World Academy of Science, Engineering and Technology
International Journal of Aerospace and Mechanical Engineering
Vol:17, No:8, 2023

Unmanned Aerial Vehicle Selection Using Fuzzy Multiple Criteria Decision Making Analysis

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***Abstract*—**The selection of an Unmanned Aerial Vehicle (UAV) involves complex decision-making due to the evaluation of numerous alternatives and criteria simultaneously. This process necessitates the consideration of various factors such as payload capacity, maximum speed, endurance, altitude, avionics systems, price, economic life, and maximum range. This study aims to determine the most suitable UAV by taking these criteria into account. To achieve this, the standard fuzzy set methodology is employed, enabling decision-makers to define linguistic terms as references. A practical numerical example is provided to demonstrate the applicability of the proposed approach. Through a successful application, a comparison of different UAVs is conducted, culminating in the selection of the most appropriate vehicle during the final stage.

***Keywords*—**Standard fuzzy sets (SFSs), Unmanned Aerial Vehicle (UAV) selection, multiple criteria decision making, MCDM.

I. INTRODUCTION

Unmanned aerial vehicles (UAVs), commonly known as drones, have gained significant attention and relevance in recent wars in Iraq, Syria, Libya, Karabakh, Ethiopia, Somalia, Yemen, and Ukraine. UAVs are progressively becoming essential components across various applications, including package delivery, military reconnaissance, and automated inspection systems. The utilization of UAVs has expanded across various domains, with increasing applications over time. Some notable applications include reconnaissance and surveillance, maritime security, meteorological research, neutralizing enemy air defenses, pre-amphibious operation area exploration, damage assessment during natural disasters, combating human trafficking, and target marking in warfare [1-2].

The advancement of unmanned aerial vehicles (UAVs) has the potential to bring about a significant transformation in the utilization of military force in future air operations. The current experience with UAVs in many military operations is promising, showing that these technologies increase the effectiveness of the use of aerospace power for military forces, resulting in reduced costs and lower risks for human pilots [3-4].

A broader consideration pertains to the judicious use of UAVs for employing lethal force, specifically identifying the air power missions best suited for unmanned, piloted, and autonomous vehicles. This necessitates a scientific examination of the advantages and drawbacks associated with deploying UAVs in various operational scenarios. By understanding these factors, informed decisions can be made regarding the optimal utilization of UAVs in military contexts. UAVs can be categorized into two groups: remotely controlled aircraft and autonomous vehicles that follow predetermined flight plans. Remotely controlled UAVs are operated by pilots from ground stations, while UAVs with flight plans can execute tasks autonomously and returning to base [5-6].

UAVs offer numerous economic and personnel advantages. From an economic standpoint, they are more affordable compared to other aircraft types, particularly when considering the unit cost of large warplanes. In terms of personnel requirements, UAVs necessitate fewer personnel compared to manned fighter aircraft. Post-use maintenance, repair, and administrative tasks can be accomplished with a reduced workforce when utilizing UAVs. Additionally, UAVs possess longer airtime capabilities. The absence of a pilot allows UAVs to remain airborne for extended periods. This feature is particularly advantageous as manned warplanes are limited by the endurance of the pilot. The ability of UAVs to operate without a physical pilot and be controlled by multiple operators from a ground control station is considered a significant advantage [7-8].

Numerous studies have been conducted in the field of aircraft selection, employing various methodologies. These include the Analytical Hierarchy Process (AHP), the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), the Preference Analysis for Reference Ideal Solution (PARIS), and the Proximity Measure Method (PMM), among others. These studies aimed to select, evaluate, or rank different aircraft types based on their specifications and sizes. Additionally, fuzzy methodology and multiple criteria decision making methods have been proposed for various decision-making problems, such aircraft selection, cargo aircraft selection, combat aircraft selection, unmanned combat aircraft evaluation and selection, stealth fighter aircraft selection, material selection, aerial firefighting aircraft selection, agricultural aircraft selection, aircraft supplier selection, fighter aircraft selection, and military training aircraft selection [9-84].

However, it is worth noting that the standard fuzzy set methodology has not been applied to UAV selection or aircraft selection in previous studies. Moreover, this study focuses specifically on the selection of unmanned aircraft, distinguishing it from previous research. By utilizing the standard fuzzy set methodology, decision-makers can make more flexible decisions by utilizing fuzzy set values for each criterion, rather than relying solely on precise values. This flexibility arises from the method's ability to accommodate decision-making using fuzzy set values. Consequently,

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subjective decision-making errors can be minimized or eliminated.

The subsequent sections of this paper are organized as follows: Chapter 2 provides a comprehensive explanation of the standard fuzzy set methodology and further elucidates the definition of UAVs. Chapter 3 presents a numerical example of UAV selection application. Finally, Chapter 4 concludes the study and offers suggestions for future research endeavors.

II. METHODOLOGY

Since the introduction of fuzzy logic and fuzzy sets, significant advancements have been made in solving a wide range of complex real-life problems. Fuzzy logic, pioneered by Lotfi Zadeh in the 1960s, provides a framework to handle uncertainty and imprecision by allowing degrees of membership in sets rather than binary membership. This led to the development of fuzzy sets, where elements are assigned membership values between 0 and 1, enabling more flexible and nuanced reasoning. Over time, researchers expanded on this foundation and introduced related techniques like intuitionistic fuzzy sets and neutrosophic sets [85-88].

Intuitionistic fuzzy sets, proposed by Atanassov in the 1980s, aimed to address situations where lack of knowledge or contradictory information exists. By introducing an additional membership function called the non-membership function, intuitionistic fuzzy sets offer a more expressive way to model uncertainty and vagueness in decision-making processes [89].

Neutrosophic sets, introduced by Smarandache in the 1990s, further extended the concepts of fuzzy logic and intuitionistic fuzzy sets by incorporating an additional indeterminacy function. This indeterminacy function accounts for incomplete or unknown information, making neutrosophic sets particularly useful when dealing with highly uncertain and conflicting data [90-91].

The combination of these developments in fuzzy logic and its related techniques has revolutionized various fields, including artificial intelligence, control systems, image processing, pattern recognition, and decision-making. They have proven especially valuable in situations where conventional binary logic falls short due to the presence of ambiguity, imprecision, and vagueness. By embracing the inherent uncertainty in real-world problems, these fuzzy-based techniques have empowered researchers and practitioners to handle complex scenarios with greater precision and adaptability, leading to improved problem-solving capabilities across diverse domains [92-134].

Definition 1. Let X be a non-empty set. A standard fuzzy set (SFS) A in X is given by

$$A = \{x, \mu_A(x) \mid x \in X\} \tag{1}$$

where the functions $\mu_A(x): X \to [0,1]$ and $\nu_A(x) = (1-\mu_A): X \to [0,1]$ define the degree of membership and the degree of non-membership of an element to the set A, respectively, with the condition that

$$\mu_A(x) + \nu_A(x) = 1, \forall x \in X \tag{2}$$

The degree of hesitancy is calculated as follows:

$$\pi_A(x) = 1 - \mu_A(x) - \nu_A(x) = 0 \tag{3}$$

Definition 2. Let $A = (\mu_A, \nu_A)$ and $B = (\mu_B, \nu_B)$ be two SFNs, then the addition and multiplication operations are defined as follows

$$A \oplus B = (\mu_A + \mu_B - \mu_A\mu_B, \nu_A\nu_B) \tag{4}$$

$$A \otimes B = (\mu_A\mu_B, \nu_A + \nu_B - \nu_A\nu_B) \tag{5}$$

$$A^C = (\nu_A, \mu_A) \tag{6}$$

Definition 3. Let $A = (\mu_A, \nu_A)$ be an SFN, then the score function $S(A)$ and accuracy function $H(A)$ of A can be respectively defined as follows

$$S(A) = \mu_A - \nu_A \tag{7}$$

$$H(A) = \mu_A + \nu_A \tag{8}$$

Definition 4. Let $A_i = (\mu_{A_i}, \nu_{A_i})$ $(i = 1, 2, ..., n)$ be a set of SFNs and $\omega = (\omega_1, \omega_2, ..., \omega_n)^T$ be weight vector of A_i $\sum_{i=1}^{n} \omega_i = 1$, then a standard fuzzy weighted average (SFWA) operator is

$$SFWA(A_1, A_2, ..., A_n) = \left(\left(1 - \prod_{i=1}^{n} (1 - \nu_{A_i})^{\omega_i}\right), \prod_{i=1}^{n} \mu_{A_i}^{\omega_i}\right) \tag{9}$$

Definition 5. Let $A_i = (\mu_{A_i}, \nu_{A_i})$ $(i = 1, 2, ..., n)$ be a set of SFNs and $\omega = (\omega_1, \omega_2, ..., \omega_n)^T$ be weight vector of A_i $\sum_{i=1}^{n} \omega_i = 1$, then a standard fuzzy weighted geometric (SFWA) operator is

$$SFWG(A_1, A_2, ..., A_n) = \left(\prod_{i=1}^{n} \mu_{A_i}^{\omega_i}, \left(1 - \prod_{i=1}^{n} (1 - \nu_{A_i})^{\omega_i}\right)\right) \tag{10}$$

Definition 6. Let $A_i = (\mu_{A_i}, \nu_{A_i})$ and $B_i = (\mu_{B_i}, \nu_{B_i})$ be two SFNs. The distance between these two SFNs is obtained by normalized Minkowski distance family as follows.

$$d(A,B) = \left(\frac{1}{2n} \sum_{i=1}^{n} (\mu_{A_i} - \mu_{B_i})^{\delta} + (\nu_{A_i} - \nu_{B_i})^{\delta} + (\pi_{A_i} - \pi_{B_i})^{\delta}\right)^{1/\delta} \tag{11}$$

where $\delta = (1, 2, 3, ..., \infty)$, $\delta = 1$ denotes Manhattan distance, $\delta = 2$ denotes Euclidean distance, $\delta = 3$ denotes Minkowski distance, and $\delta = \infty$ denotes Chebyshev distance.

Open Science Index, Aerospace and Mechanical Engineering Vol:17, No:8, 2023 publications.waset.org/10013196.pdf

III. APPLICATION

A. Multiple Criteria Decision-Making (MCDM) Analysis

In decision making theory, a multiple criteria decision-making analysis problem is characterized by a set of alternatives $A_i = \left\{A_1,...,A_i\right\}$ $(i > 2)$ which the best decision must be made, according to a given set of criteria $C_j = \left\{C_1,...,C_j\right\}$ $(j > 1)$ and the score $i\ x\ j$ $X = [X_{ij}]$ whose component X_{ij} is the score of the alternative A_i based on criterion C_j. Each criterion has an importance normalized weight $\omega_j \in [0,1]$ with $\sum_{j=1}^{J} \omega_j = 1$.

The MCDM problem is considered by using all criteria C_j and all alternatives A_i as well as all their related score values X_{ij} expressed quantitatively and the weighting factor ω_j of each criteria C_j. The set of normalized weighting factors is denoted by $\omega_j = \left\{\omega_1,...,\omega_j\right\}$. Depending on the context of the MCDMA problem, the score can be interpreted either as a cost or as a benefit. The score matrix $X = [X_{ij}]$ is sometimes also called benefit or payoff matrix in the literature. The classical MCDM problem aims to select the best alternative $A^* \in A$ given X and the weighting factors ω_j of criteria.

B. Unmanned Aerial Vehicle (UAV) Selection Problem

Unmanned Aerial Vehicles (UAVs), commonly known as drones, have traditionally been associated with military applications due to their advanced technical features. However, UAVs are now finding increasing use in the civilian sector. The civil applications of UAVs encompass a range of functions, including:

Undertaking dangerous missions where UAVs provide the only viable solution, such as operating in adverse weather conditions, environmentally hazardous areas, or regions contaminated with nuclear, biological, and chemical substances.

Performing scientific tasks that benefit from UAVs' cost-effectiveness and effectiveness, such as atmospheric and oceanic data collection, environmental and agricultural surveillance, as well as magnetic and radiological mapping.

Carrying out commercial tasks, including border security, monitoring traffic conditions in cities, surveilling air, and base stations, protecting areas of importance, firefighting, and inspecting pipelines and power transmission lines.

The multiple criteria decision-making (MCDM) methods can be effectively applied to determine the most suitable Unmanned Aerial Vehicle (UAV) selection. Therefore, in this study, a suggested MCDM approach is used to evaluate and select the best UAV among several alternatives. To evaluate the UAV alternatives, a set of criteria is determined based on a comprehensive literature review and expert opinions.

Given the diverse applications of UAVs, several performance criteria are considered. These performance criteria include:

Payload capacity (C1): Refers to the weight of equipment, excluding avionics, fuel, and necessary systems for ensuring a safe takeoff, flight, and landing. The payload varies depending on the mission requirements.

Maximum speed (C2): The velocity of a UAV depends on its engine power. Different operations may demand high, low, or average speeds.

Maximum endurance (C3): Indicates the longest duration a UAV can operate safely in the air, considering the fuel capacity from the moment it takes off until landing.

Maximum altitude (C4): The height at which a UAV can ascend influences its effectiveness in avoiding detection by air defense systems and expanding the coverage area for image acquisition.

Avionic systems (C5): These are the various onboard systems responsible for communication, navigation, display, and management of multiple functions within the UAV.

Economic life (C6): The duration over which a UAV can remain operational and provide utility while being properly maintained.

Maximum range (C7): The farthest distance a UAV can be controlled by a pilot after taking off from its base, considering the fuel capacity and payload, while ensuring a safe return.

Price (C8): The cost associated with acquiring a UAV, including ground equipment, contributes to its overall evaluation.

Operational cost per hour (C9): The operational cost of a UAV per hour refers to the expenses incurred in operating and maintaining the unmanned aerial vehicle for a duration of one hour. This cost encompasses various factors, including fuel consumption, maintenance and repair costs, personnel wages, ground support equipment, and other operational expenses associated with the UAV's mission. Calculating the operational cost per hour is crucial for budgeting, resource allocation, and evaluating the cost-effectiveness of UAV operations. It helps organizations assess the financial implications and efficiency of utilizing UAVs in different applications.

By considering these performance criteria, a comprehensive assessment can be conducted to evaluate UAVs for their intended purposes in a rigorous manner.

The initial decision matrix specifies the kind of optimization (benefit or cost) of each attribute. The decision criteria for evaluating alternative UAV options consist of two types: benefit criteria (C1-C7) and cost criteria (C8-C9). The benefit criteria encompass C1 to C7, while the cost criteria are represented by C8 and C9. The potential UAV alternatives being considered are A1, A2, and A3, which will be assessed based on the established criteria.

To tackle this problem using a standard fuzzy multiple criteria decision making (MCDM) approach, the following steps are followed:

- Identification of decision criteria: The benefit criteria (C1-C7) and cost criteria (C8-C9) relevant to the UAV evaluation are identified and defined.
- Fuzzy evaluation: Standard fuzzy sets are employed to evaluate each UAV alternative (A1, A2, and A3) with respect to the identified criteria. This allows for a more flexible and nuanced assessment, considering the uncertainties and imprecise nature of decision-making.
- Fuzzy aggregation: The fuzzy evaluations of each alternative are aggregated, considering the weights assigned to the criteria. This aggregation process synthesizes the different evaluations into a comprehensive decision.
- Ranking and selection: The aggregated evaluations are used to rank the UAV alternatives based on their overall performance. The alternative that demonstrates the highest suitability according to the criteria is selected as the preferred choice.

By following these steps within the standard fuzzy MCDM framework, a systematic approach is applied to effectively evaluate and compare the potential UAV options based on the identified decision criteria.

Step 1. The decision matrix is established.

The initial decision matrix $X = [x_{ij}]_{mxn}$ for the alternatives (A_i), the decision criteria (C_j), and the criteria weights (ω_j) is constructed. This matrix also specifies the type of optimization (benefit or cost) of each criterion.

Step 2. The decision matrix is normalized.

$$x_{ij} = \begin{cases} \{\mu_A - \nu_A\,, & \Omega_B \\ \nu_A - \mu_A\;, & \Omega_C \end{cases}$$

where Ω_B denotes benefit type criteria, and Ω_C denotes cost type criteria,

Step 3. The criteria weights are computed.

The importance weights ω_j of decision criteria are assessed by the DMs using standard fuzzy weighted geometric (SFWG) operator.

Step 4. Weighted normalized matrix is computed.

The standard fuzzy weighted geometric (SGWG) and (SFWA) operator are used to compute the weighted normalized matrix.

Step 5. The alternatives are ranked according to their score function $S(A) \in [-1,1]$ values in decreasing order. The bigger value $i^* = \arg\max S(A_i)$ corresponds to the best MCDM solution A^*, that is $A^* = A_i$.

C. Standard Fuzzy Set Application

The solutions of the defined problem through the proposed standard fuzzy method are presented in the following algorithm.

Step 1. The proposed approach is applied to the most appropriate UAV selection among three alternatives in MCDM problem. These alternatives (A1, A2, and A3) are evaluated according to seven criteria determined based on comprehensive literature review and expert opinions.

A team of experts are formed to evaluate the suppliers using the proposed approach. Three decision-makers are selected, consisting of aircraft experts and expert academics on multiple criteria decision making in a fuzzy environment and are abbreviated as DM1, DM2, and DM3 respectively.

Step 2. The evaluations of the aircraft by the decision-makers in accordance with the defined objectives and criteria, using standard fuzzy set values are presented in Table 1.

Table 1. Standard fuzzy decision matrix for each decision maker

		DM1			DM2			DM3		
C_j		A1	A2	A3	A1	A2	A3	A1	A2	A3
C1	μ_A	0,7	0,4	0,9	0,3	0,5	0,6	0,7	0,2	0,8
	ν_A	0,3	0,6	0,1	0,7	0,5	0,4	0,3	0,8	0,2
C2	μ_A	0,6	0,5	0,7	0,6	0,7	0,9	0,3	0,1	0,8
	ν_A	0,4	0,5	0,3	0,4	0,3	0,1	0,7	0,9	0,2
C3	μ_A	0,6	0,7	0,8	0,6	0,9	0,4	0,8	0,5	0,7
	ν_A	0,4	0,3	0,2	0,4	0,1	0,6	0,2	0,5	0,3
C4	μ_A	0,9	0,7	0,6	0,3	0,5	0,8	0,9	0,7	0,5
	ν_A	0,1	0,3	0,4	0,7	0,5	0,2	0,1	0,3	0,5
C5	μ_A	0,6	0,7	0,8	0,5	0,3	0,4	0,6	0,3	0,9
	ν_A	0,4	0,3	0,2	0,5	0,7	0,6	0,4	0,7	0,1
C6	μ_A	0,5	0,8	0,9	0,7	0,6	0,5	0,3	0,6	0,9
	ν_A	0,5	0,2	0,1	0,3	0,4	0,5	0,7	0,4	0,1
C7	μ_A	0,4	0,7	0,5	0,1	0,6	0,9	0,5	0,4	0,6
	ν_A	0,6	0,3	0,5	0,9	0,4	0,1	0,5	0,6	0,4
C8	μ_A	0,9	0,7	0,6	0,5	0,5	0,6	0,7	0,8	0,7
	ν_A	0,1	0,3	0,4	0,5	0,5	0,4	0,3	0,2	0,3
C9	μ_A	0,7	0,6	0,5	0,8	0,6	0,5	0,7	0,5	0,8
	ν_A	0,3	0,4	0,5	0,2	0,4	0,5	0,3	0,5	0,2

Steps 3. Original standard fuzzy set numbers are converted to

their corresponding normalized numbers as shown in Table 2.

Table 2. Normalized standard fuzzy decision matrix for each decision maker

		DM1			DM2			DM3		
C_j		A1	A2	A3	A1	A2	A3	A1	A2	A3
C1	μ_A	0,7	0,4	0,9	0,3	0,5	0,6	0,7	0,2	0,8
	ν_A	0,3	0,6	0,1	0,7	0,5	0,4	0,3	0,8	0,2
C2	μ_A	0,6	0,5	0,7	0,6	0,7	0,9	0,3	0,1	0,8
	ν_A	0,4	0,5	0,3	0,4	0,3	0,1	0,7	0,9	0,2
C3	μ_A	0,6	0,7	0,8	0,6	0,9	0,4	0,8	0,5	0,7
	ν_A	0,4	0,3	0,2	0,4	0,1	0,6	0,2	0,5	0,3
C4	μ_A	0,9	0,7	0,6	0,3	0,5	0,8	0,9	0,7	0,5
	ν_A	0,1	0,3	0,4	0,7	0,5	0,2	0,1	0,3	0,5
C5	μ_A	0,6	0,7	0,8	0,5	0,3	0,4	0,6	0,3	0,9
	ν_A	0,4	0,3	0,2	0,5	0,7	0,6	0,4	0,7	0,1
C6	μ_A	0,5	0,8	0,9	0,7	0,6	0,5	0,3	0,6	0,9
	ν_A	0,5	0,2	0,1	0,3	0,4	0,5	0,7	0,4	0,1
C7	μ_A	0,4	0,7	0,5	0,1	0,6	0,9	0,5	0,4	0,6
	ν_A	0,6	0,3	0,5	0,9	0,4	0,1	0,5	0,6	0,4
C8	μ_A	0,1	0,3	0,4	0,5	0,5	0,4	0,3	0,2	0,3
	ν_A	0,9	0,7	0,6	0,5	0,5	0,6	0,7	0,8	0,7
C9	μ_A	0,3	0,4	0,5	0,2	0,4	0,5	0,3	0,5	0,2
	ν_A	0,7	0,6	0,5	0,8	0,6	0,5	0,7	0,5	0,8

The criteria weight vector was determined by the decision makers as follows (Table 3):

Table 3. Criteria weight vector

C_j	Criteria weight value	
C1	μ_A	0,9
	ν_A	0,1
C2	μ_A	0,7
	ν_A	0,3
C3	μ_A	0,8
	ν_A	0,2
C4	μ_A	0,7
	ν_A	0,3
C5	μ_A	0,8
	ν_A	0,2
C6	μ_A	0,7
	ν_A	0,3
C7	μ_A	0,8
	ν_A	0,2
C8	μ_A	0,8
	ν_A	0,2
C9	μ_A	0,9
	ν_A	0,1

Weighted normalized standard fuzzy decision matrix for each decision maker is given as follows (Table 4):

Table 4. Weighted normalized standard fuzzy decision matrix for each decision maker

		DM1			DM2			DM3		
C_j		A1	A2	A3	A1	A2	A3	A1	A2	A3
C1	μ_A	0,63	0,36	0,81	0,27	0,45	0,54	0,63	0,18	0,72
	ν_A	0,37	0,64	0,19	0,73	0,55	0,46	0,37	0,82	0,28
C2	μ_A	0,42	0,35	0,49	0,42	0,49	0,63	0,21	0,07	0,56
	ν_A	0,58	0,65	0,51	0,58	0,51	0,37	0,79	0,93	0,44
C3	μ_A	0,48	0,56	0,64	0,48	0,72	0,32	0,64	0,40	0,56
	ν_A	0,52	0,44	0,36	0,52	0,28	0,68	0,36	0,60	0,44
C4	μ_A	0,63	0,49	0,42	0,21	0,35	0,56	0,63	0,49	0,35
	ν_A	0,37	0,51	0,58	0,79	0,65	0,44	0,37	0,51	0,65
C5	μ_A	0,48	0,56	0,64	0,40	0,24	0,32	0,48	0,24	0,72
	ν_A	0,52	0,44	0,36	0,60	0,76	0,68	0,52	0,76	0,28
C6	μ_A	0,35	0,56	0,63	0,49	0,42	0,35	0,21	0,42	0,63
	ν_A	0,65	0,44	0,37	0,51	0,58	0,65	0,79	0,58	0,37
C7	μ_A	0,32	0,56	0,4	0,08	0,48	0,72	0,40	0,32	0,48
	ν_A	0,68	0,44	0,60	0,92	0,52	0,28	0,60	0,68	0,52
C8	μ_A	0,08	0,24	0,32	0,40	0,40	0,32	0,24	0,16	0,24
	ν_A	0,92	0,76	0,68	0,60	0,60	0,68	0,76	0,84	0,76
C9	μ_A	0,27	0,36	0,45	0,18	0,36	0,45	0,27	0,45	0,18
	ν_A	0,73	0,64	0,55	0,82	0,64	0,55	0,73	0,55	0,82

Aggregated weighted standard fuzzy decision matrix is given as follows (Table 5):

Table 5. Aggregated weighted standard fuzzy decision matrix

C_j		A1	A2	A3
C1	μ_A	0,536	0,339	0,710
	ν_A	0,464	0,661	0,290
C2	μ_A	0,357	0,324	0,564
	ν_A	0,643	0,676	0,436
C3	μ_A	0,540	0,580	0,524
	ν_A	0,460	0,420	0,476
C4	μ_A	0,524	0,447	0,451
	ν_A	0,476	0,553	0,549
C5	μ_A	0,455	0,367	0,591
	ν_A	0,545	0,633	0,409
C6	μ_A	0,360	0,471	0,554
	ν_A	0,640	0,529	0,446
C7	μ_A	0,279	0,462	0,556
	ν_A	0,721	0,538	0,444
C8	μ_A	0,251	0,274	0,294
	ν_A	0,749	0,726	0,706
C9	μ_A	0,241	0,392	0,372
	ν_A	0,759	0,608	0,628

D. SFWA operator applied to the UAV selection

Step 4. Using the SFWA operator, the rankings (R_i) of the alternatives, which were obtained after aggregating the score values for each standard fuzzy number in the weighted decision matrix are presented in Table 6.

Table 6. The rankings of the alternatives

A_i	μ_A	ν_A	$S(A_i)$	R_i
A1	0,405	0,595	-0,190	3
A2	0,413	0,587	-0,174	2
A3	0,527	0,473	0,054	1

E. SFWG operator applied to the UAV selection

Step 5. Using SFWG operator, the rankings (R_i) of the alternatives, which were obtained after aggregating the score values for each standard fuzzy number in the weighted decision matrix are presented in Table 7.

Table 7. The rankings of the alternatives

A_i	μ_A	ν_A	$S(A_i)$	R_i
A1	0,376	0,624	-0,248	3
A2	0,397	0,603	-0,206	2
A3	0,498	0,502	-0,004	1

F.Distance functions applied to the UAV selection

Step 6. Using the distance functions, the rankings (R_i) of the alternatives are presented in Table 8.

Table 8. The rankings of the alternatives

A_i	A1	A2	A3
$d(A,B)L_1$	0,136	0,123	0,017
R_i	3	2	1
$d(A,B)L_2$	0,161	0,172	0,031
R_i	2	3	1
$d(A,B)L_3$	0,176	0,205	0,040
R_i	2	3	1
$d(A,B)L_\infty$	0,031	0,041	0,008
R_i	2	3	1

To analyze the ranking of alternatives A_i (A1, A2, A3) using the results provided in the above tables, one needs to consider the rankings obtained from three different methods: SFWA operator, SFWG operator, and distance functions. The summary of the ranking of the UAV alternatives is as follows:

A1: Ranked 3rd (SFWA), Ranked 3rd (SFWG), Ranked 2nd (Distance Functions)

A2: Ranked 2nd (SFWA), Ranked 2nd (SFWG), Ranked 3rd (Distance Functions)

A3: Ranked 1st (SFWA), Ranked 1st (SFWG), Ranked 1st (Distance Functions)

Based on the rankings from different methods, one can see that alternative A3 consistently ranks 1st across all three methods. On the other hand, alternatives A1 and A2 have varying rankings depending on the method used. A2 consistently ranks 2nd, while A1 ranks either 2nd or 3rd, and A3 ranks either 3rd or 2nd.

Therefore, if one considers the majority ranking, A1 would be ranked 3rd, A2 would be ranked 2nd, and A3 would be ranked 1st. However, the final decision depends on the specific weighting and aggregation methods used in each approach. It is essential to consider the methodology and the criteria used to obtain these rankings for making a well-informed decision.

IV. CONCLUSION

The selection of Unmanned Aerial Vehicles (UAVs) is a complex decision-making process involving the evaluation of numerous alternatives and criteria simultaneously. This study aimed to address this challenge by employing the standard fuzzy set methodology, which allowed decision-makers to define linguistic terms as references, making the decision-making process more practical and interpretable.

Through the successful application of the proposed approach, a practical numerical example was presented to demonstrate the methodology's applicability. The example involved the comparison of different UAVs based on criteria such as payload capacity, maximum speed, endurance, altitude, avionics systems, price, economic life, and maximum range. The results were then aggregated using the SFWA operator, the SFWG operator, and distance functions to obtain rankings for each alternative.

The findings indicated that alternative A3 consistently ranked 1st across all three methods, making it the most suitable UAV according to the specified criteria. However, it is important to note that alternatives A1 and A2 showed varying rankings depending on the method used, with A2 consistently ranking 2nd and A1 ranking either 2nd or 3rd.

The final decision on the most appropriate UAV should consider the majority ranking, which suggests that A3 is the top choice. However, the decision-making process should also consider the specific weighting and aggregation methods utilized in each approach. Decision-makers must carefully consider the methodology, criteria, and weights used to obtain the rankings, ensuring a well-informed decision.

In conclusion, the standard fuzzy set methodology provides a valuable and systematic approach to UAV selection, enabling decision-makers to efficiently compare and evaluate multiple alternatives against multiple criteria. The successful application of this methodology demonstrated its effectiveness in identifying the most suitable UAV for a given set of criteria. Future research can build upon this study by exploring other decision-making methods and considering additional criteria to further enhance the UAV selection process.

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