Integrating the Root Assessment Method with Subjective Weighting Methods for Battery Electric Vehicle Selection

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ABSTRACT

The global automotive industry is actively transitioning towards the production of BEVs (Battery Electric Vehicles) to significantly reduce carbon emissions and address climate change. In the context of a world striving for sustainable development, selecting the right BEV has become a crucial decision for consumers. This study pioneers the application of the RAM (Root Assessment Method) method for BEV selection among 10 available options. Each electric vehicle is described by 11 criteria, with weights calculated using two subjective weighting methods: the ROC method and the RS (Rank Sum) method. Regardless of the weighting method employed for the criteria, the RAM method consistently identifies the same optimal BEV. Furthermore, the top-ranked electric vehicles obtained using the RAM method in conjunction with either the ROC or RS weighting methods exhibit a high degree of similarity to those determined using other ranking methods and different criteria weighting approaches.

Keywords-BEV selection; MCDM; RAM method; weight

I. INTRODUCTION

Battery Electric Vehicles (BEVs) are more than just a mode of transportation; they represent a revolution in the automotive industry and a sustainable solution to global environmental challenges. Compared to traditional gasoline-powered vehicles, BEVs offer numerous advantages. They do not produce harmful emissions, reduce air pollution, and mitigate the greenhouse effect [1]. Furthermore, BEVs operate quietly, providing a comfortable and relaxing driving experience.

Significant advancements in battery technology have substantially increased the driving range of BEVs and shortened charging times [2]. Many modern BEVs are equipped with intelligent features such as driver-assistance systems, wireless connectivity, and partial autonomous driving capabilities, enhancing the user experience [3]. The transition to BEVs not only benefits the environment but also stimulates economic growth [4]. The BEV manufacturing industry creates numerous new jobs, from design and component production to maintenance and repair. Additionally, the development of charging infrastructure generates new business opportunities. With lower operating costs and government incentives, BEVs are becoming increasingly competitive compared to fossil fuel-powered vehicles, reducing the economic burden on consumers [5]. In summary, BEVs offer a comprehensive solution to environmental and energy challenges. With the support of new policies and technologies, BEVs will become increasingly prevalent and play a crucial role in building a green and sustainable future. However, selecting the right BEV from the myriad of options available on the market today poses a significant challenge. Each BEV model has unique specifications, ranging from price and battery charging time to driving range on a single charge, leaving consumers perplexed [6]. Additionally, factors such as design, features, and brand further contribute to the diversity and complexity of the final decision. The application of MCDM (Multiple-Criteria Decision-Making) methods is considered the best solution to overcome such challenges [7]. MCDM methods have been widely applied in the selection of transportation vehicles. The SAW (Simple Additive Weighting), MARCOS (Measurement Alternatives and Ranking according to COmpromise Solution), and PSI (Preference Selection Index) methods have been used to select electric bicycles [8]. Selection of passenger cars has been conducted using the R (Ranking of the attributes and alternatives) and CURLI (Collaborative Unbiased Rank List Integratio) methods [9], the PROMETHEE (Preference Ranking Organization Method for Enrichment Evaluation) method [10], the TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method [11], etc. In [12], both TOPSIS and MOORA (Multiobjective Optimization On the basis of Ratio Analysis) methods were simultaneously used to select trucks. The MOORA, COPRAS (COmplex PRroportional Assessment), SAW, WPM (Weighted Product Model), and ROV (Range Of Value) methods have been used to select electric motorcycles [13]. In addition to being used for selecting road vehicles, MCDM methods have also been used for the selection of air vehicles [14].

RAM is known as a simple MCDM method recently introduced in September 2023. This method has the advantage of balancing between cost and benefit criteria [15]. Furthermore, it has been revealed that this method can be combined with various data normalization techniques [16, 17]. Several studies have successfully applied this method to select the best option among multiple available options in various fields, such as fire-resistant materials [18], mushroom cultivation [19], sustainable electricity generation methods [20], cities with the best digital transformation performance [21], banks with the best financial health [22], universities [23], lecturers to teach courses [24], etc. However, the literature review did not find any published documents applying the RAM method to BEV selection. This study applies the RAM method to BEV selection to take advantage of its aforementioned advantages and address the urgent problem of BEV selection in the current context.

When using the RAM method, or most other MCDM methods in general, to rank alternatives, it is necessary to calculate weights for the criteria. The choice of weighting method for the criteria also has a significant impact on the ranking of the alternatives [25]. Many opinions suggest that when selecting a BEV, it is necessary to consult the opinions of stakeholders such as users, sellers, and experts. Based on this reason, the use of subjective weighting methods is suitable for use when selecting BEVs. Two subjective weighting methods, ROC and RS, have been used to calculate weights for the criteria in this study. These two methods have been used due to their simplicity and have been widely used in recently published studies [26-28]. With its simplicity, each method uses only one formula to calculate the weights of the criteria, making these methods suitable for consulting the opinions of evaluators with different levels of understanding of BEVs.

II. MATERIALS AND METHODS

A. Electric Vehicles

Table I summarizes the data of 10 different BEVs, denoted as BEV1 to BEV10. Eleven criteria were used to describe each alternative, including quick charge time, acceleration, full charge time, purchasing price, curb weight, energy consumption, battery capacity, range, top speed, maximum power, and permitted load, denoted as C1 to C11, respectively. C1 is the time it takes to fully charge an electric car battery using a fast charger. C2 is the acceleration capability of the car from 0 to a certain speed (usually 100 km/h) in a specific time. C3 is the total time required to fully charge an electric car battery from a depleted state or a certain battery level. C4 is the BEV's price. C5 is the weight of the car without passengers, cargo and fuel (in the case of electric cars with internal combustion engine support). C6 is the amount of electricity that the electric car consumes over a certain distance, measured in kWh/100km. C7 is the total amount of electrical energy that the electric car battery can store, measured in kWh. C8 is the maximum distance that the electric car can travel after a full charge. C9 is the maximum speed that the electric car can reach. C10 is the maximum power that the electric motor of the car can produce, measured in hp or kW. C11 is the maximum weight that the electric car can carry, including passengers and cargo. The second row of Table I also specifies which criteria are better when larger (benefit criteria) and which are better when smaller (cost criteria) [29].

TABLE I. ELECTRIC VEHICLE SPECIFICATIONS [29]

Alt.	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
	C	C	C	C	C	C	B	B	B	B	B
BEV1	90	7.9	7.5	35180	1732	18	62	382	90	150	450
BEV2	25	7.3	20	44450	1320	13	33.2	260	160	170	425
BEV3	100	7.8	9.5	36620	1616	28	60	320	146	200	480
BEV4	40	2.4	7	74490	2107	18.6	70	539	260	503	420
BEV5	30	10	10	23500	1500	15	41	300	168	92	434
BEV6	54	9.9	6	52940	1527	15.1	100	311	172	120	462
BEV7	60	9.6	9.6	36025	1567	15	36	201	150	134	341
BEV8	54	11.2	9	37000	1506	15.7	64	448	166	201	315
BEV9	45	12.7	7.5	24550	1200	21	62	132	130	82	185
BEV10	36	6.9	3.5	29900	1365	16	33	176	153	181	225

B. RAM Method

The steps for using the *RAM* method to rank alternatives are [15]:

Step 1: Construct a decision matrix with *m* rows and *n* columns, where *m* and *n* represent the number of alternatives to be ranked and the number of criteria for each alternative, respectively. Let x_{ij} be the value of criterion *j* for alternative *i*, where *j* = *1* to *n*, *i* = *1* to *m*.

Step 2: Normalize the data using (1):

$$r_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \tag{1}$$

Step 3: Calculate the normalized values considering the weights of the criteria according to (2), where w_j is the weight of the *j*th criterion.

$$y_{ij} = w_j \cdot r_{ij} \tag{2}$$

Step 4: Calculate the sum of the normalized values considering the weights of the criteria according to (3) and (4):

$$S_{+i} = \sum_{j=1}^{n} y_{+ij} \quad \text{if } j \in B \tag{3}$$

$$S_{-i} = \sum_{j=1}^{n} y_{-ij} \quad \text{if } j \in C \tag{4}$$

Step 5: Calculate the score of each alternative according to (5):

$$RI_i = \sqrt[2+S_{-i}]{2 + S_{+i}} \tag{5}$$

Step 6: Rank the alternatives in descending order of their scores.

C. Subjective Weighting Methods Used

The calculation of weights for the criteria using the ROC and RS methods was performed by applying (6) and (7), respectively, where *k* is the priority ranking of criterion *j* [26-28].

$$w_j = \frac{1}{n}\sum_{k=i}^{n}\frac{1}{k} \tag{6}$$

$$w_j = \frac{2(n+1-k)}{n(n+1)} \tag{7}$$

III. RESULTS AND DISCUSSION

To calculate the weights for the criteria using the ROC and RS methods, the opinions of stakeholders regarding the importance of the criteria were first surveyed. The respondents included customers, salespeople, and BEV industry experts. The priority of electric vehicle evaluation criteria reflects the needs and desires of consumers, in which the leading factor is battery capacity (C7), which determines the driving range, followed by charging time (C3, C1) to ensure convenience. Engine power (C10) is important for performance, followed by price (C4) and other factors such as top speed (C9), electricity consumption (C6), driving range (C8), acceleration (C2), vehicle weight (C5), and maximum load capacity (C11). In general, consumers prioritize factors related to performance, comfort, and range over the others. All respondents showed a high degree of consistency in their opinions regarding the importance of the criteria. Accordingly, the importance of the criteria was determined in the following descending order: C7 > C3 > C1 > C10 > C4 > C9 > C6 > C8 > C2 > C5 > C11. This result was the basis for calculating the weights for the criteria using the ROC and RS methods, and is summarized in Table II.

The weights of the criteria were calculated using both the ROC and RS methods. The next step was to apply the RAM method to rank the BEVs, first by ranking the BEVs when the weights of the criteria were calculated using the ROC method. Applying (1), the normalized values were calculated as shown in Table III. The normalized values considering the weights of the criteria were calculated according to (2) and are summarized in Table IV. The values of S_{+i}, S_{-i}, and RI_i were calculated according to (3), (4), and (5), respectively, and are summarized in Table V. The last column of this table lists the ranking of the BEVs.

When the weights of the criteria were calculated using the RS method, the ranking of BEVs was also performed similarly. To evaluate the effectiveness of ranking BEVs in this study, the ranking results of BEVs were compared with the ranking results of BEVs using other MCDM methods along with the use of other methods to calculate criteria weights.

TABLE II. WEIGHTS OF THE CRITERIA

Weight method	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
ROC	0.1382	0.0275	0.1836	0.0851	0.0174	0.0518	0.2745	0.0388	0.0670	0.1079	0.0082
RS	0.1364	0.0455	0.1515	0.1061	0.0303	0.0758	0.1667	0.0606	0.0909	0.1212	0.0150

TABLE III. NORMALIZED VALUES

Alt.	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
BEV1	0.1685	0.0922	0.0837	0.0891	0.1122	0.1026	0.1105	0.1245	0.0564	0.0818	0.1204
BEV2	0.0468	0.0852	0.2232	0.1126	0.0855	0.0741	0.0592	0.0847	0.1003	0.0927	0.1137
BEV3	0.1873	0.0910	0.1060	0.0928	0.1047	0.1596	0.1069	0.1043	0.0915	0.1091	0.1284
BEV4	0.0749	0.0280	0.0781	0.1887	0.1365	0.1060	0.1247	0.1756	0.1630	0.2744	0.1124
BEV5	0.0562	0.1167	0.1116	0.0595	0.0972	0.0855	0.0731	0.0978	0.1053	0.0502	0.1161
BEV6	0.1011	0.1155	0.0670	0.1341	0.0989	0.0861	0.1782	0.1013	0.1078	0.0655	0.1236
BEV7	0.1124	0.1120	0.1071	0.0913	0.1015	0.0855	0.0641	0.0655	0.0940	0.0731	0.0912
BEV8	0.1011	0.1307	0.1004	0.0938	0.0975	0.0895	0.1140	0.1460	0.1041	0.1097	0.0843
BEV9	0.0843	0.1482	0.0837	0.0622	0.0777	0.1197	0.1105	0.0430	0.0815	0.0447	0.0495
BEV10	0.0674	0.0805	0.0391	0.0758	0.0884	0.0912	0.0588	0.0573	0.0959	0.0987	0.0602

TABLE IV. NORMALIZED VALUES CONSIDERING THE WEIGHTS OF THE CRITERIA

Alt.	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
BEV 1	0.0233	0.0025	0.0154	0.0076	0.0019	0.0053	0.0303	0.0048	0.0038	0.0088	0.0010
BEV 2	0.0065	0.0023	0.0410	0.0096	0.0015	0.0038	0.0162	0.0033	0.0067	0.0100	0.0009
BEV 3	0.0259	0.0025	0.0195	0.0079	0.0018	0.0083	0.0294	0.0040	0.0061	0.0118	0.0011
BEV 4	0.0103	0.0008	0.0143	0.0161	0.0024	0.0055	0.0342	0.0068	0.0109	0.0296	0.0009
BEV 5	0.0078	0.0032	0.0205	0.0051	0.0017	0.0044	0.0201	0.0038	0.0071	0.0054	0.0010
BEV 6	0.0140	0.0032	0.0123	0.0114	0.0017	0.0045	0.0489	0.0039	0.0072	0.0071	0.0010
BEV 7	0.0155	0.0031	0.0197	0.0078	0.0018	0.0044	0.0176	0.0025	0.0063	0.0079	0.0008
BEV 8	0.0140	0.0036	0.0184	0.0080	0.0017	0.0046	0.0313	0.0057	0.0070	0.0118	0.0007
BEV 9	0.0116	0.0041	0.0154	0.0053	0.0013	0.0062	0.0303	0.0017	0.0055	0.0048	0.0004
BEV 10	0.0093	0.0022	0.0072	0.0065	0.0015	0.0047	0.0161	0.0022	0.0064	0.0107	0.0005

TABLE V. SOME PARAMETERS IN RAM AND RANKING OF BEVS

Alt.	S_{+i}	S_{-i}	RI_i	Rank
BEV1	0.0488	0.0560	1.4174	6
BEV2	0.0372	0.0647	1.4115	10
BEV3	0.0524	0.0658	1.4163	8
BEV4	0.0825	0.0494	1.4304	1
BEV5	0.0373	0.0426	1.4168	7
BEV6	0.0682	0.0470	1.4262	2
BEV7	0.0351	0.0522	1.4137	9
BEV8	0.0565	0.0503	1.4214	3
BEV9	0.0427	0.0439	1.4183	5
BEV10	0.0359	0.0314	1.4190	4

Accordingly, in [29], the ranking was performed by combining the MCRAT (Multiple Criteria Ranking by Alternative Trace) ranking method with three different weighting methods, including the AHP (Analytic Hierarchy Proces) method, the MEREC (MEthod based on the Removal Effects of Criteria), and the CRITIC (CRiteria Importance Through Intercriteria. Correlation) method, creating three combinations denoted as MCRAT & AHP, MCRAT & MEREC, and MCRAT & CRITIC. Figure 1 illustrates the ranking of BEVs when ranked using different methods. The symbols RAM & ROC and RAM & RS are understood as using the RAM method to rank alternatives when the weights of the criteria are calculated using the two corresponding methods, ROC and RS.

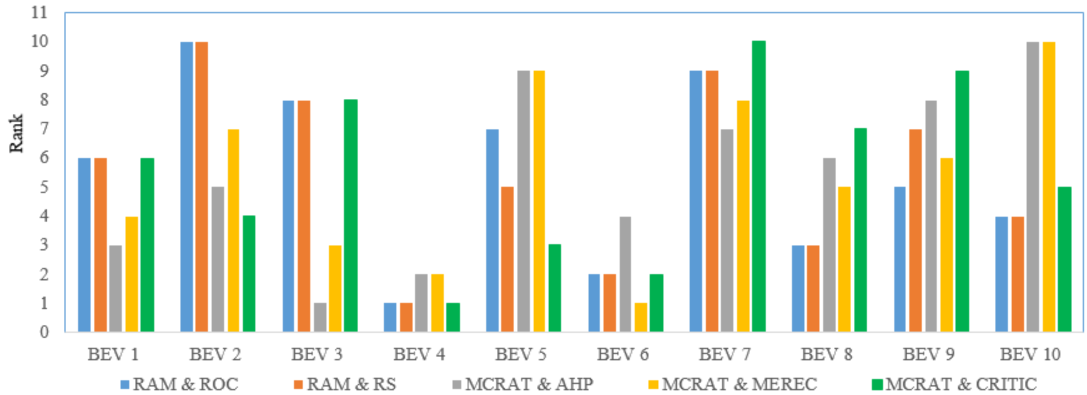

Fig. 1. Ranking of BEVs using different methods.

It is observed that the ranking of BEVs is inconsistent when using different ranking methods as well as when using different weighting methods. This is understandable and has been stated in many recent reports [30, 31]. However, BEV4 still emerged as a preferred option, ranking first when using the combinations RAM & ROC, RAM & RS, and MCRAT & CRITIC to rank alternatives, while when using the combinations MCRAT & AHP and MCRAT & MEREC, it still maintained the second position. This result suggests that among the 10 alternatives considered in this paper, BEV4 is identified as the optimum choice. BEV4 has the following criteria: quick charge time, acceleration, full charge time, purchasing price, curb weight, energy consumption, battery capacity, range, top speed, maximum power, and permitted load, with corresponding values of 40, 2.4, 7, 74490, 2107, 18.6, 70, 539, 260, 503, and 420. It is also noteworthy that when using the RAM method to rank alternatives, the first-ranked alternative (BEV4), the second-ranked alternative (BEV6), the third-ranked alternative (BEV8), the fourth-ranked alternative (BEV10), the sixth-ranked alternative (BEV1), the eighth-ranked alternative (BEV3), the ninth-ranked alternative (BEV7), and the tenth-ranked alternative (BEV2) are completely consistent when the weights are calculated using either of ROC and RS. This further strengthens the advantage of the RAM method, which can balance between cost and benefit criteria.

IV. CONCLUSION

The use of the RAM method in conjunction with the two subjective weighting methods, ROC and RS, ensures a high degree of consensus on the ranking of BEVs. The recommended BEV when using the RAM method combined with the subjective weighting methods ROC and RS is also similar to when using the MCRAT method combined with other weighting methods (AHP, MEREC, and CRITIC). The use of subjective weighting methods not only ensures the accuracy of the final choice but also provides decision-makers with great respect and high confidence as they are the ones who determine the weights for the criteria. Among the 10 BEVs surveyed, BEV4 is the optimum choice. The best-rated electric vehicle is the one with the following values for quick charge time, acceleration, full charge time, purchasing price, curb weight, energy consumption, battery capacity, range, top speed, maximum power, and permitted load: 40 min, 2.4 s, 7 h, 74490 USD, 2107 kg, 18.6 kWh/100km, 70 kWh, 539 km, 260 km/h, 503 kW, and 420 kg, respectively.

The selection of electric vehicles in this study is limited to considering only 11 criteria, all of which are quantitative. Criteria related to design, style, and driving comfort were not considered. Furthermore, the environmental impact of using electric vehicles was not considered. Future research should address these factors to make the selection of electric vehicles more comprehensive.

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