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Original paper

A hybrid IRN-based BWM–COPRAS framework for electro-optic system selection in UAVs with heterogeneous evaluations

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Abstract

The rapid proliferation of unmanned aerial vehicles (UAVs) across diverse civil and military domains has heightened the need for careful payload selection due to inherent weight and capacity constraints. Among these payloads, electro-optic (EO) systems are of paramount importance, offering capabilities such as real-time imaging, surveillance, reconnaissance, and precision targeting. Given the increasing diversity and complexity of EO systems, selecting the most appropriate system for Medium-Altitude Long-Endurance (MALE) UAVs has emerged as a multi-dimensional decision-making challenge that requires the integration of both technical specifications and expert evaluations. This study proposes a novel decision-making framework that integrates the Fuzzy Best-Worst Method (BWM) and the Complex Proportional Assessment (COPRAS) method under the Interval Rough Number (IRN) theory. The approach addresses the uncertainty and heterogeneity in expert judgments and objective data, thereby providing a more nuanced and robust evaluation mechanism. The proposed hybrid framework offers methodological contributions by extending traditional MCDM techniques to heterogeneous decision environments through the use of IRNs. Empirical results demonstrate the model's reliability and consistency, with sensitivity and comparative analyses validating its robustness across multiple scenarios. The findings provide valuable insights for decision-makers and system developers in the aerospace and defense industries, offering a structured and adaptable tool for selecting EO systems in MALE-class UAV applications.

Keywords: Fuzzy BWM, rough COPRAS, electro-optic system, unmanned aerial vehicle, heterogeneous information.

1 Introduction

The rapid evolution of technology continues to reshape industrial, military, and societal systems, prompting the development of advanced tools and platforms capable of meeting diverse operational demands. Among these, Unmanned Aerial Vehicles (UAVs) have emerged as a critical component in sectors such as logistics, agriculture, environmental monitoring, and particularly defense [10, 32, 41]. Their ability to conduct reconnaissance, surveillance, and target acquisition without direct human intervention has revolutionized modern military strategy.

At the core of a UAV's operational effectiveness lies its payload configuration, which may include communication systems, weaponry, and various sensor technologies [18]. Electro-optic (EO) systems represent one of the most vital payload components due to their indispensable role in day and night imaging, laser designation, and precision targeting. These systems integrate multiple subsystems such as infrared sensors, visible spectrum cameras, and laser rangefinders, enabling UAVs to perform complex missions across various terrains and operational scenarios [34].

The wide variety of EO systems available in the market, driven by continuous technological innovation, has made the selection of the most appropriate EO system a complex multi-criteria decision-making (MCDM) problem. Each system differs in terms of resolution, reliability, weight, cost, and operational range. Therefore, aligning EO system

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capabilities with mission-specific requirements of Medium Altitude Long Endurance (MALE)-class UAVs demands a robust and structured evaluation framework.

The available information can be heterogeneous in many real-world group decision-making problems [21]. This heterogeneity can stem from expert evaluations being presented in different formats, incomplete or missing information, or the combination of subjective and objective criteria; as well as experts having various levels of expertise or importance [5, 9, 20].

To address these challenges, this study proposes an integrated MCDM framework that combines the Fuzzy Best-Worst Method (BWM) for criteria weighting and an extended COPRAS method based on Interval Rough Numbers (IRNs) for ranking alternatives. Rough set theory, which offers a powerful means of managing vagueness and incomplete information without requiring additional assumptions, is employed to reflect the dual nature of subjective perceptions and objective data [25, 39, 44]. The IRN-based extension of COPRAS allows the methodology to operate effectively in heterogeneous group decision-making environments, where both interval-valued and fuzzy linguistic data coexist.

Unlike previous studies that either apply classical MCDM methods or focus on higher-level platform selection, this research addresses a critical and underexplored problem: the selection of EO systems for MALE-class UAVs under conditions of uncertainty and data heterogeneity. Furthermore, to the best of the authors' knowledge, this is the first study to integrate BWM and COPRAS within a rough set-based framework while accounting for heterogeneous decision environments—a key novelty and contribution to the MCDM literature in aerospace and defense.

The specific contributions of this study are as follows:

- A structured decision-making procedure was developed to support the selection of EO systems for MALE-class UAVs, grounded in expert knowledge and technical specifications.
- A hybrid BWM-COPRAS model was proposed, enhanced by fuzzy and rough set theories, to account for subjective uncertainty and information granularity.
- A novel methodological framework was introduced that effectively integrates expert evaluations presented in different formats with objective data, thereby enabling robust decision-making in heterogeneous environments.

The remainder of the study is organized as follows: the literature research on fuzzy MCDM methods, particularly BWM and COPRAS, and studies involving rough set theory, are presented in Section 2. The applied methodology, which covers BWM, COPRAS, and the proposed heterogeneous approach, is described in Section 3. A case study is provided in Section 4. Section 5 discusses a sensitivity and comparative analysis to demonstrate the validity of the results. Finally, the conclusion and future research are discussed in Section 6.

2 Literature review

The increasing adoption of UAVs across domains such as logistics, agriculture, and defense has prompted a corresponding growth in attention to their payload configurations, particularly EO systems. In MALE-class UAVs, EO systems—comprising sensors like infrared cameras, laser range finders, and high-resolution optical devices—are pivotal for surveillance, reconnaissance, and target acquisition. As the market offers a growing variety of EO systems driven by rapid technological advances, selecting the most suitable one for a specific operational context has emerged as a complex MCDM challenge.

While a substantial body of MCDM research in aerospace has focused on the selection of UAV platforms or major subsystems, the application of these methods specifically to EO systems remains relatively limited. Notably, the unique characteristics of EO system selection—combining objective technical specifications with expert subjective evaluations—require flexible and robust models capable of handling heterogeneous information and uncertainty.

The literature demonstrates the increasing integration of rough set theory and IRNs into MCDM frameworks to capture vagueness and deal with imperfect information. Stević et al. [42], for instance, introduced an Interval Rough SAW (Simple Additive Weighting) method, illustrating how IRNs can be applied to supplier selection problems under uncertainty. Similarly, Zhu et al. [47] proposed a fuzzy rough number-enhanced AHP-TOPSIS framework for early-stage product design evaluation, effectively capturing subjectivity and risk perception in group decision-making. Cao [6] applied a rough BWM for weighting and introduced the rough WISP method for ranking ERP alternatives, while Shidpour et al. [37] developed an interval-vector-based closeness index model integrating rough and fuzzy evaluations for product design concepts. In the context of renewable energy, Deveci et al. [8] utilized interval rough number-based BWM and MARCOS to select offshore wind farm sites in the Mediterranean.

Several studies have also explored hybrid models combining BWM and COPRAS, particularly under fuzzy or grey system environments [26]. Amoozad Mahdiraji et al. [1] utilized a fuzzy BWM-Grey COPRAS model to assess environmental sustainability in construction. In a military context, Pamučar and Savin [28] used BWM and COPRAS to select terrain vehicles for the Serbian Armed Forces. These studies confirm the methodological strength of BWM-

COPRAS integrations across sectors but highlight the absence of such applications in EO system selection for UAVs, particularly under heterogeneous data environments.

Recent advances have also emphasized group decision-making under mixed information formats. For instance, Arı and Dursun [2] employed a Bayesian BWM method for weighting sustainability criteria in aircraft selection, combined with consensus-based intuitionistic fuzzy EDAS to address opinion asymmetries. Song [39] proposed a rough group AHP-TOPSIS hybrid to support early product evaluations, while Roy [33] presented a collective framework using weighted interval rough numbers and COPRAS for hotel ranking under inconsistent tourist evaluations. These efforts reveal a growing awareness of the need to manage heterogeneous data in complex decisions, yet few studies offer a structured integration of subjective and objective formats through rough-theoretic reasoning.

Most MCDM studies are confined to platform-level evaluations or propulsion and structural component assessments within the UAV-focused literature. For example, Cengiz and Çelik [7] explored EO camera placement but did not engage in comparative evaluation across EO systems. This reflects a notable gap in addressing EO system selection as a standalone, structured MCDM problem, especially one that accounts for real-world data heterogeneity.

Against this backdrop, the present study proposes a novel hybrid MCDM approach that integrates BWM and COPRAS within the interval rough number theory, specifically adapted to handle heterogeneous data formats, an area underexplored in current literature. By enabling the concurrent use of fuzzy expert judgments and objective technical evaluations, the method offers a holistic, robust, and practically applicable framework for EO system selection in MALE-class UAVs. This study contributes a valuable methodological and application-oriented addition to the evolving landscape of defense and aerospace engineering decision-support systems.

Determining an appropriate set of evaluation criteria is a critical component of the electro-optic system selection process for MALE-class UAVs. This study identified six main criteria through a combination of literature synthesis, technical specification analysis, and expert validation. These criteria reflect the operational needs and technical expectations required for high-performance electro-optic systems in reconnaissance, surveillance, and targeting missions.

The selection process was informed by recent studies that examine payload optimization, sensor performance, cost-effectiveness, and system reliability in UAV applications [11, 13, 14, 19, 24, 30, 36, 45]. For instance, weight and Mean Time Between Failures (MTBF) are frequently highlighted as core determinants of UAV mission endurance and system sustainability [24, 30]. Optical and infrared resolution metrics are widely acknowledged as essential for situational awareness and target identification accuracy [13, 19, 45]. Furthermore, the increasing importance of cost considerations and extended laser range capabilities is underscored in both defense procurement literature and technical military standards [14]. Thus, the six criteria selected for this study (Weight, Optical Resolution, IR Resolution, Reliability, Cost, and Laser Range) represent a consensus in the literature regarding the most critical factors influencing EO system effectiveness in MALE-UAV operations.

3 Methodology

This section presents the methodology used in this study. First, the preliminaries of rough sets are given. A hybrid decision-making framework is introduced based on integrating the BWM and IRN-based COPRAS methods (see Figure 1).

3.1 Interval rough numbers

Rough numbers provide a mathematical framework for quantifying imprecise expert judgments by leveraging the foundational concepts of rough set theory [12, 29]. Unlike traditional interval-based approaches, rough numbers are constructed directly from raw data without requiring additional assumptions, thereby enhancing objectivity in decision-making [46]. By representing uncertainty through lower and upper approximation bounds, rough numbers effectively capture the inherent vagueness in human perceptions, making them particularly useful in multi-criteria decision-making [16, 23, 37].

Let a set of ordered preference classes of the expert be represented as $R = (J_1, J_2, \ldots, J_k)$. Another class set $R^* = (I_1, I_2, \ldots, I_k)$, having the same preference structure, is defined based on real-valued lower and upper bounds. Each class $I_i \in R^*$ is represented by an interval: $I_i = [I_{li}, I_{ui}]$, where $I_{li} \leq I_{ui}$, $I_{li}, I_{ui} \in \mathbb{R}$. If the lower bounds $I^*_{l1}, I^*_{l2}, \ldots, I^*_{lj}$ and the upper bounds $I^*_{u1}, I^*_{u2}, \ldots, I^*_{uk}$ are strictly increasing, then two distinct ordered class sets can be constructed [8, 27]:

- The lower approximation class set: $R^*_l = (I^*_{l1}, I^*_{l2}, \ldots, I^*_{lj})$,
- The upper approximation class set: $R^*_u = (I^*_{u1}, I^*_{u2}, \ldots, I^*_{uk})$.

For a given universal set of objects U, the lower approximations of these classes are defined as follows:

$$\underline{\mathrm{Apr}}(I_{li}^*) = \bigcup \{Y \in U \mid R_l^*(Y) \leq I_{li}^*\}, \tag{1}$$

$$\underline{\mathrm{Apr}}(I_{ui}^*) = \bigcup \{Y \in U \mid R_u^*(Y) \leq I_{ui}^*\}. \tag{2}$$

The upper approximations of these classes are defined as follows:

$$\overline{\mathrm{Apr}}(I_{li}^*) = \bigcup \{Y \in U \mid R_l^*(Y) \geq I_{li}^*\}, \tag{3}$$

$$\overline{\mathrm{Apr}}(I_{ui}^*) = \bigcup \{Y \in U \mid R_u^*(Y) \geq I_{ui}^*\}. \tag{4}$$

The lower and upper limits of each class can then be calculated based on these approximations:

$$\underline{\mathrm{Lim}}(I_{li}^*) = \frac{1}{M_L} \sum R_l^*(Y),\ Y \in \underline{\mathrm{Apr}}(I_{li}^*), \qquad \underline{\mathrm{Lim}}(I_{ui}^*) = \frac{1}{M_L^*} \sum R_u^*(Y),\ Y \in \underline{\mathrm{Apr}}(I_{ui}^*), \tag{5}$$

$$\overline{\mathrm{Lim}}(I_{li}^*) = \frac{1}{M_U} \sum R_l^*(Y),\ Y \in \overline{\mathrm{Apr}}(I_{li}^*), \qquad \overline{\mathrm{Lim}}(I_{ui}^*) = \frac{1}{M_U^*} \sum R_u^*(Y),\ Y \in \overline{\mathrm{Apr}}(I_{ui}^*), \tag{6}$$

where M_L, M_L^*, M_U, M_U^* denote the number of objects within the respective approximation sets.

For the lower object class I_{li}^*, the rough boundary interval $RB(I_{li}^*)$ is defined as the difference between the upper and lower bounds:

$$RB(I_{li}^*) = \overline{\mathrm{Lim}}(I_{li}^*) - \underline{\mathrm{Lim}}(I_{li}^*). \tag{7}$$

Similarly, for the upper object class I_{ui}^*:

$$RB(I_{ui}^*) = \overline{\mathrm{Lim}}(I_{ui}^*) - \underline{\mathrm{Lim}}(I_{ui}^*). \tag{8}$$

Each class is then defined as a Rough Number (RN) by its lower and upper boundaries:

$$RN(I_{li}^*) = \left[\underline{\mathrm{Lim}}(I_{li}^*),\, \overline{\mathrm{Lim}}(I_{li}^*)\right], \tag{9}$$

$$RN(I_{ui}^*) = \left[\underline{\mathrm{Lim}}(I_{ui}^*),\, \overline{\mathrm{Lim}}(I_{ui}^*)\right]. \tag{10}$$

Finally, the Interval Rough Number (IRN) of a class is obtained by combining the lower and upper rough numbers:

$$IRN(I_i^*) = [RN(I_{li}^*), RN(I_{ui}^*)]. \tag{11}$$

To eliminate the vagueness associated with rough numbers and obtain a single representative value, the following removing roughness procedure can be applied [38]. Let the rough number $I_k = [I_k^L, I_k^U]$, it is normalized using the min–max method as follows:

$$I_k^L = \frac{I_k^L - \min_k I_k^L}{\max_k I_k^U - \min_k I_k^L}, \qquad I_k^U = \frac{I_k^U - \min_k I_k^L}{\max_k I_k^U - \min_k I_k^L}. \tag{12}$$

A normalized index value σ_k is computed to reflect both bounds of the interval:

$$\sigma_k = \frac{I_k^L \cdot (1 - I_k^L) + I_k^U \cdot I_k^U}{1 - I_k^L + I_k^U}. \tag{13}$$

The crisp value I_k^* representing the interval I_k is then derived as:

$$I_k^* = \min_k I_k^L + \sigma_k \cdot \left(\max_k I_k^U - \min_k I_k^L\right). \tag{14}$$

3.2 Best worst method (BWM)

The Best Worst Method, developed by Rezaei [31], is one of the most recent approaches in MCDM. In this method, the decision-maker first identifies the most preferred (best) criterion and the least preferred (worst) criterion. Following this, pairwise comparisons are made between these two criteria (best and worst) and all other criteria. These comparisons help clarify the range of decision-making, offering better insight into preferences. BWM stands out due to its efficiency, requiring fewer comparisons and shortening the decision-making process. Additionally, the method ensures more stable comparisons and produces more reliable results. BWM has many applications, including resource planning, supply chains, career selection processes, and even UAV systems.

The steps of the BWM process are as follows [31]:

Step 1: Identify the set of n criteria $C = \{C_1, C_2, \ldots, C_n\}$ relevant to the problem.

Step 2: Determine the best criterion (C_B) and the worst criterion (C_W) according to the decision-makers' judgments.

Step 3: Using a scale of 1 to 9, assess how much important the best criterion is compared to all others. Based on these evaluations, the preference vector (A_B) for the best criterion is formed as shown in Equation (15).

$$A_B = [a_{B1}, a_{B2}, \ldots, a_{Bn}]. \tag{15}$$

Each element a_{Bj} in A_B represents how much important the best criterion is compared to criterion j, while $a_{BB} = 1$ indicates that the criterion is being compared to itself.

Step 4: Similarly, assess the relative importance of all criteria compared to the worst criterion using the 1-9 scale. The resulting preference vector (A_W) for the worst criterion is formed as in Equation (16).

$$A_W = [a_{1W}, a_{2W}, \ldots, a_{nW}], \tag{16}$$

where a_{jW} represents the importance of criterion j relative to the worst criterion, with $a_{WW} = 1$ indicating self-comparison.

Step 5: Solve the linear programming model given in (17) to calculate the criteria weights $\{w_1, w_2, \ldots, w_n\}$. The ξ value, which helps assess the consistency of the comparisons, is also determined in this step.

$$\begin{aligned} & \min \xi \\ & \text{s.t.} \\ & \left| \frac{w_B}{w_j} - a_{Bj} \right| \leq \xi, \quad \forall j \\ & \left| \frac{w_j}{w_W} - a_{jW} \right| \leq \xi, \quad \forall j \\ & \sum_j w_j = 1 \\ & w_j \geq 0, \quad \forall j \end{aligned} \tag{17}$$

Step 6: After obtaining the preference inputs a_{Bj} (best-to-others) and a_{jW} (others-to-worst) on the same scale as a_{BW} (best-to-worst), input-based consistency ratio (CR) is directly calculated from the inputs as follows [22]:

$$CR_j = \frac{|a_{Bj} \times a_{jW} - a_{BW}|}{a_{BW} \times a_{BW} - a_{BW}}, \qquad CR = \max_j CR_j. \tag{18}$$

Finally, CR is compared to the associated threshold values given in Table 1. CR values below the threshold indicate high input consistency, whereas larger values suggest that the judgments should be reconsidered.

Table 1: Associated threshold for six criteria

Scale	3	4	5	6	7	8	9
Threshold	0.1667	0.2206	0.2546	0.3044	0.3029	0.3154	0.3337

3.3 COPRAS method

The classical COPRAS method, introduced by Zavadskas et al. [17], has gained recognition for its reliability and precision. It has been widely applied to solve various multi-attribute decision-making problems in engineering and management domains [1, 4, 15, 35, 43]. One of the core strengths of the COPRAS method lies in its ability to evaluate alternatives by assuming a direct and proportional relationship between the significance of the criteria and the utility of the evaluated alternatives. The method follows steps, as outlined below [17]:

Step 1: The decision matrix (D) is formed, as shown below.

$$D = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix}.$$

Step 2: The normalized decision matrix is calculated using Equation (19).

$$x_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \quad \forall j = 1, 2, \ldots n. \tag{19}$$

Step 3: The normalized decision matrix is multiplied by the corresponding weight values of the criteria (w_j) to obtain the weighted decision matrix (D'). The w_j values are derived from previous method. The weighted decision matrix (D') is constructed using Equation (20).

$$D' = d_{ij} = x_{ij} w_j. \tag{20}$$

Step 4: The benefit and non-benefit criteria are identified. The total of the normalized values for the benefit criteria (s_{i+}) and the total for the non-benefit criteria (s_{i-}) are calculated using Equation (21).

$$\begin{aligned} S_{i+} &= \sum_{j=1}^{k} d_{ij} \quad j = 1, 2, \ldots, k \quad \text{for benefit criteria,} \\ S_{i-} &= \sum_{j=k+1}^{n} d_{ij} \quad j = k+1, k+2, \ldots, n \quad \text{for cost criteria.} \end{aligned} \tag{21}$$

Step 5: The relative importance (Q_i) for each alternative is determined using Equation (22). The alternative with the highest relative importance value (Q_i) is considered the best alternative.

$$Q_i = S_{i+} + \frac{\sum_{i=1}^{m} S_{i-}}{S_{i-} \sum_{i=1}^{m} \frac{1}{S_{i-}}}. \tag{22}$$

Step 6: The performance indices (P_i) for each alternative are calculated using Equation (23). The alternative with a performance index (P_i) value of 100 ranks first, and the other alternatives are ranked accordingly based on their performance indices.

$$P_i = \frac{Q_i}{Q_{\max}} \times 100. \tag{23}$$

3.4 Proposed heterogeneous IRN-based approach

In this study, a novel hybrid approach is proposed by integrating the BWM and the COPRAS method with IRN theory to solve heterogeneous multi-attribute group decision-making problems, particularly under conditions of uncertainty. The proposed methodology consists of two main phases: (i) weighting the evaluation criteria using fuzzy BWM and (ii) ranking the alternatives using an extended version of COPRAS based on IRNs. Figure 1 shows the flowchart of the proposed approach.

The method proceeds in the following steps:

Step 1. Identify the criteria

Relevant decision criteria are identified through a combination of expert consultations and an extensive review of the literature.

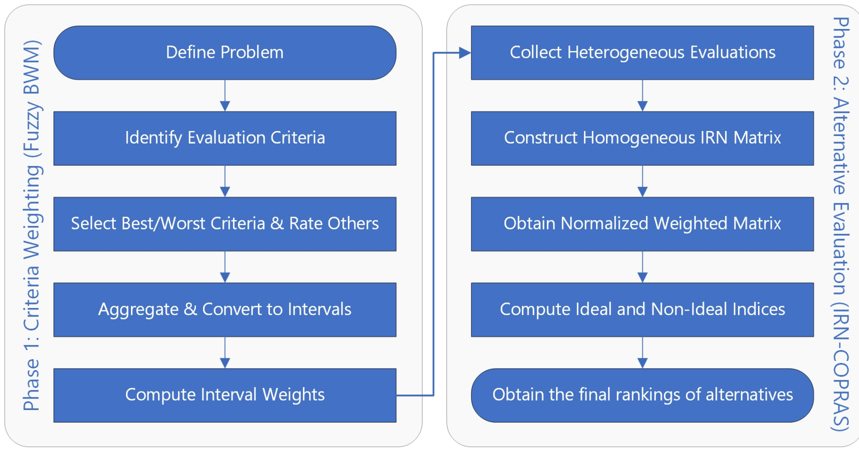

Figure 1: Framework of the proposed approach.

Step 2. Select the best and worst criteria and evaluate the criteria

Experts are asked to select the best (most important) and worst (least important) criteria. Using the fuzzy linguistic scale given in Table 2, the importance of all other criteria is rated relative to the best and worst ones.

Table 2: Linguistic term scale for weighting

Linguistic term	Abbreviation	TFN
Equally important	EI	(1,1,1)
Weakly important	WI	(1/2, 1, 3/2)
Moderately important	MI	(1, 3/2, 2)
Fairly Important	FI	(3/2, 2, 5/2)
Very Important	VI	(2, 5/2, 3)
Absolutely Important	AI	(5/2, 3, 7/2)

Step 3. Aggregate expert evaluations and transform them into interval numbers

The fuzzy triangular numbers obtained from each expert are aggregated using mathematical averaging procedures to get a collective assessment.

To bridge fuzzy BWM with rough set theory, the aggregated fuzzy values are converted into grey numbers using an α-cut approach. Each triangular fuzzy value (a, b, c) is transformed into an interval $[L, U]$ as follows:

$$[L, U] = [(b-a)\alpha + a,\ -(c-b)\alpha + c], \quad \alpha \in [0,1], \tag{24}$$

where α represents the confidence level of the expert.

Step 4. Solve the BWM model and analyze consistency

The BWM optimization model given in (17) is solved using the interval-valued preference inputs derived from the α-cut transformation using Equation (24). The consistency ratio is calculated using Equation (18).

Then, the lower and upper bounds of the weights for each criterion are determined using the models given in (25) and (26).

$$\begin{aligned}
&\min \xi \\
&\left|\frac{w_B}{w_j} - a_{Bj}\right| \leq \xi, \quad \forall j \\
&\left|\frac{w_j}{w_W} - a_{jW}\right| \leq \xi, \quad \forall j \\
&\sum_j w_j = 1 \\
&w_j \geq 0, \quad \forall j
\end{aligned} \tag{25}$$

$$
\begin{aligned}
&\max \xi \\
&\left|\frac{w_B}{w_j} - a_{Bj}\right| \leq \xi, \quad \forall j \\
&\left|\frac{w_j}{w_W} - a_{jW}\right| \leq \xi, \quad \forall j \\
&\sum_j w_j = 1 \\
&w_j \geq 0, \quad \forall j
\end{aligned}
\tag{26}
$$

Step 5. Construct the heterogeneous decision matrix

Performance evaluations of alternatives are gathered using both objective data and subjective expert evaluations. First, each expert forms an individual decision matrix ($\hat{X}_k$) for the subjective criteria ($j = 1, \ldots, z$).

$$
\hat{X}_k = \begin{bmatrix} \hat{X}_{11}^k & \hat{X}_{12}^k & \cdots & \hat{X}_{1z}^k \\ \hat{X}_{21}^k & \hat{X}_{22}^k & \cdots & \hat{X}_{2z}^k \\ \vdots & \vdots & \ddots & \vdots \\ \hat{X}_{m1}^k & \hat{X}_{m2}^k & \cdots & \hat{X}_{mz}^k \end{bmatrix}.
$$

Then, the evaluations of all experts are aggregated to form the matrix ($\bar{X}$) for subjective criteria.

$$
\bar{X} = \begin{bmatrix} \hat{x}_{11} & \hat{x}_{12} & \cdots & \hat{x}_{1z} \\ \hat{x}_{21} & \hat{x}_{22} & \cdots & \hat{x}_{2z} \\ \vdots & \vdots & \ddots & \vdots \\ \hat{x}_{m1} & \hat{x}_{m2} & \cdots & \hat{x}_{mz} \end{bmatrix}.
$$

By gathering the performance of alternatives for both subjective ($j = 1, \ldots, z$) and objective criteria ($j = z + 1, \ldots, n$), the heterogeneous group decision matrix ($\hat{X}$) is created.

$$
\hat{X} = \begin{bmatrix} \hat{x}_{11} & \hat{x}_{12} & \cdots & \hat{x}_{1(z+1)} & \cdots & \hat{x}_{1n} \\ \hat{x}_{21} & \hat{x}_{22} & \cdots & \hat{x}_{2(z+1)} & \cdots & \hat{x}_{2n} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \hat{x}_{m1} & \hat{x}_{m2} & \cdots & \hat{x}_{m(z+1)} & \cdots & \hat{x}_{mn} \end{bmatrix}.
$$

Step 6. Obtain the interval rough decision matrix

Fuzzy values in the matrix are converted into interval rough numbers, resulting in a homogeneous decision matrix ($\tilde{X}$) with a consistent format across all criteria.

$$
\tilde{X} = \begin{bmatrix} [x_{11}^L, x_{11}^U] & [x_{12}^L, x_{12}^U] & \cdots & [x_{1n}^L, x_{1n}^U] \\ [x_{21}^L, x_{21}^U] & [x_{22}^L, x_{22}^U] & \cdots & [x_{2n}^L, x_{2n}^U] \\ \vdots & \vdots & \ddots & \vdots \\ [x_{m1}^L, x_{m1}^U] & [x_{m2}^L, x_{m2}^U] & \cdots & [x_{mn}^L, x_{mn}^U] \end{bmatrix},
$$

where x_{ij}^L and x_{ij}^U represent the lower and upper interval bounds of group decision preferences as rough numbers. The transformation of a triangular fuzzy number into an interval $[L, U]$ is performed using Equation (24), where α represents the decision maker's confidence level.

Step 7. Obtain a normalized weighted matrix

The decision matrix is normalized, and the interval weights obtained from the BWM phase are applied to compute the weighted normalized matrix. The elements of the normalized matrix, $\tilde{Y} = ([y_{ij}^L, y_{ij}^U])_{m \times n}$, are determined as shown in Equations (27) and (28):

$$
y_{ij}^L = \frac{2 x_{ij}^L w_j^L}{\sum_{i=1}^m x_{ij}^L + \sum_{i=1}^m x_{ij}^U}, \tag{27}
$$

$$y_{ij}^U = \frac{2x_{ij}^U w_j^U}{\sum_{i=1}^m x_{ij}^L + \sum_{i=1}^m x_{ij}^U}, \tag{28}$$

where $\hat{w}_j = [w_j^L, w_j^U]$ represents the lower and upper weight values of the criteria.

$$\tilde{Y} = \begin{bmatrix} [y_{11}^L, y_{11}^U] & [y_{12}^L, y_{12}^U] & \cdots & [y_{1n}^L, y_{1n}^U] \\ [y_{21}^L, y_{21}^U] & [y_{22}^L, y_{22}^U] & \cdots & [y_{2n}^L, y_{2n}^U] \\ \vdots & \vdots & \ddots & \vdots \\ [y_{m1}^L, y_{m1}^U] & [y_{m2}^L, y_{m2}^U] & \cdots & [y_{mn}^L, y_{mn}^U] \end{bmatrix}.$$

Step 8. Calculate ideal and non-ideal indices

For benefit-type ($\hat{P}_i$) and cost-type criteria ($\hat{R}_i$) positive and negative solution indices are calculated using Equations (29) and (30), respectively.

$$\hat{P} = \left(\hat{P}_i = \left[\sum_{j=1}^{r} y_{ij}^L, \ \sum_{j=1}^{r} y_{ij}^U \right] \right)^T \quad i = 1, 2, \ldots, m, \tag{29}$$

$$\hat{R} = \left(\hat{R}_i = \left[\sum_{j=r+1}^{n} y_{ij}^L, \ \sum_{j=r+1}^{n} y_{ij}^U \right] \right)^T \quad i = 1, 2, \ldots, m, \tag{30}$$

where r indicates the number of benefit criteria.

These values are then refined through the roughness elimination procedure in Equations (12) - (14) outlined in Section 3.

$$p^{der} = \left(\hat{P}_1^{der}, \hat{P}_2^{der}, \ldots, \hat{P}_m^{der} \right)^T, \tag{31}$$

$$R^{der} = \left(\hat{R}_1^{der}, \hat{R}_2^{der}, \ldots, \hat{R}_m^{der} \right)^T. \tag{32}$$

Step 9. Determine the relative utility values

Finally, the relative importance ($\hat{Q}_i$) and performance score ($\hat{N}_i$) of each alternative are calculated using Equations (33) and (34). These scores represent the overall benefit degree and are used to rank the alternatives from most to least preferred.

$$\hat{Q}_i = \hat{P}_i^{der} + \frac{\sum_{i=1}^m \hat{R}_i^{der}}{\hat{R}_i^{der} \cdot \sum_{i=1}^m \frac{1}{\hat{R}_i^{der}}}, \tag{33}$$

$$\hat{N}_i = \frac{\hat{Q}_i}{\hat{Q}_{\max}} \times 100. \tag{34}$$

4 Selection of electro-optical systems used in UAVs

This section presents a case study focused on the selection of electro-optical systems for integration into MALE-class UAVs. EO systems represent mission-critical payload components due to their essential role in surveillance, reconnaissance, and targeting operations. Typically comprising IR sensors, optical cameras, and laser designators, these systems enable precision targeting and intelligence-gathering capabilities under EO systems represent mission-critical payload components due to their essential role in surveillance, reconnaissance, and targeting operations.

Given the strategic importance of EO systems in mission execution, the selection process must be guided by multiple technical and operational criteria that reflect both system performance and platform integration needs. In this study, six evaluation criteria were identified to support this selection: (C1) weight, (C2) optical resolution, (C3) IR resolution, (C4) MTBF, (C5) cost, and (C6) laser range. These criteria were established based on a thorough review of relevant literature, technical documentation of existing EO systems [3, 40], and insights obtained from expert consultations. The definitions and justifications for each criterion are presented in Table 3.

Table 3: Evaluation Criteria for Electro-Optic System Selection in MALE-Class UAVs

ID	**Criterion**	**Type**	**Description**
C1	Weight (kg)	Cost	Affects UAV endurance and payload capacity. Lighter systems improve flight duration and maneuverability, and allow integration of additional mission-critical components.
C2	Optical Resolution (evaluated linguistically, TFN)	Benefit	Determines the level of visual detail captured. Higher resolution enhances object detection and classification, enabling effective long-range surveillance and targeting.
C3	IR Resolution (evaluated linguistically, TFN)	Benefit	Governs thermal image clarity in low-visibility environments. High IR resolution ensures effective nighttime and all-weather operational capability.
C4	Reliability (mean time between failures, hours)	Benefit	Indicates system reliability. Longer MTBF reduces likelihood of mid-mission failure, ensuring consistent performance and operational continuity.
C5	Cost (million USD)	Cost	Reflects budgetary and procurement considerations. A cost-effective system enables broader deployment, supports local production, and ensures long-term affordability.
C6	Laser Range (km)	Benefit	Defines the effective targeting distance for laser-guided munitions. Extended laser range supports safer, covert, and more effective precision-strike capabilities.

To ensure that the evaluation accurately reflects field performance, data were collected from both technical specifications and expert judgments. Objective parameters ($C1, C4, C5, C6$) were normalized from publicly available manufacturer datasheets, defense program reports, and trade publications. Because optical and IR resolution ($C1, C3$) depend strongly on flight altitude, atmospheric conditions, stabilization quality, and image-processing algorithms, and are not reported uniformly across vendors, these criteria were assessed through expert evaluation rather than raw numerical GSD values. Expert judgments were obtained from five UAV experts ($E1, E5$) with significant experience in military UAV operations. These experts evaluated the subjective criteria ($C2, C3$) using the linguistic scale defined in Table 4.

Table 4: Linguistic term scale for rating alternatives

Linguistic term	Abbreviation	TFN
Very Poor	VP	(0,1,2)
Poor	P	(1, 2, 3)
Medium Poor	MP	(2, 3.5, 5)
Fair	F	(4, 5, 6)
Medium Good	MG	(5, 6.5, 8)
Good	G	(7, 8, 9)
Very Good	VG	(8, 9, 10)

To maintain scientific neutrality and adhere to confidentiality requirements while ensuring methodological transparency, the evaluation was conducted on four representative EO system alternatives, described using the following functional classifications based on their core operational characteristics: $A1-$ Medium-Range Multi-Role EO System, $A2-$ Long-Endurance IR-Optimized Surveillance System. $A3-$ High-Resolution Compact EO/IR System, $A4-$ Heavy-Duty Advanced Targeting and Surveillance System.

4.1 Calculating the interval-valued weights of the criteria

Accurate weighting of evaluation criteria is critical to ensuring the robustness and validity of multi-criteria decision-making, particularly in the selection of electro-optical systems for UAV platforms. In this study, the fuzzy BWM is employed to capture expert preferences, and the resulting fuzzy data is subsequently transformed into interval representations using an α-cut technique in line with interval rough number theory.

In the first stage of the process, five domain experts were asked to identify the most and least important criteria from the predefined set. All experts unanimously selected Weight ($C1$) as the most important criterion and Cost ($C5$) as the least important. Following this, pairwise comparisons were conducted. Experts evaluated the importance of each remaining criterion relative to both the best and worst criteria, using a fuzzy linguistic scale given in Table 2. The individual pairwise comparisons are presented in Table 5, and the aggregated fuzzy triangular values, obtained via arithmetic means, are shown in Table 6.

Table 5: Preferences of experts

Experts	Best Criterion	Worst Criterion		Linguistic preferences C1	C2	C3	C4	C5	C6
E1	C1	C5	$\tilde{a}_{Bj}$	EI	EI	MI	FI	AI	VI
			$\tilde{a}_{jW}$	AI	AI	VI	MI	EI	WI
E2	C1	C5	$\tilde{a}_{Bj}$	EI	MI	MI	WI	AI	FI
			$\tilde{a}_{jW}$	AI	MI	FI	MI	EI	WI
E3	C1	C5	$\tilde{a}_{Bj}$	EI	WI	MI	FI	VI	MI
			$\tilde{a}_{jW}$	VI	VI	FI	EI	EI	WI
E4	C1	C5	$\tilde{a}_{Bj}$	EI	WI	WI	FI	VI	VI
			$\tilde{a}_{jW}$	AI	VI	FI	MI	EI	WI
E5	C1	C5	$\tilde{a}_{Bj}$	EI	MI	WI	VI	AI	FI
			$\tilde{a}_{jW}$	VI	MI	FI	FI	EI	MI

Table 6: Collective preferences of experts

	C1	C2	C3	C4	C5	C6
$\tilde{a}_{Bj}$	(1, 1, 1)	(0.8, 1.2, 1.8)	(0.8, 1.3, 2)	(1.4, 1.9, 2.5)	(2.3, 2.8, 3.3)	(1.6, 2.1, 2.6)
$\tilde{a}_{jW}$	(2.3, 2.8, 3.3)	(1.7, 2.2, 2.7)	(1.6, 2.1, 2.6)	(1.1, 1.5, 1.9)	(1, 1, 1)	(0.6, 1.1, 2)

To bridge fuzzy logic with rough set theory, the aggregated triangular fuzzy numbers were converted into grey numbers using the formula defined in Equation (24). This conversion yields interval representations of expert preferences for both the best-to-others ($\tilde{A}_B$) and others-to-worst ($\tilde{A}_W$) vectors across various α levels, ranging from 0 to 1. Table 7 illustrates the transformed grey numbers and their consistency across multiple α values.

Table 7: Interval transformation of aggregated fuzzy numbers using the α-cut approach

α	C1C2	C1C3	C1C4	C1C5	C1C6	C2C5	C3C5	C4C5	C6C5
0	[0.8, 1.8]	[0.8, 2]	[1.4, 2.5]	[2.3, 3.3]	[1.6, 2.6]	[1.7, 2.7]	[1.6, 2.6]	[1.1, 1.9]	[0.6, 2]
0.1	[0.84, 1.74]	[0.85, 1.93]	[1.45, 2.44]	[2.35, 3.25]	[1.65, 2.55]	[1.75, 2.65]	[1.65, 2.55]	[1.14, 1.86]	[0.65, 1.91]
0.2	[0.88, 1.68]	[0.9, 1.86]	[1.5, 2.38]	[2.4, 3.2]	[1.7, 2.5]	[1.8, 2.6]	[1.7, 2.5]	[1.18, 1.82]	[0.7, 1.82]
0.3	[0.92, 1.62]	[0.95, 1.79]	[1.55, 2.32]	[2.45, 3.15]	[1.75, 2.45]	[1.85, 2.55]	[1.75, 2.45]	[1.22, 1.78]	[0.75, 1.73]
0.4	[0.96, 1.56]	[1, 1.72]	[1.6, 2.26]	[2.5, 3.1]	[1.8, 2.4]	[1.9, 2.5]	[1.8, 2.4]	[1.26, 1.74]	[0.8, 1.64]
0.5	[1, 1.5]	[1.05, 1.65]	[1.65, 2.2]	[2.55, 3.05]	[1.85, 2.35]	[1.95, 2.45]	[1.85, 2.35]	[1.3, 1.7]	[0.85, 1.55]
0.6	[1.04, 1.44]	[1.1, 1.58]	[1.7, 2.14]	[2.6, 3]	[1.9, 2.3]	[2, 2.4]	[1.9, 2.3]	[1.34, 1.66]	[0.9, 1.46]
0.7	[1.08, 1.38]	[1.15, 1.51]	[1.75, 2.08]	[2.65, 2.95]	[1.95, 2.25]	[2.05, 2.35]	[1.95, 2.25]	[1.38, 1.62]	[0.95, 1.37]
0.8	[1.12, 1.32]	[1.2, 1.44]	[1.8, 2.02]	[2.7, 2.9]	[2, 2.2]	[2.1, 2.3]	[2, 2.2]	[1.42, 1.58]	[1, 1.28]
0.9	[1.16, 1.26]	[1.25, 1.37]	[1.85, 1.96]	[2.75, 2.85]	[2.05, 2.15]	[2.15, 2.25]	[2.05, 2.15]	[1.46, 1.54]	[1.05, 1.19]
1	[1.2, 1.2]	[1.3, 1.3]	[1.9, 1.9]	[2.8, 2.8]	[2.1, 2.1]	[2.2, 2.2]	[2.1, 2.1]	[1.5, 1.5]	[1.1, 1.1]

Since the centers of the α-cut intervals were stable across α, we solved the BWM linear program in (17) to obtain the weight vector. Consistency, however, was assessed using the input-based consistency ratio (CR) defined in Equation (18). Using the $\alpha = 1$ inputs on the same scale ($a_{BW} = 2.8$ and $\{a_{Bj}, a_{jW}\}$ from Table 7) the local indices are

$CR_{C2} = 0.0317$, $CR_{C3} = 0.0139$, $CR_{C4} = 0.0099$, $CR_{C6} = 0.0972$ (others 0), yielding $CR = \max_j CR_j = 0.0972$. This value is below the associated threshold for six criteria on a 3-point scale (see Table 1) ($0.0972 < 0.1667$), indicating high input consistency.

In the final stage, the interval-valued weights for each criterion were determined by computing the lower and upper bounds using Equations (25) and (26), respectively. These computations were also performed using Lingo software; the results are presented in Table 8. The central value of the intervals, representing the central tendencies of the weights, was used for ranking the criteria and is summarized in Table 8.

Table 8: Optimal interval weights

Weights	Lower bound	Upper bound	Central value	Interval width
w_1	0.2457	0.2594	0.2526	0.0137
w_2	0.1948	0.2186	0.2067	0.0238
w_3	0.1855	0.2092	0.1973	0.0237
w_4	0.1281	0.1436	0.1359	0.0155
w_5	0.0915	0.0966	0.0940	0.0051
w_6	0.1110	0.1172	0.1141	0.0062

4.2 Evaluating the alternatives

This section presents the evaluation process of the four electro-optical system alternatives based on the identified criteria. The proposed framework systematically integrates both objective technical specifications and subjective expert assessments, ensuring a comprehensive analysis.

For criteria C2 and C3, expert opinions were elicited using the seven-level linguistic scale in Table 4. Five domain experts (E1–E5) with experience in military UAV operations provided ratings through a structured questionnaire (Table 9). Each linguistic term was modeled as a TFN, and the individual TFNs were aggregated component-wise using the arithmetic mean to obtain collective fuzzy evaluations for each alternative–criterion pair.

Table 9: Expert evaluations for subjective criteria

Experts	Subjective Criteria	A1	A2	A3	A4
1	C2	MG	G	GP	G
	C3	GP	F	G	MG
2	C2	MG	MG	P	G
	C3	F	G	G	VG
3	C2	G	F	GP	MG
	C3	P	MG	MG	G
4	C2	F	MG	GP	MG
	C3	GP	F	G	VG
5	C2	MG	G	F	VG
	C3	GP	G	VG	G

For the remaining criteria—C1 (Weight) and C5 (Cost)—objective and invariant values were taken directly from verified technical specifications. C4 (MTBF) and C6 (Laser Range), which exhibit natural variability across configurations, were expressed as intervals [L, U] derived from published specification ranges. The resulting heterogeneous decision matrix, combining quantitative, interval, and fuzzy data, is presented in Table 10.

Table 10: Heterogeneous decision matrix

	C1: Weight (kg)	C2: Optical Resolution (TFN)	C3: IR Resolution (TFN)	C4: Reliability (hours)	C5: Cost (M$)	C6: Laser Range (km)
A1	49	(5.2, 6.5, 7.8)	(2.2, 3.5, 4.8)	[200-220]	1.2	[23-26]
A2	51	(5.2, 6.5, 7.8)	(5, 6.2, 7.4)	[215-250]	1	[18-22]
A3	55	(3.2, 4.4, 5.6)	(6.8, 7.9, 9)	[200-240]	0.8	[19-23]
A4	96	(6.4, 7.6, 8.8)	(7, 8.1, 9.2)	[170-190]	1.8	[25-35]

Subsequently, to standardize the evaluation scale, fuzzy values were transformed into interval numbers using the α-cut method ($\alpha = 0.5$), as per Equation (24), resulting in the interval-valued decision matrix shown in Table 11.

Table 11: Decision matrix with interval numbers

	C1 (-)	C2 (+)	C3 (+)	C4 (+)	C5 (-)	C6 (+)
A1	[49-49]	[5.85-7.15]	[2.85-4.15]	[200-220]	[1.2-1.2]	[23-26]
A2	[51-51]	[5.85-7.15]	[5.60-6.80]	[215-250]	[1.0-1.0]	[18-22]
A3	[55-55]	[3.80-5.00]	[7.35-8.45]	[200-240]	[0.8-0.8]	[19-23]
A4	[96-96]	[7.00-8.20]	[7.55-8.65]	[170-190]	[1.8-1.8]	[25-35]

The interval decision matrix was normalized using Equation (27) as shown in Table 12. Then, a weighted normalized decision matrix was computed using Equation (28) followed by applying BWM-derived interval weights (Table 8) as illustrated in Table 13.

Table 12: Normalized decision matrix

	C1	C2	C3	C4	C5	C6
A1	[0.195, 0.195]	[0.234, 0.281]	[0.111, 0.161]	[0.237, 0.261]	[0.250, 0.250]	[0.241, 0.272]
A2	[0.203, 0.203]	[0.234, 0.281]	[0.218, 0.265]	[0.255, 0.297]	[0.208, 0.208]	[0.188, 0.230]
A3	[0.219, 0.219]	[0.152, 0.197]	[0.286, 0.329]	[0.237, 0.285]	[0.167, 0.167]	[0.199, 0.241]
A4	[0.382, 0.382]	[0.280, 0.323]	[0.294, 0.337]	[0.202, 0.226]	[0.375, 0.375]	[0.262, 0.366]
w_i	[0.246, 0.259]	[0.195, 0.219]	[0.185, 0.209]	[0.128, 0.144]	[0.091, 0.097]	[0.111, 0.117]

Table 13: Normalized weighted decision matrix

	C1	C2	C3	C4	C5	C6
A1	[0.048, 0.051]	[0.046, 0.063]	[0.021, 0.034]	[0.030, 0.038]	[0.023, 0.024]	[0.027, 0.032]
A2	[0.050, 0.053]	[0.046, 0.063]	[0.040, 0.055]	[0.033, 0.043]	[0.019, 0.020]	[0.021, 0.027]
A3	[0.054, 0.057]	[0.030, 0.044]	[0.053, 0.069]	[0.030, 0.041]	[0.015, 0.016]	[0.022, 0.028]
A4	[0.094, 0.099]	[0.055, 0.072]	[0.054, 0.070]	[0.026, 0.032]	[0.034, 0.036]	[0.029, 0.043]

The normalized weighted matrix served as the foundation for calculating the ideal and non-ideal solution indices, segregated into benefit-type ($\hat{P}$) and cost-type criteria ($\hat{R}$). These were computed using Equations (29) and (30) and presented Table 14..

Table 14: Ideal and non-ideal scores

	$\hat{P}$	$\hat{R}$
A1	[0.123, 0.166]	[0.071, 0.075]
A2	[0.140, 0.187]	[0.069, 0.073]
A3	[0.135, 0.182]	[0.069, 0.073]
A4	[0.164, 0.217]	[0.128, 0.135]

The normalized ideal and non-ideal scores of each alternative are calculated using Equation (12) and presented in Table 15.

Table 15: Normalized ideal and non-ideal scores

	$\hat{P}_{norm}$	$\hat{R}_{norm}$
A1	[0.000, 0.450]	[0.028, 0.087]
A2	[0.173, 0.682]	[0.000, 0.058]
A3	[0.126, 0.620]	[0.002, 0.060]
A4	[0.432, 1.000]	[0.892, 1.000]

As presented in Table 16, to remove roughness, total normalized index values and corresponding crisp values were calculated using Equations (13) and (14), respectively.

Finally, by Equations (33) and (34) the relative importance scores, $\hat{Q}_i$, and the performance indices, $\hat{N}_i$, which represent the overall utility levels of the alternatives, were calculated as displayed in Table 17.

Based on these results, the ranking of alternatives is determined as follows: $A2 > A3 > A4 > A1$, with A2 – *Long-Endurance IR-Optimized Surveillance System* demonstrating the highest performance and being selected as the most appropriate electro-optical system for integration into MALE-class UAVs.

Table 16: Total normalized index and crisp values

	Total normalized index values (σ)		Crisp values	
	$\hat{P}_\sigma$	$\hat{R}_\sigma$	P^{der}	R^{der}
A1	0.140	0.033	0.136	0.071
A2	0.403	0.003	0.161	0.069
A3	0.331	0.005	0.154	0.069
A4	0.794	0.989	0.198	0.135

Table 17: Total normalized net value and final net form

	$\hat{Q}_i$	$\hat{N}_i$
A1 – Medium-Range Multi-Role EO System	0.233	89.42
A2 – Long-Endurance IR-Optimized Surveillance System	0.260	100.00
A3 – High-Resolution Compact EO/IR System	0.253	97.32
A4 – Heavy-Duty Advanced Targeting and Surveillance System	0.249	95.66

5 Discussion

5.1 Comparative analysis with alternative techniques

To validate the robustness and reliability of the proposed hybrid IRN-based BWM-COPRAS approach, a comparative analysis was conducted against two well-established MCDM techniques: classical COPRAS and classical TOPSIS. This comparison was carried out using the same dataset and evaluation criteria to ensure methodological consistency and fair benchmarking.

To apply the classical methods, expert evaluations initially expressed as fuzzy linguistic terms were defuzzified using the center of gravity method, while interval-valued assessments were converted into single crisp values by averaging the respective bounds. The central values of the interval-based weights, previously computed through the BWM process (Table 8), were adopted as the fixed criteria weights in both classical COPRAS and TOPSIS implementations.

The rankings obtained from the three approaches are summarized in Table 18. Notably, all methods identified A2 as the most preferred electro-optic system for integration into MALE-class UAVs. The proposed IRN-based method yielded a ranking of $A2 > A3 > A4 > A1$, while classical COPRAS and TOPSIS produced a slightly different order of $A2 > A3 > A1 > A4$.

Table 18: Comparison of the proposed IRN-based approach with classical methods

	Proposed approach			Classical COPRAS			TOPSIS	
	Q_i	P_i	Rank	Q_i	P_i	Rank	Score	Rank
A1	0.233	89.42%	4	0.240	93.58%	3	0.58	3
A2	0.260	100.00%	1	0.262	100.0%	1	0.72	1
A3	0.253	97.32%	2	0.256	95.09%	2	0.66	2
A4	0.249	95.66%	3	0.243	90.18%	4	0.47	4

The close alignment in ranking outcomes across all three methods provides empirical evidence of the consistency and reliability of the proposed approach. Despite the integration of interval rough number theory, which introduces a more sophisticated mechanism to handle uncertainty and imprecision in expert judgments, the final rankings remain coherent with those produced by traditional methods. Therefore, it can be concluded that the proposed IRN-based BWM-COPRAS framework is theoretically sound and practically reliable. It offers a robust decision support tool that maintains consistency with classical MCDM approaches while providing enhanced capability to deal with ambiguity in expert-driven evaluations. These findings suggest that the approach can be confidently applied to similar selection problems in UAV technology and beyond, especially in domains where decision-making under uncertainty is critical.

5.2 Sensitivity analysis

Conducting a sensitivity analysis is essential to assess the stability and robustness of the proposed decision-making model under varying conditions. In this study, a sensitivity analysis was performed by systematically altering the weights of each evaluation criterion to observe the corresponding changes in the final ranking of alternatives. The weight of each criterion w_i was increased or decreased by 10%.

To maintain the overall balance of the weight distribution, proportional adjustments were also applied to the other criteria. Thirteen scenarios were developed, including an equal weight scenario (Scenario 1) and twelve single-criterion perturbation scenarios (Scenarios 2–13), where each criterion was individually increased or decreased by 10%. The adjusted weight sets for each scenario are presented in Table 19.

Table 19: Alternative weighting scenarios with interval values

Scenario	w_1^L, w_1^U	w_2^L, w_2^U	w_3^L, w_3^U	w_4^L, w_4^U	w_5^L, w_5^U	w_6^L, w_6^U
Scenario 1 (equal)	[0.167, 0.167]	[0.167, 0.167]	[0.167, 0.167]	[0.167, 0.167]	[0.167, 0.167]	[0.167, 0.167]
Scenario 2 (w_1 decreased)	[0.146, 0.159]	[0.222, 0.246]	[0.212, 0.236]	[0.146, 0.162]	[0.104, 0.109]	[0.127, 0.132]
Scenario 3 (w_1 increased)	[0.346, 0.359]	[0.167, 0.191]	[0.159, 0.183]	[0.110, 0.125]	[0.079, 0.084]	[0.095, 0.102]
Scenario 4 (w_2 decreased)	[0.278, 0.291]	[0.095, 0.119]	[0.210, 0.234]	[0.145, 0.161]	[0.103, 0.108]	[0.126, 0.131]
Scenario 5 (w_2 increased)	[0.213, 0.228]	[0.295, 0.319]	[0.161, 0.184]	[0.111, 0.126]	[0.079, 0.085]	[0.096, 0.103]
Scenario 6 (w_3 decreased)	[0.278, 0.291]	[0.220, 0.245]	[0.085, 0.109]	[0.145, 0.161]	[0.103, 0.108]	[0.125, 0.131]
Scenario 7 (w_3 increased)	[0.214, 0.228]	[0.170, 0.192]	[0.285, 0.309]	[0.112, 0.126]	[0.080, 0.085]	[0.097, 0.103]
Scenario 8 (w_4 decreased)	[0.275, 0.288]	[0.218, 0.243]	[0.208, 0.232]	[0.028, 0.044]	[0.102, 0.107]	[0.124, 0.130]
Scenario 9 (w_4 increased)	[0.216, 0.231]	[0.171, 0.194]	[0.163, 0.186]	[0.228, 0.244]	[0.080, 0.086]	[0.098, 0.104]
Scenario 10 (w_5 decreased)	[0.272, 0.286]	[0.215, 0.241]	[0.205, 0.230]	[0.142, 0.158]	[0.000, 0.000]	[0.123, 0.129]
Scenario 11 (w_5 increased)	[0.217, 0.232]	[0.172, 0.196]	[0.164, 0.187]	[0.113, 0.128]	[0.191, 0.197]	[0.098, 0.105]
Scenario 12 (w_6 decreased)	[0.275, 0.287]	[0.218, 0.242]	[0.207, 0.232]	[0.143, 0.159]	[0.102, 0.107]	[0.011, 0.017]
Scenario 13 (w_6 increased)	[0.217, 0.231]	[0.172, 0.195]	[0.164, 0.187]	[0.113, 0.128]	[0.081, 0.086]	[0.211, 0.217]

After applying these modified weight sets, the ranking of the alternatives was re-evaluated under each scenario. The impact of these perturbations on the final rankings is summarized in Table 20. The relative importance scores of each alternative on a scenario basis are shown in Figure 2.

Table 20: The impact of scenarios on the final rankings

Scenario	A1	A2	A3	A4
Baseline	4	1	2	3
Scenario 1	4	2	1	3
Scenario 2	4	2	3	1
Scenario 3	3	1	2	4
Scenario 4	4	2	1	3
Scenario 5	4	1	3	2
Scenario 6	2	1	3	4
Scenario 7	4	3	1	2
Scenario 8	4	1	3	2
Scenario 9	4	1	2	3
Scenario 10	4	2	3	1
Scenario 11	4	2	1	3
Scenario 12	4	1	2	3
Scenario 13	4	2	3	1

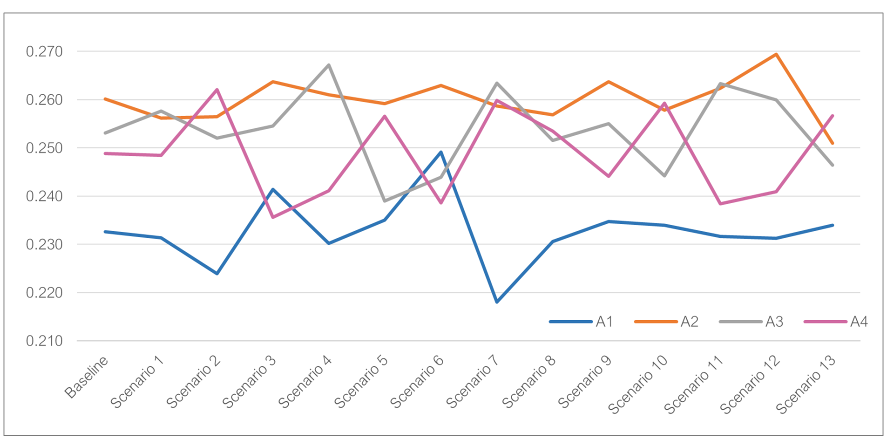

Figure 2: Sensitivity analysis results

The sensitivity analysis results reveal that minor variations in individual criterion weights do not significantly alter the overall ranking order. The A2 consistently maintains a top-tier position, ranking first or second in all but one scenario (Scenario 6), affirming its robustness as the most suitable option. This confirms the stability of the proposed IRN-based decision-making model and suggests that the model provides reliable support for selecting the optimal electro-optic system under varying decision environments.

6 Conclusion

This study addressed the complex and strategically significant problem of selecting the most appropriate EO system for MALE-class UAVs. As critical mission enablers, EO systems—comprising optical cameras, infrared sensors, and laser designators—directly influence the effectiveness of UAV operations in surveillance, target acquisition, and reconnaissance. The increasing diversity of EO technologies and varying operational demands necessitate a systematic and transparent decision-making framework that can account for both technical attributes and expert knowledge under uncertainty.

To this end, a novel hybrid MCDM methodology was developed by integrating the BWM and COPRAS within the theoretical foundation of IRNs. The proposed approach responds directly to the challenges of heterogeneous decision environments, where expert judgments and objective data coexist in different forms, often characterized by vagueness and incompleteness. By extending classical BWM-COPRAS models with rough set theory, this study offers a more resilient, adaptable, and expressive tool for complex decisions.

The core contribution of this work lies in introducing a heterogeneity-aware framework that enables the aggregation of diverse information formats through interval-valued representations. Unlike prior studies that rely on homogeneous, deterministic input or conventional fuzzy evaluations, the proposed model allows simultaneous handling of fuzzy linguistic terms, numerical data, and interval-valued judgments, thereby enhancing the fidelity and robustness of the decision-making process. This methodological advancement is particularly significant for defense and aerospace domains, where subjective expertise, uncertain contexts, and high-risk outcomes often shape decisions.

Empirical application to four EO system alternatives, evaluated by experienced UAV pilots, demonstrated the practical utility and consistency of the proposed method. Comparative results with classical COPRAS and TOPSIS models validated the ranking stability, while sensitivity analysis confirmed the model's robustness under varying weight scenarios. These findings affirm the method's reliability for strategic defense evaluations and its potential for broader applications in complex systems selection.

Future research should prioritize methodological enhancements to further enrich this hybrid decision-making framework. One promising direction is the development of advanced translation mechanisms for integrating additional evaluation formats, such as interval-valued intuitionistic fuzzy sets or probabilistic linguistic terms, into the interval rough number environment. This would enhance the model's flexibility and allow a more inclusive representation of expert inputs. Moreover, exploring dynamic weighting schemes or mission-adaptive criteria within the IRN-COPRAS structure could improve responsiveness to evolving tactical scenarios. Finally, validating the approach in interdisciplinary contexts beyond UAV systems, such as critical infrastructure planning or autonomous vehicle subsystems, would further substantiate its generalizability and cross-domain relevance.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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