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A new rough ordinal priority-based decision support system for purchasing electric vehicles

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ABSTRACT

This study proposes a novel multi-criteria decision-making (MCDM) model based on a rough extension of the Ordinal Priority Approach (OPA) to determine the order of importance of users' perspectives on Electric Vehicle (EV) purchases. Unlike conventional methods that rely on predefined ranks for criteria weighting coefficients, the proposed rough OPA method employs an aggregated rough linguistic matrix, enabling a more precise and unbiased calculation of interval values. Moreover, the model addresses inherent uncertainties by incorporating nonlinear aggregation functions, accommodating decision makers' risk attitudes for flexible decision-making. To validate the model's efficacy, a large-scale post-EV test drive survey is conducted, enabling the determination of relative criterion importance. Sensitivity analysis confirms the robustness of the model, demonstrating that marginal changes in parameters do not alter the ranking order. The results unveil the significance of the reliability criterion and reveal that vehicle-related characteristics outweigh economic and environmental attributes in the decision-making process. Overall, this innovative MCDM model contributes to a more accurate and objective analysis, enhancing the understanding of users' preferences and supporting informed decision-making in EV purchases.

1. Introduction and background

Over the past decade, electric vehicles (EVs) have emerged as an appealing option to expedite the decarbonization of the transportation sector, owing to their ability to offer numerous environmental, socioeconomic, and health benefits. These advantages encompass heightened energy efficiency, bolstered energy security, and a notable reduction in both emissions and noise levels [1].

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Although many countries are still in early phases of adoption, electric mobility across the globe has started to expand with supportive regulatory frameworks such as emission mandates [2,3]. Consequently, vehicle manufacturers have significantly broadened their portfolio by introducing a greater number of light-duty EV models. As battery technology advances, the costs of batteries continue to decline, and the charging infrastructure is also gradually expanding. Despite these positive developments, several significant near-term obstacles persist, hindering the large-scale rapid adoption of EVs. Challenges such as the immaturity of certain EV models and inadequate vehicle options, the capital costs associated with EVs, insufficient public charging infrastructure, and extended operational charging times pose formidable barriers to widespread EV adoption [4], and an underdeveloped policy landscape [2]. To facilitate a broader and accelerated EV adoption, it is crucial to address the needs of EV users while simultaneously considering the factors and support mechanisms involved in the EV transition [5].

Numerous studies have been conducted to explore effective strategies for promoting EV adoption [6]. These studies focused predominantly on the needs of EV users, since the mass acceptance of EVs, to a large extent, is dependent on EV users' perceptions [7]. In order to encourage EV adoption from a policy-making standpoint, the effect of the incentive for EV users is investigated using an optimization model [3]. The findings concluded that EV adoption is highly dependent on user incentives and will be delayed if a sufficient amount is not provided. Techno-economics of the vehicle, including the battery, user behavior, and charging infrastructure are reported to be the main drivers for EV deployment [8]. Kuhl et al. [9], compare literature and social media analytics regarding EV customer needs. It is demonstrated that price-related and vehicle-characteristic needs are overrepresented in the literature, whereas charging-related needs are disproportional in the social media data set. Bas et al. [10] apply a machine learning approach to predict EV adoption based on attitudinal, socio-demographic, and vehicle factors, as well as the frequency of ridesourcing. The study finds that frequent ridesourcing usage, knowledge of EVs, and awareness of environmental protection can influence the willingness to adopt EVs. In Rezvani et al. [7], a comprehensive perspective on the drivers and barriers to consumer adoption of EVs is provided. Technical aspects such as vehicle's performance and range, and charging time were found to be attitudinal factors, as were cost factors such as purchase and operating expenses, fuel cost, and contextual factors such as tax and financial incentives, and charging station availability. In Liao et al. [11], financial, technical, and infrastructural factors such as vehicle purchase and operating costs, driving range, charging duration, vehicle performance, and market model variety are found to have a significant impact on EV choice. Laurischkat et al. [12] explore the impact of business models on EV adoption and derived business model patterns such as battery swapping, E-car sharing, and vehicle-to-grid to increase the attractiveness of electric mobility as an entire mobility solution. The impact of policies and incentives has also been addressed [13,14]. In Langbroek et al. [14], the effect of several potential policy incentives on EV adoption as well as the influence of socio-psychological determinants is investigated, using constructs from the trans-theoretical model of change and the protection motivation theory. In Bjerkan et al. [13], it is found that exemptions from purchase tax and value added tax are critical incentives, while an up-front price reduction is the most powerful incentive in promoting EV adoption. The impact of charging infrastructure and the number of EV models available on EV adoption is explored in [15,16]. In Hardman et al. [15], residential charging stations are found to be the most important location, followed by work, and then public locations. In Sweda and Klabjan [16], a decision support system was developed for analysing patterns in residential EV ownership and driving activities in order to facilitate strategic charging infrastructure deployment. The purchase price, the expected fuel costs, environmental benefits (i.e., greenness), and social influence (i.e., being persuaded by EV owners to purchase an EV) are considered. Ensslen et al. [17] explore EV user acceptance and identify potential EV adoption decisions using collected data from various methods such as surveys, focus groups, sales documentation, EV user experiments, and social media analytic. EV purchase price, range, vehicle size and brand are found to be more important in the criterion design from surveys, while charging related needs constitute the largest share of the social data, followed by cost and vehicle-related needs. Although studies in the literature have identified various parameters that affect users' transition to electric mobility, none of them have provided a comprehensive list of factors. Furthermore, most surveys were conducted among potential EV users who had not experienced driving an EV, which could influence their attitudes towards EVs. More importantly, the relative importance of each factor is yet to be explored.

The motivation behind this study is to identify and prioritize the factors influencing the transition to electric mobility, specifically from the perspectives of EV users. To achieve this objective, the study initially introduces 12 decision-making criteria, aiming to gauge EV users' attitudinal factors towards EV purchase, gathered through a comprehensive post-EV test drive survey. Then, a new multi-criteria decision making (MCDM) model is developed to determine the degree of importance of criteria. MCDM methods have been successfully integrated into a variety of real world problems [18]. The proposed MCDM model uses a rough extension of the Ordinal Priority Approach (OPA) method [19]. This method is a novel methodology that allows objective and adequate decision support tool addressing uncertainties and inaccuracies of survey data. It is based on improved rough numbers (IRN) methodology, which has several salient features, including: (1) IRN methodology allows consideration of the interrelationships between the criteria; (2) The imprint of uncertainty in the IRN methodology is presented using flexible rough boundary intervals; and (3) The IRN methodology allows the simulation of different levels of risk depending on the dynamic environmental conditions. The OPA method belongs to the group of subjective models for defining weight coefficients of criteria. Most of the subjective models for determining the weighting coefficients of the criteria are based on comparisons in pairs of elements of the home matrix [20]. As the number of criteria increases, the number of pairwise comparisons also increases, leading to a rise in the total number of comparisons. Additionally, the consistency decreases because of increasing the pairwise comparisons. The OPA method allows decision-makers to better perceive the relationship between the criteria since it considers the relationships through the ranking among them [21]. This eliminates the problem of defining the relationship between distant criteria, which often leads to a decrease in the consistency of results in other subjective models such as Analytic Hierarchy Process - AHP [22], Measuring Attractiveness by a Categorical Based Evaluation Technique - MACBETH [23], and Best Worst Method - BWM [24] method. By ranking the criteria, obtaining weight coefficients is significantly simplified, especially when dealing with many criteria (more than eight). In such situations, it is almost impossible to get consistent results with models such as AHP, BWM, or MACBETH [25]. This is a consequence of the small scale range used in pairwise model comparisons. In models in which comparison scales are used to represent the relationship between criteria, expert preferences are limited, and the maximum ratio is n:1, where n represents the number of scale elements. This limitation further causes inconsistencies in comparisons [26]. The following example can be given to clarify the previous statement: Supposing that we aim to compare three fruits, namely F1, F2, and F3, utilizing the Analytic Hierarchy Process (AHP) method. The obtained results for the pairwise comparisons are as follows: F1:F2 = 3:1, F1:F3 = 7:1, and F2:F3 = 5:1. The degree of consistency for these comparisons is 0.83, which is considered satisfactory as it satisfies the condition of being less than 0.1. However, in this simple example, it is not possible to achieve entirely consistent results due to the inherent limitations imposed by the scale used. The law of mathematical transitivity dictates that if F1:F2 = 3:1 and F2:F3 = 5:1, then F1:F3 should be 15:1. Nonetheless, since the scale is restricted to integer values within the range of 1 to 9, the decision maker can choose between a value of seven or nine. This limitation is overcome in the Objective Preference Assessment (OPA) model, as it allows decision makers to employ any scale for objectively presenting their preferences. Consequently, the issue of a restricted range of predefined scales, which is inherent in subjective models like AHP, BWM, DEMATEL, or MACBETH, is eliminated in the OPA model. In the proposed OPA model, this problem is eliminated by applying element ranks, giving decision-makers freedom to express their preferences and relationships among criteria objectively. This eliminates the issue of a limited range of predefined scales for comparing criteria used in subjective models such as AHP, BWM, DEMATEL, or MACBETH models.

The capacity of individuals to simultaneously compare multiple criteria depends on several factors, encompassing cognitive capacity, attention span, and the complexity of the criteria under consideration. While some people may have the capability to process and compare more than eight criteria at the same time, it can be challenging for many individuals. The human brain has a limited capacity for processing information, and working memory plays a crucial role in holding and manipulating information during cognitive tasks. Research suggests that the average person's working memory can hold around seven (plus or minus two) chunks of information at a time. This means that comparing more than seven or eight criteria simultaneously can exceed the working memory's capacity for many people. For example Miller [27] proposed that the average human working memory has a limited capacity of around seven (plus or minus two) chunks of information. This concept, known as Miller's Law or the "Magical Number Seven", suggests that people have difficulty simultaneously comparing more than a handful of criteria. Also, Cowan [28] has explored the specific limitations of working memory. He has shown that individuals can hold a small number of items in their working memory simultaneously, typically ranging from three to five items. This constraint can impact the ability to compare a large number of criteria simultaneously. While the literature [27,28] indicates that people may struggle to compare more than a limited number of criteria simultaneously, it is important to consider that individual differences exist, and some individuals may possess superior cognitive abilities or use effective strategies to handle larger amounts of information. Additionally, the use of decision-support systems based on MCDM mathematical models can enhance people's capacity to compare and evaluate multiple criteria more efficiently.

The OPA method has been successfully integrated into various decision making problems in the extant literature. Le and Nhieu [29] presented a novel and robust integration model, which includes the OPA and Fuzzy Evaluation Based on Distance from Average Solution (Fuzzy EDAS) for the evaluation of post-COVID-19 production strategies in the Vietnam manufacturing industry. Abdel-Basset et al. [30] proposed a new extended OPA under the neutrosophic environment to select a suitable robot in Egypt. Mahmoudi et al. [31] improved an innovative decision-making method to solve the supplier selection problems in the post-COVID-19 era using fuzzy OPA. Mahmoudi et al. [32] presented a new robust OPA MCDM for the project portfolio selection problem. Sadeghi [33] developed a novel model for risk assessment based on the trapezoidal fuzzy OPA in MCDM context. Fuzzy systems can also be integrated into various operations: fuzzy system-based multi/many-objective evolutionary algorithm [34], and multistage evolutionary fuzzy control approach [35].

The paper is organized as follows: In Section 2, we present the survey data and the specified decision-making criteria. Section 3 includes the development of the proposed MCDM model. In Section 4, we discuss the experimental results. Lastly, Section 5 offers concluding remarks.

2. Survey data presentation

The City of Columbus and Columbus Partnership launched the Smart Columbus Ride & Drive Roadshow project in an effort to enhance EV adoption and encourage drivers to switch from conventional cars to EV. The participants were given surveys both before and after the drive, with the primary focus being on the psycho-social and experiential aspects of EV perception [36]. The questionnaires were designed to assess the impact of the test-drive experience on EV perception and likelihood of adoption [37]. As part of this study, the large-scale post-EV test drive survey data from the 2017 Roadshow [38] are used to conduct a quasi-experimental field study. The test drivers were asked to rate each criterion in order of importance using a Likert-scale with 1 being very unimportant to 5 being very important. The details of the twelve decision-making criteria used in the proposed support system are given below.

Decision-making Criteria: There are a number of vehicle attributes that are significant in purchase decisions that might impact EV adoption. The attributes may include economic and practical considerations [39]. The survey questions collected the users' opinions on the importance level of various aspects when purchasing an EV. They can be grouped into three categories and are considered as decision-making criteria as in Table 1: economic, vehicle features, and environmental effect. The economic concerns include price, fuel economy, and federal incentives, while the vehicle characteristics include driving characteristics, safety, style, utility, reviews, quality of workmanship, and reliability. The major environmental concern is environmental benefit, however fuel economy might also be included in this category because of decreased carbon emissions. The commute that people have to do each day is taken into

Table 1
The decision-making criteria for purchasing an EV based on collected data from the post-EV test drive survey [38].

Criteria	Criteria Name	Likert Scale*	Attribute	Mean	Std. Dev
C_1	Driving Characteristics	1 ~ 5	Vehicle Characteristics	4.312	0.799
C_2	Price of a Vehicle	1 ~ 5	Economic	4.338	0.661
C_3	Fuel Economy	1 ~ 5	Economic/Environmental	3.935	1.055
C_4	Safety of a Vehicle	1 ~ 5	Vehicle Characteristics	4.519	0.680
C_5	Environmental Benefits	1 ~ 5	Environmental	3.727	0.926
C_6	Style of a Vehicle	1 ~ 5	Vehicle Characteristics	4.299	0.650
C_7	Vehicle Utility Type (Truck, SUV, etc.)	1 ~ 5	Vehicle Characteristics	3.468	0.981
C_8	User Reviews of a Vehicle	1 ~ 5	Vehicle Characteristics	3.935	0.675
C_9	Reliability	1 ~ 5	Vehicle Characteristics	4.688	0.519
C_{10}	Quality of Workmanship	1 ~ 5	Vehicle Characteristics	4.571	0.571
C_{11}	Daily Commute Distance	1 ~ 5	Economic/Environmental	2.299	1.026
C_{12}	Federal Incentive	1 ~ 5	Economic	3.792	1.480

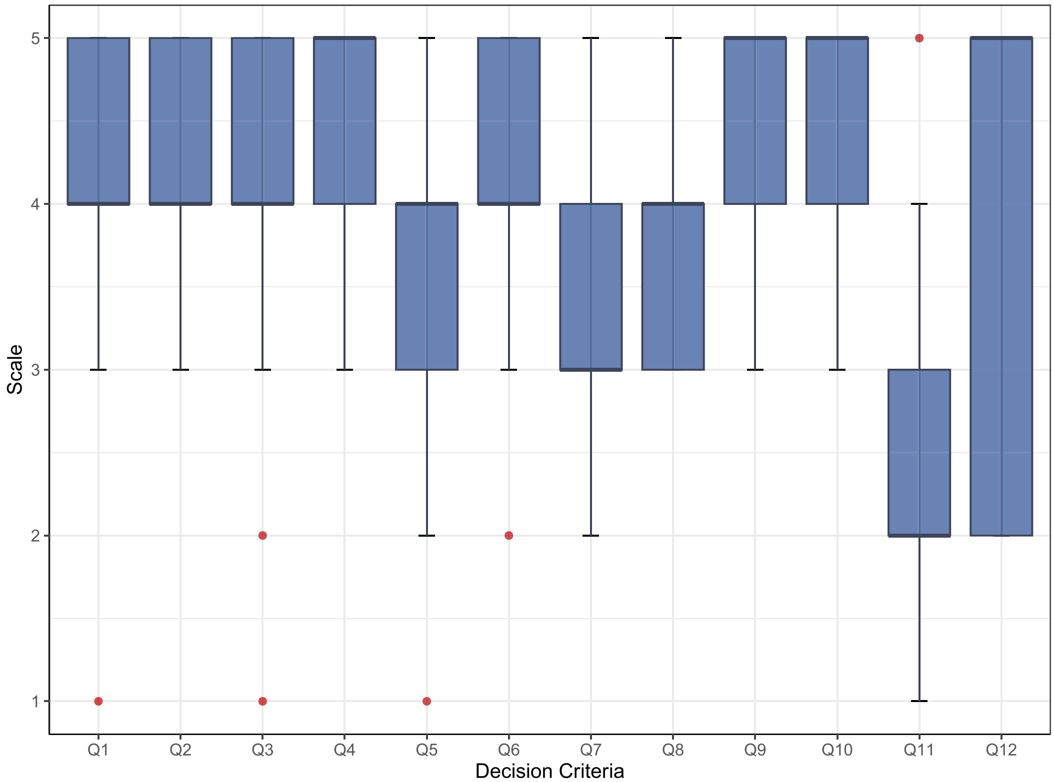

Fig. 1. Decision criteria as independent variables.

consideration by converting the mileage range to a 5-point scale as an economic component since it has an impact on the amount of fuel that is consumed, which is an aspect of the economy that is of concern. The test drivers' responses were translated to the numerical scale as given in the Table 1 to be used as decision-making criteria. The responses to each of the twelve questions are given in Fig. 1 as a box plot. The mean values reported in Table 1 show that the highest mean value is 4.68 for criterion 9 (reliability), while the lowest mean value is 2.29 for criterion 11 (daily commute). The majority of the responses varied around the mean value. On the other hand, there is more variability in responses for questions 3, 11, and 12 as evidenced by their standard deviation being greater than 1.

3. A novel rough ordinal priority approach framework

This section develops a MCDM model to rank the degree of importance of all the criteria considered. Let m be the number of survey participants and n be the number of criteria. Consider that the participant evaluated n criteria (C_j) (where $j = 1{:}n$) based on a predefined scale for assessing the significance of the criteria. Then, the steps of the rough OPA algorithm are as follows:

Step 1. Defining an aggregated rough linguistic matrix $\mathfrak{R} = \left[\hat{\wp}_j\right]_{nx1}$. After collecting participant assessments of the significance of the criteria, the participants' correspondent linguistic matrices $\mathfrak{R}^e = \left[\wp_j^e\right]_{nx1}$ $(1 \leq e \leq m)$ were formed, representing each participant's assessment of the criterion's importance. Thus, we obtain linguistic matrices $\mathfrak{R}^1, \mathfrak{R}^2, \ldots, \mathfrak{R}^e, \ldots, \mathfrak{R}^m$, which contain estimates of each of the m participants. Participant linguistic matrices can be represented by Eq. (1).

$$\mathfrak{R}^e = \begin{array}{c} C_1 \\ C_2 \\ C_3 \\ \ldots \\ C_n \end{array} I\& \begin{pmatrix} \wp_1^1 & \wp_1^2 & ,\ldots,\wp_1^e & ,\ldots, & \wp_1^m \\ \wp_2^1 & \wp_2^2 & ,\ldots,\wp_2^e & ,\ldots, & \wp_2^m \\ \wp_3^1 & \wp_3^2 & ,\ldots,\wp_3^e & ,\ldots, & \wp_3^m \\ & & \ldots & & \\ \wp_n^1 & \wp_n^2 & ,\ldots,\wp_n^e & ,\ldots, & \wp_n^m \end{pmatrix} \tag{1}$$

where $\wp_j^* = \left\{ \wp_n^1, \wp_n^2, \ldots, \wp_n^e, \ldots, \wp_n^m \right\}$ represents the sequences that describe the significance of criterion j. Suppose that the sequences $\wp_{ij}^* = \left\{ \wp_n^1, \wp_n^2, \ldots, \wp_n^e, \ldots, \wp_n^m \right\}$ are arranged in descending order $\wp_j^1 \leq \wp_j^2 \leq, \ldots, \leq \wp_j^e \leq, \ldots, \leq \wp_j^m$. Then for each $\forall \wp_j^x, \wp_j^e \in \wp_j^*$, $(1 \leq e \leq m)$, an upper and lower approximation of $\wp_j^e$ can be defined as follows:

$$\begin{aligned} \underline{\wp_j^e} &= \cup_{1\leq e\leq m} \left\{ \wp_j^e \in \wp_j^* | \wp_j^e \leq \wp_j^* \right\} \\ \overline{\wp_j^e} &= \cup_{1\leq e\leq m} \left\{ \wp_j^e \in \wp_j^* | \wp_j^e \geq \wp_j^* \right\} \end{aligned} \tag{2}$$

Then, based on the upper and lower approximation of $\wp_j^e$, Eq. (1), we can define the lower and upper limits of $\wp_j^e$ as follows:

$$\begin{aligned} \wp_j^{e-} &= \left(\frac{1}{\lambda_L} \sum_{\substack{i,j=1 \\ i\neq j}}^{\lambda_L} \wp_i^{eb_1} \left(\prod_{j=1}^{\lambda_L} \wp_j^{eb_2} \right)^{\frac{1}{\lambda_L - 1}} \right)^{\frac{1}{d_1+d_2}} \middle| \wp_i^{eb_1}, \wp_j^{eb_2} \in \underline{\wp_j^e} \\ \wp_j^{e+} &= \left(\frac{1}{\lambda_U} \sum_{\substack{i,j=1 \\ i\neq j}}^{\lambda_U} \wp_i^{eb_1} \left(\prod_{j=1}^{\lambda_U} \wp_j^{eb_2} \right)^{\frac{1}{\lambda_U - 1}} \right)^{\frac{1}{d_1+d_2}} \middle| \wp_i^{eb_1}, \wp_j^{eb_2} \in \overline{\wp_j^e} \end{aligned} \tag{3}$$

where $(1 \leq e \leq m)$, λ_L and λ_U represents the number of elements in experts' correspondent linguistic matrix (1), and $d_1, d_2 \geq 0$.

For defining the lower and upper limits of $\wp_j^e$, we have used Bonferroni functions [40]. The proposed methodology for defining the lower and upper limits eliminates the disadvantages of arithmetic averaging, which is used to define the lower and upper limits for classic rough numbers [41]. The introduction of Bonferroni functions for defining the lower and upper limit of rough numbers allows (1) consideration of mutual relations between a set of objects that are translated into rough numbers, and (2) flexible representation of the rough boundary interval and definition of the degree of risk depending on the dynamic conditions of the environment.

Based on Equations (1) and (2), we obtain rough matrices of expert estimates $\mathfrak{R}^e = \left[\hat{\wp}_j^e \right]_{nx1}$, where $\hat{\wp}_j^e = \left[\wp_i^e, \wp_i^+ \right]_{nx1}$, $(1 \leq e \leq m)$. By fusing rough values from the matrices $\mathfrak{R}^e$, we obtain the final aggregated rough linguistic matrix $\mathfrak{R} = \left[\hat{\wp}_j \right]_{nx1}$, $\hat{\wp}_j = \left[\wp_i^e, \wp_i^+ \right]$.

Step 2. Ranking of criteria according to their importance. Based on the final aggregated rough linguistic matrix values, the criteria are ranked according to their significance. The criterion should have the highest possible value of $\hat{\wp}_j$ to have a better rank. If $\hat{\wp}_{x_1} = \hat{\wp}_{x_2} (1 \leq x_1, x_2 \leq n)$, then the criteria C_{x_1} and C_{x_2} have the same rank. This is how we get the rank of criteria according to the following:

$$\hat{\xi}_j^{(1)} \geq \hat{\xi}_j^{(2)} \geq \cdots \geq \hat{\xi}_j^{(r)} \geq \hat{\xi}_j^{(r+2)} \geq \cdots \geq \hat{\xi}_j^{(m)}; \quad \forall_j \tag{4}$$

Rough weighting coefficients of successively ranked criteria from Eq. (4) should satisfy the following condition:

$$\begin{aligned} &\hat{\xi}_j^{(1)} - \hat{\xi}_j^{(2)} \geq 0, \\ &\hat{\xi}_j^{(2)} - \hat{\xi}_j^{(3)} \geq 0, \\ &\ldots \\ &\hat{\xi}_j^{(r)} - \hat{\xi}_j^{(r+1)} \geq 0, \\ &\ldots \\ &\hat{\xi}_j^{(n-1)} - \hat{\xi}_j^{(n)} \geq 0, \end{aligned} \tag{5}$$

where $\hat{\xi}_j^{(r)} = \left[\hat{\xi}_j^{(r)-} - \hat{\xi}_j^{(r)+} \right]$ represents the weighting coefficient of the jth criterion at the rth rank.

Eq. (5) can be shown in abbreviated form according to the following:

$$\frac{min_{1\leq j\leq n} \left\{ \wp_j^- \right\}}{\wp_j^+} \left(\hat{\xi}_j^{(r)} - \hat{\xi}_j^{(r+1)} \right) \geq 0; \quad \forall_j \tag{6}$$

Step 3. Based on conditions (4) - (6), a mathematical model is formed to calculate the weight coefficients of the criteria. To define the weight coefficients of the criteria, it is necessary to solve a multi-objective nonlinear mathematical model (7).

$$
\begin{array}{l}
MaxMin\left\{ \frac{min_{1\le j\le n}\left\{\wp_j^-\right\}}{\wp_j^+}\left(\hat{\xi}_j^{(r)}-\hat{\xi}_j^{(r+1)}\right), \right.\\
\left. \frac{min_{1\le j\le n}\left\{\wp_j^-\right\}}{\wp_j^+}\hat{\xi}_j^{(m)}; \right\};\forall_j \\
s.t. \\
\sum_{j=1}^{n}\hat{\xi}_j=1, \\
\hat{\xi}_j\ge 0;\quad \forall_j
\end{array}
\tag{7}
$$

We can transform a multi-objective nonlinear model (7) into a linear mathematical model, Eq. (9).

$$
h=Min\left\{ e\left(j\left(i\left(\hat{\xi}_j^{(r)}-\hat{\xi}_j^{(r+1)}\right)\right)\right), \frac{min_{1\le j\le n}\left\{\wp_j^-\right\}}{\wp_j^+}\hat{\xi}_j^{(m)}; \right\};\forall_j \tag{8}
$$

Ater that, by substituting expression Eq. (8) into Eq. (7), we can define the final linear model for determining weight coefficients, Eq. (9).

$$
\begin{array}{l}
Max\left(\chi^-+\chi^+/2\right) \\
s.t. \\
\frac{min_{1\le j\le n}\left\{\wp_j^-\right\}}{\wp_j^+}\left(\xi_j^{-(r)}-\xi_j^{+(r+1)}\right)\ge\chi^-; \\
\frac{min_{1\le j\le n}\left\{\wp_j^-\right\}}{\wp_j^-}\left(\xi_j^{+(r)}-\xi_j^{-(r+1)}\right)\ge\chi^+; \\
\frac{min_{1\le j\le n}\left\{\wp_j^-\right\}}{\wp_j^+}\xi_j^{-(n)}\ge\chi^-; \frac{min_{1\le j\le n}\left\{\wp_j^-\right\}}{\wp_j^-}\xi_j^{+(n)}\ge\chi^+; \\
\sum_{j=1}^{n}\xi_j^-=0.8;\quad \sum_{j=1}^{n}\xi_j^+=1.0; \\
\xi_j^-;\xi_j^+\ge 0;\quad \forall_j
\end{array}
\tag{9}
$$

where $\hat{\xi}_j=\left[\xi_j^-,\xi_j^+\right]$ represents the rough weight of jth criterion.

4. Determination of weight coefficients of criteria using rough OPA methodology

In this section, the application of the rough OPA for determining the weighting coefficients of the criteria is given:

Step 1: The study surveyed 77 participants who evaluated the criteria using a five-point scale: 1 = Very unimportant, 2 = Unimportant, 3 = Somewhat important, 4 = Important, 5 = Very important. By applying Equations (2) and (3), participant estimates were transformed into rough values. Rough participant estimates were aggregated using the rough Bonferroni function [40], and an aggregated rough home matrix $\Re=\left[\hat{\wp}_j\right]_{12x1}$ was formed, as follows:

$$
\Re=\begin{array}{c} C_1\\ C_2\\ C_3\\ C_4\\ C_5\\ C_6\end{array}\begin{bmatrix}[3.76,4.73]\\ [3.83,4.80]\\ [3.05,4.51]\\ [4.10,4.94]\\ [2.84,4.23]\\ [4.03,4.45]\end{bmatrix}\quad \begin{array}{c} C_7\\ C_8\\ C_9\\ C_{10}\\ C_{11}\\ C_{12}\end{array}\begin{bmatrix}[2.51,3.66]\\ [4.36,4.94]\\ [4.69,4.99]\\ [4.29,4.90]\\ [1.57,3.44]\\ [2.90,4.48]\end{bmatrix}
$$

An example of the transformation of expert estimates into rough values at the position of the first criterion C_1 is presented in the following section. Based on 77 participant estimates for criterion C_1, we can form a set of expert sequences $\hat{\wp}_1^e=(5,5,5,4,4,5,5,\ldots,3,3,4)$, $(1\le e\le m)$. Bonferroni functions were used for defining the lower and upper limit of the expert sequences. Using the Equations (2) and (3) and provided that $d_1=d_2=1$, the lower and upper limit sequences are defined according to the following:

a) Lower limits:

$$
\begin{array}{l}
\wp_1^{8-}(3)=\wp_1^{9-}(3)=\wp_1^{16-}(3)=\cdots=\wp_1^{76-}(3)=3.0; \\
\wp_1^{4-}(4)=\wp_1^{5-}(4)=\wp_1^{10-}(4)=\cdots=\wp_1^{77-}(4)= \\
=\left(\frac{1}{43}\left\{4\cdot(4\cdot3\cdot3\cdot\cdots\cdot3\cdot3\cdot4)^{1/42}+4\cdot(4\cdot3\cdot3\cdot\cdots\cdot3\cdot3\cdot4)^{1/42}+\cdots+3\cdot(4\cdot4\cdot3\cdot3\cdot\cdots\cdot3\cdot4)^{1/42}+\ldots\right.\right. \\
\quad \left.\left.+4\cdot(4\cdot3\cdot3\cdot\cdots\cdot3\cdot3)^{1/42}\right\}\right)^{\frac{1}{1+1}}=3.58 \\
\wp_1^{1-}(5)=\wp_1^{2-}(5)=\wp_1^{3-}(5)=\cdots=\wp_1^{61-}(5)= \\
=\left(\frac{1}{77}\left\{5\cdot(5\cdot5\cdot4\cdot4\cdot\cdots\cdot3\cdot3\cdot4)^{1/76}+5\cdot(5\cdot5\cdot4\cdot4\cdot\cdots\cdot3\cdot3\cdot4)^{1/76}+\cdots+3\cdot(5\cdot5\cdot5\cdot4\cdot4\cdot\cdots\cdot3\cdot4)^{1/76}+\ldots\right.\right. \\
\quad \left.\left.+4\cdot(5\cdot5\cdot5\cdot4\cdot4\cdot\cdots\cdot3\cdot3)^{1/76}\right\}\right)^{\frac{1}{1+1}}=4.24
\end{array}
$$

b) Upper limits:

$$\wp_1^{8+}(3)=\wp_1^{9+}(3)=\wp_1^{16+}(3)=\cdots=\wp_1^{76+}(3)=$$
$$=\left(\frac{1}{77}\left\{5\cdot(5\cdot5\cdot4\cdot4\cdot\cdots\cdot3\cdot3\cdot3)^{1/76}+5\cdot(5\cdot5\cdot4\cdot5\cdot\cdots\cdot3\cdot3\cdot4)^{1/76}+\cdots+3\cdot(5\cdot5\cdot5\cdot4\cdot4\cdot\cdots\cdot3\cdot4)^{1/76}+\ldots\right.\right.$$
$$\left.\left.+4\cdot(5\cdot5\cdot5\cdot4\cdot4\cdot\cdots\cdot3\cdot3)^{1/76}\right\}\right)^{\frac{1}{1+1}}=4.24$$
$$\wp_1^{4+}(4)=\wp_1^{5+}(4)=\wp_1^{10+}(4)=\cdots=\wp_1^{77+}(4)=$$
$$=\left(\frac{1}{27}\left\{5\cdot(5\cdot5\cdot4\cdot4\cdot\cdots\cdot5\cdot5\cdot4)^{1/26}+5\cdot(5\cdot5\cdot4\cdot4\cdot\cdots\cdot5\cdot5\cdot4)^{1/26}+\cdots+5\cdot(4\cdot4\cdot4\cdot4\cdot5\cdot\cdots\cdot5\cdot4)^{1/26}+\ldots\right.\right.$$
$$\left.\left.+4\cdot(4\cdot4\cdot4\cdot4\cdot5\cdot\cdots\cdot5\cdot5)^{1/26}\right\}\right)^{\frac{1}{1+1}}=4.63$$
$$\wp_1^{1+}(5)=\wp_1^{2+}(5)=\wp_1^{3+}(5)=\cdots=\wp_1^{61+}(5)=5.00.$$

By applying the Bonferroni function, we can define rough number as follows:

$$\hat{\wp}_j=\begin{cases}\left(\frac{1}{77(77-1)}\left(4.24\cdot4.24+4.24\cdot4.24+4.24\cdot4.24+\right.\right.\\ \left.\left.\cdots+3.58\cdot3+3.58\cdot3\right)\right)^{1/2}=3.76\\ \left(\frac{1}{77(77-1)}\left(5\cdot5+5\cdot5+5\cdot5+\cdots+4.63\cdot4.24+\right.\right.\\ \left.\left.4.63\cdot4.24\right)\right)^{1/2}=4.73\end{cases}=[3.76,4.73]$$

The other elements of the home matrix are defined similarly.

Parameters d_1 and d_2 are stabilization parameters of Bonferroni functions that were used to represent inaccuracy and risk in information. The parameters should meet the condition $d_1, d_1 \geq 1$. These are subjectively defined parameters, and the value $d_1 = d_1 = 1$ was adopted for the calculation of the initial values. This simulated a minimal level of risk and inaccuracy in the information, and enabled a simpler calculation of the lower and upper sequences of rough numbers. A detailed description of the influence of the mentioned parameters on the change of the results is presented in the sensitivity analysis presented in the next section of the paper.

Step 2: Based on the obtained rough values, the criteria were ranked, and the following rank was obtained: $C_9 > C_8 > C_{10} > C_4 > C_2 > C_1 > C_6 > C_3 > C_{12} > C_5 > C_7 > C_{11}$. Based on the defined rank of the criteria and the application of conditions Equations (4) - (6), the limits that need to meet the rough weight coefficients of the criteria are defined.

Step 3: Based on the constraints defined in *Step 2*, a rough number-based linear model was defined, which was used to determine the final values of the weighting coefficients of the criteria.

$$max\left(\chi^-+\chi^+\right)/2$$

s.t.

$$\begin{cases}
0.315\cdot\left(\xi_9^- -\xi_8^+\right)\geq\chi^- & \\
0.335\cdot\left(\xi_9^+ -\xi_8^-\right)\geq\chi^+ & 0.516\cdot\left(\xi_3^+ -\xi_{12}^-\right)\geq\chi^+\\
0.319\cdot\left(\xi_8^- -\xi_{10}^+\right)\geq\chi^- & 0.351\cdot\left(\xi_{12}^- -\xi_5^+\right)\geq\chi^-\\
0.361\cdot\left(\xi_8^+ -\xi_{10}^-\right)\geq\chi^+ & 0.543\cdot\left(\xi_{12}^+ -\xi_5^-\right)\geq\chi^+\\
0.321\cdot\left(\xi_{10}^- -\xi_4^+\right)\geq\chi^- & 0.372\cdot\left(\xi_5^- -\xi_7^+\right)\geq\chi^-\\
0.367\cdot\left(\xi_{10}^+ -\xi_4^-\right)\geq\chi^+ & 0.554\cdot\left(\xi_5^+ -\xi_7^-\right)\geq\chi^+\\
0.318\cdot\left(\xi_4^- -\xi_2^+\right)\geq\chi^- & 0.430\cdot\left(\xi_7^- -\xi_{11}^+\right)\geq\chi^-\\
0.384\cdot\left(\xi_4^+ -\xi_2^-\right)\geq\chi^+ & 0.626\cdot\left(\xi_7^+ -\xi_{11}^-\right)\geq\chi^+\\
0.328\cdot\left(\xi_2^- -\xi_1^+\right)\geq\chi^- & 0.457\cdot\left(\xi_{11}^-\right)\geq\chi^-\\
0.410\cdot\left(\xi_2^+ -\xi_1^-\right)\geq\chi^+ & 1.000\cdot\left(\xi_{11}^+\right)\geq\chi^+\\
0.333\cdot\left(\xi_1^- -\xi_6^+\right)\geq\chi^- & \sum_{j=1}^{12}\xi_j^-=0.8\\
0.418\cdot\left(\xi_1^+ -\xi_6^-\right)\geq\chi^+ & \\
0.353\cdot\left(\xi_6^- -\xi_3^+\right)\geq\chi^+ & \sum_{j=1}^{12}\xi_j^+=1.0\\
0.391\cdot\left(\xi_6^+ -\xi_3^-\right)\geq\chi^+ & \xi_j^-\leq\xi_j^+\\
0.349\cdot\left(\xi_3^- -\xi_{12}^+\right)\geq\chi^- & \xi_j^-,\xi_j^+\geq0;\quad\forall_j
\end{cases}$$

Table 2
Weight coefficients of criteria.

Criteria	Rough ξ_j	Crisp ξ_j	Rank	Normalized crisp ξ_j
ξ_1	[0.0700, 0.0833]	0.0752	6	0.0838
ξ_2	[0.0833, 0.0984]	0.0902	5	0.1006
ξ_3	[0.0401, 0.0553]	0.0440	8	0.0491
ξ_4	[0.0984, 0.1136]	0.1065	4	0.1187
ξ_5	[0.0186, 0.0327]	0.0208	10	0.0232
ξ_6	[0.0553, 0.0700]	0.0601	7	0.0670
ξ_7	[0.0117, 0.0186]	0.0123	11	0.0137
ξ_8	[0.1302, 0.1460]	0.1409	2	0.1571
ξ_9	[0.1460, 0.2000]	0.1885	1	0.2102
ξ_{10}	[0.1136, 0.1302]	0.1236	3	0.1378
ξ_{11}	[0.0001, 0.0117]	0.0006	12	0.0007
ξ_{12}	[0.0327, 0.0401]	0.0342	9	0.0381

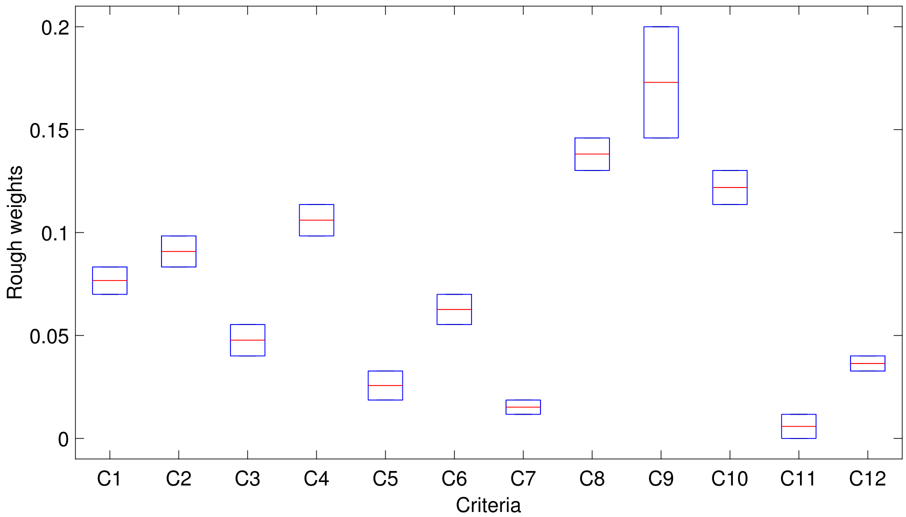

Fig. 2. Rough criteria weights.

Lingo 17.0 software was used to solve the rough linear model. Rough weighting coefficients of the criteria are presented in Table 2. A graphical representation of the rough values of the weighting coefficients of the criteria is given in Fig. 2.

Table 2 presents the rough, crisp, and normalized crisp values of the weighting coefficients that were obtained by transforming rough values. The weighting coefficients from Table 2 represent the degree of importance of attributes. Crisp values do not satisfy the condition that the sum of all coefficients is equal to one, therefore, crisp values are normalized by applying additive normalization. This resulted in normalized crisp values that satisfy the condition that $\sum_{j=1}^{12} \xi_j$.

In this study, the rough and crisp values of the weighted coefficients are presented, so the presented values can be used in models that process imprecise and uncertain information, as well as in traditional crisp MCMD models, like MABAC [42], VIKOR [43], MARCOS [44] or TODIM [45] methods. The weight coefficients from Table 2 can also be used to evaluate a set of alternatives using mathematical operators such as Muirhead operators [46], Heronian operators [47], Dombi operators [48], Aczel–Alsina operators [49] and other types of mathematical operators [50].

4.1. Results and discussion

The proposed MCDM model has found the relative importance of each decision-making criterion in relation to all other criteria. Based on the normalized crisp values calculated, the reliability of a vehicle (C_9) is found to have the highest importance. This confirms that vehicle manufacturers should pay close attention to reliability while they expend their EV portfolio. The following criteria: user reviews of a vehicle (C_8), quality of workmanship (C_{10}), safety of a vehicle (C_4), and price of vehicle (C_2) are seen to have considerably high importance. The findings have clearly shown that social influence has a strong impact on the intent to purchase an EV. It is worth to notice that while having higher importance, the price of a vehicle does not come to the forefront. Meanwhile, (C_1), (C_6), (C_3), (C_{12}), (C_5), and (C_7) have moderate importance, while daily commute distance (C_{11}) has less importance. While range anxiety is a common issue for EV drivers, daily commute is not found to be inconvenient by most drivers due to relatively

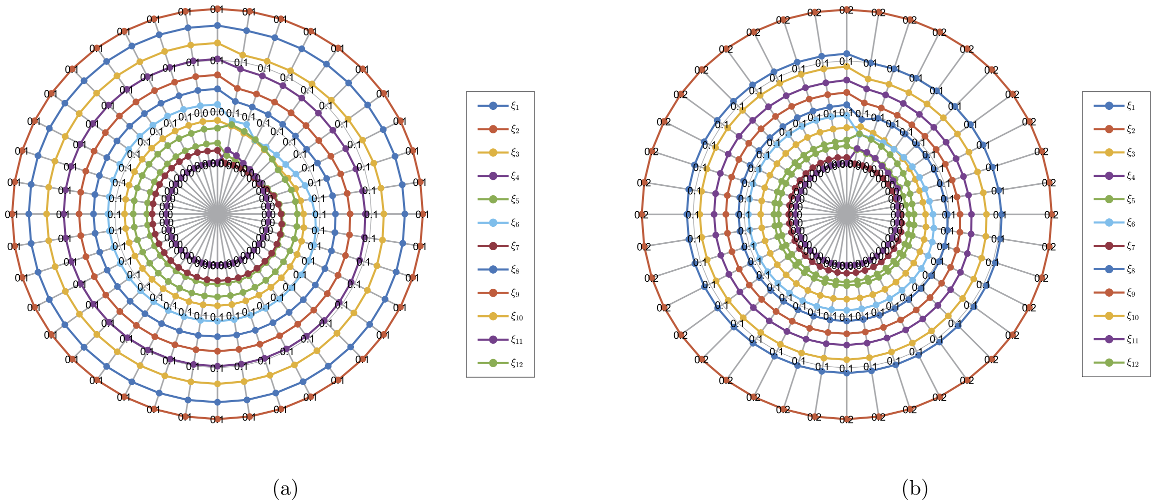

Fig. 3. Dependence of the rough boundary interval of the weighting coefficients of the criterion on the change of parameters (a) d_1 and (b) d_2.

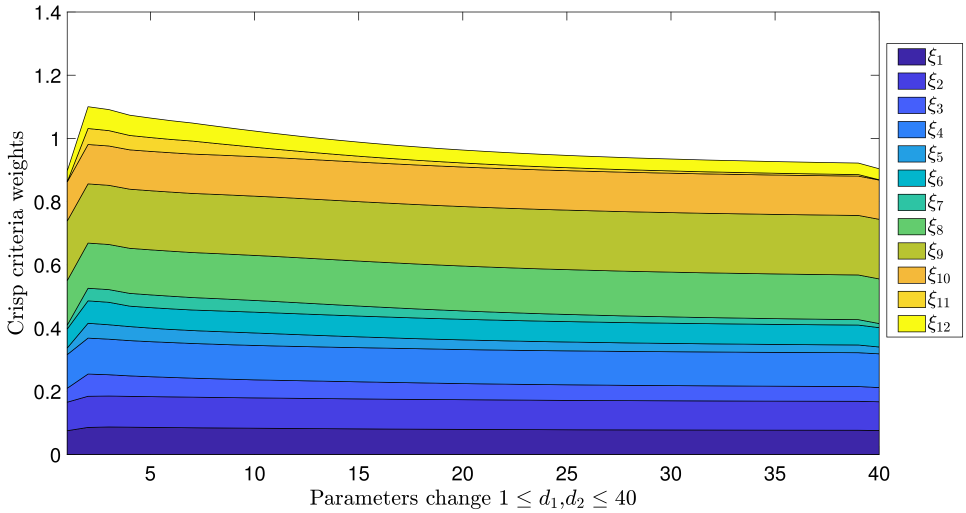

Fig. 4. Changes in the values of the criterion weight coefficients during the simulation.

shorter driving distance. As a result, the MCDM model suggests that when purchasing an EV, drivers prioritize factors linked to the vehicle's characteristics.

4.2. Checking the stability of the results

In this section, the stability of the weight coefficients when changing the parameters d_1 and d_2 is analyzed. As previously emphasized, the values $d_1 = d_2 = 1$ were adopted to define the initial values of the weighting coefficients of the criteria (Table 2 and Fig. 2). The above parameters are used to simulate inaccuracies and risks in information. Therefore, the value $d_1 = d_2 = 1$ was adopted to simulate the minimum level of risk and inaccuracies in the information. However, since these are subjectively defined parameters that affect the imprint of uncertainty in the rough boundary interval, it is necessary to answer the question, "Is there a violation of the rank and significance of the criteria in the case of choosing other parameter values?".

In the following part, the changes of the weight coefficients when changing the parameters $1 \leq d_1,\ d_2 \leq 40$ are analyzed. During forty cycles, the change in d_1 and d_2 was simulated. In parallel, we have tracked the influence of these changes on the change in values in the rough linguistic matrix. In the first cycle, the value $d_1 = d_2 = 1$ was introduced. In each subsequent cycle, the value of both parameters was increased by one. After each cycle, changes in the rough linguistic matrix were recorded, and the impact of these changes on the results of the rough linear model for defining the weight coefficients of the criteria was analyzed. Fig. 3 shows the changes in the rough boundary intervals of the weights that occurred due to changes in the values $1 \leq d_1, d_2 \leq 40$.

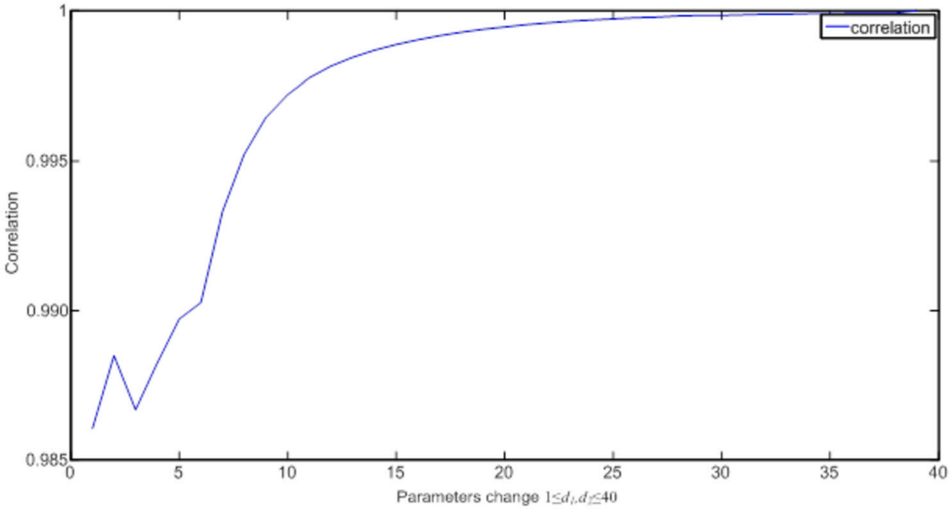

Fig. 5. Spearman's correlation coefficient.

The results from Fig. 3 indicate that changes in the values of d_1 and d_2 cause changes in the rough boundary interval of the criteria, which affects the changes in the ranks of individual criteria. Changes in the rankings occur with the worst-ranked criteria, i.e., criteria C_3, C_5, C_6, C_7, C_{11}, and C_{12}. The values of parameters $2 \le d_1, d_2 \le 7$ cause changes in the ranks of criteria C_5 and C_{11}, i.e., criteria C_5 and C_{11} have switched their positions. Similar changes occur in criteria C_3, C_6, C_7, and C_{12} for parameters $2 \le d_1, d_2 \le 7$. A graphical representation of these changes is illustrated in Fig. 4.

Fig. 3 and 4 show a sensitivity of the model to increasing levels of inaccuracy in the information. The results from Fig. 4 indicate a sensitivity of the model to changes in the parameters d_1 and d_2. This allows the simulation of different levels of risk in the information. In addition, the results from Fig. 3 and 4 indicate no significant changes in the rankings of the criteria. Minor changes occur under the worst criteria. Spearman's correlation coefficient was used to compare the initial and received scores change over the forty scenarios. The results obtained in each individual scenario were compared with the initial results given in Table 2. If the results obtained in the scenario are close to the initial results, the value of the Spearman coefficient is closer to unity. Fig. 5 shows the correlation of results over forty scenarios.

The average value of Spearman's coefficient through scenarios is 0.997, which shows a high correlation. Also, the deviation of the value of the weighting coefficients through the scenarios from their mean value is 0.0027. This confirmed that the statistical variations of the weight coefficients are small. Therefore, based on the presented analysis, we can conclude that the initial significance of the criteria presented in Table 2 and Fig. 2 is confirmed and credible.

5. Conclusion

In this study, EV adoption from the users' perspectives has been considered. A new MCDM model based on rough ordinal priority has been developed to identify the order of importance of users' perspectives when purchasing an EV. A large-scale post-EV test drive survey data has been used to implement the proposed model. Based on the data, this study identified 12 EV user attitudinal factors as decision-making criteria.

MCDM was applied to evaluate the relative importance of the 12 criteria. The results revealed that the criterion reliability, C_9, as the most significant, while daily commute distance, C_{11}, was the least significant. The remaining criteria were ranked as $C_8 > C_{10} > C_4 > C_2 > C_1 > C_6 > C_3 > C_{12} > C_5 > C_7$. This model has identified that vehicle related characteristics, such as reliability, quality of workmanship, and safety of vehicle are found to be more important than economic and environmental attributes, such as price of vehicle, fuel economy, federal incentive and environmental benefits. The results suggest that EV manufacturers should prioritize vehicle reliability to encourage adoption. The findings also revealed that word of mouth, which is a form of social influence, had a greater impact on user's decisions than price. The importance of daily commute distance, which is less likely to induce range anxiety, was found to be relatively less importance. Finally, a sensitivity analysis confirmed that changing model parameters did not affect the ranking order of the most significant criteria, while only the importance of the least significant criteria could change. Overall, the proposed model can serve as a valuable decision-making tool for EV manufacturers, policymakers, and EV initiatives to promote widespread EV adoption. The proposed rough OPA methodology provides the following advantages:

- It defines the weighting coefficients based on standardized elements of the aggregated rough linguistic matrix that enables more precise an objective definition.
- The proposed rough OPA model can be used simultaneously to prioritize and define the weighting coefficients of group and individual decision making criteria and alternatives.
- The Rough OPA algorithm allows the processing of uncertain information.

• It uses nonlinear aggregation functions that helps flexible decision making due to risk attitudes of decision makers.

The proposed methodology has certain limitations, including inadequate addressing of computational complexity and information neutrality. To address these issues, future research should focus on developing user-friendly software and enhancing the methodology's performance by applying intuitionistic fuzzy sets and picture fuzzy sets. Additionally, the proposed method can be generalized to solve other MCDM problems, such as supplier selection, renewable energy source selection, and electric charging station selection.

CRediT authorship contribution statement

Sadik Kucuksari: Conceptualization, Methodology, Software, Validation, Formal analysis, Data collection, Writing – original draft, Writing – review & editing. **Dragan Pamucar:** Methodology, Software, Validation, Formal analysis, Writing – original draft, Writing – review & editing. **Muhammet Deveci:** Conceptualization, Methodology, Software, Validation, Formal analysis, Writing – original draft, Writing – review & editing. **Nuh Erdogan:** Conceptualization, Methodology, Software, Validation, Formal analysis, Data collection, Writing – original draft, Writing – review & editing. **Dursun Delen:** Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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