RAPID SELECTING UAVs FOR COMBAT BASED ON THREE-WAY MULTIPLE ATTRIBUTE DECISION

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Abstract

Unmanned aerial vehicles (UAVs) can carry out more and more dangerous missions and strike deep in the skies over hostile military sites. Thus, selecting appropriate UAVs to attend combat through rapid assessment is a hot topic in current research. In consideration of formulating practical evaluation as a three-way multiple attribute decision making (MADM) problem, a comprehensive assessment method based on interval-valued intuitionistic fuzzy set (IVIFs) is introduced under the context of determining the precision combat mission. First, the critical attributes of the UAV combat effectiveness are determined according to battlefield intelligence. Second, the attribute weights are computed by exploring the feature information of attribute orders given by experts. Third, the conditional probability a UAV may be selected to fight is calculated in accordance with an improved IVIFs score function. Then the UAVs' classification results of three-way decisions are obtained by setting the risk avoidance coefficients. Finally, the validity of the given method is proved throughout the decision-making process of selecting UAVs in a combat mission.

Key Words

UAV, combat effectiveness, three-way decision, MADM, superiority index, IVIFs

1. Introduction

Unmanned aerial vehicles (UAVs) driven by onboard power are controlled remotely by humans and autonomously programmed to perform various tasks. Compared with the manned plane, the UAV has advantages of safely entering the danger zone, simple operation, low operation cost and flexible deployment of multiple missions [1]–[5]. With the complexity and systematization of the battlefield environment, the comprehensive efficiency of the UAV has been paid more and more attention. Each UAV shows benefits and risks, however, none of them can entirely avoid repercussions in combat. To optimize the combat effectiveness, both the enemy and us, hope to perform tasks accurately by selecting appropriate UAVs. Commanders should make quick strikes by analyzing the climatic conditions, topography and firepower distribution. The complexity, urgency and dynamic nature of the battlefield make it more challenging to choose a UAV. Therefore, the selection of UAVs is of great significance to the operational effectiveness, support cost and ground operation of UAVs.

Usually, the existing UAV performance evaluation methods based on hard calculation are inadequate to the generalized UAV evaluation. What's more, the effectiveness of the UAV is usually evaluated by cost function, which cannot solve all relevant variables and possible external environments. As a result, an inappropriate UAV cannot present a satisfactory solution for many mission scenarios and may lead to the incorrect or misleading decision. The performance of the UAV is estimated for its mission effectiveness, mission characteristics and battlefield environments. Therefore, it is essential to construct a transparent and systematic evaluation system to guide the evaluation process realistically and scientifically.

The essence of traditional methods is two-way decisions, which means that a UAV is either selected or rejected. Traditional methods lack the boundary region for UAVs that should be further investigated whether they should be chosen. Three-way decision came from a reasonable interpretation of three regions of decision theoretic rough sets, which are the acceptance of positive region, non-commitment of boundary region and rejection of negative region [6]–[12]. Compared with two-way decisions, three-way decisions can better avoid risks by adding a delayed decision option. At present, this theory has been widely used in many fields, including cognitive concept, social network and malware analysis. With the uncertainty and complexity of the decision-making process, we need

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to collect more information to reach decision conclusions. It is a new research to combine a three-way decision algorithm and multiple attribute decision making (MADM) [13]–[17] in recent years. This hybrid method can consider both the MADM matrix and different loss functions for individual UAVs. In the application of decision, it is difficult for experts to give an accurate assessment with exact numbers due to the complexity of the battle. The definition of the intuitionistic fuzzy set (IFs) as an extension of the fuzzy number [18]–[20] was proposed by Atanassov, in which both membership and non-membership degrees were introduced. As a further extension of IFs, Atanassov and Gargov proposed the concept of interval-valued intuitionistic fuzzy set (IVIFs) [21]–[29]. It is clear that IVIFs enables experts to give preference judgments on UAV performance through interval-valued membership degrees to reduce errors.

In this paper, the UAV evaluation method is given as a three-way MADM problem with IVIFs. First, a general attribute framework is constructed by discussing the influence factors on UAV performance and the battle information, and a method to determine the weight of attribute is given based on the superiority index of attribute. Second, IVIFs is used for the subjective judgment of the proposed method, and the conditional probability that the UAV can be selected is calculated based on MADM. Third, the classification of UAVs is obtained combined with the given loss functions of individual UAVs. Finally, a numerical example further illustrates the effectiveness and advantage of the proposed method. This paper is the first attempt to study the selection of UAVs based on the three-way MADM under the IVIFs environment.

The other sections are set out as follows. Section 2 proposes the evaluation system of UAVs' combat effectiveness. In Section 3, we briefly describe the proposed UAVs evaluation model based on a new three-way MADM method with IVIFs. A case study about the UAV selection in a battle shows the applicability and power of the introduced methodology in Section 4. Finally, concluding remarks and future directions are presented in Section 5.

2. Evaluation System of Unmanned Aerial Vehicles' Combat Effectiveness

Usually, specific battlefield scenarios determine the survivability and environmental adaptability of UAVs. With the continuous innovation of science and technology, war also appears with different characteristics of combat, for example, the battlefield space is more extensive, the operational command is more accurate, and the weapon killing speed is increased. All of these accurately provide intelligence for the battlefield and a basis for the formulation of accurate strategic, tactical strategies and special missions in each battle. In air combat, it is key to the current precision operations and national military strategy research. The scientific evaluation index system is an essential prerequisite for combat effectiveness evaluation. Whether the selection of evaluation system index is proper or not is directly related to the evaluation result. Therefore, we should perceive the battlefield environment to determine UAV combat missions and select attributes of UAV combat effectiveness to construct the decision framework.

2.1 Evaluation Attributes of Unmanned Aerial Vehicles' Combat Effectiveness

The evaluation system of UAVs' combat effectiveness should be established based on the basic elements of evaluation and the features of the object, which are the main factors influencing the information warfare capability. It strives to respond to UAVs' combat capability to its best and fully follow the principles of purpose, uniqueness, comprehensiveness and personality. Then, the main factors affecting the optimal selection of procedural UAVs are determined. Suppose that the assessed attribute set is $\{c_1, c_2, \ldots, c_6\}$. The various attributes are as follows:

c_1 is the reconnaissance target capability. It is the ability to explore the operation target, which is mainly decided by the performance of airborne detection equipment and airborne radar. The main parameters include detection range, search angle, resolution and the ability to discover and identify the targets and operate UAVs.

c_2 is the battlefield flexibility. This performance includes UAVs' pitching agility, axial agility, high performance, conversion performance and other parameters.

c_3 is the attack capacity. It is the capability and quantity of the UAV's airborne equipment, mainly including the power range of the missile, the payload distance of the seeker, the angle of departure from the shaft and the effective launch distance.

c_4 is the air survival ability. The parameters mainly include electronic countermeasures capability, navigation, radar reflectance area and geometry size.

c_5 is the coordinated combat capability. It denotes the ability to coordinate operation and maintain uninterrupted communication among UAVs under a unified organization and command.

c_6 is the logistics support capability. It is the maintenance capability of UAVs.

2.2 The Determination Method of Attribute Weight

The role of the attribute weights is vital in MADM problems, which can be obtained by the superiority index of attribute. Let $\{e_1, e_2, \ldots, e_t\}$ be the set of experts, and the weight of expert e_k be λ_k with $\sum_{k=1}^{t} \lambda_k = 1$. Now, we discuss the method to determine the weights of the attributes. First, the definition of superiority index is given.

Definition 1. *Suppose that the priority order of attributes is* $c^k_{i_1} \geq c^k_{i_2} \geq \cdots c^k_{i_m}$ *given by* e_k, *denote* r^k_{ij} *as:*

$$r^k_{ij} = \begin{cases} 1 & c^k_i > c^k_j \\ 0.5 & c^k_i \sim c^k_j \\ 0 & c^k_i < c^k_j \end{cases} \tag{1}$$

then $r_{ij} = \sum_{k=1}^{t} \lambda_k r_{ij}^k$ *is the superiority index of* c_i *over* c_j*, at the same time, the superiority index matrix of* c_i *can be constructed as* $U_i = (r_{ij}^k)_{t\times m}$.

Subsequently, we can get the superiority index of $c_i (i \in M)$ in C, that is

$$R_i = \sum_{j=1}^{m} r_{ij} = \sum_{k=1}^{t}\sum_{j=1}^{m} \lambda_k r_{ij} \tag{2}$$

Then, we can believe that the weight of the attribute c_i is determined by the priority index in C, where

$$\omega_i = \frac{R_i}{\sum_{i=1}^{m} R_i}, i \in M \tag{3}$$

3. Three-way Multiple Attribute Decision Making Model based on Interval-valued Intuitionistic Fuzzy Set

3.1 Interval-valued Intuitionistic Fuzzy Set

Some basic concepts and related theories of IVIFs are introduced in this section. In practical applications, information is often lacking due to the imprecision and error of data. The studies on uncertainty, which is based on IVIFs, provides an important practical application background.

The following is a brief introduction to the basic concepts of IVIFs.

Definition 2. *Let* $X = \{x_1, x_2, \ldots, x_n\}$ *be a universe of discourse. Then an IVIFs* $\tilde{p}$ *on* X *is given by* $\tilde{p} = \{< x, \tilde{u}_{\tilde{p}}(x), \tilde{v}_{\tilde{p}}(x) >, x \in X\}$*, where* $\tilde{u}_{\tilde{p}}(x)$ *denotes the interval-valued membership degree, and* $\tilde{v}_{\tilde{p}}(x)$ *denotes the non-membership degree of* x *to* $\tilde{p}$*. For* $\forall x \in X, \tilde{u}_{\tilde{p}}(x) \subseteq [0,1], \tilde{v}_{\tilde{p}}(x) \subseteq [0,1]$ *and* $0 \le \sup(\tilde{u}_{\tilde{p}}(x)) + \sup(\tilde{v}_{\tilde{p}}(x)) \le 1$*. Conveniently, let* $\tilde{u}_{\tilde{p}}(x) = [a,b], \tilde{v}_{\tilde{p}}(x) = [c,d]$*, then* $\tilde{p} = ([a,b],\ [c,d])$.

Definition 3. *Suppose* $\tilde{P} = \{\tilde{p}_1, \tilde{p}_2, \ldots, \tilde{p}_m\}$ *be a collection of IVIFs, where* $\tilde{p}_i = (\tilde{u}_i, \tilde{v}_i) = ([a_i, b_i], [c_i, d_i]) (i = 1, 2, \ldots, m)$*. Let* $\omega = (\omega_1, \omega_2, \ldots, \omega_m)$ *be the weight vector for* $\tilde{p}_i$ *with* $\omega_i \ge 0$ *and* $\sum_{i=1}^{m} \omega_i = 1$*. Then the IVIFWA is a mapping* IVIFWA: $\Omega^m \to \Omega$ *according to*

$$\begin{aligned}\tilde{p} &= IVIFWA(\tilde{p}_1, \tilde{p}_2, \ldots, \tilde{p}_m) \\ &= \omega_1 \tilde{p}_1 + \omega_2 \tilde{p}_2 + \cdots + \omega_m \tilde{p}_m \\ &= \left([\sum_{i=1}^{m} \omega_i a_i, \sum_{i=1}^{m} \omega_i b_i], [\sum_{i=1}^{m} \omega_i c_i, \sum_{i=1}^{m} \omega_i d_i] \right)\end{aligned} \tag{4}$$

The ranking of IVIFs plays a vital part in the decision problem. To solve the disadvantages of common methods [28], [29] and give a total order of IVIFs, a new IVIFs score function is given [27], which is as follows:

Definition 4 [27]. *Suppose that* $\tilde{p} = ([a,b],\ [c,d])$ *is an IVIFs, the precise score of* $\tilde{p}$ *is defined by*

$$S(\tilde{p}) = \frac{a + b + c - d + ab + cd}{3} \tag{5}$$

This new ranking procedure can improve the practicality and accuracy of the decision. According to this function, the comparison and ranking of two IVIFs are obtained; the higher the $S(\tilde{p})$, the better the $\tilde{p}$.

3.2 Three-way Decision

Let $U = \{x_1, x_2, \ldots, x_n\}$ be a finite and non-empty set, and $[x_i]$ denote the equivalence class containing $x_i \in X$ under an equivalence relation. Let $\Omega = \{A, \neg A\}$ be the state sets of choices, which means that an object belongs to A or not. Suppose that $\Pr(A|x_i)$ is the conditional probability that x_i can be selected, and $AC = \{a_P, a_B, a_N\}$ is the action set, where a_P, a_B and a_N denote $x \in POS(A)$, $x \in BND(A)$ and $x \in NEG(A)$, respectively. When an object belongs to A, let λ_{PP}, λ_{BP} and λ_{NP} represent the losses incurred for choosing actions a_P, a_B and a_N, respectively. When an object belongs to $\neg A$, let λ_{PN}, λ_{BN} and λ_{NN} represent the losses incurred for choosing actions a_P, a_B and a_N, respectively. Then, the parameters associated with the classification are calculated by

$$\alpha = \frac{\lambda_{PN} - \lambda_{BN}}{(\lambda_{PN} - \lambda_{BN}) + (\lambda_{BP} - \lambda_{PP})} \tag{6}$$

$$\beta = \frac{\lambda_{BN} - \lambda_{NN}}{(\lambda_{BN} - \lambda_{NN}) + (\lambda_{NP} - \lambda_{BP})} \tag{7}$$

Then, U can be divided into three regions, which are as follows:

(P1) If $\Pr(A|x_i) \ge \alpha$, then decide $x_i \in POS(A)$;

(B1) If $\beta < \Pr(A|x_i) < \alpha$, then decide $x_i \in BND(A)$;

(N1) If $\Pr(A|x_i) \le \beta$, then decide $x_i \in NEG(A)$.

The schematic of the three-way decision process is shown in Fig. 1.

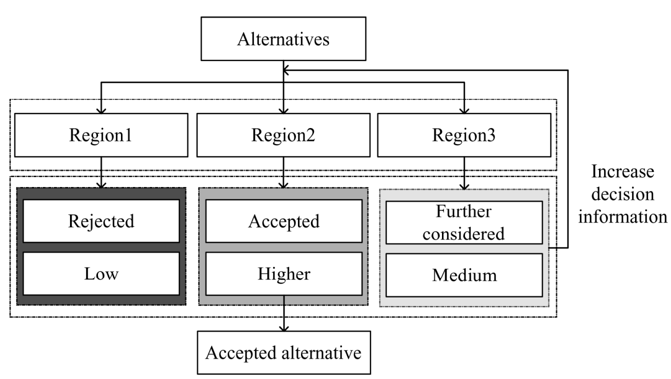

Figure 1. Three-way decision process.

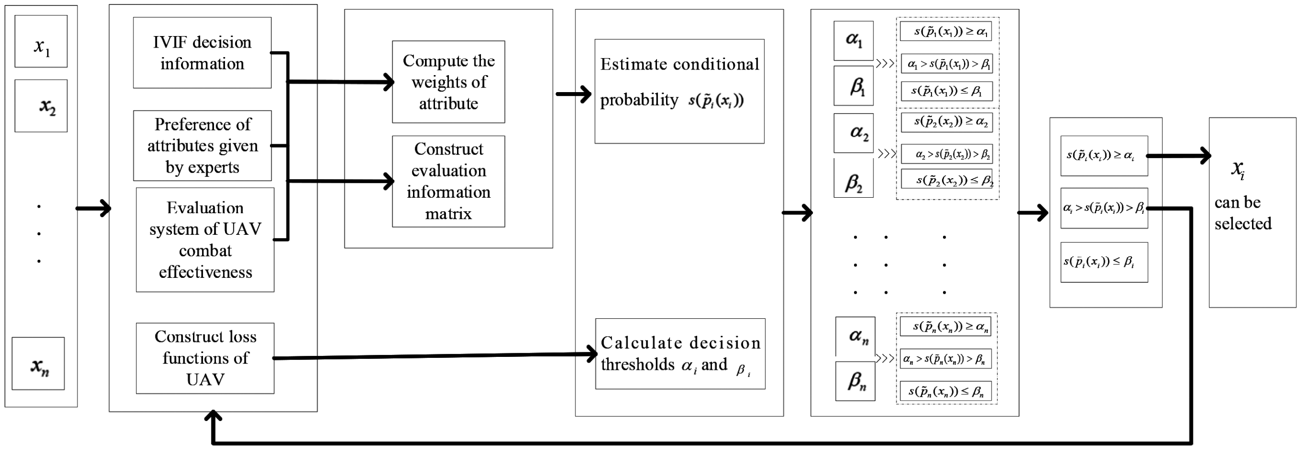

Figure 2. The three-way MADM decision process.

3.3 The Algorithm of Three-way Multiple Attribute Decision Making based on Interval-valued Intuitionistic Fuzzy Set

Now, the specific three-way MADM evaluation model is proposed, which can evaluate the combat effectiveness of UAVs and help us to select appropriate UAVs to meet the needs of combat missions.

According to a specific operational task, let $U = \{x_1, x_2, \ldots, x_n\}$ be a discrete set of UAVs, and $C = \{c_1, c_2, \ldots, c_m\}$ be the set of all attributes. Moreover, suppose that $\omega = (\omega_1, \omega_2, \ldots, \omega_m)^T$ is the weighting vector of attributes with $\sum_{j=1}^{m} \omega_j = 1$ and $\omega_j \geq 0$. In the process of fast operational command, it is difficult for us to carry out accurate testing and calculation of data to select appropriate UAVs, but experts can perceive the possibility that UAVs can complete a certain attribute or not using previous experience. Construct the IVIFs decision matrix $\tilde{P} = (\tilde{p}_{ij})_{n\times m}$, where $\tilde{p}_{ij} = (\tilde{u}_{ij}, \tilde{v}_{ij}) = ([a_{ij}, b_{ij}], [c_{ij}, d_{ij}])$ is the IVIFs decision value of UAV x_i for attribute c_j, where $\tilde{u}_{ij}$ and $\tilde{v}_{ij}$ denote the satisfaction judgment and dissatisfaction judgment of UAV x_i performance under decision attributes c_j, respectively. Here, we see the comprehensive evaluation value of the UAV as the conditional possibility that UAV can be selected. Suppose that state A denotes the UAVs that can be selected, and state $\neg A$ denotes the UAVs that cannot be selected. Then construct the loss functions of each UAV and compute decision thresholds. Finally, U is divided into three parts according to the decision rules. The whole decision process is shown in Fig. 2.

The proposed UAV evaluation model includes the following steps:

Step 1 Based on the provided sets of UAV and attribute, collect and sort out the evaluation information given by experts and transform decision information into IVIFs, then construct the IVIFs decision matrix $\tilde{P} = (\tilde{p}_{ij})$.

Step 2. In accordance with (1)–(3), determine the weights of attributes.

Step 3. Employ the given IVIFWA operator to compute the aggregate of each UAV into a specific IVIFs $\tilde{p}_i(x_i)$ using the matrix $\tilde{P}$ and the weight vector $\omega = (\omega_1, \omega_2, \ldots, \omega_m)$ based on (4).

Step 4. For $\forall x_i (i = 1, 2, \ldots, n)$, aggregate the decision information of attributes, compute the conditional probability $s(\tilde{p}(x_i))$ of UAV $x_i (i = 1, 2, \ldots, n)$ by (5).

Step 5. Based on the given loss functions $\lambda^i_{PN}, \lambda^i_{NN}, \lambda^i_{BN}, \lambda^i_{PP}, \lambda^i_{NP}$ *and* λ^i_{BP} of alternative UAV $x_i (i = 1, 2, \ldots, n)$, calculate the corresponding decision thresholds α_i and β_i for UAV x_i, which are given as follows:

$$\alpha_i = \frac{\lambda^i_{PN} - \lambda^i_{BN}}{(\lambda^i_{PN} - \lambda^i_{BN}) + (\lambda^i_{BP} - \lambda^i_{PP})} \tag{8}$$

$$\beta_i = \frac{\lambda^i_{BN} - \lambda^i_{NN}}{(\lambda^i_{BN} - \lambda^i_{NN}) + (\lambda^i_{NP} - \lambda^i_{BP})} \tag{9}$$

Then, obtain the comprehensive loss function and decision threshold matrix.

Step 6. Construct the three-way decision rules of UAVs by comparing the conditional probability $s(\tilde{p}(x_i))$ that can be selected and decision initial values α_i and β_i of $x_i \quad (i = 1, 2, \ldots, n)$, which are as follows:

(P2) If $s(\tilde{p}(x_i)) \geq \alpha$, decide $x_i \in POS(A)$, which means that the UAV x_i can be selected;

(B2) If $\beta < s(\tilde{p}(x_i)) < \alpha$, decide $x_i \in BND(A)$, which means that the UAV x_i need more information to discuss;

(N2) If $s(\tilde{p}(x_i)) \leq \beta$, decide $x_i \in NEG(A)$, which means that the UAV x_i cannot be selected.

4. The Application Analysis of the Presented Model

We will present an example to show how to use the proposed model in this section. A certain army has already made a combat plan by perceiving the battlefield situation and gathering different sets of synthetic threat information in the combat mission. Due to the shortage of time, it is necessary to select the most suitable UAVs as soon as possible. Let $U = \{x_1, x_2, \ldots, x_8\}$ be a panel with eight

Table 1
IVIFs Decision Matrix

$X\backslash C$	c_1	c_2	c_3	c_4	c_5	c_6
x_1	([0.69,0.74], [0.19,0.23])	([0.54,0.57], [0.41,0.43])	([0.66,0.74],[0.21,0.23])	([0.82,0.87],[0.11,0.17])	([0.24,0.34],[0.41,0.58])	([0.22,0.25],[0.47,0.54])
x_2	([0.72,0.75], [0.21,0.23])	([0.51,0.56], [0.38,0.43])	([0.71,0.77],[0.16,0.23])	([0.51,0.57],[0.41,0.43])	([0.18,0.25],[0.51,0.56])	([0.09,0.35],[0.46,0.54])
x_3	([0.51,0.57], [0.41,0.43])	([0.45,0.48], [0.41,0.51])	([0.68,0.74],[0.21,0.23])	([0.52,0.57],[0.38,0.43])	([0.19,0.25],[0.34,0.65])	([0.22,0.25],[0.47, 0.54])
x_4	([0.62,0.65],[0.32,0.34])	([0.62,0.65], [0.32,0.34])	([0.45,0.48],[0.41,0.48])	([0.51,0.57],[0.41,0.43])	([0.20,0.27],[0.46,0.52])	([0.54,0.58],[0.21,0.32])
x_5	([0.51,0.57],[0.41,0.43])	([0.45,0.48], [0.41,0.51])	([0.65,0.74],[0.21,0.23])	([0.52,0.57],[0.38,0.43])	([0.22,0.35],[0.41,0.53])	([0.22,0.25],[0.47,0.54])
x_6	([0.72,0.75],[0.21,0.23])	([0.52,0.57], [0.41,0.43])	([0.71,0.74],[0.18,0.23])	([0.51,0.57],[0.41,0.46])	([0.21,0.36],[0.41,0.61])	([0.92,0.95],[0.02,0.03])
x_7	([0.51,0.57],[0.41,0.43])	([0.53,0.57], [0.28,0.37])	([0.62,0.65],[0.32,0.34])	([0.51,0.56],[0.37,0.43])	([0.19,0.21],[0.41,0.65])	([0.42,0.53],[0.21,0.26])
x_8	([0.71,0.74],[0.21,0.23])	([0.51,0.54], [0.41,0.43])	([0.71,0.72],[0.21,0.26])	([0.71,0.74],[0.21,0.23])	([0.22,0.25],[0.45,0.53])	([0.32,0.47],[0.41,0.53])

possible types of combat UAVs. The decision experts evaluate the eight UAVs about the attribute set $\{c_1, c_2, \ldots, c_6\}$ given in Section 2 and build the decision matrix $\tilde{P} = (\tilde{p}_{ij})$, where $\tilde{p}_{ij} = ([a_{ij}, b_{ij}], [c_{ij}, d_{ij}])$ represents the performance of UAV x_i for attribute c_j. The satisfaction degree of x_i for c_j is between a_{ij} and b_{ij}, and the dissatisfaction degree of x_i for attribute c_j is between c_{ij} and d_{ij}. The decision matrix $\tilde{P} = (\tilde{p}_{ij})$ can be shown in Table 1.

Suppose that the expert set is E $= \{e_1, e_2, e_3, e_4\}$, and the weights of experts and the order of attributes decided by experts are given in Table 2.

Based on (1), we can obtain the superior index matrix U_i for attribute $c_i \quad (i = 1, 2, \ldots, 6)$ as follows:

$$U_1 = \begin{pmatrix} 0.5 & 0 & 1 & 0 & 0 & 0 \\ 0.5 & 1 & 1 & 1 & 1 & 1 \\ 0.5 & 0 & 1 & 1 & 1 & 1 \\ 0.5 & 1 & 0.5 & 0 & 1 & 1 \end{pmatrix}, \quad U_2 = \begin{pmatrix} 1 & 0.5 & 1 & 0 & 1 & 0 \\ 0 & 0.5 & 1 & 1 & 1 & 1 \\ 1 & 0.5 & 1 & 1 & 1 & 1 \\ 0 & 0.5 & 0 & 0 & 0 & 1 \end{pmatrix}$$

$$U_3 = \begin{pmatrix} 0 & 0 & 0.5 & 0 & 0 & 0 \\ 0 & 0 & 0.5 & 1 & 1 & 0.5 \\ 0 & 0 & 0.5 & 0 & 0 & 0 \\ 0.5 & 1 & 0.5 & 0 & 1 & 1 \end{pmatrix}, \quad U_4 = \begin{pmatrix} 1 & 1 & 1 & 0.5 & 1 & 1 \\ 0 & 0 & 0 & 0.5 & 0 & 0 \\ 1 & 0 & 1 & 0.5 & 0.5 & 1 \\ 0 & 1 & 1 & 0.5 & 1 & 1 \end{pmatrix}$$

$$U_5 = \begin{pmatrix} 1 & 0 & 1 & 0 & 0.5 & 1 \\ 0 & 0 & 0 & 1 & 0.5 & 0 \\ 0 & 0 & 1 & 0.5 & 0.5 & 1 \\ 0 & 1 & 0 & 0 & 0.5 & 1 \end{pmatrix}, \quad U_6 = \begin{pmatrix} 1 & 0 & 1 & 0 & 0 & 0.5 \\ 0 & 0 & 0.5 & 1 & 1 & 0.5 \\ 0 & 0 & 1 & 0 & 0 & 0.5 \\ 0 & 0 & 0 & 0 & 0 & 0.5 \end{pmatrix}$$

According to (2), by computing the superior index R_i for attribute c_i, we get

$$R_1 = 4.195, \quad R_2 = 3.935, \quad R_3 = 2.05,$$
$$R_4 = 3.430, \quad R_5 = 2.559, \quad R_6 = 1.807,$$

Then, based on (3), we can compute the weights of attributes as follows:

$$\omega_1 = 0.273,\ \omega_2 = 0.256,\ \omega_3 = 0.134,$$
$$\omega_4 = 0.223,\ \omega_5 = 0.166,\ \omega_6 = 0.117$$

Table 2
Weight of Expert and the Order of Attributes

E	The Order of Attributes	The Weights of Experts
e_1	$c_4^1 > c_2^1 > c_5^1 > c_6^1 > c_1^1 > c_3^1$	$\lambda_1 = 0.15$
e_2	$c_1^2 > c_2^2 > c_6^2 \sim c_3^2 > c_5^2 > c_4^2$	$\lambda_2 = 0.27$
e_3	$c_2^3 > c_1^3 > c_5^3 \sim c_4^3 > c_6^3 > c_3^3$	$\lambda_3 = 0.33$
e_4	$c_4^4 > c_1^4 \sim c_3^4 > c_5^4 > c_2^4 > c_6^4$	$\lambda_4 = 0.25$

Using (4), we can get the collective preference attribute values $\tilde{p}_i(x_i)$ of the UAV x_i as follows:

$$\tilde{p}_1(x_1) = ([0.5312, 0.5805], [0.3377, 0.3912]),$$
$$\tilde{p}_2(x_2) = ([0.4443, 0.5211], [0.3868, 0.4365])$$

$$\tilde{p}_3(x_3) = ([0.4295, 0.4709], [0.3778, 0.4860]),$$
$$\tilde{p}_4(x_4) = ([0.5131, 0.5552], [0.3557, 0.3960])$$

$$\tilde{p}_5(x_5) = ([0.4303, 0.4850], [0.3876, 0.4691]),$$
$$\tilde{p}_6(x_6) = ([0.5361, 0.5978], [0.3448, 0.3981])$$

$$\tilde{p}_7(x_7) = ([0.4776, 0.5225], [0.3125, 0.4062]),$$
$$\tilde{p}_8(x_8) = ([0.5099, 0.5496], [0.3558, 0.3977])$$

By (5), compute the conditional probability $s(\tilde{p}_i(x_i))$ of UAV x_i, which are given as follows:

$$s(\tilde{p}_1(x_1)) = 0.4996, \quad s(\tilde{p}_2(x_2)) = 0.9015,$$
$$s(\tilde{p}_3(x_3)) = 0.3927, \quad s(\tilde{p}_4(x_4)) = 0.4846,$$

$$s(\tilde{p}_5(x_5)) = 0.4081, \quad s(\tilde{p}_6(x_6)) = 0.5128,$$
$$s(\tilde{p}_7(x_7)) = 0.4276, \quad s(\tilde{p}_8(x_8)) = 0.4798$$

We can obtain the ranking results of UAV combat effectiveness according to conditional probabilities as follows:

$$s(\tilde{p}_2(x_2)) > s(\tilde{p}_6(x_6)) > s(\tilde{p}_1(x_1)) > s(\tilde{p}_4(x_4)) > s(\tilde{p}_8(x_8))$$
$$> s(\tilde{p}_7(x_7)) > s(\tilde{p}_5(x_5)) > s(\tilde{p}_3(x_3)).$$

Table 3
Loss Function and Decision Threshold Value Matrix

	λ^i_{PP}	λ^i_{BP}	λ^i_{NP}	λ^i_{PN}	λ^i_{BN}	λ^i_{NN}	α_i	β_i
x_1	0	0.2840	0.7460	0.3860	0.1600	0	0.4431	0.2417
x_2	0	0.2610	0.7548	0.4570	0.1600	0	0.5323	0.24810
x_3	0	0.2233	0.6380	0.5823	0.2038	0	0.6289	0.4710
x_4	0	0.2297	0.3520	0.5079	0.100	0	0.5897	0.2941
x_5	0	0.2175	0.5500	0.1775	0.2300	0	0.4494	0.4089
x_6	0	0.2740	0.7320	0.3800	0.1800	0	0.4219	0.2821
x_7	0	0.1709	0.4884	0.7054	0.2469	0	0.7284	0.4375
x_8	0	0.1748	0.4995	0.6923	0.2423	0	0.7202	0.4273

Table 4
Conditional Probability and Decision Threshold Matrix

UAV	α_i	β_i	$s(\tilde{p}_i(x_i))$	Decision Rule	Classification
x_1	0.4431	0.2417	0.4996	$s(\tilde{p}_1(x_1)) > \alpha_1$	$POS(A)$
x_2	0.5323	0.2481	0.9015	$s(\tilde{p}_2(x_2)) > \alpha_2$	$POS(A)$
x_3	0.6289	0.4710	0.3927	$s(\tilde{p}_3(x_3)) < \beta_3$	$NEG(A)$
x_4	0.5897	0.2941	0.4846	$\beta_4 < s(\tilde{p}_4(x_4)) < \alpha_4$	$BND(A)$
x_5	0.4494	0.4089	0.4081	$s(\tilde{p}_5(x_5)) < \beta_5$	$NEG(A)$
x_6	0.4219	0.2821	0.5128	$s(\tilde{p}_6(x_6)) > \alpha_6$	$POS(A)$
x_7	0.7284	0.4375	0.4276	$s(\tilde{p}_7(x_7)) < \beta_7$	$NEG(A)$
x_8	0.7202	0.4273	0.4798	$\beta_8 < s(\tilde{p}_8(x_8)) < \alpha_8$	$BND(A)$

For $\forall x_i$, according to the given loss functions of UAV x_i, calculate the decision initial values α_i and β_i based on (8) and (9), respectively, which are shown in Table 3.

Then, we can further obtain the classification results of U based on rules (P2)–(N2), which are presented in Table 4.

Obviously, we can get the conclusion as follows:

$$POS(A) = \{x_2, x_6, x_1\}, \quad BND(A) = \{x_4, x_8\},$$
$$NEG(A) = \{x_7, x_5, x_3\}.$$

Thus, the set of the desirable UAVs is $\{x_2, x_6, x_1\}$, the set that needs more information to discuss is $\{x_4, x_8\}$, and the set that cannot be selected is $\{x_7, x_5, x_3\}$. Therefore, we should choose $\{x_2, x_6, x_1\}$ to attend the fight. Although the expertise and the numbers of experts are limited due to the urgency of the battle situation and the shortage of time and available resources, their conclusion is important and sufficient for validating the three-way MADM process.

5. Conclusion

In this paper, we present a novel assessment method of UAV combat effectiveness based on three-way MADM. We evaluate different candidate UAVs and find out the suitable UAVs for completing the combat mission. A generic attribute framework of UAV combat effectiveness is given. The ability to give the attribute value as IVIFs can effectively deal with random uncertainties in the battlefield environment and flexibly reflect the acquisition of situation information.

The proposed algorithm does not require complicated calculations but only requires experts to give possible decision attribute values based on their accumulated experience. The essence of this method is turning traditional ranking results of two-way decisions into objective classification results of three-way decisions, which is more suitable for changeable combat situation. This method not only divides the set of UAVs into three regions but also gives a complete ranking according to the corresponding losses of UAVs. However, battlefield situation is rather complex and changeable. Fully considering these limitations, there are suggested space for future improvements and validation of the presented approach. The future research areas will also be designed to apply the given evaluation model to a more efficient level, and make the expert's professional knowledge and experience have a maximum use. Moreover, the effective algorithm can be used for UAV attack mission, route selection and other practical applications.

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