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How Do the Criteria Affect Sustainable Supplier Evaluation? - A Case Study Using Multi-Criteria Decision Analysis Methods in a Fuzzy Environment

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Abstract: Choosing a battery supplier is a vital decision-making problem, for which it is essential to obtain stable evaluations. For such sustainable supplier evaluation, multi-criteria decision analysis (MCDA) methods are often used, as their ability to handle uncertain data gives experts more significant opportunities to consider a broader range of cases. However, given the great number of MCDA approaches, it is challenging to find out which approach is the most appropriate. Therefore, this paper presents a sensitivity analysis on evaluating battery suppliers by ARAS, EDAS, MAIRCA, TOPSIS, and VIKOR methods in a fuzzy environment. The provided study presented similar results for the considered MCDA methods confirmed by the WS similarity measure of rankings and the weighted Spearman correlation r_w. On the other hand, the sensitivity analysis conducted on the considered methods indicated that the most relevant criteria for this problem are transportation cost, delivery time, and warranty period.

Keywords: Sustainability; Energy management; Batteries; Decision-making; Triangular fuzzy numbers; MCDA; Robustness

1. Introduction

Decision-makers are facing a vast number of problems on a daily basis, and what final decisions they make are influenced by many factors [1]. However, the analytical capacity of decision-makers to determine the attractiveness of the chosen options can be significantly limited. Therefore, situations in which the problem's dimensionality exceeds the decision-makers' analytical capacity should be avoided [2]. To this end, techniques have emerged to help assess decision variants' attractiveness based on input data. Among these techniques, Multi-Criteria Decision Analysis (MCDA) methods are a popular solution used in this area, mainly due to their flexibility, ability to process data in complex problems analytically, and high operational speed [3]. Being an important part of the decision-making chain, MCDA supports decision-makers with their results, and Decision Support Systems (DSS), created based on the MCDA methods, equip decision-makers with additional knowledge by informing them of the preferred hierarchy of decision variants under consideration [4]. In addition, when sensitivity analysis techniques are used in developing such systems, it is possible to obtain the possible changes in ranking depending on changes in the input data.

MCDA methods were initially based on the operations of crisp numbers. It allowed calculations to be performed in an environment where all the data were precisely known [5]. However, for decision-making on real-world problems, it is also important how the data are represented and whether the knowledge about the parameters of the decision options is complete. Due to measurement uncertainties or lack of specific data in problems, it is often necessary to consider all potential values [6]. To this end, the basic assumptions on which multi-criteria methods are based have been extended to include fuzzy logic to widen the applicability of these methods to problems where uncertain knowledge arises. One of the most widely used extensions of fuzzy logic in decision-making is using

Triangular Fuzzy Numbers (TFNs) to represent uncertain knowledge [7]. Their premise is to represent data using the minimum expected value, the expected value, and the maximum expected value for a given parameter so that possible values in the problem can be considered in the calculations.

Due to their flexibility, MCDA methods are readily used in many practical areas, and their effectiveness has been verified many times. MCDA methods operating in crisp and fuzzy environments have been used to develop dedicated systems for solutions in healthcare [8], sports management [9], sustainable transport development [10], and energy management [11], among others. Energy development is a critical topic due to the implications of different energy sources, products, or production techniques and their impacts on the environment. The negative effects of human activity and the deteriorating state of the environment require that decisions taken in this area on the most rational and preferred choices are based on precise calculations that guarantee the robustness of the rankings against potential changes [12]. Therefore, techniques, characterized by high reliability and efficiency, should be used to ensure that the decisions made by decision makers point to the most attractive and sustainable solutions. MCDA methods are one of such techniques that can be used to create dedicated decision-support systems in these areas.

This paper proposed a research approach to identify the most rational solutions based on a set of MCDA methods operating in a fuzzy environment. Five multi-criteria techniques based on Triangular Fuzzy Numbers, namely fuzzy Additive Ratio Assessment (ARAS), fuzzy Distance from Average Solution (EDAS), fuzzy Multi-Attribute Ideal Real Comparative Analysis (MAIRCA), fuzzy Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), and fuzzy VIseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR), were used in the practical problem of selecting a battery supplier for the battery swapping station. In addition, a sensitivity analysis on the robustness of the results to changes was also carried out. The proposed solution uses a set of decision-making methods that provide a robust tool for evaluating options when combined with sensitivity analysis. Consequently, they can be used by decision-makers in the field of sustainable energy development to select decision variants in the most preferred way based on the assumptions of sustainability and quality of operation. The contribution of this work is that it proposed a methodology based on precise calculations to guarantee the high reliability of the results obtained from fuzzy MCDA methods and sensitivity analysis. In addition, the multi-criteria calculations in the study were based on the PyFDM library, which provided support for decision-makers in designing decision-support systems in a fuzzy environment using the Python language [13].

The rest of the paper is organized as follows. Section 2 presents the literature review regarding supplier selection, energy development, and the multi-criteria approaches used to assess possible decision variants. Section 3 shows the preliminaries of the Triangular Fuzzy Numbers and fuzzy MCDA techniques. Section 4 presents a study case for evaluating the sustainable battery supplier for the battery swapping station. Section 5 includes a discussion of the obtained results and their practical implications. Finally, Section 6 shows the conclusions drawn from the research and presents the future research directions.

2. Related Works

Supplier evaluation is an important decision-making problem that strongly affects the quality, efficiency and reliability of a supply chain [14]. There are often complex problems encountered in the selection of suppliers, including the many criteria against which suppliers can be evaluated, of which, some can be very specific. Without specialized tools, it is difficult for experts to take so many suppliers available into account.

Therefore, a frequently used tool to evaluate suppliers is the Multi-Criteria Decision Analysis (MCDA) methods. They can be used to solve supplier selection problems related to fields such as electronics, pharmaceuticals, textiles, or railroads [15]. Chang et al. [16] used an approach combining Indifference Threshold-based Attribute Ratio Analysis (ITARA) and Preference Ranking Organization Method for Enrichment Evaluation – Aspiration Level (PROMETHEE-AL) methods to assess the sustainability and spin-out of electronics suppliers. Kocaoğlu and Küçük [17] used TOPSIS, and Multi-Objective Optimisation by Ratio Analysis (MOORA) to evaluate the performance of 6 pharmaceutical companies operating in Turkey. Li et al. [18] used the Decision Making Trial and Evaluation Laboratory (DEMATEL) approach for supplier selection in China's textile industry. Bruno et al. [19] used the Analytic Hierarchy Process (AHP) approach to evaluate suppliers operating for AnsaldoBreda, a major Italian railroad manufacturer.

Popular methods used for the supplier evaluation problem include TOPSIS, VIKOR, AHP, Analytic Network Process (ANP), Data Envelopment Analysis (DEA) and Simple Multi-Attribute Rating Technique (SMART). Birgün Barla [20] used the SMART approach to evaluate suppliers for a manufacturing company under the lean philosophy. Garg and Sharma [21] used the Best-Worst Method - VIseKriterijumska Optimizacija I Kompromisno Resenje (BWM-VIKOR) approach to evaluate sustainable outsourcing partners for the Electronics Company of India. Zhang [22] used the TOPSIS method with entropy weights to evaluate suppliers of electrical power materials. Al Hazza et al. [23] used the DELPHI and AHP methods for a supplier selection problem. Kalantary et al. [24] used the DEA approach to assess the sustainability of supply chains.

Due to the limited data acquisition conditions, data are often approximate and challenging to represent in real numbers. Therefore, many popular MCDA methods have been extended to handle uncertain data. The most common tool for handling uncertain data in MCDA methods is fuzzy sets. Cakar and Çavuş [25] used a fuzzy TOPSIS method to select a dairy supplier in Macedonia. Bahadori et al. [26] used an artificial neural network and fuzzy VIKOR to evaluate hospital suppliers. Ghorabaee et al. [27] applied an extension of the EDAS approach in a fuzzy environment in which suppliers were evaluated. Basaran and Çakir [28] used the fuzzy COPRAS method for supplier selection in the food industry.

There are other tools related to handling uncertain data, such as Interval data, Intuitionistic fuzzy sets, Pythagorean fuzzy sets, Fermatean fuzzy sets, Picture fuzzy sets, Neutrosophic fuzzy sets, and Spherical fuzzy sets. Zhang and Li [29] applied the interval extensions of the TOPSIS and GRA methods to the problem of supplier spinning. Kumari and Mishra [30] used intuitionistic fuzzy COPRAS for green supplier selection. Keshavarz-Ghorabaee et al. [31] used WASPAS and SMART methods in a Fermatean fuzzy sets environment to evaluate a green building supplier. Zhang et al. [32] used the EDAS method in the Picture fuzzy sets environment to evaluate green suppliers.

Given as many approaches related to MCDA, similarities between them are constantly being studied. Rashidi and Cullinane [33] compared the methods of fuzzy DEA and fuzzy TOPSIS in the problem of selecting sustainable suppliers. Junior et al. [34] conducted a study comparing fuzzy AHP and fuzzy TOPSIS methods for the supplier selection problem of a company in the automotive manufacturing chain. Kizielewicz et al. [35] conducted research on MCDA methods such as COMET, TOPSIS, and SPOTIS in material supplier evaluation.

Therefore, this paper takes battery suppliers as an example, and focuses on developing a framework related to sustainable supplier evaluation, using MCDA methods that operate on uncertain data. By examining the similarities between them and conducting a sensitivity analysis against the criteria, the study finds out about the stability and reliability of the proposed framework.

3. Preliminaries

3.1 Triangular Fuzzy Numbers

Fuzzy Set Theory and its extensions are important to modelling in various scientific fields where multi-criteria decision problems are considered. Some of the main assumptions for this theory are described below:

The Fuzzy Set and the Membership Function - the characteristic function μ_A of a crisp set $A \subseteq X$ assigns a value of either 0 or 1 to each member of X, and the crisp sets only allow a full membership ($\mu_A(x) = 1$) or no membership at all ($\mu_A(x) = 0$). This function can be generalized to a function $\mu_{\tilde{A}}$ so that the value assigned to the element of the universal set X falls within a specified range, i.e., $\mu_{\tilde{A}}: X \to [0,1]$. The assigned value indicates the degree of membership of the element in the set A. The function $\mu_{\tilde{A}}$ is called a membership function and the set $\tilde{A} = \left(x, \mu_{\tilde{A}}(x)\right)$, where $x \in X$, defined by $\mu_{\tilde{A}}(x)$ for each $x \in X$ is called a fuzzy set.

The Triangular Fuzzy Number (TFN) - a fuzzy set $\tilde{A}$, defined on the universal set of real numbers R, is said to be a triangular fuzzy number $\tilde{A}(a, m, b)$ if its membership function takes on the following form (1):

$$\mu_{\tilde{A}}(x, a, m, b) = \begin{cases} 0, & x \leq a \\ \dfrac{x-a}{m-a}, & a \leq x \leq m \\ 1, & x = m \\ \dfrac{b-x}{b-m}, & m \leq x \leq b \\ 0, & x \geq b \end{cases} \tag{1}$$

and the following characteristics (2) and (3):

$$x_1, x_2 \in [a, b] \wedge x_2 > x_1 \Rightarrow \mu_{\tilde{A}}(x_2) > \mu_{\tilde{A}}(x_1) \tag{2}$$

$$x_1, x_2 \in [b, c] \wedge x_2 > x_1 \Rightarrow \mu_{\tilde{A}}(x_2) > \mu_{\tilde{A}}(x_1) \tag{3}$$

The Support of a TFN - the support of a TFN $\tilde{A}$ is defined as a crisp subset of the set $\tilde{A}$ in which all elements have a non-zero membership value, as shown in (4):

$$S(\tilde{A}) = x: \mu_{\tilde{A}}(x) > 0 = [a, b] \tag{4}$$

The Core of a TFN - the core of a TFN $\tilde{A}$ is a singleton (one-element fuzzy set) with the membership value being equal to 1, as shown in (5):

$$C(\tilde{A}) = x\colon \mu_{\tilde{A}}(x) = 1 = m \quad (5)$$

The Fuzzy Rule - the single fuzzy rule can be based on the Modus Ponens tautology. The reasoning process uses the logical connectives *IF - THEN*, *OR* and *AND*.

3.2 Fuzzy Additive Ratio Assessment

The fuzzy extension of the Additive Ratio Assessment (ARAS) method was proposed by Zavadskas and Turskis [36]. It allows for operation in an uncertain environment based on the data represented as TFNs. The main steps of the fuzzy ARAS procedure can be described as follows.

Step 1. Establish the triangular fuzzy decision matrix, which contains m options and n criteria (i = 1, 2, …, m and j = 1, 2, …, n) (6).

$$X = \begin{bmatrix} x_{11} & \cdots & x_{1j} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i1} & \cdots & x_{ij} & \cdots & x_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mj} & \cdots & x_{mn} \end{bmatrix} \quad (6)$$

where x_{ij} is represented as Triangular Fuzzy Number (x^L, x^M, x^U).

Step 2. Determine the optimal value of each criterion value (7).

$$\tilde{X} = \begin{bmatrix} \widetilde{x_{01}} & \cdots & \widetilde{x_{0j}} & \cdots & \widetilde{x_{0n}} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \widetilde{x_{i1}} & \cdots & \widetilde{x_{ij}} & \cdots & \widetilde{x_{in}} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \widetilde{x_{m1}} & \cdots & \widetilde{x_{mj}} & \cdots & \widetilde{x_{mn}} \end{bmatrix} \quad (7)$$

where $\widetilde{x_{0j}}$ denotes the optimal value of criterion j (for the profit criterion,$\widetilde{x_{0j}}=\max_i x_{ij}$; and for the cost criterion, $\widetilde{x_{0j}}= \min_i x_{ij}$).

Step 3. Calculate the normalized fuzzy decision matrix (8).

$$\tilde{\bar{X}} = \begin{bmatrix} \widetilde{\bar{x}_{01}} & \cdots & \widetilde{\bar{x}_{0j}} & \cdots & \widetilde{\bar{x}_{0n}} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \widetilde{\bar{x}_{i1}} & \cdots & \widetilde{\bar{x}_{ij}} & \cdots & \widetilde{\bar{x}_{in}} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \widetilde{\bar{x}_{m1}} & \cdots & \widetilde{\bar{x}_{m1}} & \cdots & \widetilde{\bar{x}_{mn}} \end{bmatrix} \quad (8)$$

where for the profit criterion, the normalization formula is presented as follows (9):

$$\widetilde{\bar{x}_{ij}} = \frac{\widetilde{x_{ij}}}{\sum_{i=0}^{m} \widetilde{x_{ij}}} \quad (9)$$

and for the cost criterion, the normalization formula is presented as follows (10):

$$\widetilde{\bar{x}_{ij}} = \frac{\frac{1}{\widetilde{x_{ij}}}}{\sum_{i=0}^{m} \frac{1}{\widetilde{x_{ij}}}} \quad (10)$$

Step 4. Calculate the weighted normalized fuzzy decision matrix with Eq. (11):

$$\tilde{\hat{X}} = \begin{bmatrix} \widetilde{\hat{x}_{01}} & \cdots & \widetilde{\hat{x}_{0j}} & \cdots & \widetilde{\hat{x}_{0n}} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \widetilde{\hat{x}_{i1}} & \cdots & \widetilde{\hat{x}_{ij}} & \cdots & \widetilde{\hat{x}_{in}} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \widetilde{\hat{x}_{m1}} & \cdots & \widetilde{\hat{x}_{mj}} & \cdots & \widetilde{\hat{x}_{mn}} \end{bmatrix} \tag{11}$$

where $\widetilde{\hat{x}_{ij}} = \widetilde{\bar{x}_{ij}} \times \widetilde{w_j}, i = 0,1, \dots, m, j = 1,2, \dots, n.$

Step 5. Determine the overall performance index for each option (12).

$$\widetilde{S_i} = \sum_{j=1}^{n} \widetilde{\hat{x}_{ij}}, i = 0,1, \dots, m \tag{12}$$

Step 6. Calculate the defuzzified value of the performance index (13).

$$\widetilde{S_i} = \frac{1}{3}\left(\widetilde{S_i^L} + \widetilde{S_i^M} + \widetilde{S_i^U}\right), i = 0,1, \dots, m \tag{13}$$

Step 7. Determine the utility degree of each option with Eq. (14):

$$Q_i = \frac{\widetilde{S_i}}{\widetilde{S_0}}, i = 0,1, \dots, m \tag{14}$$

3.3 Fuzzy Evaluation Based on Distance from Average Solution

The Evaluation based on Distance from Average Solution (EDAS) method was proposed by Keshavarz Ghorabaee et al. [37]. Its functioning is based on the calculation of the positive distance from average (PDA) and negative distance from average (NDA). The decision variants characterized by higher PDA values and lower NDA values are preferable. The triangular fuzzy number extension of the standard EDAS method enables it to operate in the fuzzy environment where there are uncertain data. The main steps of the method are presented as follows.

Step 1. Determine the triangular fuzzy decision matrix based on the Eq. (6).

Step 2. Determine the average triangular fuzzy decision matrix based on the initial triangular fuzzy decision matrix and formula presented below (15):

$$\mathrm{AV_j} = \frac{\sum_{i=1}^{n} x_{ij}}{k} \tag{15}$$

Step 3. Calculate the fuzzy Positive Distance from Average (PDA) and fuzzy Negative Distance from Average (NDA) (16):

$$\mathrm{PDA} = \left[\mathrm{pda_{ij}}\right]_{n\times m} \mathrm{NDA} = \left[\mathrm{nda_{ij}}\right]_{n\times m} \tag{16}$$

where for the profit criterion, the values are calculated as (17):

$$\mathrm{PDA_{ij}} = \frac{\psi\left(x_{ij} - \mathrm{AV_j}\right)}{k\left(\mathrm{AV_j}\right)} \mathrm{NDA_{ij}} = \frac{\psi\left(\mathrm{AV_j} - x_{ij}\right)}{k\left(\mathrm{AV_j}\right)} \tag{17}$$

and for the cost criterion, the values are calculated with Eq. (18):

$$PDA_{ij} = \frac{\psi\left(AV_j\right) - x_{ij}}{k\left(AV_j\right)} NDA_{ij} = \frac{\psi\left(x_{ij} - AV_j\right)}{k\left(AV_j\right)} \tag{18}$$

Step 4. Calculate the fuzzy weighted positive (SP) and negative (SN) distances (19).

$$\mathrm{SP_i} = \sum_{j=1}^{m}\left(\widetilde{w_j} + \mathrm{PDA_{ij}}\right) \mathrm{SN_i} = \sum_{j=1}^{m}\left(\widetilde{w_j} + \mathrm{NDA_{ij}}\right) \tag{19}$$

Step 5. Determine the normalized fuzzy weighted positive (NSP) and negative (NSN) distances (20).

$$\mathrm{NSP_i} = \frac{SP_i}{\max_i\left(k(SP_i)\right)} \mathrm{NSN_i} = 1 - \frac{SN_i}{\max_i\left(k(SN_i)\right)} \tag{20}$$

Step 6. Calculate the fuzzy Appraisal Score (AS) for each option (21).

$$\mathrm{AS_i} = \frac{NSP_i + NSN_i}{2} \tag{21}$$

3.4 Fuzzy Multi-Attribute Ideal Real Comparative Analysis

The Multi-Attribute Ideal Real Comparative Analysis (MAIRCA) method is based on calculating the equal probability for selecting each option. Moreover, it uses a theoretical ponder matrix, and an actual ponder matrix to determine the final preferences. The subsequent steps of the method are presented below.

Step 1. Determine the triangular fuzzy decision matrix based on the Eq. (6).

Step 2. Determine the probability of selecting an option based on the Eq. (22):

$$P_{A_i} = \frac{1}{m}; \sum_{i=1}^{m} P_{A_i} = 1 \tag{22}$$

Step 3. Calculate the theoretical fuzzy decision matrix (23):

$$\overline{X} = \begin{bmatrix} \widetilde{t_{11}} & \cdots & \widetilde{t_{1j}} & \cdots & \widetilde{t_{1n}} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \widetilde{t_{i1}} & \cdots & \widetilde{t_{ij}} & \cdots & \widetilde{t_{in}} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \widetilde{t_{m1}} & \cdots & \widetilde{t_{mj}} & \cdots & \widetilde{t_{mn}} \end{bmatrix} \tag{23}$$

where $\widetilde{t_{ij}}$ is calculated as $\frac{1}{m} w_j$.

Step 4. Calculate the normalized fuzzy decision matrix (24):

$$\tilde{X} = \begin{bmatrix} \widetilde{x_{11}} & \cdots & \widetilde{x_{1j}} & \cdots & \widetilde{x_{1n}} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \widetilde{x_{i1}} & \cdots & \widetilde{x_{ij}} & \cdots & \widetilde{x_{in}} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \widetilde{x_{m1}} & \cdots & \widetilde{x_{m1}} & \cdots & \widetilde{x_{mn}} \end{bmatrix} \tag{24}$$

with the normalization formula given below (25):

$$\begin{gathered} n_{ij}^{L} = \frac{x_{ij}^{L}}{\sqrt{\sum_{i=1}^{m}\left[\left(x_{ij}^{L}\right)^2 + \left(x_{ij}^{M}\right)^2 + \left(x_{ij}^{U}\right)^2\right]}} \\ n_{ij}^{M} = \frac{x_{ij}^{M}}{\sqrt{\sum_{i=1}^{m}\left[\left(x_{ij}^{L}\right)^2 + \left(x_{ij}^{M}\right)^2 + \left(x_{ij}^{U}\right)^2\right]}} \\ n_{ij}^{U} = \frac{x_{ij}^{U}}{\sqrt{\sum_{i=1}^{m}\left[\left(x_{ij}^{L}\right)^2 + \left(x_{ij}^{M}\right)^2 + \left(x_{ij}^{U}\right)^2\right]}} \end{gathered} \tag{25}$$

Step 5. Calculate the fuzzy elements of the actual ponder matrix (26):

$$\tilde{\tilde{X}} = \begin{bmatrix} \widetilde{\tilde{t}_{11}} & \cdots & \widetilde{\tilde{t}_{1J}} & \cdots & \widetilde{\tilde{t}_{1n}} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \widetilde{\tilde{t}_{\imath 1}} & \cdots & \widetilde{\tilde{t}_{\imath J}} & \cdots & \widetilde{\tilde{t}_{\imath n}} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \widetilde{\tilde{t}_{m1}} & \cdots & \widetilde{\tilde{t}_{m1}} & \cdots & \widetilde{\tilde{t}_{mn}} \end{bmatrix} \tag{26}$$

where $\widetilde{\tilde{t}_{\imath J}}$ is calculated as $\widetilde{x_{\imath J}} \times \widetilde{t_{\imath J}}$.

Step 6. Calculate the fuzzy elements of the actual ponder matrix (27):

$$G_{ij} = \sqrt{\frac{1}{3}\left[\left(\widetilde{t_{\imath J}{}^{L}} - \widetilde{\tilde{t}_{\imath J}{}^{L}}\right)^2 + \left(\widetilde{t_{\imath J}{}^{M}} - \widetilde{\tilde{t}_{\imath J}{}^{M}}\right)^2 + \left(\widetilde{t_{\imath J}{}^{U}} - \widetilde{\tilde{t}_{\imath J}{}^{U}}\right)^2\right]} \tag{27}$$

Step 7. Determine the final preference values (28).

$$Q_i = \sum_{j=1}^{n} g_{ij}\,; i = 1,2, \ldots, m \tag{28}$$

3.5 Fuzzy Technique for Order Preference by Similarity to an Ideal Solution

The Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) method is based on the distances to ideal solutions called Positive Ideal Solution (PIS) and Negative Ideal Solution (NIS). To extend the practical possibilities of the standard TOPSIS method, many fuzzy extensions have been introduced to this technique. One proposed solution is to operate on Triangular Fuzzy Numbers in an uncertain environment. To introduce the fuzzy TOPSIS method, the main steps of the calculations are presented as follows.

Step 1. Determine the triangular fuzzy decision matrix based on Eq. (6).

Step 2. Calculate the normalized fuzzy decision matrix (29):

$$\tilde{X} = \begin{bmatrix} \widetilde{x_{11}} & \cdots & \widetilde{x_{1J}} & \cdots & \widetilde{x_{1n}} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \widetilde{x_{\imath 1}} & \cdots & \widetilde{x_{\imath J}} & \cdots & \widetilde{x_{\imath n}} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \widetilde{x_{m1}} & \cdots & \widetilde{x_{m1}} & \cdots & \widetilde{x_{mn}} \end{bmatrix} \tag{29}$$

where for the profit criterion, the values are calculated as (30):

$$\widetilde{x_{\imath J}} = \left(\frac{x_{ij}^{L}}{x_j^{*}}, \frac{x_{ij}^{M}}{x_j^{*}}, \frac{x_{ij}^{U}}{x_j^{*}}\right); x_j^{*} = \max_i\{x_{ij}^{U}\} \tag{30}$$

and for the cost criterion, the values are calculated with Eq. (31):

$$\widetilde{x_{\imath J}} = \left(\frac{x_j^{-}}{x_{ij}^{U}}, \frac{x_j^{-}}{x_{ij}^{M}}, \frac{x_j^{-}}{x_{ij}^{L}}\right); x_j^{-} = \min_i\{x_{ij}^{L}\} \tag{31}$$

Step 3. Calculate the weighted normalized fuzzy decision matrix with Eq. (32):

$$\tilde{\hat{X}} = \begin{bmatrix} \widetilde{\hat{x}_{11}} & \cdots & \widetilde{\hat{x}_{1J}} & \cdots & \widetilde{\hat{x}_{1n}} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \widetilde{\hat{x}_{\imath 1}} & \cdots & \widetilde{\hat{x}_{\imath J}} & \cdots & \widetilde{\hat{x}_{\imath n}} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \widetilde{\hat{x}_{m1}} & \cdots & \widetilde{\hat{x}_{mJ}} & \cdots & \widetilde{\hat{x}_{mn}} \end{bmatrix} \tag{32}$$

where $\widetilde{\hat{x}_{\imath J}} = \widetilde{x_{\imath J}} \times \widetilde{w_J}, i = 0,1, \ldots, m, j = 1,2, \ldots, n.$

Step 4. Determine the Fuzzy Positive Ideal Solution (FPIS) (33) and Fuzzy Negative Ideal Solution (FNIS) (34):

$$A^* = \left(\widetilde{\hat{x}_1^*}, \widetilde{\hat{x}_2^*}, \cdots, \widetilde{\hat{x}_n^*}\right); \widetilde{\hat{x}_j^*} = \max_i\left\{\widetilde{\hat{x}_{ij}}\right\} \tag{33}$$

$$A^- = \left(\widetilde{\hat{x}_1^-}, \widetilde{\hat{x}_2^-}, \cdots, \widetilde{\hat{x}_n^-}\right); \widetilde{\hat{x}_j^-} = \min_i\left\{\widetilde{\hat{x}_{ij}}\right\} \tag{34}$$

Step 5. Calculate the distance from each option to FPIS and FNIS as follows (35):

$$D_i^* = \sum_{j=1}^{n} d\left(\widetilde{\hat{x}_{ij}}, \widetilde{\hat{x}_j^*}\right) D_i^- = \sum_{j=1}^{n} d\left(\widetilde{\hat{x}_{ij}}, \widetilde{\hat{x}_j^-}\right) \tag{35}$$

Step 6. Determine the Closeness Coefficient CC_i for each option (36):

$$CC_i = \frac{D_i^-}{D_i^- + D_i^*} \tag{36}$$

3.6 Fuzzy VIseKriterijumska Optimizacija I Kompromisno Resenje

The VIseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) method is an approach that produces three distinctive rankings (S, R and compromised solution Q). The standard technique that operates on the crisp numbers was developed with many fuzzy extensions that allow for calculating results when uncertain data appear. One method applied to fuzzy problems is the Triangular Fuzzy Number VIKOR. The main steps of this technique are presented below.

Step 1. Determine the triangular fuzzy decision matrix based on Eq. (6).

Step 2. Determine the Ideal and Non-Ideal Solutions for each criterion based on the criterion type for the profit criterion (37):

$$\widetilde{f_i^*} = MAX\widetilde{f_{ij}}\widetilde{f_i^\circ} = MIN\widetilde{f_{ij}} \tag{37}$$

and for the cost criterion (38):

$$\widetilde{f_i^*} = MIN\widetilde{f_{ij}}\widetilde{f_i^\circ} = MAX\widetilde{f_{ij}} \tag{38}$$

Step 3. Calculate the normalized fuzzy difference from Ideal Solution for the profit criterion (39):

$$\widetilde{D_{ij}} = \left(\widetilde{f_i^*} - \widetilde{f_{ij}}\right)/(x_i^{*U} - x_i^{\circ L}) \tag{39}$$

and for the cost criterion (40):

$$\widetilde{D_{ij}} = \left(\widetilde{f_{ij}} - \widetilde{f_i^*}\right)/(x_i^{\circ U} - x_i^{*L}) \tag{40}$$

Step 4. Calculate the fuzzy values of $\tilde{S}$ and $\tilde{R}$ (41).

$$\widetilde{S_j} = \sum_{i=1}^{n} \oplus \left(\widetilde{w_i} \otimes \widetilde{D_{ij}}\right)\widetilde{R_j} = MAX_i\left(\widetilde{w_i} \otimes \widetilde{D_{ij}}\right) \tag{41}$$

where $\widetilde{w_i}$ is the weight of the *i-th* criterion.

Step 5. Determine the fuzzy $\tilde{Q}$ values (42).

$$\widetilde{Q_j} = v\frac{\left(\widetilde{S_j} - \widetilde{S^*}\right)}{(S^{\circ U} - S^{*L})} \oplus \frac{(1-v)\left(\widetilde{R_j} - \widetilde{R^*}\right)}{(R^{\circ U} - R^{*L})} \tag{42}$$

where v can be adjusted by expert ($v \in [0, 1]$), and

$$\begin{gathered} \widetilde{S^{*L}} = MIN\left(\widetilde{S_j^L}\right)S^{\circ U} = MAX\left(S_j^U\right) \\ \widetilde{\mathrm{R}^{*\mathrm{L}}} = \mathrm{MIN}\left(\widetilde{\mathrm{R}_\mathrm{j}^\mathrm{L}}\right)\mathrm{R}^{\circ\mathrm{U}} = \mathrm{MAX}\left(\mathrm{R}_\mathrm{j}^\mathrm{U}\right) \end{gathered} \tag{43}$$

Step 6. Calculate the defuzzified preference values (44).

$$\widetilde{N_\iota} = \frac{\left(2x_j^M + x_j^L + x_j^U\right)}{4} \tag{44}$$

4. Case Study

The following study used five fuzzy MCDA methods to obtain a comparative ranking and identify the most rational choice of battery supplier for the battery swapping station. It is an important practical problem due to the need to consider both sustainability and operational efficiency assumptions in order for the range of components used in energy processes to be continuously improved.

The study was based on the problem addressed by Wang et al. [38], where the optimal choice of sustainable battery supplier for the battery swapping station was determined using the entropy-Multiplicative Multi-Objective Optimisation by Ratio Analysis (MULTIMOORA) method. The authors defined a set of 15 criteria, which were divided into five categories by field, namely economical (C_1– C_3), environmental (C_4– C_6), social (C_7– C_9), technical (C_{10}– C_{12}), and service (C_{13}– C_{15}). Table 1 shows the decision matrix established by Wang in their study, in which there are four battery suppliers A_1, A_2, A_3 and A_4. Due to the uncertainties in the values of the individual parameters in the problem, the data were presented in the form of Triangular Fuzzy Numbers. In addition, vectors of weights in the form of crisp values were defined using the criteria weighting approach based on the entropy method of decision matrix information. The determined vectors of weights for the criteria considered in the problem are presented in Table 2.

Table 1. Decision matrix for the battery supplier selection problem [38]

Area	C_i	A_1	A_2	A_3	A_4
Economical	C_1	(0.375, 0.500, 0.750)	(0.375, 0.522, 0.857)	(0.500, 0.667, 1.000)	(0.429, 0.571, 0.857)
	C_2	(0.750, 0.857, 1.000)	(0.167, 0.200, 0.250)	(0.500, 0.600, 0.750)	(0.750, 0.857, 1.000)
	C_3	(0.500, 0.667, 0.833)	(0.833, 1.000, 1.000)	(0.500, 0.667, 0.833)	(0.333, 0.500, 0.667)
Environmental	C_4	(0.334, 0.502, 1.000)	(0.250, 0.334, 0.502)	(0.250, 0.334, 0.502)	(0.334, 0.502, 1.000)
	C_5	(0.250, 0.334, 0.502)	(0.334, 0.502, 1.000)	(0.250, 0.334, 0.502)	(0.334, 0.502, 1.000)
	C_6	(0.500, 0.667, 0.833)	(0.667, 0.833, 1.000)	(0.250, 0.334, 0.502)	(0.334, 0.502, 1.000)
Social	C_7	(0.500, 0.667, 0.833)	(0.667, 0.833, 1.000)	(0.333, 0.500, 0.667)	(0.500, 0.667, 0.833)
	C_8	(0.500, 0.667, 0.833)	(0.833, 1.000, 1.000)	(0.500, 0.667, 0.833)	(0.667, 0.833, 1.000)
	C_9	(0.334, 0.502, 1.000)	(0.334, 0.502, 1.000)	(0.250, 0.334, 0.502)	(0.334, 0.502, 1.000)
Technical	C_{10}	(0.500, 0.667, 0.833)	(0.833, 1.000, 1.000)	(0.333, 0.500, 0.667)	(0.333, 0.500, 0.667)
	C_{11}	(0.500, 0.667, 0.833)	(0.833, 1.000, 1.000)	(0.500, 0.667, 0.833)	(0.167, 0.333, 0.500)
	C_{12}	(0.667, 0.833, 1.000)	(0.833, 1.000, 1.000)	(0.500, 0.667, 0.833)	(0.333, 0.500, 0.667)
Service	C_{13}	(0.833, 1.000, 1.000)	(0.500, 0.667, 0.833)	(0.667, 0.750, 0.833)	(0.333, 0.500, 0.667)
	C_{14}	(0.833, 0.917, 1.000)	(0.833, 0.917, 1.000)	(0.667, 0.750, 0.833)	(0.667, 0.750, 0.833)
	C_{15}	(0.167, 0.333, 0.500)	(0.667, 0.833, 1.000)	(0.500, 0.667, 0.833)	(0.333, 0.500, 0.667)

Table 2. Weights determined with the entropy method

C_i	Weights	C_i	Weights	C_i	Weights	C_i	Weights	C_i	Weights
C_1	0.136	C_4	0.058	C_7	0.033	C_{10}	0.088	C_{13}	0.024
C_2	0.236	C_5	0.058	C_8	0.027	C_{11}	0.115	C_{14}	0.012
C_3	0.012	C_6	0.033	C_9	0.039	C_{12}	0.064	C_{15}	0.064

Table 3. Rankings calculated with selected fuzzy MCDA methods

A_i	fARAS	fEDAS	fMAIRCA	fTOPSIS	fVIKOR
A_1	1	1	1	1	1
A_2	2	3	3	3	4
A_3	4	4	4	4	2
A_4	3	2	2	2	3

In the reference study, the authors chose to perform calculations using the MULTIMOORA method, which is based on the Reference Point Theory and uses the ratios of the ratio system [39]. The resulting ranking was considered as a reference point in the study, with the ranking order of the options presented in Table 1. The following study extended the scope of the calculation by considering a set of selected methods operating on fuzzy data in the form of Triangular Fuzzy Numbers. The four options were evaluated using fuzzy ARAS, fuzzy EDAS, fuzzy MAIRCA, fuzzy TOPSIS, and fuzzy VIKOR. The multi-criteria evaluation was performed using the PyFDM package, which is a library dedicated to the Python language and, in its functionalities, allows multi-criteria calculations to be performed in a fuzzy environment [13]. The resulting rankings are presented in Table 3, and the rankings of options by method are shown in Figure 1. In addition, the flows of the rankings obtained by the successively used methods are visualized in Figure 2, where the changes in the ranking order of the options corresponding to the individual multi-criteria techniques can be seen.

It is worth noting the consistency in the way the options were evaluated concerning the methods used. The best-ranked decision variant was option A_1, as can be seen in Figure 1. Regardless of the evaluation technique used, this option was always the most preferred choice of battery supplier.

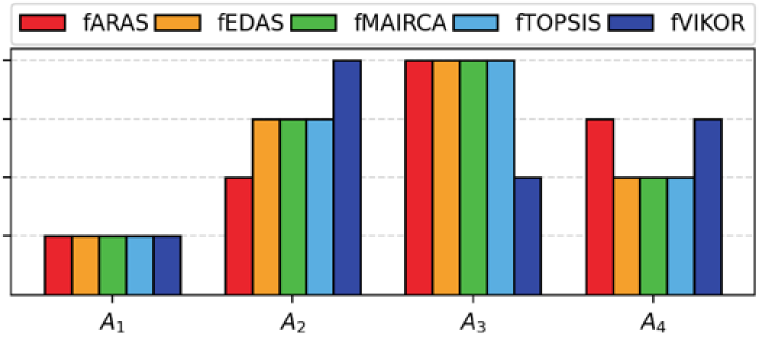


Figure 1. Rankings of battery suppliers obtained by selected MCDA methods

Figure 2 highlights explicitly where differences emerged between the ranking orders of the options by the different methods. Two significant differences can be seen: the fuzzy ARAS method ranked option A_2 more favourably, while fuzzy EDAS, fuzzy MAIRCA, and fuzzy TOPSIS ranked this option in the 3rd position in favour of the higher ranked option A_4 , and in contrast, the compromise ranking Q from the fuzzy VIKOR method indicated that option A_2 was the worst choice and that options A_4 and A_3 were at the 3rd and 2nd positions, respectively.

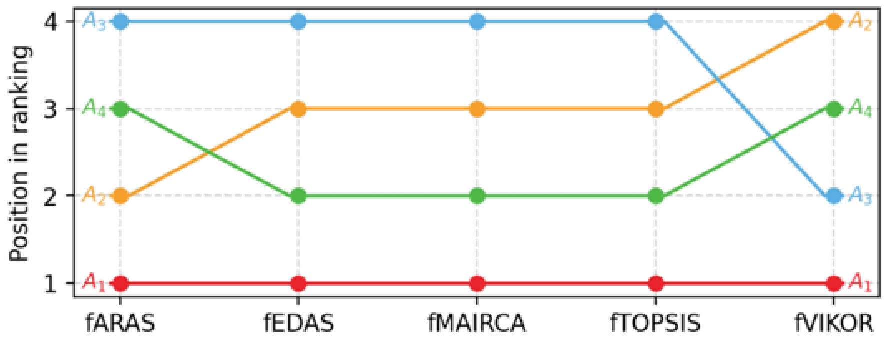
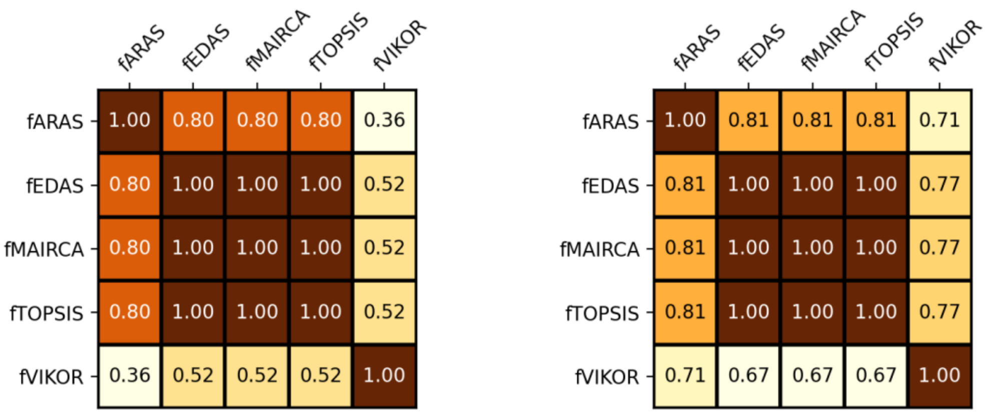


Figure 2. Flows of battery supplier rankings by selected MCDA methods



(a) correlation coefficient r_w (b) ranking similarity coefficient WS

Figure 3. Correlation of rankings from MCDM methods under comparison

The correlation results were further visualized using heatmaps, as shown in Figure 3. The left diagram shows the correlation values of the weighted Pearson coefficient (r_w), while the right one shows the consistency between rankings for the WS rank similarity coefficient (WS). It is worth noting that the fuzzy EDAS, fuzzy MAIRCA, fuzzy TOPSIS methods guaranteed the same ranking order of the options. On the other hand, the compromise ranking Q by the fuzzy VIKOR method provided the most diverse results compared to those by the other methods. The results of the coefficient r_w obtained from the fuzzy ARAS and fuzzy VIKOR methods (0.36) indicated that they were the least correlated pair of rankings, while the results of coefficient (WS) (0.67) showed that the ranking by fuzzy VIKOR was the least correlated with those by fuzzy EDAS, fuzzy MAIRCA and fuzzy TOPSIS. However, tests on the consistency of the rankings showed that most of the selected methods were consistent in their evaluation of the various options.

4.1 Sensitivity Analysis

One way to test the robustness of the results obtained from changes is to conduct a sensitivity analysis. It provides insight into the results of possible scenarios and determines how potential modifications to the input data affect the attractiveness of the proposed solutions. A sensitivity analysis also provides more comprehensive knowledge and a greater view of the overall problem, showing the decision-makers what might change in the results under changing external conditions.

In their work, Wang et al. [38] used the sensitivity analysis assumptions to broaden the scope of the study. The authors emphasized that, due to changing regulations, technical levels, and market situation, the impact of each criterion on the outcome might change. Therefore, the researchers adopted an approach in which the weight of each criterion was modified at +/- 20% from the initial value. In addition, while the value of an individual criterion was changed, the remaining weights were adjusted so that the condition was met that their values added up to 1. Using the MULTIMOORA method, this study showed that the ranking of the options was stable despite changes in the input parameters, while using the Simple Additive Weighting (SAW), TOPSIS, and Multiplicative Exponential Weighting (MEW) methods, the study showed differences in the ranking of options in positions 2, 3, and 4.

Wang et al. highlighted that by using the entropy method to determine the significance of the criteria weights, they could identify the six most significant parameters in the problem. The largest values of the weights were recorded successively in transportation cost (C_2-0.236), price of battery (C_1-0.136), battery quality (C_{11}-0.115), research and innovation ability (C_{10}-0.088), product diversity (C_{12}-0.064), and safety assurance ability and return policy (C_{15}-0.064). Consequently, this paper adopted an approach that examined how the exclusion of criteria affected the rankings obtained. Each successive criterion was skipped in the multi-criteria evaluation using the selected fuzzy MCDA methods. In addition, the remaining weights were modified so that the condition could be met that the values add up to 1. On the other hand, the correlation coefficient r_w was used to determine the consistency of rankings after exclusion of individual criteria. The results obtained are shown in the figure below.

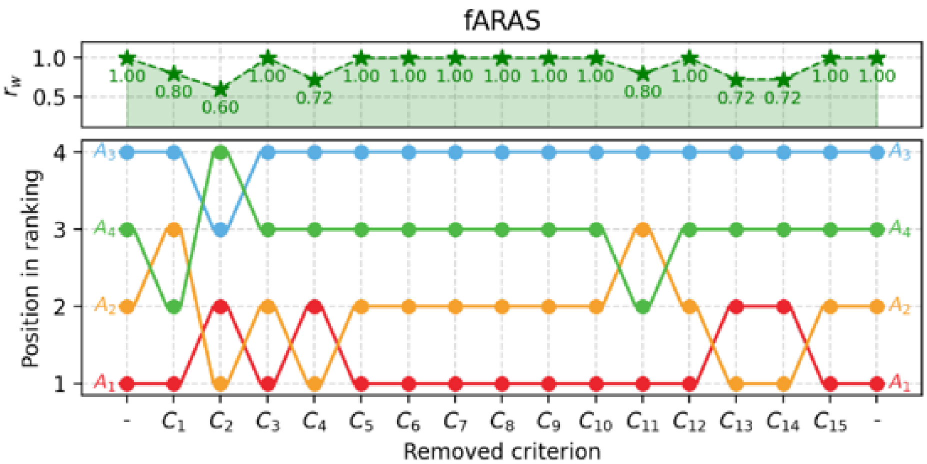


Figure 4. Sensitivity analysis of the impacts of criteria on ranking - the fARAS approach

Figure 4 shows the flows of rankings computed using the fuzzy ARAS method after exclusion of criteria one by one from the problem. It can be seen that, after exclusion of criterion C_2, which was the most relevant in the problem, significant changes took place in the ranking order of the options - the indicated order relative to the attractiveness of the decision options was A_2>A_1>A_3>A_4, which was completely different from the initial ranking obtained by this method. What is also noteworthy is that the exclusion of criteria C_5-C_{10} and C_{15} did not affect the way the decision options were ranked. Significant changes were also evident with modifications to criteria C_3, C_4, C_{13} and C_{14}, which translated into changes in the ranking order of the options in the first two ranking positions. The correlation coefficient r_w of the rankings obtained equaled 0.60 at least for the exclusion of criterion C_2, and the final similarity values oscillated between 0.60 and 1.00, indicating a strong similarity of the results.

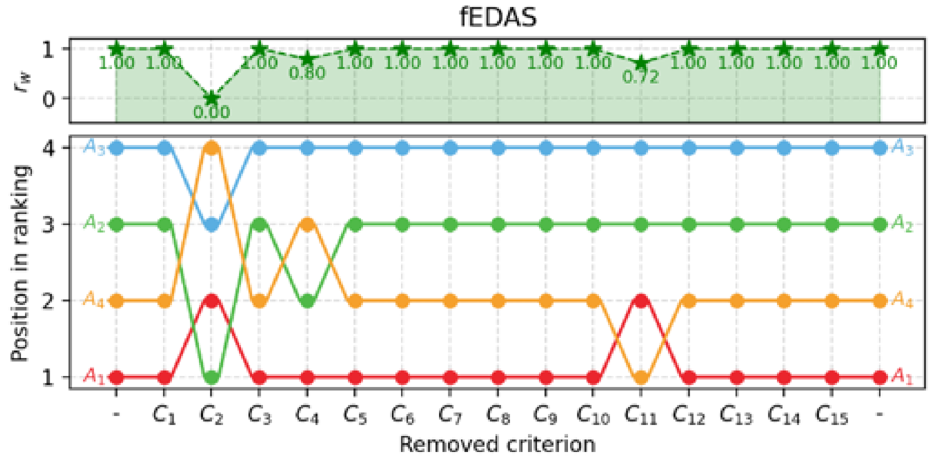


Figure 5. Sensitivity analysis of the impacts of criteria on ranking - the fEDAS approach

The flow of rankings after the exclusion of each criterion and the calculations made by the fuzzy EDAS method are shown in Figure 5. It can be seen that the rankings calculated with this method are much more stable than with the fuzzy ARAS method. In as many as 12 cases out of a possible 15, the ranking remained unchanged, indicating a high consistency of performance. However, when the most important criterion (C_2) in the problem was excluded, the ranking differed significantly. The ranking order of the options, in this case, was $A_2 > A_1 > A_3 > A_4$, which is the same as that obtained by the fuzzy ARAS method. However, due to the differences in the initial ranking considering all criteria, the changes in individual positions were more significant, making the correlation coefficient r_w equal 0.00, which indicated significantly divergent results. Other differences from the initial ranking were noted for criterion C_4, where option A_2 gained the second position over option A_4, and for criterion C_{11}, where option A_4 was placed first and A_1 second.

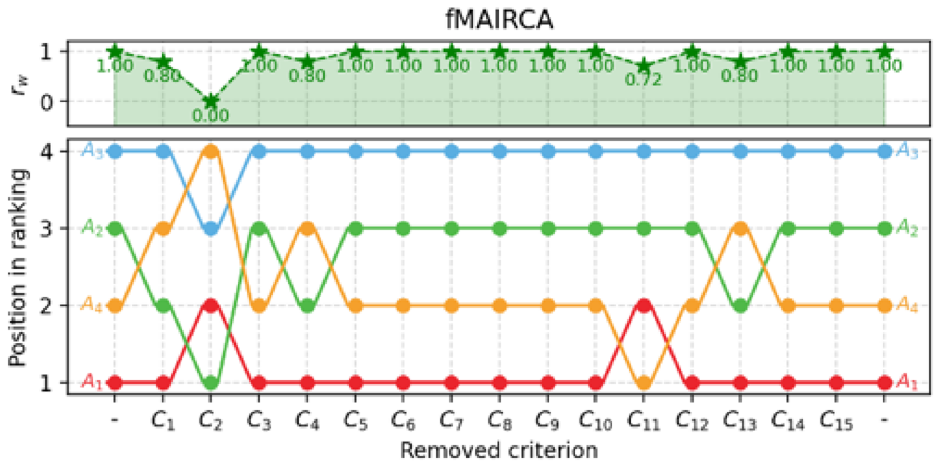


Figure 6. Sensitivity analysis of the impacts of criteria on ranking - the fMAIRCA approach

The results of the sensitivity analysis on the robustness of the rankings calculated using the fuzzy MAIRCA method are shown in Figure 6. It is worth mentioning that the ranking considering all criteria in the problem obtained by this method was the same as those by the fuzzy EDAS and fuzzy TOPSIS methods. However, through comparison of the changes in rankings of options when criteria were excluded one by one, it should be noted that this method was less stable than the fuzzy EDAS method. An additional criterion that influenced the ranking order of the options was parameter C_{13}, which contributed to swapping the positions of options A_2 and A_4 to second and third place, respectively. Similar to the case of the EDAS method, when criterion C_2 was excluded, the most significant disparity with the initial ranking appeared, and the correlation coefficient r_w also reached 0.00.

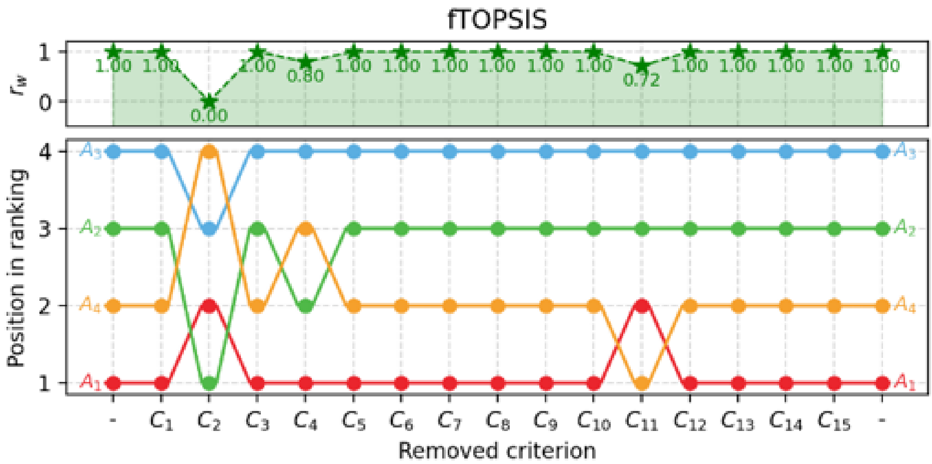


Figure 7. Sensitivity analysis of the impacts of criteria on ranking - the fTOPSIS approach

The flow of rankings after the exclusion of each criterion and the calculations made by the fuzzy TOPSIS method are shown in Figure 7. The fuzzy TOPSIS method was the third of the methods that, at the initial stage of the study, guaranteed the same ranking, together with the fuzzy EDAS and fuzzy MAIRCA methods. Furthermore, in the sensitivity analysis and robustness testing of the rankings to the exclusion of individual criteria, the TOPSIS method was characterized by the same evaluation stability as the EDAS method - 12 of the 15 test cases did not change the ranking order of the options. In addition, this indicates a high correlation in the performance of the methods.

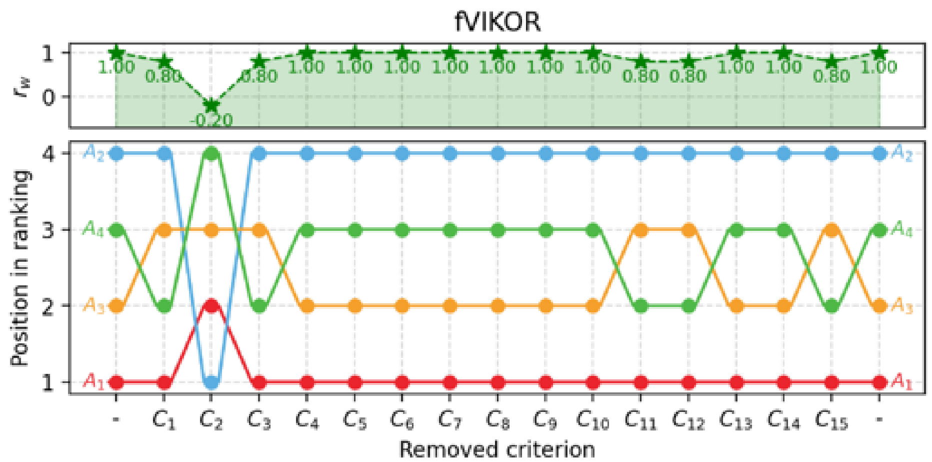


Figure 8. Sensitivity analysis of the impacts of criteria on ranking - the fVIKOR approach

The flow of rankings after the exclusion of each criterion and the calculations made by the fuzzy VIKOR method are shown in Figure 8. This was the last method on which sensitivity analysis was performed. A compromise ranking Q was considered, where six test cases showed a different ranking order from the initial ranking. These were scenarios in which criteria $C_1, C_2, C_3, C_{11}, C_{12}$ and C_{15} were excluded respectively. The largest differences in the ranking order of the options were once again observed when criterion C_2 was excluded, where the options were ranked as follows: $A_2 > A_1 > A_3 > A_4$. In addition, the correlation coefficient r_w was -0.20 for this test case, which means that the new ranking deviated significantly from the initial ranking. It was also the lowest correlation value obtained in the sensitivity analysis tests in this study. In the cases where the other five criteria whose exclusion contributed to changes in rankings, option A_3 ranked 3rd, while A_4 moved up to the 2nd place.

5. Discussion

Four suppliers were considered in the study, namely A_1, A_2, A_3, and A_4, located in Beijing, Wuhan, Baoding, and Beijing, respectively. The initial research using five selected fuzzy MCDA methods (ARAS, EDAS, MAIRCA, TOPSIS, and VIKOR) from the PyFDM package provided the potential rankings that determined the attractiveness of each option. The obtained rankings showed that the fuzzy EDAS, fuzzy MAIRCA, and fuzzy TOPSIS methods provided the same ranking order for the decision options, all indicating that the most rational choice among the options analysed was a battery supplier from Beijing, followed by suppliers from Wuhan (2nd), Beijing (3rd), and Baoding (4th). The fuzzy ARAS and fuzzy VIKOR methods indicated a different preferred order. However, all methods agreed on the most preferred choice.

To provide a more comprehensive insight into the results and proposed choices, a sensitivity analysis was performed by excluding criteria one by one and examining the impacts of these changes on the indicated rankings. This research showed that the criterion that had the most significant influence on the rankings, regardless of the multi-criteria method used, was transportation cost (C_2), for which, the highest importance of influence on the results was 0.236. When this parameter was excluded from the problem, all methods provided the same ranking order of the options - $A_2 > A_1 > A_3 > A_4$, which constituted a significant divergence from the initial rankings, with the correlation coefficient r_w varying between -0.20 and 0.60. Other parameters that influenced the ranking order of options were financial ability (C_3), pollution emissions (C_4), resource consumption (C_5), battery quality and safety assurance (C_{11}), product diversity (C_{12}), timely supply (C_{13}), warranty period (C_{14}), and return policy (C_{15}). The other criteria did not affect the ranking order of the options.

This study adopted a selected set of fuzzy MCDA methods and performed sensitivity analysis to obtain additional knowledge in terms of potential changes in the rankings, which can help improve decision makers' knowledge in this area, and also give them a comprehensive view of the potential changes that determine the attractiveness of decision variants under changing external conditions. Through the research, it can be seen that transportation cost (C_2) has a critical impact on performance and that its changes and modifications significantly affect the attractiveness of individual options. If this parameter were to change across the problem, even to a slight extent, the results could vary significantly. In addition, with the increasing number of options, slight differences in the values of the options in this criterion would be crucial in the ranking order of these options. It is also a clear indication that, during negotiation discussions, transportation cost should be the most important negotiable factor, as minimizing its amount can significantly contribute to the attractiveness of a specific individual supplier. This, in turn, enables decision-makers to select the most preferred options so that losses can be minimized and the quality of operations and the pursuit of sustainability can be maximized.

6. Conclusions

The Decision Support System based on MCDA methods are an integral part of the decision-making process, as it takes into account the large dimensionality of the problem. Thus, by their operation, they can provide decision-makers with additional knowledge so that decision-makers can make conscious and rational decisions. As the selection problem often involves many factors, it is necessary to use such tools to perform analyses in a reliable and precise manner. In addition, given the uncertainties in the data that may occur in a given area, it is worth considering possible scenarios that contribute to providing a comprehensive view of the problem.

Consequently, it is crucial to propose solutions based on approaches that meet the requirements placed on them. The reliability and comprehensiveness of such systems proposing results to decision-makers is a fundamental element influencing the quality of the proposed solutions. To this end, this paper proposed a research approach taking into account five selected fuzzy MCDA methods operating on Triangular Fuzzy Numbers, which allowed the results to be benchmarked to indicate the attractiveness of the decision options obtained different techniques. In addition, the sensitivity analysis that excluded criteria one by one from the problem provided insight into possible scenarios with changing external conditions. The initial results unanimously indicated that option A_1, representing the battery supplier from Beijing, was the most preferred option. However, further research showed that, with the exclusion of criterion (C_2) determining transportation cost, option A_2 would be the most favorable choice. The proposed approach allows decision-makers to understand the problem multidimensionally and make an informed decision based on the possible scenarios, which is crucial to pursuing sustainable and efficient energy development, as it enables the selection of components based on reliable and precise techniques to maximize the benefits of specific choices under constantly changing conditions.

For future research, it is worth considering using more sensitivity analysis approaches to identify how the results could differ while other modifications would be performed. Moreover, it would be meaningful to take different practical problems in the field of energy development as examples to provide comprehensive indications on selection of the most valuable decision variants.

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Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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