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Optimization of Anti-Drone Defense: Analyzing Non-Kinetic Gun Selection Using DIBR II-Grey MARCOS Methodology

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Abstract: The selection of appropriate anti-drone systems is critical for enhancing a military's defensive capabilities. With a range of non-kinetic anti-drone guns available, it is essential to identify the optimal system that meets specific military requirements. This study presents a comprehensive approach, combining Multiple Criteria Decision Making (MCDM) techniques to facilitate this selection process. The Defining Interrelationships Between Ranked Criteria II (DIBR II) method has been employed to determine and calculate the criteria weighting coefficients, while the Grey Measurement of Alternatives and Ranking according to Compromise Solution (MARCOS) method, modified to utilize interval grey numbers, has been applied to rank the alternatives. The criteria weighting coefficients, defined by expert input, are aggregated using the Bonferroni mean. The proposed DIBR II-Grey MARCOS model is then subjected to a sensitivity analysis, which further validates the robustness of the selection process. A comparative analysis of results, based on the applied MCDM methods, underscores the efficacy of the proposed model. The findings demonstrate that this integrated model not only provides a reliable framework for selecting anti-drone guns but also offers a versatile tool for resolving other MCDM challenges across various domains. The study highlights the potential of this model for broader application in diverse operational environments, where complex decision-making is required. The combination of MCDM techniques and sensitivity analysis offers valuable insights into optimizing resource allocation, thereby enhancing strategic decision-making processes. The proposed model's adaptability and effectiveness suggest its significant potential for adoption beyond the military sector.

Keywords: Anti-drone gun; Anti-drone system; Defining Interrelationships Between Ranked criteria II (DIBR II); Grey theory; Measurement of Alternatives and Ranking according to Compromise Solution (MARCOS); Multi-Criteria Decision-Making (MCDM); Bonfferoni Mean (BM); Sensitivity analysis

1 Introduction

The rapid advancement of technology, driven by the Fourth Industrial Revolution and the evolution of artificial intelligence (AI), has significantly accelerated the development of drones. These advancements have made drones more affordable and accessible across various sectors, including defense and security. In recent years, the use of drones in military operations worldwide has increased substantially, underscoring the urgent need for the development and deployment of diverse anti-drone systems. The integration of AI has notably enhanced the efficiency of anti-drone systems, improving their effectiveness in countering both armed and unarmed drones. The primary purpose of these systems is to detect and acquire targets at a safe distance, track, neutralize, disable, or destroy enemy drones, thereby ensuring objective protection. Anti-drone operations are typically conducted using systems operated by a one-person crew:

/1/ anti-drone guns; /2/ drone jammer; /3/ drone monitoring equipment; /4/ drone operator locating system; /5/ drone detection radar [1, 2].

The following part of this research will define anti-drone guns as effective fighting assets against enemy and hostile drones. A new model is defined in the MCDM process – the DIBR II Grey MARCOS method – to select the most effective anti-drone gun. The purpose of this research is to optimize the model mentioned before and to inspect its efficiency through the determination of criteria coefficients for the selection of an anti-drone gun and its most optimal alternative, or to provide an optimal suggestion for further development of this method and patterns of its usage as an additional tool for decision makers when there are multiple alternatives with multiple criteria.

Table 1 presents literature analysis in the field of MCDM processes for different societal spheres on the one hand and literature focused on anti-drone assets on the other hand.

Table 1. Literature analysis

Research Subject and Reference	Applied Methods
Selecting an anti-tank missile system [3]	DIBR - rough MABAC
Aircraft selection [4]	Fuzzy PIPRECIA - Fuzzy MARCOS
Selection of an unmanned aircraft [5]	Fuzzy AHP-VIKOR
Offshore wind farm site selection [6]	Rough BWM - MARCOS
Prioritization of sustainable mobility sharing systems [7]	Fuzzy DIBR- fuzzy-rough EDAS
Selecting a location for a heavy mechanized bridge [8]	DIBR - Fuzzy MARCOS
Circular economy concepts in urban mobility alternatives [9]	DIBR - fuzzy Dombi CoCoSo
Presentation of proposals for the integration of operators of anti-drone systems into army units [10]	-
Selection of automatic rifle [11]	AHP-VIKOR
Selection of UAV [12]	DIBR-FUCOM-LMAW-Bonferroni-grey-EDAS
Analysis Anti-Drone System with Multiple Surveillance Technologies [13]	-
An anti-drone system with multiple surveillance technologies [14]	-
The Existing Technologies on Anti-Drone Systems [15]	-
Identification and assessment of man-made threats to cities [16]	Grey BWM - grey MARCOS
They make supplier selections for a company that produces steel [17]	Grey MARCOS
Landfill location selection for healthcare waste in urban areas [18]	BWM - grey MARCOS
Selection of a complex combat system [19]	DIBR-DIBR II-NWBM-BM
Analysis of Lean organization systems management methods and techniques [20]	DIBR II - rough MABAC
Pontoon Bridge Selection [21]	DIBR II-NWBM-FF MAIRCA
Selection of a dump truck [22]	Fuzzy LMAW - grey MARCOS
Locating temporary waste treatment facilities in the cities [23]	Grey - AHP - OCRA
Selection of Cold Chain Logistics Service Providers [24]	Grey AHP - Grey COPRAS
Evaluation of Enterprise Decarbonization Scheme [25]	Grey-MEREC-MAIRCA

The studies mentioned encompass a diverse array of decision-making processes across various domains, employing different methodologies tailored to each context. These methodologies, ranging from fuzzy logic to MCDM techniques, are selected based on their suitability for addressing specific challenges inherent in each decision scenario.

In the realm of military procurement, such as selecting anti-tank missile systems or complex combat systems, methodologies like DIBR and MARCOS are utilized. These approaches integrate fuzzy logic to handle imprecise data and rough set theory to manage uncertainty, ensuring robust decision-making in complex and dynamic environments.

Aircraft selection and unmanned aircraft systems require intricate evaluations considering multiple criteria. Fuzzy PIPRECIA and Fuzzy AHP-VIKOR are employed, leveraging fuzzy logic and the Analytic Hierarchy Process (AHP) to handle subjective preferences and uncertainties inherent in these decisions.

In civil infrastructure planning, methodologies like Best-Worst Method (BWM) and Dombi CoCoSo are applied. These techniques facilitate the selection of optimal locations for offshore wind farms, landfill sites, and temporary waste treatment facilities by considering various environmental, social, and economic factors.

Furthermore, in supply chain management and logistics, grey systems theory is utilised for decision-making under uncertainty. Grey MARCOS and Grey COPRAS enable efficient supplier selection for steel production and cold chain logistics service providers, respectively, by incorporating both known and unknown information.

Lastly, in the context of sustainability and decarbonization, methodologies like the Method based on the removal effects of criteria (MEREC) are employed. These approaches enable the evaluation of enterprise decarbonization schemes, guiding organizations towards environmentally responsible practices. Overall, the utilization of these diverse methodologies underscores the importance of adopting tailored decision-making approaches to address the unique challenges posed by each decision context, ultimately facilitating informed and effective decision-making across various domains. Within the scope of this study, a combination of DIBR II and Grey MARCOS is employed to analyze the selection of a non-kinetic anti-drone gun.

2 Methodology

Six topic experts will be included to resolve the challenge of criteria definition and selection of criteria coefficients for the selection of the most optimal anti-drone gun. Based on content analysis, the model of the MCDM process is defined and assembled using DIBR II and the grey MARCOS method of MCDM. Figure 1 illustrates the MCDM model.

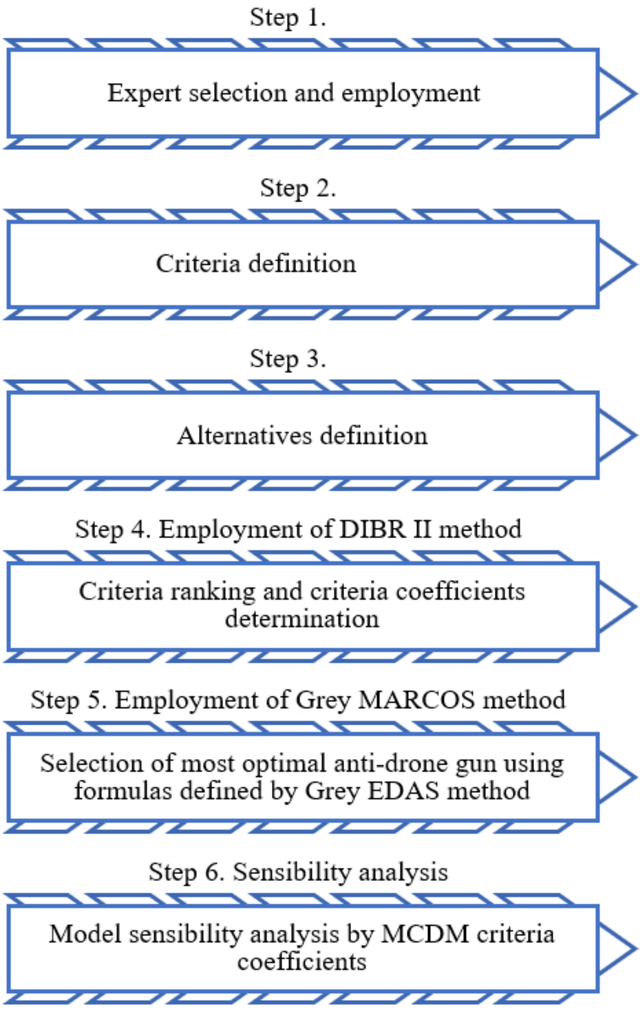

Figure 1. DIBR II – grey MARCOS model MCDM

Note: This figure was prepared by the authors

2.1 DIBR II Method MCDM

The DIBR II method for determining weight coefficients of criteria, introduced in 2023, is elucidated in the papers [19, 21, 26, 27], evolving from the earlier DIBR method [3, 8, 9, 12, 28]. This method was conceived to address limitations observed in prior methodologies for calculating criteria weight coefficients. To date, its application has been limited. The subsequent sections of the paper outline the steps of the DIBR II method [21]. The method steps of DIBR II are presented in the following part of this research.

Step 1. Evaluation criteria definition: $C = \{C_1, C_2, \ldots C_n\}$

Step 2. Evaluation and ranking of criteria by importance: $C_1 > C_2 > \ldots > C_n$

Step 3. This step presents the model of definition relations with neighboring criteria.

$$\frac{w_1}{w_2} = \frac{d_{1,2}}{1} \rightarrow \frac{w_1}{w_2} = d_{1,2} \tag{1}$$

$$\frac{w_2}{w_3} = \frac{d_{2,3}}{1} \rightarrow \frac{w_2}{w_3} = d_{2,3} \tag{2}$$

$$\frac{w_{n-1}}{w_n} = \frac{d_{n-1,n}}{1} \rightarrow \frac{w_{n-1}}{w_n} = d_{n-1,n} \tag{3}$$

The discernment between the foremost ranked criterion and the least ranked one entails a simultaneous evaluation aimed at contrasting their attributes, relevance, and significance within the context of the decision-making process. This meticulous analysis identifies nuanced differences in performance, impact, and alignment with predefined objectives, thereby facilitating a refined understanding of their respective contributions and limitations.

$$\frac{w_1}{w_n} = \frac{d_{1,n}}{1} \rightarrow \frac{w_1}{w_n} = d_{1,n} \tag{4}$$

Step 4. Establishing the relationship dynamics between the primary criterion and others.

$$w_2 = \frac{w_1}{d_{1,2}} \tag{5}$$

$$w_3 = \frac{w_2}{d_{2,3}} = \frac{w_1}{d_{1,2} \times d_{2,3}} \tag{6}$$

$$w_n = \frac{w_1}{d_{1,2} \times d_{2,3} \times \ldots \times d_{n-1,n}} \tag{7}$$

Step 5. Assigning Weight Coefficients to the Primary Criterion.

$$w_1 = \frac{1}{1 + \frac{1}{d_{1,2}} + \frac{1}{d_{1,2} \times d_{2,3}} + \ldots + \frac{1}{d_{1,2} \times d_{2,3} \times \ldots \times d_{n-1,n}}} \tag{8}$$

Step 6. Establishment of weight coefficients for residual criteria: a predefined methodology using Eqs. (5)-(7).

Step 7. Conducting a meticulous scrutiny of the interrelations among criteria involves a nuanced examination.

Specifically, the focus is on establishing a correlation between deviation values (as defined in Eq. (9)) and the corresponding control values (outlined in Eq. (10)). This analysis anticipates an approximate equivalence, allowing for a permissible variation of up to 10%. However, this expectation is contingent upon fulfilling the condition $0 \leq R \leq 0.1$, ensuring the integrity of the comparison and validation process within the defined parameters.

$$R_n = \left| 1 - \frac{w_n}{w_n^c} \right| \tag{9}$$

$$w_n^c = \frac{w_1}{d_{1,n}} \tag{10}$$

2.2 The Normalized Weighted Bonferroni Mean (NWBM) Operator

Adopting this operator within the study aimed to amalgamate the opinions of seven experts in determining the weight coefficients of criteria through the application of the DIBR II method, as delineated in Eq. (11).

$$\mathrm{NWBM}^{p,q}(t_1, t_2, \ldots, t_n) = \left(\sum_{i,j=1}^{n} \frac{w_{ij} w_j}{1 - w_i} t_i^p t_j^q \right)^{\frac{1}{p+q}} \tag{11}$$

$t_1, t_2, \ldots, t_n$ constitute a set of positive numbers, while p and q , both greater than or equal to 0 , denote the stabilization parameters of the function. The w_{ij} terms represent the weight coefficients assigned to experts' competencies.

2.3 Grey MARCOS Method

The MARCOS method is a recently developed MCDM method that specifies relations between options and referent values on the one hand and the functionality of possibilities on the other. Based on those relations, the method ranks compromised solutions compared to ideal or unsuitable solutions.

The MARCOS method is based on defining relations between alternatives and referent values (ideal and anti-ideal alternatives) [29]. The usability functions define preferences for decision-making. The usability function is the position of an alternative compared to ideal or anti-ideal solutions [30]. The best alternative is the one closest to the ideal point and furthest from the anti-ideal point. In this research, the MARCOS method is adapted using grey theory [31, 32], specifically interval grey numbers, to handle uncertain areas effectively. Deng [33] provided the fundamental principles of grey theory, which offers a framework for managing partially known and partially unknown information. According to the study of Deng [33], information is categorized into three distinct classes (refer to Figure 2).

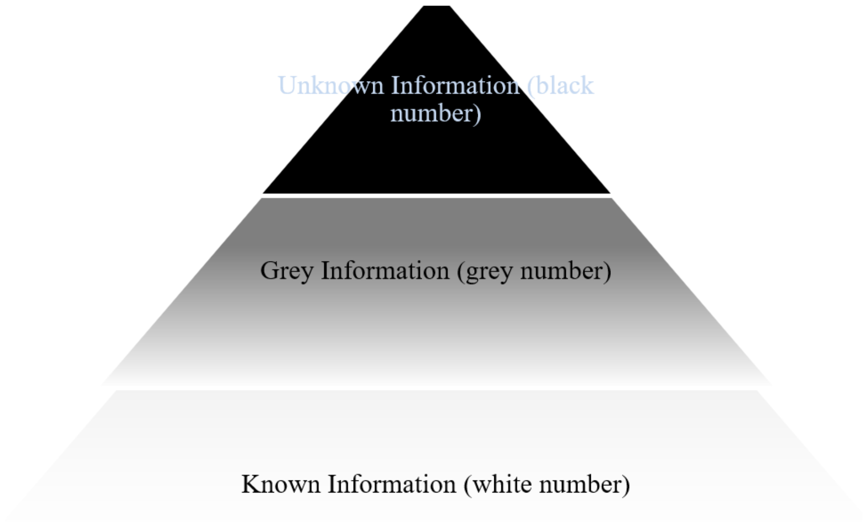

Figure 2. Grey theory

If set Z is a universal set, then set grey (G) of set Z is defined with two functions: $\bar{\mu}_G(Z)$ and $\underline{\mu}_G(Z)$, where $\bar{\mu}_G(Z): Z \rightarrow [0,1]$ and $\underline{\mu}_G(Z): Z \rightarrow [0,1]$, as well as $\bar{\mu}_G(Z) \geq \underline{\mu}_G(Z), z \in Z$. The interval Grey number ($\otimes$G) is defined as follows: $\otimes \mathrm{G} = [\underline{G}, \bar{G}]$, where $\underline{G}$ denotes the lower limit of the grey number $\otimes$G, and $\bar{G}$ signifies the upper limit, with $\underline{G} > \bar{G}$. When $\underline{G}$ equals $\bar{G}$, the grey number $\otimes$G transitions into a white number, indicating a precisely known and determined value. Fundamental computational operations concerning Grey numbers have been extensively discussed in various publications.

MARCOS methods can be implemented through the following steps [17, 34].

Step 1. Decision initial making creation (Y).

First, the experts $\mathrm{e} = \{\mathrm{e}_1, \mathrm{e}_2, \ldots, \mathrm{e}_\mathrm{k}\}$ evaluate all alternatives by every criterion, by which they obtain Grey initial decision-making matrices for every expert.

$Y^{(e)} = \left[\otimes y_{ij}^{(e)}\right]_{m\times n}$, where $\otimes y_{ij}^{(e)} = \left[\underline{y}_{ij}^{(e)}, \bar{y}_{ij}^{(e)}\right], 1 \leq \mathrm{i} \leq \mathrm{m}$ and $1 \leq \mathrm{j} \leq \mathrm{n}$. Expression (12) outlines the aggregation process for combining the decision-making matrices from all experts. This process yields the initial aggregated decision-making matrix, as detailed in expression (13).

$$\otimes y_{ij} = \left[\underline{y}_{ij}, \bar{y}_{ij}\right] = \begin{cases} \underline{y}_{ij} = \left\{\frac{1}{c(c-1)} \sum_{i,j}^{c} \underline{y}_i^p \underline{y}_i^q\right\}^{\frac{1}{p+q}} \\ \bar{y}_{ij} = \left\{\frac{1}{c(c-1)} \sum_{i,j}^{c} \bar{y}_i^p \bar{y}_i^q\right\}^{\frac{1}{p+q}} \end{cases} i \neq j \tag{12}$$

$$Y = [\otimes y_{ij}]_{m\times n} = \begin{bmatrix} \left[\underline{y}_{11}, \bar{y}_{11}\right] & \left[\underline{y}_{12}, \bar{y}_{12}\right] & \cdots & \left[\underline{y}_{1n}, \bar{y}_{1n}\right] \\ \left[\underline{y}_{21}, \bar{y}_{21}\right] & \left[\underline{y}_{22}, \bar{y}_{22}\right] & \cdots & \left[\underline{y}_{2n}, \bar{y}_{2n}\right] \\ \vdots & \vdots & \ddots & \vdots \\ \left[\underline{y}_{m1}, \bar{y}_{m1}\right] & \left[\underline{y}_{m2}, \bar{y}_{m2}\right] & \cdots & \left[\underline{y}_{mn}, \bar{y}_{mn}\right] \end{bmatrix}_{m\times n} \tag{13}$$

Step 2. Creation of an expanded initial matrix. This step defines ideal (AI) and anti-ideal (AAI) solutions. Ideal solution is an alternative with the best alternative for specific criteria, while anti-ideal solution is the opposite. The step is based on the following equations:

$$\triangle Y = \begin{array}{c} \\ AAI \\ A_1 \\ A_2 \\ \ldots \\ A_m \\ AI \end{array} \begin{array}{c} \begin{array}{cccc} K_1 & K_2 & \ldots & K_3 \end{array} \\ \begin{bmatrix} \otimes y_{aa1} & \otimes y_{aa2} & \cdots & \otimes y_{aan} \\ \otimes y_{11} & \otimes y_{12} & \cdots & \otimes y_{1n} \\ \otimes y_{21} & \otimes y_{22} & \cdots & \otimes y_{2n} \\ \ldots & \ldots & \ldots & \ldots \\ \otimes y_{m1} & \otimes y_{m2} & \cdots & \otimes y_{mn} \\ \otimes y_{ai1} & \otimes y_{ai2} & \cdots & \otimes y_{ain} \end{bmatrix} \end{array} \tag{14}$$

$$AI = \max_j \bar{y}_{ij} \text{ if } j \in B \text{ and } \min_j \underline{y}_{ij} \text{ if } j \in C \tag{15}$$

$$AAI = \min_j \underline{y}_{ij} \text{ if } j \in B \text{ and } \max_J \bar{y}_{ij} \quad \text{ if } j \in C \tag{16}$$

In these equations, B denotes a set of benefit criteria, while C denotes a set of cost criteria.

Step 3. Normalization of the expanded initial matrix (Y).

The normalized matrix $\widetilde{N}$ is represented as $\left[\widetilde{N}_{ij}\right]_{m\times n}$, the elements are derived individually through the application of expressions (17) and (18), in that order

$$\otimes\tilde{n}_{ij} = \frac{\otimes y_{ij}}{\max_{1\le i\le m}\{\bar{y}_{ij}\}} = \left(\frac{\underline{y}_{ij}}{\max_{1\le i\le m}\{\bar{y}_{ij}\}}, \frac{\bar{y}_{ij}}{\max_{1\le i\le m}\{\bar{y}_{ij}\}}\right) \text{ if } j \in B \tag{17}$$

$$\otimes\tilde{n}_{ij} = \frac{\min_{1\le i\le m}\left\{\underline{y}_{ij}\right\}}{\otimes y_{ij}} = \left(\frac{\min_{1\le i\le m}\left\{\underline{y}_{ij}\right\}}{\bar{y}_{ij}}, \frac{\min_{1 i\le m}\left\{\underline{y}_{ij}\right\}}{\underline{y}_{ij}}\right) \text{ if } j \in C \tag{18}$$

Step 4. Calculation of the weighted normalization $W = [\otimes w_{ij}]_{m\times n}$

Through the multiplication of the normalized matrix $\widetilde{N}$ by the weight coefficients assigned to each criterion, the resulting matrix W is derived.

Step 5. Assessing the usefulness of alternatives involves utilizing expressions (19) and (20) to ascertain the utility degree concerning both the anti-ideal and the ideal solutions.

$$\otimes C_i^+ = \frac{\otimes s_i}{\otimes s_{Ai}}\left[\frac{\underline{s}_i}{[\bar{s}_{Ai}}, \frac{\bar{s}_i}{\underline{s}_{Ai}}\right] \tag{19}$$

$$\otimes C_i^- = \frac{\otimes s_i}{\otimes s_{AAi}}\left[\frac{\underline{s}_i}{\bar{s}_{AAi}}, \frac{\bar{s}_i}{\underline{s}_{AAi}}\right] \tag{20}$$

Here:

$$\otimes S_i = \sum_{i=1}^{n} \otimes w_{ij} = \left(\sum_{i=1}^{n} \underline{w}_{ij}, \sum_{i=1}^{n} \bar{w}_{ij}\right) \tag{21}$$

In these equations, S_i (i = 1, 2, ..., m) signifies the total sum of the elements within the weighted matrix for both lower and upper bounds.

Step 6. Establish the utility function for the options $\otimes f\left(C_i\right)$

The utility function for the alternatives is derived through the application of expression (22).

$$f\left(C_i\right) = \frac{C_i^+ + C_i^-}{1 + \frac{1-f\left(C_i^+\right)}{f\left(C_i^+\right)} + \frac{1-f\left(C_i^-\right)}{f\left(C_i^-\right)}} \tag{22}$$

where, $f\left(C_i^-\right)$ the function represents the utility concerning the anti-ideal solution, while $f\left(C_i^+\right)$ represents the utility function concerning the ideal solution. These functions are derived by applying expressions (23) and (24).

$$\otimes f\left(C_i^+\right) = \frac{\otimes C_i^-}{\max_{1\le i\le m}\left\{\otimes C_i^+ + \otimes C_i^-\right\}} \tag{23}$$

$$\otimes f\left(C_i^-\right)=\frac{\otimes C_i^+}{\max_{1\leq i\leq m}\left\{\otimes C_i^+ + \otimes C_i^-\right\}} \tag{24}$$

Given that all values in expression (22) are crisp, it's essential to convert the grey values from expressions (23) and (24) into crisp values using the provided expression (25):

$$g_\lambda=(1-\lambda)\times \underline{g}+\lambda\times\bar{g} \tag{25}$$

where, λ denotes the whitening coefficient $\lambda\in[0,1]$.

Step 7. Ordering of alternatives based on priority.

The ranking is determined by arranging the values of utility functions $f\left(C_i\right)$ in descending order, where a higher value corresponds to a higher ranking for the respective alternative.

3 Results

The anti-drone gun represents a key part of the UAV defense system, commonly used for military purposes, the protection of critical infrastructure, or public security operations. This specialized weapon is intended for disruption, neutralization, or destruction by UAVs recognized as threatening or hostile. Anti-drone guns use different technologies and methods in order to complete a given task. That may include the emission of EM impulses in order to interfere with UAV electronics, the emission of laser beams for drone sensors or body destruction, the emission of radio-interference waves against communication channels, or the employment of physical projectiles for target takedown. This diversity of techniques enables adaptivity in the fight against different UAV types and models. The efficiency of an anti-drone gun can be measured by a few key factors. Precision in aiming and employment is critical for efficient interference and destruction of drones. Reaction time (speed), from the moment of discovery to the moment of reaction, plays a critical role in the prevention of unwanted activities [35, 36]. The range of the weapon determines how far the gun can react, while maneuverability enables quick and effective movement in the field. Gun integration with other systems, such as radars, optical sensors, or systems for friendly-hostile identification, enables more complete drone defense. Never the less, the sustainment and reliability of the weapon are key factors in providing its functionality in different conditions and throughout various environments. Basically, an anti-drone gun represents an advanced and complex weapon that has an important role in the suppression of threats from inappropriate UAV usage in military, security, or civil means.

Using the experts on this topic, eight criteria have been defined for the most optimal military anti-drone gun.

Detection efficiency and frequency range (C_1) cover different parameters to evaluate the effectiveness of the anti-drone system in precise identification and quick reaction to presence or activity within a specific frequency range [37]. The frequency range in this context is related to the radiofrequency range within which anti-drone systems can detect signals and activities of drones. In these criteria, it is necessary to cover a few very important factors that can affect it. Accuracy of detection is judging the system's ability to identify a drone from the moment it enters the frequency range. The system must possess the ability to work in a wide range of frequencies and to sustain detection accuracy while under EM jamming or other environmental abnormalities [38]. It is critical that the system can recognize drone signals, minimize fake affirmations, and possess coverage of a wider range of frequencies [39]. Criteria are beneficial and are defined by a lingual scale.

Reaction speed (C_2) evaluates the effectiveness of the anti-drone system in response to drone presence detection. Reaction speed is critical in effectively suppressing non-authorized drone activities and securing an urgent response after identification. In this time of reaction, the system needs to take certain steps after detecting the presence of a drone. Quick reaction is important for preventing potential threats and quickly acting on command for activities such as tracking, neutralization, or drone takedown. Automating can improve reaction speed when taking certain actions after drone identification. In cases where there is more than one anti-drone system, it is necessary to coordinate with other systems to have a synchronized response to threats. Also, the system should have the ability to react to various types of drones based on their specifications and potential risks they provide. The importance of a quick and precise reaction is critical for efficiently suppressing drones, which are security risk providers.

Precision (C_3) of anti-drone guns covers factors that evaluate the ability of the gun for precision aiming, tracking, and neutralizing drones with a high level of accuracy. To increase efficiency of this criteria it is needed to increase aiming speed so the effective and continuous tracking can provide high performance action on the drone itself. The anti-drone guns should be jamming-resistant to sustain aiming precision and high-performance tracking in the presence of EM interferences or other abnormal conditions in certain environments. The anti-drone guns must be accurate and precise while aiming and triggering to have a lower risk of collateral damage and secure effective target neutralization. High precision, tracking, and neutralization of the multiple drones at the time are total advantages when the selection of the anti-drone gun is conducted. Criteria are beneficial. Criteria of precision have a crucial role in drone defense system effectiveness, securing the quick, accurate, and reliable neutralization of targeted drones.

Range criteria (C_4) cover parameters that assess the range of successful detection, tracking, and neutralization of the drones. The maximum range of detection and tracking is an important factor because it defines the longest distance of the drone's presence, which the gun can detect, and the distance on which tracking can be conducted. Higher range enables early detection and identification of threats, as well as tracking and neutralizing targets at different heights and at various movement speeds. Another important factor in this criteria is the speed and effectiveness of adaptation to real-time range changes. Range criteria are crucial for securing comprehensive objective protection against drones, enabling us to detect, track, and neutralize potential threats on time. Criteria are beneficial.

Mobility and maneuverability (C_5) define the ability of an anti-drone system to move effectively and adapt to various terrain conditions. Mobility and maneuverability are critical for quickly reacting to situational changes and securing effective action on target. Agility as one of the factors in this criteria is important because it is needed that the anti-drone gun can change direction of movement quickly and adapt to the terrain. An agile system can maneuver effectively in various terrain conditions (fields, hills, forests, and urban terrain), where resistance to different terrain conditions increases the overall maneuverability of the system itself. This criterion covers sub-criteria of power autonomy, in which a system should provide a longer active state without frequent power resupply. Easy transferable systems and crews provide quick positioning in objectives that need protection against drones. Movement and maneuverability are important characteristics of an effective anti-drone system, securing the ability to quickly and adaptably react to threats from the air in different environments. Criteria are based on linguistic scale, and they are beneficial.

Financial expenses (C_6) present criteria that define economic aspects connected with the implementation, maintenance, and operations of anti-drone systems. The efficiency of the system frequently depends on its economic sustainability. When defining these criteria and giving an evaluation, it is needed to assess the initial expense related to the procurement and installation of anti-drone systems [40]. It includes the cost of gear, software, operators, and needed infrastructure adjustments; regular and preventive costs of system maintenance during its working life. Also, that includes the costs of part replacement, software upgrades, and regular controls. Training costs present investments in training operators and technical staff managing anti-drone systems. A well-trained crew improves the effectiveness of the system. Also, there are operative costs for everyday system employment, including energy costs, communications, and other resources needed for work. The costs of repair, change, and upgrade of system parts include changing old components and upgrading the system during its working life. Compatibility costs are made to make the system adapt to other systems and infrastructure—system capability to adjust its operations with changes to calculation or new demand. Flexibility and adjustments provide long-term economic sustainability. The evaluation of costs includes long-term financial implications to secure the sustained implementation of the anti-drone system through its whole working life. Criteria is lingual because it analyzes more different parameters.

Sustainment criteria (C_7) evaluate the ability of the anti-drone system to maintain high levels of performance, security, and ecological awareness throughout the whole life cycle. Sustainment of the anti-drone system is crucial for long-term effective functioning. It is needed for the system to be energetically effective and for energy consumption to be optimal about its performances. Long-lasting and reliable systems decrease the possibility of malfunctioning, and by doing so, they increase the satisfaction of this criteria. Systems that ease maintenance with minimal resources decrease the need for frequent intervention and have an advantage in the selection process. It is needed for the system to possess the ability to quickly adapt to technological changes without significantly decreasing its performance. This comprehensive evolution of sustainability enables holistic system analysis covering economic, ecological, and social factors. A sustainable system provides long-term prosperity and supports balance between different aspects of sustainable development. Criteria are lingual, and evaluation is conducted on a lingual scale.

Ability of integration with other systems (C_8) assesses the ability of the anti-drone system to integrate with different technology platforms and other security systems, enabling effective coordination and interoperability. The quality of integration plays an important role in system effectiveness. It is needed for the system to be integrated with existing security and communication systems being used in certain environments. Combability eases implementation and minimizes the need for infrastructure modifications. An anti-drone gun must possess the ability to effectively communicate and share information with different technologies, including radars, tracking systems, cameras, and other sensors, on one hand, and to have standardized communication protocols that provide clear and secure information exchange between multiple systems on the other. Integrating with centralized control systems that enable real-time coordination and activity tracking significantly increases the fighting system's effectiveness. The presence of security protocols and encryption is needed to provide security for integration with other systems. Evaluation of integration with other systems as an important factor in system functionality is important, especially in complex security environments where cooperation within different technologies is crucial for effective defense. Criteria are lingual, and evaluation of alternatives is conducted on a lingual scale.

Operative time and maximal usage time (C_9) evaluate how long the anti-drone system can effectively realize missions after activation and the system usage time before it must be maintained or resupplied. This aspect is critical for maintaining continuous anti-drone protection. Criteria is defined as the period when the anti-drone system is active and ready to detect, identify, and react to drone presence. Longer operative time means better ability of the system to provide lasting protection. The total time the anti-drone system can stay active, including operative time and eventual resting periods, represents maximal usage time. Maximal usage time covers all resources and batteries that support system usage. If an anti-drone gun uses batteries, charging speed is crucial in decreasing time spent inactive. Quicker charging enables quick reactivation of the system. System ability to effectively use resources while operative, including intelligent usage of energy and decreasing consumption of resources when inactive detection, represents an advantage in the selection process of an anti-drone gun. Anti-drone guns need indicators such as battery level or indicators of other important resources that enable users to track rest system resources quickly. Effective usage of working time and resources is critical for sustaining continuous anti-drone protection, especially in situations where continuous tracking and reaction to potential threats are needed.

The criteria mentioned for the selection of the most effective anti-drone gun can be sorted by importance, so crucial evaluation factors can be selected. Experts on a given topic conduct ranking, and it is emphasized that importance can vary depending on the specific needs and priorities of users. Table 2 presents the ranking of criteria by six experts.

Table 2. Comparison of expert criteria

Rank	1	2	3	4	5	6	7	8	9
Expert 1	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
Expert 2	C_1	C_2	C_3	C_4	C_5	C_9	C_8	C_7	C_6
Expert 3	C_5	C_2	C_1	C_3	C_4	C_9	C_8	C_7	C_6
Expert 4	C_1	C_4	C_3	C_8	C_2	C_5	C_9	C_7	C_6
Expert 5	C_1	C_2	C_3	C_5	C_9	C_4	C_7	C_6	C_8
Expert 6	C_1	C_3	C_9	C_2	C_4	C_5	C_7	C_6	C_8

In Table 3, the criteria coefficients for each expert are presented through a 1-10 statement, and the coefficient aggregation by the Bonferroni aggregator is shown in statement 11.

Table 3. Criteria coefficients

Rank	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
Expert 1	0.194	0.149	0.124	0.108	0.098	0.092	0.083	0.078	0.074
Expert 2	0.195	0.156	0.130	0.111	0.099	0.069	0.073	0.079	0.086
Expert 3	0.133	0.149	0.127	0.105	0.164	0.072	0.079	0.083	0.089
Expert 4	0.177	0.102	0.132	0.145	0.095	0.071	0.080	0.107	0.092
Expert 5	0.170	0.148	0.134	0.096	0.117	0.076	0.080	0.073	0.106
Expert 6	0.174	0.125	0.158	0.109	0.090	0.068	0.074	0.061	0.141
Bonferroni	0.174	0.138	0.134	0.113	0.110	0.075	0.078	0.080	0.098

Evaluation of alternatives is conducted with lingual scale presented in Table 4.

Table 4. Assessment of linguistic expressions and their corresponding grey values

Performance	Abbreviation	Scale of Grey Number
Very Good	VG	$[0.9, 1.0]$
Good	G	$[0.6, 0.9]$
Medium Good	MG	$[0.5, 0.6]$
Fair	D	$[0.4, 0.5]$
Medium Poor	MP	$[0.3, 0.4]$
Poor	P	$[0.1, 0.3]$
Very Poor	VP	$[0.0, 0.1]$

To resolve the selection of anti-drone guns in the military, a set of alternatives made of anti-drone guns used in various world militaries is defined. By using the suggested model of a MCDM process, the most-optimal anti-drone gun is being selected. In Table 5, the initial decision matrix is defined based on the expert ratings specified in Table 4. Forming an aggregated initial decision matrix is the first step in applying the gray MARCOS method. This matrix is based on expert ranks based on the given available data about alternatives using formulas (12) and (13). Results are presented in Table 6.

After the aggregated matrix is obtained, the initial decision-making matrix is expanded by defining the anti-ideal (AAI) and ideal (AI) solutions using expressions (15) and (16), respectively. The extended initial decision-making matrix (Y) is then presented in Table 7.

Table 5. Initial decision matrix

	0.174	**0.138**	**0.134**	**0.113**	**0.110**
	$\mathbf{C}_1$	$\mathbf{C}_2$	$\mathbf{C}_3$	$\mathbf{C}_4$	$\mathbf{C}_5$
A1	[P;MP;MP;F;F;MG]	[MP;MP;F;F;MG;MG]	[MP;F;MG;MG;G;G]	[F;F;F:F:MG;MG]	[P;P;MP;MP;F;F]
A2	[F;MG;MG;MG;G;G]	[F;F;MG;NG;G;G]	$[F; F; F; MG; G; G]$	[F;MG;MG;MG;G;G]	[MP;F;F;F;MG;MG]
A3	[F;F;MG;MG;G;G]	[F;F;F;MG;MG;MG]	[MP;MP;F;MG;G;G]	[MG;MG;MG;G;G;G]	[MP;MP;F;F;F;MG]
A4	[MP;MP;F;F;MG;MG]	[P;P;MP;MP;F;MG]	[MP;MP;F;F;MG;MG]	[MG;G;G;G;VG;VG]	[F;F;MG;MG;MG;G]
A5	[F;F;MG;MG;MG;G]	[P;MP;MP;MP;F;MG]	[F;F;F;MG;MG;MG]	[F;F;MG;MG;MG;G]	[G;G;G;VG;VG;VG]
A6	[MG;G;G;VG;VG;VG]	[MG;MG;G;G;VG;VG]	[MG;MG;G;G;G;VG]	[MG;G;G;VG;VG;VG]	[G;G;VG;VG;VG;VG]
A7	[F;MG;MG;G;G;G]	[MG;G;G;G;VG;VG]	[MG;MG;MG;G;G;G]	[MG;G;G;VG;VG;VG]	[G;G;G;G;VG;VG]
A8	[MG;MG;MG;G;G;G]	[G;G;VG;VG;VG;VG]	[G;G;VG;VG;VG;VG]	[MP;MP;F;F;FMG]	[F;F;F;MG;MG;MG]
A9	[MG;G;G;G;G;VG]	[VP;VP;P;P;P;MP]	[MG;G;G;G;VG;VG]	[MP;MP;F;F;F;MG]	[MP;MP;F;F;MG;MG]
A10	[G;G;G;VG;VG;VG]	[MG;MG;G;G;G;VG]	[F;MG;MG;MG;MG;G]	[VP;VP;P;P;P;MP]	[F;MG;MG;MG;G;G]

	0.075	**0.078**	**0.080**	**0.098**
	$\mathbf{C}_6$	$\mathbf{C}_7$	$\mathbf{C}_8$	$\mathbf{C}_9$
A1	[F;F;MG;MG;G;G]	[MP;MP;MP;F;F;F]	[F;F;MG;MG;MG;G]	[MG;MG;MG;G;G;G]
A2	[P;P;MP;MP;F;F]	[MP;F;F;F;MG;MG]	[MG;MG;MG;G;G;G]	[G;G;G;G;VG;VG]
A3	[VP;VP;P;P;MP;MP]	[MG;G;G;G;G;VG;]	[G;G;G;G;VG;VG]	[G;VG;VG;VG;VG;VG]
A4	[MG;MG;G;G;G;VG]	[G;G;VG;VG:VG:VG]	[F;MG;MG;MG;G;G]	[G;VG;VG;VG;VG;VG]
A5	[F;MG;MG;MG;MG;G]	[MP;F;F;F;MG;MG]	[F;F;MG;MG;MG;MG]	[MG;MG;G;G;G;G]
A6	[G;G;G;G;VG;VG]	[MG;MG;MG;G;G;G]	[MP;F;F;MG;MG;MG]	[F;MG;MG;MG;G;G]
A7	[G;G;G;VG;VG;VG]	[MG;MG;MG;MG;G;VG]	[F; F; F; F; F; MG]	[MG;MG;MG;MG;MG;G]
A8	[G;G;G;VG;VG;VG]	[F; F; F; F; F; MG]	[MG;G;G;G;G;G]	[G;G;G;G;VG;VG]
A9	[G;VG;VG;VG;VG;VG]	[MG;MG;MG;MG;MG;G]	[MG;MG;MG;MG;G;G]	[G;G;VG;VG;VG;VG]
A10	[F;F;MG;MG;MG;MG]	[MG;MG;MG;MG;G;G]	[F; F; F; MG; G; G]	[G;G;VG;VG;VG;VG]

Table 6. Aggregated initial decision-making matrix (Y)

	0.174	**0.174**	**0.138**	**0.138**	**0.134**	**0.134**	**0.113**	**0.113**
	$\mathbf{C_1}$		$\mathbf{C_2}$		$\mathbf{C_3}$		$\mathbf{C_4}$	
A1	0.326	0.439	0.398	0.499	0.481	0.644	0.380	0.466
A2	0.491	0.653	0.499	0.662	0.465	0.625	0.491	0.653
A3	0.499	0.662	0.401	0.491	0.446	0.609	0.491	0.664
A4	0.398	0.499	0.268	0.394	0.398	0.499	0.653	0.834
A5	0.456	0.584	0.292	0.397	0.401	0.491	0.456	0.584
A6	0.672	0.840	0.662	0.830	0.584	0.762	0.672	0.840
A7	0.497	0.672	0.653	0.834	0.491	0.664	0.672	0.840
A8	0.491	0.664	0.648	0.817	0.648	0.817	0.361	0.456
A9	0.550	0.729	0.063	0.204	0.653	0.834	0.342	0.427
A10	0.664	0.849	0.584	0.762	0.427	0.550	0.063	0.204

	0.110	**0.110**	**0.075**	**0.075**	**0.078**	**0.078**	**0.080**	**0.080**	**0.098**	**0.098**
	$\mathbf{C_5}$		$\mathbf{C_6}$		$\mathbf{C_7}$		$\mathbf{C_8}$		$\mathbf{C_9}$	
A1	0.253	0.378	0.499	0.662	0.311	0.401	0.456	0.584	0.491	0.664
A2	0.300	0.375	0.253	0.378	0.396	0.491	0.491	0.664	0.624	0.809
A3	0.361	0.456	0.103	0.239	0.550	0.729	0.624	0.809	0.561	0.683
A4	0.456	0.584	0.584	0.762	0.648	0.817	0.491	0.653	0.561	0.683
A5	0.664	0.849	0.427	0.550	0.396	0.491	0.388	0.474	0.474	0.648
A6	0.648	0.817	0.624	0.809	0.491	0.664	0.402	0.497	0.491	0.653
A7	0.624	0.809	0.664	0.849	0.519	0.642	0.306	0.376	0.376	0.490
A8	0.401	0.491	0.664	0.849	0.306	0.376	0.400	0.561	0.624	0.809
A9	0.398	0.499	0.561	0.683	0.376	0.490	0.466	0.624	0.648	0.817
A10	0.491	0.653	0.388	0.474	0.466	0.624	0.465	0.625	0.648	0.817

Utilizing expressions (17) and (18), the elements of the extended initial decision-making matrix (Y) are subjected to normalization, leading to the creation of the normalized matrix $\widetilde{N}$ (refer to Table 8).

Table 7. Extended integrated matrix (Y)

	0.174	**0.174**	**0.138**	**0.138**	**0.134**	**0.134**	**0.113**	**0.113**
	$\mathbf{C_1}$		$\mathbf{C_2}$		$\mathbf{C_3}$		$\mathbf{C_4}$	
AAI	0.326	0.439	0.063	0.204	0.398	0.491	0.063	0.204
A1	0.326	0.439	0.398	0.499	0.481	0.644	0.380	0.466
A2	0.491	0.653	0.499	0.662	0.465	0.625	0.491	0.653
A3	0.499	0.662	0.401	0.491	0.446	0.609	0.491	0.664
A4	0.398	0.499	0.268	0.394	0.398	0.499	0.653	0.834
A5	0.456	0.584	0.292	0.397	0.401	0.491	0.456	0.584
A6	0.672	0.840	0.662	0.830	0.584	0.762	0.672	0.840
A7	0.497	0.672	0.653	0.834	0.491	0.664	0.672	0.840
A8	0.491	0.664	0.648	0.817	0.648	0.817	0.361	0.456
A9	0.550	0.729	0.063	0.204	0.653	0.834	0.342	0.427
A10	0.664	0.849	0.584	0.762	0.427	0.550	0.063	0.204
AI	0.672	0.849	0.662	0.834	0.653	0.834	0.672	0.840

	0.110	**0.110**	**0.075**	**0.075**	**0.078**	**0.078**	**0.080**	**0.080**	**0.098**	**0.098**
	$\mathbf{C_5}$		$\mathbf{C_6}$		$\mathbf{C_7}$		$\mathbf{C_8}$		$\mathbf{C_9}$	
AAI	0.253	0.375	0.103	0.239	0.306	0.376	0.306	0.376	0.376	0.490
A1	0.253	0.378	0.499	0.662	0.311	0.401	0.456	0.584	0.491	0.664
A2	0.300	0.375	0.253	0.378	0.396	0.491	0.491	0.664	0.624	0.809
A3	0.361	0.456	0.103	0.239	0.550	0.729	0.624	0.809	0.561	0.683
A4	0.456	0.584	0.584	0.762	0.648	0.817	0.491	0.653	0.561	0.683
A5	0.664	0.849	0.427	0.550	0.396	0.491	0.388	0.474	0.474	0.648
A6	0.648	0.817	0.624	0.809	0.491	0.664	0.402	0.497	0.491	0.653
A7	0.624	0.809	0.664	0.849	0.519	0.642	0.306	0.376	0.376	0.490
A8	0.401	0.491	0.664	0.849	0.306	0.376	0.400	0.561	0.624	0.809
A9	0.398	0.499	0.561	0.683	0.376	0.490	0.466	0.624	0.648	0.817
A10	0.491	0.653	0.388	0.474	0.466	0.624	0.465	0.625	0.648	0.817
AI	0.664	0.849	0.664	0.849	0.648	0.817	0.624	0.809	0.648	0.817

Table 8. Normalized matrix

	0.174	**0.174**	**0.138**	**0.138**	**0.134**	**0.134**	**0.113**	**0.113**
	$\mathbf{C_1}$		$\mathbf{C_2}$		$\mathbf{C_3}$		$\mathbf{C_4}$	
AAI	0.383	0.517	0.076	0.245	0.478	0.589	0.075	0.243
A1	0.383	0.517	0.478	0.598	0.577	0.773	0.453	0.555
A2	0.578	0.769	0.598	0.794	0.557	0.750	0.584	0.777
A3	0.587	0.780	0.481	0.589	0.535	0.731	0.584	0.790
A4	0.469	0.587	0.322	0.473	0.478	0.598	0.777	0.993
A5	0.537	0.687	0.350	0.477	0.481	0.589	0.542	0.695
A6	0.791	0.990	0.794	0.995	0.700	0.914	0.799	1.000
A7	0.586	0.791	0.783	1.000	0.589	0.796	0.799	1.000
A8	0.578	0.782	0.777	0.979	0.777	0.979	0.429	0.542
A9	0.647	0.859	0.076	0.245	0.783	1.000	0.407	0.509
A10	0.782	1.000	0.700	0.914	0.512	0.659	0.075	0.243
AI	0.791	1.000	0.794	1.000	0.783	1.000	0.799	1.000

	0.110	**0.110**	**0.075**	**0.075**	**0.078**	**0.078**	**0.080**	**0.080**	**0.098**	**0.098**
	$\mathbf{C_5}$		$\mathbf{C_6}$		$\mathbf{C_7}$		$\mathbf{C_8}$		$\mathbf{C_9}$	
AAI	0.298	0.442	0.122	0.282	0.374	0.461	0.378	0.465	0.461	0.600
A1	0.298	0.445	0.587	0.780	0.381	0.491	0.563	0.721	0.601	0.813
A2	0.353	0.442	0.298	0.445	0.485	0.601	0.607	0.821	0.764	0.990
A3	0.425	0.537	0.122	0.282	0.673	0.893	0.772	1.000	0.687	0.836
A4	0.537	0.687	0.687	0.898	0.793	1.000	0.607	0.807	0.687	0.836
A5	0.782	1.000	0.503	0.647	0.485	0.601	0.480	0.586	0.580	0.793
A6	0.763	0.962	0.735	0.953	0.601	0.813	0.497	0.615	0.601	0.799
A7	0.735	0.953	0.782	1.000	0.635	0.786	0.378	0.465	0.461	0.600
A8	0.473	0.578	0.782	1.000	0.374	0.461	0.494	0.694	0.764	0.990
A9	0.469	0.587	0.661	0.805	0.461	0.600	0.576	0.772	0.793	1.000
A10	0.578	0.769	0.457	0.558	0.571	0.764	0.574	0.773	0.793	1.000
AI	0.782	1.000	0.782	1.000	0.793	1.000	0.772	1.000	0.793	1.000

The process of obtaining the weighted normalized decision matrix involves multiplying the normalized matrix by the weight coefficients of the criteria. This procedure is exemplified in Table 9.

Table 9. Weighted normalized matrix

	0.174	**0.174**	**0.138**	**0.138**	**0.134**	**0.134**	**0.113**	**0.113**
	C_1		**C_2**		**C_3**		**C_4**	
AAI	0.067	0.090	0.010	0.034	0.064	0.079	0.009	0.027
A1	0.067	0.090	0.066	0.083	0.077	0.104	0.051	0.063
A2	0.101	0.134	0.083	0.110	0.075	0.100	0.066	0.088
A3	0.102	0.136	0.066	0.081	0.072	0.098	0.066	0.089
A4	0.082	0.102	0.044	0.065	0.064	0.080	0.088	0.112
A5	0.093	0.120	0.048	0.066	0.064	0.079	0.061	0.078
A6	0.138	0.172	0.110	0.137	0.094	0.122	0.090	0.113
A7	0.102	0.138	0.108	0.138	0.079	0.107	0.090	0.113
A8	0.101	0.136	0.107	0.135	0.104	0.131	0.048	0.061
A9	0.113	0.149	0.010	0.034	0.105	0.134	0.046	0.057
A10	0.136	0.174	0.097	0.126	0.069	0.088	0.009	0.027
AI	0.138	0.174	0.110	0.138	0.105	0.134	0.090	0.113

	0.110	**0.110**	**0.075**	**0.075**	**0.078**	**0.078**	**0.080**	**0.080**	**0.098**	**0.098**
	C_5		**C_6**		**C_7**		**C_8**		**C_9**	
AAI	0.033	0.049	0.009	0.021	0.029	0.036	0.030	0.037	0.045	0.059
A1	0.033	0.049	0.044	0.059	0.030	0.038	0.045	0.058	0.059	0.080
A2	0.039	0.049	0.022	0.033	0.038	0.047	0.049	0.066	0.075	0.097
A3	0.047	0.059	0.009	0.021	0.052	0.070	0.062	0.080	0.067	0.082
A4	0.059	0.076	0.052	0.067	0.062	0.078	0.049	0.065	0.067	0.082
A5	0.086	0.110	0.038	0.049	0.038	0.047	0.038	0.047	0.057	0.078
A6	0.084	0.106	0.055	0.071	0.047	0.063	0.040	0.049	0.059	0.078
A7	0.081	0.105	0.059	0.075	0.050	0.061	0.030	0.037	0.045	0.059
A8	0.052	0.064	0.059	0.075	0.029	0.036	0.040	0.055	0.075	0.097
A9	0.052	0.065	0.050	0.060	0.036	0.047	0.046	0.062	0.078	0.098
A10	0.064	0.085	0.034	0.042	0.045	0.060	0.046	0.062	0.078	0.098
AI	0.086	0.110	0.059	0.075	0.062	0.078	0.062	0.080	0.078	0.098

The subsequent phase in this study methodology involves calculating the weighted matrix sum (S_i, depicted in Table 10) and determining the utility degree of alternatives, employing expressions (19) and (20), as illustrated in Table 11. In Table 12, the ranks of alternatives are presented.

Table 10. The values of S_i

	S_i	
A(AI)	0.296	0.432
A1	0.472	0.622
A2	0.546	0.723
A3	0.544	0.716
A4	0.566	0.727
A5	0.524	0.673
A6	0.716	0.913
A7	0.644	0.832
A8	0.615	0.791
A9	0.535	0.706
A10	0.576	0.762
AID	0.788	1.000

4 Sensitivity Analysis

Sensitivity analysis involves observing changes in alternative rankings due to modifications in the weight coefficients of criteria. Various methodologies exist for changing criteria weight coefficients [41–44], with this study

Table 11. Results of Grey MARCOS method

	$\otimes C_i^-$		$\otimes C_i^+$		$\otimes f\left(C_i^-\right) + \otimes f\left(C_i^+\right)$		$\otimes f\left(C_i^-\right)$		$\otimes f\left(C_i^+\right)$	
A1	1.092	2.100	0.472	0.4716	1.564	2.571	0.153	0.153	0.354	0.680
A2	1.265	2.442	0.5463	0.5463	1.811	2.989	0.177	0.177	0.410	0.791
A3	1.259	2.418	0.5437	0.5437	1.803	2.962	0.176	0.176	0.408	0.783
A4	1.311	2.456	0.5661	0.5661	1.877	3.022	0.183	0.183	0.425	0.795
A5	1.214	2.272	0.5243	0.5243	1.739	2.796	0.170	0.170	0.393	0.736
A6	1.658	3.084	0.7159	0.7159	2.374	3.800	0.232	0.232	0.537	0.999
A7	1.491	2.811	0.6436	0.6436	2.134	3.455	0.208	0.208	0.483	0.911
A8	1.424	2.671	0.6147	0.6147	2.038	3.286	0.199	0.199	0.461	0.865
A9	1.239	2.385	0.5348	0.5348	1.774	2.920	0.173	0.173	0.401	0.773
A10	1.334	2.572	0.5759	0.5759	1.910	3.148	0.187	0.187	0.432	0.833

Table 12. Alternative ranks

Ranking					
A1	0.276	10	A6	0.669	1
A2	0.380	6	A7	0.534	2
A3	0.375	7	A8	0.481	3
A4	0.402	5	A9	0.362	8
A5	0.341	9	A10	0.426	4

focusing on highlighting a distinct criterion in each scenario. The research delineates and presents ten scenarios involving changes to the weight coefficients of criteria, as detailed in Figure 3.

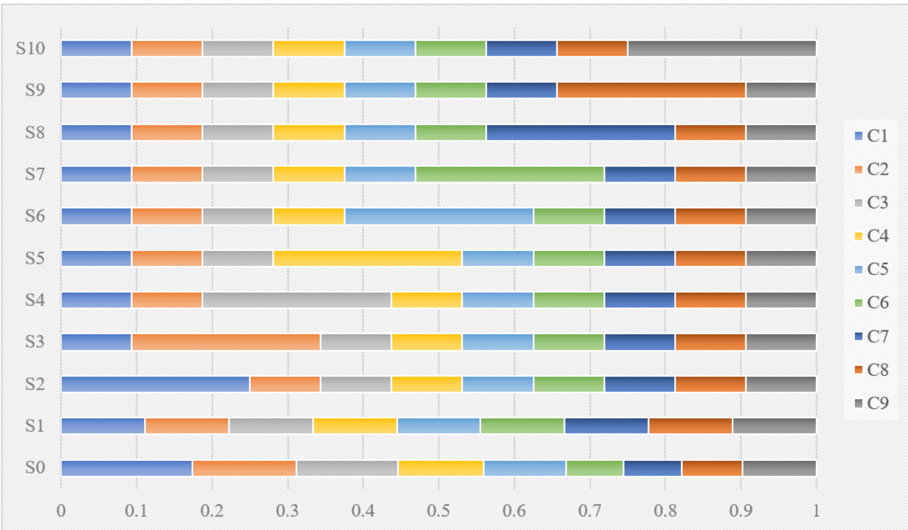

Figure 3. Formulated scenarios involving variations in weight coefficients of criteria

Note: This figure was prepared by the authors

By implementing the scenarios depicted in Figure 3, the resulting rankings of alternatives are presented in Figure 4.

After conducting sensitivity analysis, it was concluded that the top-ranked alternative consistently maintained its position, firmly anchored by its inherent characteristics. Conversely, the lowest-ranked alternative consistently retained its final position across the majority of scenarios. Additionally, it was observed that changes in rankings manifested among the remaining alternatives, except for the end alternatives. In summary, the comprehensive conclusion emphasized that while the model displayed sensitivity to modifications in criterion coefficients, it did so moderately, thus affirming its stability. Minor inaccuracies in the weights of criteria, as defined by experts, were deemed inconsequential for selecting the optimal alternative. Figure 5 presents a comparative analysis of the usage of the method MCDM in solving the anti-drone gun selection problem. Based on those results, it can be concluded that the suggested model based on the DIBR II-gray MARCOS method is stable and that there are no significant changes in alternative rankings. The most favorable alternative A6 and the most unfavorable alternative A1 kept their positions regardless of what MCDM method had been used.

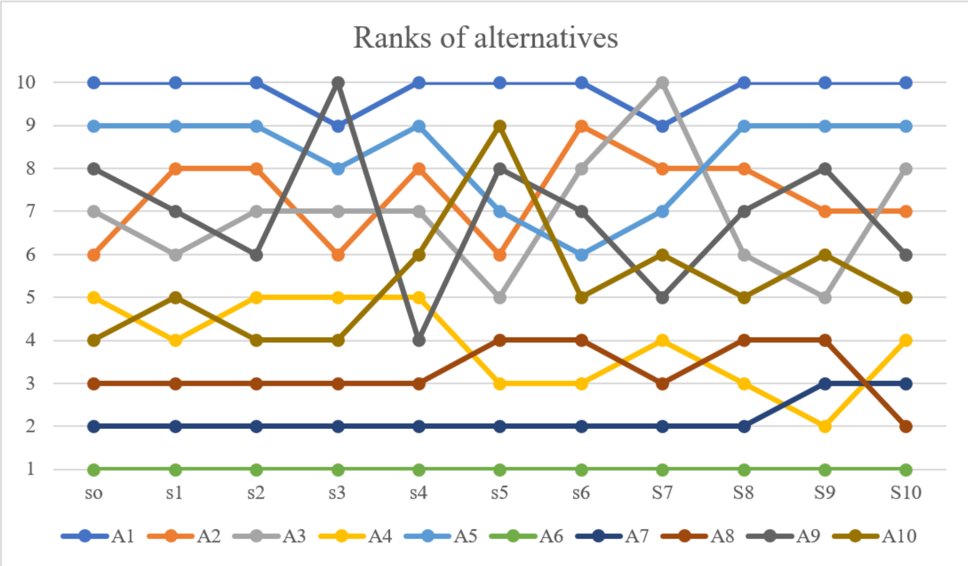

Figure 4. Alternative rankings subsequent to the implementation of scenario variations in weight coefficients of criteria

Note: This figure was prepared by the authors

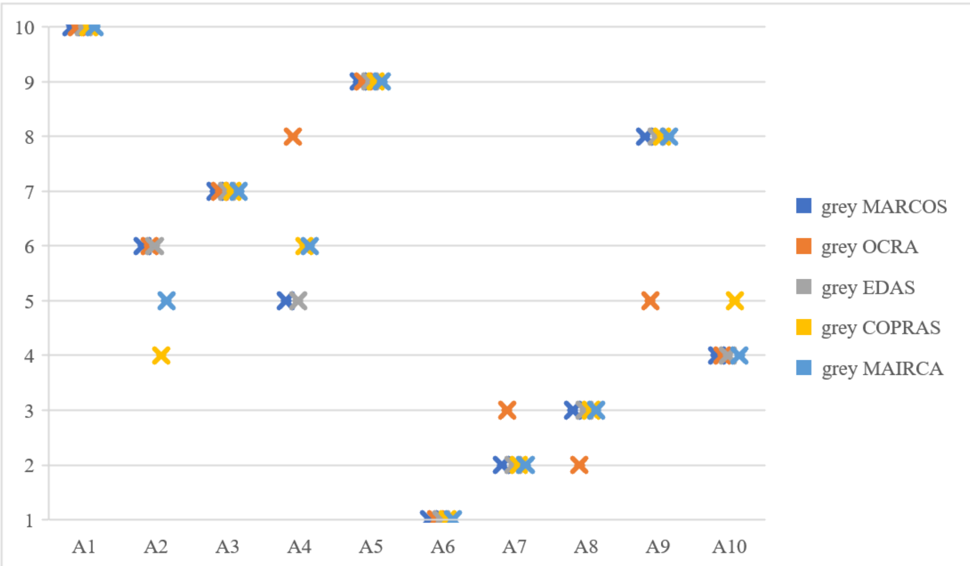

Figure 5. Comparison of results: Grey MARCOS vs. other MCDM methods

Note: This figure was prepared by the authors

5 Conclusions

MCDM techniques have gained significant traction in addressing the challenges associated with selecting military combat assets. The selection of appropriate combat systems is vital for enhancing operational capabilities within military contexts. To identify the most effective system, it is essential to meticulously analyze and define the criteria that are critical for this selection process. This research presents a novel approach to MCDM by integrating the hybrid DIBR II-Grey MARCOS model, specifically tailored for the selection of anti-drone guns for military applications.

Expert-defined criteria and corresponding weighting coefficients were established as the foundation of this model. These coefficients were subsequently aggregated using the Bonferroni mean, resulting in criteria coefficients that were then applied to identify the optimal alternative. The MARCOS method, modified with interval grey numbers (G-MARCOS), was employed for alternative ranking. Following the derivation of results, a sensitivity analysis was conducted to assess the model's responsiveness to changes in coefficient values. The model demonstrated robustness, with results indicating consistency when compared with other MCDM methods, thereby validating the reliability of the proposed approach.

Opportunities for further enhancement of this model have been identified, including the refinement of criteria definitions and the expansion of criteria sets. Additionally, incorporating a broader range of comparative consistency analyses with other MCDM methods could further solidify the model's applicability. The proposed model offers decision-makers a reliable tool for making informed decisions and holds potential for application across various domains where multiple criteria and alternatives must be evaluated.

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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