FACTA UNIVERSITATIS
Series: **Mechanical Engineering**
https://doi.org/10.22190/FUME240930019W

Original scientific paper

MAKING MORE INFORMED DECISIONS IN MULTI-CRITERIA PROBLEMS UNDER UNCERTAIN CONDITIONS OF CRITERIA WEIGHTS: DRONE SELECTION STUDY CASE

Jakub Więckowski[1], Wojciech Sałabun[1,2]

[1]National Institute of Telecommunications, Warsaw, Poland
[2]Research Team on Intelligent Decision Support Systems,
Department of Artificial Intelligence and Applied Mathematics,
Faculty of Computer Science and Information Technology,
West Pomeranian University of Technology, Szczecin, Poland

Abstract. *The growing demand for robust Decision Support Systems (DSS) highlights the need for methods that enhance decision-making under uncertainty, particularly when criteria weights in multi-criteria evaluations are unknown. This study presents a novel approach for addressing Multi-Criteria Decision-Making (MCDM) problems where precise criteria weights are uncertain, focusing on drone selection for challenging, remote locations. Using the MultiAttributive Ideal-Real Comparative Analysis (MAIRCA) method, the research explores a range of criteria weight scenarios with various distributions, enabling a more comprehensive evaluation. A key innovation is the integration of fuzzy ranking techniques to aggregate results from multiple assessments, enhancing the robustness of decision outcomes. This approach overcomes the limitations of traditional ranking aggregation methods, providing a more reliable understanding of the stability and reliability of recommendations. By offering a more adaptive and uncertainty-resilient framework, this study advances multi-criteria decision analysis and improves reliability of recommendations provided by decision support systems in problems in which criteria weights remain unknown. Furthermore, it equips decision-makers with deeper insights into the reliability of recommendations, empowering more confident decision-making in complex, uncertain environments.*

Key words: *Drone Selection, Uncertain Weights, Decision Support, Fuzzy Ranking, Decision-Making*

Received: September 30, 2024 / Accepted May 03, 2025
Corresponding author: Wojciech Sałabun
National Institute of Telecommunications, ul. Szachowa 1, 04-894, Warsaw, Poland
E-mail: W.Salabun@il-pib.pl

© 2025 by University of Niš, Serbia | Creative Commons License: CC BY-NC-ND

1. Introduction

In the complex landscape of decision-making today, operational research is fundamental for effective management [1]. Given the multitude of factors that must be considered in intricate decision problems, Decision Support Systems (DSS) provide essential tools to aid decision-makers [2,3]. Multi-Criteria Decision Analysis (MCDA) methods are commonly employed to navigate the complexities of real-world scenarios in a structured manner [4]. These methods enable the construction of decision models tailored to specific criteria, including their significance adjusted to the given requirements [5]. The effectiveness of MCDA methods has been repeatedly demonstrated in practical applications, including business analytics [6], sustainable development [7,8], and engineering problems [9,10].

Despite the widespread use and ongoing development, MCDA methods present notable challenges for decision-makers [11]. A primary issue is selecting an appropriate evaluation method, as different methods may yield varying results for the same decision problem, as stated in the literature [12,13]. Another significant challenge is determining the relevance of criteria [14]. Criteria weights are crucial input data for many MCDA methods and have a visible influence on the final results [15]. Various approaches were developed to simplify identifying criteria relevance [16,17], but their reliability can be inconsistent. Objective weighting methods, which rely solely on data from the decision matrix, may lead to misleading results [18]. Conversely, subjective weighting methods can suffer from biases or inaccuracies in expert judgments, potentially skewing obtained outcomes [19]. A major difficulty arises when the relevance of criteria is unknown, reflecting scenarios where decision-makers lack information about the multi-criteria problem or cannot precisely define criteria importance but still seek to understand potential outcomes. New approaches are needed to provide a robust and reliable analysis of decision problems despite incomplete input data.

The problem of unknown criteria weights is common in real-world scenarios, especially in fields related to engineering problems [20,21]. Decision-makers and stakeholders often lack a full understanding of the complex nature of decision problems, which limits their ability to make informed choices [22]. This uncertainty is further compounded when there is hesitation about the relevance of different criteria, complicating the decision-making process [23,24]. As a result, there is a clear need for comprehensive approaches that explore the decision problem space under various criteria weight vectors. By analyzing the criteria weight space in depth, the robustness of recommendations can be improved, and decision-makers' awareness of possible outcomes can be enhanced. Furthermore, this approach generates multiple individual results based on different weight distributions, which must be aggregated into a final ranking reliably. However, current methods for aggregating results obtained from multiple assessments scenarios are limited [25]. While they produce a single consensus ranking [26], they fail to provide a detailed overview of how individual rankings change, leaving decision-makers without a full understanding of the implications of each scenario [27]. This raises the question of whether a more effective method of presenting results from diverse evaluation scenarios could better support informed decision-making.

Thus, to enhance the comprehensiveness of supporting decisions in complex problems, it is important to provide robust frameworks for evaluating decision variants. Exploring decision problems with criteria weight vectors with different distributions of values could lead to a more nuanced understanding of the outcomes, especially in problems where uncertain conditions of criteria weights occur. Existing approaches for aggregating results from multiple evaluation scenarios often fall short in presenting insights from individual recommendations, highlighting the need for more effective result representation techniques. For this purpose, this paper is directed toward evaluating multi-criteria decision problems under unknown criteria weight values. The proposed approach extensively explores the space of criteria weight scenarios and uses the MultiAttributive Ideal-Real Comparative Analysis (MAIRCA) method to evaluate considered decision variants [28]. The problem of selecting drone for accessing remote and challenging locations is used to verify the effectiveness of the presented evaluation procedure. Moreover, this study applies a novel fuzzy ranking concept to examine the robustness of evaluation outcomes across assessment scenarios. The comparative analysis with selected weighting methods and compromise solution techniques are presented to examine the stability of the results. The proposed work aims to support decision-makers and enhance the understanding of the reliability of recommendations, leading to equipping decision-makers with deeper insights into complex decision problems under uncertain conditions of criteria weights. The main contributions of the study are:

- Providing a comprehensive framework for assessing multi-criteria decision-making problems under uncertain conditions of criteria weights;
- Demonstrating the effectiveness of the proposed approach in a practical problem of drone selection for accessing remote and challenging locations;
- Conducting a comparative analysis of selected weighting methods and compromise solution techniques to examine the stability and reliability of the results.

The rest of the paper is organized as follows. Section 2 shows the preliminaries of the methods used in the study with the procedure used for criteria weights generation, the main assumptions of the MAIRCA method, and the description of a fuzzy ranking approach. Section 3 presents a case study with the evaluation of drones for accessing remote and challenges locations under uncertain conditions of criteria weights. Section 4 presents the results obtained, while Section 5 comparatively analyzes the outcomes from selected methods. Finally, Section 6 draws conclusions from the research and indicates future development directions.

2. PRELIMINARIES

2.1 Criteria Weights Generation Procedure

Exploring the decision problem space by including all possible vectors of criteria weights in the evaluation process allows for a comprehensive assessment of each criterion's potential relevance within the considered problem. Given the requirement that criteria weights must sum to 1, each of the generated weight vector must satisfy this condition. The criteria weights generation procedure that could be used to determine the weights vectors that represent different importance of criteria in the problem is presented in Fig. 1.

```
Require: Step s, Number of criteria n

weights_points = 1 / s
procedure RECURRENCE_WEIGHTS(n, weights_points)
    if n == 2 then
        for i in range(weights_points + 1) do
            Write results(i, weights_points - i)
        end for
        return results
    else
        for i in range(weights_points + 1) do
            for rest in RECURRENCE_WEIGHTS(n - 1, i) do
                Write results(weights_points - i, rest)
            end for
        end for
        return results
    end if
end procedure
```

Fig. 1 Visualization of the procedure used for criteria weights generation

The provided procedure can be adjusted to set the precision of criteria weight vector generation. The parameter s controls the step between weight values and can influence both the number of generated vectors and the variation of values distribution between consecutive vectors. This parameter directly affects the accuracy of the results: smaller values produce a larger number of scenarios to evaluate, improving the precision of the analysis. However, this also requires more computational resources, increasing the time complexity.

2.2 The MAIRCA Method

The MultiAttributive Ideal-Real Comparative Analysis method was developed to promote alternatives with the smallest combined gap, which are treated as the closest to the ideal [29]. It proves to be highly stable, even when criteria are adjusted [30]. The method's effectiveness relies on measuring the gap between ideal and actual weights. The MAIRCA method can be applied through a five-step process, illustrated in Fig. 2.

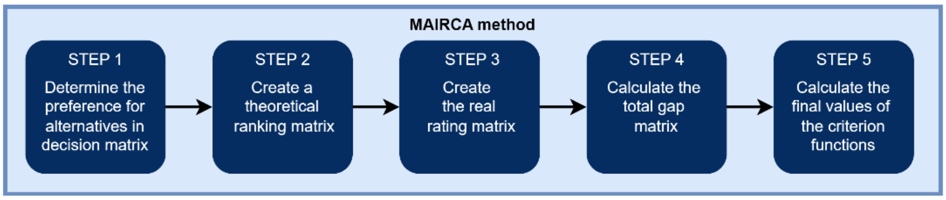

Fig. 2 Visualization of subsequent steps of the MAIRCA method

2.3 Fuzzy Ranking Approach

In contrast to traditional methods of aggregating MCDA results from multiple evaluation scenarios, the fuzzy ranking approach is based on calculating how often each alternative appears in specific ranking positions and then determines the membership degrees, which reflect the robustness of the results obtained [31]. The fuzzy ranking produces a two-dimensional matrix that represents the membership degrees of alternatives, giving decision-makers a detailed view of the uncertainty and stability of the ranking positions. By addressing the shortcomings of conventional aggregation methods, this approach offers a more comprehensive and informed perspective in multi-criteria decision analysis. The procedure used for calculating the fuzzy ranking is presented in Fig. 3.

```
Require: Rankings from multiple assessments R

M_RANK = zeros(len(alternatives), len(alternatives))
for each ranking in R do
    for each alternative (a) in alternatives do
        for each position (p) in range(1, len(ranking)) do
            M_RANK(a,p) += 1 if ranking(a) == position else 0
        end for
    end for
    M_RANK(a) = M_RANK(a) / len(R)
end for
```

Fig. 3 Flowchart presenting steps for calculating the fuzzy ranking

3. STUDY CASE

This study presents a methodology aimed at enhancing decision-making in multi-criteria problems where criteria weights are uncertain. The proposed approach utilizes a systematic procedure to generate a range of criteria weight scenarios that thoroughly explore the decision space. The level of precision in this exploration can be adjusted by modifying the step parameter, allowing for a balance between detailed analysis with finer weight increments and improved computational efficiency with larger steps that produce fewer weight combinations. These weight scenarios are then applied within the MAIRCA method to assess the alternatives across different weight distributions. While various MCDA methods are available, the MAIRCA method is chosen due to its proven performance across multiple applications and problem domains [32,33]. Its robustness has been verified in numerous studies, establishing solid foundations for developing reliable decision models within the MCDA field [34,35]. The resulting rankings are analyzed using a fuzzy ranking approach, which offers a more comprehensive and nuanced presentation of the findings, helping decision-makers make better-informed decisions.

The proposed work addresses the growing need for effective solutions in accessing remote and challenging locations, a significant concern in today's landscape. In problems connected to planning and management, particularly site accessibility, drones offer a transformative approach to reach areas that are otherwise difficult or unsafe to access, enhancing operational efficiency and safety. This research provides insights into optimizing drone selection, which is essential for improving logistical operations and expanding capabilities in various industrial and engineering applications. The criteria considered in the drone selection problem are presented in Table 1, with name of the criterion, its label, unit and type.

Table 1 Criteria set considered in the problem of drone selection evaluation

Name	Label	Unit	Type
Price	C1	EUR	Cost
Maximum flight distance	C2	KM	Profit
Maximum flight time	C3	min	Profit
Battery power	C4	mAh	Profit
Megapixels of camera	C5	MP	Profit
Maximum ISO	C6	ISO	Profit
Weight	C7	grams	Cost
Width	C8	mm	Cost

Based on the identified criteria, the specifications of six selected drones were gathered and stored in the decision matrix, presented in Table 2.

Table 2 Decision matrix showing specification of selected drones used for the multi-criteria evaluation

Alternative	C1	C2	C3	C4	C5	C6	C7	C8
A1	5477.17	22.5	32	3350	48	6400	898	440
A2	3084.30	7.0	30	5870	20	12800	1390	300
A3	4728.48	30.0	46	5000	20	6400	899	283
A4	3791.06	7.0	30	5870	20	6400	1380	225
A5	5415.41	32.0	45	5000	48	25600	920	347
A6	3656.86	32.0	45	5000	20	6400	915	347

Using the defined input data, the evaluation of drones was conducted through multi-criteria decision analysis. Traditional assessments within the MCDA field assume that criteria weights are accurately defined and known, which could simplify the evaluation process as it could not reflect the actual importance of criteria. Moreover, significant challenges arise when the importance of criteria weights is uncertain. Standard approaches in the literature often involve objective weighting methods that derive criteria relevance from the decision matrix data. A major limitation of this approach is that it produces a single vector of criteria weights, which may not reflect the true importance of the criteria and covers only one of multiple possible criteria weight vectors.

To address this challenge, a more effective solution could be to analyze multiple scenarios to evaluate the robustness of the results under varying conditions. It also enables assessing a given decision problem, even with the criteria relevance remaining completely unknown. To bridge this gap, the proposed research extensively explores the decision problem space by generating combinations of criteria weights with a defined resolution, covering the whole decision problem space. It allows for examining the single decision problem with multiple weighting scenarios which translates into more robust outcomes, especially in problems with unknown criteria weight values. For this analysis, the weight generation step was set to 0.05 to ensure high precision in exploring the decision space. The generated weighting scenarios were then applied within the MAIRCA method to assess the alternatives. The resulting multiple rankings from different scenarios were used to calculate a fuzzy ranking matrix, providing a detailed analysis of the robustness of the ranking order under performed evaluations.

4. RESULTS

Following the procedure outlined in Fig. 1, combinations of criteria weight vectors were generated for 8 criteria with a step size of 0.05. A sample of these resulting weight vectors is shown in Table 3. The procedure produced a total of 50,388 scenarios to cover all possible combinations for the 8 criteria vector. It can be seen that the number of obtained scenarios is substantial, as the procedure generates criteria weights for the examined decision space with high resolution. With bigger values of steps, the number of scenarios could be reduced. Nevertheless, the proposed extensive approach allows for a thorough evaluation of the decision problem space under various criteria weight distributions, providing in-depth insights into the outcomes across different conditions.

Table 3 Sample of criteria weights vectors generated with the presented procedure using step of 0.05

Scenario	C1	C2	C3	C4	C5	C6	C7	C8
S1	0.05	0.50	0.05	0.05	0.05	0.05	0.05	0.20
S2	0.10	0.45	0.05	0.05	0.05	0.05	0.05	0.20
S3	0.06	0.40	0.05	0.05	0.05	0.05	0.05	0.20
S4	0.08	0.35	0.05	0.05	0.05	0.05	0.05	0.20
S5	0.10	0.30	0.05	0.05	0.05	0.05	0.05	0.20
...	...	...	...	...	...	...	...	...
S50388	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.65

The evaluation process utilized the generated criteria weight scenarios to assess the decision matrix shown in Table 2 using the MAIRCA method. Each weight vector from the possible combinations was applied individually, and the resulting rankings were gathered for further analysis. In total, 50,388 rankings were generated from this evaluation process. These rankings were used to calculate a fuzzy ranking, which was achieved by counting the occurrence of each alternative at specific ranking positions and normalizing these values to determine membership degrees. These degrees indicate the robustness of the results. Fig. 4 illustrates the fuzzy ranking matrix derived from the calculations, represented as a heatmap. This matrix displays the membership degree of each alternative for each ranking position, ranging from 0 (indicating no membership degree for that position) to 1 (indicating strong confidence in that position).

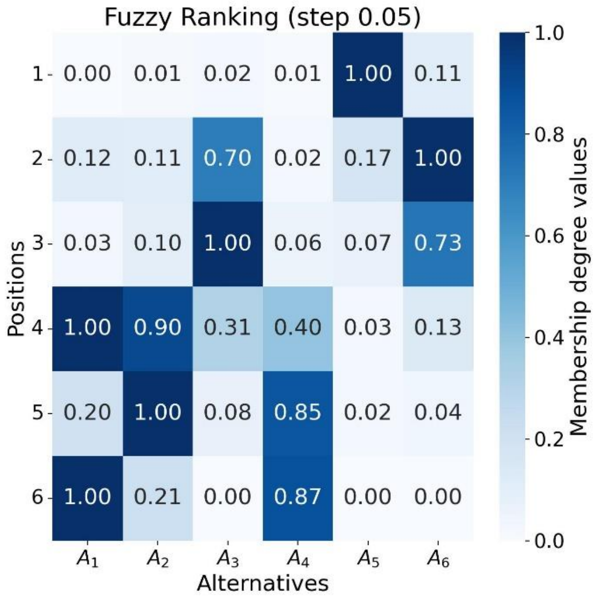

Fig. 4 Heatmap representing results of the calculated fuzzy ranking based on 50,388 evaluation scenarios using step of 0.05

From the obtained results, it could be seen that the alternative A5 was the most robust selection under the examined space of decision problem with a given step of 0.05. This decision variant visibly outperforms other drones, obtaining a membership degree value of 1.00, while the second-best drone (A6) for the 1st position reached the value of 0.11. For the second position in the ranking, it could be seen that two alternatives reached high membership degree values. Alternative A6 obtained a value of 1.00, while alternative A3 reached the certainty of 0.70 regarding the recommendation to be placed in the 2nd position. Similar cases can be seen for the rest of the positions in the ranking where small differences between subsequent positions and classified alternatives are notices regarding the obtained membership degree values. The smallest difference between the alternatives can be observed for the 4th position, where A1 reached 1.00 membership degree and A2 obtained a value of 0.90, also showing high certainty of being placed in this position.

5. Comparative Analysis

The obtained results were analyzed with a critical evaluation of the proposed methodology's efficiency and effectiveness. To validate the robustness of the results, further experiments compared the outcomes generated using different step sizes in the criteria weight scenarios. Specifically, scenarios with step sizes of 0.10 and 0.04 were contrasted with the primary step size of 0.05. This comparison assesses how variations in step size affect the number of generated scenarios and, consequently, the precision of the decision space exploration. By analyzing these different resolutions, the study aimed to determine the impact of step size adjustments on the overall accuracy and computational efficiency of the evaluation process.

Additionally, the comparative analysis involves benchmarking the proposed approach against selected weighting techniques and compromise solution methods. This comparison includes evaluating traditional weighting methods and various aggregation techniques to determine how well the proposed methodology performs in aggregating and interpreting results. The effectiveness of the fuzzy ranking approach is tested against these conventional methods to highlight its advantages and limitations. By integrating results from different weighting and aggregation techniques, the study examined how the proposed approach holds up in practice in multiple scenarios evaluation, providing a comprehensive understanding of its effectiveness and reliability in multi-criteria decision-making scenarios.

5.1 Impact of the Step Size in Weights Generation Procedure

The substantial difference in the number of generated vectors with varying step sizes highlights the trade-off between precision and computational efficiency. With a step size of 0.10, only 36 vectors are generated, providing a simplified but computationally manageable overview of the decision space. Using a step of 0.04 to generate the weighting vectors provided 346,104 scenarios, offering finer resolution and more detailed exploration of the criteria weighting space, albeit at the cost of slightly increased computational complexity and time required. However, with today's computational capabilities, this is not a demanding task for personal use machines, as long as the results are not to be obtained in real time. On the other hand, striving for greater accuracy using step 0.02 would produce 85,900,584 scenarios which could be challenging to process. While the finer step size improves the precision of the analysis and potentially yields more robust results, the higher computational burden may limit its practical applicability in large-scale problems.

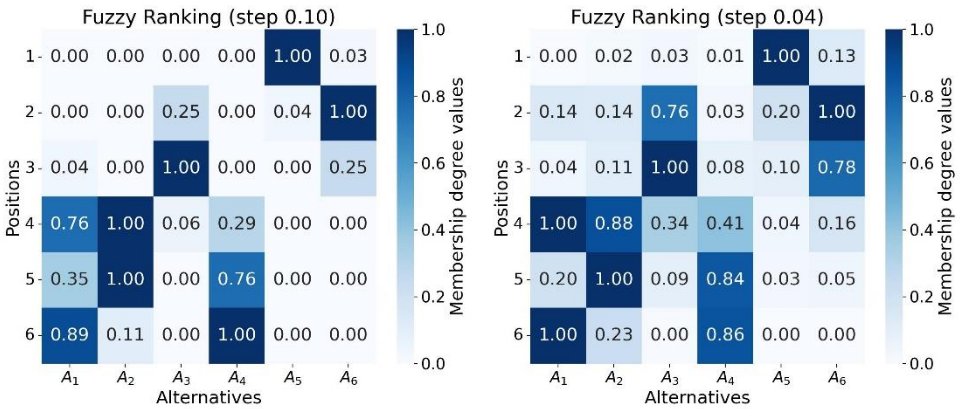

Fig. 5 Heatmaps of fuzzy rankings obtained based on generated weighting scenarios using steps of 0.10 and 0.04

Despite the significant difference between the number of weighting scenarios generated with the examined steps of 0.10 (36) and 0.04 (346,104), in Fig. 5, it can be seen, that the obtained fuzzy rankings do not differ substantially. The most visible difference can be observed for the 3rd position and the case of alternative A6, where it obtained the membership degree values of 0.25 and 0.78 for steps of 0.10 and 0.04, respectively. For the more general evaluation using step 0.10, the same alternatives reach the highest membership degree values as in the case of assessment with step 0.04. The alterations can be observed for the 4th and 6th positions, where for the step of 0.10 the alternatives A2 and A4 obtained the highest membership degree and were ranked 4th and 6h, respectively. For the lower step of 0.04, the alternative A1 was recommended as the most robust choice for 4th and 6th place, showing that with evaluated weighting scenarios, it can be stated with the same certainty that it could be ranked in those positions.

5.2 Comparison of Weighting Techniques

To thoroughly evaluate the proposed approach, the study compared it against several established weighting methods, including Angle [36], Entropy [37], Gini [38], MEthod based on the Removal Effects of Criteria (MEREC) [39], and Integrated Determination of Objective CRIteria Weight (IDOCRIW) [40]. These methods were used to determine the criteria weights and assess their impact on decision outcomes. For calculating consensus rankings, the study employed Borda Count [41], Dominance Directed Graph (DDG) [42] and Rank Position [43] methods. The calculations were performed with the *pymcdm* tool [44] and *pysensmcda* library [45]. By comparing these traditional consensus techniques with the fuzzy ranking results, the study aimed to analyze how well each method aligns with the proposed approach and its ability to handle uncertain criteria weights. This comparison helps to provide insights into the robustness and reliability of the proposed methodology relative to established practices.

Table 4 Rankings calculated based on using selected objective weighting methods for the problem of drones evaluation

Alternative	Angle	Entropy	Gini	MEREC	IDOCRIW	Fuzzy ranking
A1	4	3	4	4	2	5
A2	5	5	5	5	5	4
A3	3	4	3	3	4	3
A4	6	6	6	6	6	6
A5	1	1	1	1	1	1
A6	2	2	2	2	3	2

Table 4 presents the rankings of considered drones evaluated using five objective weighting methods. The obtained rankings revealed general consistency across the methods but also highlighted several differences. Alternative A5 was consistently ranked highest across all methods, indicating strong performance regardless of the weighting approach. Conversely, alternative A4 was ranked lowest in all cases, reflecting its relatively weak performance. Alternatives A2 and A1 showed variability, with A2 placed highest in all methods except IDOCRIW, where it was ranked second, while A1's positions ranged from second to fourth. Alternatives A3 and A6 varied regarding assigned positions, with A3 performing slightly better in the Angle, Entropy, and IDOCRIW methods compared to A6, which has a more uniform placement across examined methods. The results obtained from the proposed approach, which involved generating a comprehensive set of weighting scenarios to explore the entire decision space, aligned closely with those derived from traditional objective weighting methods. However, the proposed approach provided deeper insights by offering membership degree values that reflect the stability and reliability of the recommendations. The fuzzy ranking, calculated with a step size of 0.05, revealed that multiple alternatives were likely to be ranked in the 2nd, 3rd, 4th, 5th, and 6th positions, highlighting the potential variability in rankings. In contrast, the crisp rankings from the selected objective weighting techniques offered a more simplified view, lacking the nuanced information about ranking stability and certainty that the fuzzy ranking approach provides.

Table 5 shows the consensus rankings for the considered problem using three different compromise solution methods: Borda count, Dominance Directed Graph, and Rank Position. The compromise rankings were calculated based on the individual rankings obtained from the evaluation using generated weighting scenarios from the proposed procedure and the application of the MAIRCA method.

Table 5 Consensus rankings calculated with selected compromise solution methods

Alternative	Borda	DDG	Rank position	Fuzzy Ranking
A1	5	5	5	5
A2	4	4	4	4
A3	3	3	3	3
A4	6	6	6	6
A5	1	1	1	1
A6	2	2	2	2

Across the examined methods, alternative A5 was ranked highest, reflecting its superior performance relative to the others. Conversely, alternative A4 was consistently ranked the lowest. It is worth noticing that all alternatives were ranked in the same positions despite applying different compromise solution methods. This consistency underscored the similar manner of performance of those techniques. Nevertheless, compared to the results obtained from the fuzzy ranking approach, it also highlighted that these methods provide a simplified view compared to the detailed membership degree values, which can be particularly useful when multiple scenarios of assessments are considered.

6. Conclusion

Making reliable recommendations in decision-making problems characterized by uncertainty and unknown criteria weights poses a significant challenge. The evaluation approach presented in this study, which involves an extensive exploration of the decision problem space with varying criteria weights, offers a robust and comprehensive solution. By utilizing a defined step size for generating criteria weights, the presented approach ensures that recommendations account for diverse input conditions regarding the importance of criteria. The integration of a fuzzy ranking concept provides decision-makers with a nuanced perspective, enhancing their ability to make well-informed decisions. The results from the drone selection problem demonstrate that this approach is effective for dealing with unknown criteria weights and offers a more detailed analysis compared to traditional weighting techniques and compromise solution methods.

However, the study is not without limitations. One significant limitation is the computational complexity associated with generating and analyzing a large number of criteria weight scenarios, which can be resource-intensive and time-consuming. Additionally, the effectiveness of the proposed method may vary with different types of decision problems and criteria.

Future research should focus on optimizing the procedure to enhance its efficiency for scenarios involving a large number of criteria. Additionally, exploring the application of various MCDA methods could reveal whether different techniques yield significantly different results from fuzzy rankings, providing further insights into the sensitivity of these methods to changes in criteria weights.

Acknowledgement: *The work was supported by the National Science Centre in Poland, 2021/41/B/HS4/01296 (W.S.).*

REFERENCES

1. Yazdi, M., Khan, F., Abbassi, R., Rusli, R., 2020, *Improved DEMATEL methodology for effective safety management decision-making*, Safety science, 127, 104705.
2. Zhai, Z., Martínez, J. F., Beltran, V., Martínez, N. L., 2020, *Decision support systems for agriculture 4.0: Survey and challenges*, Computers and Electronics in Agriculture, 170, 105256.
3. Hussain, A., Ullah, K., 2024, *An intelligent decision support system for spherical fuzzy sugeno-weber aggregation operators and real-life applications,* Spectrum of Mechanical Engineering and Operational Research, 1(1), pp. 177-188.
4. Yalcin, A. S., Kilic, H. S., Delen, D., 2022, *The use of multi-criteria decision-making methods in business analytics: A comprehensive literature review,* Technological forecasting and social change, 174, 121193.
5. Biswas, S., 2020, *Measuring performance of healthcare supply chains in India: A comparative analysis of multi-criteria decision making methods*, Decision Making: Applications in Management and Engineering, 3(2), pp. 162-189.
6. Jana, S., Chandra Giri, B., Sarkar, A., Asharaf, S., Jana, C., Pamucar, D., Marinkovic, D., 2024, *Selection of brokerage firms for e-services using fuzzy decision making process with AHP and MACROS approaches*, Engineering Review, 44 (4 SI), pp. 1 - 21.
7. Jamwal, A., Agrawal, R., Sharma, M., Kumar, V., 2021, *Review on multi-criteria decision analysis in sustainable manufacturing decision making,* International Journal of Sustainable Engineering, 14(3), pp. 202-225.
8. Tadić, D., Lukić, J., Komatina, N., Marinković, D., Pamučar, D., 2025, *A Fuzzy Decision-Making Approach to Electric Vehicle Evaluation and Ranking*, Tehnički Vjesnik, 32(3), 1066-1075.
9. Zavadskas, E. K., Pamučar, D., Stević, Ž., Mardani, A., 2020, *Multi-criteria decision-making techniques for improvement sustainability engineering processes,* Symmetry, 12(6), 986.
10. Komatina, N., Marinković, D., Tadić, D., Pamučar, D., 2025, *Advancing PFMEA decision-making: FRADAR-based prioritization of failure modes using AP, RPN, and multi-attribute assessment in the automotive industr*y, Tehnički Glasnik/Technical Journal, accepted for publishing.
11. Hafezalkotob, A., Hafezalkotob, A., Liao, H., Herrera, F., 2019, *An overview of MULTIMOORA for multi-criteria decision-making: Theory, developments, applications, and challenges,* Information Fusion, 51, pp. 145-177.
12. Ceballos, B., Lamata, M. T., Pelta, D. A., 2016, *A comparative analysis of multi-criteria decision-making methods*, Progress in Artificial Intelligence, 5, pp. 315-322.
13. Sałabun, W., Wątróbski, J., Shekhovtsov, A., 2020, *Are mcda methods benchmarkable? a comparative study of topsis, vikor, copras, and promethee ii methods*, Symmetry, 12(9), 1549.
14. Odu, G. O., 2019, *Weighting methods for multi-criteria decision making technique*, Journal of Applied Sciences and Environmental Management, 23(8), pp. 1449-1457.

15. Paradowski, B., Shekhovtsov, A., Bączkiewicz, A., Kizielewicz, B., Sałabun, W., 2021, *Similarity analysis of methods for objective determination of weights in multi-criteria decision support systems,* Symmetry, 13(10), 1874.
16. Liu, Y., Eckert, C. M., Earl, C., 2020, *A review of fuzzy AHP methods for decision-making with subjective judgements,* Expert Systems with Applications, 161, 113738.
17. Kizielewicz, B., Sałabun, W., 2024, *SITW method: A new approach to re-identifying multi-criteria weights in complex decision analysis*, Spectrum of Mechanical Engineering and Operational Research, 1(1), pp. 215-226.
18. Şahin, M., 2021, *Location selection by multi-criteria decision-making methods based on objective and subjective weightings,* Knowledge and Information Systems, 63(8), pp. 1991-2021.
19. Božanić, D., Epler, I., Puška, A., Biswas, S., Marinković, D., Koprivica, S., 2024, *Application of the DIBR II–rough MABAC decision-making model for ranking methods and techniques of lean organization systems management in the process of technical maintenance,* Facta Universitatis-Series Mechanical Engineering, 22(1), pp. 101-123.
20. Nabavi, S. R., Wang, Z., Rangaiah, G. P., 2023, *Sensitivity analysis of multi-criteria decision-making methods for engineering applications,* Industrial & Engineering Chemistry Research, 62(17), pp. 6707-6722.
21. Nasr, A., Johansson, J., Larsson Ivanov, O., Björnsson, I., Honfi, D., 2023, *Risk-based multi-criteria decision analysis method for considering the effects of climate change on bridges,* Structure and Infrastructure Engineering, 19(10), pp. 1445-1458.
22. Pluchinotta, I., Salvia, G., Zimmermann, N., 2022, *The importance of eliciting stakeholders' system boundary perceptions for problem structuring and decision-making*, European Journal of Operational Research, 302(1), pp. 280-293.
23. Chen, N., Xu, Z., 2015, *Hesitant fuzzy ELECTRE II approach: a new way to handle multi-criteria decision making problems*, Information Sciences, 292, pp. 175-197.
24. Wang, L., Yu, Y., Liu, Z., Liu, Z., Liu, X., 2024, *An enhanced failure mode and effects analysis risk identification method based on uncertainty and fuzzines*s, Journal of Engineering Management and Systems Engineering, *3*, 116-131.
25. Hulkower, N. D., Neatrour, J., 2016, *Deflecting arrow by aggregating rankings of multiple correlated criteria according to Borda,* Journal of Multi-Criteria Decision Analysis, 23(3-4), pp. 75-86.
26. Mohammadi, M., Rezaei, J., 2020, *Ensemble ranking: Aggregation of rankings produced by different multi-criteria decision-making methods*, Omega, 96, 102254.
27. Azadfallah, M., 2016, *A New Aggregation Rule for Ranking Suppliers in Group Decision Making under Multiple Criteria,* Journal of Supply Chain Management Systems, 5(4).
28. Ozcalici, M., 2022, *Asset allocation with multi-criteria decision making techniques*, Decision Making: Applications in Management and Engineering, 5(2), pp. 78-119.
29. Gigović, L., Pamučar, D., Bajić, Z., Milićević, M., 2016, *The combination of expert judgment and GIS-MAIRCA analysis for the selection of sites for ammunition depots*, Sustainability, 8(4), 372.
30. Zolfani, S. H., Ecer, F., Pamučar, D., Raslanas, S., 2020, *Neighborhood selection for a newcomer via a novel BWM-based revised MAIRCA integrated model: a case from the Coquimbo-La Serena conurbation, Chile*, International Journal of Strategic Property Management, 24(2), pp. 102-118.
31. Więckowski J., Sałabun W., 2025, *Supporting multi-criteria decision-making processes with unknown criteria weights,* Engineering Applications of Artificial Intelligence, 140, 109699.
32. Ozdemir, S., Demirel, N., Zaralı, F., Çelik, T., 2024, *Multi-criteria assessment framework for evaluation of Green Deal performance*, Environmental Science and Pollution Research, *31*(3), pp. 4686-4704.
33. Tešić, D., Božanić, D., Milić, A., 2023, *A multi-criteria decision-making model for pontoon bridge selection: An application of the DIBR II-NWBM-FF MAIRCA approach,* Journal of Engineering Management and Systems Engineering, *2*(4), 212-223.
34. Nguyen, H. Q., Nguyen, V. T., Phan, D. P., Tran, Q. H., Vu, N. P., 2022, *Multi-criteria decision making in the PMEDM process by using MARCOS, TOPSIS, and MAIRCA methods*, Applied sciences, 12(8), 3720.
35. Rani, P., Chen, S. M., Mishra, A. R., 2023, *Multiple attribute decision making based on MAIRCA, standard deviation-based method, and Pythagorean fuzzy sets*, Information Sciences, 644, 119274.
36. Ayan, B., Abacıoğlu, S., Basilio, M. P., 2023, *A comprehensive review of the novel weighting methods for multi-criteria decision-making*, Information, 14(5), 285.
37. Arya, V., Kumar, S., 2021, *Multi-criteria decision making problem for evaluating ERP system using entropy weighting approach and q-rung orthopair fuzzy TODIM*, Granular Computing, 6(4), pp. 977-989.
38. Bandyopadhyay, S., 2021, *Comparison among multi-criteria decision analysis techniques: A novel method,* Progress in Artificial Intelligence, 10(2), pp. 195-216.

39. Keshavarz-Ghorabaee, M., Amiri, M., Zavadskas, E. K., Turskis, Z., Antucheviciene, J., 2021, *Determination of objective weights using a new method based on the removal effects of criteria (MEREC),* Symmetry, 13(4), 525.
40. Zavadskas, E. K., Podvezko, V., 2016, *Integrated determination of objective criteria weights in MCDM,* International Journal of Information Technology & Decision Making, 15(02), pp. 267-283.
41. Çalık, A., Erdebilli, B., Özdemir, Y. S., 2023, *Novel integrated hybrid multi-criteria decision-making approach for logistics performance index,* Transportation Research Record, 2677(2), pp. 1392-1400.
42. Er, A., Özkale, C., Coşkun, S., 2024, *Project portfolio selection criteria in the oil & gas industry and a decision support tool based on fuzzy Multimoora*, Journal of Project Management, 9(3), pp. 197-212.
43. Altuntas, S., Dereli, T., Yilmaz, M. K., 2015, *Evaluation of excavator technologies: application of data fusion based MULTIMOORA methods,* Journal of Civil Engineering and Management, 21(8), pp. 977-997.
44. Kizielewicz, B., Shekhovtsov, A., Sałabun, W., 2023, *pymcdm—The universal library for solving multi-criteria decision-making problems,* SoftwareX, 22, 101368.
45. Paradowski, B., Więckowski, J., Sałabun, W., 2024, *PySensMCDA: A novel tool for sensitivity analysis in multi-criteria problems,* SoftwareX, 27, 101746.