	0	0	0	0	0
E
A	0	0	0	0	0	0	0	0	0	0	0	0
8	2	1	6	3	1	0	5	5	3	2	2	2
	8	8	3	1	0	9	2	5	1	3	4	8
	7	9	5	7	8	9	4	6	5	3	1	7
	2	9	9	3	2	8	6	7	3	7	3	2
	2	6	8	3	1		4		8	7	9	2

Table 7. The positive and negative distance by the TOPSIS method

	Positive Distance	Negative Distance
BEA ₁	0.052191	0.061795
BEA ₂	0.0548	0.057671
BEA ₃	0.041583	0.059258
BEA ₄	0.061702	0.048752
BEA ₅	0.048868	0.054288
BEA ₆	0.055759	0.063716
BEA ₇	0.071723	0.045538
BEA ₈	0.053964	0.063111

Table 8. The closeness value by the TOPSIS method

	Closeness value
BEA ₁	0.54213
BEA ₂	0.512762
BEA ₃	0.587636
BEA ₄	0.441379
BEA ₅	0.526272
BEA ₆	0.533298
BEA ₇	0.388347
BEA ₈	0.539066

5. Managerial Implications

From a management viewpoint, eleven criteria for the adoption of electric vehicles were identified after a comprehensive literature review. According to the entropy technique, the most weight is given to "price." In addition, the overall rankings of BEVs were displayed in decreasing order, with Tesla at the top.

The findings of this study have the following management ramifications.

Cost is the most important aspect. The percentage of BEVs in the automobile market is predicted to rise as a result of lower purchase costs. Therefore, lowering the cost of BEVs might hasten their global adoption. The third most significant aspect is the amount of energy used. Increasing energy security and decreasing energy usage are the goals of the development of BEVs. Battery-electric vehicles have already made their mark on the automobile industry, although recharging speed and travel are not as important as they might be. For quick travel, BEVs are more popular than gasoline-powered vehicles. It is, however, imperative that the range and recharging periods of electric cars be improved since they are expected to replace petroleum vehicles over the next few years.

Tesla Model S is rated as the finest vehicle in four distinct categories. Despite this, other BEVs still hold sway in many areas. Policymakers must continue to encourage BEVs since they are environmentally friendly. BEVs, as ecologically sound cars, should be provided more incentives to boost their share of the market in the near term. Manufacturers should take the relevance of criteria into account when designing sales policies for the continued global adoption of BEVs.

6. Conclusion

Several factors must be taken into account while deciding on a battery-electric car, many of which are at odds with one another. This is a common MCDM challenge, and MCDM is a powerful tool for tackling these kinds of difficult situations. Because various MCDM approaches might provide different rankings, researchers must be vigilant regarding the validity of their findings. So even though the robustness and efficacy of each MCDM technique have been shown, the findings may be inconsistent amongst methods. A framework based on MCDM techniques is presented to address this issue, and the results are combined using the new framework. As a consequence, stakeholders such as buyers, producers, consumers, and others may make more intelligent judgments than if they just relied on the ranking system.

In order to find the optimum BEV, this study provides a framework based on a variety of MCDM techniques. Two MCDM approaches were coupled utilizing to build an integrated method that specifies one BEV in this study (entropy, TOPSIS). The framework given by MCDM approaches may be used to evaluate BEVs. It is also possible to help consumers, decision-makers, and regulators in analyzing BEVs.

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