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A Fuzzy Decision-Making Approach to Electric Vehicle Evaluation and Ranking

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Abstract: One of the key challenges facing the modern automotive industry is aligning customer demands with increasingly stringent environmental regulations and policies. In addition to introducing various modifications and improvements to internal combustion engine vehicles, manufacturers are increasingly focusing on the development of electric and hybrid vehicles. Moreover, the goal is to ensure that the product remains both cost-effective for manufacturers and sufficiently affordable for potential customers. This study addresses the problem of selecting electric vehicles based on features that are significant from both the customer and manufacturer perspectives. The objective of this research is to evaluate and rank electric vehicle models from various global manufacturers based on features collected and integrated from diverse literature sources. A total of 18 electric vehicle models were analysed and assessed according to 10 features. This research introduces a fuzzy multi-criteria decision-making model for mathematically determining the rank of electric vehicles. The obtained results serve as input data for benchmarking and optimizing business strategies in automotive companies, which represents the practical contribution of this study. The evaluation of the relative importance of features is framed as a fuzzy group decision-making problem, where decision-makers express their assessments using predefined linguistic terms modelled with triangular fuzzy numbers. The ranking of the analysed electric vehicles is conducted using modified fuzzy TOPSIS and fuzzy COPRAS methods, which constitute the main scientific contribution of this research. A methodology for ranking similarity comparison was applied to examine the consistency of the results obtained through these two methods.

Keywords: automotive industry; electric vehicles; fuzzy multi-criteria decision-making; fuzzy TOPSIS; fuzzy COPRAS

1 INTRODUCTION

1.1 Sustainable Alternative for Electric Vehicles

Changes in the business environment, such as the development of new technologies and increased demands for environmental protection, generate demands from customers of automotive companies to develop new strategies for sustainable transportation. One way to achieve sustainable transportation is through the development of electric vehicles (EVs). China currently produces two-thirds of the world's EVs. In the first-half of 2024, electric car sales increased by around 25% compared to the same period in 2023, driven by strong performance in China, which accounted for 60% of global sales [1].

Nowadays, many automotive companies produce EVs that use lithium-ion batteries. Research findings in this field, as well as results obtained during the exploitation of these batteries, indicate the necessity of replacing lithium-ion batteries with sodium-ion batteries [2, 3].

This assertion is based on two reasons. First, mining and extracting lithium ore significantly and irreversibly damages the environment and depletes water reserves, which are considered the most crucial resource of this century. On the other hand, sodium is found in rock salt and saline deposits worldwide and can be easily obtained through the electrolysis of table salt. The second reason, which is economic and less important than the ecological one, is that the production of sodium-ion batteries requires significantly lower costs compared to lithium-ion batteries.

Today, research centers around the world, as well as many companies, are developing sodium-ion batteries with desirable characteristics. For instance, at the Korea Advanced Institute of Science and Technology, a sodium-ion battery has been developed with high storage capacity and fast charging and discharging rates. The Swedish company Northvolt has produced a sodium-ion battery that is safer than lithium-ion batteries because it does not contain lithium, nickel, manganese, or cobalt and is made from raw materials abundantly available in nature. Research conducted at this company shows that sodium-ion batteries can withstand three times higher heat exposure than lithium-ion batteries, making energy storage significantly safer. At the beginning of last year, China began constructing the world's largest factory for sodium-ion battery production. Some Chinese automotive companies have started producing EVs with sodium-ion batteries, representing a major innovation in the EV market.

The choice of EVs by customers is almost always based on the evaluation of numerous features of EVs. It can be considered that defining EV features is a task in itself. In this research, the set of features is based on literature data [4-7] as well as best practice experience. It is worth noting that these features can also be used when evaluating vehicles powered by other alternative energy sources. Furthermore, in the relevant literature, there are also studies in which authors ranked vehicles of different types and purposes based on various criteria. For example, in the study [8], the authors conducted an analysis and selection of a Small Electric Vans.

1.2 Application of TFNs for Modelling the Relative Importance of EV Features

Many authors believe that decision-makers (DMs) can express their assessments of the relative importance of EV features more accurately using natural language. The fuzzy set theory allows for uncertainty, imprecision, randomness, and ambiguity in data to be quantitatively represented. In this research, existing uncertainties in the relative importance of features are modelled using triangular fuzzy numbers (TFNs). It can be stated that TFNs capture the uncertainties of natural language sufficiently well while not requiring more complex calculations. Therefore, many authors recommend using TFNs for modelling various uncertainties and imprecisions. In this research, the authors considered that uncertainties in the relative importance of features can be adequately modelled by using TFNs.

In previous studies [9-13], the relative importance of evaluation attributes, described using linguistic expressions modelled by TFNs as in this manuscript, or

TrFNs [14-17], suggests using a common measurement scale for assessing the relative importance of attributes.

Some authors recommend employing a seven-point scale [15, 16], which is also adopted in this research. In other analyzed studies, authors use five linguistic expressions to describe the relative importance of attributes. The domains of fuzzy numbers are defined on common measurement scales [10, 12, 13], as in this research.

The determination of relative importance is framed as a fuzzy group decision-making problem [15, 16]. Given the nature of the problem, it can be assumed that determining the weights of features should also be treated as a fuzzy decision-making problem. Each decision-maker (DM) evaluates the relative importance of the considered features using one of the pre-defined linguistic expressions modelled by TFNs.

When all DMs are equally significant in the decision-making process, the relevant literature most commonly employs the fuzzy arithmetic mean [15] or the fuzzy root mean square [16], as in this paper. The authors believe that using the fuzzy root mean square enhances the accuracy of determining feature weights.

Some researchers argue that applying multi-attribute decision-making (MADM) methods extended with fuzzy set theory [10, 12, 13, 18] provides more accurate values for the weights vector. Considering that fuzzy MADM applications involve greater computational effort, other analyzed studies determine the weights vector based on DM assessments [9, 11, 15, 16], as is done in this research.

In the studies by [11] and [9], the elements of the weights vector are crisp. In this paper, the feature weights are determined using a linear normalization procedure [19] combined with fuzzy algebra rules [20, 21]. Through this approach, the weights of features are described by TFNs.

1.3 An Analysis of Fuzzy MADM Methods for EV Model Ranking

Based on purchasing management practices in the automotive industry, it is well-known that customers evaluate EV models based on numerous features, which often conflict with one another. The problem becomes significantly more complex when considering the assumption that the weights of the evaluated features are described by uncertain numbers and hold varying relative importance. This issue can be formulated as a MADM problem under uncertain conditions. The solution to the considered problem can be obtained by applying various MADM methods extended with fuzzy set theory [22-26], as well as by applying other approaches for describing imprecision and uncertainty, such as (fuzzy) rough sets [27, 28]. It should be noted that the application of different MADM methods does not necessarily yield a unique solution [29, 30]. Therefore, it is considered a good practice to compare the solutions obtained by different methods before providing recommendations, as demonstrated in this manuscript.

In this research, two fuzzy MADM methods are proposed for ranking various alternative-powered vehicle models: (i) TOPSIS [31] extended with triangular fuzzy numbers (FTOPSIS), which is the most widely used in the literature [32], and (ii) COPRAS [33] extended with triangular fuzzy numbers (FCOPRAS).

The decision matrix element values can be crisp, as in this research, or uncertain, as demonstrated in previous studies [9-16, 34]. It is common for features to conflict and to be expressed in different units of measurement. Therefore, it is necessary to transform the decision matrix into a normalized decision matrix to make the element values comparable. In the analyzed studies, authors most commonly applied: (i) linear normalization procedures [10, 11, 16, 34], and (ii) linear normalization procedures combined with fuzzy algebra rules [9, 15].

In this research, the normalized decision matrix is constructed by applying the Jüttler-Korth procedure [35-37], which distinguishes this work from other analyzed studies. The weighted fuzzy decision matrix is derived following the additive principle and fuzzy algebra rules, as described in this paper. In the literature, numerous studies describe procedures for determining the Fuzzy Positive Ideal Solution (FPIS) and Fuzzy Negative Ideal Solution (FNIS) based on the approach proposed by [11, 14, 16, 34, 38]. In this research, FPIS and FNIS are determined using the vertex method [39], which differentiates this study from other analyzed papers.

When using the procedure proposed by [38], the distance between elements of the fuzzy decision matrix and FPIS/FNIS are crisp values, which are propagated into the calculation of closeness coefficient values using the conventional TOPSIS procedure. While this simplifies the problem significantly, it also reduces the accuracy of the obtained solution. In this research, distance values and closeness coefficient values are determined using a procedure that combines conventional TOPSIS with fuzzy algebra rules [20, 21]. In this way, the calculated values are described by TFNs. The ranking is determined based on precise closeness coefficient values obtained using a defuzzification procedure.

In paper [12] authors transformed the fuzzy decision matrix into a crisp decision matrix using a defuzzification procedure and ranked alternatives using conventional COPRAS. In many other studies [9, 10, 13, 15], as in this research, proposed procedures in conventional COPRAS combined with fuzzy algebra rules were used to calculate index values [9], transformed the calculated index values into crisp values through a defuzzification procedure and obtained the ranking using conventional COPRAS. In other studies [10, 13, 15], as in this manuscript, the significance coefficient values were determined using conventional COPRAS and fuzzy algebra rules, and these values were described by uncertain data. The ranking was determined using representative scalars obtained through a defuzzification procedure. The authors of this paper believe that this approach improves the accuracy of ranking.

This study indirectly represents an upgrade and continuation of the research conducted by [40], where the authors addressed the problem of evaluating and ranking small Battery Electric Vehicles. In this paper, a larger number of features were considered, along with the inclusion of other EV models. Moreover, various MADM methods extended by the application of fuzzy logic were utilized, which was not the case in the aforementioned study.

By comparing the analyzed papers with the proposed models, it can be concluded that certain differences, as described above, exist. This analysis also highlights the advantages of the proposed MADM models. The development of an appropriate methodology for ranking EV models in an uncertain environment serves as the motivation for this research.

The development of an appropriate methodology for ranking EV models in an uncertain environment can be identified as the motivation for this research.

The broader objective of this research can be interpreted as the integration of the following methods: a) expressing the relative importance of features as a fuzzy group decision-making problem and determining feature weights using the fuzzy root mean square; b) determining the rank of EV models by applying the proposed FTOPSIS and FCOPRAS methods; and c) comparing the obtained results.

The rest of the paper is organized as follows: Section 2 presents the proposed FTOPSIS and FCOPRAS models. These models are illustrated with real-life data in Section 3, and Section 4 provides the conclusion.

2 MATERIALS AND METHODS

The proposed model can be divided into three parts (Fig. 1). In the first part, the importance of EV features is determined. In the second part, the ranking of EVs is established using the FTOPSIS method, while in the third part, the ranking of EVs is determined using the FCOPRAS method. Finally, a comparison of the obtained results is performed.

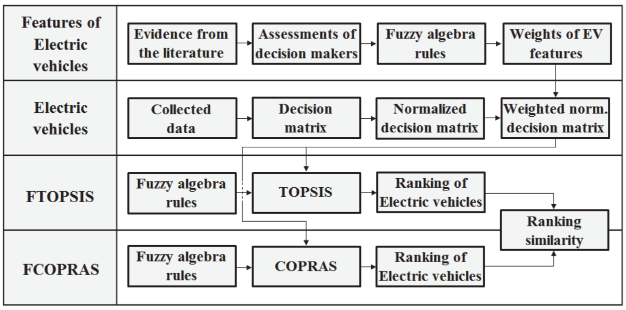

Figure 1 The proposed model

Decision makers (DMs) participating in this research belong to different economic sectors, such as private, research, and consultancy. Formally, DMs are represented by a set of indices $\{1, \ldots, e, \ldots, E\}$. The total number of DMs is denoted as E. The index of a DM is marked as e, $e = 1, \ldots, E$.

The decision makers include one employee from the University of Kragujevac conducting research in the automotive industry, one researcher specializing in renewable energy sources, one expert from a Serbian company engaged in the production of electric vehicles, and one fleet manager in a taxi company that operates electric/hybrid vehicles.

2.1 Definition of a Finite Set of EVs

According to automotive industry practices, it is known that the use of EVs varies across different countries. The set of vehicle models considered in this research was defined through a panel discussion. The panel discussion lasted approximately 60 minutes. The DMs based their evaluations primarily on their knowledge, experience, literature sources, and business reports from automotive companies.

Generally, the identified models of alternative-powered vehicles can be represented by the set of indices, $\{1, \ldots, i, \ldots, I\}$. where I denotes the total number of considered models, and the index of each model in the set is represented as i, $i = 1, \ldots, I$.

Many authors [41, 42] believe that the selection of features used to evaluate the treated EVs should be based on satisfying the dynamic demands of customers. The most commonly considered features important to customers are: color, style, quality, size, battery capacity, charging time, etc. According to [4], the most important features are battery capacity, charging time, driving range, acceleration, etc.

Formally, the set of features is represented by a set of indices $\{1, \ldots, k, \ldots, K\}$. . The total number of features is denoted as K, and k, $k = 1, \ldots, K$ is the index of each feature.

2.2 Choice of Appropriate Linguistic Variables for Describing the Relative Importance of Features and Determining Weights Vector

The importance or weight of criteria can be determined in various ways. Primarily, criteria can be compared pairwise based on assessments provided by DMs, expressed through direct evaluation by DMs, or determined using objective, mathematically based methods [43].

In this research, it is assumed that the relative importance of features can best be assessed by DMs using natural language expressions. The development of fuzzy sets theory has enabled linguistic terms to be quantitatively represented in a sufficiently precise manner. In other words, linguistic terms are modelled by fuzzy numbers characterized by three main aspects: the shape of the membership function, granulation, and domain.

In the relevant literature, the relative importance of features is commonly described using linguistic expressions modelled by triangular fuzzy numbers (TFNs) or trapezoidal fuzzy numbers (TrFNs). In this research, the authors argue that TFNs sufficiently capture the uncertainty and imprecision inherent in natural language expressions, ensuring satisfactory result accuracy. Additionally, triangular membership functions require less computational complexity compared to trapezoidal membership functions or functions described by higher-order polynomials.

The literature does not provide specific recommendations or rules for determining the granulation and domain of fuzzy numbers. Based on relevant sources, the number of linguistic expressions is primarily determined by the size of the problem. Some authors propose linguistic rating systems, such as seven-point scales [44, 45], which are adopted in this research. The domains of TFNs are defined on the real line within a specified interval. In this study, domains of TFNs are defined into a common measurement scale [46]. Determining the upper and lower bounds and the modal values of TFNs can be considered a challenge in its own right. Typically, these values are derived from relevant literature and the authors' expertise.

The linguistic expressions and their corresponding TFNs for describing the relative importance of features are represented as follows:

- low importance (W1):(1, 1, 2.5),
- very low importance (W2):(1.5, 3, 4.5),
- fairly low importance (W3):(2.5, 4, 5.5),
- medium importance (W4):(3.5, 5, 6.5),
- fairly high importance (W5):(4.5, 6, 7.5),
- high importance (W6):(5.5, 7, 8.5),
- extremely high importance (W7):(7.5, 9, 9).

The value of 1 or 9 denotes that the relative importance of attributes is the lowest or highest, respectively.

In this research, the determination of feature weights is formulated as a fuzzy group decision-making problem. The assessment of the relative importance of each feature k, $k = 1, \ldots, K$ is conducted by all DMs. Formally, each DM may use one of the predefined linguistic expressions to describe the relative importance of each considered feature, which can formally be represented by the TFN, $\widetilde{W}_k^e$:

$$\widetilde{W}_k^e = \left(a_k^e, b_k^e, c_k^e\right) \tag{1}$$

It is assumed that all DMs have equal importance in the decision-making process. The aggregated fuzzy relative importance of feature k, $k = 1, \ldots, K$ is given by applying the fuzzy quadratic mean, such that:

$$\widetilde{W}_k = \\ =\left(\sqrt{\frac{1}{E}\cdot\sum_{e=1,\ldots,E}\left(a_k^e\right)^2}, \sqrt{\frac{1}{E}\cdot\sum_{e=1,\ldots,E}\left(b_k^e\right)^2}, \sqrt{\frac{1}{E}\cdot\sum_{e=1,\ldots,E}\left(c_k^e\right)^2}\right) \tag{2}$$

The normalized weights vector:

$$\left[\tilde{\omega}_k\right]_{K\times 1} \tag{3}$$

where:

$$\tilde{\omega}_k = \frac{\widetilde{W}_k}{\sum_{K=1,\ldots,k}\widetilde{W}_K} \tag{4}$$

2.3 The Proposed FTOPSIS

The proposed FTOPSIS method is realized through the following steps:

Step 1. The decision matrix is stated as follows:

$$[x_{ik}]_{I\times K} \tag{5}$$

where: x_{ik} is the value of feature k, $k = 1, \ldots, K$ for vehicle model i, $i = 1, \ldots, I$ obtained from the literature; these values are described by precise numbers.

Step 2. The normalized fuzzy decision matrix is constructed by applying the Juttler-Korth normalization [36]:

$$[r_{ik}]_{I\times K} \tag{6}$$

where: a) benefit type:

$$r_{ik} = 1 - \left|\frac{x_k^{\max} - x_{ik}}{x_k^{\max}}\right| \tag{7}$$

b) cost type:

$$r_{ik} = 1 - \left|\frac{x_k^{\min} - x_{ik}}{x_k^{\min}}\right| \tag{8}$$

and

$$x_k^{\max} = \max_{i=1,\ldots,I} x_{ik} \tag{9}$$

$$x_k^{\min} = \min_{i=1,\ldots,I} x_{ik} \tag{10}$$

Step 3. The construction of the weighted normalized fuzzy decision matrix is based on the product principle:

$$\left[\tilde{z}_{ik}\right]_{I\times K} \tag{11}$$

Step 4. Determining the FPIS, $\tilde{z}_k^+$ and FNIS, $\tilde{z}_k^-$, according to the veto concept, is done as follows:

$$\tilde{z}_k^+ = (1, 1, 1) \tag{12}$$

$$\tilde{z}_k^- = (0, 0, 0) \tag{13}$$

Step 5. Determining the distances from FPIS, $\tilde{d}_k^+$ and FNIS, $\tilde{d}_k^-$ is based on fuzzy algebra rules [21], as follows:

$$\tilde{d}_k^+ = \sum_{k=1,\ldots,K}\left(\tilde{z}_k^+ - \tilde{z}_{ik}\right) \tag{14}$$

$$\tilde{d}_k^- = \sum_{k=1,\ldots,K}\left(\tilde{z}_{ik} - \tilde{z}_k^-\right) \tag{15}$$

Step 6. The fuzzy closeness coefficient, $\tilde{\xi}_i$ is calculated as follows:

$$\tilde{\xi}_i = \frac{\tilde{d}_i^-}{\tilde{d}_i^- + \tilde{d}_i^+} \tag{16}$$

Step 7. The representative scalars, ζ_i of TFNs $\tilde{\xi}_i$ are calculated by applying the defuzzification procedure, which is referred to as the averaging method [47].

Step 8. Let's sort the values of ζ_i in descending order. Based on the values of ζ_i the rank of alternatives is determined.

2.4 The Proposed FCOPRAS

The proposed FCOPRAS method is implemented through the following steps:

Step 1. The decision matrix is stated as follows:

$$[x_{ik}]_{I\times K} \tag{17}$$

Step 2. The normalized fuzzy decision matrix is constructed:

$$[r_{ik}]_{I\times K} \tag{18}$$

where:

$$r_{ik} = 1 - \left| \frac{x_k^{\max} - x_{ik}}{x_k^{\max}} \right| \tag{19}$$

$$x_k^{\max} = \max_{i=1,\,...,\,I} x_{ik} \tag{20}$$

Step 3. The construction of the weighted normalized fuzzy decision matrix is based on the multiplication principle:

$$\left[\tilde{z}_{ik}\right]_{I\times K} \tag{21}$$

Step 4. Determine the index values, $\tilde{S}_i$ and $\tilde{R}_i$, as follows:

$$\tilde{S}_i = \sum\nolimits_{i=1,\,...\,,\,I} \tilde{z}_{ik},\ k = 1,\,...,\,K' \tag{22}$$

$$\tilde{R}_i = \sum\nolimits_{i=1,\,...\,,\,I} \tilde{z}_{ik},\ k = K'+1,\,...,\,K \tag{23}$$

The total number of features of benefit type is K'.

Step 5. Let us calculate the relative significance of the considered car models as follows:

$$\tilde{\xi}_i = \tilde{S}_i + \frac{\sum_{i=1,...,I} \tilde{R}_i}{\tilde{R}_i \cdot \sum_{i=1,...,I} \left(\frac{1}{\tilde{R}_i}\right)} \tag{24}$$

Step 6. The representative scalars, ζ_i of TFNs $\tilde{\xi}_i$ are calculated by applying the defuzzification procedure known as the averaging method [47].

Step 7. Let us sort the values of ζ_i in descending order. The ranking of the alternatives is determined based on the values of ζ_i.

2.5 Comparison of Obtained Results

In order to determine the consistency of the obtained results, [30, 48] defined the ranking similarity coefficient, WS. This coefficient is calculated as follows:

$$WS = 1 - \sum_i^I 2^{-R_{x_i}} \cdot \frac{\left|R_{x_i} - R_{y_i}\right|}{max\left\{\left|1 - R_{x_i}\right|, \left|I - R_{x_i}\right|\right\}} \tag{25}$$

According to [30, 48], a WS coefficient value lower than 0.234 indicates that there is no similarity in ranking. If the coefficient value is between 0.352 and 0.689, there is a certain degree of similarity in ranking, but it is moderate. In cases where the coefficient value exceeds 0.808, the similarity in ranking is considered absolute. There are also intermediate values that can be discussed.

3 CASE STUDY

In the last decade, many automotive companies have started developing and manufacturing electric vehicles (EVs). Consequently, the literature contains data on various types of EVs that use lithium-ion batteries, which served as the basis for testing the methodology developed in this study using these input data.

Sport utility vehicles (SUVs) accounted for two-thirds of the battery-electric models available on the market, according to Global EV Outlook 2023. In 2023, there were about 590 electric car models available, a 15% rise from the previous year. Even though small and compact models are more suited for urban use, consumers tend to prefer larger, longer-range cars for their primary vehicles. Customers' decisions may also be influenced by SUVs' higher marketing expenditures relative to smaller models. Therefore, making the switch to electric vehicles in the SUV and larger car classes can result in rapid and significant reductions in CO2 emissions. Electrification also has significant advantages in terms of lowering non-tailpipe emissions and air pollution, particularly in metropolitan areas [1].

In this research, considered EV models are: BYD ATTO 3 (i = 1), Volkswagen ID.4 Pro (i = 2), Kia Niro EV (i = 3), Renault Scenic E-Tech EV87 220 hp (i = 4), BMW iX1 xDrive30 (i = 5), Skoda Enyaq 85 (i = 6), Kia EV6 Long Range 2WD (i =7), Toyota bZ4X FWD (i = 8), Hyundai IONIQ 5 Long Range 2WD (i = 9), Mercedes Benz EQB 250+ (i = 01), Nissan Ariya 87 kWh (i = 11), Audi Q4 e-tron 45 (i = 12), Peugeot e-3008 73 kW (i = 13), Ford Explorer Extended Range RWD (i = 14), Mazda MX-30 (i = 15), BMW iX2 xDrive30 (i = 16), Subaru Solterra AWD (i = 17), and Volvo EX Single Motor ER (i = 18). The SUV C-segment includes all vehicles, and manufacturer websites include information about EVs.

The set of features used to evaluate EVs is defined based on the results of research [4-7] and the experience of best practices. These features are: driving range (k = 1), price (expressed in euros) (k = 2), nominal capacity battery (kWh) (k = 3), usable battery capacity (kWh) (k = 4), charging time (expressed in hours) (k = 5), seating capacity (k = 6) torque (Nm) (k = 7), power (kW) (k = 8), top speed (km/h) (k = 9), and acceleration (0 - 100 km/h, s)

(k = 10). The EV feature (k = 2) is of the cost type. The other considered EV features are of the benefit type.

3.1 Determining of Weights Vector

The relative importance of the treated EV features is assessed by four DMs, as presented in Tab. 1.

Table 1 Fuzzy rating of the relative importance of EV features

	k = 1	k = 2	k = 3	k = 4	k = 5
e = 1	*W7*	*W6*	*W6*	*W6*	*W6*
e = 2	*W7*	*W6*	*W5*	*W4*	*W1*
e = 3	*W7*	*W6*	*W4*	*W6*	*W7*
e = 4	*W6*	*W6*	*W5*	*W5*	*W6*
	k = 6	k = 7	k = 8	k = 9	k = 10
e = 1	*W4*	*W4*	*W4*	*W3*	*W4*
e = 2	*W1*	*W6*	*W5*	*W2*	*W3*
e = 3	*W5*	*W6*	*W6*	*W6*	*W6*
e = 4	*W4*	*W6*	*W5*	*W5*	*W6*

The normalized weights vector of EV features is calculated, so that:

$$\tilde{\omega}_1 = (0.093, 0.136, 0.145);\ \tilde{\omega}_2 = (0.072, 0.111, 0.175);$$
$$\tilde{\omega}_3 = (0.060, 0.096, 0.155);\ \tilde{\omega}_4 = (0.063, 0.100, 0.160);$$
$$\tilde{\omega}_5 = (0.071, 0.106, 0.156);\ \tilde{\omega}_6 = (0.044, 0.074, 0.125);$$
$$\tilde{\omega}_7 = (0.067, 0.104, 0.165);\ \tilde{\omega}_8 = (0.060, 0.096, 0.155);$$
$$\tilde{\omega}_9 = (0.051, 0.083, 0.137);\ \tilde{\omega}_{10} = (0.058, 0.094, 0.151).$$

3.2 An Application the Proposed FTOPSIS

The decision matrix (Step 1 of the proposed Algorithm) is presented in Tab. 2.

By applying the proposed FTOPSIS (Step 2 to Step 4), the normalized weighted fuzzy decision matrix is constructed and presented in Tab. 3 and Tab. 4.

The calculated values of distances from FPIS and FNIS, the approximation coefficient, and the ranking of considered EV models (Step 5 to Step 8 of the proposed Algorithm) are presented in Tab. 5.

Table 2 The decision matrix

	k = 1	k = 2	k = 3	k = 4	k = 5	k = 6	k = 7	k = 8	k = 9	k = 10
i = 1	330	37990	62	60.5	6.5	5	310	150	160	7.3
i = 2	435	46335	82	77	8.25	5	545	210	180	6.7
i = 3	385	45690	68	64.8	7	5	255	150	167	7.8
i = 4	490	48900	92	87	4.75	5	160	300	170	7.9
i = 5	380	55000	66.5	64.7	7	5	494	230	180	5.6
i = 6	450	48900	82	77	8.25	5	545	210	180	6.7
i = 7	410	51900	77.4	74	8	5	350	168	185	7.3
i = 8	340	47490	71.4	64	11.3	5	265	150	160	7.5
i = 9	390	47900	77.4	74	8	5	350	168	185	7.3
i = 10	415	53514	73.9	70.5	7.75	7	385	140	160	8.9
i = 11	450	58990	91	87	14	5	300	178	160	7.6
i = 12	420	52950	82	77	8.25	5	545	210	180	6.7
i = 13	385	48650	77	73	8	5	343	157	170	8.7
i = 14	430	49500	82	77	8.25	5	545	210	180	6.4
i = 15	170	35990	35.5	30	3.25	5	271	107	140	9.7
i = 16	380	56500	66.5	64.7	7	5	494	230	180	5.6
i = 17	320	57490	71.4	64	11.5	5	336	160	160	6.9
i = 18	400	55490	82	79	8.5	5	420	185	180	7.3

Table 3 The normalized weighted fuzzy decision matrix

	k = 1	k = 2	k = 3	k = 4	k = 5
i = 1	(0.063, 0.092, 0.098)	(0.070, 0.107, 0.169)	(0.040, 0.065, 0.104)	(0.043, 0.069, 0.111)	(0.032, 0.049, 0.072)
i = 2	(0.083, 0.121, 0.129)	(0.059, 0.091, 0.144)	(0.053, 0.086, 0.138)	(0.056, 0.088, 0.142)	(0.041, 0.062, 0.092)
i = 3	(0.073, 0.107, 0.114)	(0.060, 0.093, 0.146)	(0.044, 0.071, 0.115)	(0.046, 0.074, 0.119)	(0.035, 0.053, 0.078)
i = 4	(0.093, 0.136, 0.145)	(0.056, 0.087, 0.137)	(0.060, 0.096, 0.155)	(0.063, 0.100, 0.160)	(0.024, 0.036, 0.053)
i = 5	(0.072, 0.106, 0.114)	(0.049, 0.075, 0.118)	(0.043, 0.069, 0.112)	(0.047, 0.074, 0.119)	(0.035, 0.053, 0.078)
i = 6	(0.085, 0.125, 0.133)	(0.063, 0.097, 0.152)	(0.053, 0.086, 0.138)	(0.056, 0.088, 0.142)	(0.041, 0.062, 0.092)
i = 7	(0.078, 0.114, 0.121)	(0.053, 0.081, 0.128)	(0.050, 0.081, 0.130)	(0.053, 0.085, 0.136)	(0.041, 0.062, 0.089)
i = 8	(0.065, 0.094, 0.101)	(0.058, 0.089, 0.141)	(0.047, 0.074, 0.120)	(0.046, 0.074, 0.118)	(0.057, 0.086, 0.126)
i = 9	(0.074, 0.108, 0.115)	(0.057, 0.089, 0.140)	(0.050, 0.081, 0.130)	(0.053, 0.085, 0.136)	(0.041, 0.061, 0.089)
i = 10	(0.079, 0.115, 0.113)	(0.051, 0.078, 0.123)	(0.048, 0.077, 0.124)	(0.051, 0.081, 0.130)	(0.039, 0.059, 0.086)
i = 11	(0.085, 0.125, 0.133)	(0.044, 0.068, 0.107)	(0.059, 0.095, 0.153)	(0.051, 0.081, 0.130)	(0.071, 0.106, 0.156)
i = 12	(0.079, 0.117, 0.124)	(0.051, 0.079, 0.125)	(0.053, 0.086, 0.138)	(0.056, 0.088, 0.142)	(0.042, 0.062, 0.092)
i = 13	(0.073, 0.107, 0.114)	(0.057, 0.087, 0.137)	(0.050, 0.080, 0.130)	(0.053, 0.084, 0.134)	(0.041, 0.061, 0.089)
i = 14	(0.081, 0.119, 0.127)	(0.055, 0.086, 0.135)	(0.053, 0.086, 0.138)	(0.056, 0.088, 0.142)	(0.041, 0.062, 0.092)
i = 15	(0.032, 0.047, 0.050)	(0.072, 0.111, 0.175)	(0.023, 0.037, 0.060)	(0.021, 0.034, 0.055)	(0.016, 0.025, 0.036)
i = 16	(0.072, 0.106, 0.113)	(0.047, 0.072, 0.114)	(0.043, 0.069, 0.112)	(0.047, 0.074, 0.119)	(0.035, 0.053, 0.078)
i = 17	(0.061, 0.089, 0.095)	(0.046, 0.071, 0.111)	(0.047, 0.074, 0.120)	(0.046, 0.074, 0.118)	(0.058, 0.087, 0.128)
i = 18	(0.076, 0.111, 0.118)	(0.048, 0.074, 0.117)	(0.053, 0.086, 0.138)	(0.057, 0.091, 0.145)	(0.043, 0.064, 0.095)

In the first place in the ranking by applying the proposed FTOPSIS is the EV model Skoda Enyaq 85 ($i = 6$). In addition to this EV model, from the customer's perspective, the following should be considered: Volkswagen ID.4 Pro ($i = 2$) and Ford Explorer Extended Range RWD ($i = 14$).

Table 4 The normalized weighted fuzzy decision matrix (continued)

	k = 6	k = 7	k = 8	k = 9	k = 10
i = 1	(0.031, 0.052, 0.089)	(0.038, 0.059, 0.093)	(0.030, 0.048, 0.077)	(0.044, 0.072, 0.119)	(0.044, 0.071, 0.114)
i = 2	(0.031, 0.053, 0.089)	(0.067, 0.104, 0.165)	(0.042, 0.067, 0.108)	(0.050, 0.081, 0.133)	(0.040, 0.065, 0.104)
i = 3	(0.031, 0.053, 0.089)	(0.032, 0.050, 0.079)	(0.030, 0.048, 0.077)	(0.046, 0.075, 0.124)	(0.047, 0.076, 0.121)
i = 4	(0.031, 0.053, 0.089)	(0.020, 0.031, 0.049)	(0.060, 0.096, 0.155)	(0.046, 0.076, 0.126)	(0.047, 0.077, 0.122)
i = 5	(0.031, 0.053, 0.089)	(0.060, 0.094, 0.149)	(0.046, 0.074, 0.119)	(0.049, 0.081, 0.133)	(0.033, 0.054, 0.087)
i = 6	(0.031, 0.053, 0.089)	(0.067, 0.104, 0.165)	(0.042, 0.067, 0.108)	(0.049, 0.081, 0.133)	(0.040, 0.065, 0.104)
i = 7	(0.031, 0.053, 0.089)	(0.043, 0.068, 0.106)	(0.034, 0.054, 0.087)	(0.051, 0.083, 0.137)	(0.044, 0.071, 0.114)
i = 8	(0.031, 0.053, 0.089)	(0.032, 0.050, 0.080)	(0.030, 0.048, 0.077)	(0.044, 0.072, 0.119)	(0.045, 0.073, 0.117)
i = 9	(0.031, 0.053, 0.089)	(0.043, 0.067, 0.106)	(0.034, 0.054, 0.087)	(0.051, 0.083, 0.137)	(0.045, 0.073, 0.117)
i = 10	(0.044, 0.074, 0.125)	(0.047, 0.073, 0.116)	(0.028, 0.045, 0.073)	(0.044, 0.072, 0.119)	(0.053, 0.086, 0.138)
i = 11	(0.031, 0.053, 0.089)	(0.037, 0.057, 0.091)	(0.036, 0.057, 0.092)	(0.044, 0.072, 0.119)	(0.046, 0.074, 0.118)
i = 12	(0.031, 0.053, 0.089)	(0.067, 0.104, 0.165)	(0.042, 0.067, 0.108)	(0.049, 0.081, 0.133)	(0.040, 0.065, 0.104)
i = 13	(0.031, 0.053, 0.089)	(0.042, 0.065, 0.104)	(0.032, 0.050, 0.081)	(0.046, 0.076, 0.126)	(0.052, 0.084, 0.135)
i = 14	(0.031, 0.053, 0.089)	(0.067, 0.104, 0.165)	(0.042, 0.067, 0.108)	(0.049, 0.081, 0.133)	(0.039, 0.063, 0.101)
i = 15	(0.031, 0.053, 0.089)	(0.033, 0.052, 0.082)	(0.021, 0.034, 0.055)	(0.038, 0.063, 0.104)	(0.058, 0.094, 0.151)
i = 16	(0.031, 0.053, 0.089)	(0.060, 0.094, 0.149)	(0.046, 0.074, 0.119)	(0.049, 0.081, 0.133)	(0.033, 0.054, 0.087)
i = 17	(0.031, 0.053, 0.089)	(0.041, 0.064, 0.102)	(0.032, 0.051, 0.083)	(0.044, 0.072, 0.119)	(0.041, 0.067, 0.107)
i = 18	(0.031, 0.053, 0.089)	(0.051, 0.080, 0.127)	(0.037, 0.059, 0.096)	(0.049, 0.081, 0.133)	(0.044, 0.071, 0.114)

Table 5 Rank of EV models

	$\tilde{d}_i^+$	$\tilde{d}_i^-$	$\tilde{\xi}_i$	ζ_i	Rank
i = 1	(8.952, 9.315, 9.563)	(0.437, 0.685, 1.048)	(0.041, 0.068, 0.112)	0.071	17
i = 2	(8.755, 9.182, 9.477)	(0.523, 0.818, 1.245)	(0.049, 0.082, 0.134)	0.085	2
i = 3	(8.937, 9.301, 9.554)	(0.446, 0.699, 1.063)	(0.042, 0.070, 0.113)	0.072	16
i = 4	(8.809, 9.213, 9.499)	(0.494, 0.787, 1.191)	(0.046, 0.079, 0.111)	0.079	7 - 8
i = 5	(8.882, 9.267, 9.532)	(0.468, 0.733, 1.118)	(0.044, 0.073, 0.121)	0.076	12 - 13
i = 6	(8.742, 9.172, 9.471)	(0.529, 0.828, 1.257)	(0.049, 0.083, 0.136)	0.086	1
i = 7	(8.863, 9.252, 9.522)	(0.478, 0.748, 1.137)	(0.045, 0.075, 0.122)	0.078	9 - 11
i = 8	(8.912, 9.287, 9.544)	(0.456, 0.713, 1.087)	(0.042, 0.071, 0.116)	0.074	14
i = 9	(8.857, 9.250, 9.521)	(0.479, 0.750, 1.143)	(0.045, 0.075, 0.122)	0.078	9 - 11
i = 10	(8.843, 9.240, 9.516)	(0.485, 0.760, 1.157)	(0.045, 0.076, 0.124)	0.079	7-8
i = 11	(8.812, 9.213, 9.496)	(0.504, 0.787, 1.188)	(0.047, 0.079, 0.127)	0.082	5
i = 12	(8.779, 9.198, 9.488)	(0.512, 0.802, 1.221)	(0.048, 0.080, 0.131)	0.083	4
i = 13	(8.860, 9.252, 9.523)	(0.477, 0.748, 1.140)	(0.045, 0.075, 0.122)	0.078	9 - 11
i = 14	(8.769, 9.191, 9.483)	(0.517, 0.809, 1.231)	(0.048, 0.081, 0.133)	0.084	3
i = 15	(9.142, 9.450, 9.652)	(0.348, 0.550, 0.858)	(0.033, 0.055, 0.090)	0.057	18
i = 16	(8.886, 9.270, 9.534)	(0.466, 0.730, 1.114)	(0.043, 0.073, 0.119)	0.076	12 - 13
i = 17	(8.928, 9.299, 9.552)	(0.448, 0.701, 1.072)	(0.042, 0.070, 0.114)	0.073	15
i = 18	(8.827, 9.230, 9.509)	(0.491, 0.770, 1.173)	(0.046, 0.077, 0.126)	0.080	6

3.3 An Application the Proposed FCOPRAS

The difference between the normalized weighted fuzzy decision matrix constructed in the proposed FCOPRAS is only within the EV feature (k = 2). Therefore, this matrix is not presented in this Section. By applying the proposed Algorithm (Step 1 to Step 4), the values of the coefficient $\tilde{S}_i$ and $\tilde{R}_i$ are calculated and presented in Tab. 6.

Table 6 The values of the proposed COPRAS coefficient

	$\tilde{S}_i$	$\tilde{R}_i$		$\tilde{S}_i$	$\tilde{R}_i$
i = 1	(0.367, 0.578, 0.878)	(0.367, 0.578, 0.878)	i = 10	(0.079, 0.682, 1.034)	(0.079, 0.682, 1.034)
i = 2	(0.046, 0.071, 0.113)	(0.046, 0.071, 0.113)	i = 11	(0.065, 0.101, 0.159)	(0.065, 0.101, 0.159)
i = 3	(0.464, 0.727, 1.101)	(0.464, 0.727, 1.101)	i = 12	(0.460, 0.719, 1.081)	(0.460, 0.719, 1.081)
i = 4	(0.057, 0.087, 0.137)	(0.057, 0.087, 0.137)	i = 13	(0.072, 0.111, 0.175)	(0.072, 0.111, 0.175)
i = 5	(0.368, 0.606, 0.916)	(0.368, 0.606, 0.916)	i = 14	(0.461, 0.802, 1.096)	(0.461, 0.802, 1.096)
i = 6	(0.057, 0.086, 0.136)	(0.057, 0.086, 0.136)	i = 15	(0.065, 0.100, 0.157)	(0.065, 0.100, 0.157)
i = 7	(0.445, 0.700, 1.054)	(0.445, 0.700, 1.054)	i = 16	(0.421, 0.661, 1.002)	(0.421, 0.661, 1.002)
i = 8	(0.060, 0.092, 0.145)	(0.060, 0.092, 0.145)	i = 17	(0.059, 0.092, 0.144)	(0.059, 0.092, 0.144)
i = 9	(0.419, 0.658, 1)	(0.419, 0.658, 1)	i = 18	(0.462, 0.724, 1.096)	(0.462, 0.724, 1.096)

The proposed Algorithm (Step 5 to Step 6) is illustrated for the EV model (i = 1):

$$\xi_1 = \left(0.367,\ 0.578,\ 0.878\right) + \\ + \frac{\left(1.098,\ 1.692,\ 2.668\right)}{\left(0.046,\ 0.071,\ 0.113\right)\cdot\left(123.453,\ 194.633,\ 300.059\right)} = \\ = \left(0.399,\ 0.670,\ 1.344\right)$$

The representative scalar, ζ_1 is:

$$\zeta_1 = \frac{0.399 + 4\cdot 0.670 + 1.344}{6} = 0.757$$

In a similar way, the values of the coefficients of the proposed FCOPRAS were calculated and assigned to the other considered EV models. The rank of EV models (Step 7 of the proposed Algorithm) is determined according to the given coefficient values, as presented in Tab. 7.

Table 7 The values of the proposed FCOPRAS coefficient

	$\tilde{\xi}_1$	ζ_1	Rank		$\tilde{\xi}_1$	ζ_1	Rank
$i = 1$	(0.399, 0.670, 1.344)	0.737	17	$i = 10$	(0.102, 0.768, 1.365)	0.757	14-15
$i = 2$	(0.491, 0.827, 1.483)	0.880	2	$i = 11$	(0.481, 0.797, 1.381)	0.842	6
$i = 3$	(0.413, 0.707, 1.303)	0.757	14-15	$i = 12$	(0.484, 0.889, 1.430)	0.912	1
$i = 4$	(0.470, 0.794, 1.416)	0.844	5	$i = 13$	(0.446, 0.756, 1.366)	0.806	9
$i = 5$	(0.441, 0.742, 1.322)	0.789	11	$i = 14$	(0.487, 0.817, 1.454)	0.868	4
$i = 6$	(0.492, 0.825, 1.467)	0.877	3	$i = 15$	(0.306, 0.567, 1.175)	0.625	18
$i = 7$	(0.449, 0.756, 1.351)	0.804	10	$i = 16$	(0.441, 0.740, 1.313)	0.785	12
$i = 8$	(0.424, 0.721, 1.320)	0.771	13	$i = 17$	(0.423, 0.711, 1.267)	0.756	16
$i = 9$	(0.447, 0.758, 1.374)	0.809	8	$i = 18$	(0.465, 0.778, 1.374)	0.825	7

In the first place in the ranking by applying the proposed FCOPRAS is the EV model Audi Q4 e-tron 45 ($i = 12$). This type of EV model can be considered the best respecting all the considered EV features as well as their weights. Some authors suggest that, in addition to the alternative (in this case, the EV model) which is placed in the first place in the rank, alternatives placed in the top three should also be taken into account. In this case, it can be calculated that the best EV models are: Audi Q4 e-tron 45 ($i = 12$), Volkswagen ID.4 Pro ($i = 2$), and Skoda Enyaq 85 ($i = 6$).

3.4 Comparative Analysis of the Obtained Results

In this section, a comparative analysis of the obtained results was performed by applying the proposed FTOPSIS and FCOPRAS.

Primarily, to make the obtained results more visually comparable, Fig. 2 presents a graphical representation of the alternative rankings obtained using the two proposed approaches.

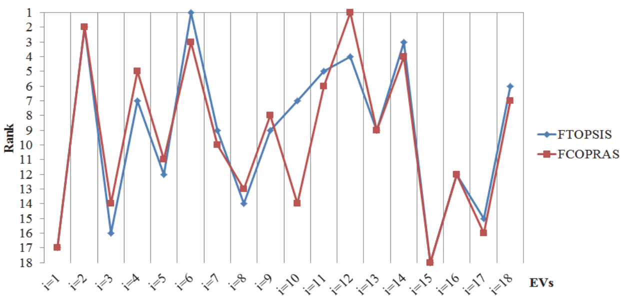

Figure 2 Graphical representation of the ranking of EVs

The ranking similarity coefficient, WS [30, 48], is calculated based on the results obtained by applying the two proposed methods, FTOPSIS and FCOPRAS. In this case, the coefficient value is 0.91.

Since the value of the coefficient is greater than 0.808, according to [30, 48], it can be considered that the ranking similarity is absolute. Therefore, it can be stated that the stability of the solution has been achieved.

In this case, it can be stated that the best EV models with respect to the considered features as well as their weights are: Skoda Enyaq 85 ($i = 6$), Volkswagen ID.4 Pro ($i = 2$), Ford Explorer Extended Range RWD ($i = 14$), Audi Q4 e-tron 45 ($i = 12$), and Ford Explorer Extended Range RWD ($i = 14$).

4 CONCLUSION

This research proposes two MADM models, the application of which should lead to a ranking of EVs under uncertainty. The obtained results aim to: (1) assist management in automotive companies in defining production plans and (2) help customers in making more informed purchase decisions.

The main methodological contributions of the presented research are: (1) Modeling the relative importance of features of EVs using TFNs; (2) Setting the relative importance of features as a fuzzy group decision-making problem; (3) Determining the weights vector of features through fuzzy quadratic mean and linear normalization combined with fuzzy algebra rules, which has certain advantages compared to the application of other methods, especially in terms of practical use in the automotive industry; (4) Ranking the considered set of EVs using the proposed FTOPSIS and FCOPRAS methods and determining the similarity of the obtained results; (5) Ensuring the model's flexibility, allowing for easy incorporation of changes in the number and values of features, as well as changes in the number of considered EV models.

Regarding the research contributions related to sustainability and sustainable management in the automotive industry, they are: (1) By analyzing various features that are often conflicting and inversely proportional, the selected EV strikes a balance between cost, performance, user experience, and reducing environmental impact; (2) Supporting environmentally conscious individuals and organizations in making informed EV purchasing decisions; (3) Providing guidance to EV manufacturers to offer optimal solutions for both themselves and consumers, while primarily minimizing environmental harm and promoting clean energy propulsion.

The main advantage of the proposed methodology over existing models found in the literature is the definition of the set of EVs with the highest importance for customers. In this way, the obtained set of EVs is defined so that strategic management can implement effective benchmarking. The proposed model can be extended to the analysis of EV models that use sodium-ion batteries.

The main limitations of the hybrid model are: (1) subjectivity in the process of obtaining the relative importance of features, and (2) a higher computational complexity compared to conventional MADM models.

Future research should focus on: (1) developing a software solution that enables a user-friendly application of the proposed methodology, (2) using different approaches for modelling uncertainty and imprecision, and (3) applying other MADM methods to compare the obtained results.

5 REFERENCES

[1] International Energy Agency. (2024). *World Energy Outlook 2024*. International Energy Agency. https://www.iea.org/reports/world-energy-outlook-2024

[2] Eftekhari, A. & Kim, D. W. (2018). Sodium-ion batteries: New opportunities beyond energy storage by lithium. *Journal of Power Sources, 395*, 336-348. https://doi.org/10.1016/j.jpowsour.2018.05.089

[3] Sawicki, M. & Shaw, L. L. (2015). Advances and challenges of sodium ion batteries as post lithium ion batteries. *RSC Advances, 5*(65), 53129-53154. https://doi.org/10.1039/C5RA08321D

[4] Das, M. C., Pandey, A., Mahato, A. K., & Singh, R. K. (2019). Comparative performance of electric vehicles using evaluation of mixed data. *OPSEARCH, 56*(3), 1067-1090. https://doi.org/10.1007/s12597-019-00398-9

[5] Dwivedi, P. P. & Sharma, D. K. (2023). Evaluation and ranking of battery electric vehicles by Shannon's entropy and TOPSIS methods. *Mathematics and Computers in Simulation, 212*, 457–474. https://doi.org/10.1016/j.matcom.2023.05.013

[6] Singh, V., Singh, V., & Vaibhav, S. (2020). A review and simple meta-analysis of factors influencing adoption of electric vehicles. *Transportation Research Part D: Transport and Environment, 86*, 102436. https://doi.org/10.1016/j.trd.2020.102436

[7] Sonar, H. C. & Kulkarni, S. D. (2021). An Integrated AHP-MABAC Approach for Electric Vehicle Selection. *Research in Transportation Business & Management*, *41*, 100665. https://doi.org/10.1016/j.rtbm.2021.100665

[8] Stević, Ž., Baydaş, M., Kavacık, M., Ayhan, E., & Marinković, D. (2024). Selection of Data Conversion Technique via Sensitivity-Performance Matching: Ranking of Small E-Vans with PROBID Method. *Facta Universitatis, Series: Mechanical Engineering, 22*(4), 643-671. https://doi.org/10.22190/FUME240305023S

[9] Bathrinath, S., Saravana Kumar, P., Venkadesh, S., Suprriyan, S. S., Koppiahraj, K., & Bhalaji, R. K. A. (2022). A fuzzy COPRAS approach for analysing the factors affecting sustainability in ship ports. *Materials Today: Proceedings, 50*, 1017-1021. https://doi.org/10.1016/j.matpr.2021.07.350

[10] Narang, M., Joshi, M. C., & Pal, A. K. (2021). A hybrid fuzzy COPRAS-base-criterion method for multi-criteria decision making. *Soft Computing, 25*(13), 8391-8399. https://doi.org/10.1007/s00500-021-05762-w

[11] Rani, P., Mishra, A. R., Mardani, A., Cavallaro, F., Alrasheedi, M., & Alrashidi, A. (2020). A novel approach to extended fuzzy TOPSIS based on new divergence measures for renewable energy sources selection. *Journal of Cleaner Production, 257*, 120352. https://doi.org/10.1016/j.jclepro.2020.120352

[12] Torabzadeh Khorasani, S. (2018). Green Supplier Evaluation by Using the Integrated Fuzzy AHP Model and Fuzzy Copras. *Process Integration and Optimization for Sustainability, 2*(1), 17-25. https://doi.org/10.1007/s41660-017-0027-9

[13] Zarbakhshnia, N., Soleimani, H., & Ghaderi, H. (2018). Sustainable third-party reverse logistics provider evaluation and selection using fuzzy SWARA and developed fuzzy COPRAS in the presence of risk criteria. *Applied Soft Computing, 65*, 307-319. https://doi.org/10.1016/j.asoc.2018.01.023

[14] Solangi, Y. A., Longsheng, C., & Shah, S. A. A. (2021). Assessing and overcoming the renewable energy barriers for sustainable development in Pakistan: An integrated AHP and fuzzy TOPSIS approach. *Renewable Energy, 173*, 209-222. https://doi.org/10.1016/j.renene.2021.03.141

[15] Tolga, A. C. & Durak, G. (2020). Evaluating Innovation Projects in Air Cargo Sector with Fuzzy COPRAS. In C. Kahraman, S. Cebi, S. Cevik Onar, B. Oztaysi, A. C. Tolga, & I. U. Sari (Eds.). *Intelligent and Fuzzy Techniques in Big Data Analytics and Decision Making, 1029*, 702-710. https://doi.org/10.1007/978-3-030-23756-1_84

[16] Ziemba, P., Becker, A., & Becker, J. (2020). A Consensus Measure of Expert Judgment in the Fuzzy TOPSIS Method. *Symmetry, 12*(2), 204. https://doi.org/10.3390/sym12020204

[17] Tadić, D., & Komatina, N. (2025). A Hybrid Interval Type-2 Fuzzy DEMATEL-MABAC Approach for Strategic Failure Management in Automotive Manufacturing. *Journal of Engineering Management and Systems Engineering*, *4*(1), 21–38. https://doi.org/10.56578/jemse040102

[18] Božanić, D., Pamučar, D., Milić, A., Marinković, D., & Komazec, N. (2022). Modification of the Logarithm Methodology of Additive Weights (LMAW) by a Triangular Fuzzy Number and Its Application in Multi-Criteria Decision Making. *Axioms, 11*(3), 89. https://doi.org/10.3390/axioms11030089

[19] Jahan, A. & Edwards, K. L. (2015). A state-of-the-art survey on the influence of normalization techniques in ranking: Improving the materials selection process in engineering design. *Materials & Design (1980-2015), 65*, 335-342. https://doi.org/10.1016/j.matdes.2014.09.022

[20] Dubois, D. & Prade, H. (1980). Systems of linear fuzzy constraints. *Fuzzy Sets and Systems, 3*(1), 37-48. https://doi.org/10.1016/0165-0114(80)90004-4

[21] Zimmermann, H. J. (2010). Fuzzy set theory. *WIREs Computational Statistics, 2*(3), 317-332. https://doi.org/10.1002/wics.82

[22] Komatina, N., Djapan, M., Ristić, I., & Aleksić, A. (2021). Fulfilling External Stakeholders' Demands-Enhancement Workplace Safety Using Fuzzy MCDM. *Sustainability, 13*(5), 2892. https://doi.org/10.3390/su13052892

[23] Milanovic, M., Misita, M., & Komatina, N. (2020). Determination of the optimal production plan by using fuzzy AHP and fuzzy linear programming. *Journal of Intelligent & Fuzzy Systems, 38*(4), 4315-4325. https://doi.org/10.3233/JIFS-190913

[24] Đurić, G., Mitrović, Č., Komatina, N., Tadić, D., & Vorotović, G. (2019). The hybrid MCDM model with the interval Type-2 fuzzy sets for the software failure analysis. *Journal of Intelligent & Fuzzy Systems, 37*(6), 7747-7759. https://doi.org/10.3233/JIFS-182541

[25] Banduka, N., Aleksić, A., Komatina, N., Aljinović, A., & Tadić, D. (2020). The prioritization of failures within the automotive industry: The two-step failure mode and effect analysis integrated approach. *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture, 234*(12), 1559-1570. https://doi.org/10.1177/0954405420926906

[26] Komatina, N., Marinković, D., Tadić, D., & Pamučar, D. (2025). Advancing PFMEA Decision-Making: FRADAR Based Prioritization of Failure Modes Using AP, RPN, and Multi-Attribute Assessment in the Automotive Industry. *Tehnički Glasnik/Technical Journal, 19*(3).

[27] Božanić, D., Epler, I., Puška, A., Biswas, S., Marinković, D., & Koprivica, S. (2024). Application of the DIBR II - rough MABAC decision-making model for ranking methods and techniques of lean organization systems management in the process of technical maintenance. *Facta Universitatis, Series: Mechanical Engineering, 22*(1), 101. https://doi.org/10.22190/FUME230614026B

[28] Pamucar, D., Žižović, M., & Đuričić, D. (2022). Modification of the CRITIC method using fuzzy rough numbers. *Decision Making: Applications in Management and Engineering, 5*(2), 362-371. https://doi.org/10.31181/dmame0316102022p

[29] Komatina, N. (2025). A Novel BWM-RADAR Approach for Multi-Attribute Selection of Equipment in the Automotive Industry. *Spectrum of Mechanical Engineering and Operational Research, 2*(1), 104-120. https://doi.org/10.31181/smeor21202531
[30] Więckowski, J., Kizielewicz, B., Shekhovtsov, A., & Sałabun, W. (2023). How Do the Criteria Affect Sustainable Supplier Evaluation? - A Case Study Using Multi-Criteria Decision Analysis Methods in a Fuzzy Environment. *Journal of Engineering Management and Systems Engineering, 2*(1), 37-52. https://doi.org/10.56578/jemse020102
[31] Yoon, K. P. & Kim, W. K. (2017). The behavioral TOPSIS. *Expert Systems with Applications, 89*, 266-272. https://doi.org/10.1016/j.eswa.2017.07.045
[32] Aleksić, A. & Tadić, D. (2023). Industrial and Management Applications of Type-2 Multi-Attribute Decision-Making Techniques Extended with Type-2 Fuzzy Sets from 2013 to 2022. *Mathematics, 11*(10), 2249. https://doi.org/10.3390/math11102249
[33] Alinezhad, A. & Khalili, J. (2019). COPRAS Method. *New Methods and Applications in Multiple Attribute Decision Making (MADM),* 277, 87-91. Springer International Publishing. https://doi.org/10.1007/978-3-030-15009-9_12
[34] Raja, S. & Rajan, A. J. (2022). A Decision-Making Model for Selection of the Suitable FDM Machine Using Fuzzy TOPSIS. *Mathematical Problems in Engineering, 2022*, 1-15. https://doi.org/10.1155/2022/7653292
[35] Brauers, W. K. & Zavadskas, E. K. (2006). The MOORA method and its application to privatization in a transition economy. *Control and Cybernetics, 35*(2), 445-469.
[36] Gardziejczyk, W. & Zabicki, P. (2017). Normalization and variant assessment methods in selection of road alignment variants - case study. *Journal of Civil Engineering and Management, 23*(4), 510-523. https://doi.org/10.3846/13923730.2016.1210223
[37] Zavadskas, E. K. & Turskis, Z. (2011). Multiple Criteria Decision Making (MCDM) Methods in Economics: An Overview. *Technological and Economic Development of Economy, 17*(2), 397-427. https://doi.org/10.3846/20294913.2011.593291
[38] Kuo, M. S. & Liang, G. S. (2012). A soft computing method of performance evaluation with MCDM based on interval-valued fuzzy numbers. *Applied Soft Computing, 12*(1), 476-485. https://doi.org/10.1016/j.asoc.2011.08.020
[39] Işıklar, G. & Büyüközkan, G. (2007). Using a multi-criteria decision making approach to evaluate mobile phone alternatives. *Computer Standards & Interfaces, 29*(2), 265-274. https://doi.org/10.1016/j.csi.2006.05.002
[40] Tadić, D., Lukić, J., & Komatina, N. (2024). A two-stage model for electric vehicle evaluation: CRITIC-ELECTRE approach. *Mobility and Vehicle Mechanics, 50*(1), 39-55. https://doi.org/10.24874/mvm.2024.50.01.04
[41] Yagcitekin, B., Uzunoglu, M., Karakas, A., & Erdinc, O. (2015). Assessment of electrically-driven vehicles in terms of emission impacts and energy requirements: A case study for Istanbul, Turkey. *Journal of Cleaner Production, 96*, 486-492. https://doi.org/10.1016/j.jclepro.2013.12.063
[42] Zarazua De Rubens, G., Noel, L., Kester, J., & Sovacool, B. K. (2020). The market case for electric mobility: Investigating electric vehicle business models for mass adoption. *Energy, 194*, 116841. https://doi.org/10.1016/j.energy.2019.116841
[43] Kizielewicz, B. & Sałabun, W. (2024). SITW Method: A New Approach to Re-identifying Multi-criteria Weights in Complex Decision Analysis. *Spectrum of Mechanical Engineering and Operational Research, 1*(1), 215-226. https://doi.org/10.31181/smeor11202419
[44] Celik, E., Gumus, A. T., & Erdogan, M. (2016). A New Extension of the ELECTRE Method Based Upon Interval Type-2 Fuzzy Sets for Green Logistic Service Providers Evaluation. *Journal of Testing and Evaluation, 44*(5), 1813-1827. https://doi.org/10.1520/JTE20140046
[45] Zhong, L. & Yao, L. (2017). An ELECTRE I-based multi-criteria group decision making method with interval type-2 fuzzy numbers and its application to supplier selection. *Applied Soft Computing, 57*, 556-576. https://doi.org/10.1016/j.asoc.2017.04.001
[46] Saaty, T. L. (2013). The Modern Science of Multicriteria Decision Making and Its Practical Applications: The AHP/ANP Approach. *Operations Research, 61*(5), 1101-1118. https://doi.org/10.1287/opre.2013.1197
[47] Hasheminasab, H., Hashemkhani Zolfani, S., Bitarafan, M., Chatterjee, P., & Abhaji Ezabadi, A. (2019). The Role of Façade Materials in Blast-Resistant Buildings: An Evaluation Based on Fuzzy Delphi and Fuzzy EDAS. *Algorithms, 12*(6), 119. https://doi.org/10.3390/a12060119
[48] Sałabun, W. & Urbaniak, K. (2020). A new coefficient of rankings similarity in decision-making problems. *Computational Science-ICCS 2020: 20th International Conference,* 632-645. https://doi.org/10.1007/978-3-030-50417-5_47

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