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RESEARCH ARTICLE

Data-Driven Decision Aids for Purchasing Battery Electric Vehicles Based on PROMETHEE-II Methodology

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ABSTRACT Considering the significant contribution of the transport sector to carbon emissions, the importance of battery electric vehicles (BEVs) as environmentally friendly vehicles is self-evident. Due to the rapid expansion of the BEV market in recent years, a comprehensive evaluation of BEV options from the consumer perspective has become an important issue. This paper proposes a data-driven decision aids for purchasing BEVs based on a multiple criteria decision-making methodology (i.e., PROMETHEE-II). A hierarchical evaluation criteria system of BEVs is constructed and correlation analysis between indicators is performed to eliminate duplicate indicators. Then, a comprehensive weighting method by integrating large-scale group decision making method and the Entropy-based method is proposed to identify the weights of criteria. Based on which, the ranking of candidate BEVs can be obtained based on the PROMETHEE-II with a hierarchical evaluative criteria, which can help consumers make BEV purchase choices. Furthermore, the robustness and reliability of the results are tested by applying the sensitivity analysis and contrastive analysis.

INDEX TERMS Multiple criteria decision-making, hierarchical decision modelling, battery electric vehicle, decision support, PROMETHEE II.

I. INTRODUCTION

As the global warming trend continues and the surface temperature continues to rise, the impact of climate change is increasingly severe, which not only causes social and economic losses, but also affects the balance and development of the ecosystem. Sustainable development is a promising solution, especially in environmental, social, and economic development. In traffic field, in order to solve the problem of environmental pollution and support sustainable development, many developed countries in the world have begun to turn to electric vehicles (EVs) [1]. The EVs referring to hybrid electric vehicles (HEVs), battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs) are seen as one of the important ways to energy crisis and solve global warming, and they have developed rapidly [2], [3]. Moreover, compared with conventional vehicles, BEVs, also known as zero-emission vehicles, rely entirely on electric motors and on-board batteries to run [4], [5]. Since BEVs do not require any fossil fuels, in this sense, they offer a cleaner means of transportation. Therefore, the promotion of BEVs is more likely to be the most promising route to an eco-friendly transport system [6].

In order to encourage consumers to adopt BEVs, many countries have put forward a number of incentive policies, including tax exemptions, financial subsidies, free parking, free license plates, etc. Existing literature points out that consumers' lack of knowledge or experience is a barrier to the adoption of BEVs [7], [8], [9], [10]. In this way, it is necessary to create a decision aids tool to evaluate BEVs and select the most proper one in the market. When consumers seek to purchase BEVs, they often prefer to evaluate and compare

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candidate BEVs from multiple perspectives [11]. To be specific, price [6], driving range, top speed [2], and other factors may affect consumers' purchase of BEV. Therefore, the evaluation and selection of the optimal BEV becomes a typical multiple criteria decision-making (MCDM) problem. Based on the above observations, the main objective of this paper is to propose a MCDM-based purchase decision aids framework for purchasing BEVs.

A. LITERATURE REVIEW

This part reviews the literature from two aspects: MCDM methods in BEV evaluation and the methods of determining criteria weights.

1) MCDM METHODS IN BEV EVALUATION

What is most relevant to this study is the evaluation and ranking of BEVs. At present, there is relatively few research on the evaluation and ranking of BEVs. Biswas and Das [12] used fuzzy AHP and multi-attribute border approximation area comparison (MABAC) to rank alternative BEVs considering the multiple attributes including cost, acceleration time, range, top speed, and combined fuel economy. Ecer [13] proposed a BEVs' evaluation tool by integrating six MCDM technologies based on price, acceleration, battery, driving range and other indicators. Subsequently, Ren et al. [14] divided topics by LDA and established an evaluation standard system. VIKOR method was adopted to rank BEVs based on six criteria. Recently, Song et al. [15] proposed a decision support process of buying BEVs considering consumers' consumer learning and regret avoidance behavior.

Although the aforementioned literature has proposed some decision support methods to rank BEVs from different perspectives, the evaluation criteria system of BEVs established in the early research has two shortcomings: (a) hierarchical evaluation criteria are not established; (b) correlations between criteria are not considered, which may lead to poor evaluation results. On the one hand, because BEVs have more product attributes, the establishment of hierarchical evaluation criteria system is more scientific and easy to understand. AHP proposed by Saaty [16] is a method to organize complex problems into hierarchical structures. With hierarchical decision models, decision makers are able to better understand the problem at hand and deal with it more effectively because the approach breaks down complex problems into smaller ones [17]. On the other hand, high correlation of constructed evaluation indexes will lead to inaccurate weights of evaluation indexes. For example, if horsepower, torque, and 0-100 km/h acceleration are selected as the relevant attributes of the vehicle performance indicators in order to build the MCDM model for evaluating the vehicle, careful reflection may lead us to realize that horsepower and torque may be related to the basic goal of acceleration. So taking all three into account can lead to "double-counting" our performance goals and placing too much weight on performance [18], which can lead to inaccurate estimates. That is, there is a high degree of correlation between the three attributes, which may be incompatible with these independent assumptions that are required in MCDM methods [18]. While, a hierarchical structure can help consumers to better understand the structure of the identified criteria [19]. Therefore, this paper is intended to fill gaps stated above in the literature by establishing a hierarchical evaluation criteria system.

The preference ranking organization method for enrichment of evaluations (PROMETHEE) is a well-known outranking decision-making method in solving complex MCDM problems [20]. There are several types of PROMETHEE methods. PROMETHEE II can provide a complete ranking of alternatives; compared with reference point based methods (such as TOPSIS [21] and VIKOR [22]), it is more robust (avoiding inversion); compared with other outranking methods (such as ELECTRE [23] and QUALIFLEX [24]), it has the advantages of simple calculation, flexible preference function selection and strong adaptability to decision environment [25]. Besides, the consideration set is a set of alternatives that consumers seriously consider [26]. To prevent inferior alternatives from entering the consideration set, the decision support model constructed should be able to distinguish inferior products from superior products. In order to achieve this goal, PROMETHEE-II method, which is a powerful outranking technology based on the dominance scores, is used in this paper. According to the obtained net flow values by PROMETHEE-II, alternative BEVs can be divided into two classes: important (positive net flow values) and unimportant (negative net flow values) categories. Thus, the number of options for consideration set is greatly reduced, further reducing the difficulty of consumer choice.

2) METHODS OF DETERMINING CRITERIA WEIGHTS

There are many methods to determine the criteria weights in MCDM, which are mainly divided into subjective, objective and hybrid methods. The subjective methods depend on the experience knowledge of experts to determine the criteria weights. Experts often use pair-based comparison technology to compare each evaluation criteria in pairs to determine the priority weights of the criteria, such as AHP [27], extended AHP [28], and Best Worst Method (BWM) method [29]. While the objective methods rely on objective evaluation matrices. Ali et al. [30] generalized the entropy method to uncertain probabilistic linguistic term set context. Rani and Mishra [31] determined the criteria weights through the maximizing deviation method. Liu et al. [32] introduced a weight determining method based on the correlation coefficients between attributes. Subjective and objective techniques has its own advantages and disadvantages [33]. Therefore, some studies strongly recommend the combination weighting methods to take into account both subjective and objective weights. The mixed method synthesizes experts' subjective experiences and objective evaluation matrix to generate weight values. Liu et al. [34] proposed an integrated weights of the attributes with objective weighting based on simple statistical variance method and subjective weighting based on simple additive weighting. Wu et al. [35] presented a combined weight determining method where the probability linguistic multiplicative AHP method was proposed to determine the subjective weights and the objective weights was derived by correlation coefficients.

Although the method of aggregative subjective and objective criteria weights has been used in some literatures, few literatures have adopted the large-scale group decision making method [36], [37] to determine the subjective weights of evaluation criteria. A large-scale group decision making method allows multiple fields, including university professors, salesman, and users of BEVs, which are more familiar with the various attributes of BEVs, to participate in the process of determining evaluation criteria weights and then more realistic criteria weights are obtained. Based on which, in this paper, we apply a large-scale group decision making method to get subjective criteria weights. Besides, for the hierarchical criteria system, we establish an Entropy-based method to obtain the objective weights of criteria. Finally, the subjective and objective weights are fused to obtain the comprehensive criteria weights to participate in the final MCDM method.

B. CONTRIBUTIONS OF THE STUDY

This study develops a data-driven decision aids framework for purchasing BEVs based on PROMETHEE-II method with a hierarchical evaluation criteria system. We believe that our study has three contributions as follows:

(1) To our knowledge, this is the first attempt to establish a hierarchical decision framework to rank candidate BEVs. More importantly, a hierarchical evaluation criteria system of BEVs is established, which can make the evaluative criteria more scientific and easy to understand.

(2) A simplified evaluation criteria algorithm based on correlation analysis is proposed to reduce the redundancy of criteria.

(3) A composite method by integrating large-scale group decision making method and Entropy-based method is established to determine the weights of evaluative criteria.

The rest of this article is structured as follows. In Section II, a hierarchical MCDM mechanism for ranking alternative BEVs is established. In Section III, the proposed model is applied to a real case of purchasing BEVs. The comparative analysis, sensitivity analysis and management implications are elaborated in Section IV. In Section V, the conclusions are summarized.

II. A MCDM-BASED RANKING MODEL OF ALTERNATIVE BEVS WITH A HIERARCHICAL EVALUATIVE CRITERIA

The objective of this paper is to evaluate and rank alternative BEVs offered by consumers based on the perspective of product multiple attributes. The basic assumptions of the model are as follows: (a) it is assumed that consumers have identified the alternative product set (also known as consideration set) through preliminary screening. On this basis, we evaluate and rank alternative products through a MCDM method to support consumers' purchase decisions; (b) we assume that the evaluation criteria only consider the benefit type and the cost type, that is, the higher the value of the benefit type, the better the performance, while the cost type is just the opposite. In subsection A, we establish a hierarchical assessment criteria system of BEVs. Subsection B introduces criteria streamlining by correlation analysis from all criteria under the same main criteria. Collect criteria values of alternative BEVs and determining the criteria weights based on combination weighting approach are presented in Subsection C and D, respectively. The procedure of decision support model based on PROMETHEE II is presented in Subsection E. Moreover, Fig. 1 shows the basic flow of the decision support framework proposed in this research.

A. CONSTRUCTING A HIERARCHICAL ASSESSMENT INDEX SYSTEM OF BEVs

Many previous empirical studies have provided a comprehensive perspective on the major barriers or drivers for consumer adoption of BEVs by means of questionnaires or experiments. The factors that affect the adoption of BEVs for consumers can be classified into three categories: existing policy incentive properties, product properties, and emerging market incentive properties [38]. Specifically, product attributes include purchase prices, brand, driving range, fast/normal charging time, driving range, charging stations, costs, battery warranty, and depreciation. Through the literature search, the key performance specifications that influence consumers' choice of BEVs are described below:

1) BATTERY ATTRIBUTE

Consumers are most concerned about battery problems of BEVs, mainly including charging, driving range and maintenance, which are also the main considerations of consumers in the BEV market [39]. Concerns about battery charge time, battery safety and battery life were major technical barriers to BEV adoption [40]. Smith et al. [41] emphasized that fast charging in adverse weather conditions was a key factor supporting the adoption of BEVs. Research shows that more than 83 percent of Chinese consumers supported fast charging [42]. Additionally, Ma et al. [42] found that Chinese consumers tended to buy BEVs with low energy consumption due to range anxiety.

2) POWER SYSTEM

Power is also important for BEVs, providing the power they need to accelerate [9]. Ma et al. [42] emphasized that Chinese consumers are more likely to choose more powerful BEVs. Moreover, speed and design matter as much as size [43].

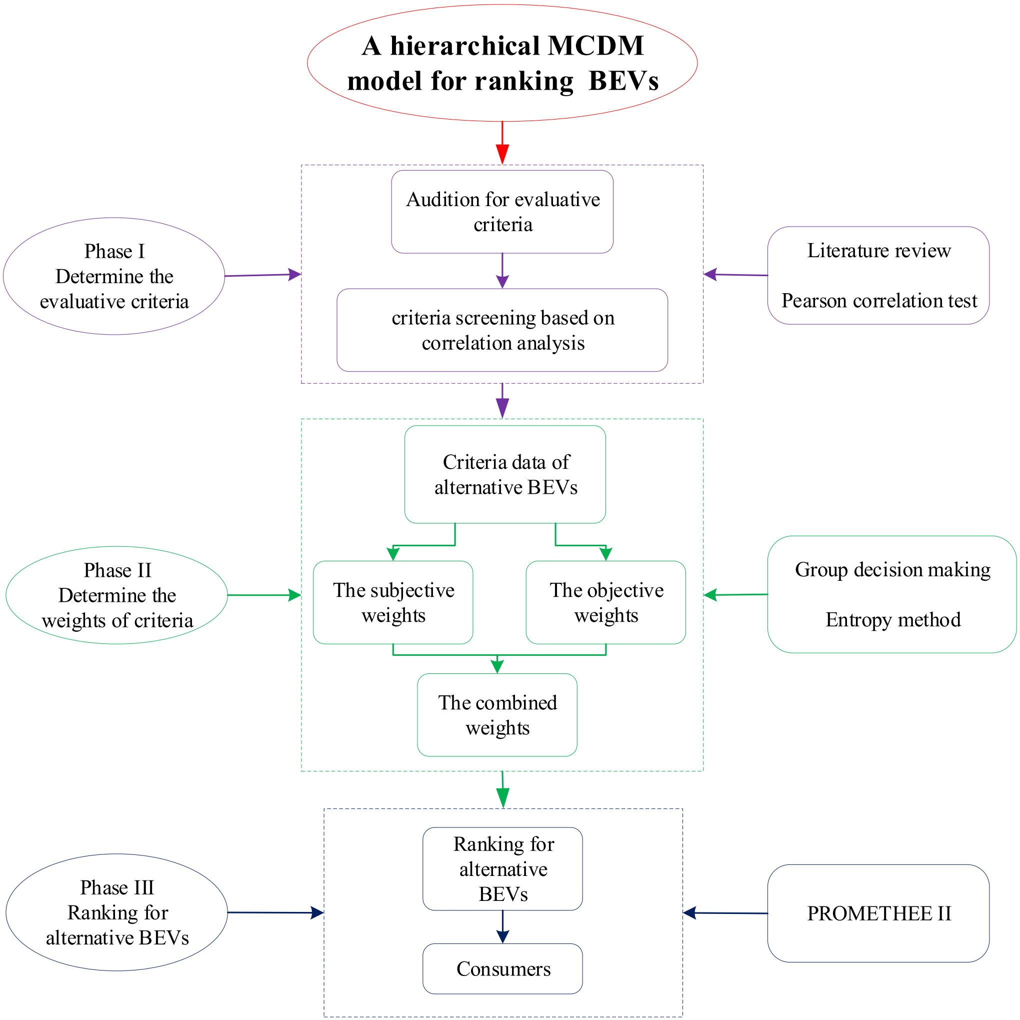

FIGURE 1. Flowchart of the proposed decision support method.

3) COST

Price is another key factor when consumers consider buying BEVs. Extant literature has shown that purchase price has significantly negative impact on the adoption of BEVs [3], [44]. Nearly 70% of respondents said high price was the biggest obstacle to widespread adoption of BEVs [45].

4) SIZE AND WEIGHT

Size (i.e., length, width, height, and wheelbase) and weight (curb weight) have been proved to be the focus of consumers' attention to BEVs by previous scholars, and these indicators will affect consumers' purchase choices [42], [43], [44], [45], [46]. As the technical level of BEVs has not reached the mature level, it is necessary to reduce the weight of batteries without reducing the performance of BEVs [47].

Through the literature review above, the evaluative criteria of BEVs are extracted from the literature based on the availability of data, as listed in Table 1. Furthermore, the established hierarchical evaluation index system established is shown in Fig.2. The evaluative criteria system consists of five first level indicators and ten second level indicators.

B. REDUCTION OF EVALUATION INDICATORS BASED ON CORRELATION ANALYSIS

Based on the mass-election evaluative criteria of BEVs introduced in Subsection A, we simplify indicators through correlation analysis. In this paper, the correlation analysis is carried out in the criterion layer, and the index pair with the correlation coefficient greater than 0.75 is taken as the high correlation indexes. It is important to note that correlation analysis is carried out only on the sub-indexes which belong to the same main index. One is because the correlation analysis within the criterion layer must be related in economic meaning. The second is to take the index pair whose correlation coefficient is greater than 0.75 as the high correlation index, then there must be numerical correlation. So ensuring is both relevant in economic terms and in numerically related. Avoid mistakenly deleting indicators that are only numerically relevant but not economically relevant.

TABLE 1. Summary of the mass-election evaluative criteria for bevs by the literature.

Criteria	Sub-criteria	Definitions	Type	References
Cost	Price (ten thousand yuan)	Purchase price.	Cost (min)	[44,45]
Size	Size (mm)	(length + width + height + wheelbase)/4.	Benefit (max)	[9,42,46]
Weight	Weight (kg)	Curb weight.	Cost (min)	[42,46]
Battery	Driving range(km)	Range that can be reached from a single charge.	Benefit (max)	[48,49]
	Rapid charging time (h)	20%–80% charging time.	Cost (min)	[41,42]
	Battery capacity (kWh)	Battery capacity.	Benefit (max)	[9,42]
	Power consumption (kWh/100 km)	Power consumption.	Cost (min)	[9,42]
Power performance	Top speed (km/h)	Top speed.	Benefit (max)	[39,43]
	Acceleration (s)	Time to accelerate from 0 to 100 km.	Cost (min)	[9,50]
	Total motor power (kW)	Total motor power.	Benefit (max)	[42]

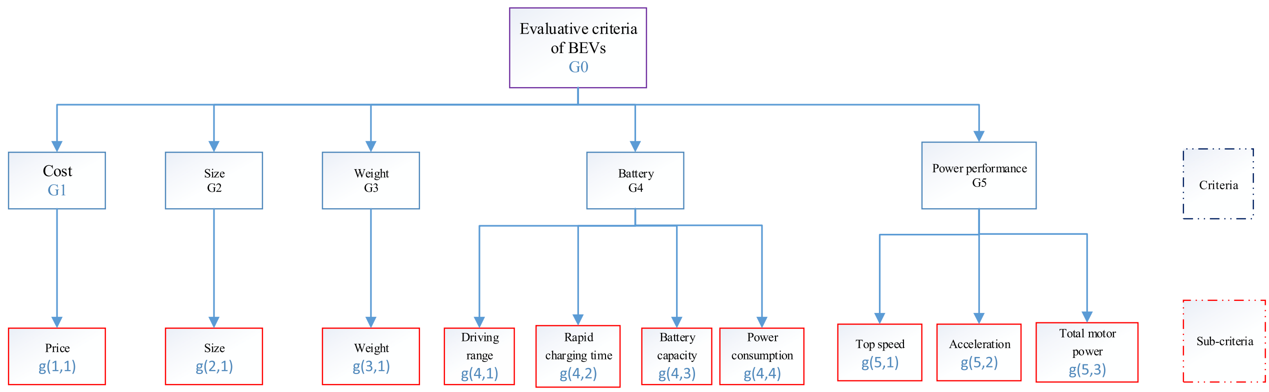

FIGURE 2. Hierarchical structure of evaluative criteria for BEVs.

In this paper, we carry out the correlation of variables by conducting a Pearson correlation test using SPSS v20.0 in the criterion layer based on the following

$$r_{ij} = \frac{\sum_{k=1}^{n} (x_{ik} - \overline{x_i})(x_{jk} - \overline{x_j})}{\sqrt{\sum_{k=1}^{n} (x_{ik} - \overline{x_i})^2 \sum_{k=1}^{n} (x_{jk} - \overline{x_j})^2}} \tag{1}$$

For two highly correlated indicators, we look at their correlation coefficients with the remaining indicators, and delete the index with the largest correlation coefficient with other indicators, and the other criterion is retained. Loop through the above detection steps until no Pearson correlation is higher than the 0.75 benchmark.

C. COLLECT CRITERIA VALUES OF ALTERNATIVE BEVs

For the evaluative criteria system with five first level indicators and ten second level indicators, we need to collect performance levels for each alternative BEV on each evaluation criterion through relevant automotive professional e-commerce platforms or manufacturers' official websites. In this paper, we collected evaluation data through the Autohome (http://www.autohome.com.cn/), founded in 2005, is China's largest auto Internet platform.

D. DETERMINING THE CRITERIA WEIGHTS BASED ON COMBINATION WEIGHTING APPROACH

In order to overcome the deficiencies of subjective and objective weight determination methods, we combined subjective weights with large-scale group decision making and objective weights by our established Entropy method. The process can now be reformulated with more detail as follows.

(1) The subjective weights by large-scale group decision making

In order to make full use of the professional knowledge and experience of decision-makers (DMs) in various fields, large-scale group decision making methods have been widely used and favored [51]. On the other hand, using linguistic terms to express their opinions for DMs is consistent with people's cognitive habits [52]. Based on which, in this work, the subjective criteria weights are determined using the PLPR [51] and specific steps are as follows.

Step 1: Identify DMs from various branches.

Step 2: Collect DMs' preferences information and obtain the PLPRs.

Step 3: Calculate the criteria weights using the probability computation model.

The probability computation model based on PLPRs is developed as follows:

$$\min f=\sum_{i=1}^{n-1}\sum_{j=2,j>i}^{n}\left(d_{ij}^{+}+d_{ij}^{-}\right)$$
$$s.t.\begin{cases}\left(\sum_{k=1}^{\#L_{ij}} I\left(L_{ij,k}\right)\cdot p_{ij,k}-2\tau\right)\omega_i \\ +\sum_{k=1}^{\#L_{ij}} I\left(L_{ij,k}\right)\cdot p_{ij,k}\omega_j-d_{ij}^{+}+d_{ij}^{-}=0 \\ d_{ij}^{+},d_{ij}^{-}\geq 0 \\ \sum_{i=1}^{n}\omega_i=1,\omega_i\geq 0 \\ i,j=1,2,\cdots,n,i<j\end{cases} \tag{2}$$

where d_{ij}^{+} and d_{ij}^{-} are the positive and negative deviations with respect to the goal ε_{ij}, respectively.

Step 4: Calculate the final criteria weights of each subsystem with a satisfactory level of consistency by means of implement consistency-improving algorithm.

(2) The objective weights by an Entropy-based method

For the hierarchical criteria system with two-layer, we propose an Entropy-based method to obtain the weights of criteria. The basic idea of the solution is as follows. If a first-level criterion contains more than two sub-indicators, we use the Entropy method to calculate the sub-indicators weights, and then, based on the obtained secondary index weights, WA (weighted averaging) operator assembled each secondary index assessment data are used to get the first-level index assessment data, and finally, the first-level index weights using the entropy weight method are obtained. Next, we give the specific solution steps.

Step 1: Obtain the weights of the second-level criteria by Entropy method. Suppose that the second-level criteria $c_{t-1}, c_{t-2}, \cdots, c_{t-p}$ attaches to the first-level criteria $c_t \in c_j\,(j=1,2,\cdots,m)$.

1) Calculate the normalized decision matrix

$$R=[r_{uv}]_{n\times p}\,, u=1,2,\cdots n;\, v=1,2,\cdots,p \tag{3}$$

The normalized value r_{uv} is calculated for all criteria as follows

$$r_{uv}=x_{uv}\Big/\sqrt{\sum_{u=1}^{n}(x_{uv})^2} \tag{4}$$

2) Calculate information entropy value. The entropy of each second-level criterion $c_{t-z}\,(z=1,2,\cdots,p)$ is defined as follows

$$E_{c_{t-z}}=-\frac{1}{\ln(n)}\sum_{u=1}^{n}f_{uv}\cdot\ln f_{uv}, z=1,2,\cdots,p \tag{5}$$

3) Calculate the weights of the second-level criteria $c_{t-1}, c_{t-2}, \cdots, c_{t-p}$, which attach to the first-level criteria $c_t \in c_j\,(j=1,2,\cdots,m)$.

$$w_{c_{t-z}}=1-E_{c_{t-z}}\Big/\sum_{z=1}^{p}\left(1-E_{c_{t-z}}\right), z=1,2,\cdots,p \tag{6}$$

Step 2: Obtain the evaluative data of the first-level criterion $c_t \in c_j\,(j=1,2,\cdots,m)$ by WA operator.

$$\begin{aligned}x_{ij,t}&=WA\left(x_{u1},x_{u2},\cdots,x_{up}\right)\\&=w_{c_{t-1}}x_{u1}+w_{c_{t-2}}x_{u2}+\cdots+w_{c_{t-p}}x_{up}\end{aligned} \tag{7}$$

Step 3: Based on the obtained evaluative data of all first-level criteria, we repeat all steps of Step 1 and then obtain the weights of the first-level criteria. *Step 4:* The composite weights are obtained by multiplying each sub-criterion (the second-level criteria) weight by its corresponding main criterion (the first-level criteria) weight. (3) The combined weights Based on the obtained composite subjective weights and the objective weights, we calculate the final combing criterion weights as:

$$w_{j,CW}=\frac{\left[\left(w_{j,subjective}\right)^{\alpha}\cdot\left(w_{j,objective}\right)^{\beta}\right]^{1/(\alpha+\beta)}}{\sum_{j=1}^{n}\left[\left(w_{j,subjective}\right)^{\alpha}\cdot\left(w_{j,objective}\right)^{\beta}\right]^{1/(\alpha+\beta)}} \tag{8}$$

where parameters α and β represent corresponding importance degree for subjective weight and the objective weight, respectively. In practice, consumers may choose the specific values of the parameters according to their preferences.

E. THE PROCEDURE OF DECISION SUPPORT MODEL BASED ON PROMETHEE II

In this Subsection, we use PROMETHEE II method to rank alternative BEVs, based on this, consumers can narrow down the consideration set and make a final purchase decision based on their own preferences. Consumers provide alternative BEVs according to their basic needs and the performance levels of alternative BEVs are collected. Then, the criteria weights are obtained by means of aggregating subjective and objective weights. Finally, based on PROMETHEE II method, the alternative BEVs are ranked to help consumers make purchasing decisions. PROMETHEE II proposed by Brans [55] is an outranking relation-based MCDM method, which can be used to rank a finite set of alternatives. In the PROMETHEE II, the preference function P(a,b) between two alternatives a and b under each evaluative criterion can be selected according to the six recommended types [56]. A preference function(P), which is a function of the difference (d=f(a)-f(b)) between two alternatives a and b

TABLE 2. Eleven alternative bevs provided by the consumer.

Alternative BEVs	VW-ID.4 X	BYD - Tang	Tesla-Model Y	BMW-IX3	NextEV -ES6	GAC - AION V	VW-ID.4 CROZZ	ROEWE - Marvel X	Audi - Q2L	Xiaopen g-G3	NextEV -EC6
Symbolic representation	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11

under each criterion, is defined through function H(d) as in Eq. (9).

$$H\left(d\right) = \begin{cases} P\left(a, b\right), d \geq 0 \\ P\left(b, a\right), d \leq 0 \end{cases} \tag{9}$$

The preference function P indicates the degree of preference of a to b, which is a value between 0 and 1. The larger the function value is, the bigger the difference between alternatives. Especially, when $P\left(a, b\right) = 0$, then a and b are indifferent; while if $P\left(a, b\right) = 1$, then a is strictly preferential to b.

Definition 1 ([53],): [54]. Let $w_j \left(j = 1, 2, \cdots, m\right)$ be the weight of criterion $c_j \left(j = 1, 2, \cdots, m\right)$, and then the preference index in a finite set of alternatives A can be determined as:

$$\forall a, b \in A, \pi\left(a, b\right) = \sum_{j=1}^{m} w_j \cdot P_j\left(a, b\right). \tag{10}$$

Based on the preference index, the leaving flow $\phi^+\left(a\right)$ and entering flow $\phi^-\left(a\right)$ for alternative a can be defined respectively as:

$$\phi^+\left(a\right) = \sum_{x \in A} \pi\left(a, x\right), \tag{11}$$

$$\phi^-\left(a\right) = \sum_{x \in A} \pi\left(x, a\right). \tag{12}$$

where the leaving flow $\phi^+\left(a\right)$ measures that alternative a is dominating the other alternatives and entering flow $\phi^-\left(a\right)$ measures that alternative a is dominated by the remaining alternatives. Furthermore, the corresponding net flow $\phi(a)$ can be calculated as:

$$\phi(a) = \phi^+\left(a\right) - \phi^-\left(a\right). \tag{13}$$

The higher the net flow, the better the alternative. If $\phi(a)$ is a positive value, alternative a is important; if $\phi(a)$ is a negative value, alternative a is unimportant. Therefore, based on the net flow of alternatives, we can not only prioritize all alternatives, but also classify them into important and unimportant categories, which is important for decision makers.

III. THE CASE STUDY

A case where a consumer prepares to buy a BEV is solved by the proposed model and the practicability of the model is further verified. In Subsection A, we collect evaluative data of alternative BEVs, and then filtration of evaluation indexes based on related analysis is implemented in Subsection B. Moreover, the final criteria weights are obtained in Subsection C. In Subsection D, we obtain the ranking of alternative BEVs based on PROMETHEE II method.

A. COLLECTING EVALUATIVE DATA OF ALTERNATIVE BEVs

A consumer is ready to buy a BEV of SUV type and gives 11 kinds of optional BEVs of different brands according to his needs. Table 2 shows a detailed list of 11 kinds of optional BEVs and their symbolic representation. The evaluation index data of alternative BEVs can easily be obtained online through the official website of automobile manufacturers or third-party network platforms (such as https://www.autohome.com.cn/). We take Tesla MODE Y as an example to illustrate the data acquisition process. Figure 3 shows part of the data of Tesla MODE Y thought Automobile e-commerce platform (https://www.autohome.com.cn/). By collecting the data under each index of alternative BEVs of each brand, we finally obtained the data of 11 alternative BEVs under 10 indicators, as shown in Table 3.

B. FILTRATION OF EVALUATION INDEXES BASED ON CORRELATION ANALYSIS

Correlation analysis is carried out so as to eliminate the information redundant indicators. Pearson correlation coefficients on any two indicators in the same criterion layer can be obtained by SPSS v20.0 based on evaluative data in Table 3. The correlation coefficients of the four second-level indicators belonging to the battery index and the three second-level indicators belonging to the power are respectively calculated by SPSS v20.0 in the same criterion layer, and the results are shown in Table 4.

According to Table 4, it can be seen that in the battery index layer, the correlation coefficient of two indexes (battery capacity and driving range) is greater than 0.75. That is, these two indexes are highly correlated, so one should be removed and the other retained. Similarly, within the dynamic index layer there are two highly correlated indexes: Total motor power and Acceleration. Below, one of the two highly correlated indicators is deleted according to the proposed elimination rule. For two secondary indexes (battery capacity and driving range) in the battery index layer, we should exclude the index: battery capacity, because the correlation coefficient between battery capacity and the remaining indexes is larger than that between driving range and the remaining indexes. Similarly, for the two highly correlated indexes in the power performance index layer, we should delete the index: total motor power. Thus, the final evaluation indicators and the performance data of the alternative BEVs on each indicator are shown in Table 5.

TABLE 3. Performance levels of alternative bevs on evaluative criteria.

Criteria	Cost	Size	Weight	Battery				Power performance		
Sub-criteria	Price (ten thousand yuan)	Size (mm)	Weight (kg)	Driving range(km)	Rapid charging time (h)	Battery capacity (kWh)	Power consumption (kWh/100 km)	Top speed (km/h)	Acceleration (s)	Total motor power (kW)
A1	26.89	2717	2120	520	0.7	83.4	17.2	160	6.6	230
A2	28.35	2841	2455	505	0.5	86.4	17.9	180	4.6	380
A3	34.79	2796	1997	594	1	76.8	13.9	217	5.1	317
A4	39.99	2796	2205	500	0.8	74	16.7	180	6.8	210
A5	35.8	2868	2200	420	0.8	70	16.7	200	5.6	320
A6	23.96	2766	1930	600	0.58	80	14.8	175	7.7	135
A7	27.99	2710	2130	500	0.5	84.8	13.6	160	6.6	225
A8	30.88	2754	1870	370	0.7	53	14.2	170	4.8	222
A9	22.68	2550	1405	265	0.6	39.7	13.9	150	8.7	100
A10	19.68	2643	1637	520	0.5	66.5	14.6	170	8.6	145
A11	36.8	2862	2345	430	0.8	70	16.3	200	5.4	320

FIGURE 3. Evaluation criteria data acquisition of Tesla-Model Y thought Automobile e-commerce platform.

TABLE 4. Pearson correlation coefficient in the battery and power performance index layers, respectively.

Pearson correlation coefficient

	Driving range	Rapid charging time	Battery capacity	Power consumption
Driving range	1	.090	**0.831**	.121
Rapid charging time	.090	1	-.043	.060
Battery capacity	**0.831**	-.043	1	.435
Power consumption	.121	.060	.435	1

Pearson correlation coefficient

	Top speed	Acceleration	Total motor power
Top speed	1	-.591	0.687
Acceleration	-.591	1	**-0.888**
Total motor power	0.687	**-0.888**	1

TABLE 5. The final evaluative criteria and criteria data for alternative bevs after screening analysis.

Criteria	Cost	Size	Weight	Battery			Power performance	
Sub-criteria	Price (ten thousand yuan)	Size (mm)	Weight (kg)	Driving range(km)	Rapid charging time (h)	Power consumption (kWh/100 km)	Top speed (km/h)	Acceleration (s)
A1	26.89	2717	2120	520	0.7	17.2	160	6.6
A2	28.35	2841	2455	505	0.5	17.9	180	4.6
A3	34.79	2796	1997	594	1	13.9	217	5.1
A4	39.99	2796	2205	500	0.8	16.7	180	6.8
A5	35.8	2868	2200	420	0.8	16.7	200	5.6
A6	23.96	2766	1930	600	0.58	14.8	175	7.7
A7	27.99	2710	2130	500	0.5	13.6	160	6.6
A8	30.88	2754	1870	370	0.7	14.2	170	4.8
A9	22.68	2550	1405	265	0.6	13.9	150	8.7
A10	19.68	2643	1637	520	0.5	14.6	170	8.6
A11	36.8	2862	2345	430	0.8	16.3	200	5.4

TABLE 6. Pairwise comparison matrix for the first-level indexes.

Pairwise	Cost	Size	Weight	Battery	Power performance
Cost	$\{s_4(1)\}$	$\{s_6(0.6), s_7(0.4)\}$	$\{s_7(0.4), s_8(0.6)\}$	$\{s_3(0.6), s_4(0.4)\}$	$\{s_5(0.2), s_6(0.8)\}$
Size	$\{s_2(0.6), s_1(0.4)\}$	$\{s_4(1)\}$	$\{s_5(1)\}$	$\{s_1(0.8), s_2(0.2)\}$	$\{s_2(1)\}$
Weight	$\{s_1(0.4), s_0(0.6)\}$	$\{s_3(1)\}$	$\{s_4(1)\}$	$\{s_1(1)\}$	$\{s_1(0.4), s_2(0.6)\}$
Battery	$\{s_5(0.6), s_4(0.4)\}$	$\{s_7(0.8), s_6(0.2)\}$	$\{s_7(1)\}$	$\{s_4(1)\}$	$\{s_5(0.2), s_6(0.4), s_7(0.4)\}$
Power performance	$\{s_3(0.2), s_2(0.8)\}$	$\{s_6(1)\}$	$\{s_7(0.4), s_6(0.6)\}$	$\{s_3(0.2), s_2(0.4), s_1(0.4)\}$	$\{s_4(1)\}$

TABLE 7. Pairwise comparison matrix for the second-level indexes.

	Driving range	Rapid charging time	Power consumption
Driving range	$\{s_4(1)\}$	$\{s_4(0.2), s_5(0.8)\}$	$\{s_6(0.4), s_7(0.6)\}$
Rapid charging time	$\{s_4(0.2), s_3(0.8)\}$	$\{s_4(1)\}$	$\{s_6(1)\}$
Power consumption	$\{s_2(0.4), s_1(0.6)\}$	$\{s_2(1)\}$	$\{s_4(1)\}$
	Top speed	Acceleration	
Top speed	$\{s_4(1)\}$	$\{s_1(0.4), s_2(0.6)\}$	
Acceleration	$\{s_7(0.4), s_6(0.6)\}$	$\{s_4(1)\}$	

C. CRITERIA WEIGHTS ANALYSIS

As presented in Section III-C, the criteria weights of the alternative BEVs are determined by merging subjective and objective weights. First, to obtain the subjective weights by large-scale group decision making, 20 qualified participants, including 5 university professors, 5 salesman, and 10 users, are invited to independently provide the judgment on the relative importance of each of the two indicators in each subsystem using pairwise comparison techniques based on linguistic items set = {0: extremely less important, 1: very less important, 2: less important, 3: slightly less important, 4: equally important, 5: slightly more important, 6: more important, 7: very more important, 8: extremely more important}. By collating, we obtained PLPRs from the 20 participants for two layers, represented in Table 6 and Table 7, respectively. Thus, the criteria weights are obtained by using MATLAB software, and the obtained subjective weights of evaluating criteria are presented in Table 8. Second, based on the data in Table 5, we carried out the proposed Entropy-based method to get the objective weights of criteria shown in Table 9. Here, we assume that the subjective and objective weights are equally important,

TABLE 8. The subjective weights for evaluating criteria.

Main Criteria	Weight of main criteria	Sub-criteria	Weight of sub-criteria	Final weight
Cost	0.3317	Price	0.3317	0.3317
Size	0.0792	Size	0.0792	0.0792
Weight	0.0281	Weight	0.0281	0.0281
Battery	0.4488	Driving range	0.5323	0.2389
		Rapid charging time	0.3548	0.1592
		Power consumption	0.1129	0.0507
Power performance	0.1122	Top speed	0.2	0.0224
		Acceleration	0.80	0.0898

TABLE 9. The objective weights for evaluating criteria.

Criteria	Criteria weight	Sub-criteria	Sub-criteria weight	Final weight
Cost	0.4602	Price	0.4602	0.4602
Size	0.0123	Size	0.0123	0.0123
Weight	0.0232	Weight	0.0232	0.0232
Battery	0.2232	Driving range	0.4123	0.092
		Rapid charging time	0.4976	0.111
		Power consumption	0.09	0.02
Power performance	0.2811	Top speed	0.1917	0.0539
		Acceleration	0.8083	0.2272

i.e. $\alpha = \beta = 1$. Then, we obtain the combined weights according to Eq. (8), shown in Table 10 and Fig. 4. The criteria weights describe the importance for purchasing BEVs. For the first-level indexes, the order of index weights is as follows: Cost (0.4165) > Battery (0.3336) > Power performance (0.1893) > Size (0.0333) > Weight (0.0272), which shows that purchase price, battery performances and power performances play a dominant role on ranking of alternative BEVs.

TABLE 10. The combined weights by subjective weights and objective weights ($\alpha = \beta = 1$).

Criteria	Sub-criteria	Final weight
Cost	Price	0.4165
Size	Size	0.0333
Weight	Weight	0.0272
Battery	Driving range	0.1580
	Rapid charging time	0.1417
	Power consumption	0.0339
Power performance	Top speed	0.0370
	Acceleration	0.1523

D. RANKING OF ALTERNATIVE BEVs BASED ON PROMETHEE II

In applying the PROMETHEE II method, there are six generalized priority function types, and our study selects type IV for all criteria. The analytical definition of the IV-shape is shown in Eq. (14) [54].

$$H(d) = \begin{cases} 0 & \text{if } |d| \leq q \\ 1/2 & \text{if } q < |d| \leq p \\ 1 & \text{if } |d| > p. \end{cases} \tag{14}$$

This is consistent with existing research [55], the indifference threshold (q) is set at 10% of the difference between the highest and lowest score, while the preference threshold (p) is set at 30% of the same difference for each criterion. The calculated values are shown in Table 11.

For the difference (d) of the pair of alternatives (A_i, A_j) $(i \neq j, i, j = 1, 2, \cdots, 11)$ from all the different alternatives is calculated as follows:

$$d = \begin{cases} f(A_i) - f(A_j) & \textit{if criterion is benifical} \\ f(A_j) - f(A_i) & \textit{if criterion is cost} \end{cases} \tag{15}$$

By implementing PROMETHEE II, the leaving flow ϕ^+, entering flow ϕ^-, and net flow ϕ of alternative BEVs are obtained, which are shown in Table 12. From Table 12, it can be seen that the net flows of the eleven BEVs follow the order and ranking for alternative BEVs. Based on the ranking of alternative BEVs $A_{10} \succ A_6 \succ A_2 \succ A_7 \succ A_1 \succ A_9 \succ A_8 \succ A_3 \succ A_5 \succ A_{11} \succ A_4$, the A_{10} (Xiaopeng-G3) is recommended first to the consumer.

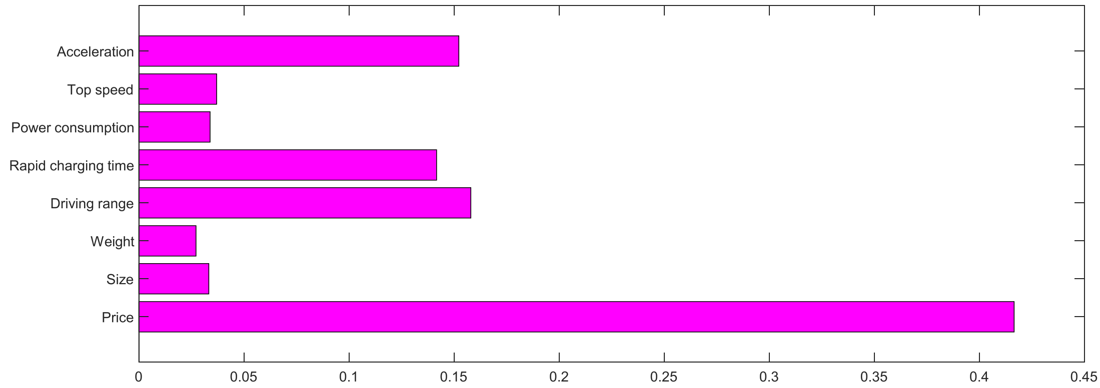

FIGURE 4. **Weights of sub-criteria.**

TABLE 11. **The performance levels of alternative bevs on eight evaluative criteria and promethee parameters.**

	The performance levels of alternative BEVs on eight evaluative criteria											PROMETHEE parameters	
Criteria\Alternative BEVs	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	q	p
Price	26.89	28.35	34.79	39.99	35.8	23.96	27.99	30.88	22.68	19.68	36.8	2.03	6.09
Size	2717	2841	2796	2796	2868	2766	2710	2754	2550	2643	2862	31.8	95.4
Weight	2120	2455	1997	2205	2200	1930	2130	1870	1405	1637	2345	105	315
Driving range	520	505	594	500	420	600	500	370	265	520	430	33.5	100.5
Rapid charging time	0.7	0.5	1	0.8	0.8	0.58	0.5	0.7	0.6	0.5	0.8	0.05	0.15
Power consumption	17.2	17.9	13.9	16.7	16.7	14.8	13.6	14.2	13.9	14.6	16.3	0.43	1.29
Top speed	160	180	217	180	200	175	160	170	150	170	200	6.7	20.1
Acceleration	6.6	4.6	5.1	6.8	5.6	7.7	6.6	4.8	8.7	8.6	5.4	0.41	1.23

TABLE 12. **The evaluative results of alternative bevs based on promethee II.**

Alternative	ϕ^+	ϕ^-	ϕ	Classes	Ranking
A1	3.20945	2.9626	0.24685	**important**	5
A2	4.7599	1.58435	3.17555	**important**	3
A3	2.98695	4.3017	-1.31475	non-important	8
A4	1.2851	5.6533	-4.3682	non-important	11
A5	1.90165	4.8276	-2.92595	non-important	9
A6	4.96825	1.7136	3.25465	**important**	2
A7	4.0505	2.0654	1.9851	**important**	4
A8	3.11105	4.02735	-0.9163	non-important	7
A9	3.87755	3.9077	-0.03015	non-important	6
A10	5.67365	1.8524	3.82125	**important**	1
A11	1.905	4.83305	-2.92805	non-important	10

The reasons why alternative A_{10} can be ranked first are as follows: (a) among the 11 alternative BEVs, the price of A_{10} is the cheapest one, that is, it has the best performance in this cost-type indicator. Meanwhile, the weight of price is 0.4165, which is also the highest proportion; (b) in the second important indicator of battery performance (weight 0.3336) is also good, specifically for the driving range of 520 kilometers, fast charge time of 0.5 hours, power consumption of 14.6 kWh/100 km; (c) despite the poor performance in terms of size and weight, these two indicators have less weight. The alternative product ranking results above are based on the results under the weight model we built. Of course, if the consumer has a clear indicator weight preferences, they can enter the weight values they

TABLE 13. Criteria weights in five different scenarios.

Sub-criteria	α=1,β=0	α=0,β=1	α=β=1	α=2,β=1	α=1,β=2
Price	0.3317	0.4602	0.4165	0.3700	0.4126
Size	0.0792	0.0123	0.0333	0.0426	0.0229
Weight	0.0281	0.0232	0.0272	0.0264	0.0247
Driving range	0.2389	0.092	0.158	0.1738	0.1265
Rapid charging time	0.1592	0.111	0.1417	0.1412	0.1252
Power consumption	0.0507	0.02	0.0339	0.0372	0.0273
Top speed	0.0224	0.0539	0.037	0.0300	0.0402
Acceleration	0.0898	0.2272	0.1523	0.1224	0.1667

provide to merit a personalized ranking results that match their preferences. In order to verify the proposed model's robustness and applicability, we put into effect the sensitivity analysis by changing the evaluation criteria weights in the following subsection C.

Furthermore, according to the net flow of alternative BEVs obtained by PROMETHEE II, the classification takes a step towards identifying the important from the non-important alternatives. The alternative BEVs can be grossly divided into two groups: the available ($A_{10}, A_6, A_2, A_7, A_1$) and non-available ($A_9, A_8, A_3, A_5, A_{11}, A_4$) based on whether the net flow value is greater than zero. By this, the alternative BEVs greatly are reduced and consumers only select the final purchase BEV from the set of the reduced considerations. That is, the buyer only need consider a set ($A_{10}, A_6, A_2, A_7, A_1$) instead of the original 11 alternative cars, which could improve the consumer's decision confidence, thereby reducing cognitive effort and avoiding the possibility of choosing inferior products. Finally, buyers make the purchase choices according to their personal preferences on the basis of the ranking provided by the proposed model.

IV. COMPARATIVE ANALYSIS AND MANAGERIAL IMPLICATIONS

In this section, we make a comparative analysis from two aspects. One is to do contrastive analysis considering five different scenarios and two is to contrast with TOPSIS method. Besides, the managerial implications of this study is given.

A. FIVE DIFFERENT SCENARIOS ARE CONSIDERED

As in the previous case application, the subjective and objective weights with the same level of importance was employed. Moreover, in order to simulate more real-life decision-making environments, four scenarios are hypothesized based on the degree of consumer trust in subjective and objective weights. These scenarios as well as the scenario considered in Section IV are as follows: **Scenario I** (α =1 and β =0), **Scenario II** (α =0 and β =1), **Scenario III** (α = β =1), **Scenario IV** (α =2 and β =1), and **Scenario V** (α =1 and β =2).

The corresponding combinative weights of criteria can be obtained for five different scenarios according to Eq. (8), shown in Table 13. The combinative weights of every scenario are then used as an input in the PROMETHEE II method to get the ranking among the eleven alternative BEVs, which are shown in Table 14 and Fig. 5. Of course, in addition to the above five cases, consumers can also assign other values for parameters (α and β) according to their preferences for subjective and objective weights to obtain the composite weight of indicators, which is more in line with different consumers' preferences for indicator weights.

B. COMPARATIVE ANALYSIS WITH TOPSIS AND VIKOR METHODS

TOPSIS is a classic MCDM method, which is often used to deal with practical problems. The case in Section IV is implemented by the TOPSIS procedure [56] and then the ranking of alternative BEVs is acquired, which is reported in Table 15. Furthermore, Table 16 displays the comparison between the ranking of the proposed model and the TOPSIS method. From Table 16, it can be seen that the order of A_1 and A_7 is reversed, and the other positions are not changed. Sorting is different because the two MCDM methods use different principles. For TOPSIS method, the method applied the Euclidean distance to measure the distances of the alternatives to the two ideal solutions. While, the PROMETHEE-II technique used by this paper is an outranking method with giving a preference function for each option versus the others.

VIKOR is another frequently used MCDM method that can provide an eclectic ranking list [57]. Based on the final evaluative criteria data in Table 5, the VIKOR method is implemented to get a sorted list of alternatives, which are also represented in Table 16. From Table 16, we see that the optimal candidate obtained by the VIKOR method is different from the other two methods. The reason for this result is that the principles of the three methods are different, and VIKOR provides a compromise solution with an advantage rate [57]. Although the optimal solutions of the three methods differ,

TABLE 14. The net flow and ranking of alternative bevs in five different scenarios.

	α=1,β=0		α=0,β=1		α=β=1		α=2,β=1		α=1,β=2	
	Net flow	Ranking	Net flow	Ranking	Net flow	Ranking	Net flow	Ranking	Net flow	Ranking
A1	0.08835	5	0.21465	5	0.24685	5	0.2037	5	0.24165	5
A2	2.84355	3	3.5637	1	3.17555	3	2.8814	3	3.12385	2
A3	-0.7446	6	-1.23935	8	-1.31475	8	-1.1286	8	-1.28525	8
A4	-3.43465	11	-4.82205	11	-4.3682	11	-3.8769	11	-4.32665	11
A5	-2.8264	9	-2.53015	10	-2.92595	9	-2.791	9	-2.68665	10
A6	3.72645	1	2.52235	3	3.25465	2	3.2527	2	2.87085	3
A7	2.1709	4	1.54175	4	1.9851	4	1.9673	4	1.75775	4
A8	-1.6756	8	-0.0886	7	-0.9163	7	-1.1163	7	-0.60825	7
A9	-0.96535	7	0.09085	6	-0.03015	6	-0.2349	6	0.09115	6
A10	3.67185	2	3.2346	2	3.82125	1	3.6462	1	3.49765	1
A11	-2.8545	10	-2.48775	9	-2.92805	10	-2.8036	10	-2.6761	9

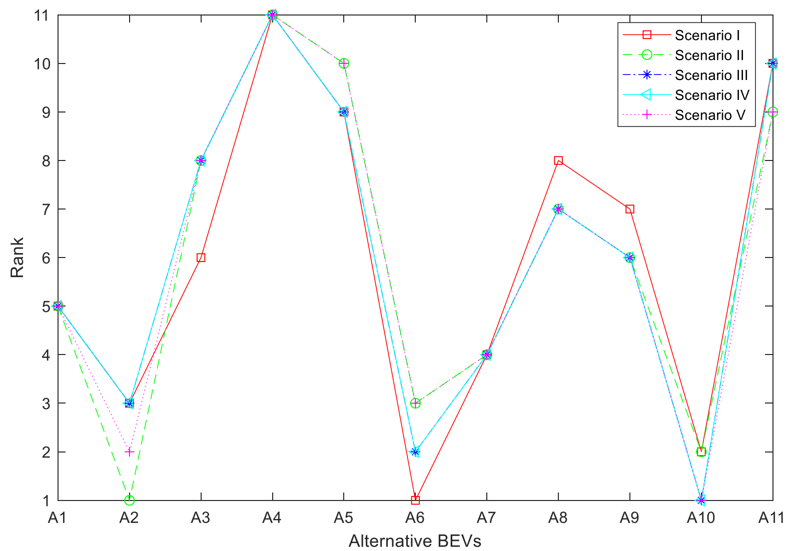

FIGURE 5. The ranking of alternative BEVs in five different scenarios.

TABLE 15. The sorted results by implementing topsis method.

Alternative BEVs	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11
R	0.6379	0.6451	0.4008	0.2509	0.3224	0.7330	0.6251	0.4907	0.6216	0.7601	0.3089
Ranking	4	3	8	11	9	2	5	7	6	1	10

the top three objects are the same, namely A_{10}, A_6, and A_2, which further verifies the validity of our proposed method.

C. SENSITIVITY ANALYSIS

Through the sensitivity analysis of the influence of the change of evaluation criteria weights on the ranking results, the applicability of the proposed framework for the purchase of BEVs is verified. In the following, we check whether the ranking changes by floating the criteria weights.

Under the premise that the sum of weights of all criteria is 1, for the sake of simplicity, we take the weight of the index with the largest proportion (i.e., price) as the basis, and the weights of other criteria are changed accordingly while the weight ratio of other criteria remains constant. To be specific, we vary criteria weights from the initial value of price weight 0.417 to $0.417 \times (1 + 25\%)$ with an increment of $0.417 \times 5\%$ and from the initial value 0.417 to $0.417 \times (1 - 25\%)$ with a decrement of $0.417 \times 5\%$. Thus, 10 sensitivity analysis experiments are conducted and the results are shown in Table 17.

TABLE 16. Comparison of ranking for topsis, vikor, and the proposed model.

Methods	The order of alternative BEVs
The proposed model	$A_{10} \succ A_6 \succ A_2 \succ A_7 \succ A_1 \succ A_9 \succ A_8 \succ A_3 \succ A_5 \succ A_{11} \succ A_4$
TOPSIS	$A_{10} \succ A_6 \succ A_2 \succ A_1 \succ A_7 \succ A_9 \succ A_8 \succ A_3 \succ A_5 \succ A_{11} \succ A_4$
VIKOR	$A_6 \succ A_{10} \succ A_2 \succ A_7 \succ A_1 \succ A_9 \succ A_8 \succ A_3 \succ A_5 \succ A_{11} \succ A_4$

TABLE 17. The impact of changing the criteria weights on the ranking results.

Weight variation of price	Global utility	Ranking
+25%	$(0.654, 3.052, -2.1525, -5.107, -3.4805, 3.747, 2.0805, -1.1115, 1.05, 4.749, -3.481)^T$	$A_{10} \succ A_6 \succ A_2 \succ A_7 \succ A_9 \succ A_1 \succ A_8 \succ A_3 \succ A_5 \succ A_{11} \succ A_4$
+20%	$(0.5665, 3.0935, -1.981, -4.9595, -3.3625, 3.6495, 2.0605, -1.0755, 0.8145, 4.557, -3.363)^T$	$A_{10} \succ A_6 \succ A_2 \succ A_7 \succ A_9 \succ A_1 \succ A_8 \succ A_3 \succ A_5 \succ A_{11} \succ A_4$
+15%	$(0.493, 3.108, -1.8195, -4.814, -3.2545, 3.551, 2.037, -1.0355, 0.614, 4.376, -3.2555)^T$	$A_{10} \succ A_6 \succ A_2 \succ A_7 \succ A_9 \succ A_1 \succ A_8 \succ A_3 \succ A_5 \succ A_{11} \succ A_4$
+10%	$(0.4175, 3.129, -1.6555, -4.663, -3.1485, 3.456, 2.02, -1.002, 0.401, 4.1955, -3.15)^T$	$A_{10} \succ A_6 \succ A_2 \succ A_7 \succ A_1 \succ A_9 \succ A_8 \succ A_3 \succ A_5 \succ A_{11} \succ A_4$
+5%	$(0.3245, 3.155, -1.487, -4.525, -3.0395, 3.355, 2.008, -0.9535, 0.191, 4.012, -3.0405)^T$	$A_{10} \succ A_6 \succ A_2 \succ A_7 \succ A_1 \succ A_9 \succ A_8 \succ A_3 \succ A_5 \succ A_{11} \succ A_4$
+0%	$(0.2469, 3.1756, -1.3148, -4.3682, -2.9260, 3.2547, 1.9851, -0.9163, -0.0302, 3.8213, -2.9281)^T$	$A_{10} \succ A_6 \succ A_2 \succ A_7 \succ A_1 \succ A_9 \succ A_8 \succ A_3 \succ A_5 \succ A_{11} \succ A_4$
-5%	$(0.1715, 3.2045, -1.153, -4.225, -2.824, 3.1595, 1.9725, -0.8795, -0.2435, 3.6425, -2.8255)^T$	$A_{10} \succ A_2 \succ A_6 \succ A_7 \succ A_1 \succ A_9 \succ A_8 \succ A_3 \succ A_5 \succ A_{11} \succ A_4$
-10%	$(0.0855, 3.2295, -0.984, -4.0725, -2.7015, 3.058, 1.945, -0.842, -0.464, 3.4495, -2.7035)^T$	$A_{10} \succ A_2 \succ A_6 \succ A_7 \succ A_1 \succ A_9 \succ A_8 \succ A_3 \succ A_5 \succ A_{11} \succ A_4$
-15%	$(0.001, 3.2495, -0.808, -3.9285, -2.597, 2.9605, 1.933, -0.7965, -0.6795, 3.264, -2.5985)^T$	$A_{10} \succ A_2 \succ A_6 \succ A_7 \succ A_1 \succ A_9 \succ A_8 \succ A_3 \succ A_5 \succ A_{11} \succ A_4$
-20%	$(-0.074, 3.271, -0.6565, -3.788, -2.494, 2.8655, 1.9165, -0.758, -0.8765, 3.09, -2.496)^T$	$A_2 \succ A_{10} \succ A_6 \succ A_7 \succ A_1 \succ A_3 \succ A_8 \succ A_9 \succ A_5 \succ A_{11} \succ A_4$
-25%	$(-0.1545, 3.293, -0.4835, -3.636, -2.3815, 2.7695, 1.8945, -0.727, -1.0975, 2.907, -2.384)^T$	$A_2 \succ A_{10} \succ A_6 \succ A_7 \succ A_1 \succ A_3 \succ A_8 \succ A_9 \succ A_5 \succ A_{11} \succ A_4$

From Table 17, it can be seen that when the weight of price is relatively large, A_{10} is the first place in the ranking, and when the weight value of price is reduced to a certain extent, A_2 is the best alternative. Although the alternatives at the top of the ranking list have changed with the change of criteria weight, the alternatives included in the first four options of the ranking are stable (i.e., A_{10}, A_2, A_6, and A_7) in the 10 experiments, which indicates that the ranking of alternative BEVs is relatively robust. Thus, buyers can trust our decision support model to make their final purchase choices based on their personal preferences.

D. MANAGERIAL IMPLICATIONS

For consumers, they usually have limited cognitive abilities (i.e., bounded rationality) and are often unable to process the vast amount of information potentially available about alternative products. One possible solution is to provide consumers with decision aids tool. Once consumers actually take advantage of decision aids tools, they will be able to eliminate unwanted products from the consideration set more quickly and accurately, reducing the number of alternatives considered by decision makers [58], [59]. Through the case study, it can be seen that the decision support model constructed in this paper can cost consumers less cognitive effort and reduce inferior product choice, and further improve consumers' decision-making confidence. More specially, the established decision aids model would be particularly useful for inexperienced consumers who need help specifying attributes, their relationships, and their relative importance.

Additionally, the results of this study also have important practical significances for manufacturers. On the one hand, priority of indicator weights (Topping that ranking: price, driving range, and acceleration) could give a certain guidance for manufacturers in product upgrading and understanding the market environments. Price is the most important factor. As purchase prices fall, BEVs will, as expected, increase their share of the automotive market. Thus, lowering the purchase price of BEVs could accelerate their global implementation. Driving range is placed second and acceleration third, which further shows that the battery and power of BEVs are also important indicators for consumers to consider. On the other hand, manufacturers can clearly see where their products rank in the same category according to the ranking results, which can help manufacturers understand consumer preferences, based on which they can take steps to improve the performance of their products.

V. CONCLUSION

In order to provide purchasing decision support to consumers who buy BEVs, this research presents a data-driven decision aids framework to rank alternative BEVs based on a MCDM methodology. First, a hierarchical evaluation criteria system is established based on the influencing factors of the adoption of BEVs. In order to eliminate the high correlation among intra-class indicators that belong to the same level, a criteria simplification rule based on the correlation coefficient is proposed. Second, we propose a composite method to determine the weights of criteria by integrating large-scale group decision making method and the Entropy-based method. Furthermore, a decision aids model based on PROMETHEE-II technique is proposed to rank alternative BEVs. For the proposed data-driven decision aid method, the sensitivity analysis results show that the ranking results of this method are relatively stable.

Some limitations provide avenues for future research. First, the updated criteria set could be extended by combining qualitative criteria with the help of text mining technology [60]. Second, this study assumes that consumers are homogeneous, without considering the personalized characteristics of consumers [61], which is also one of the limitations of our study. This is also a very meaningful research direction to build a decision support model suitable for heterogeneous consumers [62].

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