A Multi-Criteria Decision-Making Model Based on Bipolar Neutrosophic Sets for the Selection of Battery Electric Vehicles

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Abstract

In the current time, global warming has compelled the automotive vehicle tech sector to undertake a paradigm shift from internal combustion engines that are fueled by fossil fuels to electrical motors that are used for traction instead. It has become an important problem to evaluate BEV options in a thorough manner from the perspective of the consumer because of the recent fast expansion that the BEV industry has seen. This evaluation may be carried out by looking at the fundamental characteristics of every BEV. In addition, effective tools for making the correct choice on the purchase of a BEV are those that use multiple criteria decision-making (MCDM). The selection process of BEVs involves vague and uncertain problems, so that, this work aims to introduce a new multi-criteria decision-making model based on the neutrosophic sets and TOPSIS method to overcome this problem. The results concluded that the proposed model could handle unclear information and uncertainty which exist usually in the selection process and present an effective model to rank and select the best BEVs.

Keyword: Neutrosophic Sets; MCDM; Battery Electric Vehicles; TOPSIS method

1. **Introduction**

The megatrends of electrification and robotics are presenting new problems for the automotive industry. These issues are giving birth to new needs for future cars and are paving the way for new mobility systems that have not yet been explored[1], [2]. Electrification of powertrains, for instance, holds the promise of a more environmentally friendly future, while the advent of autonomous driving is expected to bring about improvements in safety, accessibility, and economy. Yet, as a result of these developments, new boundary requirements are imposed throughout the vehicle development process, which results in distinct cost structures[3], [4]. In the case of BEVs, the traction battery leads to a rise in both the vehicle's overall weight and its purchasing price in comparison to cars powered by internal combustion engines (ICEVs). In addition, the sensors and processors found in autonomous vehicles (AVs) influence the amount of supplemental power used and the expenses associated with their procurement. The capacity of automobile manufacturers to design future vehicle ideas and ensure the success of such concepts in the market is dependent on their having in-depth understanding of the latest technologies as well as the costs associated with those technologies[5], [6].

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Lately, customers have started to accept electric vehicles (EVs), and as a result, the quantity of EVs and the use of electric mobility have expanded rapidly, and this increasing trend is still going strong[7], [8]. In 2018, there were 5.1 million electric automobiles on the road, which is a 2 million increase over the previous year. Despite the fact that there has been a rise in the quantity of BEVs, predictions made by the industry show that the spread of BEVs has not yet reached its full maturity[9], [10]. By the year 2030, EV sales and stock will have virtually doubled, which implies that early sales will have reached 43 million, and overall stock, excluding two-wheelers and three-wheelers, will have surpassed 250 million. Hence, it is anticipated that thirty percent of all automobiles will be electric by the year 2030[11]–[13]. So, it is self-evident that a decision methodology is required to evaluate BEVs available on the market and choose the model that is the most appropriate. Bearing in mind the information presented above, the purpose of this research is to precisely suggest a multi-criteria paradigm that is all-encompassing, dependable, and easy to grasp[14], [15]. In addition, choosing the best BEV is a difficult task that is affected by several competing elements such as the amount of energy it consumes, its peak speed, its battery, the amount of time it takes to charge, and so on. In this context, multi-criteria decision-making, often known as MCDM, may be a technique that is both structural and successful[16], [17]. The Multi-Criteria Decision Model addresses issues of the selection of the optimal solution from a set of options, considering a variety of criteria. The people making the decisions would want to discover the best possible answer, but this is something that can only be accomplished in scenarios where decisions are made based on a single criterion[16], [18], [19]. In many cases, the choices that are made in response to circumstances result in disputes. Similar to how the choice of BEVs for use in the production of EVs is an important and time-sensitive operation, the implications of bad or contradictory judgments might lead to harmful circumstances in certain industrial settings[20]–[22]. In the fields of science and engineering, the approaches of MCDM have seen significant use for decision-making procedures in a variety of contexts[23], [24]. This work aims to introduce a new Multi-Criteria Decision-Making Model based on the neutrosophic sets and TOPSIS method to select the best BEV. This model involves multiple steps and uses the neutrosophic sets used to overcome the uncertainty. Then the neutrosophic sets are integrated with the TOPSIS method to rank the BEV. The results concluded that the proposed model can handle unclear information which exists usually in the selection process and present an effective model to rank and select the best BEV. This paper is organized as follows: the first section presents the introduction for this work; the second section introduces and presents the framework of the neutrosophic TOPSIS method and shows its steps. The third section presented the application of the neutrosophic TOPSIS method and showed the weights of criteria and the best BEV selected. Fourth, the fourth section gives a conclusion and future work; the final section provides references.

2. Neutrosophic MCDM TOPSIS Method

The strategy of making a decision based on many criteria at the same time, also known as MCDM, is a method for selecting the best possible option from a group of choices that are described in terms of numerous competing criteria[25], [26]. Hwang and Yoon came up with the TOPSIS approach, which is now considered to be one of the most advantageous and successful MCDM strategies for resolving MCDM issues. When using traditional MCDM approaches, the values and scores are calculated with a high level of accuracy[22], [27], [28]. In this paper, we integrated the TOPSIS method with the bipolar neutrosophic sets (BNs).

Let X is a BNs as:

$$X = < T_X^+, I_X^+, F_X^+, T_X^-, I_X^-, F_X^- > \quad (1)$$

Where $T_X^+, I_X^+, F_X^+; X \to [0,1]$ and $T_X^-, I_X^-, F_X^-; X \to [-1,0]$

Let $BEVC = \{BEVC_1, BEVC_2, BEVC_3, BEVC_4 \dots \dots . BEVC_n\}$ set of criteria and $BEVA = \{BEVA_1, BEVA_2, BEVA_3, BEVA_4 \dots \dots . BEVA_m\}$ set of alternatives

The decision matrix presented by the set of criteria and set of alternatives [26] as:

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$$D = \begin{bmatrix} d_{11} & d_{12} & d_{13} & \cdots & d_{1n} \\ d_{21} & d_{22} & d_{23} & & d_{2n} \\ & \vdots & & \ddots & \vdots \\ d_{m1} & d_{m2} & d_{m3} & \cdots & d_{mn} \end{bmatrix} \quad (2)$$

The weights of criteria are computed by the average method.

Then normalize the decision matrix.

$$N_{ij} = \frac{d_{ij}}{\sqrt{\sum_{i=1}^{m} d_{ij}^2}} \quad (3)$$

Compute the weighted normalized decision matrix as:

$$WN_{ij} = N_{ij} * W_j \quad (4)$$

Compute the positive and negative solution.

$$P^+ = \{\max b_{ij} \; for \; positive \; criteria\} \quad (5)$$

$$P^+ = \{\min b_{ij} \; for \; negative \; criteria\} \quad (6)$$

$$P^- = \{\min b_{ij} \; for \; positive \; criteria\} \quad (7)$$

$$P^- = \{\max b_{ij} \; for \; negative \; criteria\} \quad (8)$$

Compute the Euclidian distance

$$E_i^+ = \sqrt{\sum_{j=1}^{n} \left(b_{ij} - b_j^+\right)^2} \quad (9)$$

$$E_i^- = \sqrt{\sum_{j=1}^{n} \left(b_{ij} - b_j^-\right)^2} \quad (10)$$

Compute the closeness value as

$$S_i = \frac{E_i^-}{E_i^- + E_i^+} \quad (11)$$

Rank the alternatives based on the highest value of S_i

3. Application of TOPSIS Method and Rank of BEV

The proposed model consists of 11 steps as the follows:

Step 1: This step presents the nine criteria and five alternatives. As shown in the following figure.

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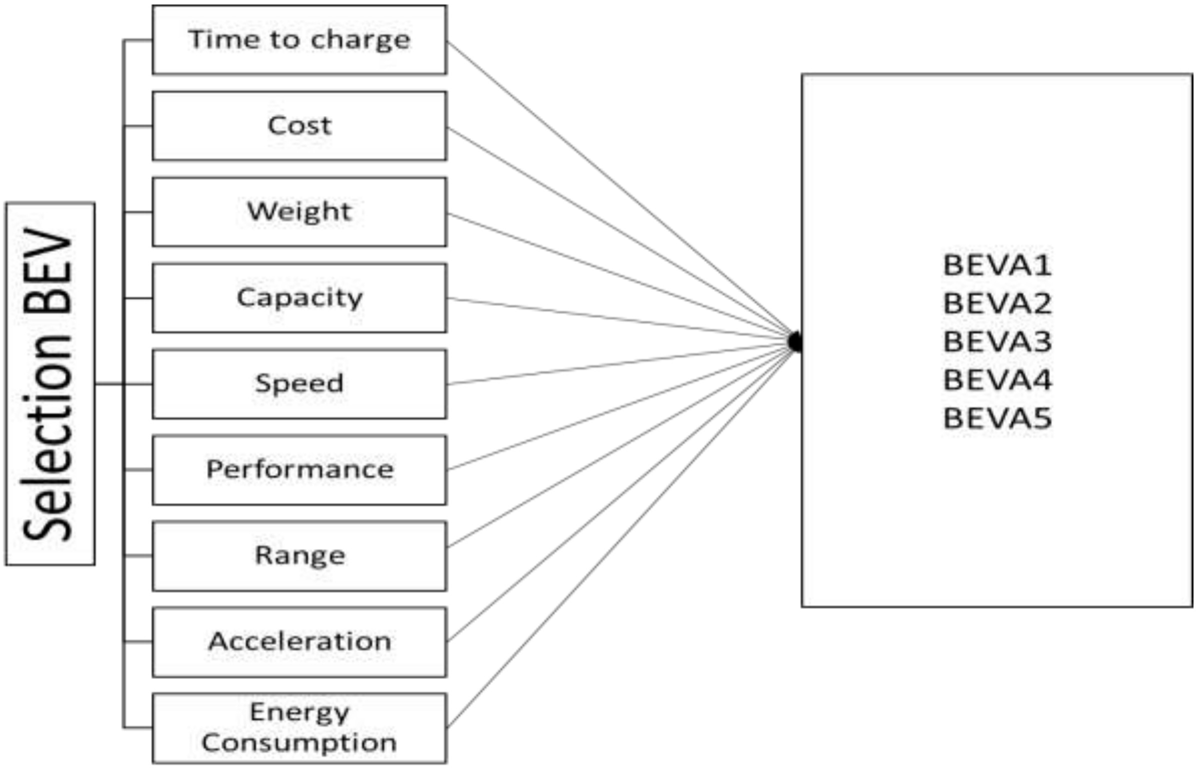

Figure 1: The selection criteria and alternatives.

Step 2:
In the second step, the weights of the criteria are computed. Let three experts who have expertise in the field of BEV evaluate the criteria. Then apply the average method to compute the weights of criteria. The weights of criteria are shown in table 1.

Table 1: The weights of nine criteria.

Criteria	Weights	Rank
$BEVC_1$	0.16391	1
$BEVC_2$	0.16625	2
$BEVC_3$	0.11676	5
$BEVC_4$	0.08019	7
$BEVC_5$	0.06840	9
$BEVC_6$	0.11789	4
$BEVC_7$	0.08963	6
$BEVC_8$	0.07548	8
$BEVC_9$	0.12148	3

Step 3: Let three experts evaluate the criteria and alternatives to build the decision matrix as shown in tables 2. The experts used linguistic terms to evaluate the criteria and alternatives.

Step 4: Replace the linguistic terms by the BNs[26].

Step 5: Apply the score function to compute the crisp value[26].

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Table 2: The decision matrix one by the BNS.

	$BEVC_1$	$BEVC_2$	$BEVC_3$	$BEVC_4$	$BEVC_5$	$BEVC_6$	$BEVC_7$	$BEVC_8$	$BEVC_9$
$BEVA_1$	<0.7, 0.6, 0.5, -0.2, -0.5, -0.6>	<1.0, 0.0, 0.1, -0.3, -0.8, -0.9>	<0.8, 0.5, 0.6, -0.1, -0.8, -0.9>	<0.4, 0.4, 0.3, -0.5, -0.2, -0.1>	<0.3, 0.1, 0.9, -0.4, -0.2, -0.1>	<0.7, 0.6, 0.5, -0.2, -0.5, -0.6>	<0.7, 0.6, 0.5, -0.2, -0.5, -0.6>	<0.7, 0.6, 0.5, -0.2, -0.5, -0.6>	<1.0, 0.0, 0.1, -0.3, -0.8, -0.9>
$BEVA_2$	<1.0, 0.0, 0.1, -0.3, -0.8, -0.9>	<0.8, 0.5, 0.6, -0.1, -0.8, -0.9>	<0.4, 0.4, 0.3, -0.5, -0.2, -0.1>	<0.1, 0.9, 0.8, -0.9, -0.2, -0.1>	<0.3, 0.1, 0.9, -0.4, -0.2, -0.1>	<1.0, 0.0, 0.1, -0.3, -0.8, -0.9>	<1.0, 0.0, 0.1, -0.3, -0.8, -0.9>	<0.8, 0.5, 0.6, -0.1, -0.8, -0.9>	<1.0, 0.0, 0.1, -0.3, -0.8, -0.9>
$BEVA_3$	<0.7, 0.6, 0.5, -0.2, -0.5, -0.6>	<0.8, 0.5, 0.6, -0.1, -0.8, -0.9>	<0.4, 0.4, 0.3, -0.5, -0.2, -0.1>	<0.3, 0.1, 0.9, -0.4, -0.2, -0.1>	<0.8, 0.5, 0.6, -0.1, -0.8, -0.9>	<0.7, 0.6, 0.5, -0.2, -0.5, -0.6>	<1.0, 0.0, 0.1, -0.3, -0.8, -0.9>	<0.3, 0.1, 0.9, -0.4, -0.2, -0.1>	<0.5, 0.2, 0.3, -0.3, -0.1, -0.3>
$BEVA_4$	<0.7, 0.6, 0.5, -0.2, -0.5, -0.6>	<0.1, 0.9, 0.8, -0.9, -0.2, -0.1>	<1.0, 0.0, 0.1, -0.3, -0.8, -0.9>	<0.3, 0.1, 0.9, -0.4, -0.2, -0.1>	<0.8, 0.5, 0.6, -0.1, -0.8, -0.9>	<0.7, 0.6, 0.5, -0.2, -0.5, -0.6>	<0.7, 0.6, 0.5, -0.2, -0.5, -0.6>	<0.3, 0.1, 0.9, -0.4, -0.2, -0.1>	<0.5, 0.2, 0.3, -0.3, -0.1, -0.3>
$BEVA_5$	<0.5, 0.2, 0.3, -0.3, -0.1, -0.3>	<0.8, 0.5, 0.6, -0.1, -0.8, -0.9>	<0.8, 0.5, 0.6, -0.1, -0.8, -0.9>	<1.0, 0.0, 0.1, -0.3, -0.8, -0.9>	<1.0, 0.0, 0.1, -0.3, -0.8, -0.9>	<0.7, 0.6, 0.5, -0.2, -0.5, -0.6>	<0.1, 0.9, 0.8, -0.9, -0.2, -0.1>	<0.1, 0.9, 0.8, -0.9, -0.2, -0.1>	<0.4, 0.4, 0.3, -0.5, -0.2, -0.1>

Table 3: The decision matrix two by the BNS.

	$BEVC_1$	$BEVC_2$	$BEVC_3$	$BEVC_4$	$BEVC_5$	$BEVC_6$	$BEVC_7$	$BEVC_8$	$BEVC_9$
$BEVA_1$	<0.4, 0.4, 0.3, -0.5, -0.2, -0.1>	<0.4, 0.4, 0.3, -0.5, -0.2, -0.1>	<0.8, 0.5, 0.6, -0.1, -0.8, -0.9>	<0.4, 0.4, 0.3, -0.5, -0.2, -0.1>	<0.4, 0.4, 0.3, -0.5, -0.2, -0.1>	<0.7, 0.6, 0.5, -0.2, -0.5, -0.6>	<1.0, 0.0, 0.1, -0.3, -0.8, -0.9>	<0.7, 0.6, 0.5, -0.2, -0.5, -0.6>	<0.4, 0.4, 0.3, -0.5, -0.2, -0.1>
$BEVA_2$	<0.1, 0.9, 0.8, -0.9, -0.2, -0.1>	<0.8, 0.5, 0.6, -0.1, -0.8, -0.9>	<0.4, 0.4, 0.3, -0.5, -0.2, -0.1>	<0.1, 0.9, 0.8, -0.9, -0.2, -0.1>	<0.3, 0.1, 0.9, -0.4, -0.2, -0.1>	<1.0, 0.0, 0.1, -0.3, -0.8, -0.9>	<1.0, 0.0, 0.1, -0.3, -0.8, -0.9>	<0.8, 0.5, 0.6, -0.1, -0.8, -0.9>	<1.0, 0.0, 0.1, -0.3, -0.8, -0.9>
$BEVA_3$	<0.7, 0.6, 0.5, -0.2, -0.5, -0.6>	<0.4, 0.4, 0.3, -0.5, -0.2, -0.1>	<0.4, 0.4, 0.3, -0.5, -0.2, -0.1>	<0.3, 0.1, 0.9, -0.4, -0.2, -0.1>	<0.7, 0.6, 0.5, -0.2, -0.5, -0.6>	<0.7, 0.6, 0.5, -0.2, -0.5, -0.6>	<1.0, 0.0, 0.1, -0.3, -0.8, -0.9>	<0.4, 0.4, 0.3, -0.5, -0.2, -0.1>	<0.4, 0.4, 0.3, -0.5, -0.2, -0.1>
$BEVA_4$	<0.4, 0.4, 0.3, -0.5, -0.2, -0.1>	<0.1, 0.9, 0.8, -0.9, -0.2, -0.1>	<1.0, 0.0, 0.1, -0.3, -0.8, -0.9>	<0.7, 0.6, 0.5, -0.2, -0.5, -0.6>	<0.8, 0.5, 0.6, -0.1, -0.8, -0.9>	<0.4, 0.4, 0.3, -0.5, -0.2, -0.1>	<0.4, 0.4, 0.3, -0.5, -0.2, -0.1>	<0.3, 0.1, 0.9, -0.4, -0.2, -0.1>	<0.5, 0.2, 0.3, -0.3, -0.1, -0.3>
$BEVA_5$	<0.1, 0.9, 0.8, -0.9, -0.2, -0.1>	<0.4, 0.4, 0.3, -0.5, -0.2, -0.1>	<0.1, 0.9, 0.8, -0.9, -0.2, -0.1>	<1.0, 0.0, 0.1, -0.3, -0.8, -0.9>	<0.4, 0.4, 0.3, -0.5, -0.2, -0.1>	<0.4, 0.4, 0.3, -0.5, -0.2, -0.1>	<0.1, 0.9, 0.8, -0.9, -0.2, -0.1>	<0.1, 0.9, 0.8, -0.9, -0.2, -0.1>	<0.4, 0.4, 0.3, -0.5, -0.2, -0.1>

Table 4: The decision matrix three by the BNS.

	$BEVC_1$	$BEVC_2$	$BEVC_3$	$BEVC_4$	$BEVC_5$	$BEVC_6$	$BEVC_7$	$BEVC_8$	$BEVC_9$
$BEVA_1$	<0.4, 0.4, 0.3, -	<0.4, 0.4, 0.3, -	<0.8, 0.5, 0.6, -	<0.4, 0.4, 0.3, -	<0.3, 0.1, 0.9, -	<0.7, 0.6, 0.5, -	<0.7, 0.6, 0.5, -	<0.4, 0.4, 0.3, -	<1.0, 0.0, 0.1, -

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	0.5, -0.2, -0.1>	0.5, -0.2, -0.1>	0.1, -0.8, -0.9>	0.5, -0.2, -0.1>	0.4, -0.2, -0.1>	0.2, -0.5, -0.6>	0.2, -0.5, -0.6>	0.5, -0.2, -0.1>	0.3, -0.8, -0.9>
BEVA$_2$	<1.0, 0.0, 0.1, -0.3, -0.8, -0.9>	<0.7, 0.6, 0.5, -0.2, -0.5, -0.6>	<0.7, 0.6, 0.5, -0.2, -0.5, -0.6>	<0.1, 0.9, 0.8, -0.9, -0.2, -0.1>	<0.7, 0.6, 0.5, -0.2, -0.5, -0.6>	<1.0, 0.0, 0.1, -0.3, -0.8, -0.9>	<1.0, 0.0, 0.1, -0.3, -0.8, -0.9>	<0.8, 0.5, 0.6, -0.1, -0.8, -0.9>	<1.0, 0.0, 0.1, -0.3, -0.8, -0.9>
BEVA$_3$	<0.4, 0.4, 0.3, -0.5, -0.2, -0.1>	<0.4, 0.4, 0.3, -0.5, -0.2, -0.1>	<0.7, 0.6, 0.5, -0.2, -0.5, -0.6>	<0.4, 0.4, 0.3, -0.5, -0.2, -0.1>	<0.8, 0.5, 0.6, -0.1, -0.8, -0.9>	<0.4, 0.4, 0.3, -0.5, -0.2, -0.1>	<1.0, 0.0, 0.1, -0.3, -0.8, -0.9>	<0.4, 0.4, 0.3, -0.5, -0.2, -0.1>	<0.5, 0.2, 0.3, -0.3, -0.1, -0.3>
BEVA$_4$	<0.7, 0.6, 0.5, -0.2, -0.5, -0.6>	<1.0, 0.0, 0.1, -0.3, -0.8, -0.9>	<1.0, 0.0, 0.1, -0.3, -0.8, -0.9>	<0.7, 0.6, 0.5, -0.2, -0.5, -0.6>	<0.8, 0.5, 0.6, -0.1, -0.8, -0.9>	<0.7, 0.6, 0.5, -0.2, -0.5, -0.6>	<0.7, 0.6, 0.5, -0.2, -0.5, -0.6>	<0.3, 0.1, 0.9, -0.4, -0.2, -0.1>	<0.5, 0.2, 0.3, -0.3, -0.1, -0.3>
BEVA$_5$	<0.4, 0.4, 0.3, -0.5, -0.2, -0.1>	<0.4, 0.4, 0.3, -0.5, -0.2, -0.1>	<0.8, 0.5, 0.6, -0.1, -0.8, -0.9>	<0.4, 0.4, 0.3, -0.5, -0.2, -0.1>	<1.0, 0.0, 0.1, -0.3, -0.8, -0.9>	<0.4, 0.4, 0.3, -0.5, -0.2, -0.1>	<0.1, 0.9, 0.8, -0.9, -0.2, -0.1>	<0.1, 0.9, 0.8, -0.9, -0.2, -0.1>	<0.7, 0.6, 0.5, -0.2, -0.5, -0.6>

Step 6: Aggregate the decision matrices into one matrix. Then normalize the decision matrix using Eq. (3).

Step 7: Use Eq. (4) to compute the weighted normalized decision matrix by multiplying the weights of criteria by the normalization matrix as shown in Table 5.

Step 8: Compute the ideal solution using Eqs. (5-8).

Step 9: Compute the positive and negative ideal solution. Then compute the Euclidean distance using Eqs. (9 and 10).

Step 10: Compute the closeness value by using Eq. (11).

Step 11: Rank the alternatives by the highest value of the closeness value. The rank of alternatives is shown in Figure 2.

Table 5: The weighted normalized decision matrix.

	BEVC$_1$	BEVC$_2$	BEVC$_3$	BEVC$_4$	BEVC$_5$	BEVC$_6$	BEVC$_7$	BEVC$_8$	BEVC$_9$
BEVA$_1$	0.067689	0.078726	0.058985	0.031444	0.019358	0.049882	0.040179	0.037907	0.061997
BEVA$_2$	0.090783	0.092484	0.038866	0.010062	0.022164	0.075536	0.051938	0.051474	0.075248
BEVA$_3$	0.075653	0.071083	0.038866	0.028929	0.033947	0.045132	0.051938	0.02873	0.041174
BEVA$_4$	0.075653	0.052739	0.072702	0.038572	0.036192	0.045132	0.031032	0.026336	0.044013
BEVA$_5$	0.050966	0.071083	0.042981	0.054923	0.036753	0.040381	0.00784	0.009577	0.040227

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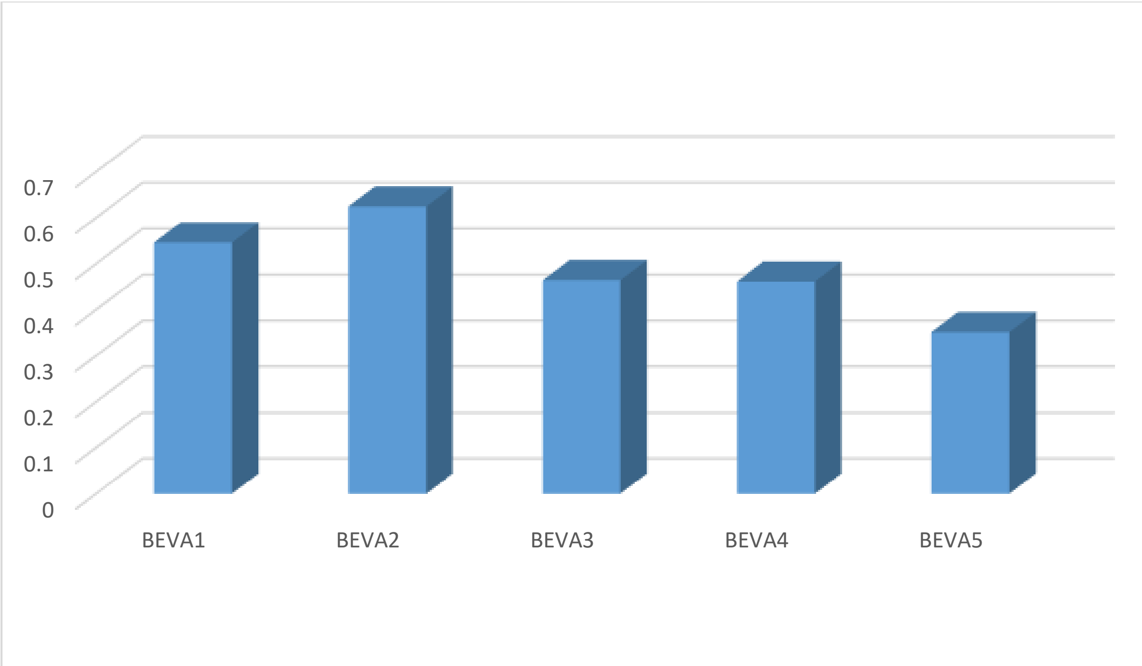

Figure 2: The rank of five alternatives.

4. Conclusions

While selecting a battery-powered electric car, it is necessary to take several factors into consideration, many of which are in direct opposition to one another. This hard challenge is, as a result, a classic MCDM problem, and MCDM is a useful technique for tackling situations like this one that are particularly challenging. Because various MCDM approaches might provide varying ranking outcomes, researchers have a responsibility to carefully consider the dependability of a ranking result. Even though each of the MCDM approaches has been suggested by demonstrating their robustness and efficacy, they may still provide findings that are not comparable to one another. Considering this worry, the present research presents a system that utilises several MCDM approaches to provide appropriate rankings. This paper used the BNs integrated with TOPSIS method to rank the alternatives. $BEVA_2$ is the best alternative and $BEVA_5$ is the worst alternative. The neutrosophic sets are integrated with the TOPSIS method to rank and select the best BEV. The results concluded that the proposed model could handle unclear information which exists usually in the selection process and present an effective model to rank and select the best BEV. For future work, the criteria can be extended as a future direction. Also, their many methods can be used to compute the weights of criteria such as entropy and AHP.

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