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ORIGINAL PAPER

Evaluation of unmanned combat aerial vehicles using q-rung orthopair fuzzy entropy based multi-attribute border approximation area comparison method

Betül Turanoğlu Şirin[1]

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Abstract

Unmanned combat aerial vehicles (UCAVs) have become an indispensable part of modern military operations. As they can be used for both defensive and offensive purposes, they play a crucial role in shaping military strategies and improving the operational capabilities of security forces. Many countries are investing in UCAV technology and placing these vehicles at the centre of their defence strategies. Choosing the right UCAV enables a country to strengthen its national security and its position in international relations by enhancing its defence capabilities. This study considers the evaluation of UCAVs as a multi-criteria decision making (MCDM) problem. In the study, the q-ROF (q-rung orthopair fuzzy) entropy-based MABAC (Multi-Attribute Border Approximation Area Comparison) method is proposed as a new integrated MCDM technique to solve the problem. The theoretical framework of the proposed method is explained in detail and applied to an UCAV selection problem. In practise, fourteen different UCAV alternatives were evaluated based on nine criteria (length, wingspan, height, empty weight, maximum takeoff weight, payload capacity, maximum cruising speed, maximum altitude, duration in the air). As a result of the application, the best-performing alternative was identified as UCAV-9 (A_9). In addition, the results of the proposed method were compared with the results of the classical q-ROF MABAC, q-ROF MAIRCA (Multi Attributive Ideal-Real Comparative Analysis), q-ROF TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution), q-ROF CRITIC-EDAS (Criteria Importance through Inter-criteria Correlation-Evaluation based on Distance from Average Solution), and q-ROF BWM-MARCOS (Best–Worst-Method-Measurement of Alternatives and Ranking according to COmpromise Solution) methods. UCAV-9 (A_9) emerged as the strongest alternative based on the comparison analysis. In addition, two different sensitivity analyses were also carried out. The sensitivity analysis on the criteria weights revealed that the alternatives were highly influenced by these weights. Based on these results, it can be concluded that this study offers a practical

Extended author information available on the last page of the article

framework for countries to select the appropriate UCAV and makes a significant contribution to the literature in this field.

Keywords Multi-criteria decision making · Unmanned combat aerial vehicles · q-rung orthopair fuzzy sets · Multi-attribute border approximation area comparison

1 Introduction

The rapid development of today's technology has significantly affected the technologies used in military operations. One of the most important of these technologies is armed unmanned aerial vehicles. These vehicles offer many advantages in terms of flexibility and cost in military operations. They are widely used in surveillance, target tracking, and firepower attacks (Niu et al. 2023). UCAVs are remotely controlled aircraft with high-resolution cameras and sensors that minimize human loss in precise and effective attacks. This situation requires countries to make the right decision about the UCAV they will include in their air defense systems.

In this study, the most appropriate UCAV selection is considered as a multi-criteria decision making (MCDM) problem. The MCDM approach evaluates multiple options under various criteria in decision-making processes. In real-life problems, it offers a systematic approach that prevents decision-makers from deciding based on their prejudices and intuitions. This approach ensures that a decision is made by considering all objective and realistic factors (Farid and Riaz 2023). The development of MCDM methods began with the AHP (Analytic Hierarchy Process) introduced by Saaty (1980) and rapidly diversified thereafter. AHP revolutionized decision-making processes. Following AHP, the TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) method, developed by Hwang and Yoon (1981), enabled the ranking of alternatives based on their proximity to the ideal solution. Brans and Vincke (1985) introduced the PROMETHEE (Preference Ranking Organization Method for Enrichment Evaluations) method, which allowed for more flexible alternative rankings. After the 2000s, methods such as MARCOS (Measurement of Alternative Ranking based on COmpromise Solution) and MABAC (Multi-criteria Decision Analysis Based on the Aggregated Weights of Criteria) have evolved, becoming more sophisticated.

MCDM has a wide range of applications across various disciplines, including business, engineering, economics, healthcare, and politics. In the business sector, it is employed in processes such as selecting the most suitable supplier, hiring employees, identifying the most profitable investments, and developing effective marketing strategies (Xu 2023; Güneri and Deveci 2023; Çalikoğlu and Łuczak 2024). In engineering, MCDM is a valuable tool for determining optimal designs, selecting appropriate materials, and enhancing system performance. In healthcare, it aids in comparing treatment options, allocating resources efficiently, and assessing the quality of care (Tang et al. 2022; Li et al. 2024). In the political arena, MCDM actively supports decision-making processes, such as shaping public policies, prioritizing projects, and allocating public resources (Alkan and Kahraman 2021).

In MCDM problems, when the criteria weights are unknown, various methods can be used to cope with such uncertainties. Objective weighting methods (e.g., entropy or variance-based approaches) determine the weights by analyzing the intrinsic properties of the criteria in the data, thus preventing subjective bias. Uncertainty models such as fuzzy sets provide effective solutions when the criteria weights are unknown by modelling the uncertainty and ambiguity in the decision-making process. In addition, optimization-based models such as linear programming or hybrid approaches allow determining the weights in a more balanced and consistent way. These methods increase the reliability and robustness of the decision-making process when dealing with unknown weights.

In real-world decision-making processes, decision-makers (*DMs*) often rely on their intuition and prior experiences. However, the complexity of these processes necessitates an accurate representation of information, particularly when dealing with fuzzy and uncertain data. Atanassov (1986) first introduced the concept of intuitionistic fuzzy sets (IFSs), defined by the degree of membership and the degree of non-membership. Later, Yager (2014) developed the concept of Pythagorean fuzzy sets (PFSs), which introduced a limitation: the sum of the squares of the membership and non-membership degrees must not exceed one. This feature makes PFSs more robust and effective than IFSs. Nevertheless, despite their success in addressing certain real-world multi-criteria decision-making (MCDM) problems, PFSs face limitations in situations where the sum of the squares of membership and non-membership degrees exceeds one. To overcome this issue, Yager (2017) proposed the concept of q-rung orthopair fuzzy sets (q-ROFSs), which allow the sum of the membership degree and the non-membership degree, each raised to the q*th* power, to exceed one. q-ROFSs are more flexible than traditional fuzzy sets, enabling DMs to expand or contract their preference ranges as needed. This flexibility is one of the main reasons q-ROFSs were employed in this study.

The aim of this study is to consider the evaluation of UCAVs based on their technical specifications as a multi-criteria decision making (MCDM) problem. In this problem, fourteen different UAVs were evaluated based on nine criteria. The novelty of the study can be evaluated from three different perspectives:

- A fuzzy-based MCDM method was proposed to evaluate UCAVs, which are considered an important decision problem. Traditionally, air power is considered as one of the most important indicators of a country's military capabilities. With the development of UCAVs, the ability to achieve air superiority has become more accessible and sustainable. Furthermore, when considering the role of UCAVs in military operations and their impact on global security, it becomes clear how important it is for a state to make the right decision on which UCAVs to select for its air power. From this perspective, this study provides a decision support system for the evaluation of UCAVs.
- The q-ROF (q-rung orthopair fuzzy) entropy-based MABAC (Multi-Attributive Border Approximation Area Comparison) method was proposed for the evaluation of UCAVs. In the proposed hybrid method, the MABAC method was used to rank the alternatives, while the criteria weights were calculated using q-ROF entropy. Due to the limitations of Pythagorean Fuzzy and Intuitionistic Fuzzy

Sets, the decision model is presented as q-ROF based. Q-ROF sets were developed to solve problems with uncertainty and complexity beyond the traditional clusters. Therefore, it is very applicable in various domains. Moreover, each element is precisely identified based on the parameter q, which determines its degree of membership. This enables more precise results by considering details in complex systems. In this study, q-ROF sets were used to better represent the uncertainties that arise when decision makers evaluate criteria and alternatives. The concept of entropy describes the uncertainty of the occurrence of each possible event of an information source. The inclusion of this uncertainty in the proposed method is ensured by the entropy calculation. Thus, calculating the criteria weights with the q-ROF entropy has enhanced the representation of lack of information and uncertainty. The reasons for using the MABAC technique in the alternatives ranking in the proposed MCDM method are as follows: MABAC structures the decision-making process in a simple and clear way. It provides the decision makers with the ability to clearly evaluate and compare the importance of each criterion and the performance of the decision alternatives. This reduces complexity and makes the decision-making process easier to understand. It can work with both quantitative and qualitative data.

- A detailed sensitivity analysis and a comparative analysis were carried out in the study. The sensitivity analysis was performed in two different ways depending on both the variability of the criterion and the changes in the parameter q, and the results were interpreted. The results of the proposed method in the comparative analysis; The results of the classical q-ROF MABAC, q-ROF MAIRCA and q-ROF TOPSIS were compared.

The rest of the study is organized as follows: Sect. 2 mentions the literature review of UCAVs and q-ROF-based MCDM methods. In Sect. 3, some introductory information about intuitionistic fuzzy sets, pythagorean fuzzy sets and q-rung orthopair fuzzy sets is given. Section 4 explains the details of the proposed method. Section 5 presents the application of the proposed method, the sensitivity analysis and the results of the comparative analysis. Finally, Sect. 6 concludes the paper.

2 Literature review

The literature review in this study is organized under three main subheadings, as outlined below.

2.1 Literature review on UCAVs

A look at the literature shows that there are more studies on UCAVs, especially in recent years. But their number is also quite limited. The articles reviewed in this study can be listed as follows:

Xu et al. (2010) developed an artificial bee colony algorithm for UCAV path planning. The results showed the effectiveness of the proposed algorithm. Duan et al.

(2010) proposed a hybrid heuristic algorithm including ant colony optimization and differential evolution algorithm for three-dimensional path planning of UCAVs. Lin and Hang (2011) proposed a fuzzy weighted average algorithm for evaluation of military UAVs. Yu et al. (2013) made a real-time trajectory planning for an air-to-surface attack of a UCAV using the inverse dynamic optimization method and receding horizon control. Duan and Huang (2014) used artificial neural networks method based on imperialist competitive algorithm to solve the UCAV path planning problem. Zhu and Duan (2014) proposed an algorithm based on chaotic predator prey biogeography for UCAV path planning. Wang et al. (2016) developed the differential evolution-based bat algorithm for three-dimensional path planning of UCAVs. Nangia et al. (2019) evaluated the aerodynamic design of the MULDICON UCAV and made suggestions for improvements. Bacci et al. (2019) investigated the effects of the angle of attack in the weapons bay of a UCAV on the aeroacoustic environment. Van Rooij et al. (2019) prepared a prospective risk analysis of future UCAV systems supported by artificial intelligence. Kaya et al. (2019) used the co-kriging technique to create the aerodynamic model of a UCAV. Although the study worked with one-dimensional data, the proposed technique was able to create high-resolution and multi-dimensional aerodynamic models for modern aircraft with reasonable effort. You et al. (2020) developed a deterministic method to solve the problem of ensuring the continuity of target tracking of UCAVs at high altitude. This method is an effective method that helps to perform various navigation tasks in real time in the electronic warfare environment. Hamurcu and Eren (2020) used AHP TOPSIS method for the selection of UAVs. In the study, four UAVs were evaluated under seven criteria. Stradtner et al. (2020) proposed a variable accuracy model to create an aerodynamic data set during the product identification phase of a UCAV with low traceability. The proposed model was tested on a UCAV of the type in question and effective results were obtained. Wang et al. (2020a, b) quantitatively investigated the effect of UCAV flight agility on short-range air combat effectiveness. This study is based on one-to-one three-dimensional aerial combat missions. Aslan (2022) proposed the immune plasm algorithm, a new metaheuristic algorithm for UCAV trajectory planning. The proposed algorithm was first studied in detail by assigning different values to the control parameters and using different battlefield scenarios. Then, it was compared with different metaheuristic algorithms. Jia et al. (2022) proposed a two-layer model based on particle swarm optimization for path planning of UCAVs. The results showed that the proposed method always generates feasible flight paths in complex situations. Li et al. (2022a, b, c) proposed a deep learning algorithm based decision-making method developed to solve the problem of quickly and accurately performing the autonomous aerial combat decision process for UCAVs in an uncertain environment. Niu et al. (2022) developed an ecosystem optimizer based on adaptive neighborhood search algorithm for UCAV path planning. Li et al. (2022a, b, c) developed a limited strategy game method to create an intelligent decision-making process with air combat situation information and time-critical information for multiple UCAVs in a complex air combat environment. In their study, Shao et al. (2022) talked about state-of-the-art jet aircraft that enable flight control of UCAVs in a wide speed range. Li et al. (2022a, b, c) proposed an armed conflict-based multiple UCAV invasion method for beyond visual range air combat. Zhu et al. (2022) used the spider monkey algorithm for obstacle removal in UCAV path planning. Niu et al. (2023) proposed an evolutionary artificial ecosystem optimizer based on reinforcement learning to solve the path planning problem of multiple UCAVs in complex environments with multiple constraints. The aim of this study is to generate the most suitable candidate paths for each UCAV and ensure that they reach the goal simultaneously, considering temporal variables. Gurmani et al. (2023) developed the interval-valued q-ROF based TOPSIS method for the selection of UAVs used in agriculture.

2.2 Literature review on q-ROF-based MCDM studies

Especially if we look at the studies conducted in recent years, it is evident that q-ROF sets are now quite commonly used in MCDM methods. Some q-ROF-based MCDM studies in the literature can be summarized as follows:

In their study, Darko and Liang (2020) developed several q-ROF Hamacher aggregation operators. They then applied the modified EDAS method using these operators for the selection of a mobile payment platform. Wang et al. (2020a, b) introduced the q-ROF-based MABAC method, a novel approach for multi-attribute decision-making. This method was applied and tested on a small sample dataset to assess its effectiveness and practical utility. Alkan and Kahraman (2021) proposed the q-ROF TOPSIS method to evaluate government strategies against COVID-19. In the study, a comparative analysis was conducted with different MCDM methods. The results proved the effectiveness of the proposed method. Sun et al. (2022) proposed the gold-cut q-ROF DEMATEL method for coalition-oriented strategic selection of alternatives for renewable energy systems. In addition, the results were validated using intuitionistic fuzzy sets and Pythagorean fuzzy sets. A comparative analysis was also carried out using the M-SWARA method. Deveci et al. (2022) developed the q-ROF Einstein-based WASPAS method for the evaluation of safe e-scooter strategies. The results obtained showed that the developed method is feasible. Zolfani et al. (2022) proposed a q-ROF-based decision-making approach to evaluate the potential of Southern and Eastern European countries in the regionalization process of global supply chains. Tang et al. (2022) developed a new MCDM method based on q-ROF for the evaluation of medical applications used on mobile devices. Xiao et al. (2022) applied the q-ROF BWM-based WASPAS method in manufacturer selection. A new evaluation function for q-ROF is also proposed. Ali (2022) applied the q-ROF MARCOS method using a novel score function for solid waste management. Yang et al. (2022) presented a cloud-based q-ROF approach for the evaluation of green distribution transformers. Zhang et al. (2022) proposed the q-ROF entropy-based RSWM method to identify the critical success factors of blockchain technology for sustainable supply chain development. Xu (2023) proposed the interval value q-ROF TOPSIS method to evaluate recycling suppliers. Sensitivity and comparative analyses were conducted as part of the study. Aytekin et al. (2023) used the q-ROF CRITIC-ARAS technique to select critical business processes of Lean Six Sigma in a food company. Güneri and Deveci (2023) used the q-ROF-based EDAS method for supplier selection in the defense industry. In addition, a sensitivity analysis was conducted regarding the change in q-values. Peng et al. (2023) proposed the q-ROF MARCOS method for evaluating content-centric network options. The advantages of the proposed method are verified by a comparative analysis. Krishankumar and Ecer (2023) presented a q-ROF CRADIS-based method for evaluating service providers for the Internet of Things. Yin et al. (2023) presented a decision-making method based on BERT and q-ROF to evaluate products online. The proposed method was tested and validated on six different phones. Farid and Riaz (2023) developed a new q-ROF aggregation operator based on Aczel-Alsina processes. These operators offer several advantages when dealing with real-world problems. Fetanat and Tayebi (2023) proposed the q-ROF MAIRCA method for the selection of industrial filtering technologies used in natural gas processing. Seker et al. (2023) used the interval value q-ROF COPRAS method to assess the risks contributing to the success of measures against COVID-19. Ecer et al. (2023) proposed the q-rung fuzzy LOPCOW-VIKOR method to evaluate the role of UAVs used in precision agriculture. Farid et al. (2024) developed the q-ROF CRITIC-EDAS method to rank sustainable approaches for waste management of fuel cells for road freight vehicles. Li et al. (2024) used q-ROF BWM, Shannon entropy and MARCOS methods as a hybrid to evaluate the quality of medical mobile applications. Rong et al. (2024) presented an IVq-ROF-based LOPCOW-WASPAS-FUCOM model for risk analysis. Rani et al. (2024) developed an IVq-ROF-based SWARA-WISP method for ranking micromobility risk management alternatives. Yüksel et al. (2025) proposed a q-ROF-DEMATEL-SRP model for the evaluation of renewable energy projects. Peng et al. (2025) developed a q-ROF-based WENSLO model for evaluating Internet of Things (IoT) platforms. Sarkar et al. (2025) introduced a new decision-making approach based on DHLq-ROF to assess the financial performance of third-party logistics providers.

2.3 Literature review on MABAC method

Pamučar and Ćirović (2015) developed the MABAC method. Since its introduction, this method has been applied in various fields:

Peng and Yang (2016) proposed the PS-Choquet Integral Geometric-MABAC method for investment evaluation. Xue et al. (2016) developed the IVIFS-Linear Programming-MABAC approach for material selection in the automotive industry. Yu et al. (2017) introduced the IT2FS-MABAC method for hotel selection using online tourism platforms. Peng and Yang (2017) applied the HFS-WASPAS-COPRAS-MABAC method for investment selection. Shi et al. (2017) developed the TFS-ANP-TODIM-COPRAS-GRA hybrid approach for risk assessment in renewable energy systems. Pamučar et al. (2018) proposed the R-BWM-MABAC method for selecting firefighting helicopters, while Can and Toktas (2018) developed the TFS-DEMATEL-MABAC approach for warehouse risk assessment. Zhu et al. (2018) utilized the IVPFS-Entropy-MABAC method for ranking risks causing product failures. Noureddine and Ristic (2019) applied the FUCOM-TOPSIS-MABAC method for selecting routes in hazardous waste transportation. Jia et al. (2019) developed the IFRS-MABAC method for supplier selection in medical devices, while Liu et al. (2019) conducted risk analysis of radiation therapies in health centers using the IVIFS-FEMA-Entropy-MABAC approach. Chakraborty et al. (2020) proposed the BWM-MABAC method for evaluating international airline companies. Liu et al. (2020) applied the HFS-MABAC method for the safety assessment of marine ecological systems. Büyüközkan et al. (2020) developed the HFS-SWOT-AHP-MABAC approach to evaluate health tourism strategies. Rahim et al. (2020) used the GIS-DEMATEL-ANP-MABAC approach for selecting suitable sites for wind turbines. Bozanic et al. (2020) introduced the Z-FUCOM-MABAC method for locating brigade command centers during combat operations. Verma (2021) proposed the IFS-Entropy-MABAC method for personnel selection. Aydın et al. (2022) developed the FMA-BWM-PF-MABAC method for risk assessment in the oil and gas industry. Mandal and Seikh (2023) applied the IVSF-MABAC method for selecting plastic waste management processes. Božanić et al. (2024) created the Fuzzy DIBR II–MABAC model to select a suitable flood protection method for the Veliki Rzav River in Serbia. Fan et al. (2024) proposed the PFS-MEREC-MABAC method for evaluating the performance of wearable healthcare devices. Dai et al. (2024) used the SMAA-MABAC approach for supplier selection in healthcare. Mehdiabadi et al. (2025) introduced the fuzzy SWARA-MABAC method to rank supply chain capabilities in the Iranian oil and gas industry. Naz et al. (2025) developed a 2TLq-RPFS-based MABAC method for evaluating blockchain software systems. Finally, Kizielewicz et al. (2025) introduced the fuzzy normalization-based MABAC method, successfully applying it to e-commerce decision-making processes.

3 Research gap

Studies on the evaluation of UCAVs are rarely found in the literature (Lin and Hang, 2011; Hamurcu and Eren, 2020; Gurmani et al. 2023). These studies typically focus on evaluating only a small number of UCAVs. Furthermore, there are even fewer studies that consider military UAVs (Lin and Hang, 2011; Hamurcu and Eren, 2020). In this study, fourteen different UCAVs were evaluated using the q-ROF entropy MABAC method across nine criteria. The q-ROF MABAC method was first developed by Wang et al. (2020a, b). However, it is noteworthy that the q-ROF entropy MABAC method, which incorporates entropy, has not been previously used in the literature. In this context, a new hybrid method was applied to the evaluation of UCAVs, and the implementation of this method was demonstrated. The proposed method is particularly suitable for situations involving high uncertainty and complexity in the evaluation of UCAVs. In this study, the q-ROF entropy method enabled the objective determination of the criteria weights and was integrated with the MABAC method to clearly highlight the differences between the alternatives. Therefore, the q-ROF entropy MABAC approach proves to be a powerful and effective method for addressing uncertainty and achieving a reliable ranking in MCDM processes for UCAVs. Consequently, it can be concluded that this study makes a significant contribution to the literature.

4 Preliminaries

In this section, some preliminary information about intuitionistic fuzzy sets, Pythagorean fuzzy sets and q-rung orthopair fuzzy sets is given (Alkan and Kahraman 2021).

4.1 Intuitionistic fuzzy sets

Intuitionistic fuzzy sets (IFSs) were introduced by Atanassov in 1986 as an extension of sequential fuzzy set theory. IFSs are characterized by the degree of membership and the degree of non-membership, which sum to one or less than one. The following definitions are proved for IFS numbers (Atanassov 1986; Alkan and Kahraman 2021):

Definition I Let X be a fixed set. An IFS $\widetilde{I}$ in X is an object of the form:

$$\widetilde{I} = \left\{ \left(x, \mu_{\widetilde{I}}(x), \vartheta_{\widetilde{I}}(x) \right) | x \in X \right\} \tag{1}$$

Here; the functions $\mu_{\widetilde{I}} : X \to [0,1]$ and $\vartheta_{\widetilde{I}} : X \to [0,1]$ define the degree of membership and degree of non-membership of an element of the sets $\widetilde{I}$, respectively, with the condition given in Eq. 2.

$$0 \leq \mu_{\widetilde{I}}(x) + \vartheta_{\widetilde{I}}(x) \leq 1, for \forall x \in X \tag{2}$$

The degree of hesitancy is calculated according to the formula in Eq. 3:

$$\pi_{\widetilde{I}}(x) = 1 - \mu_{\widetilde{I}}(x) - \vartheta_{\widetilde{I}}(x) \tag{3}$$

Definition II Let $\widetilde{A} = \left(\mu_{\widetilde{A}}, \vartheta_{\widetilde{A}} \right)$ and $\widetilde{B} = \left(\mu_{\widetilde{B}}, \vartheta_{\widetilde{B}} \right)$ be two intuitionistic fuzzy numbers (IFNs). The addition and multiplication operations of these two IFNs are given in Eq. 4 and Eq. 5 respectively:

$$\widetilde{A} \oplus \widetilde{B} = \left(\mu_{\widetilde{A}} + \mu_{\widetilde{B}} - \mu_{\widetilde{A}}\mu_{\widetilde{B}}, \vartheta_{\widetilde{A}}\vartheta_{\widetilde{B}} \right) \tag{4}$$

$$\tilde{A} \otimes \tilde{B} = \left(\mu_{\tilde{A}}\mu_{\tilde{B}}, \vartheta_{\tilde{A}} + \vartheta_{\tilde{B}} - \vartheta_{\tilde{A}}\vartheta_{\tilde{B}} \right) \tag{5}$$

4.2 Pythagorean fuzzy sets

Pythagorean fuzzy sets (PFSs) were introduced by Yager (2014) as an extension of intuitionistic fuzzy sets. PFSs are defined by their membership and non-membership degrees. In PFSs, the sum of membership degrees can be more than 1, but the sum of their squares must be at most 1. PFSs can be defined as specified in Definition III.

Definition III Let X be a fixed set. An PFS $\widetilde{P}$ in X is an object of the form:

$$\widetilde{P} = \left\{ \left(x, \mu_{\widetilde{P}}(x), \vartheta_{\widetilde{P}}(x) \right) | x \in X \right\} \tag{6}$$

Here, the functions $\mu_{\widetilde{P}} : X \rightarrow [0,1]$ and $\vartheta_{\widetilde{P}} : X \rightarrow [0,1]$ express the degree of membership and non-membership of an element in sets $\widetilde{P}$, respectively, with the condition given in Eq. 7.

$$0 \leq \left(\mu_{\widetilde{P}}(x) \right)^2 + \left(\vartheta_{\widetilde{P}}(x) \right)^2 \leq 1, for \forall x \in X \tag{7}$$

The degree of hesitancy is calculated according to the formula in Eq. 8:

$$\pi_{\widetilde{P}}(x) = \sqrt{1 - \left(\mu_{\widetilde{P}}(x) \right)^2 - \left(\vartheta_{\widetilde{P}}(x) \right)^2} \tag{8}$$

Definition IV Let $\widetilde{P}_1 = \left(\mu_{\widetilde{P}_1}, \vartheta_{\widetilde{P}_1} \right)$ and $\widetilde{P}_2 = \left(\mu_{\widetilde{P}_2}, \vartheta_{\widetilde{P}_2} \right)$ two PFSs. The addition and multiplication operations of these two PFSs are given in Eq. 9 and Eq. 10, respectively:

$$\widetilde{P}_1 \oplus \widetilde{P}_2 = \left(\sqrt{\mu_{\widetilde{P}_1}{}^2 + \mu_{\widetilde{P}_2}{}^2 - \mu_{\widetilde{P}_1}{}^2 \mu_{\widetilde{P}_2}{}^2}, \vartheta_{\widetilde{P}_1} \vartheta_{\widetilde{P}_2} \right) \tag{9}$$

$$\tilde{P}_1 \otimes \tilde{P}_2 = \left(\mu_{\tilde{P}_1} \mu_{\tilde{P}_2}, \sqrt{\vartheta^2_{\tilde{P}_1} + \vartheta^2_{\tilde{P}_2} - \vartheta^2_{\tilde{P}_1} \vartheta^2_{\tilde{P}_2}} \right) \tag{10}$$

4.3 Q-rung orthopair fuzzy sets

Q-rung orthoair fuzzy sets (Q-ROFSs), proposed by Yager (2017), are represented by membership and non-membership degrees. In Q-ROFSs, the sum of the q*th* power of membership and non-membership degrees must be at most equal to 1. Figure 1 shows that the space of acceptable membership degrees is larger in Q-ROFSs than in IFSs and PFSs (Fetanat and Tayebi 2023).

Some basic theories of q-ROFSs are explained in the following definitions:

Definition V In set X, a q-ROFS can be defined as follows (Liu and Wang 2018):

$$\widetilde{O} = \left\{ \left(x, \mu_{\widetilde{O}}(x), \vartheta_{\widetilde{O}}(x) \right) | x \in X \right\} \tag{11}$$

Here, the functions $\mu_{\widetilde{O}} : X \rightarrow [0,1]$ and $\vartheta_{\widetilde{O}} : X \rightarrow [0,1]$ express the degree of membership and non-membership of an element in sets $\widetilde{Q}$, respectively, with the condition given in Eq. 12.

$$0 \leq \mu_{\widetilde{O}}(x) + \vartheta_{\widetilde{O}}(x) \leq 1, for \forall x \in X \tag{12}$$

The degree of indeterminacy is given in Eq. 13.

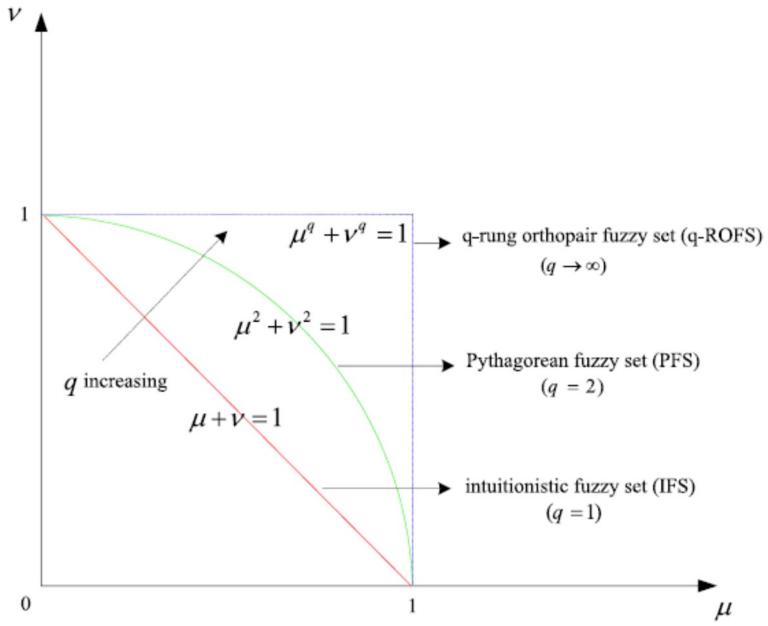

Fig. 1 Geometric space range of IFSs, PFSs, and q-ROFSs

$$\pi_{\widetilde{O}}(x) = \sqrt[q]{1 - \left(\mu_{\widetilde{O}}(x)\right)^q - \left(\vartheta_{\widetilde{O}}(x)\right)^q} \tag{13}$$

Definition VI Let $\widetilde{O} = \left(\mu_{\widetilde{O}}, \vartheta_{\widetilde{O}}\right)$, $\widetilde{Q}_1 = \left(\mu_{\widetilde{Q}_1}, \vartheta_{\widetilde{Q}_1}\right)$, and $\widetilde{Q}_2 = \left(\mu_{\widetilde{Q}_2}, \vartheta_{\widetilde{Q}_2}\right)$ be three q-rung orthopair fuzzy numbers (q-ROFNs). Some basic operations regarding these numbers can be defined as follows (Liu and Wang 2018; Alkan and Kahraman 2021):

$$\widetilde{Q}_1 \cap \widetilde{Q}_2 = \left(min\left\{\mu_{\widetilde{Q}_1}, \mu_{\widetilde{Q}_2}\right\}, max\left\{\vartheta_{\widetilde{Q}_1}, \vartheta_{\widetilde{Q}_2}\right\}\right) \tag{14}$$

$$\widetilde{Q}_1 \cup \widetilde{Q}_2 = \left(max\left\{\mu_{\widetilde{Q}_1}, \mu_{\widetilde{Q}_2}\right\}, min\left\{\vartheta_{\widetilde{Q}_1}, \vartheta_{\widetilde{Q}_2}\right\}\right) \tag{15}$$

$$\widetilde{Q}_1 \oplus \widetilde{Q}_2 = \left(\sqrt[q]{\mu_{\widetilde{Q}_1}{}^q + \mu_{\widetilde{Q}_2}{}^q - \mu_{\widetilde{Q}_1}{}^q \mu_{\widetilde{Q}_2}{}^q}, \vartheta_{\widetilde{Q}_1}\vartheta_{\widetilde{Q}_2}\right) \tag{16}$$

$$\tilde{Q}_1 \otimes \tilde{Q}_2 = \left(\mu_{\tilde{Q}_1}\mu_{\tilde{Q}_2}, \sqrt[q]{\vartheta^q_{\tilde{Q}_1} + \vartheta^q_{\tilde{Q}_2} - \vartheta^q_{\tilde{Q}_1}\vartheta^q_{\tilde{Q}_2}}\right) \tag{17}$$

$$\lambda\widetilde{O} = \left(\sqrt[q]{\left(1-\left(1-\mu_{\widetilde{O}}{}^{q}\right)^{\lambda}\right)}, \vartheta_{\widetilde{O}}{}^{\lambda}\right), \lambda > 0 \tag{18}$$

$$\widetilde{O}^{\lambda} = \left(\mu_{\widetilde{O}}{}^{\lambda}, \sqrt[q]{\left(1-\left(1-\vartheta_{\widetilde{O}}{}^{q}\right)^{\lambda}\right)}\right), \lambda > 0 \tag{19}$$

Definition VII Let $\widetilde{Q}_1 = \left(\mu_{\widetilde{Q}_1}, \vartheta_{\widetilde{Q}_1}\right)$ and $\widetilde{Q}_2 = \left(\mu_{\widetilde{Q}_2}, \vartheta_{\widetilde{Q}_2}\right)$ be two q-ROFNs. The score and accuracy values of these numbers are calculated by Eqs. 20 and 21 (Liu and Wang 2018; Fetanat and Tayebi 2023).

$$S\left(\widetilde{Q}_1\right) = \mu_{\widetilde{Q}_1}{}^{q} - \vartheta_{\widetilde{Q}_1}{}^{q} and S\left(\widetilde{Q}_2\right) = \mu_{\widetilde{Q}_2}{}^{q} - \vartheta_{\widetilde{Q}_2}{}^{q} \tag{20}$$

$$H\left(\widetilde{Q}_1\right) = \mu_{\widetilde{Q}_1}{}^{q} + \vartheta_{\widetilde{Q}_1}{}^{q} and H\left(\widetilde{Q}_2\right) = \mu_{\widetilde{Q}_2}{}^{q} + \vartheta_{\widetilde{Q}_2}{}^{q} \tag{21}$$

where, if $S\left(\widetilde{Q}_1\right) < S\left(\widetilde{Q}_2\right)$, then $\widetilde{Q}_1 < \widetilde{Q}_2$; if $S\left(\widetilde{Q}_1\right) = S\left(\widetilde{Q}_2\right)$, then the following two conditions are evaluated:

- if $H\left(\widetilde{Q}_1\right) = H\left(\widetilde{Q}_2\right)$, then $\widetilde{Q}_1 = \widetilde{Q}_2$.
- if $H\left(\widetilde{Q}_1\right) < H\left(\widetilde{Q}_2\right)$, then $\widetilde{Q}_1 < \widetilde{Q}_2$.

Definition VIII Let $\widetilde{Q}_1 = \left(\mu_{\widetilde{Q}_1}, \vartheta_{\widetilde{Q}_1}\right)$ and $\widetilde{Q}_2 = \left(\mu_{\widetilde{Q}_2}, \vartheta_{\widetilde{Q}_2}\right)$ be two q-ROFNs. The q-rung orthopair fuzzy normalized Hamming distance (q-ROFNHD) is denoted by using Eq. 22 (Yang et al. 2021; Fetanat and Tayebi 2023).

$$q - ROFNHD = \frac{1}{2}\left(\left|\mu_{\widetilde{Q}_1}{}^{q} - \mu_{\widetilde{Q}_2}{}^{q}\right| + \left|\vartheta_{\widetilde{Q}_1}{}^{q} - \vartheta_{\widetilde{Q}_2}{}^{q}\right| + \left|\pi_1^{q} - \pi_2^{q}\right|\right) \tag{22}$$

where, $\pi_1 = \sqrt[q]{1-(\mu_{\widetilde{Q}_1}{}^{q} + \vartheta_{\widetilde{Q}_1})}$ and $\pi_2 = \sqrt[q]{1-(\mu_{\widetilde{Q}_2}{}^{q} + \vartheta_{\widetilde{Q}_2})}$.

Definition IX Let $\widetilde{Q}_i = \left(\mu_{\widetilde{Q}_i}, \vartheta_{\widetilde{Q}_i}\right)$, $i=1, \ldots, n$ be a list of q- ROF numbers. According to, the operators of the q-rung orthopair fuzzy weighted average (q-ROFWA) and q-rung orthopair fuzzy weighted geometric (q-ROFWG) can be computed as follows (Liu and Wang 2018; Alkan and Kahraman 2021; Fetanat and Tayebi 2023):

$$q - ROFWA = \left(\widetilde{Q}_1, \widetilde{Q}_2, \widetilde{Q}_3, \ldots, \widetilde{Q}_n\right) = \left(\sqrt[q]{1-\prod_{i=1}^{n}\left(1-\mu_{\widetilde{Q}_i}{}^{q}\right)^{w_i}}, \prod_{i=1}^{n}\vartheta_{\widetilde{Q}_i}{}^{w_i}\right) \tag{23}$$

$$q - ROFWG = \left(\widetilde{Q}_1, \widetilde{Q}_2, \widetilde{Q}_3, \ldots, \widetilde{Q}_n\right) = \left(\prod_{i=1}^{n} \mu_{\widetilde{Q}_i}{}^{w_i}, \sqrt[q]{1 - \prod_{i=1}^{n} \left(1 - \vartheta_{\widetilde{Q}_i}{}^{q}\right)^{w_i}}\right) \tag{24}$$

In two Eq. (23) and (24), the term w_i is weighting vector of Q_i $(i=1, 2, \ldots, n)$, which satisfies, $0 \leq w_i \leq 1$, $\sum_{i=1}^{n} w_i = 1$.

5 Methodology

In this section, the steps of the q-ROF entropy-based MABAC method proposed for the evaluation of UCAVs are explained. The flow chart of the proposed method is given in Fig. 2.

Step-1 The alternatives, criteria and decision makers (*DMs*) are defined as follows:

$A_i=(A_1, A_2, \ldots, A_n);\ i=1, 2, \ldots, m$

$C_j=(C_1, C_2, \ldots, C_n);\ j=1, 2, \ldots, n$

$DM_k=(DM_1, DM_2, \ldots, DM_l);\ k=1, 2, \ldots, l$

$w_j=(w_1, w_2, \ldots, w_n);\ j=1, 2, \ldots, n$

Here; A_i is the set of alternatives, C_j is the set of criteria, DM_k is the set of decision makers, and w_j is the set of criterion weights. Also, $w_j > 0$ and $\sum_{j=1}^{n} w_j = 1$.

Step-2 q-ROF decision matrices (D^k) are created according to *DM* opinions using the scale given in Table 1 (Alkan and Kahraman 2021). The q-ROF decision matrix, in which each decision maker (k) evaluates the alternatives according to the criteria, can be shown as follows:

$$D^k = \left[d_{ij}^k\right]_{mxn} = \begin{array}{c c} & \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{array}{c} A_1 \\ A_2 \\ \vdots \\ A_m \end{array} & \begin{bmatrix} \left(\mu_{11}^k, \vartheta_{11}^k\right) & \left(\mu_{12}^k, \vartheta_{12}^k\right) & \cdots & \left(\mu_{1n}^k, \vartheta_{1n}^k\right) \\ \left(\mu_{21}^k, \vartheta_{21}^k\right) & \left(\mu_{22}^k, \vartheta_{22}^k\right) & \ldots & \left(\mu_{2n}^k, \vartheta_{2n}^k\right) \\ \vdots & \vdots & \ddots & \vdots \\ \left(\mu_{m1}^k, \vartheta_{m1}^k\right) & \left(\mu_{m2}^k, \vartheta_{m2}^k\right) & \cdots & \left(\mu_{mn}^k, \vartheta_{mn}^k\right) \end{bmatrix} \end{array} \tag{25}$$

Here, the term d_{ij}^k refers to the performance of the k*th* decision maker for the i*th* alternative according to the j*th* criterion.

Step-3 In this step, the decision matrix (D^k) created by each decision maker is normalized as follows (Fetanat and Tayebi 2023):

$$r_{ij}^k = \begin{cases} d_{ij}^k = \left(\mu_{ij}^k, \vartheta_{ij}^k\right), forbenefitcriteria \\ (d_{ij}^k)^c = \left(\vartheta_{ij}^k, \mu_{ij}^k\right), forcostcriteria \end{cases} \tag{26}$$

The q-ROF normalized decision matrix can be denoted as $R^k = \left[r_{ij}^k\right]_{mxn}$

Step-4 According to the importance of *DMs*, a weight value is assigned for each *DM*. The importance of *DMs* is defined using the linguistic variables given in Table 2 (Alkan and Kahraman 2021). Let $D^k = \left(\mu^k, \vartheta^k\right)$ be the q-ROF number of

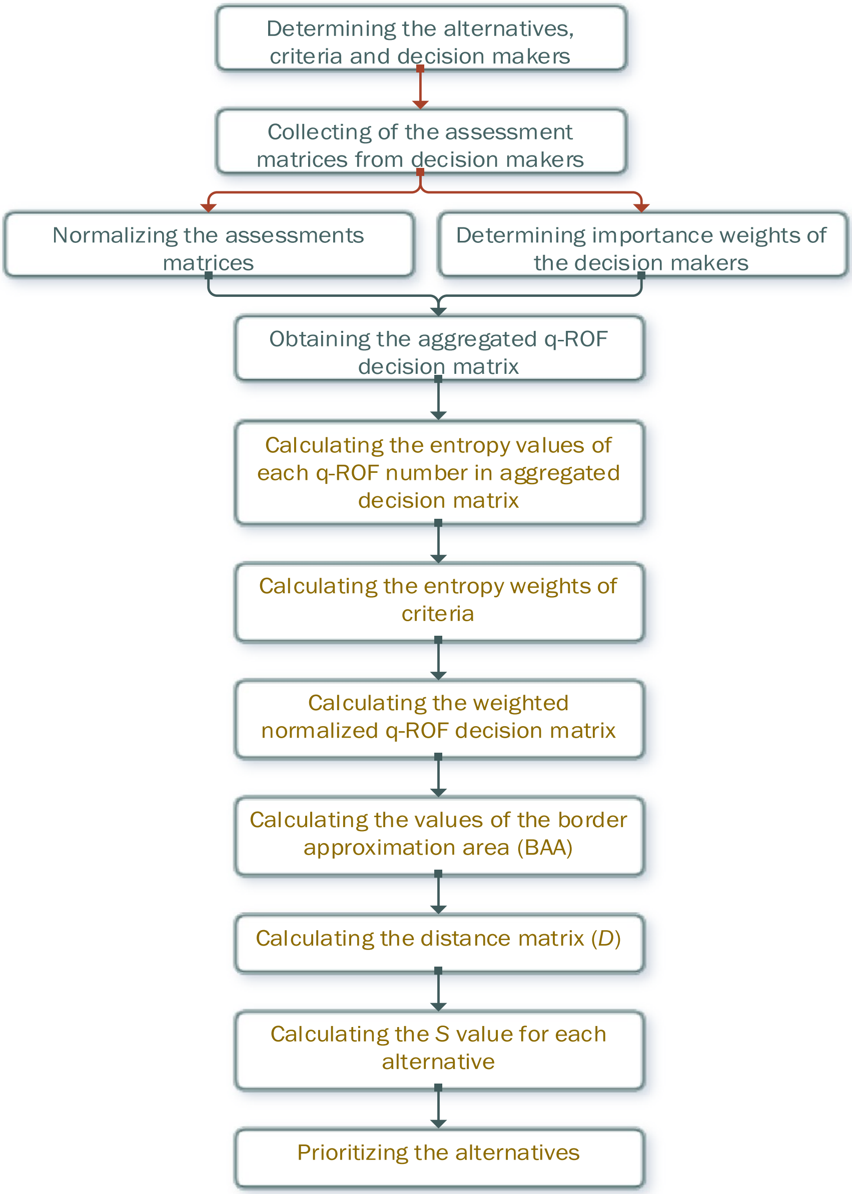

Fig. 2 The steps of q-ROF entropy based MABAC approach

the kth decision maker. The weight (λ^k) of the kth decision maker can be calculated by the following formula (Fetanat and Tayebi 2023):

Table 1 Linguistic scale for alternatives

Linguistic terms	q-ROF numbers	
	μ	υ
Certainly high value (CHV)	0.99	0.11
Very high value (VHV)	0.88	0.22
High value (HV)	0.77	0.33
Above average value (AAV)	0.66	0.44
Average value (AV)	0.55	0.55
Under average value (UAV)	0.44	0.66
Low value (LV)	0.33	0.77
Very low value (VLV)	0.22	0.88
Certainly low value (CLV)	0.11	0.99

Table 2 Linguistic scale for criteria

Linguistic terms	q-ROF numbers	
	μ	υ
Certainly high importance (CHI)	0.99	0.11
Very high importance (VHI)	0.88	0.22
High importance (HI)	0.77	0.33
Above average importance (AAI)	0.66	0.44
Average importance (AI)	0.55	0.55
Under average importance (UAI)	0.44	0.66
Low importance (LI)	0.33	0.77
Very low importance (VLI)	0.22	0.88
Certainly low importance (CLI)	0.11	0.99

$$\lambda^k = \frac{\left[\mu^k + \pi^k[\mu^k/\left(1-\pi^k\right)]\right]}{\sum_{k=1}^{l}\left[\mu^k + \pi^k[\mu^k/\left(1-\pi^k\right)]\right]} \tag{27}$$

where, $\pi^k = \sqrt[q]{1-((\mu^k)^q + (\vartheta^k)^q)}$ ve $\sum_{k=1}^{l}\lambda^k = 1$.

Step-5 The aggregated q-ROF decision matrix (R_a) is calculated using the *q-ROFWG* formula given in Eq. 24:

$$r_{a_{ij}} = q - ROFWG = \left(r_{ij}^1, r_{ij}^2, \dots, r_{ij}^k\right) = \left(\prod_{i=1}^{n}(\mu_{r_{ij}^k})^{\lambda_k}, \sqrt[q]{1-\prod_{i=1}^{n}\left(1-(\vartheta_{r_{ij}^k})^q\right)^{\lambda_k}}\right) \tag{28}$$

where $r_{a_{ij}} = (\mu_{ij}, \vartheta_{ij})$ denotes the aggregated q-ROF number of the i*th* alternative according to criterion *j*. The term λ_k indicates the weight value of the k*th* decision maker. Therefore, $R_a = \left[r_{a_{ij}}\right]_{mxn}$.

Step-6 The entropy value of each q-ROF number in the aggregated decision matrix is calculated by the help of the formulas given in Eq. 29 and Eq. 30 (Alkan and Kahraman 2021):

$$KE_{q,ij}(x) = \frac{1}{\sqrt{2}}\sqrt{\left(\mu(x)^q\right)^2 + \left(\vartheta(x)^q\right)^2 + \left(\mu(x)^q + \vartheta(x)^q\right)^2} \tag{29}$$

$$EN_{q,ij}(x) = 1 - KE_{q,ij}(x) \tag{30}$$

Step-7 In this step, entropy-based criterion weights are calculated as follows (Alkan and Kahraman 2021):

$$\varepsilon_j = \frac{\sum_{i=1}^{m} EN_{q,ij}}{\sum_{i=1}^{m}\sum_{j=1}^{n} EN_{q,ij}} \tag{31}$$

$$w_j = \frac{1-\varepsilon_j}{\sum_{j=1}^{n}(1-\varepsilon_j)} \tag{32}$$

Here, w_j and ε_j denote the weight of the j*th* criterion and the q-ROF entropy value, respectively.

Step-8 The weighted normalized decision matrix (X) is calculated. For this, each row of aggregated q-ROF decision matrix (R_a) is multiplied by the weight vector w using Eq. 33. The weighted normalized decision matrix is denoted as $X = \left[x_{ij}\right]_{m\times n}$.

$$x_{ij} = r_{a_{ij}} \otimes w_j; i = 1,2,\ldots,m; j = 1,2,\ldots,n \tag{33}$$

Step-9 The border approximation area (BAA) value for each criterion is calculated as follows (Wang et al. 2020a, b):

$$g_j = \left(\prod_{i=1}^{m} x_{ij}\right)^{1/m} = \left(\left(\prod_{i=1}^{m}\mu_{ij}\prime\right)^{1/m}, \sqrt[q]{1-\prod_{i=1}^{m}\left(\left(1-\left(\vartheta_{ij}\prime\right)^q\right)^{1/m}\right)}\right) \tag{34}$$

Here, $x_{ij} = (\mu_{ij}\prime, \vartheta_{ij}\prime)$ refers to the weighted q-ROF number of the i*th* alternative according to criterion j. The BAA matrix can be represented by $G = \left[g_j\right]_{1xn}$.

Step-10 The D matrix is obtained by calculating the distance between each alternative and its BAA value as follows (Wang et al. 2020a, b):

$$d_{ij} = \begin{cases} d(x_{ij}, g_j), if x_{ij} > g_j \\ 0, if x_{ij} = g_j \\ -d(x_{ij}, g_j), if x_{ij} < g_j \end{cases} \tag{35}$$

Here, $d(x_{ij}, g_j)$ is calculated by the *q-ROFNHD* formula given in Eq. 22.

Step-11 In this step, the S_i value of each alternative is calculated by Eq. 36. The alternative with the highest S_i value is selected as the best alternative.

$$S_i = \sum_{j=1}^{n} d_{ij}; i = 1, 2, \ldots, m \tag{36}$$

6 Application and results

One of the most important elements of air superiority today are UCAVs. UCAVs have quickly become indispensable in air warfare. Because they are uninhabited, they can be sent on dangerous missions and more easily sacrificed. In addition, these remote-controlled vehicles are simpler and cheaper than other combat aircraft. They can be produced at different altitudes and in different sizes. For these reasons, the question of which UCAV best contributes to the air defense of countries has become a very important decision problem for them. Because there are many UCAVs with different characteristics in the world. In this study, the evaluation of fourteen different commonly accepted UCAVs based on 9 criteria is treated as an MCDM problem. The decision hierarchy of the problem is shown in Fig. 3.

The UCAVs under consideration were evaluated by applying the steps of the q-ROF entropy-based MABAC method shown in Fig. 2 as follows:

Step 1 The opinions of three *DMs* were sought for the evaluation of UCAVs (Unmanned Combat Aerial Vehicles). Two of the decision-makers are engineers employed by a UCAV manufacturer, while the third is a military pilot. This *DM* group evaluated the alternatives based on defined criteria. General information about the alternative UCAVs discussed in the problem is provided below. The real names of the UCAVs are not disclosed here for privacy reasons; instead, they are identified by coding.

- ***UCAV-1 (A_1)***: UCAV-1 features an integrated network-based system architecture that provides the user with comprehensive solutions. Designed as a medium altitude-long endurance (MALE) unmanned aerial vehicle, it is tailored for reconnaissance and intelligence missions. Equipped with fully autonomous take-off, landing, and normal cruise capabilities, it ensures operational efficiency. With a built-in laser target designator, it enables precise targeting and can deploy up to four smart munitions payloads to engage targets effectively. Its quick see-and-shoot feature minimizes collateral damage to areas surrounding the target, emphasizing civilian security as a priority.
- ***UCAV-2 (A_2):*** With its unique wing structure, UCAV-2 is capable of carrying a significant quantity of smart ammunition. Its advanced artificial intelligence system enhances user experience by providing sophisticated flight and diagnostic functions. Moreover, it can accommodate more advanced payloads, including electronic support pods, satellite communication systems, air-to-air radars, obstacle detection radars, and synthetic aperture radars.
- ***UCAV-3 (A_3):*** Equipped with double redundant computers, redundant flight control sensors, and redundant control surface actuators, UCAV-3 guarantees autonomous and safe operations from takeoff to landing. It is capable of fully auto-

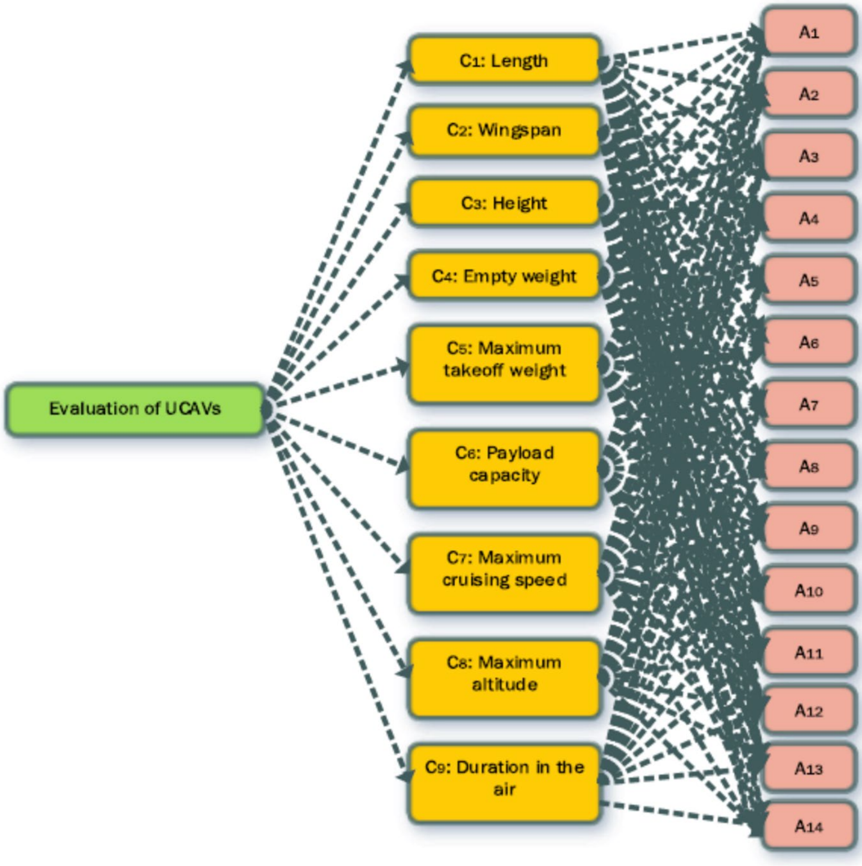

Fig. 3 The decision hierarchy of the decision-making problem

matic take-off and landing procedures, eliminating the requirement for pilot or operator intervention. Classified within MALE unmanned aerial vehicle class, it boasts a modular platform featuring synthetic aperture radar, precision weapons, and satellite communications capabilities.

- ***UCAV-4 (A_4)***: Designed for extended surveillance, intelligence gathering, maritime patrol missions, and UCAV applications, UCAV-4 excels in fully autonomous operations, ensuring the effectiveness of combat missions. Equipped with 2 twin-turbocharged PD-170 engines, it is optimized to carry heavier payloads and execute prolonged operations. Furthermore, it shares common internal systems and avionics features with UCAV-3.
- ***UCAV-5 (A_5):*** UCAV-5 stands out as a premier striker among UCAVs, boasting variable flight durations contingent on its payload. With a capacity to transport missiles weighing up to 1.5 tons, it undertakes diverse missions including intelligence gathering, surveillance, close air support, and search and rescue opera-

tions. Additionally, it features a built-in multi-spectral targeting system facilitating visual identification of targets, enhancing its operational efficacy.

- ***UCAV-6 (A_6):*** Propelled by a turbofan engine, UCAV-6 incorporates an internal weapons storage system enabling the carriage of laser-guided bombs. Its distinct S-shaped exhaust design minimizes visibility to infrared and radar signals, enhancing its stealth capabilities. Additionally, it is equipped with an electro-optical targeting system akin to that of F-35 warplanes, further augmenting its precision targeting capabilities.
- ***UCAV-7 (A_7):*** This UCAV offers both remote control and autonomous flight capabilities, making it versatile for surveillance, aerial reconnaissance, and precision attack missions. Leveraging satellite connectivity, it possesses long-range attack capabilities. Featuring retractable landing gear, it is equipped with two main wheels under the fuselage and a single wheel under the nose. Each wing is outfitted with three hardpoints capable of carrying bombs, rockets, or air-to-surface missiles, further enhancing its combat versatility.
- ***UCAV-8 (A_8):*** This UCAV boasts the capability to carry 16 missiles simultaneously, with an impressive airtime of 60 h. Offering both remote-controlled and autonomous flight operations, it is highly versatile. In addition to its offensive capabilities, it can be outfitted with an airborne early warning system and various electronic warfare systems for electronic intelligence gathering. Moreover, it is purported to possess the capability to engage in electronic warfare against enemy communication systems and radars, further enhancing its strategic value.
- ***UCAV-9 (A_9):*** This UCAV holds the distinction of being one of the earliest of its kind, playing a significant role in the Kosovo War. Equipped with autonomous take-off and landing capabilities, it features foldable landing gear for enhanced flexibility. Notably, it is powered by a heavy-fuel engine, a choice that not only enhances performance but also streamlines logistics and support efforts in the field. To facilitate extended-range operations, the unit utilizes three airborne relay data links.
- ***UCAV-10 (A_{10}):*** This UCAV belongs to the MALE class, capable of extended flights at medium altitudes. With a wingspan of 17 m, it boasts a payload capacity of 360 kg. Primarily utilized for reconnaissance, surveillance, target detection, and attack missions, it is equipped with advanced communication and sensor systems. These include infrared and high-resolution cameras, enabling effective surveillance operations day and night.
- ***UCAV-11 (A_{11}):*** Belonging to MALE class, this UCAV features automatic taxi takeoff and landing systems, satellite communications for extended range, and fully redundant avionics among its key attributes. Engineered as a versatile multi-mission platform, it excels in executing a wide range of strategic tasks, including intelligence gathering, surveillance, target acquisition, and reconnaissance. Its high reliability, coupled with the ability to utilize various payloads, ensures effectiveness across diverse operational scenarios.
- ***UCAV-12 (A_{12}):*** Originally designed in the 1990s solely for observation and advanced reconnaissance purposes, this UCAV underwent subsequent modifications, incorporating new cameras and missiles into its arsenal. With dimensions

measuring 8.23 m in length, 14.8 m in wingspan, and 2.1 m in height, it achieves a speed of 217 km per hour.

- ***UCAV-13 (A_{13}):*** This UCAV is engineered to operate via satellite for up to 40 h continuously, regardless of weather conditions, while ensuring safe integration into civil airspace. It features a multi-mode radar, an advanced electro-optical/infrared sensor, and automatic takeoff and landing capabilities. Moreover, it is equipped with a versatile system enabling integration of advanced sensor payloads for intelligence gathering, surveillance, and operations in complex environments.
- ***UCAV-14 (A_{14}):*** This UCAV is categorized within the MALE class, capable of executing both remotely controlled and autonomous flight operations. Equipped with a fixed tricycle landing gear, it ensures safe takeoff and landing procedures. Furthermore, its capability to operate in hot and high conditions enhances its versatility. Primarily designed for a wide array of missions, including special operations, reconnaissance, humanitarian aid, intelligence gathering, and military operations, it proves to be a valuable asset in various operational scenarios.

The following criteria were considered for the evaluation of UCAVs:

- ***Length (C_1):*** It is the length of the aircraft from its head to its tail.
- ***Wingspan (C_2):*** It is the distance between the wing tips of the aircraft.
- ***Height (C_3):*** It refers to the height from the base of the aircraft to the top.
- ***Empty weight (C_4):*** It refers to the basic weight carried by the aircraft without fuel, ammunition and other equipment.
- ***Maximum takeoff weight (C_5):*** It refers to the maximum weight that the aircraft can take off when fully loaded.
- ***Payload capacity (C_6):*** Refers to the amount of extra payload the aircraft can carry, this usually includes weapons, sensors or other equipment.
- ***Maximum cruising speed (C_7):*** Indicates the maximum speed that the aircraft can reach under optimum cruising conditions.
- ***Maximum altitude (C_8):*** It refers to the maximum altitude that the aircraft can rise to the highest point.
- ***Duration in the air (C_9):*** The time the aircraft remains in the air during a mission. This usually has to do with fuel capacity and engine efficiency.

The actual values of the alternatives according to the criteria given above are shown in Table 3. The information provided in this table was obtained from the official websites of the UCAVs.

Step 2 and 3 In this study, the opinions of three decision makers (*DMs*) were obtained through a survey. These are engineers working in an important company that produces UCAVs. The first is an aeronautical engineer, the second is a mechanical engineer, and the third is an electrical and electronics engineer. The linguistic evaluations made by the *DMs*, using the scale provided in Table 1, are presented as linguistic decision matrices in Tables 4, 5, and 6, respectively. According to these tables, the q-ROF decision matrices (D^1, D^2 and D^3) obtained for each *DM* are normalized (Tables 7, 8, and 9). During normalization, empty weight (C_4) was

Table 3 The actual values of the alternatives according to the criteria

Alternatives	Length (m)	Wingspan (m)	Height (m)	Empty weight (kg)	Max. take-off weight (kg)	Payload capacity (kg)	Max. cruising speed (km/hour)	Max. altitude (feet)	Duration in the air (hour)
A_1	6.50	12.00	2.20	400	700	150	222	25,000	27
A_2	12.20	20.00	4.10	1800	6000	1500	361	40,000	24
A_3	8.60	17.50	3.25	1600	1700	350	217	30,000	30
A_4	11.60	24.00	3.00	1800	3300	750	250	25,000	50
A_5	11.00	20,00	3.81	2223	4763	1747	313	50,000	27
A_6	13.00	20.00	4.50	6350	8255	2948	740	50,000	20
A_7	11.00	20.50	4.10	1100	4200	480	370	32,500	32
A_8	8.50	21.00	4.00	1200	3300	1000	220	30,000	60
A_9	7.01	10.57	1.90	727	885	90	170	18,000	30
A_{10}	8.53	17.00	2.10	1318	1633	360	309	25,000	36
A_{11}	14.00	26.00	6.10	5400	11,000	2700	407	45,000	30
A_{12}	8.22	16.84	2.10	513	1020	387	217	25,000	24
A_{13}	11.70	24.00	3.81	223	670	2155	388	40,000	40
A_{14}	20.00	11.13	4.38	520	1500	1000	220	30,000	100

Table 4 Linguistic evaluation matrix of *DM1*

Alternatives	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
A_1	UAV	AV	AAV	AV	LV	UAV	AV	HV	HV
A_2	HV	HV	HV	AAV	CHV	AAV	AAV	CHV	HV
A_3	AV	AAV	AAV	AV	AAV	AV	AV	VHV	VHV
A_4	HV	VHV	AAV	AV	HV	AAV	AV	HV	CHV
A_5	HV	VHV	HV	AAV	VHV	HV	AAV	CHV	HV
A_6	VHV	VHV	HV	CHV	CHV	VHV	VHV	CHV	AAV
A_7	HV	HV	VHV	HV	HV	AV	AAV	HV	HV
A_8	AV	VHV	AAV	AV	AAV	HV	AV	HV	CHV
A_9	UAV	UAV	AV	VLV	LV	CLV	LV	AAV	HV
A_{10}	AV	HV	AV	UAV	AV	VLV	AAV	AAV	VHV
A_{11}	VHV	CHV	AAV	VLV	HV	VHV	HV	CHV	HV
A_{12}	AV	AAV	AAV	VLV	UAV	VLV	HV	HV	AAV
A_{13}	HV	VHV	HV	VLV	LV	VHV	AV	VHV	VHV
A_{14}	CHV	AV	VHV	VLV	AV	AV	AV	AV	AAV

Table 5 Linguistic evaluation matrix of *DM2*

Alternatives	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
A_1	AV	AAV	AV	AAV	VLV	AV	AAV	VHV	VHV
A_2	VHV	AAV	AAV	AV	CHV	HV	AAV	VHV	CHV
A_3	AV	AV	AAV	AV	AV	AV	AAV	HV	VHV
A_4	HV	HV	HV	AAV	HV	AAV	AAV	HV	CHV
A_5	AAV	HV	HV	AAV	CHV	HV	HV	HV	HV
A_6	HV	HV	AAV	VHV	HV	HV	VHV	VHV	HV
A_7	AAV	AAV	HV	HV	HV	AAV	UAV	HV	AAV
A_8	UAV	VHV	AAV	AV	AAV	AAV	AV	VHV	VHV
A_9	AV	UAV	UAV	LV	LV	LV	VLV	AV	AAV
A_{10}	LV	VHV	AAV	AV	AAV	CLV	AV	UAV	VHV
A_{11}	CHV	VHV	AV	LV	HV	HV	HV	VHV	HV
A_{12}	AV	AAV	AAV	VLV	UAV	VLV	HV	HV	AAV
A_{13}	HV	VHV	HV	VLV	LV	VHV	AV	VHV	VHV
A_{14}	CHV	AV	VHV	VLV	AV	AV	AV	AV	AAV

considered as the cost criterion and other criteria were considered as the benefit criteria.

Step 4 In this step, weight values are calculated according to the importance of *DMs*. For this purpose, *DMs* were evaluated linguistically using Table 2 and Eq. 27. The weights of *DMs* were obtained as in Table 10.

Step 5 In this step, the aggregated q-ROF decision matrix (R_a) was calculated as in Table 11. The values in this table were derived using the weights of each *DM* provided in Table 10 and Eq. 28. Also, the q parameter used in this calculation can be

Table 6 Linguistic evaluation matrix of *DM3*

Alternatives	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
A_1	AAV	UAV	AAV	AAV	LV	AV	AAV	VHV	VHV
A_2	AAV	HV	HV	AV	HV	HV	HV	CHV	VHV
A_3	AV	HV	AV	AAV	AV	AAV	AV	CHV	VHV
A_4	VHV	HV	AV	AAV	AV	HV	UAV	HV	CHV
A_5	VHV	HV	VHV	UAV	HV	HV	HV	CHV	VHV
A_6	CHV	HV	VHV	HV	CHV	CHV	AAV	CHV	HV
A_7	AAV	AAV	HV	HV	HV	AV	UAV	VHV	AAV
A_8	UAV	CHV	AV	LV	UAV	HV	AAV	HV	CHV
A_9	UAV	LV	UAV	CLV	VLV	VLV	VLV	AV	AAV
A_{10}	AAV	VHV	LV	LV	AAV	LV	AV	AAV	VHV
A_{11}	HV	HV	AV	VLV	AAV	LV	VHV	HV	VHV
A_{12}	AV	AAV	AAV	CLV	UAV	CLV	HV	VHV	AV
A_{13}	VHV	HV	VHV	CLV	UAV	HV	AV	VHV	HV
A_{14}	VHV	UAV	CHV	VLV	AV	AV	AV	UAV	AAV

given any value that reflects the optimistic or pessimistic attitudes of the decision-making group. In this study, the q parameter was taken as 5 in order to define uncertainty more strongly and provide more flexible information (Alkan and Kahraman 2021).

Step 6 and 7 In this step, firstly, entropy values are calculated using Eqs. 29 and 30. Then, entropy-based criterion weights are obtained with Eqs. 31 and 32. The calculated criterion weights are given in Table 12.

Step 8 Using Eq. 33, the weighted normalized decision matrix is created as in Table 13.

Step 9 With the help of Eq. 34, BAA values (g_j) are obtained as in Table 14.

Step 10 The distance matrix D calculated using Eq. 35 is given in Table 15.

Step 11 The S_i value and ranking of each alternative are given in Table 16. According to this table, A_9 with the highest S_i value is the best alternative. The order of the alternatives was found to be $A_9 > A_{14} > A_6 > A_{13} > A_{11} > A_{12} > A_{10} > A_5 > A_2 > A_4 > A_8 > A_7 > A_1 > A_3$.

6.1 Sensitivity analysis

In this section, sensitivity analyzes performed to measure the robustness of the proposed method are described. First, a sensitivity analysis was conducted to see how the change in criterion weights would affect the ranking of alternatives. In this analysis, the weight of each criterion was changed to 0.1, 0.5 and 0.9, respectively, while the weight of the other criteria was kept constant (Alkan and Kahraman 2021). For example; If the weight of C_1 is set equal to 0.1, the weights of the other criteria are fixed at 0.1125. In this way, a total of 27 different scenarios are generated. The outputs of all scenarios are shown in Fig. 4. Accordingly, it shows that the proposed method is sensitive to changes in criterion weights. It can be seen that A_1 and A_3

Table 7 Normalized decision matrix for *DM1*

Alternatives	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
A_1	(0.44, 0.66)	(0.55, 0.55)	(0.66, 0.44)	(0.55, 0.55)	(0.33, 0.77)	(0.44, 0.66)	(0.55, 0.55)	(0.77, 0.33)	(0.77, 0.33)
A_2	(0.77, 0.33)	(0.77, 0.33)	(0.77, 0.33)	(0.44, 0.66)	(0.99, 0.11)	(0.66, 0.44)	(0.66, 0.44)	(0.99, 0.11)	(0.77, 0.33)
A_3	(0.55, 0.55)	(0.66, 0.44)	(0.66, 0.44)	(0.55, 0.55)	(0.66, 0.44)	(0.55, 0.55)	(0.55, 0.55)	(0.88, 0.22)	(0.88, 0.22)
A_4	(0.77, 0.33)	(0.88, 0.22)	(0.66, 0.44)	(0.55, 0.55)	(0.77, 0.33)	(0.66, 0.44)	(0.55, 0.55)	(0.77, 0.33)	(0.99, 0.11)
A_5	(0.77, 0.33)	(0.88, 0.22)	(0.77, 0.33)	(0.44, 0.66)	(0.88, 0.22)	(0.77, 0.33)	(0.66, 0.44)	(0.99, 0.11)	(0.77, 0.33)
A_6	(0.88, 0.22)	(0.88, 0.22)	(0.77, 0.33)	(0.11, 0.99)	(0.99, 0.11)	(0.88, 0.22)	(0.88, 0.22)	(0.99, 0.11)	(0.66, 0.44)
A_7	(0.77, 0.33)	(0.77, 0.33)	(0.88, 0.22)	(0.33, 0.77)	(0.77, 0.33)	(0.55, 0.55)	(0.66, 0.44)	(0.77, 0.33)	(0.77, 0.33)
A_8	(0.55, 0.55)	(0.88, 0.22)	(0.66, 0.44)	(0.55, 0.55)	(0.66, 0.44)	(0.77, 0.33)	(0.55, 0.55)	(0.77, 0.33)	(0.99, 0.11)
A_9	(0.44, 0.66)	(0.44, 0.66)	(0.55, 0.55)	(0.88, 0.22)	(0.33, 0.77)	(0.11, 0.99)	(0.33, 0.77)	(0.66, 0.44)	(0.77, 0.33)
A_{10}	(0.55, 0.55)	(0.77, 0.33)	(0.55, 0.55)	(0.66, 0.44)	(0.55, 0.55)	(0.22, 0.88)	(0.66, 0.44)	(0.66, 0.44)	(0.88, 0.22)
A_{11}	(0.88, 0.22)	(0.99, 0.11)	(0.66, 0.44)	(0.88, 0.22)	(0.77, 0.33)	(0.88, 0.22)	(0.77, 0.33)	(0.99, 0.11)	(0.77, 0.33)
A_{12}	(0.55, 0.55)	(0.66, 0.44)	(0.66, 0.44)	(0.88, 0.22)	(0.44, 0.66)	(0.22, 0.88)	(0.77, 0.33)	(0.77, 0.33)	(0.66, 0.44)
A_{13}	(0.77, 0.33)	(0.88, 0.22)	(0.77, 0.33)	(0.88, 0.22)	(0.33, 0.77)	(0.88, 0.22)	(0.55, 0.55)	(0.88, 0.22)	(0.88, 0.22)
A_{14}	(0.99, 0.11)	(0.55, 0.55)	(0.88, 0.22)	(0.88, 0.22)	(0.55, 0.55)	(0.55, 0.55)	(0.55, 0.55)	(0.55, 0.55)	(0.66, 0.44)

Table 8 Normalized decision matrix for *DM2*

Alternatives	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
A_1	(0.55, 0.55)	(0.66, 0.44)	(0.55, 0.55)	(0.44, 0.66)	(0.22, 0.88)	(0.55, 0.55)	(0.66, 0.44)	(0.88, 0.22)	(0.88, 0.22
A_2	(0.88, 0.22)	(0.66, 0.44)	(0.66, 0.44	(0.55, 0.55)	(0.99, 0.11)	(0.77, 0.33)	(0.66, 0.44)	(0.88, 0.22)	(0.99, 0.11)
A_3	(0.55, 0.55)	(0.55, 0.55)	(0.66, 0.44)	(0.55, 0.55)	(0.55, 0.55)	(0.55, 0.55)	(0.66, 0.44)	(0.77, 0.33)	(0.88, 0.22)
A_4	(0.77, 0.33)	(0.77, 0.33)	(0.77, 0.33)	(0.44, 0.66)	(0.77, 0.33)	(0.66, 0.44)	(0.66, 0.44)	(0.77, 0.33)	(0.99, 0.11)
A_5	(0.66, 0.44)	(0.77, 0.33)	(0.77, 0.33)	(0.44, 0.66)	(0.99, 0.11)	(0.77, 0.33)	(0.77, 0.33)	(0.77, 0.33)	(0.77, 0.33)
A_6	(0.77, 0.33)	(0.77, 0.33)	(0.66, 0.44)	(0.22, 0.88)	(0.77, 0.33)	(0.77, 0.33)	(0.88, 0.22)	(0.88, 0.22)	(0.77, 0.33)
A_7	(0.66, 0.44)	(0.66, 0.44)	(0.77, 0.33)	(0.33, 0.77)	(0.77, 0.33)	(0.66, 0.44)	(0.44, 0.66)	(0.77, 0.33)	(0.66, 0.44)
A_8	(0.44, 0.66)	(0.88, 0.22)	(0.66, 0.44)	(0.55, 0.55)	(0.66, 0.44)	(0.66, 0.44)	(0.55, 0.55)	(0.88, 0.22)	(0.88, 0.22)
A_9	(0.55, 0.55)	(0.44, 0.66)	(0.44, 0.66)	(0.77, 0.33)	(0.33, 0.77)	(0.33, 0.77)	(0.22, 0.88)	(0.55, 0.55)	(0.66, 0.44)
A_{10}	(0.33, 0.77)	(0.88, 0.22)	(0.66, 0.44)	(0.55, 0.55)	(0.66, 0.44)	(0.11, 0.99)	(0.55, 0.55)	(0.44, 0.66)	(0.88, 0.22)
A_{11}	(0.99, 0.11)	(0.88, 0.22)	(0.55, 0.55)	(0.77, 0.33)	(0.77, 0.33)	(0.77, 0.33)	(0.77, 0.33)	(0.88, 0.22)	(0.77, 0.33)
A_{12}	(0.66, 0.44)	(0.55, 0.55)	(0.55, 0.55)	(0.88, 0.22)	(0.55, 0.55)	(0.99, 0.11)	(0.88, 0.22)	(0.66, 0.44)	(0.44, 0.66)
A_{13}	(0.77, 0.33)	(0.88, 0.22)	(0.88, 0.22)	(0.77, 0.33)	(0.22, 0.88)	(0.99, 0.11)	(0.66, 0.44)	(0.99, 0.11)	(0.77, 0.33)
A_{14}	(0.88, 0.22)	(0.66, 0.44)	(0.77, 0.33)	(0.88, 0.22)	(0.44, 0.66)	(0.66, 0.44)	(0.44, 0.66)	(0.33, 0.77)	(0.55, 0.55)

Table 9 Normalized decision matrix for *DM3*

Alternatives	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
A_1	(0.66, 0.44)	(0.44, 0.66)	(0.66, 0.44)	(0.44, 0.66)	(0.33, 0.77)	(0.55, 0.55)	(0.66, 0.44)	(0.88, 0.22)	(0.88, 0.22)
A_2	(0.66, 0.44)	(0.77, 0.33)	(0.77, 0.33)	(0.55, 0.55)	(0.77, 0.33)	(0.77, 0.33)	(0.77, 0.33)	(0.99, 0.11)	(0.88, 0.22)
A_3	(0.55, 0.55)	(0.77, 0.33)	(0.55, 0.55)	(0.44, 0.66)	(0.55, 0.55)	(0.66, 0.44)	(0.55, 0.55)	(0.99, 0.11)	(0.88, 0.22)
A_4	(0.88, 0.22)	(0.77, 0.33)	(0.55, 0.55)	(0.44, 0.66)	(0.55, 0.55)	(0.77, 0.33)	(0.44, 0.66)	(0.77, 0.33)	(0.99, 0.11)
A_5	(0.88, 0.22)	(0.77, 0.33)	(0.88, 0.22)	(0.66, 0.44)	(0.77, 0.33)	(0.77, 0.33)	(0.77, 0.33)	(0.99, 0.11)	(0.88, 0.22)
A_6	(0.99, 0.11)	(0.77, 0.33)	(0.88, 0.22)	(0.33, 0.77)	(0.99, 0.11)	(0.99, 0.11)	(0.66, 0.44)	(0.99, 0.11)	(0.77, 0.33)
A_7	(0.66, 0.44)	(0.66, 0.44)	(0.77, 0.33)	(0.33, 0.77)	(0.77, 0.33)	(0.55, 0.55)	(0.44, 0.66)	(0.88, 0.22)	(0.66, 0.44)
A_8	(0.44, 0.66)	(0.99, 0.11)	(0.55, 0.55)	(0.77, 0.33)	(0.44, 0.66)	(0.77, 0.33)	(0.66, 0.44)	(0.77, 0.33)	(0.99, 0.11)
A_9	(0.44, 0.66)	(0.33, 0.77)	(0.44, 0.66)	(0.99, 0.11)	(0.22, 0.88)	(0.22, 0.88)	(0.22, 0.88)	(0.55, 0.55)	(0.66, 0.44)
A_{10}	(0.66, 0.44)	(0.88, 0.22)	(0.33, 0.77)	(0.77, 0.33)	(0.66, 0.44)	(0.33, 0.77)	(0.55, 0.55)	(0.66, 0.44)	(0.88, 0.22)
A_{11}	(0.77, 0.33)	(0.77, 0.33)	(0.55, 0.55)	(0.88, 0.22)	(0.66, 0.44)	(0.33, 0.77)	(0.88, 0.22)	(0.77, 0.33)	(0.88, 0.22)
A_{12}	(0.55, 0.55)	(0.66, 0.44)	(0.66, 0.44)	(0.99, 0.11)	(0.44, 0.66)	(0.11, 0.99)	(0.77, 0.33)	(0.88, 0.22)	(0.55, 0.55)
A_{13}	(0.88, 0.22)	(0.77, 0.33)	(0.88, 0.22)	(0.99, 0.11)	(0.44, 0.66)	(0.77, 0.33)	(0.55, 0.55)	(0.88, 0.22)	(0.77, 0.33)
A_{14}	(0.88, 0.22)	(0.44, 0.66)	(0.99, 0.11)	(0.88, 0.22)	(0.55, 0.55)	(0.55, 0.55)	(0.55, 0.55)	(0.44, 0.66)	(0.66, 0.44)

Table 10 The weights of DMs

DM	*DM1*	*DM2*	*DM3*
Weight	0.3049	0.5398	0.1553

are not affected much by the change in criterion weights. It can also be said that they rank 13*th* and 14*th* overall. A_2 exhibits moderate fluctuations across different criteria values, indicating that its performance is highly sensitive to the weights of certain criteria. Conversely, A_4, A_5, and A_6 generally demonstrate more stable performance, although they experience small ranking losses in some criteria. A_7 and A_8 show minimal ranking changes with varying criteria values, meaning their rankings are quite stable. In contrast, the significant fluctuations observed in A_9, A_{10}, A_{11}, and A_{12} highlight their sensitivity to criteria weights. Finally, A_{13} and A_{14} exhibit moderate ranking fluctuations. These results indicate that while some alternatives are more advantageous or disadvantageous against specific criteria, others maintain consistent performance across a broader range of criteria.

The second sensitivity analysis was performed on the q parameter. q is a parameter that significantly affects the results. The analysis results to measure the sensitivity of this parameter are given in Fig. 5. The most obvious results seen in the figure are as follows: A_9 is the best alternative at all values from q = 3 to q = 10. A_1 and A_3 were the 13*th* and 14*th* alternatives, respectively, at all q values. A_5 and A_2 ranked 8*th* and 9*th*, respectively, in all values between q = 4 and q = 10. A_7 and A_8 are the 12*th* and 13*th* alternatives respectively for all values between q = 2 and q = 6. A_6 ranked 4*th* in all values after q = 6. A_4 ranks 10*th* for all values between q = 3 and q = 7. A_{11} was the 5*th* alternative at values where q was between 5 and 9.

6.2 Comparative analysis

In this section, the results obtained from the q-ROF entropy MABAC method, proposed for the evaluation of UCAVs, are compared with five alternative methods. The first is the classical q-ROF MABAC method, which does not incorporate entropy weights. The others include the q-ROF MAIRCA, q-ROF TOPSIS, q-ROF CRITIC EDAS, and q-ROF BWM MARCOS methods, with the q parameter set to 5 in all cases. The comparative analysis results are illustrated in Fig. 6. According to the findings, the alternative ranking of the q-ROF MABAC method is $A_9 > A_6 > A_2 > A_{10} > A_{13} > A_4 > A_8 > A_{14} > A_5 > A_{12} > A_1 > A_{11} > A_3 > A_7$. For the q-ROF MAIRCA method, the ranking is $A_9 > A_{10} > A_1 > A_3 > A_8 > A_{11} > A_{14} > A_7 > A_{12} > A_4 > A_5 > A_{13} > A_2 > A_6$. The q-ROF TOPSIS method yields a ranking of $A_2 > A_4 > A_8 > A_5 > A_{11} > A_3 > A_{13} > A_1 > A_7 > A_{14} > A_6 > A_{10} > A_{12} > A_9$. Meanwhile, the q-ROF CRITIC EDAS method ranks the alternatives as $A_9 > A_{14} > A_{13} > A_6 > A_{11} > A_{10} > A_{12} > A_5 > A_8 > A_7 > A_2 > A_4 > A_1 > A_3$. Lastly, the q-ROF BWM MARCOS method produces a ranking of $A_9 > A_{13} > A_{14} > A_{11} > A_{12} > A_{10} > A_5 > A_6 > A_2 > A_4 > A_7 > A_8 > A_3 > A_1$.

The comparison indicates that the proposed q-ROF entropy MABAC method excels in objectively determining criteria weights and consistently ranking alternatives. Across all methods, A_9 emerges as the strongest alternative. This dominance

Table 11 Aggregated q-ROF decision matrix

Alternatives	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
A_1	(0.53, 0.59)	(0.57, 0.54)	(0.60, 0.51)	(0.47, 0.63)	(0.27, 0.84)	(0.51, 0.59)	(0.62, 0.49)	(0.84, 0.27)	(0.84, 0.27)
A_2	(0.81, 0.33)	(0.71, 0.40)	(0.71, 0.40)	(0.51, 0.59)	(0.95, 0.23)	(0.73, 0.38)	(0.68, 0.43)	(0.93, 0.20)	(0.90, 0.26)
A_3	(0.55, 0.55)	(0.61, 0.51)	(0.64, 0.47)	(0.53, 0.57)	(0.58, 0.53)	(0.57, 0.54)	(0.61, 0.50)	(0.83, (0.30)	(0.88, 0.22)
A_4	(0.77, 0.32)	(0.80, 0.31)	(0.70, 0.43)	(0.47, 0.63)	(0.73, 0.41)	(0.68, 0.43)	(0.59, 0.54)	(0.77, 0.33)	(0.99, 0.11)
A_5	(0.72, 0.40)	(0.80, 0.31)	(0.79, 0.32)	(0.47, 0.64)	(0.92, 0.24)	(0.77, 0.33)	(0.73, 0.38)	(0.86, 0.29)	(0.79, 0.32)
A_6	(0.83, 0.30)	(0.80, 0.31)	(0.72, 0.40)	(0.19, 0.94)	(0.86, 0.29)	(0.83, 0.30)	(0.84, 0.31)	(0.93, 0.20)	(0.73, 0.38)
A_7	(0.69, 0.42)	(0.69, 0.42)	(0.80, 0.31)	(0.33, 0.77)	(0.77, 0.33)	(0.61, 0.50)	(0.50, 0.62)	(0.79, 0.32)	(0.69, 0.42)
A_8	(0.47, 0.63)	(0.90, 0.21)	(0.64, 0.47)	(0.58, 0.53)	(0.62, 0.51)	(0.71, 0.40)	(0.57, 0.54)	(0.83, 0.29)	(0.93, 0.20)
A_9	(0.50, 0.61)	(0.42, 0.68)	(0.47, 0.63)	(0.83, 0.30)	(0.31, 0.80)	(0.22, 0.93)	(0.25, 0.86)	(0.58, 0.53)	(0.69, 0.42)
A_{10}	(0.43, 0.70)	(0.84, 0.27)	(0.56, 0.59)	(0.61, 0.51)	(0.62, 0.49)	(0.16, 0.97)	(0.58, 0.53)	(0.53, 0.60)	(0.88, 0.22)
A_{11}	(0.92, 0.24)	(0.89, 0.25)	(0.58, 0.53)	(0.82, 0.30)	(0.75, 0.36)	(0.70, 0.55)	(0.79, 0.32)	(0.89, 0.25)	(0.79, 0.32)
A_{12}	(0.61, 0.50)	(0.60, 0.51)	(0.60, 0.51)	(0.90, 0.21)	(0.50, 0.61)	(0.45, 0.87)	(0.83, 0.30)	(0.72, 0.40)	(0.52, 0.61)
A_{13}	(0.77, 0.32)	(0.86, 0.25)	(0.84, 0.27)	(0.83, 0.30)	(0.28, 0.84)	(0.92, 0.23)	(0.61, 0.50)	(0.94, 0.19)	(0.80, 0.31)
A_{14}	(0.91, 0.21)	(0.58, 0.54)	(0.83, 0.30)	(0.88, 0.22)	(0.49, 0.62)	(0.61, 0.50)	(0.49, 0.62)	(0.40, 0.72)	(0.60, 0.51)

Table 12 The weights of criterion

Criteria	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
Weight	0.1105	0.1109	0.1092	0.1110	0.1114	0.1117	0.1092	0.1131	0.1129

is particularly supported by the results of the classical q-ROF MABAC, q-ROF MAIRCA, q-ROF CRITIC EDAS, and q-ROF BWM MARCOS methods. However, the q-ROF TOPSIS method exhibits different rankings, with certain alternatives, such as A_{13} and A_{14}, advancing to higher positions. A_6 demonstrated strong performance in the q-ROF entropy MABAC, classical q-ROF MABAC and q-ROF CRITIC EDAS methods but lagged behind in the q-ROF MAIRCA and q-ROF TOPSIS methods. Similarly, A_2 showcased the impact of an ideal solution-oriented structure by securing the top rank in the q-ROF TOPSIS method but remained in the mid-tier rankings in other methods. A_{10} achieved a high ranking in the q-ROF MAIRCA method but fell behind in the q-ROF entropy MABAC and other approaches. These variations stem from the different criteria weighting and ranking mechanisms employed by each method, highlighting the sensitivity of each alternative to specific criteria weights.

7 Conclusion

Technological developments in the field of defense and security are at the center of international relations and military balance dynamics. In this context, UCAVs have become one of the cornerstones of modern military strategies. Choosing the right UCAV makes a significant contribution to countries strengthening their defense capabilities. However, there are multiple types of UCAVs with various features from around the world. This situation resembles a complex MCDM problem. Therefore, in this study, it is emphasized that the evaluation to be made for the selection of the right UCAVs should be considered as an MCDM problem. For this, the q-ROF entropy-based MABAC method is proposed.

Within the framework of the study, sensitivity analyses were conducted to assess how alterations in both criterion weights and the q parameter would impact alternative rankings. Specifically, changes in criterion weights were examined to ascertain the average ranking of alternatives using the proposed method. Furthermore, it was noted that A_1 and A_3 displayed minimal sensitivity to changes in criterion weights. Regarding variations in the q parameter, it was observed that A_9 consistently ranked first across all values except when $q=2$.

In this study, the q-ROF entropy MABAC method proposed for the evaluation of UAVs is compared with five alternative methods: classical q-ROF MABAC (without entropy weights), q-ROF MAIRCA, q-ROF TOPSIS, q-ROF CRITIC EDAS, and q-ROF BWM MARCOS. In all methods, the q parameter is set to 5. The results demonstrate the superiority of the proposed method in objectively determining criterion weights and consistently ranking alternatives. Among all methods, A_9 emerged

Table 13 Weighted normalized decision matrix

Alternatives	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
A_1	(0.34, 0.94)	(0.38, 0.93)	(0.39, 0.93)	(0.30, 0.95)	(0.17, 0.98)	(0.33, 0.94)	(0.40, 0.92)	(0.57, 0.86)	(0.57, 0.86)
A_2	(0.54, 0.88)	(0.46, 0.90)	(0.46, 0.91)	(0.33, 0.94)	(0.69, 0.84)	(0.48, 0.90)	(0.44, 0.91)	(0.66, 0.83)	(0.62, 0.86)
A_3	(0.36, 0.93)	(0.40, 0.93)	(0.42, 0.92)	(0.34, 0.94)	(0.38, 0.93)	(0.37, 0.93)	(0.39, 0.93)	(0.56, 0.87)	(0.61, 0.84)
A_4	(0.52, 0.88)	(0.54, 0.88)	(0.45, 0.91)	(0.30, 0.95)	(0.48, 0.90)	(0.44, 0.91)	(0.38, 0.93)	(0.51, 0.88)	(0.78, 0.78)
A_5	(0.48, 0.90)	(0.54, 0.88)	(0.52, 0.88)	(0.30, 0.95)	(0.64, 0.85)	(0.51, 0.88)	(0.48, 0.90)	(0.59, 0.87)	(0.52, 0.88)
A_6	(0.56, 0.87)	(0.54, 0.88)	(0.47, 0.90)	(0.12, 0.99)	(0.59, 0.87)	(0.56, 0.87)	(0.57, 0.88)	(0.66, 0.83)	(0.48, 0.90)
A_7	(0.45, 0.91)	(0.45, 0.91)	(0.53, 0.88)	(0.21, 0.97)	(0.51, 0.88)	(0.39, 0.93)	(0.32, 0.95)	(0.52, 0.88)	(0.45, 0.91)
A_8	(0.30, 0.95)	(0.62, 0.84)	(0.42, 0.92)	(0.38, 0.93)	(0.40, 0.93)	(0.46, 0.90)	(0.37, 0.93)	(0.56, 0.87)	(0.66, 0.83)
A_9	(0.32, 0.95)	(0.27, 0.96)	(0.30, 0.95)	(0.56, 0.87)	(0.20, 0.98)	(0.14, 0.99)	(0.16, 0.98)	(0.38, 0.93)	(0.45, 0.91)
A_{10}	(0.28, 0.96)	(0.57, 0.87)	(0.36, 0.94)	(0.40, 0.93)	(0.41, 0.92)	(0.10, 1.00)	(0.38, 0.93)	(0.34, 0.94)	(0.61, 0.84)
A_{11}	(0.64, 0.85)	(0.62, 0.86)	(0.38, 0.93)	(0.55, 0.87)	(0.50, 0.89)	(0.46, 0.94)	(0.52, 0.88)	(0.62, 0.85)	(0.52, 0.88)
A_{12}	(0.39, 0.93)	(0.39, 0.93)	(0.37, 0.93)	(0.62, 0.84)	(0.32, 0.94)	(0.29, 0.98)	(0.55, 0.87)	(0.48, 0.90)	(0.33, 0.94)
A_{13}	(0.52, 0.88)	(0.59, 0.86)	(0.57, 0.87)	(0.56, 0.87)	(0.18, 0.98)	(0.65, 0.85)	(0.39, 0.93)	(0.67, 0.83)	(0.54, 0.88)
A_{14}	(0.64, 0.94)	(0.38, 0.93)	(0.56, 0.88)	(0.60, 0.85)	(0.32, 0.95)	(0.39, 0.93)	(0.31, 0.95)	(0.26, 0.96)	(0.39, 0.93)

Table 14 g_j values of the criterion

Criteria	g_j
C_1	(0.437, 0.961)
C_2	(0.469, 0.904)
C_3	(0.437, 0.915)
C_4	(0.367, 0.939)
C_5	(0.378, 0.935)
C_6	(0.363, 0.950)
C_7	(0.389, 0.931)
C_8	(0.511, 0.891)
C_9	(0.527, 0.883)

Table 15 The distance matrix D

Alternatives	g_1	g_2	g_3	g_4	g_5	g_6	g_7	g_8	g_9
A_1	0.0988	0.1027	0.0501	0.0474	0.1925	0.0296	0.0235	0.0815	0.0550
A_2	0.1012	0.0017	0.0337	0.0192	0.2767	0.1936	0.0674	0.1653	0.0653
A_3	0.0735	0.0797	0.0155	0.0053	0.0173	0.0673	0.0102	0.0603	0.1114
A_4	0.1118	0.0827	0.0105	0.0474	0.1094	0.1514	0.0144	0.0284	0.2492
A_5	0.0427	0.0827	0.1058	0.0524	0.2659	0.2364	0.1091	0.0642	0.0121
A_6	0.1348	0.0827	0.0370	0.2385	0.2124	0.2681	0.1669	0.1653	0.0410
A_7	0.0281	0.0107	0.1153	0.1353	0.1769	0.0935	0.0745	0.0371	0.0739
A_8	0.1328	0.1812	0.0155	0.0240	0.0295	0.1723	0.0156	0.0653	0.1389
A_9	0.1169	0.2047	0.1371	0.2208	0.1641	0.1862	0.2215	0.1325	0.0739
A_{10}	0.1781	0.1173	0.1061	0.0449	0.0476	0.2074	0.0065	0.1854	0.1114
A_{11}	0.1920	0.1464	0.0608	0.2189	0.1519	0.0592	0.1601	0.1107	0.0121
A_{12}	0.0389	0.0839	0.0501	0.3058	0.0443	0.1511	0.1879	0.0327	0.2170
A_{13}	0.1118	0.1383	0.1497	0.22008	0.1885	0.3255	0.0102	0.1720	0.0203
A_{14}	0.2284	0.1027	0.1287	0.2981	0.0500	0.0935	0.0728	0.2646	0.1479

as the strongest alternative, with its dominance particularly supported by the classical q-ROF MABAC, q-ROF MAIRCA, q-ROF CRITIC EDAS, and q-ROF BWM MARCOS methods. However, the q-ROF TOPSIS method presented variations in the ranking of some alternatives. For instance, A_2 ranked first in q-ROF TOPSIS but occupied middle positions in other methods, while A_{10} performed well in q-ROF MAIRCA but ranked lower in others. These discrepancies arise from the differing criteria weighting and ranking mechanisms of each method, highlighting the sensitivity of the alternatives to the criteria weights.

Upon comprehensive evaluation, this study highlighted certain limitations that occasionally introduced variability in results. Among these limitations, the number and quality of decision-makers, the number and quality of criteria emerged as significant factors. These limitations underscore the importance of ensuring robust

Table 16 Ranking of alternatives

Alternatives	S_i	*Ranking*
A_1	0.6812	13
A_2	0.9240	9
A_3	0.4404	14
A_4	0.8052	10
A_5	0.9712	8
A_6	1.3467	3
A_7	0.7451	12
A_8	0.7748	11
A_9	1.4577	1
A_{10}	1.0046	7
A_{11}	1.1120	5
A_{12}	1.1118	6
A_{13}	1.3371	4
A_{14}	1.3867	2

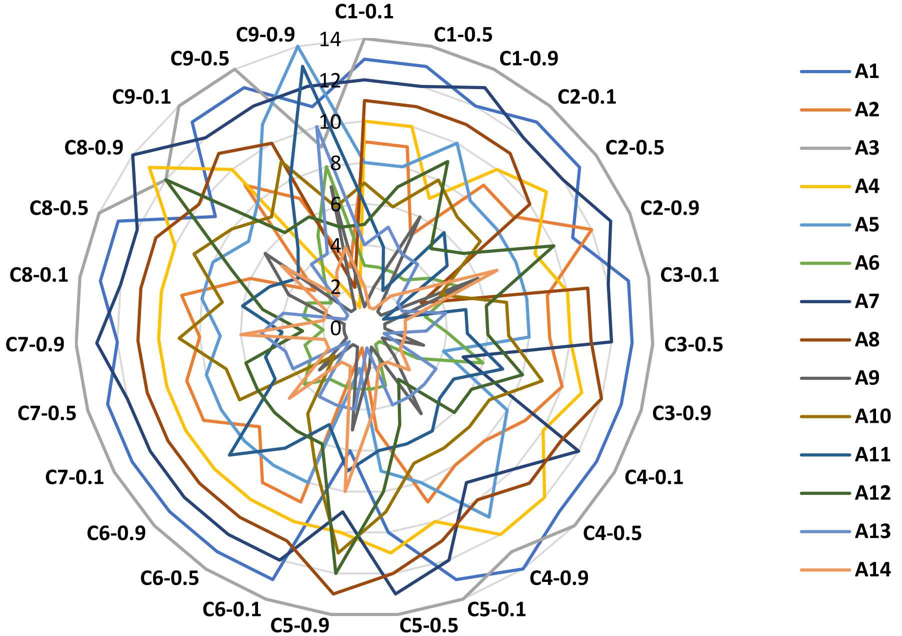

Fig. 4 Results of sensitivity analysis based on the criteria weights

decision-making processes and criteria selection methodologies to enhance the reliability and consistency of results in similar studies.

Based on the findings and limitations identified in this study, the following recommendations can be proposed for future research:

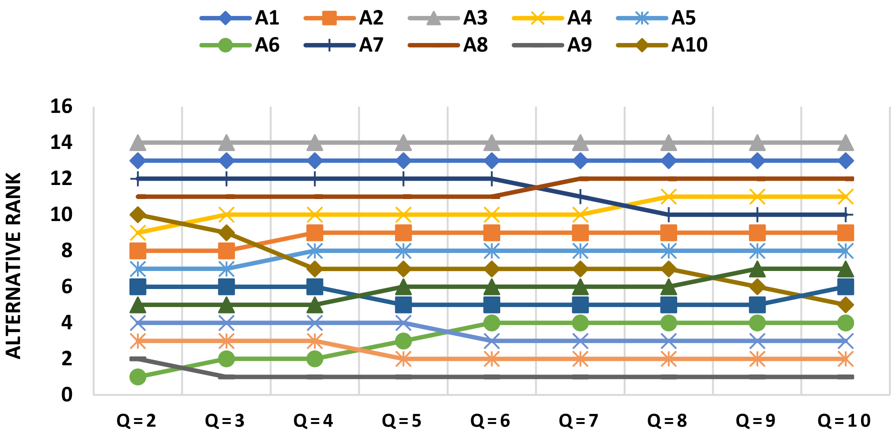

Fig. 5 Results of sensitivity analysis based on q parameter

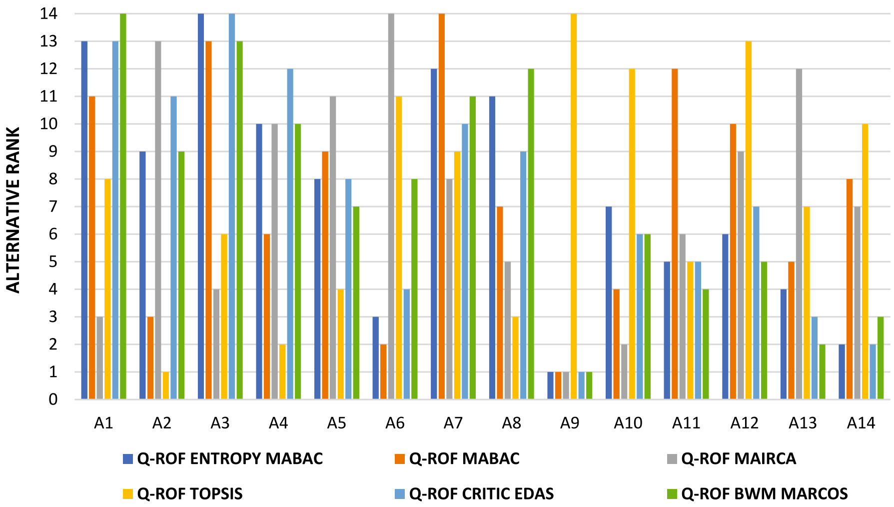

Fig. 6 Results of comparative analysis

- Future studies may benefit from diversifying the decision-making group for UCAV selection, incorporating perspectives from various stakeholders such as military personnel, and policymakers. Additionally, considering a broader range of criteria beyond those examined in this study could provide a more comprehensive assessment of UCAV capabilities and performance.
- Including a wider array of UCAV options in the problem statement could enrich the analysis and offer a more nuanced understanding of the strengths and weaknesses of different UCAV platforms. This expanded selection would enable researchers to explore a greater variety of technological capabilities, mission profiles, and operational characteristics.

- Beyond UCAV selection, future studies may explore the application of MCDM methodologies to evaluate various defense technologies. By adopting a systematic approach to assess the performance, suitability, and effectiveness of different defense systems, researchers can contribute to informed decision-making processes in defense procurement and strategic planning.

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Data availability All data are available in the study.

Declarations

Conflict of interest The author declares no confict of interest.

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Authors and Affiliations

Betül Turanoğlu Şirin[1]

Betül Turanoğlu Şirin
b.turanoglu@atauni.edu.tr

[1] Department of Industrial Engineering, Faculty of Engineering, Atatürk University, Erzurum 25240, Turkey