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A TWO-STAGE MODEL FOR ELECTRIC VEHICLE EVALUATION: CRITIC-ELECTRE APPROACH

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RESEARCH ARTICLE

ABSTRACT: Sustainable development represents one of the primary strategic management challenges for organizations operating across various economic sectors. The production and utilization of transportation means aimed at reducing greenhouse gas emissions lead to an enhancement of environmental protection. Many automotive companies are deploying electric vehicles, thus contributing to sustainable development. However, selecting the most suitable electric vehicle from the available options poses a challenge. This paper aims to introduce a two-stage model that integrates the CRiteria significance Through Intercriteria Correlation and Elimination (CRITIC) method with ÉLimination Et Choix Traduisant la REalité (ELECTRE). The CRITIC method is used to obtain weighs vector of electric vehicle attributes, while the ELECTRE method is used for ranking the considered electric vehicle models. The proposed model is demonstrated using a sample of 17 feasible electric vehicle variants, evaluated based on seven features. Input data are sourced from relevant literature. The novelty of this research lies in the combined CRITIC-ELECTRE approach, which has not been previously applied in this domain.

KEY WORDS: *Electric vehicles, CRITIC, ELECTRE*

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DVOSTEPENI MODEL OCENJIVANJA ELEKTRIČNIH VOZILA: CRITIC-ELECTRE PRISTUP

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REZIME: Održivi razvoj predstavlja jedan od primarnih izazova strateškog upravljanja za organizacije koje posluju u različitim privrednim sektorima. Proizvodnja i korišćenje transportnih sredstava u cilju smanjenja emisije gasova staklene bašte dovode do unapređenja zaštite životne sredine. Mnoge automobilske kompanije koriste električna vozila i na taj način doprinose održivom razvoju. Međutim, izbor najpogodnijeg električnog vozila među dostupnim opcijama predstavlja izazov. Ovaj rad ima za cilj da uvede dvostepeni model koji integriše metodu značajnosti kriterijuma kroz međukriterijumsku korelaciju i eliminaciju (CRITIC) sa ELimination Et Choik Traduisant la REalite (ELECTRE). Metoda CRITIC se koristi za dobijanje vektora težine atributa električnih vozila, dok se metoda ELECTRE koristi za rangiranje razmatranih modela električnih vozila. Predloženi model je demonstriran na uzorku od 17 varijanti električnih vozila, procenjenih na osnovu sedam karakteristika. Ulazni podaci su dobijeni iz relevantne literature. Novina ovog istraživanja leži u kombinovanom pristupu CRITIC-ELECTRE, koji do sada nije primenjivan u ovoj oblasti.

KLJUČNE REČI: *Električno vozilo*, *CRITIC*, *ELECTRE*

A TWO-STAGE MODEL FOR ELECTRIC VEHICLE EVALUATION: CRITIC-ELECTRE APPROACH

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INTRODUCTION

These days, one of the most crucial tasks for logistic managers in industrial organizations is to develop a well-defined sustainable transport system. This is aimed at minimizing environmental problems and resource depletion, and this objective is understood in a broader sense. Additionally, it should aim to maximize social and economic welfare (1). Batery Electric Vehicles (BEVs) hold significant potential for advancing sustainable transport, primarily due to their relatively high efficiency and the potential to operate independently from unsustainable energy sources (2). Some authors (3), (4) argue that electric vehicles (EVs) possess several advantages, including efficient battery capacity, reduced emissions of hazardous gases, government subsidies and other incentives for purchases, enhanced vehicle performance, and various other environmental benefits. Based on the findings of the study by (5), it can be concluded that BEVs exhibit up to a 70% lower environmental impact compared to diesel vehicles. However, customer demand for BEVs primarily depends on support measures, such as financial incentives (6).

Many automotive companies have begun developing various models of BEVs with diverse features. These features aim to satisfy the dynamic demands of customers, as highlighted by (7). Numerous studies in the relevant literature focus on measuring customer preferences for BEV selection. For instance, (8) consider BEV features such as battery capacity, charging time, driving range, and acceleration. Some authors argue that it's essential to consider factors like style, colour, quality, size, and performance of BEVs (9).

According to (10) the battery is a crucial component of an BEV, and the car's success largely depends on battery technology, which impacts driving range, recharging time, acceleration, and cost savings. They identify battery capacity, seating capacity, driving range, price, torque, acceleration, charging time, and charging infrastructure as the most important EV features. Similarly, (9) also consider various BEV features such as driving range, price, battery capacity, charging time, seating capacity, and torque.

Therefore, evaluating and selecting the most suitable BEV model while considering various features is a challenging task for customers. This problem can be framed as a multi-attribute decision-making (MADM) task.

In MADM problems, determining weights is a critical issue that can significantly influence the final outcome. Over the last few decades, researchers worldwide have focused their attention on addressing this problem. Most authors suggest dividing the model for determining criteria weights into subjective and objective approaches (11). Subjective approaches reflect the personal assessments of decision makers (DMs), which are based on their knowledge, experience, and intuition. In the literature, the Analytic Hierarchy Process (AHP) (12) is the most commonly used subjective MADM method for determining weights. On the other hand, CRiteria significance Through Intercriteria Correlation (CRITIC) (13) is one of the most well-known and frequently used objective methods. This MADM method belongs to the category of correlation methods, which utilize the standard deviations of the elements of the normalized decision matrix and the correlation coefficients of all pairs of attributes.

The ranking problem can be addressed by applying numerous MADM methods, which can be classified into different groups (14). There are no recommendations or rules on how to choose an MADM method for determining the rank of alternatives. This decision can be considered a problem in itself and Depends on the Assessments of DMs. In (15) a detailed review of the literature on the application of MADM techniques in various research domains is provided. To determine the stability of solutions, many authors use two or more MADM methods (16), (17).

In the relevant literature, several papers address the problem through two-stage models integrating two or more MADM methods (3), (18),(9). In the initial stage, weights of electric vehicle (EV) features are determined using the Analytic Hierarchy Process (AHP) (3), (9). Subsequently, in the second stage, various other MADM methods are employed to ascertain the ranking of EVs. For example, the Multi-Attributive Border Approximation Area Comparison (MABAC) method developed by (19) is utilized in (3) and (9), while the ELimination Et Choix Traduisant la REalité (ELECTRE) method developed by (20) is employed in (18).

When comparing papers that propose models for ranking EV models, certain differences can be observed and further described. This analysis also highlights the advantages of the proposed model.

In (3), five BEV features were considered, determined based on DMs' assessments. In (17) conducted a detailed literature review on the number and models of EV features described in relevant literature. This author suggests 14 EV features. In (9) defined a list of EV features based on research results. Firstly, they made a shortlist of BEV features from past academic literature based on subjective assessments. Secondly, they conducted a survey involving customers who already use BEVs or intend to buy them in the future. Customers expressed their assessments of the importance of BEV features. Pareto analysis was used to shortlist the most significant criteria (9). This list contains 6 EV features. Therefore, it can be considered that the BEV features obtained in the exact manner (9) are more reliable than in other papers found in the relevant literature. In this research, the authors expanded the list of BEV features defined in (9). The authors believe that the considered EV models can be adequately assessed respecting the seven features.

In papers (3), (9), the weight vector of BEV features is determined using AHP. This approach means that the calculated weights of EV features are influenced by the subjective opinions of DMs. In this research, the CRITIC method was used to determine BEV features weights as in (21). The authors believe that: (i) the sample of considered EVs is sufficiently large and (ii) the values of elements in the decision matrix are obtained from literature sources, so the applied statistical data analysis is reliable. In other words, the obtained values of EV feature weights by applying CRITIC are sufficiently accurate.

The rank of considered BEVs is determined by MABAC in (9), (3). By applying the MABAC method, all types of BEVs are divided into two groups. BEV models belonging to the upper approximation area can adequately meet customer demand, while those in the lower approximation area are undesirable from the customers' perspective. In (18) classified BEV models using ELECTRE, as in this research. In papers found in the literature, the normalized decision matrix is constructed by applying different normalization procedures (18),(22). In this research, the procedure of enhanced normalization (23), is used. The introduced modifications of the ELECTRE method do not compromise the rigor of the research according to the authors' opinions.

The paper is organized as follows. The proposed integrated multi-attribute model for the evaluation and selection of BEVs is presented in Section 2. Section 3 provides a test and verification of the proposed model using real-life data. Concluding remarks and directions for future research are discussed in Section 4.

1 METHODOLOGY

The evaluation and ranking of EVs are conducted through a two-stage MADM model. In the first stage, the weights of EV features used to evaluate EV models are determined using CRITIC. In the second stage, the ranking of EVs is obtained by applying ELECTRE.

1.1 Defining set of EV models

The share of small and medium electric car models is decreasing among available BEV models. In 2023, two-thirds of the battery-electric models on the market were SUVs 5 pick-up trucks or large cars. Just 25% of BEV car sales in the United States were for small and medium models, compared to 40% in Europe and 50% in China. EVs are following the same trend as conventional cars, and getting bigger on average. In 2023, SUVs, pick-up trucks and large models accounted for 65% of total ICE vehicle sales worldwide, and more than 80% in the United States, 60% in China and 50% in Europe (24).

In Emerging Market and Developing Economies (EMDEs), the absence of small and cheaper EV models is a significant hindrance to wider market uptake. Many of the available BEV models are SUVs or large models, targeting consumers of high-end goods, and far too expensive for mass-market consumers, who often do not own a personal vehicle in the first place.

In EMDEs, some EV can be cheaper than ICE equivalents over their lifetime. Access to finance is typically much more challenging in EMDEs due to higher interest rates and the more limited availability of cheap capital. Passenger EV have also a significantly lower market penetration in the first place, and many car purchases are made in second-hand markets.

Achieving price parity between electric and ICE cars will be an important tipping point. Even when the TCO for electric cars is advantageous, the upfront retail price plays a decisive role, and mass-market consumers are typically more sensitive to price premiums than wealthier buyers. This holds true not only in EMDEs, which have comparatively high costs of capital and comparatively low household and business incomes, but also in advanced economies. In the United States, for example, surveys suggest affordability was the top concern for consumers considering EV adoption in 2023. Other estimates show that even among SUV and pick-up truck consumers, only 50% would be willing to purchase one above USD 50 000.

Larger batteries for longer ranges increase car prices, equipment, digital technology and luxury features that are often marketed on top of the base model. A disproportionate focus on larger, premium models is pushing up the average price, which added to the lack of available BEV models in second-hand markets limits potential to reach mass-market consumers. Importantly, geopolitical tension, trade and supply chain disruptions, increasing battery prices in 2022 relative to 2021, and rising inflation, have also significantly affected the potential for further cost declines (24).

The “city” group consists of compact vehicles with a universal character, mostly for daily urban but also extra-urban driving as well as most everyday applications. The “small” segment includes cars with small dimensions, practically suitable only for urban driving, as their range does not allow for a longer trip without the need for additional charging.

Over the past years, BEVs has gained increasing attention by policymakers and consumers, especially due to their potential to reduce Green House Gasses (GHG) emissions. Thus, electric vehicle market has been shown significant growth in today. Many Famous manufacturers have converted to electrical concept the vehicle portfolio of themself. There are many electric vehicle models and firms that are present in market with different combinations. So, many car manufacturers have started to the development studies on BEVs for better performance and this process continues rapidly. However, BEVs have some disadvantage, existing limitations and difference to each other such as limited driving ranges, insufficient chargers, long recharging duration and upfront purchasing cost. These differences show varies according to automobile company and automobile types. Besides, BEVs make a significant contribution sustainability in terms of environmental effect in cities. To do this, BEVs as cleaner technology should be supported by decision makers, and all society. While technical aspects are very relevant for the successful introduction of these new vehicles, to decide for the best automobile among alternatives need multi-criteria evaluation process. When a customer needs to acquire a new electric auto-mobile or automobile for its daily life, many factors must be taken into account. This requires a good command of conflicting factors, which can benefit from the domain of Multi-Criteria Decision Making (MCDM). There are various factors which affect the performance of an electric vehicle such as battery capacity, charging time, price, driving range etc. All these factors are improved further by manufacturers day by day. So, the BEV technology has been getting momentum rapidly every passing day. These differences and limitations of BEVs have been necessitated the decision-making process for purchase preferences of customers. In addition, we will find the answer to the question of which vehicle is the most suitable or optimal with this study, we will help to customers for their purchase preference with analytic and optimization models. The effective selection of electric automobile for multiple criteria types is essential for the sustainable practice of trans-portation. Besides, when the problem has got constraints and goal values, mathematical models such as goal programming (GP) give optimal results.

In general, it is possible to consider various types of electric vehicles I which are formally represented by a set of indices $\{1,..,i,..,I\}$. The index of electric vehicles is denoted as i, where $i = 1,..,I$. This paper considers the following types of electric vehicles: Fiat 500 e hatchback 42 kWh $(i = 1)$, Renault 5 E Tech 52 kWh 150hp $(i = 2)$, Renault ZOE ZE50 R110 $(i = 3)$, Lancia Ypsilon $(i = 4)$, Renault ZOE ZE50 R135 $(i = 5)$, Renault ZOE ZE50 R135 $(i = 6)$, Mini Cooper SE $(i = 7)$, Renault 5 E Tech 40 kWh 150hp $(i = 8)$, Opel Corsa electric 50 kWh $(i = 9)$, Peugeot e-208 51 kWh $(i = 10)$, Opel Corsa electric 51 kWh $(i = 11)$, Mini Cooper E $(i = 12)$, Renault 5 E-Tech 40 kWh 120 hp $(i = 13)$, Fiat 500 e hatchback 24 kWh $(i = 14)$, Fiat 500e 3+1 42 kWh $(i = 15)$, Abarth 500e Hatchback $(i = 16)$, and Abarth 500e Convertible $(i = 17)$ which are collected in May 2024.

1.2 Defining EV Features

In general, each type of EV can be evaluated based on K features. These attributes are formally represented by a set of indices $\{1,..,k,..,K\}$. The index of a feature is denoted as k, where $k = 1,..,K$. In this research, features are defined by decision makers based on the results of the study (9) and the best practices. These features are: driving range (measured in kilometres) $(k = 1)$, price (measured in euros) $(k = 2)$, nominal battery capacity (measured in kWh) $(k = 3)$, usable battery capacity (measured in kWh) $(k = 4)$, charging time (measured in hours) ($k = 5$), seating capacity (number of passengers) ($k = 6$), and torque (measured in Nm) ($k = 7$).

1. 3 Determining the weight vector of EV features based on CRITIC

The proposed algorithm can be implemented through the following steps, as outlined below:

Step 1. The decision matrix is stated:

$$\left[x_{ik}\right]_{lxK}, \tag{1}$$

The values of elements x_{ik} are obtained based on empirical data.

Step 2. The normalized decision matrix is constructed using the Linear Normalization Procedure (25), as proposed in conventional CRITIC.

$$\left[r_{ik}\right]_{IxK}, \tag{2}$$

where:

$$r_{ik} = \frac{x_{ik}}{\sum_{i=1,\dots,l} x_{ik}}. \tag{3}$$

Step 3. Determine weights of EV features, $W_k, k = 1,..,K$ according to formula:

$$W_k = \sigma_k \sum_{k=1,\dots,K} \left(1 - \rho_{kk`}\right). \tag{4}$$

where:

- σ_k is standard deviation values for each EV feature $k, k = 1,..,K$
- $\rho_{kk'}$ is the correlation coefficient between each pair of EV features.

Step 4. The normalized weights vector of EV features is denoted as:

$$\left[\omega_k\right]_{Kx1}, \tag{5}$$

where:

$$\omega_k = \frac{W_k}{\sum_{i=1,\dots,\mathrm{K}} W_k}. \tag{6}$$

1.4 Ranking of EVs based on ELECTRE

Step 1. The decision matrix is stated:

$$\left[x_{ik}\right]_{IxK}, \tag{7}$$

The values of elements x_{ik} are obtained based on empirical data.

Step 2. The normalized decision matrix is constructed using the enhanced normalization method (26):

$$\left[r_{ik}\right]_{IxK}, \tag{8}$$

where:

a) benefit type

$$r_{ik} = 1 - \frac{x_k^{\max} - x_{ik}}{\sum_{i=1}^{I}\left(x_k^{\max} - x_{ik}\right)}. \quad (9)$$

b) cost type

$$\begin{aligned} r_{ik} &= 1 - \frac{x_{ik} - x_k^{\min}}{\sum_{i=1}^{I}\left(x_{ik} - x_k^{\min}\right)} \\ x_k^{\max} &= \max_{i=1,\ldots,I} x_{ik} \\ x_k^{\min} &= \min_{i=1,\ldots,I} x_{ik} \end{aligned} \quad . \quad (10)$$

Step 3. The weighted normalized decision matrix is constructed in this way:

$$\left[z_{ik}\right]_{IxK}, \quad (11)$$

where:

$$z_{ik} = \omega_k \cdot r_{ik}, \quad (12)$$

Step 4. Determine the concordance sets, $S_{ii'}$ and discordance sets, $NS_{ii'}$:

$$\begin{aligned} z_{i`k} \geq z_{ik} &\to k \in S_{ii`} \\ z_{i`k} < z_{ik} &\to k \in NS_{ii`} \end{aligned}, \quad (13)$$

Step 5. The concordance matrix is constructed:

$$\left[c_{ii`}\right]_{IxI}, \quad (14)$$

where:

$$c_{ii`} = \sum_{k=1,\ldots,K`} \omega_k . \quad (15)$$

The concordance level is calculated as:

$$\bar{c} = \frac{1}{I \cdot (I-1)} \sum_{i=1,\ldots,I} \sum_{i`=1,\ldots,I} c_{ii`} . \quad (16)$$

Step 6. The discordance matrix is constructed:

$$\left[n_{ii`}\right]_{IxI}, \quad (17)$$

where:

$$n_{ii`} = \frac{\max\limits_{k \in NS_{ii`}} \left|z_{i`k} - z_{ik}\right|}{\max\limits_{k=1,\ldots,K} \left|z_{i`k} - z_{ik}\right|} . \quad (18)$$

The disconcordance level is calculated as:

$$\bar{n} = \frac{1}{I \cdot (I-1)} \sum_{i=1,\ldots,I} \sum_{i`=1,\ldots,I} n_{ii`} . \tag{19}$$

Step 7. To construct the general matrix based on Boolean matrices, we first create Boolean matrices using a minimum concordance level and a minimum discordance level:

2 CASE STUDY

In this section, the proposed methodology is illustrated using real-life data. The section is divided into two parts. In the first part, the proposed CRITIC method is applied to obtain the weights vector of criteria. In the second part, the ranking of the considered EV models is determined using the proposed ELECTRE method.

2. 1 An application of CRITIC

The attribute values for each considered type of BEV are provided based on literature sources and presented in Table 1 (Step 1 of the proposed algorithm).

Table 1. Decision matrix

	$k=1$	$k=2$	$k=3$	$k=4$	$k=5$	$k=6$	$k=7$
$i=1$	235	34990	42	37.3	4	4	220
$i=2$	330	32000	55	52	5.75	5	245
$i=3$	315	36840	54.7	52	3	5	225
$i=4$	305	40000	51	48.1	5.25	5	260
$i=5$	310	37840	54.7	52	3	5	245
$i=6$	290	37475	50	46.3	7.3	5	260
$i=7$	310	36900	54.2	49	5.25	4	330
$i=8$	260	25000	43	40	4.5	5	215
$i=9$	295	34650	50	46.3	7.5	5	260
$i=10$	310	40325	51	48.1	7.75	5	260
$i=11$	315	38045	51	48.1	7.75	5	260
$i=12$	235	32900	40.7	37	4	4	290
$i=13$	260	28000	43	40	4.5	5	225
$i=14$	135	30990	23.8	21.3	2.3	4	220
$i=15$	235	36990	42	37.3	4	4	220
$i=16$	225	37990	42.2	37.8	4.25	4	235
$i=17$	225	40990	42.2	37.8	4.25	4	235

The normalized decision matrix (Step 2 of the proposed algorithm) is constructed, and the standard deviation of criteria values is determined. These values are presented in Table 2.

Table 2. The normalized decision matrix

	$k=1$	$k=2$	$k=3$	$k=4$	$k=5$	$k=6$	$k=7$
$i=1$	0.054	0.058	0.053	0.051	0.047	0.051	0.052
$i=2$	0.076	0.053	0.070	0.071	0.068	0.064	0.058
$i=3$	0.072	0.061	0.069	0.071	0.036	0.064	0.054
$i=4$	0.070	0.066	0.065	0.066	0.062	0.064	0.062
$i=5$	0.071	0.063	0.069	0.071	0.036	0.064	0.058
$i=6$	0.067	0.062	0.063	0.063	0.087	0.064	0.062
$i=7$	0.071	0.061	0.069	0.067	0.062	0.051	0.078
$i=8$	0.060	0.042	0.054	0.055	0.053	0.064	0.051
$i=9$	0.068	0.058	0.063	0.063	0.089	0.064	0.062
$i=10$	0.071	0.067	0.065	0.066	0.092	0.064	0.062
$i=11$	0.072	0.063	0.065	0.066	0.092	0.064	0.062
$i=12$	0.054	0.055	0.051	0.051	0.047	0.051	0.069
$i=13$	0.060	0.047	0.054	0.055	0.053	0.064	0.054
$i=14$	0.031	0.051	0.030	0.029	0.027	0.051	0.052
$i=15$	0.054	0.061	0.053	0.051	0.047	0.051	0.052
$i=16$	0.052	0.063	0.053	0.052	0.050	0.051	0.056
$i=17$	0.052	0.068	0.053	0.052	0.050	0.051	0.056
σ_k	0.012	0.007	0.010	0.011	0.020	0.007	0.007

The normalized weight vector of the considered attributes is obtained by applying the proposed algorithm (Step 3 to Step 4), so that:

$$\omega = [0.112 \quad 0.142 \quad 0.096 \quad 0.105 \quad 0.299 \quad 0.117 \quad 0.129]$$

2. 3 An application of ELECTRE

The decision matrix is shown in Table 1. The normalized decision matrix (Step 2 of the proposed algorithm) is presented in Table 3.

Table 3 The normalized decision matrix

	$k=1$	$k=2$	$k=3$	$k=4$	$k=5$	$k=6$	$k=7$
$i=1$	0.899	0.941	0.910	0.904	0.962	0.857	0.915
$i=2$	1	0.959	1	1	0.924	1	0.934
$i=3$	0.984	0.930	0.998	1	0.985	1	0.917
$i=4$	0.974	0.912	0.972	0.975	0.935	1	0.946
$i=5$	0.979	0.924	0.998	1	0.985	1	0.934
$i=6$	0.958	0.926	0.965	0.963	0.889	1	0.946
$i=7$	0.979	0.930	0.994	0.980	0.935	0.857	1
$i=8$	0.926	1	0.917	0.922	0.951	1	0.911
$i=9$	0.963	0.943	0.965	0.963	0.885	1	0.946
$i=10$	0.979	0.910	0.972	0.975	0.880	1	0.946
$i=11$	0.984	0.923	0.972	0.975	0.880	1	0.946
$i=12$	0.899	0.953	0.899	0.902	0.962	0.857	0.969
$i=13$	0.926	0.982	0.917	0.922	0.951	1	0.917
$i=14$	0.794	0.965	0.784	0.800	1	0.857	0.915
$i=15$	0.899	0.929	0.910	0.904	0.962	0.857	0.915
$i=16$	0.889	0.923	0.911	0.908	0.957	0.857	0.926
$i=17$	0.889	0.906	0.911	0.908	0.957	0.857	0.926

By applying the proposed algorithm (Step 4), the weighted normalized decision matrix is obtained and presented in Table 4.

Table 4 The weighted normalized decision matrix

	$k=1$	$k=2$	$k=3$	$k=4$	$k=5$	$k=6$	$k=7$
$i=1$	0.101	0.134	0.087	0.095	0.288	0.100	0.118
$i=2$	0.112	0.136	0.096	0.105	0.276	0.117	0.120
$i=3$	0.110	0.132	0.096	0.105	0.295	0.117	0.118
$i=4$	0.109	0.130	0.093	0.102	0.280	0.117	0.122
$i=5$	0.110	0.131	0.096	0.105	0.295	0.117	0.120
$i=6$	0.107	0.131	0.093	0.101	0.266	0.117	0.122
$i=7$	0.110	0.132	0.095	0.103	0.280	0.100	0.129

$i = 8$	0.104	0.142	0.088	0.097	0.284	0.117	0.118
$i = 9$	0.108	0.134	0.093	0.101	0.265	0.117	0.122
$i = 10$	0.110	0.129	0.093	0.102	0.263	0.117	0.122
$i = 11$	0.110	0.131	0.093	0.102	0.263	0.117	0.122
$i = 12$	0.101	0.135	0.086	0.095	0.288	0.100	0.125
$i = 13$	0.104	0.139	0.088	0.097	0.284	0.117	0.118
$i = 14$	0.089	0.137	0.075	0.084	0.299	0.100	0.118
$i = 15$	0.101	0.132	0.087	0.095	0.288	0.100	0.118
$i = 16$	0.100	0.131	0.087	0.095	0.286	0.100	0.119
$i = 17$	0.100	0.129	0.087	0.095	0.286	0.100	0.119

Determining the sets of concordance and discordance (Step 4 of the proposed algorithm) is illustrated by example:

$$S_{12} = \{k = 1, k = 2; k = 3; k = 4; k = 6; k = 7\}$$

In a similar manner, all sets of concordance and discordance for each pair of considered BEVs are determined.

$$c_{12} = 0.112 + 0.142 + 0.096 + 0.105 + 0.117 + 0.129 = 0.70$$

$$n12 = \frac{\max(0.012)}{\max(0.011, 0.002, 0.009, 0.010, 0.012, 0.017, 0.002)} = \frac{0.012}{0.017} = 0.71$$

In a similar manner, the remaining values of the concordance matrix and discordance matrix are determined, which are presented in Table 5 and Table 6, respectively.

Table 5 The concordance matrix

-	0.30	0.27	0.44	0.14	0.44	0.56	0.43	0.44	0.44	0.44	0.73	0.43	0.56	1	0.87	0.87
0.70	-	0.70	0.57	0.70	0.87	0.57	0.56	0.87	0.87	0.87	0.57	0.56	0.56	0.70	0.70	0.70
0.86	0.62	-	0.87	0.81	0.87	0.87	0.86	0.73	0.87	0.87	0.73	0.86	0.56	1	0.87	0.87
0.56	0.55	0.25	-	0.25	0.86	0.42	0.61	0.86	0.89	0.75	0.43	0.56	0.56	0.56	0.56	0.70
0.86	0.75	0.86	0.87	-	0.87	0.73	0.86	0.73	0.87	0.87	0.73	0.86	0.56	0.86	1	1
0.56	0.25	0.25	0.48	0.39	-	0.12	0.56	0.75	0.78	0.78	0.43	0.56	0.56	0.56	0.70	0.70
0.56	0.43	0.38	0.88	0.38	0.88	-	0.44	0.74	0.88	0.88	0.56	0.44	0.56	0.70	0.70	0.70
0.70	0.56	0.39	0.56	0.26	0.56	0.56	-	0.56	0.56	0.56	0.57	1	0.70	0.70	0.57	0.57
0.70	0.25	0.39	0.48	0.39	0.70	0.26	0.56	-	0.78	0.78	0.43	0.56	0.56	0.70	0.70	0.70
0.56	0.25	0.36	0.56	0.36	0.56	0.23	0.56	0.56	-	0.86	0.43	0.56	0.56	0.56	0.56	0.70
0.56	0.25	0.36	0.70	0.50	0.70	0.23	0.56	0.56	1	-	0.43	0.56	0.56	0.56	0.70	0.70

0.90	0.43	0.27	0.57	0.27	0.57	0.56	0.43	0.57	0.57	0.57	-	0.43	0.44	0.90	0.90	0.90
0.70	0.56	0.39	0.44	0.26	0.56	0.56	0.86	0.57	0.56	0.56	0.57	-	0.70	0.70	0.57	0.57
0.69	0.44	0.57	0.44	0.44	0.44	0.56	0.43	0.44	0.44	0.44	0.56	0.43	-	0.69	0.56	0.56
0.90	0.30	0.27	0.44	0.14	0.44	0.56	0.43	0.30	0.44	0.44	0.73	0.43	0.56	-	0.87	0.87
0.45	0.30	0.13	0.44	0.14	0.44	0.42	0.43	0.30	0.44	0.44	0.32	0.43	0.56	0.45	-	1
0.45	0.30	0.13	0.30	0.30	0.30	0.42	0.43	0.30	0.44	0.30	0.32	0.43	0.56	0.45	0.86	-

$$\bar{c} = \frac{1}{17 \cdot 16} \cdot 156.818 = 0.58$$

Table 6 The disconcordance matrix

-	1	1	1	1	0.77	1	0.77	0.68	0.68	1	0.29	1	1	0	0.5	0.2
0.71	-	1	0.67	1	0.20	0.53	1	0.18	0.15	0.15	0.71	1	1	0.71	0.59	0.59
0.12	0.21	-	0.27	1	0.14	0.65	0.91	0.13	0.12	0.12	0.41	0.64	0.24	0	0.06	0.06
0.47	1	1	-	1	0.07	0.41	1	0.27	0.06	0.06	0.47	1	0.95	0.47	0.35	0.35
0.18	0.26	0.50	0.13	-	0.07	0.53	1	0.10	0.06	0.06	0.29	0.73	0.29	0.06	0	0
1	1	1	1	1	-	0.82	1	1	1	1	1	1	1	1	1	1
0.73	1	1	1	1	1	-	1	1	1	1	0.89	1	0.90	0.73	0.60	0.60
1	1	1	0.42	1	0.28	0.65	-	0.26	0.29	0.29	0.41	0	0.88	0.24	0.12	0.12
1	1	1	1	1	0.33	0.88	1	-	0.40	0.67	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	-	1	1	1	1	1	1	1
0.14	1	1	1	1	1	1	1	1	0	-	1	1	1	1	1	1
1	1	1	1	1	0.77	1	1	0.74	0.68	0.68	-	1	0.92	0.14	0.14	0.17
0.92	1	1	0.56	1	0.28	0.65	1	0.26	0.29	0.29	0.41	-	0.88	0.24	0.12	0.12
0	1	1	1	1	0.55	1	1	0.56	0.58	0.50	1	1	-	1	0.92	0.92
1	1	1	1	1	0.77	1	1	0.74	0.68	0.68	1	1	0.92	-	0.50	0.33
1	1	1	1	1	0.85	1	1	0.81	0.74	0.74	1	1	1	1	-	0
1	1	1	1	1	0.85	1	1	0.81	0.74	0.74	1	1	1	1	1	-

$$\bar{n} = \frac{1}{17 \cdot 16} \cdot 202.869 = 0.75$$

According to the defined rules (Step 7 of the proposed algorithm), the concordance dominance matrix is determined and presented in Table 7.

Table 7 The general matrix

-	0	0	0	0	0	0	0	0	0	0	1	0	0	1	1	1
1	-	0	0	0	1	0	0	1	1	1	0	0	0	1	1	1
1	1	-	1	0	1	1	0	1	1	1	1	1	0	1	1	1
0	0	0	-	0	1	0	0	1	1	1	0	0	0	0	0	1
1	1	1	1	-	1	1	0	1	1	1	1	1	0	1	1	1
0	0	0	0	0	-	0	0	0	0	0	0	0	0	0	0	0

0	0	0	0	0	0	-	0	0	0	0	0	0	0	1	1	1
0	0	0	0	0	0	0	-	0	0	0	0	1	0	1	0	0
0	0	0	0	0	1	0	0	-	1	1	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	-	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	1	-	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	-	0	0	1	1	1
0	0	0	0	0	0	0	0	0	0	0	0	-	0	1	0	0
1	0	0	0	0	0	0	0	0	0	0	0	0	-	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	-	1	1
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-	1
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-

By applying the proposed procedure (Step 7 to Step 8), the determined values are presented in Table 8.

Table 8 Rank of considered BEVs

	M_i	rank		M_i	rank
$i = 1$	4	5	$i = 10$	0	15-17
$i = 2$	8	3	$i = 11$	1	11-14
$i = 3$	13	2	$i = 12$	3	6-8
$i = 4$	5	4	$i = 13$	1	11-14
$i = 5$	14	1	$i = 14$	1	11-14
$i = 6$	0	15-17	$i = 15$	2	9-10
$i = 7$	3	6-8	$i = 16$	1	11-14
$i = 8$	2	9-10	$i = 17$	0	15-17
$i = 9$	3	6-8			

Based on the obtained ranking, it is evident that all considered BEVs can be divided into 9 groups. In the first place, i.e. second place in the rank, we have the Renault ZOE ZE50 R135, i.e. the Renault ZOE ZE50 R110, respectively. It can be considered that these two types of BEVs are the best with respect to all BEV characteristics as well as their weights. The obtained result can be beneficial for customers to make decisions more easily. For BEV manufacturers, these results should enable designers, production managers, and sales managers to benchmark and thus improve their products.

CONCLUSIONS

The demands for strong competition require the automotive strategic management team to define, implement, and monitor a strategy constructed based on changes in customer preferences. It is believed that stricter environmental regulations will lead to increased usage of BEVs. In this paper, the problem of evaluating and ranking small BEVs most commonly used in the worldwide markets is considered.

The first novelty lies in the method used for rating the relative importance of criteria. CRITIC does not involve cumbersome mathematical operations. This characteristic of CRITIC is important when the dimensions of the problem under consideration are large. The application of the CRITIC method enables objective determination of criteria weights, thereby reducing the burden of subjective assessments by DMs and ensuring greater accuracy.

The second novelty is the ranking of BEV models performed using the proposed ELECTRE method. A modification of conventional ELECTRE has been made in the domain of constructing the normalized decision matrix. In conventional ELECTRE methods, linear normalization is applied without considering the type of criterion. In this research, the authors used an enhanced normalization method with respect to criterion type. This increased the complexity of calculating the normalized decision matrix. However, the authors believe that the applied normalization procedure is more suitable for the problem under consideration. On the other hand, the complexity of computation in subsequent steps is significantly reduced. It can be considered that the modification of ELECTRE reduces computational complexity on one hand while increasing the accuracy of the obtained results on the other hand.

By using the ELECTRE method, many BEV models are placed at the same rank position. Through the application of the ELECTRE method, all considered BEV models are grouped into several groups. Therefore, it can be concluded that this MADM method is highly useful for solving the considered problem.

The advantages of the proposed two-stage MADM compared to models found in the literature include: (i) consideration of criteria weights obtained accurately, (ii) ranking of BEV models determined by the proposed ELECTRE on a sufficiently large sample, and (iii) application of the proposed two-stage MADM for improving the development strategy of BEVs in the automotive industry.

The proposed method is flexible in accommodating changes in the number of criteria, the number of BEV models, and adjustments to criteria weights.

However, the proposed model has certain constraints. The main constraints include the selection of BEV models and defining features of BEVs that meet customer demand.

Future research directions involve analysing the robustness of solutions when changing the method for determining criteria weights. Additionally, the proposed model can be extended to analyse other management decision problems in various research areas.

In theoretical terms, future research should include sensitivity analysis of the obtained solution when criteria weights are determined using subjective methods or different normalization procedures. In practical terms, future research involves developing a software solution that would facilitate the user-friendly application of the proposed two-stage model for strategic management of automotive companies.

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REFERENCES

1. Zhao X, Ke Y, Zuo J, Xiong W, Wu P. Evaluation of sustainable transport research in 2000–2019. J Clean Prod. 2020;256:120404.
2. Borén S, Nurhadi L, Ny H, Robèrt KH, Broman G, Trygg L. A strategic approach to sustainable transport system development - Part 2: the case of a vision for electric vehicle systems in southeast Sweden. J Clean Prod. 2017;140:62–71.
3. Biswas TK, Das MC. Selection of Commercially Available Electric Vehicle using Fuzzy AHP-MABAC. Vol. 100, Journal of The Institution of Engineers (India): Series C. Springer; 2019. p. 531–7.
4. Langbroek JHM, Franklin JP, Susilo YO. The effect of policy incentives on electric vehicle adoption. Energy Policy. 2016;94:94–103.

5. Gustafsson M, Svensson N, Eklund M, Fredriksson Möller B. Well-to-wheel climate performance of gas and electric vehicles in Europe. Transp Res Part D Transp Environ. 2021;97:102911.
6. Francisco S, Mock P, Yang Z. DRIVING ELECTRIFICATION A GLOBAL COMPARISON OF FISCAL INCENTIVE POLICY FOR ELECTRIC VEHICLES. 2014.
7. Zarazua de Rubens G, Noel L, Kester J, Sovacool BK. The market case for electric mobility: Investigating electric vehicle business models for mass adoption. Energy. 2020;194:116841.
8. Das MC, Pandey A, Mahato AK, Singh RK. Comparative performance of electric vehicles using evaluation of mixed data. OPSEARCH. 2019;56(3):1067–90.
9. Sonar HC, Kulkarni SD. An Integrated AHP-MABAC Approach for Electric Vehicle Selection. Res Transp Bus Manag. 2021;41:100665.
10. Dijk M, Orsato RJ, Kemp R. The emergence of an electric mobility trajectory. Energy Policy. 2013;52:135–45.
11. Zhu G-N, Hu J, Qi J, Gu C-C, Peng Y. An integrated AHP and VIKOR for design concept evaluation based on rough number. Adv Eng Informatics. 2015;29:408–18.
12. Saaty TL. How to make a decision: The analytic hierarchy process. Eur J Oper Res. 1990;48(1):9–26.
13. Diakoulaki D, Mavrotas G, Papayannakis L. Determining objective weights in multiple criteria problems: The critic method. Comput Oper Res. 1995;22(7):763–70.
14. Zayat W, Kilic HS, Yalcin AS, Zaim S, Delen D. Application of MADM methods in Industry 4.0: A literature review. Comput Ind Eng. 2023;177:109075.
15. Aleksić A, Tadić D. Industrial and Management Applications of Type-2 Multi-Attribute Decision-Making Techniques Extended with Type-2 Fuzzy Sets from 2013 to 2022. Mathematics. 2023;11(10).
16. Komatina N, Djapan M, Ristić I, Aleksić A. Fulfilling External Stakeholders' Demands—Enhancement Workplace Safety Using Fuzzy MCDM. Sustainability. 2021;13(5).
17. Ziemba P. Selection of electric vehicles for the needs of sustainable transport under conditions of uncertainty—a comparative study on fuzzy mcda methods. Energies. 2021 Nov 1;14(22).
18. Romero-Ania A, Rivero Gutiérrez L, De Vicente Oliva MA. Multiple Criteria Decision Analysis of Sustainable Urban Public Transport Systems. Mathematics. 2021;9(16).
19. Pamučar D, Ćirović G. The selection of transport and handling resources in logistics centers using Multi-Attributive Border Approximation area Comparison (MABAC). Expert Syst Appl. 2015;42(6):3016–28.
20. Roy B. The Outranking Approach and the Foundations of Electre Methods. In: e Costa CA, editor. Readings in Multiple Criteria Decision Aid. Berlin, Heidelberg: Springer Berlin Heidelberg; 1990. p. 155–83.
21. Rostamzadeh R, Ghorabaee MK, Govindan K, Esmaeili A, Nobar HBK. Evaluation of sustainable supply chain risk management using an integrated fuzzy TOPSIS-CRITIC approach. J Clean Prod. 2018 Feb 20;175:651–69.
22. Daneshvar Rouyendegh B, Erman Erkan T. SELECTION OF ACADEMIC STAFF USING THE FUZZY ANALYTIC HIERARCHY PROCESS (FAHP): A PILOT

STUDY. Teh Vjesn. 2012;19:923–9.
23. Zhou P, Ang BW, Poh KL. Comparing aggregating methods for constructing the composite environmental index: An objective measure. Ecol Econ. 2006 Sep 20;59(3):305–11.
24. Energy Agency I. Global EV Outlook 2024 Moving towards increased affordability. 2024.
25. GARDZIEJCZYK W, ZABICKI P. Normalization and variant assessment methods in selection of road alignment variants – case study. J Civ Eng Manag. 2017 Apr 21;23(4):510–23.
26. Jahan A, Edwards KL. A state-of-the-art survey on the influence of normalization techniques in ranking: Improving the materials selection process in engineering design. Mater Des. 2015;65:335–42.