Traffic & Transportation

Electric Vehicle Selection Using the Technique of Precise Order Preference

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Original Scientific Paper
Submitted: 17 May 2025
Accepted: 27 July 2025
Published: 28 Apr 2026

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Publisher:
Faculty of Transport and Traffic Sciences, University of Zagreb

ABSTRACT
Conventional vehicles rely on petrol and its derivatives to deliver strong performance and extended range. However, these vehicles significantly contribute to environmental pollution and the depletion of fossil fuels. Consequently, alternative-fuelled vehicle technologies have been developed, leading to a paradigm shift in the transportation sector toward electric vehicles (EVs) that reduce greenhouse gas emissions and lessen their environmental impact. For potential EV buyers, a selection problem exists due to the diverse range of alternatives. This study proposes an integrated model that selects and ranks EVs based on three main criteria: cost, driving performance and technical features. Hierarchical best worst method (HBWM), full consistency method (FUCOM), and step-wise weight assessment ratio analysis (SWARA) methods are employed to determine the importance weights for the main criteria and their sub-criteria. A sample EV set consisting of 10 potential alternatives was created for the study, and these EVs were ranked by combining the weights of the main criteria and sub-criteria obtained using the three aforementioned methods employing the technique of precise order preference (TPOP) method. Our experiments suggest that the most critical criterion among the 10 sub-criteria was price, and the least important criterion was high speed.

KEYWORDS
electric vehicles selection; hierarchical best worst method; full consistency method; step-wise weight assessment ratio analysis; technique of precise order preference.

1. INTRODUCTION

Energy has always played a crucial role in economic development; however, the intensive use of fossil fuels has resulted in significant environmental impacts. Today, the degradation of ecosystems and the depletion of natural resources have led to serious issues, including environmental pollution and an energy crisis, posing significant challenges to sustainable development [1]. Increasing global warming affects both the environment and the quality of life. The dependence on fossil fuels in the transport sector damages the environment through greenhouse gas emissions. To reduce reliance on fossil fuels, the global community must adopt renewable, clean and cost-effective energy sources. In the transportation sector, the shift toward electric mobility is a significant step in that direction [2].

Automobiles, among the most widely used vehicles globally, have greatly enhanced daily convenience while also contributing to significant environmental issues. Exhaust emissions and high oil consumption have intensified air pollution and accelerated resource depletion. To this end, developing clean, pollution-free electric vehicles (EVs) has emerged as an effective strategy for energy conservation and emission reduction [3, 4]. Given that the transportation sector is a major contributor to carbon emissions, EVs have emerged as a crucial eco-friendly alternative [5]. Compared to gasoline and diesel cars, EVs, powered by electric motors instead of internal combustion engines (ICEs), offer a promising approach to mitigating the greenhouse effect. Advancements in technology have diversified automotive offerings and shifted production toward zero-emission EVs. Unlike conventional ICE vehicles that emit harmful pollutants, these eco-friendly vehicles address environmental concerns and are increasingly in demand. Consequently, identifying the key criteria that influence EV purchases has become essential [6].

EVs have many advantages. For example, their electric motors eliminate the need for oil changes, and the energy lost during braking is recaptured and stored in the battery. Additionally, EVs offer a significantly larger interior space due to their technical infrastructure, which consists of fewer parts than that of ICEs; their maintenance is also easier and less costly than that of other motorised vehicles. Furthermore, EVs are not only financially attractive but also offer performance benefits over ICE vehicles. They provide smoother acceleration and deceleration, operate quietly and produce no tailpipe emissions. These features make them especially appealing to environmentally conscious consumers. However, apart from these advantages, there are some disadvantages of EVs, including high production and purchasing costs, a generally smaller size, limited features and speed, longer charging times and the need for charging stations [7].

Most real-world problems present multiple solution alternatives, requiring a decision-maker to select the most appropriate option based on specific criteria. Typically, these issues involve several criteria, each with its level of importance, which are used to evaluate the available alternatives. In this context, multi-criteria decision-making (MCDM) offers a systematic and mathematically grounded approach to selecting the most suitable alternative. It involves ranking or choosing among options based on multiple weighted criteria [8, 9], requiring decision-makers to evaluate several criteria and alternatives simultaneously. For instance, EV selection is a complex decision-making process that involves assessing multiple criteria and alternatives simultaneously. To this end, MCDM methods provide essential tools to identify the most promising solution [10, 11].

In this study, cost, technical, and driving features are identified as the main criteria for assessing and selecting the best EV alternative. Price, service cost, and maintenance cost are determined as sub-criteria for the main criteria of cost; range, acceleration, and highest speed are defined as sub-criteria for the main criteria of driving features; and torque, charging time, battery capacity, and weight are determined as sub-criteria for the main criteria of technical features. The hierarchical best-worst method (HBWM), full consistency method (FUCOM), and step-wise weight assessment ratio analysis (SWARA) are employed to determine the weights of the criteria and sub-criteria. The weights obtained by these three MCDM methods are combined using the technique of precise order preference (TPOP), through which the ten selected EVs are evaluated accordingly.

This study focuses primarily on the following two research questions:

1) RQ1: Methodologically, how can TPOP be effectively combined with different MCDM methods under realistic and complex conditions?
2) RQ2: Practically, which EV alternative offers optimal performance when evaluated through the hybrid HBWM–FUCOM–SWARA–TPOP framework?

By addressing these research questions, we aim to make both methodological and practical contributions to the fields of MCDM and EV selection. The rest of the paper is organised as follows. The literature review is given in Section 2. The methodological framework and the MCDM methods used in the study are presented in Section 3. In Section 4, the EVs and experiment setups are detailed, and the results obtained are presented. Managerial implications are discussed in Section 5, and Section 6 gives discussions and conclusions.

2. LITERATURE REVIEW

Many studies employ multiple methods to address a decision-making problem for EV ranking and selection. In many of these studies, ranking results obtained from various methods are compared. For instance, Khan et al. [2] used fuzzy TOPSIS to select Pakistan's most sustainable hybrid vehicle, considering local infrastructure and economic constraints. The study found that the Toyota Aqua ranked highest among the seven alternatives in terms of economic, environmental, and social criteria. Biswas and Das [6] developed a holistic EV selection model using the MABAC method to evaluate battery electric vehicles on fuel economy, pricing, acceleration, range, and top speed. Sensitivity analysis confirmed the stability of the results and identified the Hyundai Ioniq Electric as the top-ranked alternative. Golui et al. [12] proposed a new correlation-based FF-TOPSIS method for EV selection under uncertainty. The study indicates that incorporating hesitations through fuzzy data enhances decision accuracy. Więckowski et al. [13] presented a sensitivity analysis framework using interval arithmetic and MCDA to improve decision making under data uncertainty, where TOPSIS was applied to EV evaluation. Tian et al. [14] proposed an MCDM method that utilises sentiment analysis of online EV reviews, transformed into hesitant intuitionistic fuzzy data, to rank EV alternatives. This approach can help consumers make informed choices and offer insights into market preferences for automakers.

Bošković et al. [15] presented AROMAN, a new MCDM method that combines linear and vector normalisation in two steps to rank EVs for last-mile delivery. Through a case study, comparative and sensitivity analyses confirm AROMAN's precision, stability, and managerial relevance. Ziemba [16] evaluated Poland's A–C segment EVs using three fuzzy MCDA methods, i.e., TOPSIS, SAW, NEAT-f-PROMETHEE II, under data uncertainty, the results of which highlighted the Volkswagen ID.3 Pro S and Nissan LEAF e+ as the most attractive options for sustainable transport. Sonar and Kulkarni [17] combined AHP and MABAC into a novel MCDM framework that weights criteria and ranks six EV options to identify the best choice. Sejwal et al. [18] weighted five key criteria, i.e., cost, range, acceleration, charging time, and top speed, among eight EV models using AHP, then ranked them using TOPSIS and MOORA. Both methods provide clear guidance for consumers by identifying the BYD E6 as the best performer. Ren et al. [19] extracted online reviews using LDA to determine five key BEV attributes (dynamics, technology, safety, comfort, cost). They then applied DEMATEL-DANP to weigh them (price proved to be the most critical factor) and VIKOR to rank the ten models.

There are only a few studies that combine the results obtained from multiple MCDM methods. For instance, in Ecer [5], ten EVs were selected as alternatives. These vehicles were then ranked based on technical characteristics, e.g., acceleration, price, battery, and range, using SECA, MARCOS, MAIRCA, COCOSO, ARAS, and COPRAS methods. Then, the results obtained from various MCDM techniques were combined by applying Borda counting and Copeland ranking methodologies. Arslan and Bircan [32] combined the ranking results obtained from TOPSIS, GIA, VIKOR, and MOORA reference point methods, which serve the same purpose as the Copeland method, and combined them into a single ranking. In this study, 23 OECD member countries were taken as alternatives. Five generally accepted criteria obtained from the World Bank database were used to rank these countries. *Table 1* provides a comprehensive overview of the application of MCDM methods in solving EV-related selection and ranking problems.

Table 1 – Literature review

References	Methodology	Issue
[1]	Linguistic entropy weight	Site selection of EV charging stations
[2, 12, 13]	TOPSIS	EVs selection
[3]	AHP, TOPSIS, COPRAS	Site selection of EV charging stations
[4]	MULTIMOORA, DEMATEL	Site selection of EVs battery replacement station
[5]	MARCOS, MAIRCA, SECA, COCOSO, ARAS, COPRAS	Performance evaluation of EVs
[6, 17]	AHP, MABAC	EVs selection
[9]	Gained and lost dominance score	Site selection of EVs charging stations
[14]	ORESTE	EVs selection
[15]	AROMAN	EVs selection
[16]	TOPSIS, SAW, PROMETHEE	EVs selection
[18]	TOPSIS, MOORA, AHP	EVs selection
[19]	DEMATEL, VIKOR	EVs selection
[21, 22]	CORPAS	EVs selection for industrial users
[23]	DEMATEL, TOPSIS	Site selection of EVs charging stations
[24]	AHP, WLC, TOPSIS, VIKOR	Site selection of EVs charging stations
[25]	AHP	Site selection of EVs charging stations
[26]	PROMETHEE, AHP	EVs selection
[27]	TOPSIS	EVs supplier selection

References	Methodology	Issue
[28]	BWM, VIKOR	EVs supplier selection
[29]	CODAS, BWM	Site selection of EVs charging stations
[30]	CODAS-BWM	Sustainable network design in the supply chain
[31]	Weighted sum model (WSM)	Selection of Li-ion batteries for EVs
[32]	TOPSIS	Performance evaluation of EVs charging stations
[33]	TOPSIS	Comparison of sustainability models in the development of EVs
[34]	FUCOM, EDAS	EVs selection and selection
[35]	MULTIMOORA	Site selection of EVs charging stations
[36]	TOPSIS, MOORA	Site selection of EVs charging stations
[37]	COMET	EVs selection

The literature review reveals several critical gaps in the existing studies on EV selection. First, only a limited number of studies have combined the results obtained from multiple MCDM methods, which restricts the opportunity for cross-method validation and weakens robustness in the face of conflicting expert opinions or uncertain data. Second, although popular methods such as AHP, TOPSIS and MOORA have been widely applied, they often rely on static weighting schemes or deterministic frameworks that fail to reflect the complexity and uncertainty inherent in real-world decision-making contexts. Third, there is limited focus on developing integrated models that simultaneously ensure methodological rigor and practical applicability. While traditional methods offer simplicity, they may be limited by factors such as rank reversal or inconsistent judgments. In contrast, more recent approaches such as HBWM and TPOP, which offer improved consistency and structured preference modelling, remain underutilised. To address these shortcomings, this study proposes a hybrid framework that combines HBWM, FUCOM, SWARA, and the newly developed TPOP method. The proposed model contributes to the literature by offering a more adaptable, precise, and reliable approach to EV selection, capable of bridging methodological sophistication with real-world relevance.

3. METHODS

Decision-making is a crucial process encountered in every aspect of life. Researchers have extensively studied MCDM problems, leading to the development of various methods for effectively addressing issues that involve multiple criteria [1, 31]. The most commonly used MCDM methods in the literature can be classified into three categories: scoring, ranking, and pairwise comparison. These approaches simplify the decision-making process, thereby enhancing decision quality. A key advantage of MCDM techniques is their ability to resolve problems that involve multiple, often conflicting, criteria [22, 38].

In MCDM methods where expert opinions are obtained through pairwise comparisons, such as the analytic hierarchy process (AHP), the number of pairwise comparisons required increases with the number of criteria or alternatives to be evaluated, making it difficult for decision-makers to make consistent decisions [39]. Rezaei [40] introduced a structured pairwise comparison-based best-worst method (BWM) to the literature in 2015 to overcome this difficulty. FUCOM is one method for determining the weights of criteria that influence a selection problem. FUCOM makes evaluations by comparing the criteria, and one less comparison of the number of criteria is sufficient [41]. In the SWARA method, the criteria for evaluating alternatives are ranked from most important to least important, and the ranking created by the decision-makers is considered [42]. The TPOP method combines the results obtained from multiple MCDM methods. These methods are explained below.

3.1 Hierarchical best-worst method

The BWM is based on a pairwise comparison rule, comparing alternatives with the best and worst [8, 43, 44]. By identifying the best and worst criteria first and then comparing the remaining criteria with these, the decision maker can use this method without assessing all criteria pairwise [45]. The BWM method simplifies the process by requiring only $2n-3$ comparisons, where n is the number of criteria, making it easier to use [46, 47].

The identification of sub-criteria, as well as main criteria, is essential for evaluating alternatives when making a decision. It can be helpful to introduce a model that can incorporate sub-criteria into the decision-making process and requires less data and information to make decisions while maintaining the benefits of previous approaches [48, 49, 50].

The hierarchical BWM (HBWM) can be used effectively by researchers and managers. In this study, a "global weight" is calculated by combining the weights of the sub-criteria (local weights) [51, 52].

The steps of the model are given below:

Step 1. Identify decision criteria $\{c_1, c_2, \ldots, c_n\}$ and sub-criteria $\{c_{1k}, c_{2k}, \ldots, c_{nk}\}$.

Step 2. The best (most important) and worst (least important) criteria and sub-criteria are identified.

Step 3. The priority of the best criterion among the other criteria (A_B) is determined as a number between 1 and 9.

$$A_B = \{a_{B1}, a_{B2}, \ldots, a_{Bn}\} \tag{1}$$

a_{Bj}: The priority of the best criterion over the *j-th* criterion,

Step 4. The priority of the other criteria compared to the worst criterion (A_W) is determined as a number between 1 and 9.

$$A_W = \{a_{w1}, a_{w2}, \ldots, a_{wn}\} \tag{2}$$

a_{Wj}: Priority of the *j-th* criterion over the worst criterion,

Step 5. The priority of the best sub-criterion of the *s'th* criterion with each of the other sub-criteria $\left(A_{Bj}^s\right)$ is determined as a number between 1 and 9.

$$A_B^s = \{a_{B1}^s, a_{B2}^s, \ldots, a_{Bk}^s\} \tag{3}$$

a_{Bj}^s: The priority of the best sub-criterion of the *s'th* criterion over the *j-th* sub-criterion,

Step 6. The priority of the other sub-criterion (*s'th* criterion) compared to the worst sub-criterion $\left(A_{Wj}^s\right)$ is determined as a number between 1 and 9.

$$A_W^s = \{a_{W1}^s, a_{W2}^s, \ldots, a_{Wk}^s\} \tag{4}$$

a_{Wj}^s: The priority of each of the other sub-criterion of the *s'th* criterion over the worth sub-criterion,

Step 7. The weights of the criteria $(w_1^*, w_2^*, \ldots, w_n^*)$ and the weights of the sub-criteria of the *j-th* criterion $\left(w_1^{j*}, w_2^{j*}, \ldots, w_n^{j*}\right)$ are calculated.

HBWM can be written as follows.

$$Min\ \xi^L = \sum_j \xi_j^L \tag{5}$$

$$\left|w_B - a_{Bj} w_j\right| \leq \xi^L, \forall j \tag{6}$$

$$\left|w_j - a_{jW} w_{jW}\right| \leq \xi^L, \forall j \tag{7}$$

$$\left|w_B^j - a_{Bk}^j w_k^j\right| \leq \xi_j^L, \forall j, \forall k \tag{8}$$

$$\left|w_k^j - a_{kW}^j w_W^j\right| \leq \xi_j^L, \forall j, \forall k \tag{9}$$

$$Gw_k^j = w_j w_k^j, \forall k \tag{10}$$

$$\sum_j w_j = 1,\ w_j \geq 0 \tag{11}$$

$$\sum_j w_k^j = 1, w_k^j \geq 0 \tag{12}$$

Equation (5) is the objective function of the model and gives the minimum deviations of the comparisons for the criteria and sub-criteria.

Equation (6) is the constraint that determines the priority of the best criterion over the other criteria.

Equation (7) is the constraint that determines the priority of each criterion over the worst criteria.

Equation (8) is the constraint that determines the priority of the best sub-criteria of each criterion over the other sub-criteria of that criterion.

Equation (9) is the constraint that determines the priority of the sub-criteria of each criterion over the worst sub-criteria of that criterion.

Equation (10) calculates the global weights $\left(Gw_k^j\right)$ of the sub-criteria.

Equation (11) is the constraint that the sum of the criteria weights must be equal to 1, and the weight of each criterion must not be negative.

Equation (12) is the constraint that the sum of the weights of the sub-criteria of each criterion must be equal to 1, and the weight of each sub-criterion must be non-negative.

By solving the min-max linear programming model, the weights of all criteria and sub-criteria are determined. Consistency ratios ξ^L values are also calculated as a result of the model's solution. The increase in the consistency ratios indicates that the reliability of the results decreases [52].

3.2 FUCOM

FUCOM is a method used to determine the weights of criteria influencing a decision-making problem. FUCOM is preferred over MCDM methods, as FUCOM makes one fewer comparison than the number of criteria. The operation of the method is presented as follows [41, 53].

Step 1. The criteria $C = \{C_1, C_2, \dots, C_n\}$ in the problem are determined by utilising expert opinions.

Step 2. These criteria are ordered from the most important to the least important.

$$C_{j(1)} > C_{j(2)} > \cdots > C_{j(k)} \tag{13}$$

where k represents the order of the criteria observed, if there is a statement that there are two or more criteria of the same importance, ">" can be replaced by "=" in the expression.

Step 3. The priority of each criterion over the following criterion $\left(\varphi_{k/(k+1)}\right)$ is determined by the experts. The comparative priorities of the evaluation criteria are obtained as follows:

$$\Phi = \left(\varphi_{1/2}, \varphi_{1/2}, \dots, \varphi_{k/(k+1)}\right) \tag{14}$$

Step 4. The evaluation criteria's weight coefficients final values $(w_1, w_2, \dots, w_n)^T$ are computed. The weight coefficients' final values should meet the two requirements:

1) The relative priority among the observed criteria $\left(\varphi_{k/(k+1)}\right)$ as stated in Step 3, is equal to the ratio of the weight coefficients; that the following condition is satisfied:

$$\frac{w_k}{w_{k+1}} = \left(\varphi_{k/(k+1)}\right) \tag{15}$$

2) The final values of the weight coefficients should satisfy the mathematical transitivity (*Eq. 8*) condition:

$$\frac{w_k}{w_{k+2}} = \varphi_{k/(k+1)} \otimes \varphi_{(k+1)/(k+2)} \tag{16}$$

Based on the definitions, the model for determining the final values of the weights can be defined as follows.

$$\min \chi$$

$$\textit{subject to}$$

$$\left|\frac{w_{j(k)}}{w_{j(k+1)}} - \varphi_{k/(k+1)}\right| \leq \chi, \forall j \tag{17}$$

$$\left|\frac{w_{j(k)}}{w_{j(k+2)}} - \varphi_{k/(k+1)} \otimes \varphi_{(k+1)/(k+2)}\right| \leq \chi, \forall j$$

$$\sum_{j=1}^{n} w_j = 1, \forall j$$

$$w_j \geq 0, \forall j$$

Equation 17 shows how the model calculates the values of the weight coefficients $(w_1, w_2, \dots w_n)^T$ that minimise χ when conditions $\left|\frac{w_{j(k)}}{w_{j(k+1)}} - \varphi_{k/(k+1)}\right| \leq \chi, \forall j$ and $\left|\frac{w_{j(k)}}{w_{j(k+2)}} - \varphi_{k/(k+1)} \otimes \varphi_{(k+1)/(k+2)}\right| \leq \chi, \forall j$ are satisfied together.

Full consistency is achieved when conditions $\frac{w_k}{w_{k+1}} = (\varphi_{k/(k+1)})$ and $\frac{w_k}{w_{k+2}} = \varphi_{k/(k+1)} \otimes \varphi_{(k+1)/(k+2)}$ are satisfied. If $\chi = 0$ 0 for the obtained values of the weight coefficients, the maximum consistency condition is satisfied.

3.3 SWARA

The SWARA (step-wise weight assessment ratio analysis) method, one of the criterion weighting methods frequently used recently, was first introduced by Keršuliene et al. [42].

Step 1. The criteria $C = \{C_1, C_2, \dots, C_n\}$ in the problem are determined by making use of expert opinions.

Step 2. These criteria are ordered from the most important to the least important.

$$C_{j(1)} > C_{j(2)} > \dots > C_{j(k)} \tag{18}$$

Step 3. The relative importance of each criterion is determined. For this purpose, the j*th* criterion is compared with the (j+1)*th* criterion to determine its importance [54]. This value is shown as s_j (comparative importance of average value) [42].

Step 4. The coefficient k_j is determined as in *Equation (11).*

$$k_j = \begin{cases} 1, & j = 1 \\ s_j + 1, & j > 1 \end{cases} \tag{19}$$

Step 5. q_j is calculated as in *Equation (12).*

$$q_j = \begin{cases} 1, & j = 1 \\ \frac{q_{j-1}}{k_j}, & j > 1 \end{cases} \tag{20}$$

Step 6. Weights of criteria w_j is calculated as in *Equation (13).*

$$w_j = \frac{q_j}{\sum_{k=1}^{n} q_k} \tag{21}$$

In the SWARA method, the relative importance of criteria is determined step by step based on expert opinion as above. The variables used in SWARA are as follows:

— s_j: The relative importance (or comparative importance) coefficient of the j*th* criterion compared to the previous criterion.
— k_j: The recalculated coefficient that adjusts the difference in importance between the criteria.
— q_j: The recalculated weighting factor of the j*th* criterion.
— w_jThe final normalised weight of the j*th* criterion, obtained by dividing each q_j value by the sum of all q_j values.

This stepwise process allows for the incorporation of expert preferences while maintaining mathematical consistency in weighting multiple criteria.

3.4 Technique of precise order preference

The application of the TPOP to rankings derived from conventional methods was proposed by Bairagi et al. [55]. Different prioritisations and rankings are obtained in decision-making problems with MCDM approaches. Since there is no consensus on which MCDM approach is the best, uncertainty appears for decision-makers [48]. In the TPOP approach, the results of the weights obtained using more than one method are integrated to get a single weight. As a result, the results obtained by various techniques are integrated into a single scale without loss of information [55, 56].

The TPOP is implemented in the following 10 steps.

Step 1. Decision-makers evaluate each alternative according to predefined criteria using various methods. A decision matrix (*Equation 14*) is created for the final selection values and alternatives obtained by using the MCDM methods [57].

$$S = \begin{array}{c} A_1 \\ \vdots \\ A_i \\ \vdots \\ A_m \end{array} \begin{bmatrix} f_{11} & \cdots & f_{1j} & \cdots & f_{1t} \\ \vdots & \cdots & \vdots & \cdots & \vdots \\ f_{i1} & \cdots & f_{ij} & \cdots & f_{1t} \\ \vdots & \cdots & \vdots & \cdots & \vdots \\ f_{m1} & \cdots & f_{mj} & \cdots & f_{mt} \end{bmatrix} \tag{22}$$

A_j: The i_{th} alternative $(i = 1,2,\dots,m)$,

f_{ij}: The weight values of the i_{th} alternative obtained by using the j_{th} MCDM method $(i = 1,2,\dots,m)$ and $(j = 1,2,\dots,t)$,

Step 2. The weighting values (τ_{ij}) obtained by using different MCDM methods, the results vary in an extensive range. In order to evaluate these weight values together, the weight values obtained by using j different MCDM methods are normalised, and the final weight values are calculated as in *Equation 15.*

$$\tau_{ij} = \frac{|f_{ij}|}{\sum_{i=1}^{m}|f_{ij}|} \tag{23}$$

Step 3. The entropy (e_j) for each MCDM method is calculated using the normalised values of the final choice values using *Equation 16.*

$$e_j = \frac{1}{\ln(m)}\sum_{i=1}^{m}|\tau_{ij}\ln(\tau_{ij})| \tag{24}$$

Step 4. *Equation (17)* is used to calculate the apparent weight value of the j_{th} MCDM method (s_j).

$$s_j = \frac{1-e_j}{\sum_{j=1}^{t}(1-e_j)} \tag{25}$$

Step 5. *Equation (18)* is used to calculate the $\left(s_j'\right)$ values.

$$s_j' = 1 + \sqrt{s_j'} \tag{26}$$

Step 6. The values of $\left(s_j'\right)$ calculated for each MCDM method are summed to obtain the value of $\left(S_j'\right)$ *(Equation 19).*

$$S_j' = \sum_{j=1}^{t} s_j' = \sum_{j=1}^{t}(1+\sqrt{s_j}) \tag{27}$$

Step 7. The absolute weight w_j of the final selection value of the j_{th} MCDM method is obtained by the proportion of s_j' to S_j' (Equation 20).

$$w_j = \frac{s_j'}{S_j'} = \frac{1+\sqrt{s_j}}{\sum_{j=1}^{t}(1+\sqrt{s_j})} \tag{28}$$

Step 8. The g_{ij} values are calculated as in *Equation 21* by normalising the weight values of the i_{th} alternative obtained by using the j_{th} MCDM method.

$$g_{ij} = \begin{cases} \dfrac{(f_j)_{max} - f_{ij}}{(f_j)_{max} - (f_j)_{min}}, & f_{ij} \in H \\ \dfrac{f_{ij} - (f_j)_{min}}{(f_j)_{max} - (f_j)_{min}}, & f_{ij} \in L \end{cases} \quad (29)$$

Step 9. The exponentially weighted normalised final selection values (h_{ij}) are calculated by *Equation 22.*

$$h_{ij} = exp(w_j + g_{ij}) \quad (30)$$

Step 10. The precise selection index (PSI) for each alternative is computed using *Equation 23.*

$$PSI_i = \sum_{j=1}^{t} h_{ij} = \sum_{j=1}^{t} exp(w_j + g_{ij}) \qquad i = 1,2,\dots,m \quad (31)$$

The TPOP method integrates weight values from multiple MCDM methods to generate a unified ranking. The main variables are:
— f_{ij}: Initial weight of alternative *i* from method *j*.
— τ_{ij}: Normalised weight of alternative *i* under method *j*.
— e_j: Entropy of method *j*, indicating information diversity.
— s_j: Divergence of method *j*.
— w_{ij}: Absolute weight of method *j*, derived from its divergence share.
— g_{ij}: Weighted normalised value of alternative *i* under method *j*.
— h_{ij}: Exponentially weighted score of alternative *i* from method *j*.
— PSI_i: Final performance score (precise selection index) for alternative *i*.

This process ensures a robust and integrated evaluation across multiple methods.

The integration of HBWM, FUCOM, and SWARA allows the model to benefit from different weighting philosophies (pairwise comparison, ranking-based, and step-wise adjustment), enhancing robustness. TPOP plays a critical role by consolidating the resulting weights without information loss, enabling a balanced and comprehensive final ranking. Although the individual methods are well-established, their structured combination contributes to decision-making consistency under diverse expert inputs.

4. EXPERIMENTS

An expert group of three individuals was determined to provide their opinions in this study. Expert team profiles are provided in *Table 2*. Although only three experts were consulted in this study, they were carefully selected based on their substantial experience and expertise in the relevant field. Nonetheless, future studies are encouraged to involve a larger and more diverse expert group to enhance the robustness of the findings.

Table 2 – Expert team profile

Expert	Experience (years)	Education	Title
Expert 1	22	PhD	Professor
Expert 2	24	Master’s degree	Electrical Engineer
Expert 3	11	Bachelor’s degree	Sales Agent

The overall methodology follows a structured sequence in which HBWM, FUCOM, and SWARA refine them based on expert judgements to provide the weighting of the criteria. Finally, the TPOP method aggregates the refined weights to comprehensively rank the electric vehicle alternatives. *Figure 1* illustrates the overall methodological flow adopted in this study.

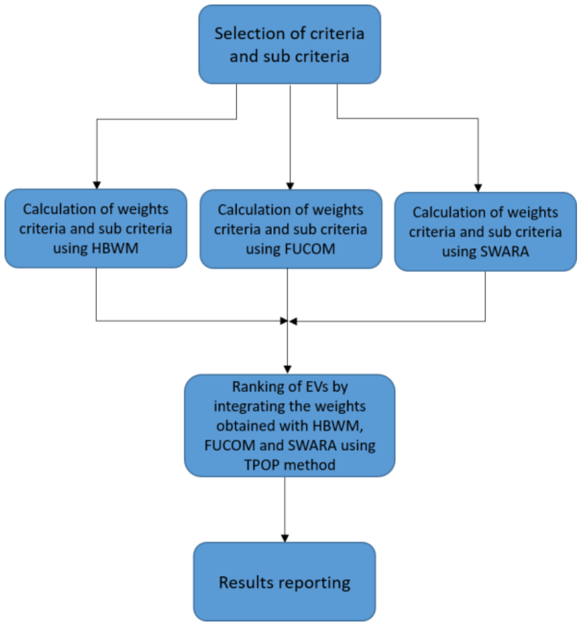

Figure 1 – Structural framework of the study

First, experts and authors, considering the literature *(Table 3)*, used the Delphi technique to identify the criteria and sub-criteria for selecting EVs. Three main criteria, i.e., costs, drive features, and technical features, and 10 sub-criteria were identified. The determined sub-criteria are explained as follows.

Price: The total cost required to purchase the EV from a dealer, including taxes and potential incentives. ***Service cost:*** Expenses incurred from scheduled maintenance at authorised centres, including software updates, coolant checks, and replacements of brake fluid or filters. These are typically planned, periodic costs. ***Maintenance cost:*** Expenses for wear-and-tear items, such as tires, wipers, and brake pads, which may require replacement over time. These are generally unplanned and occur outside of scheduled services. ***Range:*** The maximum distance the EV can travel on a full charge, measured in kilometres. ***Acceleration:*** The time the vehicle takes from 0 to a specified speed (typically 0–100 km/h), measured in seconds. Since a lower acceleration time indicates better performance, this sub-criterion is treated as a negative-impact criterion in the evaluation process. ***Highest speed:*** The maximum speed the EV can reach under normal driving conditions, expressed in kilometres per hour (km/h). ***Torque:*** The maximum rotational force produced by the electric motor, measured in Newton-meters (Nm), affects initial performance and responsiveness. ***Charging time:*** The average duration needed to fully charge the battery from 0% to 100%, depending on the charging infrastructure used. ***Battery capacity:*** The total energy the EV's battery can store, measured in kilowatt-hours (kWh), directly influences driving range. ***Weight:*** The total mass of the EV, including the battery and onboard equipment, measured in kilograms. Although excess weight typically reduces performance and efficiency, in this study, it is considered a positively influential criterion based on expert opinions, due to its correlation with larger battery capacity (and thus longer range) as well as enhanced safety features.

Table 3 – The criteria and sub-criteria

Criteria	Sub-criteria	References
Costs	Price	[2] [12] [15] [16] [17] [18] [19] [21]
	Service cost	[19]
	Maintenance cost	[19]
Drive features	Range	[12] [13] [17] [18] [19] [58]
	Acceleration	[12] [13] [16] [18] [19] [59]
	Highest speed	[13] [16] [18] [19] [22] [59]
Technical features	Torque	[12] [13] [17] [18] [22]
	Charging time	[12] [13] [16] [17] [18] [19] [21]
	Battery capacity	[2] [12] [13] [15] [16] [17] [18] [21] [22] [59]
	Weight	[13] [19] [22] [59]

The hierarchical structure was then developed, including the criteria and sub-criteria customers consider when purchasing EVs (see *Figure 2*).

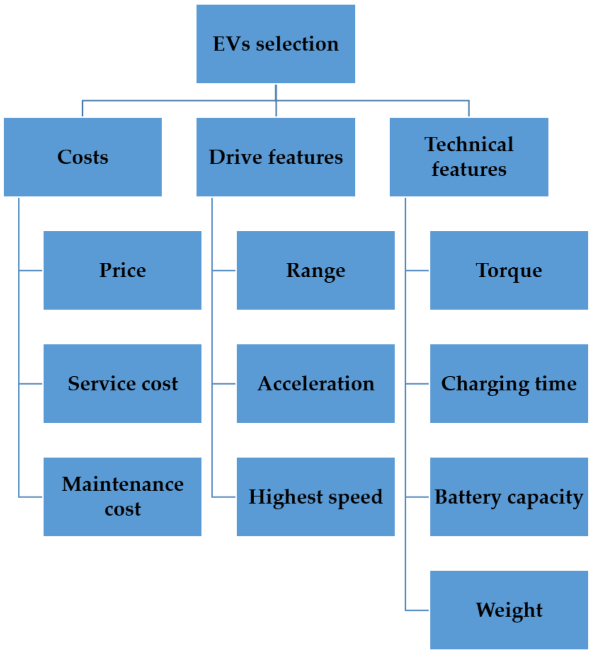

Figure 2 – Hierarchical structure

Then, the experts evaluated the criteria and sub-criteria following HBWM, FUCOM, and SWARA methods. Finally, TPOP was used to combine the weights obtained from these different MCDM methods for EV selection. The weights obtained by the HBWM method are given in *Table 4*, those obtained by the FUCOM method are given in *Table 5,* and those obtained by the SWARA method are given in *Table 6*, respectively.

Table 4 – The weights obtained by the HBWM method

Criteria	Weights of criteria	Sub-criteria	Weights of sub-criteria*	
			Local	Global
Costs	0.6667	Price	0.6923	0.4616
		Service cost	0.0769	0.0513
		Maintenance cost	0.2308	0.1539
Drive features	0.0833	Range	0.8133	0.0677
		Acceleration	0.1200	0.0100
		Highest speed	0.0667	0.0056
Technical features	0.2500	Torque	0.0506	0.0127
		Charging time	0.2328	0.0582
		Battery capacity	0.5769	0.1442
		Weight	0.1397	0.0349

**"Local" weight refers to the relative importance of a sub-criterion within its main criterion. "Global" weight represents the overall contribution of a sub-criterion to the entire decision hierarchy.*

Table 4 presents the weights calculated by the HBWM method for the criteria and sub-criteria considered in selecting EVs. The most crucial criterion is cost, with a weight of 0.6667. The weight of the drive features is 0.0833, and the weight of the technical features is 0.2500. Examining the weights of the sub-criteria, it is seen that the most crucial criterion is the price criterion with a value of 0.4616. The weights of the maintenance cost and battery capacity are 0.1539 and 0.1442, respectively. The criterion with the lowest weight is acceleration, with a value of 0.0100.

Table 5 – The weights obtained by the FUCOM method

Criteria	Weights of criteria	Sub-criteria	Weights of sub-criteria	
			Local	Global
Costs	0.6774	Price	0.6923	0.4690
		Service cost	0.2308	0.0521
		Maintenance cost	0.0769	0.1563
Drive features	0.0968	Range	0.7627	0.0738
		Acceleration	0.1525	0.0148
		Highest speed	0.0848	0.0082
Technical features	0.2258	Torque	0.0980	0.0221
		Charging time	0.1961	0.0443
		Battery capacity	0.5882	0.1328
		Weight	0.1177	0.0266

The weights calculated using the FUCOM method for the criteria and sub-criteria used in the selection of EVs are given in *Table 5*. The cost was determined as the most important criterion, with a weight of 0.6774. The weight of the drive features was 0.0968, and the weight of the technical features was 0.2258. When the weights of the sub-criteria are analysed, it is seen that the most important criterion is the price, with a value of 0.4690. The weights of the maintenance cost and battery capacity are 0.1563 and 0.1328, respectively. The criterion with the lowest weight is acceleration, with a value of 0.0148.

Table 6 – The weights obtained by the SWARA method

Criteria	Weights of criteria	Sub-criteria	Weights of sub-criteria	
			Local	Global
Costs	0.7547	Price	0.7619	0.5750
		Service cost	0.0476	0.0359
		Maintenance cost	0.1905	0.1438
Drive features	0.0566	Range	0.8060	0.0456
		Acceleration	0.1343	0.0076
		Highest speed	0.0597	0.0034
Technical features	0.1887	Torque	0.0210	0.0040
		Charging time	0.1822	0.0344
		Battery capacity	0.7286	0.1375
		Weight	0.0682	0.0129

The weights calculated by the SWARA method for the criteria and sub-criteria used in the selection of EVs are presented in *Table 6*. Cost was determined as the most important criterion. The weight of cost was 0.7547, the weight of drive features was 0.0566, and the weight of technical features was 0.1887. When the weights of the sub-criteria are analysed, it is evident that the most important criterion is price, with a value of 0.5750. The weights of the maintenance cost and battery capacity are 0.1438 and 0.1375, respectively. The criterion with the lowest weight is torque, with a value of 0.0148.

The weights obtained from all three MCDM methods show slight differences. To evaluate these weights together and rank the EVs using the TPOP method, 10 sample EVs were created. The criteria values of the created EVs are given in *Table 7*. The EVs listed in *Table 7* are hypothetical and were designed by the authors to reflect realistic and representative parameter ranges observed in the current EV market.

Table 7 – Sub-criteria values of EVs

EVs	Price	Service cost	Maintenance cost	Range	Acceleration	Highest speed	Torque	Charging time	Battery capacity	Weight
EV1	77850	5	5	574	6.3	210	765	285	89	2510
EV2	68900	5	5	567	7.3	180	420	480	79	2075
EV3	47500	4	4	642	7.9	150	320	660	86	2005
EV4	47200	4	3	440	8.6	175	280	372	72.6	1620
EV5	42700	4	5	327	9.2	150	260	450	50	1528
EV6	38500	3	4	386	9.5	140	245	135	80	1502
EV7	38000	3	3	314	7.4	185	350	195	52.4	1974
EV8	37200	3	3	350	7.7	160	250	480	51	1635
EV9	34000	4	4	354	8.2	150	260	450	50	1459
EV10	30500	2	3	310	13.7	125	125	300	26.8	975

The values of the sub-criteria were normalised for use in the TPOP method. Since the price, acceleration and charging time sub-criteria are negative impact criteria, the value 1 is first divided by the criterion value of EVs. Then, the normalised values were found by dividing the obtained values by the sum of these values. The normalisation method differs based on the preference direction of the sub-criteria. For criteria with a negative impact (e.g. price, charging time, acceleration), a reciprocal transformation (1/x) is applied before normalisation to reflect inverse preference. For positive impact criteria (e.g. range, battery capacity), direct normalisation is performed by dividing the value by the total sum. This distinction ensures that the normalised values are aligned with the decision-makers' preferences. Experts were asked for their opinions on the values of the service cost and maintenance cost sub-criteria. The experts assessed EVs between 1 and 5 (1 being the worst and 5 being the best). Then, the normalised values were calculated by dividing the values provided by the experts by the sum of these values. Range, highest speed, torque, battery capacity and weight sub-criteria values are positively influential variables. The normalisation process was performed by dividing the values of EVs for these sub-criteria by the total values of these sub-criteria. The normalised values of the sub-criteria of the 10 EVs are given in *Table 8*.

Table 8 – Normalised values of EVs

EVs	Price	Service cost	Maintenance cost	Range	Acceleration	Highest speed	Torque	Charging time	Battery capacity	Weight
EV1	0.0548	0.1351	0.1282	0.1346	0.1309	0.1292	0.2336	0.1090	0.1398	0.1452
EV2	0.0619	0.1351	0.1282	0.1330	0.1130	0.1108	0.1282	0.0647	0.1241	0.1201
EV3	0.0898	0.1081	0.1026	0.1506	0.1044	0.0923	0.0977	0.0471	0.1351	0.1160
EV4	0.0904	0.1081	0.0769	0.1032	0.0959	0.1077	0.0855	0.0835	0.1140	0.0937
EV5	0.0999	0.1081	0.1282	0.0767	0.0896	0.0923	0.0794	0.0690	0.0785	0.0884
EV6	0.1108	0.0811	0.1026	0.0905	0.0868	0.0862	0.0748	0.2301	0.1256	0.0869
EV7	0.1123	0.0811	0.0769	0.0736	0.1115	0.1138	0.1069	0.1593	0.0823	0.1142
EV8	0.1147	0.0811	0.0769	0.0821	0.1071	0.0985	0.0763	0.0647	0.0801	0.0946
EV9	0.1215	0.1081	0.1026	0.0830	0.1006	0.0923	0.0794	0.0690	0.0785	0.0844
EV10	0.1399	0.0541	0.0769	0.0727	0.0602	0.0769	0.0382	0.1035	0.0421	0.0564

The weight values obtained from the HBWM, FUCOM, and SWARA methods are combined with TPOP, and the rankings of EVs are calculated accordingly. The ranking scores of the EVs, the normalised values of which are presented in *Table 7* and obtained using the TPOP method, are shown in *Table 9*.

Table 9 – Ranking of EVs obtained with TPOP

EVs	Ranking scores
EV9	4.6785
EV3	4.6575
EV2	4.6398
EV4	4.6311
EV8	4.6200
EV10	4.6189
EV5	4.6102
EV7	4.6102
EV1	4.6059
EV6	4.6006

5. DISCUSSION

5.1 Interpretation of results

The approach proposed in this study enhances the reliability of the process by providing managers with the opportunity to evaluate multiple solution methods simultaneously for complex MCDM problems. Combining the weights obtained by HBWM, FUCOM, and SWARA with TPOP has resulted in a more consistent weighting of the criteria and, therefore, a more objective ranking of the alternatives. The proposed approach can be applied to similar decision-making problems, such as supplier selection, location selection, and financial performance evaluation. This study provides valuable insights for consumers, automotive managers, and policymakers. Moreover, the consistency observed across the different weighting methods reinforces the robustness of the proposed hybrid model and supports its applicability in real-world multi-criteria environments.

Price is found to be the most important criterion in EV preferences. In addition to price, battery capacity and maintenance cost are found to be more important than other criteria. This pattern indicates that economic and functional concerns are prioritised over purely technical or performance-related attributes such as speed or acceleration. This reveals that managers in the EV sector, like those in other sectors, should prioritise competitive pricing strategies to gain a market advantage. Maintenance cost criteria also have a high weight. This suggests that managers should also consider issues such as pricing and extended warranties. Additionally, it is revealed that battery capacity is a crucial criterion in the case of EVs and is taken into account when making a purchase decision. This further underlines the importance of driving range, charging efficiency, and energy density from the consumer perspective. Therefore, it can be stated that battery capacity should be studied in EVs, which is a relatively new technology. Its development remains crucial not only for improving performance but also for increasing consumer acceptance and long-term sustainability in electric mobility.

5.2 Managerial implications

The findings of this study provide several practical guidelines for decision-makers in both the public and private sectors regarding the selection and promotion of electric vehicles (EVs). Based on the experimental results, the following implications can be drawn:

- Prioritised selection of EVs: The proposed model enables the ranking of alternative EVs. Managers can use the resulting rankings to guide procurement strategies, focusing on top-performing EVs based on aggregated criteria, including environmental impact, cost efficiency, and technological features.
- Enhanced decision support: The integration of HBWM, FUCOM, SWARA, and TPOP enables managers to make more robust decisions, even when faced with incomplete or ambiguous data.
- Comprehensive evaluation framework: The study confirms that MCDM methods are practical tools for evaluating complex products, such as EVs. Managers are encouraged to adopt such models to capture diverse stakeholder preferences and performance indicators.

- Sustainability-focused strategy: Since environmental and sustainability criteria were emphasised in the evaluation process, the results support organizations aiming to align their fleet choices with sustainability goals and carbon reduction commitments.
- Customizability of the method: The model is conceptually adaptable to different regional or organisational contexts. While the implementation requires technical understanding, the input parameters can, in principle, be adjusted to reflect local policy, consumer preferences, or infrastructure conditions with appropriate computational support.
- Strategic investment decisions: Policymakers and fleet managers can use the outcomes to allocate incentives or subsidies more effectively, favouring EV models that offer a higher overall benefit-to-cost ratio.
- Competitive benchmarking: EV manufacturers can analyse the results to benchmark their vehicles against competitors, identifying which features or criteria contribute most to top rankings and adjusting their product strategies accordingly.

6. CONCLUSIONS

Due to the increasing consumption of fossil fuels, which may lead to resource depletion in the near future, there is an urgent need for alternative and clean energy sources. Sustainable development seeks to address the challenges posed by industrialisation and population growth. Thus, the adoption of renewable energy and EVs in the transportation sector is steadily increasing, particularly in the EU and China [60]. It is essential to identify the factors that influence customer purchasing behaviour and the adoption and dissemination of EVs. The proposed model for selecting EVs deals with finding the most suitable EVs among a set of alternatives. For this purpose, in this study, the results obtained from three MCDM methods are combined using the TPOP method to rank EVs. This framework offers a structured decision-support tool for policymakers and industry stakeholders seeking to promote EV adoption based on evidence-based prioritisation.

Our experiments reveal that the most important criterion for all three MCDM methods is the cost criterion. While the technical features criterion is the second most important criterion, the driving features criterion is the least important one. Examining the sub-criteria, it is seen that the price sub-criterion is the most important in each MCDM method. The maintenance cost and battery capacity sub-criteria follow the price sub-criterion. The least important sub-criteria are highest speed, acceleration and weight. This outcome suggests that EV purchasing behaviour is still predominantly driven by economic concerns, rather than performance attributes, indicating a gap between consumer expectations and some aspects of EV marketing strategies.

In summary, this study presents a novel and integrated approach for EV selection that combines a hybrid of HBWM, FUCOM, SWARA, and the recently developed TPOP method. The results not only demonstrate the applicability of the proposed framework in ranking EV alternatives under multiple criteria but also highlight the dominant influence of economic factors, particularly price, on consumer preferences. From a methodological standpoint, the study contributes to the growing field of hybrid MCDM by offering a structured yet adaptable approach that can handle both subjective judgments and objective data. Moreover, the precision and consistency observed in the rankings underscore the value of integrating preference modelling techniques, such as TPOP, into real-world decision-making scenarios. This alignment across different methods strengthens the credibility of the findings. It supports the transferability of the model to other domains beyond EV selection, such as sustainability-focused procurement or technology evaluation.

While the individual methods used in this study, HBWM, FUCOM, and SWARA, are well-established, their structured integration, combined with the TPOP technique, provides a novel perspective by leveraging different expert judgment approaches in a unified framework. This hybrid model aims to enhance decision-making robustness through methodological diversity and aggregation, without compromising information loss. Although the methodological novelty is incremental, it offers practical value in terms of stability and consistency. Future studies can further validate the effectiveness of this combined approach through comparative analyses with other hybrid or standalone MCDM models. In particular, benchmarking this framework against real market outcomes or aligning it with behavioural data would allow for a more rigorous test of its predictive validity.

Although this study offers an effective approach, it has some limitations. First, the views of consumers as decision makers could be consulted. This would take into account the preferences of consumers who engage in purchasing behaviour, thereby reducing subjectivity. Secondly, segments of EVs are not considered in the study. Separate evaluations for EVs in different segments may provide more accurate information. In future studies, the weights of the criteria can be determined based on consumer opinions, EVs can be segmented and evaluated, and various MCDM methods can be employed. In addition, fuzzy logic can be integrated with MCDM to overcome uncertainty in the system, such as evaluators' perceptions, etc. Addressing these limitations would not only strengthen the generalisability of the findings but also contribute to the development of more user-centric and context-sensitive decision-making tools in the EV sector.

Declaration of generative AI and AI-assisted technology in the writing process

During the preparation of the manuscript, the authors used ChatUiT (a tailored version of ChatGPT) and Grammarly to polish the scientific writing. After using these tools, the authors reviewed and edited the content as needed, taking full responsibility for the content of the paper.

REFERENCES

[1] Feng J, Xu SX, Li M. A novel multi-criteria decision-making method for selecting the site of an electric-vehicle charging station from a sustainable perspective. *Sustainable Cities and Society*. 2021;65(102623):1-20. DOI: 10.1016/j.scs.2020.102623.

[2] Khan F, Ali Y, Khan A. Sustainable hybrid electric vehicle selection in the context of a developing country. *Air Quality, Atmosphere & Health*. 2020;13(4):489-499. DOI: 10.1007/s11869-020-00812-y.

[3] Ghosh A, et al. Application of hexagonal fuzzy MCDM methodology for site selection of electric vehicle charging station. *Mathematics*. 2021;9(4):1-27. DOI: 10.3390/math9040393.

[4] Wang R, et al. Study on location decision framework of electric vehicle battery swapping station: Using a hybrid MCDM method. *Sustainable Cities and Society.* 2020;61(102149):1-12. DOI: 10.1016/j.scs.2020.102149.

[5] Ecer F. A consolidated MCDM framework for performance assessment of battery electric vehicles based on ranking strategies. *Renewable and Sustainable Energy Reviews*. 2021;143(110916):1-19. DOI: 10.1016/j.rser.2021.110916.

[6] Biswas TK, Das MC. Selection of commercially available electric vehicle using fuzzy AHP-MABAC. *Journal of the Institution of Engineers (India): Series C.* 2019;100(3):531-537. DOI: 10.1007/s40032-018-0481-3.

[7] Von Rosenstiel DP, Heuermann DF, Hüsig S. Why has the introduction of natural gas vehicles failed in Germany? —Lessons on the role of market failure in markets for alternative fuel vehicles. *Energy Policy.* 2015;78(1):91-101. DOI: 10.1016/j.enpol.2014.12.022.

[8] Safarzadeh S, Khansefid S, Rasti-Barzoki M. A group multi-criteria decision-making based on best-worst method. *Computers & Industrial Engineering.* 2018;126(1):111-121. DOI: 10.1016/j.cie.2018.09.011.

[9] Liang X, Wu X, Liao H. A gained and lost dominance score II method for modelling group uncertainty: Case study of site selection of electric vehicle charging stations. *Journal of Cleaner Production.* 2020;262(121239):1-9. DOI: 10.1016/j.jclepro.2020.121239.

[10] Abdel-Basset M, Mohamed R. A novel plithogenic TOPSIS-CRITIC model for sustainable supply chain risk management. *Journal of Cleaner Production.* 2020;247(119586):1-15. DOI: 10.1016/j.jclepro.2019.119586.

[11] Ali A, Rashid T. Hesitant fuzzy best-worst multi-criteria decision-making method and its applications. *International Journal of Intelligent Systems.* 2019;34(8):1953-1967. DOI: 10.1002/int.22131.

[12] Golui S, Mahapatra BS, Mahapatra GS. A new correlation-based measure on Fermatean fuzzy applied on multi-criteria decision making for electric vehicle selection. *Expert Systems with Applications.* 2024;237(121605):1-13. DOI: 10.1016/j.eswa.2023.121605.

[13] Więckowski J, et al. Complex sensitivity analysis in Multi-Criteria Decision Analysis: An application to the selection of an electric car. *Journal of Cleaner Production*. 2023;390(136051):1-15. DOI: 10.1016/j.jclepro.2023.136051.

[14] Tian ZP, et al. Data-driven multi-criteria decision support method for electric vehicle selection. *Computers & Industrial Engineering.* 2023;177(109061):1-14. DOI: 10.1016/j.cie.2023.109061.

[15] Bošković S, et al. An alternative ranking order method accounting for two-step normalization (AROMAN) – A case study of the electric vehicle selection problem. *IEEE Access*. 2023;11(1):1-12. DOI: 10.1109/ACCESS.2023.3265818.

[16] Ziemba P. Selection of electric vehicles for the needs of sustainable transport under conditions of uncertainty—a comparative study on fuzzy MCDA methods. *Energies.* 2021;14(22):1-25. DOI: 10.3390/en14227786.

[17] Sonar HC, Kulkarni SD. An integrated AHP-MABAC approach for electric vehicle selection. *Research in Transportation Business & Management.* 2021;41(100665):1-8. DOI: 10.1016/j.rtbm.2021.100665.

[18] Sejwal R, et al. Selection of electric vehicles using MCDM techniques. In: Ranganath MS, Pavan KK. (eds.) *Advanced Production and Industrial Engineering,* Amsterdam, Netherlands: IOS Press; 2022. p. 598-607.

[19] Ren X, Sun S, Yuan R. A study on selection strategies for battery electric vehicles based on sentiments, analysis, and the MCDM model. *Mathematical Problems in Engineering*. 2021;1(9984343):1-23. DOI: 10.1155/2021/9984343.

[20] Arslan R, Bircan H. Çok kriterli karar verme teknikleriyle elde edilen sonuçların Copeland yöntemiyle birleştirilmesi ve karşılaştırılması. *Yönetim ve Ekonomi Dergisi.* 2020;27(1):109-127. DOI: 10.18657/yonveek.540125.

[21] Görçün ÖF, et al. Electric vehicle selection for industrial users using an interval-valued intuitionistic fuzzy COPRAS-based model. *Environment, Development and Sustainability.* 2024;2024(1):1-42. DOI: 10.1007/s10668-024-05562-w.

[22] Pradhan P, Shabbiruddin, Pradhan S. Selection of electric vehicle using integrated Fuzzy-MCDM approach with analysis on challenges faced in hilly terrain. *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects.* 2022;44(2):2651-2673. DOI: 10.1080/15567036.2022.2056665.

[23] Zhao H, Hao X. Location decision of electric vehicle charging station based on a novel grey correlation comprehensive evaluation multi-criteria decision method. *Energy.* 2024;299(131356):1-16. DOI: 10.1016/j.energy.2024.131356.

[24] Chumbi WE, et al. Suitable site selection of public charging stations: a fuzzy TOPSIS MCDA framework on capacity substation assessment. *Energies.* 2024;17(14):1-27. DOI: 10.3390/en17143452.

[25] Mhana KH, Awad HA. An ideal location selection of electric vehicle charging stations: Employment of integrated analytical hierarchy process with geographical information system. *Sustainable Cities and Society.* 2024;107(105456):1-19. DOI: 10.1016/j.scs.2024.105456.

[26] Gomes CFS, et al. Multicriteria methodology for selection of a personal electric vehicle. *Brazilian Journal of Operations & Production Management.* 2023;20(2):415-1415. DOI: 10.14488/BJOPM.1415.2023.

[27] Althaqafi T. Cultivating sustainable supply chain practises in electric vehicle manufacturing: A MCDM Approach to assessing GSCM performance. *World Electric Vehicle Journal.* 2023;14(10):1-18. DOI: 10.3390/wevj14100290.

[28] Wei Q, Zhou C. A multi-criteria decision-making framework for electric vehicle supplier selection of government agencies and public bodies in China. *Environmental Science and Pollution Research.* 2023;30(4):10540-10559. DOI: 10.1007/s11356-022-22783-6.

[29] Deveci M, Simic V, Torkayesh AE. Remanufacturing facility location for automotive Lithium-ion batteries: An integrated neutrosophic decision-making model. *Journal of Cleaner Production.* 2021;317(128438):1-20. DOI: 10.1016/j.jclepro.2021.128438.

[30] Abdali H, Sahebi H, Pishvaee M. The water-energy-food-land nexus at the sugarcane-to-bioenergy supply chain: A sustainable network design model. *Computers & Chemical Engineering.* 2021;145(107199):1-19. DOI: 10.1016/j.compchemeng.2020.107199.

[31] Loganathan MK, et al. Multi-Criteria decision making (MCDM) for the selection of Li-Ion batteries used in electric vehicles (EVs). *Materials Today: Proceedings.* 2021;41(1):1073-1077. DOI: 10.1016/j.matpr.2020.07.179.

[32] Zhang L, et al. A multi-criteria decision method for performance evaluation of public charging service quality. *Energy.* 2020;195(116958):1-13. DOI: 10.1016/j.energy.2020.116958.

[33] Samaie F, et al. Comparison of sustainability models in development of electric vehicles in Tehran using fuzzy TOPSIS method. *Sustainable Cities and Society*. 2020;53(101912):1-13. DOI: 10.1016/j.scs.2019.101912.

[34] Nunic Z, Staevic Z. A Novel Integrated Multi-Criteria Decision-Making Model: FUCOM-EDAS-M. *Innovation as An Initiator of The Development Conference 2019, 7-10 Dec. 2019, Belgrade, Serbia*. p. 19-34.

[35] Rani P, Mishra AR. Fermatean fuzzy Einstein aggregation operators-based MULTIMOORA method for electric vehicle charging station selection. *Expert Systems with Applications.* 2021;182(115267):1-23. DOI: 10.1016/j.eswa.2021.115267.

[36] Yagmahan B, Yılmaz H. An integrated ranking approach based on group multi-criteria decision making and sensitivity analysis to evaluate charging stations under sustainability. *Environment, Development and Sustainability.* 2023;25(1):96-121. DOI: 10.1007/s10668-021-02044-1.

[37] Sałabun W, Karczmarczyk A. Using the comet method in the sustainable city transport problem: an empirical study of the electric powered cars. *Procedia Computer Science.* 2018;126(1):2248-2260. DOI: 10.1016/j.procs.2018.07.224.

[38] Zavadskas EK, Turskis Z. A new additive ratio assessment (ARAS) method in multicriteria decision-making. *Technological and Economic Development of Economy*. 2010; 16(2):159-172. DOI: 10.3846/tede.2010.10.

[39] Yıldız A, et al. Best-worst yöntemi ile otomat makinası ürün dağıtımındaki risklerin değerlendirilmesi. *El-Cezeri*. 2022;9(4):1215-1227. DOI: 10.31202/ecjse.1132087.

[40] Rezaei J. Best-worst multi-criteria decision-making method. *Omega*. 2015;53(1):49-57. DOI: 10.1016/j.omega.2014.11.009.

[41] Pamučar D, Stević Ž, Sremac S. A new model for determining weight coefficients of criteria in MCDM models: Full consistency method (FUCOM). *Symmetry*. 2018;10(1):393: 1-22. DOI: 10.3390/sym10090393.

[42] Keršuliene V, Zavadskas EK, Turskis Z. Selection of rational dispute resolution method by applying new step-wise weight assessment ratio analysis (SWARA). *Journal of Business Economics and Management*. 2010;11(2):243-258.

[43] Sarwar A, Zafar A, Qadir A. Analysis and prioritization of risk factors in the management of Halal supply chain management. *Discover Sustainability*. 2021;2(1):1-10. DOI: 10.1007/s43621-021-00039-6.

[44] Hasan MG, Ashraf Z, Khan MF. Multi-choice best-worst multi-criteria decision-making method and its applications. *International Journal of Intelligent Systems*. 2022;37(2):1129-1156. DOI: 10.1002/int.22663.

[45] Rezaei J, Wang J, Tavasszy L. Linking supplier development to supplier segmentation using Best Worst Method. *Expert Systems with Applications*. 2015;42(23):9152-9164. DOI: 10.1016/j.eswa.2015.07.073.

[46] Sadjadi S, Karimi M. Best-worst multi-criteria decision-making method: A robust approach. *Decision Science Letters*. 2018; 7(4):323-340. DOI: 10.5267/j.dsl.2018.3.003.

[47] Guo S, Qi Z. A fuzzy best-worst multi-criteria group decision-making method. *IEEE Access*. 2021;9(1):118941-118952. DOI: 10.1109/ACCESS.2021.3106296.

[48] Wan Ahmad WNK, et al. Evaluation of the external forces affecting the sustainability of oil and gas supply chain using Best Worst Method. *Journal of Cleaner Production*. 2017;153(1):242-252. DOI: 10.1016/j.jclepro.2017.03.166.

[49] Gupta H, Barua MK. Identifying enablers of technological innovation for Indian MSMEs using best–worst multi criteria decision making method. *Technological Forecasting and Social Change*. 2016;107(1):69-79. DOI: 10.1016/j.techfore.2016.03.028.

[50] Mohtashami A. A novel modified fuzzy best-worst multi-criteria decision-making method. *Expert Systems with Applications*. 2021;181(115196):1-10. DOI: 10.1016/j.eswa.2021.115196.

[51] Zhou T, et al. Selecting industrial IoT Platform for digital servitisation: a framework integrating platform leverage practices and cloud HBWM-TOPSIS approach. *International Journal of Production Research*. 2023; 61(12):4022-4044. DOI: 10.1080/00207543.2021.2002458.

[52] Tabatabaei MH, et al. Hierarchical decision-making using a new mathematical model based on the best-worst method. *International Journal of Computers Communications & Control*. 2019;14(6):710-725. DOI: 10.15837/ijccc.2019.6.3675.

[53] Nemati A, Zolfani SH, Khazaelpour P. A novel gray FUCOM method and its application for better video games experiences. *Expert Systems with Applications*. 2023;234(121041):1-20. DOI: 10.1016/j.eswa.2023.121041.

[54] Ruzgys A, et al. Integrated evaluation of external wall insulation in residential buildings using SWARA-TODIM MCDM method. *Journal of Civil Engineering and Management*. 2014;20(1):103-110. DOI: 10.3846/13923730.2013.843585.

[55] Bairagi B, et al. A De Novo multi-approaches multi-criteria decision-making technique with an application in performance evaluation of material handling device. *Computers & Industrial Engineering*. 2015;87(1):267-282. DOI: 10.1016/j.cie.2015.05.015.

[56] Mutlu NG, Altuntas S. Technique of precise order preference for multiple risk assessment in occupational health and safety: Industrial case study. *Journal of Engineering Research*. 2023;11(3):238-248. DOI: 10.36909/jer.14153.

[57] Altuntaş S, Dereli T, Erdoğan Z. Decision making in the manufacturing environment using the technique of precise order preference. *Sigma Journal of Engineering and Natural Sciences*. 2023;41(1):178-193.

[58] Lundström A. Differentiated driving range: Exploring a solution to the problems with the" guess-o-meter" in electric cars. *6th international conference on automotive user interfaces and interactive vehicular applications, 17-19 Sept. 2014, Seattle, WiA USA*. 2014. p. 1-8. DOI: 10.1145/2667317.2667347.

[59] Kubiczek J, HadasikB. Segmentation of passenger electric cars market in Poland. *World Electric Vehicle Journal*. 2021; 12(1): 1-23. DOI: 10.3390/wevj12010023.

[60] He H, et al. China's battery electric vehicles lead the world: achievements in technology system architecture and technological breakthroughs. *Green Energy and Intelligent Transportation*. 2022;1(1):1-24. DOI: 10.1016/j.geits.2022.100020.