Evaluation of agricultural drones based on the COmpromise Ranking from Alternative SOlutions (CORASO) methodology

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Abstract:

The development of agriculture is closely linked to technology and innovation. Drones have become a practical tool that helps improve agricultural production. This research focuses on choosing the spraying drone with the best features for the company Agricultural goods Semberija. A multi-criteria decision-making process based on expert opinions was used to evaluate eight different drones across ten criteria. The fuzzy SiWeC (Simple Weight Calculation) method was applied to determine the importance of each criterion, showing that all criteria were similarly important in the decision-making process. To select the best drone, the fuzzy COmpromise Ranking from Alternative SOlutions (CORASO) method was used. The results show that the DJI Agras T30 drone has the best features and is the preferred choice for purchase. These findings were confirmed by further comparative and sensitivity analyses. This study highlights the use of new methods for selecting equipment in agriculture.

1 Introduction

Every field tends to modernize and adopt innovations, with technological advances playing a key role. These innovations are crucial for improving competitiveness [1]. Agriculture, as the oldest industry, has evolved over time [2], and today, many innovations focus on increasing the productivity and efficiency of farming [3]. Technology is becoming more integrated into agricultural processes, with a growing emphasis on the development of Farming 4.0 [4] and smart agricultural practices.

One example of this technological expansion is the use of drones in agriculture [5]. Drones, or unmanned aerial vehicles [6], can perform various tasks on farmland. They are used for spraying crops, scattering seeds, and applying herbicides and pesticides from the air [7]. However, the adoption of drones in agriculture has followed the progress of information and telecommunication technology (ITC). Future technological advancements will likely lead to the automated use of drones in farming, incorporating machine learning [8] to further develop smart agriculture [9]. To successfully integrate drones into farming, farmers need training and a basic understanding of ITC [10]. Continuous learning is essential to enhance human capital in agriculture [11], which is as important as the equipment itself in boosting productivity.

There are many drones available to farmers on the market. To choose the one that best fits their needs, it's important to evaluate the options and select the drone that aligns with the goals of agricultural production. Since numerous factors need to be considered when selecting a drone, a multi-criteria decision-making (MCDM) process is used to identify the best choice, based on specific criteria. If one drone clearly meets all the criteria, the decision becomes straightforward, and further analysis may not be necessary [12]. However,

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this is rarely the case in practice. It is challenging for a single option to be the best in every category [13]. As a result, a compromise is often needed in the decision-making process [14-15], where the drone with the best overall performance across all criteria is selected.

To make such decisions, various MCDM methods are used. There are many such methods in theory and practice, each with its own unique steps and characteristics [16]. To make the process simpler, the methods used should involve fewer steps, be easy to apply, and offer flexibility [17]. For this reason, a new MCDM method called COmpromise Ranking from Alternative SOlutions (CORASO was developed in this research. This method ranks the alternatives based on how close or far they are from the best or worst values for certain criteria, calculating the deviation of each alternative and determining the final ranking.

Unlike methods such as Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) [18], Measurement of Alternatives and Ranking according to COmpromise Solution (MARCOS) [19] or Compromise Ranking of Alternatives from Distance to Ideal Solution (CRADIS) [20], the CORASO method involves fewer steps and offers simpler calculations, similar to the Additive Ratio Assessment (ARAS) [21] and Simple Additive Weighting (SAW) [22] methods. However, unlike ARAS, which only considers the deviation from the best alternative values, CORASO also takes into account deviations from the worst alternative values. This dual approach offers new insights for the further development of MCDM methods.

To select a drone for the company "Agricultural Goods Semberija" (AG Semberija), decision-makers' evaluations of both the importance of criteria and the performance of the drones will be used. A combination of methods is required for this, so in addition to the CORASO method, the Simple Weight Calculation (SiWeC) method will be used to determine the weight of the criteria. This is a relatively new method for subjectively determining the importance of criteria, and its use is further promoted in this research. A key advantage of SiWeC is that it simplifies the decision-making process, requiring decision-makers to evaluate the criteria without needing to rank or compare them [23]. The SiWeC is easy to apply and allows for different levels of decision-maker involvement, giving preference to certain individuals based on their evaluations. The more diverse the evaluations, the greater the influence of that particular decision-maker.

The motivation for this research is to simplify the process of selecting an agricultural drone and to promote new MCDM methods in practice. The goal is to use these methods to identify the agricultural drone that best supports the objectives of AG Semberija. Additionally, based on the aim of this paper, specific objectives are set to:

- Evaluate the agricultural drones and determine which one best meets the needs of the AG Semberija.
- Develop a decision-making model and a unique methodology based on fuzzy logic to evaluate the drones.
- Create a new ranking method that evaluates alternatives based on deviations from both the best and worst values for specific criteria.
- Provide guidelines for developing decision-making theory in agriculture and other fields.

Based on these research objectives, the contributions of this paper include the following. First, it uses MCDM and fuzzy logic methods to rank agricultural drones based on how well they satisfy the established research objectives as defined by the criteria. Second, it introduces a new MCDM method that enhances understanding of how much individual alternatives deviate from the maximum and minimum values for specific criteria. Ideally, an alternative should be as close as possible to the best values for the criteria to outperform others. Third, the innovative methodology, which incorporates these two new MCDM methods, aims to contribute to the evolution of decision theory by simplifying the decision-making process and making it more user-friendly.

In addition to the introduction, the paper is organized into three sections. The research methodology explains how the research was conducted as well as which methodologies were used. Then, those methods are applied in the results section to identify the drones that most successfully satisfy the research's objectives. In the conclusion, the research results and limitations are stated.

2 Research methodology

Research was conducted using the procedures described in Figure 1 in order to identify an agricultural drone that offers the best results for its use.

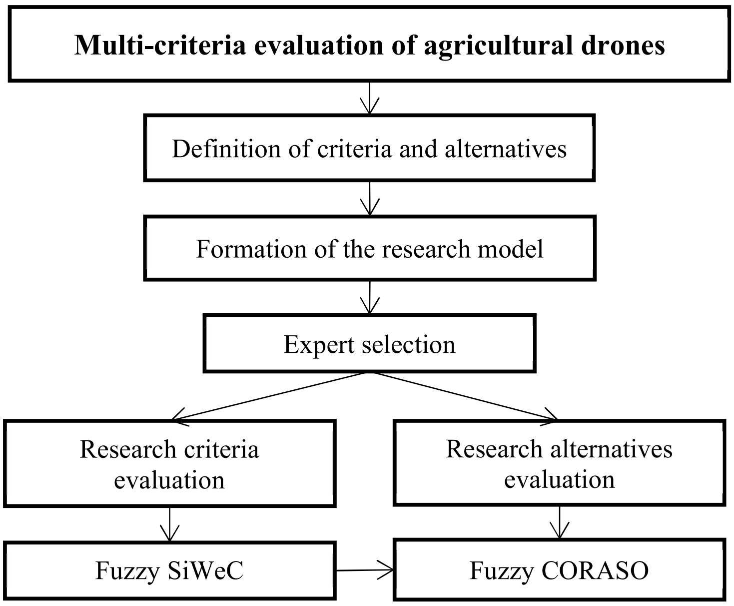

Figure 1. Research methodology.

The first step in implementing an MCDM approach is to determine the criteria and alternatives [24], in this case, agricultural drones. This research focuses on both technical and economic criteria (Table 1). For technical characteristics, aspects such as the drone's characteristics, spray tank capacity, flight performance, range on a single charge, spraying systems, and battery or tank capacity are examined. Economic criteria include the price of the drones, their availability in the market, any additional equipment included with the purchase, and maintenance costs. The goal is to maximize the values for benefit criteria (e.g., spray tank capacity) and minimize the values for cost criteria (e.g., price and maintenance costs) (Table 1). Benefit criteria should be optimized for higher values, while cost criteria should be minimized.

Table 1. Drone evaluation criteria

Id	Criteria	Description	Criteria type	Reference
C1	Drone characteristics	It describes the drone's technical characteristics and functionality	Benefit	[5][7][10]
C2	Spray tank capacity	It indicates how much liquid can fit within the tank	Benefit	[7][10]
C3	Flight performance	It relates to the drone's stability, agility, and speed when in flight	Benefit	[5][8][10]
C4	Hover time	It refers to how long the drone can operate when the battery is fully charged	Benefit	[5][7]
C5	Spraying systems	It refers to spraying technology that allows evenness and precision	Benefit	[7][10]
C6	Battery/Tank capacity	It refers to the capacity of the battery or tank	Benefit	[5] [10]
C7	Price	Indicates the drone costs	Cost	[7][10]
C8	Market availability	It indicates the market availability of drones	Benefit	[5] [10]
C9	Accessories	It represents the possibility of adding additional equipment	Benefit	[7][10]
C10	Maintenance costs	It refers to the costs related to regular drone maintenance and servicing	Cost	[5][8]

Once the criteria for the decision-making model are established, the next step is to select the agricultural drones for evaluation. The focus was on their ability to spray crops with different chemicals, either for enhancing crop growth or managing diseases and pests. When identifying the drones for use in this research, it was taken into account that these are the drones that are most commonly used in agricultural production and that they are available for the Bosnia and Herzegovina market. Based on this, eight agricultural drones were chosen for evaluation:

- DJI Agras T30 (D1): This agricultural drone has a tank capacity of 30 liters and is equipped with advanced obstacle avoidance radars and RTK (Real-Time Kinematics) positioning, ensuring precise spraying and seeding.
- Yamaha RMAX (D2): An autonomous helicopter with a 16-liter tank, designed for crop spraying. It runs on a gasoline engine, allowing for extended flight times of up to 60 minutes. This drone is ideal for large farms requiring long-term, precise operations.
- DJI Agras MG-1P (D3): A small and flexible drone with a 10-liter tank. It features multidirectional radar and RTK positioning for safe navigation and accurate spraying.
- XAG V40 (D4): A modern agricultural drone with a 20-liter tank. It includes advanced sensors and intelligent functions that enable autonomous route planning and precise spraying.
- Kray Protection UAS (D5): A specialized spraying drone with a 16-liter tank, known for its efficiency and ability to cover large areas quickly and with innovative technology that ensures precise spraying.
- DJI Agras T20 (D6): A mid-range agricultural drone with a 20-liter tank, suitable for small to medium-sized farms. It features advanced spraying systems and RTK positioning for efficient, precise spraying.
- Hylio AG-116 (D7): An agricultural drone with a 10-liter tank. Its main qualities are reliability and simple construction.
- TTA M6E (D8): A smaller agricultural drone with a 10-liter tank. This economical option has limited capabilities and autonomy, making it ideal for beginners and smaller-scale operations.

Based on the selected criteria and alternatives, a decision-making model and research survey was developed [25]. The focus of this research was to identify which agricultural drone would best meet the needs of AG Semberija for spraying crops. As AG Semberija is involved in agricultural production, they need to treat their crops effectively. To accomplish this, experts were selected to first evaluate the criteria based on their importance and then assess how well the different drone options meet these criteria [26-27]. Since AG Semberija had no prior experience with drones, they engaged six researchers from agricultural institutes in Belgrade, who have extensive experience with drone applications for crop spraying.

The research survey was divided into two parts: the first part required the experts to determine the importance of the criteria, while the second part focused on evaluating how well each drone met those criteria. The experts rated both the criteria and the drones on a scale ranging from very low to very good, with seven levels (Table 2). These linguistic evaluations were then processed using fuzzy logic to quantify the experts' opinions, first to determine the importance of the criteria and then to assess and rank the drones.

Fuzzy logic enables linguistic evaluations to be transformed into fuzzy values using a utility function, and further using appropriate methods [28]. In this research, the fuzzy SiWeC and fuzzy CARASO methods were used for these purposes. Additionally, a comparative analysis of the fuzzy CORASO results with other fuzzy methods will be conducted to validate the findings, along with a sensitivity analysis. In the following, the fuzzy research methods used will be explained.

Table 2. Linguistic evaluations and fuzzy membership function

Linguistic Values	Fuzzy numbers
Very low (VL)	(1, 1, 2)
Low (L)	(1, 2, 4)
Medium low (ML)	(2, 4, 6)
Medium (M)	(3, 5, 7)
Medium good (MG)	(5, 7, 9)
Good (G)	(7, 9, 10)
Very good (VG)	(9, 10, 10)

Fuzzy SiWeC is a method applied to determine the importance of criteria by calculating their weights [23]. This method is classified as subjective approach used for determination of criteria weights. Experts evaluate the importance of each criterion based on their judgment and provide ratings accordingly. Unlike other methods, SiWeC does not require experts to directly compare criteria against each other; instead, they rate each criterion independently based on its perceived importance. This characteristic tells apart SiWeC from other subjective weight determination methods.

The steps of the SiWeC method are as follows:

Step 1. Experts determine the importance of each criterion.

Step 2. Linguistic values are transformed into fuzzy numbers, represented as:

$$\tilde{x}_{ij} = \left(x_{ij}^{l}, x_{ij}^{m}, x_{ij}^{u}\right) \tag{1}$$

where x_{ij}^{l} represents first, x_{ij}^{m} second, and x_{ij}^{u} third fuzzy number.

Step 3. The fuzzy numbers are normalized as:

$$\tilde{n}_{ij} = \frac{x_{ij}^{l}}{max\ x_{ij}^{u}}, \frac{x_{ij}^{m}}{max\ x_{ij}^{u}}, \frac{x_{ij}^{u}}{max\ x_{ij}^{u}} \tag{2}$$

where $max\ x_{ij}^{u}$ is the maximum value across all criteria.

Step 4. Calculation of standard deviation ($st.dev_j$).

Step 5. The normalized ratings are weighted using the standard deviation values:

$$\tilde{v}_{ij} = \tilde{n}_{ij} \times st.dev_j \tag{3}$$

Step 6. The sum of the weighted values for each criterion is calculated:

$$\tilde{s}_{ij} = \sum_{j=1}^{n} \tilde{v}_j \tag{4}$$

Step 7. The fuzzy values of the criteria weights are computed as:

$$\widetilde{w}_{ij} = \frac{s_{ij}^{l}}{\sum_{j=1}^{n} s_{ij}^{u}}, \frac{s_{ij}^{m}}{\sum_{j=1}^{n} s_{ij}^{m}}, \frac{s_{ij}^{u}}{\sum_{j=1}^{n} s_{ij}^{l}} \tag{5}$$

After calculating the weights of the criteria, the next step is to rank the alternatives based on their ability to meet the research objectives. The new fuzzy CORASO method is used to calculate the drone rankings. This method was developed to provide decision-makers with an innovative approach to ranking alternatives in the context of numerous evaluation criteria. The steps in this method are designed to compare each alternative to the best and worst values for individual criteria. To be ranked as the best alternative, the alternative should be as close to the greatest value as possible while remaining as distant from the worst value as possible. Additionally, the steps involved in this method are simple and straightforward, making decision-making easier. The method follows these steps:

Step 1. Evaluation of alternatives. Alternatives are evaluated using linguistic values, which are then used to create an initial decision matrix.

Step 2. Transformation of linguistic values into fuzzy numbers. As with all fuzzy methods, linguistic values are transformed into fuzzy numbers to enable mathematical operations.

Step 3. Normalization of fuzzy numbers. In this step, the type of each criterion is first identified (either benefit or cost), and normalization is performed accordingly. For benefit criteria, the value of each alternative is divided by the highest value in that criterion. For cost criteria, the smallest value is divided by the values of other alternatives in that criterion. This normalization is calculated as follows:

$$n_{ij} = \frac{x_{ij}^{l}}{\max x_j^{u}}, \frac{x_{ij}^{m}}{\max x_j^{u}}, \frac{x_{ij}^{n}}{\max x_j^{u}} \text{ ; for benefit criteria} \tag{6}$$

$$n_{ij} = \frac{\min x_j^{l}}{x_{ij}^{n}}, \frac{\min x_j^{l}}{x_{ij}^{m}}, \frac{\min x_j^{l}}{x_{ij}^{l}}\text{; for cost criteria} \tag{7}$$

where $x_{j\,min}$ is the minimum value for a particular criterion, and $x_{j\,max}$ is the maximum value for a particular criterion.

Step 4. Calculation of alternative solutions. In this step, the maximum and minimum values of the alternatives for each criterion are identified for each fuzzy number.

Step 5. Weighting of alternatives with criteria weights. The normalized values of the alternatives are multiplied by the corresponding criteria weights. Alternative solutions are multiplied with these weights as well.

$$\tilde{v}_j = \tilde{w}_j \cdot \tilde{n}_{ij} \tag{8}$$

Step 6. Calculation of sum values for the weighted alternatives. This step involves calculating the sum value for each weighted alternative, including the alternative solutions.

$$\tilde{S}_j = \sum_{i=1}^{n} \tilde{v}_j \tag{9}$$

Step 7. Calculation of deviations from alternative solutions. The sum values of the weighted alternatives are compared with the weighted alternative solutions, and deviations are determined. For an alternative to rank higher, it should be closer to the maximum alternative solution and further from the minimum alternative solution.

$$\tilde{R}_j = \frac{\tilde{S}_j}{\tilde{S}_{j\,max\,AS}} \tag{10}$$

$$\tilde{R}'_j = \frac{\tilde{S}_{j\,min\,AS}}{\tilde{S}_j} \tag{11}$$

Step 8. Defuzzification of the sum values of weighted alternatives. Fuzzy numbers are converted into crisp numbers using the following formula.

$$R_{j\,def} = \frac{R_i^l + 4R_i^m + R_i^u}{6} \tag{12}$$

$$R'_{j\,def} = \frac{R'^l_i + 4R'^m_i + R'^u_i}{6} \tag{13}$$

Step 9. Final calculation of the CORASO method value. The final value is calculated as:

$$Q_i = \frac{R_j - R'_j}{R_j + R'_j} \tag{14}$$

The goal is for the values relative to the deviation from the maximum alternative solution to be as large as possible, while the values relative to the deviation from the minimum alternative solution should be as small as possible. This ensures that the alternative with the highest CORASO method value is ranked as the best, while alternatives with lower values are ranked accordingly.

3 Results and discussion

When evaluating agricultural drones for AG Semberija, the importance of the criteria used will first be assessed using the SiWeC method. The initial step involves expert evaluation of the criteria (Table 3). In this phase, the experts use linguistic values to express how important they find each criterion in evaluating agricultural drones. According to their evaluation, the lowest rating is "Medium," indicating that all criteria are important for drone evaluation.

Once the experts have rated the criteria, these linguistic values are transformed into fuzzy numbers using a membership function (Table 2). For instance, the value "Medium" is converted into the fuzzy number (3, 5, 7), while "Medium Good" is transformed into the next fuzzy number (5, 7, 9). Using this function, all linguistic values are translated into corresponding fuzzy numbers, creating a fuzzy decision matrix (Table 4).

Table 3. Experts' evaluations of the criteria importance

Expert	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
Expert 1 (E1)	VG	G	G	MG	G	VG	G	MG	G	MG
Expert 2 (E2)	G	G	MG	MG	VG	MG	VG	M	MG	MG
Expert 3 (E3)	VG	MG	MG	MG	G	G	VG	M	G	MG
Expert 4 (E4)	G	MG	MG	G	G	G	G	M	G	MG
Expert 5 (E5)	VG	MG	VG	G	G	G	VG	M	G	G
Expert 6 (E6)	VG	G	VG	VG	G	G	VG	M	G	G

Table 4. Fuzzy decision matrix

	C1	C2	C3	C4	C5	C6	…	C10
E1	(9, 10, 10)	(7, 9, 10)	(7, 9, 10)	(5, 7, 9)	(7, 9, 10)	(9, 10, 10)	…	(5, 7, 9)
E2	(7, 9, 10)	(7, 9, 10)	(5, 7, 9)	(5, 7, 9)	(9, 10, 10)	(5, 7, 9)	…	(5, 7, 9)
E3	(9, 10, 10)	(5, 7, 9)	(5, 7, 9)	(5, 7, 9)	(7, 9, 10)	(7, 9, 10)	…	(5, 7, 9)
E4	(7, 9, 10)	(5, 7, 9)	(5, 7, 9)	(7, 9, 10)	(7, 9, 10)	(7, 9, 10)	…	(5, 7, 9)
E5	(9, 10, 10)	(5, 7, 9)	(9, 10, 10)	(7, 9, 10)	(7, 9, 10)	(7, 9, 10)	…	(7, 9, 10)
E6	(9, 10, 10)	(7, 9, 10)	(9, 10, 10)	(9, 10, 10)	(7, 9, 10)	(7, 9, 10)	…	(7, 9, 10)

The next step involves normalizing the fuzzy decision matrix, where all fuzzy values are divided by the largest fuzzy number, which in this case is ten (10). Through this normalization, fuzzy values are converted into decimal numbers—for example, the number nine becomes 0.9, and the number seven becomes 0.7. After normalization, the standard deviation is calculated for the values provided by each expert. A higher standard deviation indicates a greater variance in an expert's evaluations, and vice versa. This step ensures the evaluations of the experts are weighted according to their consistency. The experts' ratings are then multiplied by the standard deviation values. For example, for the first expert and the first criterion, the calculation is as follows (15):

$$v_{11} = (0.9 \times 0.163 = 0{,}147, 1 \times 0.163 = 0.163, 1 \times 0.163 = 0.163) \tag{15}$$

Next, the values of each criterion are summed, and the weight of each criterion is calculated (Table 5). The results indicate that only criterion C8, "Market availability," deviates from the others, having a lower weight than the other criteria. The weights of the remaining criteria are relatively similar, with minimal deviations. This consistency is due to the experts' generally aligned evaluations, leading to limited variation in the results.

Table 5. Calculation of criterion weights using the fuzzy SiWeC method

	C1	C2	C3	C4	...	C10
$\tilde{s}_{ij}$	(0.92, 1.07, 1.11)	(0.66, 0.88, 1.05)	(0.73, 0.91, 1.05)	(0.70, 0.90, 1.05)	...	(0.62, 0.85, 1.03)
$\tilde{w}_{ij}$	(0.09, 0.12, 0.15)	(0.06, 0.10, 0.15)	(0.07, 0.10, 0.14)	(0.07, 0.10, 0.15)	...	(0.06, 0.09, 0.14)

With the criteria weights established, the evaluation of agricultural drones begins, assessing how each drone satisfies the defined decision criteria. The first steps - expert assessment (Table 6) and the transformation of linguistic values into fuzzy numbers - are the same as those used in determining the criteria weights. Since the same value scale and membership function are applied, the process is identical. Given that six experts are involved, their opinions must be harmonized, resulting in a fuzzy decision-making matrix that represents the average of the individual matrices from each expert. This method ensures that all experts contribute equally to the final decision by averaging their evaluation ratings.

After forming this decision-making matrix, normalization is performed. The type of criterion (benefit or cost) must first be identified before normalization can proceed. To illustrate, we will consider one benefit criterion (C1) and one cost criterion (C7) and explain the normalization for drone D1. For benefit criteria, the values of the summed fuzzy numbers are divided by the highest value of those numbers for each criterion, while for cost criteria, the lowest value of the alternatives is divided by the summed fuzzy numbers (16).

$$n_{11} = \left(\frac{7.67}{10.00} = 0.77, \frac{9.33}{10.00} = 0.93, \frac{10.00}{10.00} = 1.00\right); n_{17} = \left(\frac{1.00}{2.00} = 0.5, \frac{1.00}{1.00} = 1.00, \frac{1.00}{1.00} = 1.00\right) \quad (16)$$

Once this extended decision matrix is normalized, the next step is to determine the minimum and maximum alternative solutions. These values help identify the best and worst alternatives for each criterion. Depending on the fuzzy numbers, some of these values may be shared by multiple alternatives (Table 7).

Table 6. Expert assessment

E1	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
D1	G	MG	M	MG	G	G	VL	MG	MG	L
D2	M	M	MG	MG	MG	MG	M	MG	MG	M
D3	MG	ML	MG	MG	M	MG	ML	G	G	M
D4	MG	MG	M	ML	MG	MG	ML	MG	MG	ML
D5	G	MG	MG	G	G	MG	L	M	G	L
D6	MG	M	G	MG	M	MG	L	MG	MG	ML
D7	MG	M	M	G	G	M	L	MG	G	L
D8	G	M	MG	MG	G	G	M	ML	M	M
E2	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
D1	VG	G	M	MG	G	G	VL	MG	MG	ML
D2	M	M	G	MG	MG	MG	M	MG	MG	M
D3	MG	ML	MG	MG	MG	G	ML	M	G	M
D4	MG	MG	M	M	M	MG	ML	MG	MG	ML
D5	VG	MG	G	G	G	MG	L	M	G	L
D6	MG	M	G	MG	M	MG	L	MG	MG	ML
D7	MG	M	M	G	G	MG	L	MG	G	L
D8	VG	M	MG	MG	G	G	M	MG	M	M
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
E6	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
D1	G	G	M	MG	VG	G	VL	MG	MG	VL
D2	MG	M	G	MG	G	G	MG	M	MG	MG
D3	MG	G	VG	G	MG	VG	L	M	G	M
D4	MG	MG	ML	G	G	VG	ML	G	MG	M
D5	G	MG	G	VG	VG	MG	M	M	G	L
D6	MG	VG	G	M	G	VG	VL	G	MG	VL
D7	VG	M	M	G	G	VG	M	VG	VG	L
D8	VG	M	VG	MG	VG	MG	M	MG	M	L

Table 7. Extended normalized decision matrix

	C1	C2	C3	C4	…	C10
D1	(0.77, 0.93, 1.00)	(0.68, 0.88, 1.00)	(0.30, 0.50, 0.70)	(0.50, 0.70, 0.90)	…	(0.18, 0.27, 0.46)
D2	(0.43, 0.63, 0.83)	(0.31, 0.51, 0.71)	(0.67, 0.87, 0.98)	(0.50, 0.70, 0.90)	…	(0.14, 0.19, 0.30)
D3	(0.50, 0.70, 0.90)	(0.37, 0.58, 0.75)	(0.57, 0.75, 0.92)	(0.53, 0.73, 0.92)	…	(0.14, 0.20, 0.33)
D4	(0.50, 0.70, 0.90)	(0.51, 0.71, 0.92)	(0.28, 0.48, 0.68)	(0.42, 0.62, 0.78)	…	(0.15, 0.21, 0.38)
D5	(0.67, 0.85, 0.97)	(0.51, 0.71, 0.92)	(0.67, 0.87, 0.98)	(0.83, 0.97, 1.00)	…	(0.25, 0.50, 1.00)
D6	(0.50, 0.70, 0.90)	(0.61, 0.76, 0.86)	(0.70, 0.90, 1.00)	(0.37, 0.57, 0.77)	…	(0.19, 0.29, 0.55)
D7	(0.57, 0.75, 0.92)	(0.31, 0.51, 0.71)	(0.30, 0.50, 0.70)	(0.70, 0.90, 1.00)	…	(0.25, 0.50, 1.00)
D8	(0.87, 0.98, 1.00)	(0.31, 0.51, 0.71)	(0.63, 0.80, 0.93)	(0.50, 0.70, 0.90)	…	(0.18, 0.29, 0.50)
MIN AS	(0.43, 0.63, 0.83)	(0.31, 0.51, 0.71)	(0.28, 0.48, 0.68)	(0.37, 0.57, 0.77)	…	(0.14, 0.19, 0.30)
MAX AS	(0.87, 0.98, 1.00)	(0.68, 0.88, 1.00)	(0.70, 0.90, 1.00)	(0.83, 0.97, 1.00)	…	(0.25, 0.50, 1.00)

The next step involves weighting the normalized decision matrix, which follows a procedure similar to most methods: multiplying the normalized decision matrix by the criteria weights. In this example, the normalized decision matrix is multiplied by the weights calculated by the fuzzy SiWeC method. Using the example of criterion C1 and drone D1, this process is illustrated as follows (17):

$$v_{11} = (0.09 \times 0.77 = 0{,}07, 0.12 \times 0.93 = 0.11, 0.15 \times 1.00 = 0.15) \tag{17}$$

This procedure is repeated for all values and alternative solutions, resulting in the formation of a weighted decision matrix. The next step calculates the sum of values for each alternative and alternative solution, followed by determining the deviation of each alternative from the corresponding solution. For the D1 drone, the calculation is as follows (18):

$$R_1 = \left(\frac{0.39}{1.45} = 0.27, \frac{0.77}{0.90} = 0.86, \frac{1.29}{0.48} = 2.70\right), R'_1 = \left(\frac{0.23}{1.29} = 0.18, \frac{0.50}{0.77} = 0.65, \frac{0.99}{0.23} = 2.56\right) \tag{18}$$

After calculating the deviation values, defuzzification is performed, and the final CORASO value is determined (Table 8). For the D1 drone, the result is as follows (19):

$$Q_1 = \frac{1.07-0.89}{1.07+0.89} = 0.092 \tag{19}$$

The results from the CORASO method indicate that the best-performing drone, according to the experts' evaluations for AG Semberija, is drone D1 (DJI Agras T30), followed by drone D5 (Kray Protection UAS), while drone D2 (Yamaha RMAX) ranks the lowest. The reasons for these rankings can be traced back to the characteristics of the drones. The DJI Agras T30 stands out due to its large storage capacity, relatively favorable price, and other specifications that outperform the other drones. Given that the primary focus of this research is acquiring a drone for crop spraying, it makes sense that this drone ranks the highest. In the opposite order, the Yamaha RMAX performed poorly due to its nature as a mini helicopter, which is more challenging to maintain and uses fuel rather than batteries like electric drones. While this drone may be suitable for large agricultural operations, its price and other factors contribute to its lower ranking. However, this ranking order may not apply to other agricultural businesses, as the optimal choice of drone depends on specific needs, which can vary across different companies and operations.

Table 8. Ranking results using the fuzzy CORASO method

	$\tilde{S}_j$	$\tilde{R}_j$	$\widetilde{R'}_j$	$R_{j\,def}$	$R'_{j\,def}$	Q_i	Rank
D1	(0.39 0.77 1.29)	(0.27 0.86 2.70)	(0.18 0.65 2.56)	1.07	0.89	0.092	1
D2	(0.29 0.59 1.11)	(0.20 0.66 2.31)	(0.21 0.84 3.41)	0.86	1.17	-0.154	8
D3	(0.32 0.64 1.17)	(0.22 0.71 2.44)	(0.19 0.78 3.04)	0.92	1.06	-0.072	6
D4	(0.30 0.61 1.14)	(0.21 0.68 2.38)	(0.20 0.82 3.28)	0.88	1.13	-0.121	7
D5	(0.38 0.72 1.30)	(0.26 0.81 2.70)	(0.17 0.69 2.63)	1.03	0.93	0.053	2
D6	(0.34 0.70 1.27)	(0.24 0.78 2.64)	(0.18 0.71 2.90)	1.00	0.99	0.005	3
D7	(0.34 0.68 1.24)	(0.23 0.75 2.59)	(0.18 0.74 2.91)	0.97	1.01	-0.018	4
D8	(0.34 0.65 1.15)	(0.24 0.72 2.39)	(0.20 0.77 2.89)	0.92	1.03	-0.056	5
MAX AS	(0.48 0.90 1.45)						
MIN AS	(0.23 0.50 0.99)						

Once the drones have been compared and ranked based on their characteristics, a comparative analysis will be conducted to evaluate the results of the fuzzy CORASO method against other fuzzy methods. Comparative analysis serves to verify the research outcomes [29]. This process examines whether the method used provides similar or consistent results compared to other methods [30], and validating the findings. To conduct this analysis, six fuzzy methods were employed: fuzzy Ranking of Alternatives with Weights of Criterion (RAWEC), fuzzy Measurement of Alternatives and Ranking according to COmpromise Solution (MARCOS), fuzzy Weighted aggregated sum product assessment (WASPAS), fuzzy Simple Additive Weighting (SAW), fuzzy Multi-Attributive Border Approximation Area Comparison (MABAC), and fuzzy Additive Ratio ASsessment (ARAS). These methods were selected for the following reasons:

- Fuzzy RAWEC is used because it employs two normalizations, and alternatives are compared using the criteria weights.
- Fuzzy MARCOS uses the same normalization process as the CORASO method and also compares alternatives against ideal and anti-ideal solutions while incorporating utility functions.
- Fuzzy WASPAS offers a compromise between two approaches-the weighted sum model (WSM) and the weighted product model (WPM).
- Fuzzy SAW is the simplest of all MCDM methods, using only normalization and weighting while still providing results comparable to more complex methods.
- Fuzzy MABAC was selected because it applies a different normalization technique than the methods mentioned earlier, and the complexity of its calculations differs.
- Fuzzy ARAS employs a distinct normalization approach and compares alternatives using a utility function relative to the optimal alternative.

Due to these specific characteristics, these methods were selected for comparison with the results of the CORASO method. The findings reveal a difference in the ranking order for two drones, specifically drones D3 and D8 (Figure 2). The ranking order for these drones differs in the fuzzy RAWEC, fuzzy WASPAS, and fuzzy ARAS methods. When looking into the results of the fuzzy CORASO method, it becomes clear that the smallest difference between rankings is observed for these two drones. This is why it is not surprising that applying two normalizations in the fuzzy RAWEC method, having a compromise between two methods in fuzzy WASPAS, or using a different normalization in fuzzy ARAS results in a change in the ranking—but only for these two drones. For all other drones, the ranking remains consistent across all methods. This demonstrates that the fuzzy CORASO method produces results comparable to those from other methods, confirming its validity. Moreover, this analysis demonstrates that if certain alternatives have similar characteristics, the method used can influence the results.

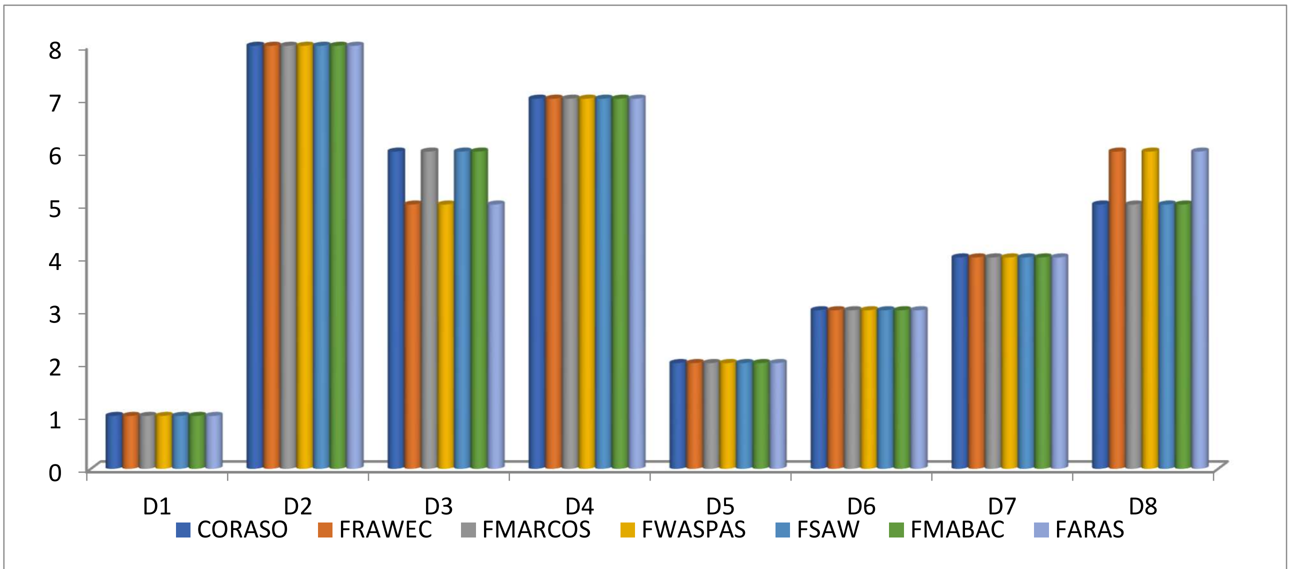

Figure 2. Comparative analysis

The reason why the results of the fuzzy CORASO method are more closely related to certain methods than others is because of the methodology procedures followed by those methods. For example, the fuzzy MARCOS method compares alternatives to optimal solutions before calculating a utility function. The fuzzy SAW method weights the normalized decision matrix rather than comparing alternative values. Since it follows the identical initial four steps as the other methods, the results are the same. The fuzzy MABAC method is different from the fuzzy CORASO method because it compares the alternatives to the geometric mean of the alternative's value, which is exactly the middle point of the best and worst values for specified criteria. The ranking is different between the fuzzy RAWEC and fuzzy CORASO methods because the former uses two normalizations while the latter uses only one. The fuzzy ARAS method compares the best value of the alternative for particular criteria while overlooking the worst value of the alternative, resulting in a difference in the ranking order. The fuzzy WASPAS method includes two methods with the Weighted Product Model (WPM) method scaling the normalized values with the weight values of the criterion, resulting in a difference in ranks. Taking this into account, the fuzzy CORASO method is closer in comparison to related methods with comparable steps.

After confirming the results obtained by the fuzzy CORASO method, a sensitivity analysis is performed. The purpose of sensitivity analysis is to examine whether the ranking of alternatives changes when the weights of the criteria are altered [31]. This type of analysis can be conducted in various ways, such as modifying the weight of a single criterion or multiple criteria [32]. In this research, the focus will be on changing one criterion at a time to observe how the ranking of drones shifts as the importance of that criterion is reduced. Sensitivity analysis will be conducted by reducing the weight of individual criteria by 30%, 60%, and 90%, while proportionally increasing the weights of the remaining criteria. This approach generates three scenarios for each criterion, and since there are ten criteria in total, thirty scenarios will be generated for the sensitivity analysis.

The results of sensitivity analysis show that, for drones D4 and D2, the ranking order remains unchanged across all scenarios (Figure 3). Now, the focus shifts to six drones whose rankings do change with the variation in scenarios. Drone D1 maintains the top ranking in 28 scenarios, while in two scenarios, drone D5 outperforms it. In these two scenarios, the weight of criterion C7 (Price) was reduced by 60% and 90%. This suggests that, according to the experts, drone D5 has a higher price than D1, and as the weight of this criterion decreases, D5 moves up in the rankings. Additionally, D5 ranked third in scenario S12, where the weight of criterion C4 (Hover time) was reduced by 90%. This indicates that drone D6 has a lower hovering capacity compared to D5, and by reducing the weight of this criterion, D6 performed better than D5.

Similarly, changes for other drones can be analyzed to identify their weaknesses, which can then be addressed to better meet the goals of AG Semberija. This sensitivity analysis also reinforces the previous results, as ranking changes occurred in only a small number of scenarios.

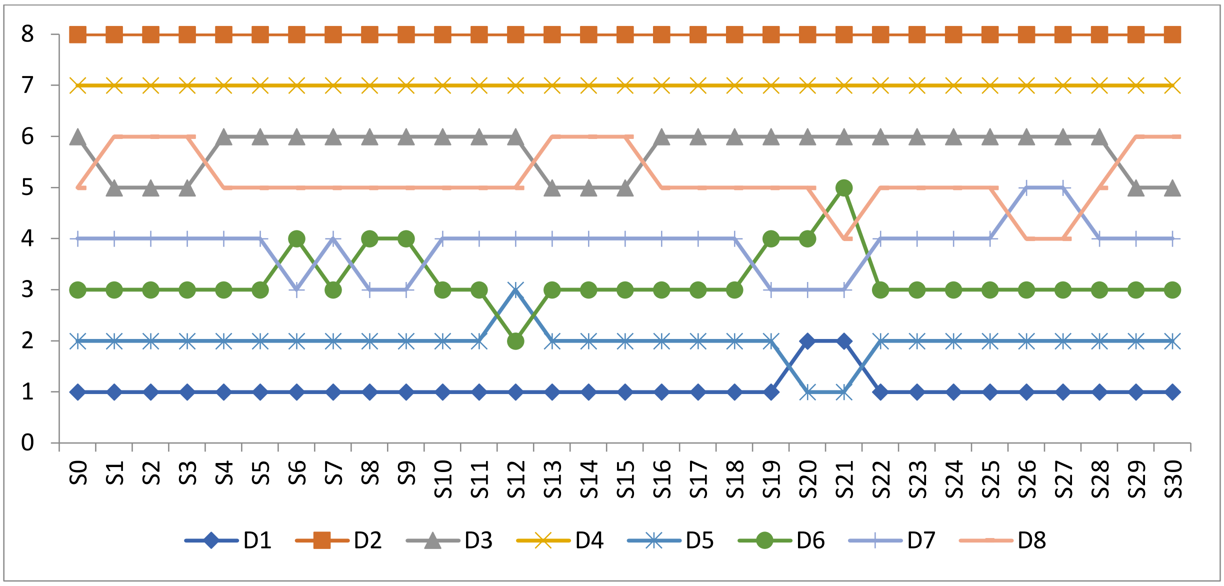

Figure 3. Sensitivity analysis results

4 Conclusion

The trend in modern agriculture is increasingly leaning toward the adoption of technological innovations. One such innovation is the use of drones in agriculture. While drones can be used for various purposes, this research focused on their application for crop spraying. To select the drone that best meets the needs of AG Semberija, a combination of MCDM and expert evaluation was used. Given that AG Semberija had no prior experience with drones, external experts were consulted. A total of six experts were involved, first evaluating the importance of specific criteria and then evaluating the drones based on these criteria. Ten criteria were included in the evaluation, which included the drones' technical and economic aspects. Because there were more technical criteria than economic ones, the former were given more emphasis. These criteria were applied to a total of eight drones.

During the expert evaluation, linguistic values were applied using a seven-level scale. To make these values applicable for determining the importance of the criteria and the alternatives, fuzzy logic was used. This approach made possible the transformation of linguistic values into corresponding fuzzy numbers. For determining the criteria's importance, the fuzzy SiWeC method was used. This is a relatively new method for assigning subjective weights, and its use in this research was intended to highlight its functionality. The results of the fuzzy SiWeC method showed that all criteria held nearly equal importance, with the exception of criterion C8 (Market availability), which had a slightly lower weight. This indicated that all the observed criteria are highly important in the process of selecting drones. To identify the drone with the best characteristics, the newly developed MCDM method, CORASO, was used.

The CORASO method ranks alternatives based on how they compare to the highest and lowest values for each criterion. The ideal outcome is for an alternative to be as close as possible to the highest value and as far as possible from the lowest value, ensuring it performs optimally. Applying this method led to the conclusion that the DJI Agras T30 agricultural drone performed best and was the top choice for AG Semberija. This is primarily due to its larger reservoir capacity and its ability to cover the greatest surface area compared to the other drones. The results were validated through a comparative analysis, which showed that the fuzzy CORASO method provided results consistent with those of the other fuzzy methods used in the research. The drone rankings were also confirmed through a sensitivity analysis.

The methodology, based on the fuzzy SiWeC and CORASO methods, proved to be both flexible and simple to implement, highlighting the potential for these methods in future research. Further development of these methods in different forms would contribute to the enhancement of the MCDM system, making the decision-making process more efficient. By using the fuzzy SiWeC method, experts only need to evaluate individual criteria without the need for more complex operations, such as comparing or ranking criteria against each other. Meanwhile, the fuzzy CORASO method simplifies the ranking process by focusing on deviations from alternative solutions, which helps reduce the number of necessary steps in the decision-making process.

However, the research presented in this paper has some limitations, mainly related to the criteria used for selection of agricultural drones. In practice, there are many ways to evaluate drones. This research used ten criteria that were considered the most suitable for achieving the research objectives. However, future research should include more criteria to provide a broader evaluation. This is also a limitation of the model, as it would need to be adjusted to fit the new criteria. It's important to investigate if these other criteria lead to different results, and to understand why, assuming the same drones are being studied. If different drones are chosen, the results wouldn't be comparable. Future research should focus on either all-electric drones or all fuel-powered drones to clearly identify which type performs best.

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References

[1] C. Wang and X. Fu, "Environmental cost accounting in the sugar industry: An MFCA perspective on 'sweet' environmental burdens," *Journal of Green Economy and Low-Carbon Development*, vol. 3, no. 1, pp. 45–55, 2024, doi: 10.56578/jgelcd030105

[2] N. A. Essien, C. A. Umah, L.-A. U. Amarachi, and T. K. Samson, "Modeling retail price volatility of selected food items in Cross River state, Nigeria using GARCH models," *Acadlore Transactions on Applied Mathematics and Statistics*, vol. 2, no. 2, pp. 94–103, 2024, doi: 10.56578/atams020204.

[3] S. Peng, G. Xi, Y. Wei, and L. Yu, "Enhanced detection of soybean leaf diseases using an improved Yolov5 model," *International Journal of Knowledge and Innovation Studies*, vol. 2, no. 1, pp. 45–56, 2024, doi: 10.56578/ijkis020105.

[4] M. Javaid, A. Haleem, R. P. Singh, and R. Suman, "Enhancing smart farming through the applications of Agriculture 4.0 technologies," *International Journal of Intelligent Networks*, vol. 3, pp. 150–164, 2022, doi: 10.1016/j.ijin.2022.09.004.

[5] W. Li, X. Han, Z. Lin, and A.-U. Rahman, "Enhanced pest and disease detection in agriculture using deep learning-enabled drones," *Acadlore Transactions on AI and Machine Learning*, vol. 3, no. 1, pp. 1-10, 2024, doi: 10.56578/ataiml030101.

[6] S. U. Ullah, M. Zeb, A. Ahmad, S. Ullah, F. Khan, and A. Islam, "Monitoring the billion trees afforestation project in Khyber Pakhtunkhwa, Pakistan through remote sensing," *Acadlore Transactions on Geosciences*, vol. 3, no. 2, pp. 89–97, 2024, doi: 10.56578/atg030203.

[7] B. Berner et al., "Spraying wheat plants with a drone moved at low altitudes," *Agronomy*, vol. 14, no. 9, p. 1894, 2024, 10.3390/agronomy14091894.

[8] U. Karaoğlu, O. Mbah, and Q. Zeeshan, "Applications of machine learning in aircraft maintenance," *Journal of Engineering Management and Systems Engineering*, vol. 2, no. 1, pp. 76-95, 2022, doi: 10.56578/jemse020105.

[9] K. Lipianina-Honcharenko, M. Komar, N. Melnyk, and R. Komarnytsky, "Sustainable Information System for enhancing virtual company resilience through machine learning in smart city Socio-economic scenarios," *Economics*, vol. 12, no. 2, pp. 69-96, 2024, doi: 10.2478/eoik-2024-0022.

[10] A. Hafeez, M. A. Husain, S.P. Singh, A. Chauhan, M. T. Khan, N. Kumar, A. Chauhan, and S. K. Soni, "Implementation of drone technology for farm monitoring & pesticide spraying: A review," *Information Processing in Agriculture*, vol. 10, no. 2, pp. 192–203, 2023, doi: 10.1016/j.inpa.2022.02.002.

[11] O. Demchenko, N. Basiurkina, N. Popadynets, S. Minenko, and K. Sokoliuk, "Factors and determinants of the development of human capital in rural areas in the conditions of global challenges," *Economics*, vol. 11, no. s1, pp. 93-108, 2023, doi: 10.2478/eoik-2023-0026.

[12] M. Radovanović, D. Božanić, D. Tešić, A. Puška, I. Hezam and C. Jana, "Application of hybrid DIBR-FUCOM-LMAW-Bonferroni-grey-EDAS model in multicriteria decision-making," *Facta Universitatis, Series: Mechanical Engineering,* vol. 21, no. 3, pp. 387-403, 2023, doi: 10.22190/FUME230824036R.

[13] D. Tešić and , D. Marinković, "Application of fermatean fuzzy weight operators and MCDM model DIBR-DIBR II-NWBM-BM for efficiency-based selection of a complex combat system," *Journal of Decision Analytics and Intelligent Computing*, vol. 3, no. 1, pp. 243–256, 2023, doi: 10.31181/10002122023t.

[14] B. Kizielewicz and W. Sałabun, "SITW Method: A New Approach to Re-identifying Multi-criteria Weights in Complex Decision Analysis," *Spectrum of Mechanical Engineering and Operational Research*, vol. 1, no. 1, pp. 215-226, 2024, doi: 10.31181/smeor11202419.

[15] S. Bošković, L. Švadlenka, S. Jovčić, V. Simic, M. Dobrodolac and A. Elomiya, "Sustainable propulsion technology selection in penultimate mile delivery using the FullEX-AROMAN method," *Socio-Economic Planning Sciences,* vol. 95, p. 102013, 2024, doi: 10.1016/j.seps.2024.102013.

[16] A. Hussain and K. Ullah, "An Intelligent Decision Support System for Spherical Fuzzy Sugeno-Weber Aggregation Operators and Real-Life Applications," *Spectrum of Mechanical Engineering and Operational Research*, vol. 1, no. 1, pp. 177-188, 2024, 10.31181/smeor11202415.

[17] A. Mahmoodirad and S. Niroomand, "A heuristic approach for fuzzy fixed charge transportation problem," *Journal of Decision Analytics and Intelligent Computing*, vol. 3, no. 1, pp. 139–147, 2023, doi: 10.31181/jdaic10005092023m.

[18] C.-L. Hwang and K. Youn, *"Multiple Attribute Decision Making - Methods and Application: A State of the Art Survey"*, Springer, New York, 1981.

[19] Ž. Stević, D. Pamučar, A. Puška, and P. Chatterjee, "Sustainable supplier selection in healthcare industries using a new MCDM method: Measurement of alternatives and ranking according to COmpromise solution (MARCOS)," *Computers & Industrial Engineering*, vol. 140, no. 106231, p. 106231, 2020, doi: 10.1016/j.cie.2019.106231.

[20] A. Puška, Ž. Stević, and D. Pamučar, "Evaluation and selection of healthcare waste incinerators using extended sustainability criteria and multi-criteria analysis methods," *Environment, Development and Sustainability*, vol. 24, no. 9, pp. 11195-11225, 2022, doi: 10.1007/s10668-021-01902-2.

[21] E. K. Zavadskas and Z. Turskis, "A new additive ratio assessment (ARAS) method in multicriteria decision-making," *Technological and Economic Development of Economy*, vol. 16, no. 2, pp. 159-172, 2010, doi: 10.3846/tede.2010.10.

[22] C. W. Churchman and R. L. Ackoff, "An approximate measure of value", *Journal of Operations Research Society of America*, vol. 2, no. 1, pp. 172–87, 1954, 10.1287/opre.2.2.172.

[23] A. Puška, M. Nedeljković, D. Pamučar, D. Božanić, and V. Simić, "Application of the new SImple WEight Calculation (SIWEC) method in the case study in the sales channels of agricultural products," *MethodsX*, vol. 13, p. 102930, 2024, doi: 10.1016/j.mex.2024.102930.
[24] S. Dhouib, "Unravelling the Assignment Problem Under Intuitionistic Triangular Fuzzy Environment by the Novel Heuristic Dhouib-Matrix-AP1," *Yugoslav Journal Of Operations Research,* vol. 33, no. 3, pp. 467-480, 2023, doi: 10.2298/YJOR220915005D.
[25] M. Rakić, M. Žižović, B. Miljković, A. Njeguš, M. Žižović and I. Đorđević, "Multi-criteria selection of standards for system analyst activities in organizations," *Facta Universitatis, Series: Mechanical Engineering,* vol. 21, no. 3, pp. 433-451, 2023, doi: 10.22190/FUME230521023R.
[26] S. Jana and S. Islam, "A Pythagorean Hesitant Fuzzy Programming Approach and Its Application to Multi Objective Reliability Optimization Problem," *Yugoslav Journal Of Operations Research,* vol. 34, no. 2, pp. 201-227, 2024, doi: 10.2298/YJOR230417024J.
[27] R. Imran, K. Ullah, Z. Ali and M. Akram, "A Multi-Criteria Group Decision-Making Approach for Robot Selection Using Interval-Valued Intuitionistic Fuzzy Information and Aczel-Alsina Bonferroni Means," *Spectrum of Decision Making and Applications*, vol. 1, no. 1, pp. 1-32, 2024, doi: 10.31181/sdmap1120241.
[28] S. Majumder and S. Kar, "Utilizing a hybrid decision-making approach with fuzzy and rough sets on linguistic data for analyzing voting patterns," *Vojnotehnički glasnik/Military Technical Courier*, vol. 72, no. 2, pp. 605-629, 2024, doi: 10.5937/vojtehg72-48652.
[29] D. D. Trung, B. Dudić, H. T. Dung, and N. X. Truong, "Innovation in financial health assessment: Applying MCDM techniques to banks in Vietnam," *Economics*, vol. 12, no. 2, pp. 21-33, 2024, doi: 10.2478/eoik-2024-0011.
[30] M. Asif, U. Ishtiaq and I. K. Argyros, "Hamacher Aggregation Operators for Pythagorean Fuzzy Set and its Application in Multi-Attribute Decision-Making Problem," *Spectrum of Operational Research*, vol. 2, no. 1, pp. 27-40, 2025, doi: 10.31181/sor2120258.
[31] M. B. Bouraima, S., Jovčić, M. Dobrodolac, D. Pamucar, I. Badi and N. D. Maraka, "Sustainable Healthcare System Devolution Strategy Selection Using the AROMAN MCDM Approach," *Spectrum of Decision Making and Applications*, vol. 1, no. 1, pp. 46-63, 2024, doi: 10.31181/sdmap1120243.
[32] J. Kannan, V. Jayakumar and M. Pethaperumal, "Advanced Fuzzy-Based Decision-Making: The Linear Diophantine Fuzzy CODAS Method for Logistic Specialist Selection," *Spectrum of Operational Research*, vol. 2, no. 1, pp. 41-60, 2025, doi: 10.31181/sor2120259.