

The 11th International Congress
Motor Vehicles & Motors 2026
Kragujevac, Serbia
October 8th - 9th, 2026



MVM2026-050

<https://doi.org/10.24874/CMVM2026.050>

Review paper

Danijela Tadić¹

Jasna Glišović²

Nikola Komatina³

COMPARATIVE ANALYSIS OF OBJECTIVE CRITERIA WEIGHTING METHODS FOR ELECTRIC VEHICLE EVALUATION

ABSTRACT: Electric vehicles (EVs) play an important role in sustainable development. Nowadays, many automotive companies manufacture different types of EVs. The selection of the most suitable EV depends on the number and type of criteria used for evaluation, as well as on the weights assigned to these criteria. Determining criteria weights is often based on the subjective judgments of decision-makers, which may affect the accuracy of the final selection. Therefore, this paper presents several objective multi-criteria decision-making methods for determining criteria weights. This constitutes the main contribution of the study. The proposed methods are applied to determine the weights of six criteria for EV evaluation identified from the relevant literature.

KEYWORDS: Electric vehicles, criteria weights, FANMA, Entropy method, CRITIC method

KOMPARATIVNA ANALIZA OBJEKTIVNIH METODA ZA ODREĐIVANJE TEŽINA KRITERIJUMA PRI OCENJIVANJU ELEKTRIČNIH VOZILA

REZIME: Električna vozila (EV) imaju značajnu ulogu u održivom razvoju. Danas mnoge automobilske kompanije proizvode različite tipove električnih vozila. Izbor najpogodnijeg električnog vozila zavisi od broja i vrste kriterijuma koji se koriste za njihovu ocenu, kao i od težina koje su tim kriterijumima dodeljene. Određivanje težina kriterijuma često se zasniva na subjektivnim procenama donosilaca odluka, što može uticati na tačnost konačnog izbora. Stoga ovaj rad predstavlja nekoliko objektivnih višekriterijumskih metoda za određivanje težina kriterijuma. To predstavlja glavni doprinos rada. Predložene metode primenjene su za određivanje težina šest kriterijuma za ocenu električnih vozila identifikovanih na osnovu relevantne literature.

¹ Danijela Tadić, University of Kragujevac, Faculty of Engineering, Sestre Janjić 6, 34000 Kragujevac, Serbia, galovic@kg.ac.rs, <https://orcid.org/0000-0003-2236-967X>

² Jasna Glišović, University of Kragujevac, Faculty of Engineering, Sestre Janjić 6, 34000 Kragujevac, Serbia, jaca@kg.ac.rs, <https://orcid.org/0000-0002-8251-1722>

³ Nikola Komatina, University of Kragujevac, Faculty of Engineering, Sestre Janjić 6, 34000 Kragujevac, Serbia, nkomatina@kg.ac.rs, <https://orcid.org/0000-0001-6964-5673>

INTRODUCTION

Strategy development in almost all countries is based on the concept of sustainable development, which, among other things, implies environmental protection and the use of renewable energy sources. This approach is particularly important for the automotive industry. Many automotive companies, such as Ford, Hyundai, Fiat, General Motors, BMW, Tata Motors, Mitsubishi, and others, have already started the commercial production of electric vehicles (EVs) with distinct features. These vehicles use alternative energy sources, including natural gas, ethanol, methanol, propane, electricity, biodiesel, and hydrogen, which are considered substitutes for gasoline and other fossil fuels. Therefore, the use of EVs can contribute to sustainable development (Deuten et al., 2020; Egnér & Trosvik, 2018). Compared with conventional vehicles with internal combustion engines, EVs can contribute to reducing greenhouse gas emissions by minimizing dependence on fossil fuels (Liu et al., 2020). Nowadays, EVs are gaining popularity due to several advantages, including efficient battery capacity, reduced emissions of hazardous gases, government subsidies and other purchase incentives, improved vehicle performance, and other environmental benefits (Biswas & Das, 2019; Langbroek et al., 2017). Nowadays, many government organizations are promoting the adoption of EVs by introducing various policies, incentives, and other support measures.

At the operational management level, one of the most crucial tasks for logistics managers in industrial organizations is to develop a well-defined sustainable transport system. This is aimed at minimizing environmental problems and resource depletion while, in a broader sense, also maximizing social and economic welfare (Zhao et al., 2020). Some authors (Biswas & Das, 2019; Langbroek et al., 2017) argue that EVs possess several advantages, including efficient battery capacity, reduced emissions of hazardous gases, government subsidies and other purchase incentives, enhanced vehicle performance, and various other environmental benefits. Based on the findings of the study by (Gustafsson et al., 2021), the negative environmental impact can be reduced by using EVs instead of diesel vehicles. However, customer demand for EVs primarily depends on support measures, such as financial incentives.

Defining the distinct features of EVs and evaluating different EV models with respect to the considered features is a very complex task. Almost all authors dealing with this problem consider that defining the list of criteria according to which EVs are evaluated represents one of the most important issues, as its solution directly affects the selection of EVs. In the literature, numerous studies can be found in which authors have defined lists of criteria with respect to different aspects (Biswas & Das, 2019; Das et al., 2019; Sonar & Kulkarni, 2021; Tadić et al., 2024, 2025; Yagcitekin et al., 2015; Zarazua De Rubens et al., 2020).

Determining criteria 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 approaches to determining criteria weights into subjective and objective approaches (Zhu et al., 2015). In the literature, many studies can be found in which determining criteria weights is adequately based on the assessments of decision-makers (DMs) (Arsić et al., 2025; Komatina et al., 2023; Milanovic et al., 2020). They base their assessments on their knowledge, experience, and the results of best practices. In this case, criteria weights are significantly influenced by the subjective attitudes of DMs. In order to increase the accuracy of criteria weights, many authors promote the use of subjective multi-criteria decision-making methods, which are briefly described below. The Analytic Hierarchy Process (AHP) (Saaty, 2013) is the most commonly used subjective Multi-Criteria Decision-Making (MCDM) method for determining criteria weights. The criteria weights of EVs have been determined using the AHP (Biswas & Das, 2019; Sonar & Kulkarni, 2021). Other subjective MCDM methods that have been widely applied to determining criteria weights include the Best–Worst Method (BWM) (Rezaei, 2015), the Decision-Making Trial and Evaluation Laboratory (DEMATEL) method (Falatoonitoosi et al., 2013), and Data Envelopment Analysis (DEA) (Charnes et al., 1978).

The main advantage of these methods is that they enable DMs to assess the relative importance of the considered criteria based on their knowledge and experience. The estimated or measured values of alternatives do not affect the assessments of DMs. The main disadvantage of subjective MCDM methods is that the assessment of the relative importance of the considered criteria is, to a significant extent, related to the value system, experience, and personal preferences of DMs, as well as the influence of the social groups to which they belong and other related factors.

On the other hand, objective MCDM methods used for determining criteria weights include the FANMA (Mandal et al., 2025; Milićević & Župac, 2012), Entropy (Eskov et al., 2017; Saraiva, 2023), and Criteria Importance Through Intercriteria Correlation (CRITIC) methods (Diakoulaki et al., 1995). In the literature, many papers can be found in which authors use objective MCDM methods for determining criteria weights (Chen, 2021; Komatina & Marinković, 2025; Krishnan, 2025).

The values of criteria weights depend on the amount and accuracy of the values contained in the elements of the decision matrix. On the other hand, if the set of alternatives in the considered problem changes, for example, if the set of considered EVs is expanded or different types of EVs are considered, this leads to changes in the values of criteria weights. This dependence of the obtained weights on the considered set of alternatives can be regarded as one of the main limitations of objective MCDM methods.

Based on the above brief discussion of MCDM methods used for determining criteria weights, it can be concluded that both approaches have their advantages as well as disadvantages. DMs must possess sufficient knowledge and experience when selecting an appropriate method, since criteria weights can significantly influence the selection of the most suitable EV.

The increasing number of available EV models and the diversity of their characteristics make the selection of the most suitable EV a complex decision-making problem. Since the final selection can be significantly influenced by the criteria weights, it is important to investigate different approaches for their determination and to analyse the differences in the obtained results.

The aim of this paper is to apply and compare three objective methods, namely FANMA, Entropy, and CRITIC, for determining the weights of criteria used for EV evaluation. The obtained criteria weights are also compared with the AHP weights reported by (Sonar & Kulkarni, 2021), which were determined based on DMs' assessments.

The paper is organized as follows. The methodology used in this study is presented in Section 2. Section 3 presents the determination of criteria weights using data obtained from the literature and compares the obtained results. Concluding remarks and directions for future research are discussed in Section 4.

METHODOLOGY

In this section, the considered objective MCDM methods used in this research are briefly presented.

Defining EV Criteria

Nowadays, automotive companies produce and offer customers EVs with numerous characteristics, such as style, color, quality, size, battery capacity, seating capacity, driving range, price, torque, acceleration, charging time, charging infrastructure, and others. In this paper, the set of criteria is adopted from (Sonar & Kulkarni, 2021), where the criteria were identified based on purchasers' preferences when selecting an EV. The procedure used for defining the list of criteria is briefly described below.

In (Sonar & Kulkarni, 2021) authors defined a list of criteria based on the preferences of customers who had already purchased passenger EVs or were willing to purchase EVs in the near future. By using Pareto analysis (Flores & Whybark, 1987), they defined a list of the most significant criteria. It should be noted that, in the MCDM approach, the number of criteria should be optimal in order to enable DMs to assess the relative importance of the criteria in a sufficiently simple and accurate manner. This statement is particularly important when subjective methods for determining criteria weights are used.

These criteria are formally represented by a set of indices $\{1, \dots, k, \dots, K\}$, where $K = 6$. The considered criteria are: price (measured in Lakh Rs.) ($k = 1$), driving range (measured in kilometres) ($k = 2$), charging time (measured in hours) ($k = 3$), battery capacity (measured in kWh) ($k = 4$), seating capacity (number of passengers) ($k = 5$), and torque (measured in Nm) ($k = 6$).

FANMA method

The FANMA method is based on determining the distances from the ideal point. The algorithm for implementing the FANMA method is carried out through the following steps:

Step 1. The decision matrix is defined as:

$$[x_{ik}]_{I \times K} \quad (1)$$

Step 2. The normalized decision matrix is constructed by applying the linear normalization procedure:

$$[r_{ik}]_{I \times K} \quad (2)$$

where:

$$r_{ik} = \frac{x_{ik}}{\sum_{i=1, \dots, I} x_{ik}} \quad (3)$$

Step 3. The reference point, r_k^* , is determined as:

$$r_k^* = \max_{i=1, \dots, I} r_{ik} \quad (4)$$

Step 4. The weight of criterion $k, k = 1, \dots, K$, is determined as:

$$\omega_k = \frac{1}{\sum_{i=1, \dots, I} (r_k^* - r_{ik})^2 \cdot \sum_{k=1, \dots, K} \frac{1}{\sum_{i=1, \dots, I} (r_k^* - r_{ik})^2}} \quad (5)$$

Entropy method

In the Entropy method, the determination of criteria weights is based on Shannon's concept of the entropy measure of information contained in the decision matrix (Shannon, 1948). Based on the determined measures of uncertainty associated with the criteria, a set of criteria weights can be obtained. The algorithm for implementing the Entropy method is carried out through the following steps:

Step 1. The decision matrix is defined as:

$$[x_{ik}]_{I \times K} \quad (6)$$

Step 2. The normalized decision matrix is constructed by applying the linear normalization procedure:

$$[r_{ik}]_{I \times K} \quad (7)$$

Step 3. The entropy degree for each criterion $k, k = 1, \dots, K$, is determined as:

$$E_k = -\frac{1}{\ln I} \cdot \sum_{i=1, \dots, I} r_{ik} \cdot \ln r_{ik} \quad (8)$$

Step 4. The entropy deviation degree is obtained according to the following expression:

$$\vartheta_k = 1 - E_k \quad (9)$$

Step 5. The normalized vector of criteria weights is determined by applying the linear normalization procedure:

$$\omega_k = \frac{\vartheta_k}{\sum_{k=1, \dots, K} \vartheta_k} \quad (10)$$

CRITIC method

The proposed algorithm can be implemented through the following steps:

Step 1. The decision matrix is defined as:

$$[x_{ik}]_{I \times K} \quad (11)$$

Step 2. The normalized decision matrix is constructed using the linear normalization procedure, as proposed in the conventional CRITIC method.

$$[r_{ik}]_{I \times K} \quad (12)$$

Step 3. The weights of the EV criteria, $W_k, k = 1, \dots, K$, are determined according to the following formula:

$$W_k = \sigma_k \cdot \sum_{k=1, \dots, K} (1 - \rho_{kk'}) \quad (13)$$

Where σ_k is the standard deviation of the values for criterion k , and $\rho_{kk'}$ is the correlation coefficient between each pair of EV criteria.

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

$$[\omega_k]_{K \times 1} \quad (14)$$

where:

$$\omega_k = \frac{W_k}{\sum_{k=1, \dots, K} W_k} \quad (15)$$

Application of the Proposed Methods and Results Analysis

The objective of the study is to determine the weights of the criteria used for EV evaluation. Initially, six criteria have been identified based on purchasers' preferences when selecting an electric vehicle.

Application of the FANMA Method

The decision matrix was adopted from (Sonar & Kulkarni, 2021) and is presented in Table 1 (Step 1).

Table 1 The decision matrix

	$k = 1$	$k = 2$	$k = 3$	$k = 4$	$k = 5$	$k = 6$
$i = 1$	23.86	452	6.10	39.20	5	395
$i = 2$	13.95	140	11.30	18.55	5	91
$i = 3$	8.23	110	6	10.08	4	70
$i = 4$	20.88	340	16	44.50	5	353
$i = 5$	10.61	213	11.5	21.50	5	105
$i = 6$	14.99	312	8.50	30.20	5	245

By applying the linear normalization procedure, the normalized decision matrix and the reference point are obtained (Steps 2 and 3) and presented in Table 2.

Table 2 The normalized decision matrix

	$k = 1$	$k = 2$	$k = 3$	$k = 4$	$k = 5$	$k = 6$
$i = 1$	0.2579	0.2884	0.1027	0.2389	0.1724	0.3137
$i = 2$	0.1508	0.0893	0.1902	0.1131	0.1724	0.0723
$i = 3$	0.0889	0.0702	0.1010	0.0615	0.1379	0.0556
$i = 4$	0.2257	0.2169	0.2694	0.2713	0.1724	0.2804
$i = 5$	0.1147	0.1359	0.1936	0.1311	0.1724	0.0834
$i = 6$	0.1620	0.1991	0.1431	0.1841	0.1724	0.1946
r_k^*	0.2579	0.2884	0.2694	0.2713	0.1724	0.3137

The criteria weights are determined using the proposed FANMA algorithm (Step 4). The input data are presented in Table 3.

Table 3 The input data

	$k = 1$	$k = 2$	$k = 3$	$k = 4$	$k = 5$	$k = 6$
$i = 1$	0	0	0.0278	0.0010	0	0
$i = 2$	0.011	0.0396	0.0063	0.0250	0	0.0583
$i = 3$	0.0286	0.0476	0.0284	0.0440	0.0012	0.0667
$i = 4$	0.0010	0.0051	0	0	0	0.0011
$i = 5$	0.0205	0.0233	0.0057	0.0197	0	0.0530
$i = 6$	0.0092	0.0080	0.0159	0.0076	0	0.0142
Step 4 results	14.1300	8.0930	11.8833	10.2771	833.3333	5.1737

$$\omega_1 = \frac{1}{0.0708 \cdot (14.1300 + 8.093 + 11.8833 + 10.2771 + 833.3333 + 5.1737)}$$

$$\omega_1 = \frac{1}{0.0708 \cdot 882.8904} = 0.016$$

The weights of the remaining criteria are determined in a similar manner. Thus, the criteria weights vector is:

Application of the Entropy Method

The decision matrix (Step 1) and the normalized decision matrix (Step 2) are obtained and presented in Tables 1 and 2, respectively. The entropy degree and entropy deviation degree are determined using the proposed procedure (Steps 3 and 4) and presented in Table 4.

Table 4 The entropy degree of the considered criteria

	$k = 1$	$k = 2$	$k = 3$	$k = 4$	$k = 5$	$k = 6$
$i = 1$	-0.3495	-0.3586	-0.2337	-0.3421	-0.3031	-0.3637
$i = 2$	-0.2853	-0.2158	-0.3157	-0.2465	-0.3031	-0.1899
$i = 3$	-0.2152	-0.1865	-0.2316	-0.1714	-0.2732	-0.1607
$i = 4$	-0.3359	-0.3315	-0.3533	-0.3539	-0.3031	-0.3565
$i = 5$	-0.2483	-0.2713	-0.3179	-0.2663	-0.3031	-0.2072
$i = 6$	-0.2949	-0.3213	-0.2782	-0.3116	-0.3031	-0.3185
E_k	0.9651	0.9404	0.9658	0.9442	0.9983	0.8910
ϑ_k	0.0349	0.0596	0.0342	0.0558	0.0017	0.1089

The weight of the first criterion (Step 5) is determined as follows:

$$\omega_1 = \frac{0.03492}{0.03492 + 0.0596 + 0.03424 + 0.05579 + 0.0017 + 0.1089} = 0.118$$

The weights of the remaining criteria are determined in a similar manner. Thus, the criteria weights vector is:

$$[0.118 \ 0.202 \ 0.116 \ 0.189 \ 0.006 \ 0.369]$$

Application of the CRITIC Method

The decision matrix (Step 1) and the normalized decision matrix (Step 2) are obtained and presented in Tables 1 and 2, respectively.

The standard deviation values for each criterion are:

$$\sigma_1 = 0.0645$$

$$\sigma_2 = 0.0832$$

$$\sigma_3 = 0.0645$$

$$\sigma_4 = 0.0796$$

$$\sigma_5 = 0.0141$$

$$\sigma_6 = 0.1127$$

The correlation coefficients are calculated and presented in Table 5.

Table 5 Correlation coefficients

	$k = 1$	$k = 2$	$k = 3$	$k = 4$	$k = 5$	$k = 6$
$k = 1$	1					
$k = 2$	0.9029	1				
$k = 3$	0.1760	0.0100	1			
$k = 4$	0.9176	0.9061	0.4049	1		
$k = 5$	0.5899	0.5678	0.4989	0.6475	1	
$k = 6$	0.9475	0.9616	0.1221	0.9524	0.4827	1

By applying the described procedure, the criteria weights are determined (Step 3). The calculation procedure for the first criterion is illustrated as follows:

$$W_1 = 0.0645 \cdot \left(\frac{(1 - 1) + (1 - 0.9029) + (1 - 0.1760) + (1 - 0.9176) + (1 - 0.5899) + (1 - 0.9475)}{1} \right) = 0.0946$$

The weights of the remaining criteria are determined in a similar manner, resulting in:

$$W_2 = 0.1374$$

$$W_3 = 0.2346$$

$$W_4 = 0.0933$$

$$W_5 = 0.0312$$

$$W_6 = 0.1729$$

The normalized criteria weights are then calculated (Step 4) as:

$$[0.124 \ 0.180 \ 0.307 \ 0.122 \ 0.041 \ 0.226]$$

Discussion of the Obtained Results

In (Sonar & Kulkarni, 2021), the criteria weights were determined using the AHP method. The authors defined a representative group of DMs. These DMs were considered technology enthusiasts and possessed good knowledge of the technological criteria relevant to EV selection. They belonged to various economic sectors, and semi-structured interviews were conducted with the selected DMs. The assessed relative importance of the considered criteria was expressed using a pairwise comparison matrix:

$$\begin{bmatrix} 1 & 3 & 3 & 3 & 5 & 9 \\ & 1 & 3 & 1 & 7 & 7 \\ & & 1 & 1 & 5 & 3 \\ & & & 1 & 5 & 3 \\ & & & & 1 & 3 \\ & & & & & 1 \end{bmatrix}, CR = 0,0892$$

Since the consistency ratio (CR) was lower than 0.1, the judgments provided by the DMs can be considered sufficiently consistent, and therefore, the inconsistency of the pairwise comparisons does not significantly affect the reliability of the obtained results.

The criteria weights vector obtained using the AHP method is:

$$[0.036 \quad 0.054 \quad 0.154 \quad 0.134 \quad 0.233 \quad 0.390]$$

The criteria weights obtained by applying the AHP, FANMA, Entropy, and CRITIC methods are presented in Figure 1 and Table 6.

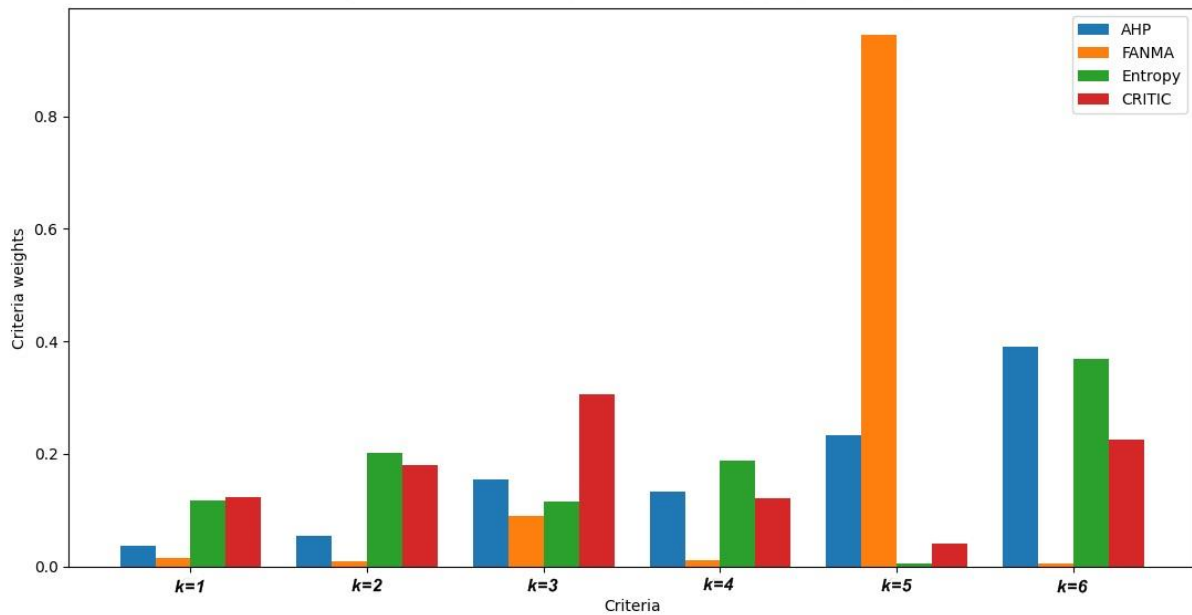


Figure 1 Comparison of criteria weights obtained using different methods

Table 6 Comparative analysis of the obtained criteria weights

Method	Criterion with the highest weight	Criterion with the lowest weight
AHP	$k = 7$	$k = 1$
FANMA	$k = 6$	$k = 1$
Entropy	$k = 7$	$k = 6$
CRITIC	$k = 3$	$k = 6$

Based on the obtained results, it can be clearly observed that the criteria weights used for EV evaluation differ significantly depending on the applied method. This raises the question of which method is the most appropriate. A definitive answer cannot be provided based solely on the obtained results.

If DMs possess sufficient knowledge and experience, and if the data collection procedure is properly conducted while considering the problem from different perspectives, the AHP method can be considered an appropriate approach for determining criteria weights. However, one of the main limitations of the AHP method is related to the increasing number of criteria, since a larger number of criteria requires a substantially larger number of pairwise comparisons.

On the other hand, if a larger number of criteria is considered and sufficiently accurate data are available, objective MCDM methods may be preferred. Based on the obtained results (see Table 6), it can be observed that the obtained criteria weights are not stable with respect to the applied weighting method.

Based on the results obtained for the considered sample, it is not possible to draw a clear and precise conclusion regarding which method is the most appropriate for determining criteria weights in the considered domain. However, it is well known that changes in criteria weights can lead to changes in the ranking results of the considered EVs. Therefore, the problem of determining criteria weights represents an important task for DMs.

CONCLUSIONS

The demands of an increasingly competitive automotive market require automotive strategic management teams to define, implement, and monitor strategies based on changes in customer preferences. It is believed that stricter environmental regulations will lead to the increased adoption of EVs. In this paper, the problem of evaluating a set of electric vehicles selected from the literature is addressed.

The first novelty of the paper lies in the application of objective MCDM methods for determining the criteria weights used for EV evaluation. The characteristics of these methods are particularly important when decision-making problems involve a large number of criteria and alternatives. The application of objective MCDM methods enables the objective determination of criteria weights, thereby reducing the influence of subjective assessments provided by DMs and providing an alternative approach to subjective weighting procedures.

The second novelty is the comparison of the criteria weights obtained using different objective MCDM methods, as well as their comparison with the weights obtained using the AHP method. In this research, the authors used an linear normalization procedure that does not distinguish between benefit and cost criteria. However, the authors believe that the applied normalization procedure is suitable for the problem under consideration.

The proposed approach is flexible with respect to changes in the number of criteria and the number of considered EV models.

However, the proposed approach has certain constraints. The main constraints include the selection of an appropriate number and type of EV models, as well as the identification of EV characteristics that adequately reflect customer preferences and other requirements of the decision-making environment.

Future research should investigate the robustness and sensitivity of the obtained results under different normalization procedures, particularly when a larger number of different types of EVs is considered. Additionally, the proposed approach can be extended to analyse other management decision-making problems in various research areas.

REFERENCES

- Arsić, D., Ivković, D., Sudžum, R., Marinković, D., & Komatina, N. (2025). Selection of Base Materials for Repair Welding Using BWM-TOPSIS and BWM-RADAR Approaches. *Materials*, 18(24), 5696. <https://doi.org/10.3390/ma18245696>
- Biswas, T. K., & Das, M. C. (2019). Selection of Commercially Available Electric Vehicle using Fuzzy AHP-MABAC. *Journal of The Institution of Engineers (India): Series C*, 100(3), 531–537. <https://doi.org/10.1007/s40032-018-0481-3>
- Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research*, 2(6), 429–444. [https://doi.org/10.1016/0377-2217\(78\)90138-8](https://doi.org/10.1016/0377-2217(78)90138-8)
- Chen, P. (2021). Effects of the entropy weight on TOPSIS. *Expert Systems with Applications*, 168, 114186. <https://doi.org/10.1016/j.eswa.2020.114186>
- 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>
- Deuten, S., Gómez Vilchez, J. J., & Thiel, C. (2020). Analysis and testing of electric car incentive scenarios in the Netherlands and Norway. *Technological Forecasting and Social Change*, 151, 119847. <https://doi.org/10.1016/j.techfore.2019.119847>
- Diakoulaki, D., Mavrotas, G., & Papayannakis, L. (1995). Determining objective weights in multiple criteria problems: The critic method. *Computers & Operations Research*, 22(7), 763–770. [https://doi.org/10.1016/0305-0548\(94\)00059-H](https://doi.org/10.1016/0305-0548(94)00059-H)

- Egnér, F., & Trosvik, L. (2018). Electric vehicle adoption in Sweden and the impact of local policy instruments. *Energy Policy*, 121, 584–596. <https://doi.org/10.1016/j.enpol.2018.06.040>
- Eskov, V. M., Eskov, V. V., Vochmina, Yu. V., Gorbunov, D. V., & Ilyashenko, L. K. (2017). Shannon entropy in the research on stationary regimes and the evolution of complexity. *Moscow University Physics Bulletin*, 72(3), 309–317. <https://doi.org/10.3103/S0027134917030067>
- Falatoonitoosi, E., Leman, Z., Sorooshian, S., & Salimi, M. (2013). Decision-Making Trial and Evaluation Laboratory. *Research Journal of Applied Sciences, Engineering and Technology*, 5(13), 3476–3480. <https://doi.org/10.19026/rjaset.5.4475>
- Flores, B. E., & Whybark, D. C. (1987). Implementing multiple criteria ABC analysis. *Journal of Operations Management*, 7(1–2), 79–85. [https://doi.org/10.1016/0272-6963\(87\)90008-8](https://doi.org/10.1016/0272-6963(87)90008-8)
- Gustafsson, M., Svensson, N., Eklund, M., & Fredriksson Möller, B. (2021). Well-to-wheel climate performance of gas and electric vehicles in Europe. *Transportation Research Part D: Transport and Environment*, 97, 102911. <https://doi.org/10.1016/j.trd.2021.102911>
- Komatina, N., & Marinković, D. (2025). An Objective Multi-Attribute Decision-Making Framework for Identifying Critical Phases in Automotive Component Manufacturing. *Journal of Engineering Management and Systems Engineering*, 5(1), 1–9. <https://doi.org/10.56578/jemse050101>
- Komatina, N., Tadić, D., Aleksić, A., & Jovanović, A. D. (2023). The assessment and selection of suppliers using AHP and MABAC with type-2 fuzzy numbers in automotive industry. *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability*, 237(4), 836–852. <https://doi.org/10.1177/1748006X221095359>
- Krishnan, A. R. (2025). Research trends in criteria importance through intercriteria correlation (CRITIC) method: A visual analysis of bibliographic data using the Tableau software. *Information Discovery and Delivery*, 53(2), 233–247. <https://doi.org/10.1108/IDD-02-2024-0030>
- Langbroek, J. H. M., Franklin, J. P., & Susilo, Y. O. (2017). Electric vehicle users and their travel patterns in Greater Stockholm. *Transportation Research Part D: Transport and Environment*, 52, 98–111. <https://doi.org/10.1016/j.trd.2017.02.015>
- Liu, J., Wang, J., Ding, X., Shao, W., Mei, C., Li, Z., & Wang, K. (2020). Assessing the mitigation of greenhouse gas emissions from a green infrastructure-based urban drainage system. *Applied Energy*, 278, 115686. <https://doi.org/10.1016/j.apenergy.2020.115686>
- Mandal, N., Sarkar, P., & Petrović, N. (2025). Multi-Criteria Decision-Making for Ranking Renewable Energy Sources: A Case Study from the Republic of Serbia. *Journal of Engineering Management and Systems Engineering*, 4(2), 109–121. <https://doi.org/10.56578/jemse040203>
- 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>
- Milićević, M. R., & Župac, G. Ž. (2012). An objective approach to determining criteria weights. *Vojnotehnicki Glasnik*, 60(1), 39–56. <https://doi.org/10.5937/vojtehg1201039M>
- Rezaei, J. (2015). Best-worst multi-criteria decision-making method. *Omega*, 53, 49–57. <https://doi.org/10.1016/j.omega.2014.11.009>
- 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>
- Saraiva, P. (2023). On Shannon entropy and its applications. *Kuwait Journal of Science*, 50(3), 194–199. <https://doi.org/10.1016/j.kjs.2023.05.004>
- Shannon, C. E. (1948). A Mathematical Theory of Communication. *Bell System Technical Journal*, 27(3), 379–423. <https://doi.org/10.1002/j.1538-7305.1948.tb01338.x>
- 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>
- 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>
- Tadić, D., Lukić, J., Komatina, N., Marinković, D., & Pamučar, D. (2025). A Fuzzy Decision-Making Approach to Electric Vehicle Evaluation and Ranking. *Tehnicki Vjesnik/Technical Gazette*, 32(3), 1066–1075. <https://doi.org/10.17559/TV-20250223002410>

- 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>
- 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>
- Zhao, X., Ke, Y., Zuo, J., Xiong, W., & Wu, P. (2020). Evaluation of sustainable transport research in 2000–2019. *Journal of Cleaner Production*, 256, 120404. <https://doi.org/10.1016/j.jclepro.2020.120404>
- Zhu, G.-N., Hu, J., Qi, J., Gu, C.-C., & Peng, Y.-H. (2015). An integrated AHP and VIKOR for design concept evaluation based on rough number. *Advanced Engineering Informatics*, 29(3), 408–418. <https://doi.org/10.1016/j.aei.2015.01.010>