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Unmanned Aerial Vehicle Selection with Different MCDM Methods in Defense Industry

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Abstract: Unmanned aerial vehicles (UAVs) have gained increasing importance due to their expanding application areas and operational flexibility. Selecting the most suitable UAV, however, represents a complex multi-criteria decision-making (MCDM) problem that involves numerous technical and performance-related factors. This study addresses the UAV selection problem by employing four distinct MCDM approaches: Evidential fuzzy MCDM based on Belief Entropy, Intuitionistic Fuzzy Dempster-Shafer Theory (DST), Spherical Fuzzy Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), and Type-2 Neutrosophic Fuzzy CRITIC-MABAC. Each method incorporates different fuzzy set theories, while a common seven-point linguistic scale is utilized to ensure consistency across models. The evaluation criteria were determined through a comprehensive literature review, and expert opinions were collected from experienced UAV pilots and technical personnel. The analysis identified the most suitable UAV alternative among the considered options. Sensitivity analyses were conducted to assess the robustness of the obtained results. The findings demonstrate that the proposed framework enables a simultaneous comparison of different fuzzy set environments on a unified linguistic scale. Overall, the results are consistent, reliable, and practically applicable, offering valuable insights and methodological contributions to the field of UAV selection and fuzzy MCDM applications.

Keywords: UAV; MCDM; DST; TOPSIS; CRITIC; MABAC

1 Introduction

Throughout history, aerial vehicles have undergone continuous transformation, evolving in design, function, and purpose in parallel with technological advancements. While early aircraft were primarily developed for military purposes, such as reconnaissance, surveillance, and combat operations, their applications have gradually expanded to include cargo transportation, passenger mobility, and a wide range of civilian uses. The evolution of aircraft technology has been shaped by multiple factors, with military demands playing a central role. Strategic objectives such as achieving air superiority, enhancing intelligence capabilities, and improving electronic warfare systems have significantly contributed to the advancement of aviation technologies. At the same time, rapid industrial and technological progress has provided the foundation for the emergence of modern aircraft equipped with sophisticated systems and advanced materials.

Initially, aerial vehicles were entirely dependent on human control and operation. However, the structural and functional evolution of aviation systems has led to the development of unmanned aerial vehicles (UAVs)—aircraft capable of being operated without an onboard pilot. Unlike conventional manned systems, UAVs are remotely controlled by operators located in ground-based command centers, providing substantial operational flexibility. This remote operation significantly reduces human risk, particularly in dangerous missions, and decreases personnel-related training and development costs compared to manned aviation. As a result, UAVs have become indispensable assets in both military and civilian applications.

Despite their relatively lower speed and maneuverability compared to traditional aircraft, UAVs offer several critical advantages that enhance operational efficiency. One of the most important advantages is their exceptional reconnaissance and surveillance capability. Equipped with high-resolution cameras and advanced sensors, UAVs enable continuous monitoring, target identification, and precision tracking under diverse environmental conditions. In military contexts, UAVs play a vital role in intelligence gathering, mission feedback, and situational awareness, thereby improving mission effectiveness and reducing the need for direct human involvement in hazardous environments.

The rapid pace of technological development has further accelerated the evolution of UAVs. Advances in aerodynamics, propulsion systems, and sensor technology have resulted in UAVs with greater payload capacity, endurance, and flight altitude capabilities. Research and development efforts continue to focus on enhancing UAV performance through improved materials, stealth technologies, and integrated weapon systems. These innovations are not only transforming traditional warfare strategies but are also expanding UAV utilization in fields such as environmental monitoring, disaster management, agriculture, and logistics.

As both military and commercial competition intensify globally, the demand for advanced UAV systems has grown significantly. Consequently, nations and organizations are increasingly investing in both the development and procurement of UAV technologies. However, selecting the most suitable UAV for a specific operational requirement presents a complex decision-making problem, often characterized by uncertainty and multiple conflicting criteria. These criteria may include technical specifications, cost, endurance, payload capacity, and mission adaptability, among others. Addressing such multidimensional decision problems necessitates a systematic and rational approach that can effectively evaluate and balance various factors.

In this context, the multi-criteria decision-making (MCDM) framework has emerged as a robust analytical tool for solving UAV selection problems. MCDM techniques allow decision-makers to evaluate multiple alternatives based on a set of quantitative and qualitative criteria, ultimately identifying the most appropriate solution under complex and uncertain conditions. In the literature, numerous studies have demonstrated the effectiveness of MCDM approaches, particularly when integrated with fuzzy logic, which enables the modeling of uncertainty and linguistic assessments inherent in expert judgments. Fuzzy set theory supports the conversion of qualitative expert evaluations into quantitative data through linguistic scales, thereby improving the interpretability and consistency of decision outcomes.

Motivated by these considerations, the present study aims to develop a comprehensive decision-making framework for UAV selection based on advanced MCDM methodologies integrated with fuzzy set extensions. The study employs four distinct approaches: Evidential Fuzzy MCDM based on Belief Entropy (EFMCDM), Intuitionistic Fuzzy Dempster Shafer Theory (IF-DST), Spherical Fuzzy (SF) Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), and Type-2 Neutrosophic Fuzzy (T2NN) CRITIC-MABAC, each representing different perspectives in handling uncertainty and inter-criteria relationships. A unified seven-point linguistic scale is adopted across all methods to ensure comparability and methodological consistency.

The contributions of this study are threefold. First, it provides an integrated evaluation framework that simultaneously incorporates multiple fuzzy environments into the UAV selection process. Second, it identifies and prioritizes UAV selection criteria through a comprehensive literature review and expert consultation involving experienced UAV pilots and technical specialists. Third, the proposed framework demonstrates the robustness and applicability of the selected MCDM methods through sensitivity analyses, offering valuable insights for both academic research and practical decision-making in UAV procurement and design. Overall, this research seeks to enrich the existing body of knowledge by presenting a structured, reliable, and adaptable decision-support model for UAV selection under uncertainty.

UAVs, commonly referred to as drones, are aircraft capable of being operated without an onboard crew through remote control systems or autonomous navigation technologies. Initially developed in the early 20th century, UAVs have evolved in parallel with rapid technological advancements, particularly following World War I and II [1, 2]. Early systems, such as Low's 1914 Aerial Target and the Hewitt-Sperry Automatic Airplane, introduced foundational concepts of remote guidance and automatic piloting, which laid the groundwork for subsequent UAV development [3]. During and after World War II, military innovations, including the U.S. Navy's Aerial Torpedo and Germany's Vergeltungswaffen-1 cruise missiles, further accelerated UAV technological capabilities [4]. In the 1950s and 1960s, target drones such as the Falconer series were adapted for reconnaissance purposes through onboard cameras and remote-control interfaces, marking the beginning of operationally oriented UAV applications [5].

The progression toward modern UAVs continued in the 1970s with platforms like the Lockheed Aquila, which enabled automated flight and real-time data transmission. The Ryan Model 147, also known as LightningBug, represents one of the first UAVs meeting contemporary definitions, deployed in operational theaters in China and Vietnam [6]. UAVs have been increasingly integrated into combat operations, with Israel's 1982 deployment over Syrian air defenses demonstrating their utility in providing tactical support [7]. The introduction of GPS-enabled UAVs in the 1990s, exemplified by the Predator series, further expanded operational capabilities, allowing precise navigation, extended mission endurance, and effective intelligence gathering, as evidenced during operations in Bosnia-Herzegovina [8, 9]. Collectively, these developments underscore the transition of UAVs from experimental and target systems to versatile platforms with strategic and operational significance in both military and civilian contexts.

1.1 Limitations of the Study

This study has several limitations that should be acknowledged. First, the analysis is confined to the evaluation of four specific MCDM approaches under a unified framework, thereby excluding other potential methods that could provide alternative perspectives. Second, the linguistic assessments used to evaluate the identified criteria and alternatives may involve a degree of subjectivity, potentially influencing the consistency of the results. Additionally, expert weights were determined using a single weighting technique, which may not fully capture variations in expertise and judgment across different expert groups.

The Likert-type linguistic scales employed in the evaluation process may also introduce minor measurement errors, limiting the complete objectivity of the results. Furthermore, the methods used to quantify uncertainty levels of the criteria may not yield absolutely precise outcomes due to the inherent complexity of fuzzy environments. Finally, potential limitations exist regarding the objectivity of the distance metrics utilized in calculating the proximity of each alternative to the boundary approximation area, which may affect the robustness of the comparative analysis.

1.2 Contribution to the Literature

This study makes several noteworthy contributions to the literature on UAV selection and MCDM applications. By employing four distinct fuzzy MCDM approaches, the research introduces novel perspectives for addressing the UAV selection problem. Specifically, the Evidential Fuzzy MCDM (EFMCDM) method based on belief entropy incorporates belief entropy into UAV selection, providing a new analytical tool for handling uncertainty. The Intuitionistic Fuzzy Dempster-Shafer Theory (IF-DST) approach leverages information entropy to determine expert weights, offering a unique methodology for expert-based evaluation in UAV selection.

In the Spherical Fuzzy (SF) TOPSIS method, the use of a global weighted arithmetic mean facilitates a systematic assessment of UAV alternatives, enhancing comparative decision-making processes. Moreover, the Type-2 Neutrosophic Fuzzy (T2NN) CRITIC–MABAC method contributes to the literature by addressing both expert weighting and alternative ranking under uncertainty. Finally, the adoption of a unified seven-point Likert-type linguistic scale establishes a standardized framework for multi-criteria evaluation, enabling consistent comparisons across the applied methods. Collectively, these contributions advance both the theoretical and practical understanding of fuzzy MCDM techniques in the context of UAV selection.

2 Literature Review

Recent studies on UAV selection demonstrate a growing interest in applying MCDM approaches to evaluate and rank different platforms based on technical, operational, and economic criteria. Researchers have employed a wide range of methodologies, including fuzzy and intuitionistic fuzzy (IF) techniques, Analytic Hierarchy Process (AHP), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), VIKOR, MULTIMOORA, and Choquet integral, to accommodate the inherent uncertainties and subjective judgments in expert evaluations.

These studies consider diverse criteria, ranging from payload capacity, flight duration, operational altitude, and communication range to more detailed technical specifications such as sensor capabilities, autonomy, and avionics systems. The number of alternatives evaluated varies across studies, reflecting both military and civilian UAVs, and experts' opinions are frequently incorporated to ensure informed decision-making. Collectively, the literature indicates that fuzzy MCDM methods provide a systematic framework for integrating multiple performance criteria, facilitating robust and comparable UAV selection processes across different operational contexts.

3 Application of the UAV Selection Methodology

3.1 Overview of the Application Process

The UAV selection problem in this study was implemented using four MCDM methods. The literature review on UAV Selection Studies is shown in Table 1. The application was structured to ensure a systematic, reliable, and comprehensive evaluation of UAV alternatives. A literature review was first conducted to define the decision model components, including criteria, alternatives, and expert evaluators. Expert assessments were standardized using a seven-point Likert scale, allowing for quantitative comparisons across all methods. The application was executed in five sequential stages:

1. Identification of criteria
2. Determination of alternatives
3. Selection of experts
4. Data collection
5. Data analysis using the four MCDM methods

Table 1. Literature review on UAV selection studies

Authors	Year	Criteria	Alternatives	Methods
[10]	2022	3 main criteria, 8 sub-criteria (cost, tech support, durability, eco-friendly)	4	Spherical Fuzzy BWM & MULTIMOORA
[11]	2022	6 criteria (cost, duration, payload, wing span, takeoff weight, altitude)	10	MULTIMOORA
[12]	2022	8 criteria (payload, altitude, range, duration, speed, maneuverability)	9	AHP; ARAS, EDAS, WASPAS, MAUT, TOPSIS, VIKOR
[13]	2022	4 main criteria (performance, awareness, sensors, communication), 32 sub-criteria	4	AHP
[14]	2022	TOPSIS (3 criteria); Fuzzy TOPSIS (5 criteria)	13	TOPSIS & Fuzzy TOPSIS
[15]	2021	8 criteria (payload, altitude, range, duration, speed, maneuverability)	9	AHP; ARAS, EDAS, WASPAS, MAUT, TOPSIS, VIKOR
[16]	2021	8 criteria (payload, speed, durability, altitude, avionics, price, distance)	3	Fuzzy Choquet Integral
[17]	2021	6 criteria (speed, autonomy, range, altitude, cost, payload)	7	Fuzzy AHP & VIKOR
[18]	2020	7 criteria (wing span, length, payload, durability, speed, altitude, range)	6	AHP & TOPSIS
[19]	2019	10 criteria (safety, distance to facilities, traffic, logistics, weather)	15	Fuzzy DEMATEL & Fuzzy TOPSIS
[20]	2016	12 criteria (avionics, cost, mission, life, altitude, control)	4	Delphi & Grey Relational Analysis
[21]	2015	12 criteria (nationality, class, duration, range, sensors, autopilot, safety)	-	-
[22]	2011	3 main criteria (flexibility, suitability, evaluation)	4 (RQ-1 Predator, RQ-5 Hunter, RQ-7 Shadow 200, Hermes 450)	Fuzzy Weighted Average
[23]	2008	6 main (structural, propulsion, performance, communication, control, cost)	5 (ScanEagle, Macopter S100, RQ2 Pioneer, Orbiter, Aerostar)	AHP

3.2 Identification of UAV Selection Criteria

The first stage focused on determining the criteria relevant to UAV selection. An extensive literature review was conducted to identify commonly used performance, operational, and logistical indicators. From this review, fourteen criteria were selected in consultation with experts. These criteria encompass technical capabilities, operational flexibility, endurance, payload capacity, sensor performance, and communication range. Each criterion was precisely defined to ensure consistency in expert evaluations. UAV Selection Criteria are shown in Table 2.

Table 2. UAV selection criteria

Criteria	Identification	Studies
Cost (C_1)	This criterion represents the total acquisition cost of the UAV.	[10, 11, 16, 17, 20, 23]
Payload capacity (C_2)	This criterion indicates the payload capacity of the UAV.	[11–18, 20, 22, 23]
Fuel capacity (C_3)	This criterion refers to the fuel capacity of the UAV.	[22]
Domestic goods status (C_4)	This criterion indicates whether the UAV is domestically produced.	[21]
Engine power (C_5)	This criterion refers to the engine power of the UAV.	[13, 22]
Endurance (C_6)	This criterion indicates the durability level of the UAV.	[11–15, 20, 21, 23]
Maximum speed (C_7)	This criterion shows the maximum speed achievable by the UAV.	[13, 14, 16, 17, 22, 23]
Cruise speed (C_8)	This criterion refers to the UAV's cruise speed.	[12, 14, 15, 18, 22, 23]
Ceiling (C_9)	This criterion indicates the UAV's ceiling altitude.	[11, 13, 14, 17, 20, 22, 23]
Mission/operational altitude (C_{10})	This criterion indicates the UAV's operational altitude.	[12, 15, 18, 23]
Maximum takeoff weight (C_{11})	This criterion shows the maximum takeoff weight that the UAV can carry.	[11, 13, 22, 23]
Communication range (C_{12})	This criterion refers to the communication range of the UAV.	[12, 13, 15, 17, 18, 20–23]
Covering material (C_{13})	This criterion refers to the covering material used in the production of the UAV.	[13, 16]
Sensor systems (C_{14})	This criterion indicates the sensor systems possessed by the UAV.	[13, 17, 20–23]

3.3 Determination of UAV Alternatives

In the second stage, UAV alternatives were identified through literature review and operational relevance assessment. Eight UAVs were selected as candidates for counter-terrorism operations, representing diverse technical specifications, operational ranges, and payload configurations. This ensured that the decision model captured realistic options with strategic and tactical applicability. UAV alternatives are shown in Table 3.

3.4 Expert Panel Composition

The third stage involved assembling a panel of fifteen experts with diverse expertise, including UAV pilots, engineers, and technical personnel. The panel was selected based on technical knowledge, practical experience, and the ability to evaluate UAVs against the defined criteria. This heterogeneous composition enhanced the reliability and validity of the collected assessments.Information regarding the experts is shown in Table 4.

Table 3. UAV selection criteria (alternatives 1–8)

Criteria	Alt-1	Alt-2	Alt-3	Alt-4
Cost (C_1)	5.37 million \$ (2022)	5 million \$ (2021)	1.2 million \$ (2003)	3 million € (2021)
Payload capacity (C_2)	150 kg.	70 kg. + 120 kg.	90 kg.	50 kg.
Fuel capacity (C_3)	300 litres	220 litres	127 kg.	80 litres
Domestic goods status (C_4)	Türkiye	Türkiye	USA	Israel
Engine power (C_5)	1×105 HP	1×97 HP	2×57 HP	1×38 HP
Endurance (C_6)	24 hours	20 hours	20.5 hours	12 hours
Maximum speed (C_7)	120 knots	80 knots	106 knots	110 knots
Cruise speed (C_8)	70 knots	60 knots	70 knots	60 knots
Ceiling (C_9)	25,000 feet	22,500 feet	18,000 feet	18,000 feet
Mission/operational altitude (C_{10})	18,000 feet	18,000 feet	15,000 feet	10,000 feet
Maximum takeoff weight (C_{11})	700 kg.	630 kg.	820 kg.	230 kg.
Communication range (C_{12})	150 km.	200 km.	250 km.	200 km.
Covering material (C_{13})	Composite	Composite	Aluminum alloy	Composite
Sensor systems (C_{14})	Fully Automatic Flight Control and 3 Redundant Autopilot System (Triple Redundant), Navigation with Internal Sensor Fusion Without Dependency on GPS, Fully Automatic Landing and Take-off Feature Without Dependence on Ground Systems, Switchable EO/IR/LD or Multi-Purpose AESA Radar	Automatic takeoff/flight/landing system, Pneumatic de-icing system, Triple redundant avionics architecture, Lightning protection	EO / IR / LD / LRF / Illuminator	EO, IR, SAR, SIGINT and COMINT

Criteria	Alt-5	Alt-6	Alt-7	Alt-8
Cost (C_1)	2 million \$ (2011)	5 million \$ (2005)	10 million \$ (2013)	1 million \$ (2011)
Payload capacity (C_2)	150 kg.	150 kg.	100 kg.	200 kg.
Fuel capacity (C_3)	300 lt.	170 lt.	230 lt.	320 lt.
Domestic goods status (C_4)	Israel	UK / Israel	Italy	China
Engine power (C_5)	1×52 HP	1×35 HP	1×65 HP	1×100 HP
Endurance (C_6)	20 hours	17 hours	20 hours	20 hours
Maximum speed (C_7)	95 knots	95 knots	116 knots	150 knots
Cruise speed (C_8)	70 knots	77 knots	80 knots	80 knots
Ceiling (C_9)	18,000 feet	18,000 feet	21,325 feet	16,400 feet
Mission/operational altitude (C_{10})	15,000 feet	16,000 feet	18,000 feet	10,000 feet
Maximum takeoff weight (C_{11})	450 kg.	450 kg.	650 kg.	1,100 kg.
Communication range (C_{12})	200 km.	200 km.	200 km.	200 km.
Covering material (C_{13})	Composite	Aluminum alloy	Composite	Composite
Sensor systems (C_{14})	DGPS, Automatic takeoff and landing, fully autonomous flight with rerouting during flight	SAR, GMTI, HD EO, IR, LD, Fully autonomous takeoff, landing, and mission system	EO/IR turret, Gabbiano 20 multi-mode surveillance radar and PicoSAR radar, GMTI, SAGE electronic warfare suite, Automatic Identification System	IR turret and SAR

Table 4. Expert panel summary

Experts	Experience (Years)	Expertise	Education	Duty	Level of Professionalism
U_1	5	Good	Bachelor's degree	Pilot	Expert
U_2	5	Good	Bachelor's degree	Pilot	Expert
U_3	4	Very Good	Master's degree	Pilot/ Engineer	Professional
U_4	4	Good	Bachelor's degree	Pilot	Professional
U_5	4	Very good	Master's Degree	Pilot	Professional
U_6	5	Medium good	Bachelor's degree	Pilot	Competent
U_7	2	Medium bad	Bachelor's degree	Pilot	Beginner level
U_8	2	Medium good	Bachelor's degree	Pilot/ Engineer	Expert
U_9	3	Good	Pre-Bachelor's degree	Pilot/ Technical Staff	Expert
U_{10}	4	Medium bad	Bachelor's degree	Pilot	Beginner level
U_{11}	5	Good	Bachelor's degree	Pilot	Expert
U_{12}	4	Very good	Bachelor's degree	Pilot/ Engineer	Professional
U_{13}	6	Very good	Bachelor's degree	Pilot	Professional
U_{14}	4	Very good	Bachelor's degree	Pilot	Expert
U_{15}	4	Very good	Bachelor's degree	Pilot	Competent

3.5 Data Collection

The fourth stage focused on gathering expert evaluations. Structured questionnaires were administered during face-to-face interviews, asking experts to rate each UAV against the fourteen criteria using a seven-point Likert scale. Ethical approval was obtained from the Kırıkkale University Social and Human Sciences Research Ethics Committee prior to data collection. The survey was conducted from November 2023 to January 2024, and responses were compiled into datasets suitable for analysis using the four MCDM methods.

3.6 Data Analysis Using MCDM Methods

The fifth stage involved analyzing the collected data using four MCDM approaches:

- EFMCDM [24]
- IF-DST [25, 26]
- SF-TOPSIS [27, 28]
- T2NN-CRITIC-MABAC [29, 30]

Each method was applied to calculate criteria weights, aggregate expert judgments, and rank UAV alternatives. The unified Likert scale enabled consistent comparisons across methods. The results were tabulated, providing a clear overview of UAV rankings and the relative performance of each alternative across multiple criteria. The UAV selection rankings obtained from the methods are shown in Table 5.

Table 5. UAV ranking results

Methods	$\mathbf{A_1}$	$\mathbf{A_2}$	$\mathbf{A_3}$	$\mathbf{A_4}$	$\mathbf{A_5}$	$\mathbf{A_6}$	$\mathbf{A_7}$	$\mathbf{A_8}$
EFMCDM	0.414 (1)	0.190 (2)	0.055 (6)	0.012 (8)	0.061 (5)	0.031 (7)	0.076 (4)	0.161 (3)
IF-DST	0.434 (1)	0.207 (2)	0.057 (4)	0.006 (8)	0.048 (5)	0.025 (6)	0.019 (7)	0.148 (3)
SF-TOPSIS	0.0000 (1)	0.0981 (2)	1.4531 (6)	2.9397 (8)	1.3632 (4)	1.7594 (7)	1.4510 (5)	0.5812 (3)
T2NN-CRITIC-MABAC	0.1403 (1)	0.1034 (2)	-0.0197 (5)	-0.1769 (8)	-0.0307 (6)	-0.0515 (7)	0.0598 (3)	0.0461 (4)

4 Results and Recommendations

4.1 Overview

This thesis investigated the UAV selection problem using four distinct MCDM methodologies: belief entropy-based evidential fuzzy MCDM (EFMCDM), IF-DST, SF-TOPSIS, and T2NN-CRITIC-MABAC. A decision model comprising 14 criteria, 8 tactical UAV alternatives, and a panel of 15 domain experts was constructed; expert evaluations were elicited using a unified seven-point Likert-type linguistic scale. Each method was applied in accordance with its algorithmic steps, and sensitivity analyses were performed to examine the robustness of the resulting rankings. The following subsections summarize the principal outcomes and synthesize cross-method comparisons.

4.2 Individual Method Outcomes

The four methods produced broadly consistent top selections while differing in the ordering of mid-rank alternatives:

- **EFMCDM:** Produced the ranking $A_1 > A_2 > A_8 > A_7 > A_5 > A_3 > A_6 > A_4$. Alternative A_1 scored highest largely due to superior localization (domestic production), flight endurance, operational ceiling, and engine power; communication range was comparatively less influential in this method's outputs.
- **IF-DST:** Produced the ranking $A_1 > A_2 > A_8 > A_3 > A_5 > A_6 > A_7 > A_4$. The top three alternatives are identical to the EFMCDM results, whereas some mid-rank shifts occurred, specifically A_3 moving up relative to A_7.
- **SF-TOPSIS:** Produced the ranking $A_1 > A_2 > A_8 > A_5 > A_7 > A_3 > A_6 > A_4$. Again, A_1 and A_2 lead the selection; the relative positions of A_3–A_7 vary slightly compared to other approaches.
- **T2NN-CRITIC-MABAC:** Produced the ranking $A_1 > A_2 > A_7 > A_8 > A_3 > A_5 > A_6 > A_4$. In this method, expert and criterion weights were explicitly computed; Expert U_{13} emerged as the most influential respondent, while Experts U_7 and U_{10} had the smallest weights.

Across all four approaches, A_1 is consistently identified as the preferred UAV, suggesting a stable decision outcome under differing fuzzy frameworks and aggregation logics.The ranking of alternatives according to the methods is shown in Table 6.

Table 6. UAV alternative rankings and spearman correlations

Alternatives	EFMCDM	IF-DST	SF-TOPSIS	T2NN-CRITIC-MABAC
A_1	1	1	1	1
A_2	2	2	2	2
A_3	6	4	6	5
A_4	8	8	8	8
A_5	5	5	4	6
A_6	7	6	7	7
A_7	4	7	5	3
A_8	3	3	3	4

4.3 Cross-method Agreement (Quantitative Assessment)

To quantify inter-method agreement, Spearman's rank correlation coefficients were computed between each pair of rankings based on the eight alternatives. The pairwise correlations indicate high agreement: EFMCDM vs. SF-TOPSIS $\rho = 0.976$, EFMCDM vs. T2NN-CRITIC-MABAC $\rho = 0.952$, EFMCDM vs. IF-DST $\rho = 0.833$, IF-DST vs. SF-TOPSIS $\rho = 0.881$, IF-DST vs. T2NN-CRITIC-MABAC $\rho = 0.762$, and SF-TOPSIS vs. T2NN-CRITIC-MABAC $\rho = 0.881$. All p-values are less than 0.05. These statistics corroborate the qualitative observation of substantial concordance among methods, particularly for the top-ranked alternatives. Spearman's rank correlation coefficients are shown in Table 7.

Table 7. Spearman rank correlations (ρ)

Method Pair	p	p-value
EFMCDM vs. DST	0.833	<0.05
EFMCDM vs. TOPSIS	0.976	<0.05
EFMCDM vs. CRITIC	0.952	<0.05
DST vs. TOPSIS	0.881	<0.05
DST vs. CRITIC	0.762	<0.05
TOPSIS vs. CRITIC	0.881	<0.05

4.4 Sensitivity and Robustness Findings

Sensitivity analyses, including perturbation of criterion weights and alternate expert weight scenarios, show that small to moderate changes in weights can alter mid-range rankings (typically between positions 3–7), but do not change the first rank decision (A_1). This stability suggests the decision model is robust with respect to plausible uncertainties in expert judgments and weighting procedures. Recommended sensitivity visualizations include spider/radar plots or tornado charts that display how rank position varies with each perturbed criterion.

4.5 Practical Implications

The consistent selection of A_1 across heterogeneous fuzzy methods indicates that, for the set of criteria and experts involved, A_1 represents a balanced operational choice combining endurance, operational ceiling, propulsion capability, and domestic availability. Decision makers can therefore treat this result as a strong recommendation for procurement or further operational testing. However, mid-rank variability highlights the importance of context-specific priorities: missions emphasizing extreme range, payload, or communications might lead to different operational preferences.

4.6 Recommendations for Future Research

Building on the present findings, the following research directions are proposed:

- Model sensitivity extension: Perform Monte Carlo style uncertainty propagation across weight distributions to quantify rank probabilities for each alternative.
- Alternative and criterion expansion: Evaluate updated UAV models and additional mission-specific criteria (e.g., cyber resilience, ISR sensor fusion).
- Methodological diversification: Apply other fuzzy families and weighting schemes (e.g., entropy-based, subjective-objective hybrid methods) to generalize the present results.
- Cross-jurisdictional studies: Replicate the framework with international expert panels to examine the effect of cultural and doctrinal differences on UAV choice.
- Operational validation: Couple the MCDM outputs with field trials to reconcile modelled ranks with empirical mission performance.

Author Contribution

Conceptualization, G.C.Y. and G.A.; methodology, G.C.Y. and G.A.; validation, G.C.Y. and G.A.; formal analysis, G.C.Y.; writing—original draft preparation, G.C.Y.; writing—review and editing, G.C.Y. and G.A.; visualization, G.C.Y. and G.A.; supervision, G.C.Y. and G.A.; project administration, G.C.Y. All authors have read and agreed to the published version of the manuscript.

Data Availability

The data used in this study are derived from the corresponding author's doctoral dissertation entitled "UAV selection with fuzzy multi-criteria decision making". The data are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflict of interest.

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