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Optimizing Military Decision-Making: Application of the FUCOM–EWAA–COPRAS-G MCDM Model

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Abstract: In contemporary military contexts, the determination of an optimal course of action (COA) in combat operations emerges as a critical challenge. This study delineates a decision support methodology for military applications, employing sophisticated decision analysis techniques. The initial phase entails the identification of pivotal criteria for assessing and ranking COAs, followed by the assignment of weight coefficients to each criterion via the full consistency method (FUCOM). Subsequently, the Einstein weighted arithmetic average operator (EWAA) was utilized for the aggregation of expert opinions, ensuring a consensual evaluation of these criteria and culminating in the final values of their weight coefficients. The ensuing phase focuses on the selection of an optimal COA, incorporating the grey complex proportional assessment (COPRAS-G) method. This method addresses uncertainties and varying criterion values. Expert ratings were again aggregated using the EWAA operator. The findings from this phase are designed to provide military commanders with precise, data-driven guidance for decision-making. To validate and verify the stability of the proposed model, a series of tests were conducted, including a rank reversal test, sensitivity analysis regarding changes in weight coefficients, and a comparative analysis with alternative methods. These assessments uniformly indicated the model's consistency, stability, and validity as a military decision support tool. Emphasizing a high degree of confidence in COA selection, the methodology advocated herein is applicable to decision-making processes in the planning and execution of military operations. The uniform application of professional terms, consistent with the broader context of this research, ensures clarity and coherence in its presentation. The approach outlined in this study stands as a testament to rigorous analytical methodologies in the realm of military strategic planning, offering a robust framework for decision-making under conditions of uncertainty and complexity.

Keywords: Course of action (COA); Multi-criteria decision making (MCDM); Full consistency method (FUCOM); Einstein weighted arithmetic average (EWAA) operator; Grey complex proportional assessment (COPRAS-G); Army

1 Introduction

Dynamic shifts in contemporary combat environments necessitate the prediction and real-time response to unfolding scenarios, as highlighted in recent studies [1]. Within this context, decision-making in military operations emerges as a multifaceted challenge, encompassing both execution and preparatory phases. Central to these decisions is the COA, a term in military parlance referring to a sequence of planned or spontaneous activities undertaken by armed forces to achieve specific objectives on the battlefield, a product of operational planning [1]. Determining a COA involves analyzing the current and desired states, identifying obstacles impeding transition from the former to the latter, and strategizing the necessary actions [2]. Addressing such complex problems, particularly from multiple perspectives, calls for the application of MCDM methods. These methods, adept at handling inaccuracies and uncertainties in decision-making, have found applications across various sectors [3–13], including the military [14–23]. A review of existing literature reveals diverse approaches to COA selection using MCDM methods.

Guitouni et al. [24] conducted COA selection to address emergency scenarios in the Air Operation Center (AOC), focusing on criteria encompassing complexity, sustainability, risk, flexibility, and resource cost. This process employed decision-making analysis tools integrated into the Commander's Advisory System for Airspace Protection. Similarly, Pamucar et al. [21] approached COA selection for obstacle employment groups using a fuzzy logic system, basing their criteria on potential enemy penetration along specific routes, the ramifications of route closure, the adverse impacts of minefields on subsequent actions, and the characteristics of the group's chosen route. In the realm of security forces operations, Karavidić and Projović [25] applied the ROSSETA software, which operates on rough numbers, to select an optimal COA. Their approach incorporated an extensive set of 15 criteria within a simulation software framework. In a related study, Božanić et al. [26] employed the Multi-Attributive Border Approximation Area Comparison (MABAC) method for COA selection in defensive operations, considering eight critical criteria: maneuver, fire, command, intelligence, mobility, logistics, simplicity, and anti-aircraft operations. These authors, in subsequent work [27], addressed COA selection in attack operations using the same criteria set but through the lens of an Adaptive Neural Network. Further, Božanić et al. [28] tackled the challenge of selecting a COA for groups responsible for additional hindrances in military operations. This task was approached using the Fuzzy Analytic Hierarchy Process (AHP), examining alternatives across a two-tiered hierarchy of criteria, with three criteria at the first level and eight at the second. In the context of amphibious operations, Yudy Arie Bintoro [29] adopted the MCDM model comprising Decision Making Trial and Evaluation Laboratory (DEMATEL) and Adaptive Neural Network. The evaluation of alternatives here was conducted using a three-level criteria matrix, focusing on personnel, logistics, operational capabilities, and a comprehensive set of technical criteria, including electronics and communications. This overview of previous research indicates the successful application of various MCDM methods and theories in the selection of optimal COAs, particularly at lower levels of command where the number of criteria tends to be extensive. This observation is corroborated by Milovanović [30], who also notes that criteria tend to be more generalized at higher levels of command, a focus that will be further explored in this paper.

This paper introduces the FUCOM–EWAA–COPRAS-G MCDM model for optimal COA selection in military operations at higher command levels. The FUCOM method was utilized to determine weight coefficients of identified criteria, based on inputs from five field experts. The COPRAS method, enhanced with Grey theory, was employed for selecting the optimal COA. To affirm the methodology's stability and validate the MCDM model, rank reversal tests, sensitivity analysis, and comparative evaluations were conducted. The following sections detail the proposed model, its methods, and underlying theories.

2 Methodology

To address the complexities inherent in selecting a COA, a MCDM model has been developed, as illustrated in Figure 1.

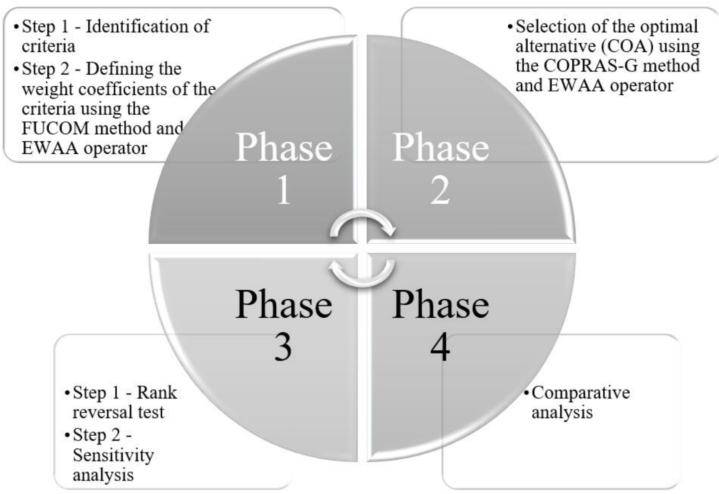

Figure 1. MCDM model FUCOM-EWAA-COPRAS-G

The proposed model encompasses four distinct phases. Initially, relevant criteria are identified, and their respective weight coefficients are determined utilizing the FUCOM, facilitated by the insights of five area-specific experts. These expert opinions are collectively aggregated employing the EWAA operator. The subsequent phase involves implementing these weighted criteria into an initial decision matrix, proceeding to the selection of the optimal COA via the COPRAS-G method. Here, expert ratings are again aggregated using the EWAA operator. In the third phase, the model's robustness is tested. This involves examining the consistency of the derived results against variations in weight coefficients through a sensitivity analysis, followed by conducting a rank reversal test. Upon completion of these analyses and tests, the fourth phase is initiated. This final stage involves a comparative analysis of the results yielded by the proposed methodology against those obtained via alternative methods. The objective of this comparative analysis is to validate the efficacy and reliability of the model. The forthcoming sections will provide detailed descriptions of each method employed in the model.

2.1 FUCOM Method

The FUCOM is a relatively recent methodology for determining the weight coefficients of criteria, notable for its straightforward mathematical framework and minimal procedural steps [31]. Its application has been wide-ranging, covering diverse research fields such as human resources [32], maintenance [33], the video game industry [34], construction machinery selection [35, 36], the electric car industry [37], postal traffic [38], healthcare management [39, 40], and location problems [41, 42], among others. The mathematical formulation of this method is detailed in the following section [31].

Step 1. Ranking of Criteria Based on Importance: The initial step involves arranging the criteria in order of importance, starting with the most significant and ending with the least significant.

Step 2. Comparative Analysis of Adjacent Criteria: This step entails comparing adjacent, ranked criteria to determine their relative priorities. The comparative priority of a criterion (represented by $\pi_{k/(k+1)}$) can be mathematically expressed as follows:

$$\Pi = \left(\pi_{1/2}, \pi_{1/2}, \ldots, \pi_{k/(k+1)}\right) \tag{1}$$

where, k represents the rank of the criteria.

Step 3. Computation of Final Weight Coefficients: The final phase involves calculating the definitive values of the weight coefficients for each criterion (ω_j). This calculation is represented by the following equation:

$$\begin{aligned}
&\min \Omega \\
&\text{s.t.} \\
&\left|\frac{\omega_{j(k)}}{\omega_{j(k+1)}} - \pi_{k/(k+1)}\right| \leq \Omega, \forall j \\
&\left|\frac{\omega_{j(k)}}{\omega_{j(k+2)}} - \pi_{k(k+1)} \odot \pi_{(k+1)(k+2)}\right| \leq \Omega, \forall j \\
&\sum_{j=1}^{n} \omega_j, \forall j \\
&\omega_j \geq 0, \forall j
\end{aligned} \tag{2}$$

where, j represents the number of criteria, and Ω denotes the deviation from full consistency (DFC).

2.2 EWAA Operator

The EWAA operator is a significant tool in decision-making processes, particularly when aggregating expert opinions. The fundamental concept of this operator, presented in the study [43], originates from the fuzzy Einstein weighted arithmetic average (FEWAA) operator. This operator's unique feature is its ability to treat each distribution of a triangular fuzzy number as a crisp value, facilitating their effective aggregation.

$$EWAA\{\chi_1, \chi_2, \ldots, \chi_j\} = \sum_{j=1}^{e} \chi_j^e \frac{\prod_{j=1}^{e}\left(1 + f\left(\chi_j^e\right)\right)^{\lambda} - \prod_{j=1}^{e}\left(1 - f\left(\chi_j^e\right)\right)^{\lambda}}{\prod_{j=1}^{e}\left(1 + f\left(\chi_j^e\right)\right)^{\lambda} + \prod_{j=1}^{e}\left(1 - f\left(\chi_j^e\right)\right)^{\lambda}} \tag{3}$$

where, $\mathrm{X} = \{\chi_1, \chi_2, \ldots, \chi_j\}$ represents a set of data that needs to be aggregated, $\mathrm{E} = \{\mathrm{E}_1, \mathrm{E}_2, \ldots, \mathrm{E}_\mathrm{e}\}$ represents the set of experts, e – the total number of experts, $\lambda = 1/e$ when the competence coefficients of the experts (ω^e) are equal, and $\lambda = \omega^e$ when the competence coefficients of the experts are different.

2.3 COPRAS-G Method

The complex proportional assessment (COPRAS) method, initially introduced in the 2004 paper titled "Housing credit access model: The case for Lithuania" [44], has since been widely applied in various research domains, as evidenced by studies [45–50]. Over time, the method has been enhanced by integrating theories adept at handling uncertainties and inaccuracies, such as Fuzzy [51–54], Rough [55–58], and Grey [59–62].

Step 1: Formation of the Initial Decision Matrix ($\otimes X_{ij}$). This matrix is created by aggregating the decision matrices from all experts ($\mathrm{E} = \{\mathrm{E}_1, \mathrm{E}_2, \ldots, \mathrm{E}_\mathrm{e}\}$) using the EWAA operator, as per Eq. (3).

Step 2: Normalization of the Initial Matrix. The initial matrix is normalized using Eqs. (4) and (5), resulting in a normalized matrix:

$$\underline{n}_{ij} = \frac{2\underline{x}_{ij}}{\sum_{i=1}^{m} \underline{x}_{ij} + \sum_{i=1}^{m} \bar{x}_{ij}} \tag{4}$$

$$\bar{n}_{ij} = \frac{2\bar{x}_{ij}}{\sum_{i=1}^{m} \underline{x}_{ij} + \sum_{i=1}^{m} \bar{x}_{ij}} \tag{5}$$

Thus, a normalized matrix ($\otimes N_{ij}$) is obtained.

$$\otimes N_{ij} = \begin{array}{c} \\ A_1 \\ A_2 \\ \dots \\ A_i \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \dots & C_j \end{array} \\ \begin{bmatrix} \otimes n_{11} & \otimes n_{12} & \dots & \otimes n_{1j} \\ \otimes n_{21} & \otimes n_{22} & \dots & \otimes n_{2j} \\ \dots & \dots & \dots & \dots \\ \otimes n_{i1} & \otimes n_{i2} & \dots & \otimes n_{ij} \end{bmatrix} \end{array} \tag{6}$$

Step 3: Formation of Weighted Grey Normalized Matrix ($\otimes V_{ij}$). This step involves creating a weighted grey normalized matrix, as per Eq. (7):

$$\otimes V_{ij} = \begin{array}{c} \\ A_1 \\ A_2 \\ \dots \\ A_i \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \dots & C_j \end{array} \\ \begin{bmatrix} \otimes v_{11} & \otimes v_{12} & \dots & \otimes v_{1j} \\ \otimes v_{21} & \otimes v_{22} & \dots & \otimes v_{2j} \\ \dots & \dots & \dots & \dots \\ \otimes v_{i1} & \otimes v_{i2} & \dots & \otimes v_{ij} \end{bmatrix} \end{array} \tag{7}$$

where, $\otimes v_{ij} = \otimes \omega_j \bullet \otimes N_{ij}$.

Step 4: Defining the Relative Importance of Alternatives (Q_i). The relative importance of alternatives is determined using Eqs. (8)-(10):

$$Q_i = P_i + \frac{\sum_{i=1}^{m} R_i}{R_i \sum_{i=1}^{m} \frac{1}{R_i}}, i = 1, 2, \dots, m \tag{8}$$

where,

$$P_i = \frac{1}{2} \sum_{j=1}^{n} \left(\underline{v}_{ij} + \bar{v}_{ij} \right), i = 1, 2, \dots, m; j = 1, 2, \dots, \mathrm{n} \text{ applies only to Benefit type criteria} \tag{9}$$

$$R_i = \frac{1}{2} \sum_{j=1}^{n} \left(\underline{v}_{ij} + \bar{v}_{ij} \right), i = 1, 2, \dots, m; j = 1, 2, \dots, \mathrm{n} \text{ applies only to Cost type criteria} \tag{10}$$

Step 5: Calculation of the Utility Degree of Alternatives (U_i). The utility degree of each alternative is calculated using Eq. (11):

$$U_i = \frac{Q_i}{Q_{i_{\max}}} \times 100\%, i = 1, 2, \dots, m \tag{11}$$

Step 6: Ranking of Alternatives. Alternatives are ranked based on the value of U_i, where a higher value indicates a better option.

3 Results

Implementing the MCDM model delineated in Figure 1, the initial phase of the process commenced with its first step. This involved identifying five general criteria crucial for defining the optimal COA, as corroborated by references [30, 63] and displayed in Table 1. These criteria were methodically ranked based on their importance, in descending order from the most to the least significant, a ranking upon which the panel of experts reached consensus.

Table 1. Criteria for selecting an optimal COA

Criterion	Criterion Description
C_1- The time required to complete the task	This criterion focuses on the necessity of accomplishing each task within the shortest possible time or within a predetermined duration. It is quantitative and categorized as a Cost type, measured in hours.
C_2- Risk level	Risk represents the likelihood and impact of events causing harm to valuable resources. In combat operation planning, it's essential to consider the potential consequences on engaged resources, encompassing personnel, weaponry, and other combat systems. This criterion is linguistic and classified as a Cost type.
C_3- Required resources	The execution of tasks demands the mobilization of specific forces and combat assets. However, the overarching aim of each operation is to minimize resource utilization. This criterion is linguistic and falls under the Cost type.
C_4- Expected effects	This criterion relates to the outcomes envisaged by the operation's objectives. It evaluates the extent to which each COA addresses the assigned tasks, considering factors like completeness, partial fulfillment, and other positive impacts. It is linguistic and categorized as a Benefit type.
C_5- Reliability	Reliability pertains to the probability of fully accomplishing the task and achieving the expected outcomes through a specific COA. This criterion is linguistic and identified as a Benefit type.

Table 2. Relationships between criteria defined by experts

	$\mathbf{E_1}$	$\mathbf{E_2}$	$\mathbf{E_3}$	$\mathbf{E_4}$	$\mathbf{E_5}$
$\pi_{1/2}$	1.10	1.20	1.40	1.10	1.30
$\pi_{2/3}$	1.30	1.50	1.50	1.20	1.50
$\pi_{3/4}$	1.50	1.70	1.60	1.50	1.70
$\pi_{4/5}$	1.60	2.00	1.70	1.70	2.00

Table 3. Values of criteria weights calculated for each of the experts

	$\mathbf{C_1}$	$\mathbf{C_2}$	$\mathbf{C_3}$	$\mathbf{C_4}$	$\mathbf{C_5}$
E_1	0.2519	0.2290	0.1938	0.1679	0.1574
E_2	0.2787	0.2322	0.1858	0.1639	0.1393
E_3	0.2782	0.1987	0.1855	0.1739	0.1637
E_4	0.2502	0.2274	0.2085	0.1668	0.1472
E_5	0.2838	0.2183	0.1892	0.1669	0.1419

After the establishment of the criteria pivotal for selecting the optimal COA, the process progressed to Step 2 of Phase 1, focusing on the determination of the criteria's weight coefficients. This calculation was conducted utilizing the FUCOM, with the involvement of five field experts ($\mathrm{E} = \{\mathrm{E}_1, \mathrm{E}_2, \mathrm{E}_3, \mathrm{E}_4, \mathrm{E}_5\}$). Each expert assessed the criteria, and the interrelations defined between adjacent criteria are delineated in Table 2.

Employing Eq. (2), the weight coefficients for the criteria were computed for each expert, with the results presented in Table 3.

Upon the determination of criteria weights by each expert, the next step involves aggregating these individual results to ascertain the final values of the weight coefficients for the criteria. This aggregation was achieved by utilizing the EWAA operator, specifically through the application of Eq. (3). In this process, the competence coefficients of the experts are denoted as $\omega^e = (0.20, 0.18, 0.22, 0.22, 0.18)$. The aggregation led to the derivation of the final weight coefficients for each criterion, which are detailed in Table 4.

Table 4. The final values of the weight coefficients of the criteria (ω_j)

Criterion	ω_j
C_1	0.2679
C_2	0.2207
C_3	0.1929
C_4	0.1680
C_5	0.1505

Having determined the weight coefficients, the focus shifts to Phase 2, which involves selecting the optimal COA from a range of feasible alternatives. This selection process employed the COPRAS-G method, a variant of the COPRAS method integrated with Grey theory. The first step in this phase is to define the alternatives (COAs). While in practical scenarios the number of COAs is typically limited to a manageable count, often around three as suggested in the study [1], this research adopts a model featuring five alternatives $\mathrm{A} = \{\mathrm{COA}_1, \mathrm{COA}_2, \ldots, \mathrm{COA}_5\}$. This approach allows for a more comprehensive presentation of the results and facilitates the application of this model in evaluating multiple COAs for military staff training, education, and future research.

Subsequently, each of the five experts is required to construct their own decision-making matrix. This involves evaluating each alternative against every criterion. While Criterion C_1 is quantitative in nature, the others are linguistic. To effectively quantify these linguistic criteria, Grey theory is applied to develop linguistic scales. These scales are illustrated in Table 5.

Table 5. Linguistic descriptors

$\mathbf{C}_2$	$\mathbf{C}_3$	$\mathbf{C}_4$	$\mathbf{C}_5$	**Grey Number**
High (H)	Very large resources (VLR)	Fully with other positive effects (FO)	Absolutely reliable (AR)	[9,10]
Significant (S)	Large resources (LR)	Fully (F)	Very reliable (VR)	[6,9]
Moderate (M)	Medium resources (MR)	Partially with other positive effects (PO)	Reliable (R)	[3,6]
Low (L)	Small resources (SR)	Partially (P)	Partially reliable (PR)	[1,3]

The decision matrices, as formulated by each of the experts, are compiled and displayed in Table 6.

Table 6. Decision matrices of experts

		$\mathbf{C}_1$	$\mathbf{C}_2$	$\mathbf{C}_3$	$\mathbf{C}_4$	$\mathbf{C}_5$			$\mathbf{C}_1$	$\mathbf{C}_2$	$\mathbf{C}_3$	$\mathbf{C}_4$	$\mathbf{C}_5$
E_1	COA_1	8.0	S	SR	F	R	E_3	COA_1	8.0	S	SR	F	VR
	COA_2	8.5	M	MR	F	VR		COA_2	9.0	S	LR	PO	VR
	COA_3	8.0	S	SR	FO	R		COA_3	8.0	M	MR	F	VR
	COA_4	9.0	S	MR	F	VR		COA_4	9.0	S	MR	F	R
	COA_5	7.5	M	MR	PO	R		COA_5	8.0	M	MR	PO	R
E_2	COA_1	7.5	S	SR	PO	VR	E_4	COA_1	8.0	S	SR	PO	VR
	COA_2	8.0	S	SR	F	R		COA_2	8.5	S	MR	F	VR
	COA_3	8.0	S	MR	F	R		COA_3	8.0	S	MR	F	R
	COA_4	8.5	S	MR	F	R		COA_4	8.5	S	MR	F	R
	COA_5	7.0	S	MR	PO	R		COA_5	8.0	S	MR	PO	R
E_5	COA_1	8.5	S	MR	PO	R							
	COA_2	8.5	M	MR	F	R							
	COA_3	8.0	S	SR	F	R							
	COA_4	8.5	S	MR	PO	VR							
	COA_5	8.0	M	SR	F	VR							

To prepare the input data for the COPRAS-G method, the individual decision matrices from each expert (as shown in Table 6) must be aggregated. This aggregation is conducted using the EWA) operator, as per Eq. (3). It's important to note that the competence coefficients of the experts for this aggregation are consistent with those used earlier in defining the weight coefficients of the criteria. Following this aggregation process, the consolidated initial decision matrix is obtained, the details of which are presented in Table 7.

With the assembly of the initial decision matrix, the first step in applying the COPRAS-G method is completed. The process then progresses to the second step, which involves creating a normalized matrix ($\otimes N_{ij}$). This normalization is achieved using Eqs. (4) and (5). The results of this step, showcasing the normalized matrix, are comprehensively detailed in Table 8.

In the third step of the COPRAS-G method, Eq. (7) is employed alongside the weight coefficients of the criteria (as outlined in Table 4) to calculate the weighted normalized matrix ($\otimes V_{ij}$). The outcomes of this calculation, detailing the weighted normalized matrix, are presented in Table 9.

In the fourth step of the COPRAS-G method, the relative importance of the alternatives (Q_i) is determined. This is achieved by applying Eqs. (9)–(11). The results of these calculations, which establish the relative importance of each alternative, are displayed in Table 10.

Table 7. Initial decision matrix ($\otimes X_{ij}$)

	$\mathbf{C}_1$		$\mathbf{C}_2$		$\mathbf{C}_3$		$\mathbf{C}_4$		$\mathbf{C}_5$	
COA_1	8.0005	8.0005	6.0000	9.0000	1.3844	3.5586	4.2832	7.2732	4.8777	7.8710
COA_2	8.5205	8.5205	4.8777	7.8710	3.3397	6.1456	5.3504	8.3470	4.9373	7.9308
COA_3	8.0000	8.0000	5.3504	8.3470	2.2569	4.8777	6.6101	9.2007	3.6818	6.6709
COA_4	8.7103	8.7103	6.0000	9.0000	3.0000	6.0000	5.4690	8.4661	4.1623	7.1527
COA_5	7.7208	7.7208	4.2228	7.7514	2.6479	5.4690	3.5586	6.5493	3.5586	6.5493

Table 8. Normalized decision matrix ($\otimes N_{ij}$)

	$\mathbf{C}_1$		$\mathbf{C}_2$		$\mathbf{C}_3$		$\mathbf{C}_4$		$\mathbf{C}_5$	
COA_1	0.1954	0.1954	0.1754	0.2631	0.0716	0.1840	0.1316	0.2234	0.1700	0.2743
COA_2	0.2081	0.2081	0.1426	0.2301	0.1727	0.3178	0.1644	0.2564	0.1721	0.2764
COA_3	0.1954	0.1954	0.1564	0.2440	0.1167	0.2522	0.2031	0.2826	0.1283	0.2325
COA_4	0.2127	0.2127	0.1754	0.2631	0.1551	0.3102	0.1680	0.2601	0.1450	0.2493
COA_5	0.1885	0.1885	0.1234	0.2266	0.1369	0.2828	0.1093	0.2012	0.1240	0.2282

Table 9. Weighted normalized matrix ($\otimes V_{ij}$)

	$\mathbf{C}_1$		$\mathbf{C}_2$		$\mathbf{C}_3$		$\mathbf{C}_4$		$\mathbf{C}_5$	
COA_1	0.0523	0.0523	0.0387	0.0581	0.0138	0.0355	0.0221	0.0375	0.0256	0.0413
COA_2	0.0557	0.0557	0.0315	0.0508	0.0333	0.0613	0.0276	0.0431	0.0259	0.0416
COA_3	0.0523	0.0523	0.0345	0.0538	0.0225	0.0487	0.0341	0.0475	0.0193	0.0350
COA_4	0.0570	0.0570	0.0387	0.0581	0.0299	0.0598	0.0282	0.0437	0.0218	0.0375
COA_5	0.0505	0.0505	0.0272	0.0500	0.0264	0.0545	0.0184	0.0338	0.0187	0.0343

Table 10. Values of the importance of the alternatives (Q_i)

	$\boldsymbol{P_i}$	$\boldsymbol{R_i}$	$\boldsymbol{Q_i}$
COA_1	0.0633	0.1254	0.2107
COA_2	0.0691	0.1442	0.1974
COA_3	0.0679	0.1321	0.2079
COA_4	0.0656	0.1502	0.1887
COA_5	0.0526	0.1296	0.1953

In the final stage of the COPRAS-G method, the degree of utility for each alternative (U_i) is defined. This is accomplished by utilizing Eq. (11). Based on the values derived from this equation, the final ranking of the alternatives (COAs) is determined. The calculated utility degrees and the corresponding ranks of the alternatives are presented in Table 11.

Table 11. Values of the degree of alternatives (U_i) and final rank of alteratives

	$\boldsymbol{U_i}$	**Rank**
COA_1	100.0000	1
COA_2	93.6469	3
COA_3	98.6650	2
COA_4	89.5409	5
COA_5	92.6517	4

From the data presented in Table 11, it is evident that the optimal alternative is COA_1, whereas COA_4 is deemed unsuitable as a solution for this problem. To further validate the reliability and robustness of the proposed methodology, a sensitivity analysis is conducted in the subsequent section of the article.

4 Rank Reversal Test and Sensitivity Analysis

Following the guidelines set out in the study [64], a rank reversal test was conducted to evaluate the robustness of the methodology when faced with the removal of one or more alternatives. This test aimed to observe any potential impact on the final ranking of the alternatives. The outcomes of this test are documented in Table 12. The results indicate that the methodology exhibits stability, as there is no significant alteration in the ranking order upon the exclusion of alternatives.

Table 12. Rank reversal test results

	$\mathbf{COA_1}$	$\mathbf{COA_2}$	$\mathbf{COA_3}$	$\mathbf{COA_4}$	$\mathbf{COA_5}$
Initial rank	1	3	2	5	4
Rank without A_4	1	3	2		4
Rank without A_4 and A_5	1	3	2		
Rank without A_4, A_5 and A_2	1		2		

Regarding sensitivity analysis, various approaches can be adopted. One such approach, as referenced in the studies [4, 15, 17], involves analyzing the sensitivity of the methodology to changes in the weight coefficients of the criteria. For this specific analysis, 20 different scenarios were constructed. The first scenario assigns equal weights to all criteria. In subsequent scenarios, the weight distribution is altered by reducing the weight of the most influential criterion and redistributing it equally among the other criteria. This approach and its resulting impact on the decision-making process are illustrated in Figure 2.

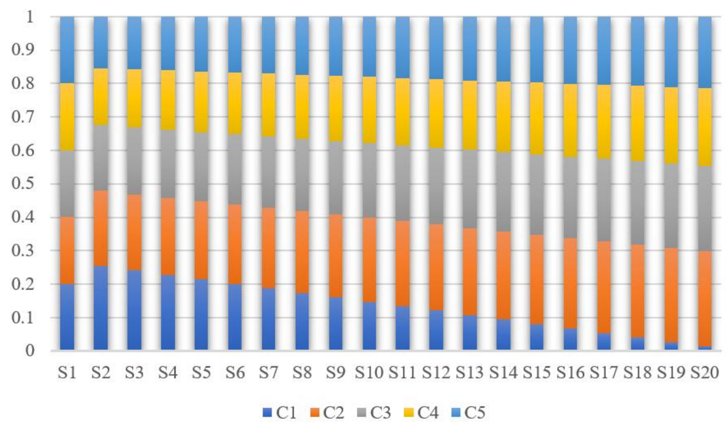

Figure 2. Scenarios of changes in criteria weights

After applying the scenarios in the COPRAS-G method, the ranks of the alternatives are obtained, which are presented in Figure 3.

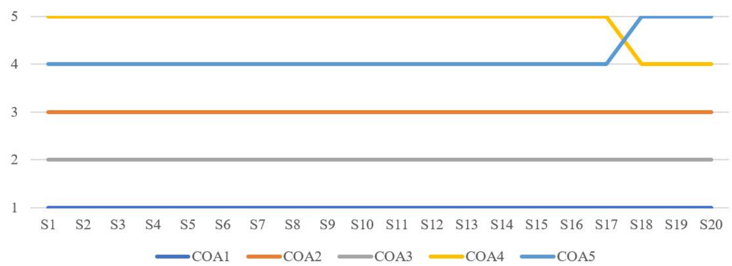

Figure 3. Rankings of alternatives obtained by applying scenarios

From the insights gleaned from Figure 3, it is evident that the ranking of the optimal alternative, COA_1, remains constant, while COA_4 consistently occupies the lowest position, reinforcing its status as an inadmissible option. This consistency in ranking, particularly under varied scenarios, underscores the robustness and stability of the methodology. The subsequent section of the text is devoted to a comparative analysis, examining the output results of the methodology in relation to other decision-making approaches.

5 Comparative Analysis

The comparative analysis entails juxtaposing the outcomes of the proposed methodology with those of other established methods, a crucial step for model validation [65–67]. This comparison encompasses results from several methodologies, including Grey EDAS (Evaluation Based on Distance from Average Solution) [68], Grey MARCOS (Measurement of Alternatives and Ranking according to the Compromise Solution) [69], Grey OCRA (OCcupational Repetitive Action) [70], COPRAS [44], and Fuzzy COPRAS [71]. The ranking of alternatives as determined by each of these methods, along with the proposed methodology, is depicted in Figure 4. An examination of these results reveals a consistent trend across the different methods. There is a minor deviation observed in the rankings given by the Fuzzy COPRAS method, particularly for the lowest and second-lowest ranked alternatives. Notably, alternative COA_1 consistently secures the top rank in all methodologies, reinforcing the validity of the proposed model.

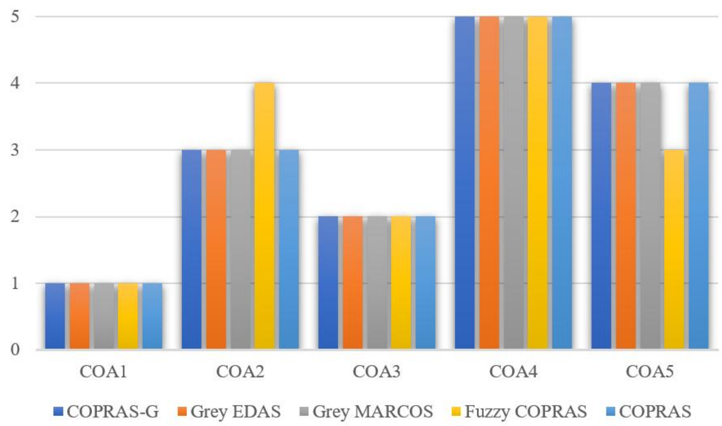

Figure 4. Rankings of alternatives obtained by other MCDM methods and COPRAS-G

6 Conclusions

In the contemporary military milieu, decision-making regarding the optimal COA in combat operations presents a formidable challenge. This research is dedicated to enhancing military decision support through the integration of advanced decision analysis methods. The initial phase, crucial in its scope, involved identifying key criteria for the evaluation and ranking of various COAs, ensuring that decisions encompass all pertinent factors.

Subsequently, the determination of weight factors for these criteria was undertaken, utilizing the FUCOM. This method, reliant on expert assessments, gauged the relative significance of each criterion. A pivotal aspect of this research was the meticulous aggregation of expert opinions through the EWAA operator. This step ensured a consensus in criteria evaluation, affirming that weight coefficients were grounded in collective expert judgement in the realm of military decision-making.

Following the successful definition of criteria weights, the selection of the optimal COA was addressed using the COPRAS-G method. This method's consideration of uncertainty and inaccuracies is vital in the fluid and unpredictable context of military operations. Additionally, expert ratings were aggregated using the EWAA operator to foster consensus and minimize individual biases in the final decision.

The results of this study underscore the developed model's consistency, stability, and reliability, a significant achievement that instills confidence in COA selection. The model was subjected to rigorous testing, including rank reversal tests, sensitivity analyses regarding weight factor variations, and comparative analyses with other methodologies. These evaluations uniformly corroborated the model's effectiveness and efficiency as a decision-making tool in military contexts.

In summary, this paper constitutes a noteworthy contribution to military decision-making and decision science. By leveraging advanced analytical techniques and incorporating expert opinions, it offers a systematic approach to COA selection. Extensive testing and validation underscore its practical applicability. Military leaders can utilize this methodology to enhance decision-making, leading to more effective military operations.

In an era where precision and expediency are paramount in decision-making, the described methodology markedly enhances military leaders' capacity to navigate the complexities and uncertainties of modern military conflicts with confidence and accuracy. This contributes significantly to the success of military operations and the safeguarding of resources.

A notable limitation of this study lies in the exclusion of the "civilian aspect" in criteria definition, particularly the impact of COAs on civilian populations, material and cultural assets, and the environment. Addressing this aspect is an imperative for future research, potentially incorporating methods and theories adept at managing imprecision and uncertainty in decision-making processes.

Data Availability

The data used to support the research findings are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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