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Induced Generalized Intuitionistic Fuzzy OWA Operator on GRA Method for Evaluation of Self-Propelled Artillery System: Ammunition Based Computer Assisted Military Simulation Experiment

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ABSTRACT

The Self-Propelled Artillery System selection problem, a sub-problem of the Weapon Systems Selection Problems (WSSP), is an extremely important strategic-level decision problem and constitutes the main focus of this study. To solve the problem, 3 different weapon systems were evaluated based on 7 criteria. The solution methodology consists of integrating induced generalized ordered weighted averaging (IG-IFOWA) operator and Grey Relational Analysis (GRA). Such a solution proposal has not been seen in previous WSSP applications. To test the proposed methodology's validity and applicability, the study's results were tested on an ammunition-based computer-aided military experiment. The results reveal the effectiveness of the selected weapon system.

1. Introduction

Armed forces constitute a fundamental defense component for implementing security policies in every advanced country. To fulfill such a role effectively, armed forces must be prepared against the most likely threats to national security. Hence, identifying and implementing the most suitable capabilities are paramount for national security. Capability-Based Planning (CBP) is a relatively new paradigm that employs an analytical framework for strategic or long-term planning, utilizing capabilities.

In defense literature, capability can be defined as the capacity or ability to achieve operational effects [1]. The CBP process is defined as an inclusive planning framework aimed at providing capabilities tailored to today's diverse challenges and conditions, necessitating planning under uncertainty within an economic framework. Defense units across various regions worldwide, including the Armed Forces of the United States, United Kingdom, Canada, and Australia, employ CBP to develop force structures capable of operating effectively in future scenarios, thereby optimizing their future capabilities [2].

Within capability-based defense planning, program management and selecting specific project portfolios (such as weapon systems) are critical to the planning and execution. A program is

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described as a temporary, flexible plan established to coordinate, direct, and oversee the implementation of a series of related projects and activities aimed at achieving the institution's strategic objectives and benefits [3]. Program management encompasses four fundamental processes, including prioritization of projects based on their strategic importance, selection of the optimal project mix, progress monitoring, and evaluation [4].

In the defense sector, the CBP process presents additional challenges beyond standard project portfolio selection issues encountered in other sectors. These challenges include making highly costly investment decisions, long-term capability development processes, and strict budget constraints imposed by management. Two primary factors distinguish defense planning issues from those in other sectors: the nature of optimization objectives and the associated uncertainty. National security is the paramount concern in defense. Therefore, minimizing strategic risk is prioritized in defense portfolio optimization. Strategic risks in defense are typically associated with deep uncertainty stemming from general business issues such as management and policy changes, national security policies, and threat scenarios. Scenario-based approaches are often preferred for planning under such conditions.

This study focuses on the evaluation of self-propelled Artillery System for offensive operations within the scope of CBP. Specifically, alternative weapon systems are evaluated using a methodology based on fuzzy multi-criteria decision making (FMCDM), similar to literature reviews. Subsequently, the selected weapon system is tested in a generic scenario reflecting combat conditions through a simulation program. The study comprises a literature review in the second section, information on the weapon system in the third section, the FMCDM methodology and simulation scenario results in the fourth and fifth section, and concluding remarks in the final section.

2. Literature Review

The allocation of resources often involves conflicting or competing objectives. When there are multiple objectives, decision-makers can adjust the relative importance (weights) of these objectives and find the weights of options using any Multiple Criteria Decision Making (MCDM) technique. They then rank these options based on their importance and evaluate the ranked list according to desired capabilities to decide which alternative to choose. In military decision problems, these situations are often addressed using fuzzy set theory. Additionally, in defense management planning, many military problem areas that can be tackled with Operations Research (OR) in deterministic situations and MCDM and Fuzzy MCDM in subjective situations are considered.

In a review of the literature, it has been observed that while there are studies focusing on the selection of weapon systems, there is a notable lack of comprehensive studies that integrate this with defense planning. Various studies and applications have highlighted the usefulness of employing scientific decision support methods in identifying and prioritizing critical sensitivities, needs, and capabilities [6-13]. Multi Criteria Decision Making (MCDM), in particular, proves highly beneficial for solving complex problems that involve multiple criteria. Defense planning encompasses various factors such as different threat scenarios, resource constraints, and strategic objectives converging into a single plan, often necessitating a complex and multi-dimensional decision-making process. Each system may involve various criteria including different costs, capacities, levels of effectiveness, and maintenance requirements.

In the critical field of capability-based defense planning, especially in areas like Weapon System Selection Problem (WSSP), MCDM methods can effectively consider such complex variables. WSSP poses a challenging problem that is difficult to analyze with simple procedures among available options. Depending on the nature of the problem, an error in selecting weapon systems could adversely affect states economically, diplomatically, and in many other aspects. Moreover, such an error could potentially jeopardize the state's ability to sustain its existence. Therefore, to prevent any possible negative scenarios, it is essential to evaluate all details of alternative weapon systems and select them based on military expert opinions according to the requirements of combat conditions. This situation underscores the significant advantage of employing fuzzy sets in linguistic expression assessment.

In this study, due to the uncertainty and subjectivity of criteria evaluations by decision-makers, Intuitionistic Fuzzy Set theory (IFS) and Grey Relational Analysis (GRA) methods have been utilized. It is well-known in the literature that IFS and GRA have been beneficial in various fields of study involving uncertainty.

3. Weapon System Selection

An artillery gun is a firearm system capable of firing shells in high-angle trajectories, either with direct or indirect fire (using spotters). Modern artillery guns used on land typically range in caliber from 105mm to 203mm. Artillery guns are categorized into towed and self-propelled types based on their mobility. Self-propelled artillery guns, often tracked vehicles, can move independently or be towed by another vehicle without needing external towing power.

Self-Propelled Artillery System (SPAS) refers to a gun mounted on a wheeled or tracked chassis that can maneuver without the need for external towing power. This term encompasses both self-propelled howitzers and rocket-launching platforms. These vehicles, generally tracked for high mobility, carry artillery guns, mortars, rockets, or guided missiles and provide long-range indirect fire support in conflict zones. Despite resembling tanks in appearance, these systems lack the thick armor required for close combat support, offering only limited protection against small arms fire and shell fragments. Many are equipped with machine guns to engage infantry threats.

The primary advantage of these systems is their ability to swiftly reach deployment areas without relying on a towing vehicle. However, the vehicle must stop and be set up for firing, requiring time to aim and fire the gun. Repositioning necessitates the vehicle to be retracted before moving to a new position. Nevertheless, their self-propelled capability allows these vehicles to exert intense pressure on adversaries during combat engagements.

In contrast, conventional towed artillery guns are easier to manufacture and maintain. Their light weight enables them to be transported to places inaccessible to self-propelled artillery. Despite the advantages of self-propelled artillery, conventional towed guns remain in the inventories of many armies.

3.1. *Criteria Determination*

Determining the criteria for selecting weapons involves assessing various factors crucial to achieving operational effectiveness and cost efficiency. According to searches conducted on the Scopus, Mendeley, and Google Scholar databases using the keyword "weapon selection," the three most cited studies [14-16] have been reviewed. These studies indicate that the criterion of system cost, commonly referred to as "price" or "cost," is considered in the selection process of weapon systems. Studies on weapon system selection reveal a wide range of criteria depending on the specific system under examination [17-19]. Cost, performance, capability, reliability and operational flexibility stand out in the literature. In this study, in addition to partially adhering to these criteria, the criteria recommended by experts within the scope of CBP for Self-Propelled Artillery System and which can contribute to the literature were used.

In this study, a total of 7 criteria, including the OLI criterion not commonly used in defense management, along with other less frequently used criteria identified in the literature, have been addressed and presented in Table 1.

Table 1: Criteria for Weapon Selection

Criteria	References
Operational Lethality Index (OLI)	[20-22]
Cost	[14-16]
Lifetime	[15,16]
Effectiveness of Ammunition Used	[14-16,18]
Crew	[14-16,18]
Performance	[19]
Reliability	[19]

3.1.1. *Operational Lethality Index (OLI)*

Defense planning processes are lengthy and require serious planning. Prioritizing defense systems not only provides decision-makers with a framework for creating an effective force structure but also offers projections to defense industry firms. Due to the vast amount of information and data involved, analytical methods are necessary for decision-makers and planners to make informed decisions. Specifically, the use of operations research methods like analytical processes and multi-criteria decision-making methods is recommended. In military and other applications, approaches such as MCDA (Multi-Criteria Decision Analysis) and Fuzzy MCDA (Fuzzy Multi-Criteria Decision Analysis) are frequently used due to their superior qualities [23-27].

Quantitative Analysis of Warfare differs from historical analyses by focusing on the mathematical and statistical aspects of conflicts. Quantitative analyses offer a broad range of information and data. Quantitative measurements have the capacity to determine trends in warfare, test weapon systems according to specified tactics, train personnel in simulated combat conditions, and validate combat lessons under various scenarios. Each quantitative analysis is an analytical study that attempts to simulate real combat environments, acknowledging the inclusion of simplified assumptions and the acceptance that not every factor can be accounted for in the model. Nevertheless, when applied with careful selection and in appropriate contexts, quantitative methods significantly contribute to enhancing force effectiveness.

The lessons drawn from warfare do not solely focus on positive outcomes; often, the negative lessons from a battle can be more instructive. A defeat in a battle prompts a meticulous examination of the factors that led to that defeat. The internal review and analysis of failures in combat and their causes can significantly contribute to improving performance in future conflicts [20].

The Quantified Judgment Method (QJMA) is a tool developed by Dupuy Associates, Inc., and used by the Historical Evaluation and Research Organization to assess and measure military power [20]. The QJMA model is designed for computer-based war simulations to determine the outcomes of battles or conflicts. At its core, QJMA quantifies the lethality of individual weapon systems or the Theoretical Lethal Index (TLI). TLI provides a rigorous quantitative approach to evaluate the combat potential or effectiveness of a weapon system, considering factors such as rate of fire, impact on targets, range, accuracy, and reliability. Various metrics are combined to calculate the TLI value of a weapon system under ideal conditions. The TLI value is then converted into Operational *Lethality Index* (OLI), reflecting its effectiveness on the battlefield [20]. OLI is currently the most comprehensive assessment tool for evaluating the effectiveness of weapon systems, comprising up to 73 sub-criteria and validated through experiences in real combat situations [20-22]. The rationale for using this metric in the study is its proven validity under real combat conditions in the existing literature. Currently, various armed forces utilize it for force planning and military preparations. In this study, parameter values for weapon systems will be used as a lethality coefficient influencing the selection process.

4. Methodology

4.1. Intuitionistic fuzzy set theory;

It is an extension of fuzzy set theory proposed by Zadeh in 1965 [28]. Intuitionistic fuzzy set theory, which is a very functional method in situations such as uncertainty and variability, was put forward by Atanassov [29]. In this section, some basic concepts about Intuitionistic fuzzy set theory are given.

Definition 1

X is a non-empty set and $x \in X$, $I \in [0,1]$;

$\mu_s(x)$: X, I; The degree to which the x element belongs to the set S and $v_s(x)$: X, I; for two functions that show the degree to which the element x does not belong to the set S;

$$S = \{(x, \mu_s(x), v_s(x)): x \in X\} \tag{1}$$

The set is called intuitionistic fuzzy set - IFS. Here, there is a relationship between the degree to which the x element belongs to the S set and the degree to which the x element does not belong to the S set.

$$0 \leq \mu_s(x) + v_s(x) \leq 1 \tag{2}$$

Definition 2

The hesitation index is defined as equation (3), where X is a non-empty set and S is an Intuitionistic fuzzy set defined on X.

$$\pi_s(x) = 1 - (\mu_s(x) + v_s(x)) \tag{3}$$

The index that indicates the level of hesitation whether an element x belongs to the set S or not is known as the hesitation index. Comments are made about the element x according to the value of $\pi_s(x)$. If the value is large, the information is more uncertain; if it is small, it can be said to be more certain. If the value is zero, the information is certain, so the Intuitionistic fuzzy set turns into a fuzzy set thanks to this feature.

Definition 3

$\pi_s(x) \in [0-1]$, $v_s(x) \in [0-1]$, $0 \leq \mu_s(x) + v_s(x) \leq 1$ ve $\pi_s(x) = 1 - (\mu_s(x) + v_s(x))$; $\alpha = (\pi_s(x), \mu_s(x), v_s(x))$; It is called an Intuitionistic fuzzy number.

Definition 4

$\alpha = (\pi_s(x), \mu_s(x), v_s(x))$ ve $\beta = (\pi_t(x), \mu_t(x), v_t(x))$; There are two intuitive fuzzy numbers defined in the set X and $\gamma \in [0-1]$;

$$\alpha \times \beta = (\mu_s(x) * \mu_t(x), v_s(x) + v_t(x) - v_s(x) * v_t(x)) \tag{4}$$

$$\gamma\alpha = (1 - (1 - (\mu_s(x))^{\gamma}), (v_s(x))^{\gamma})) \tag{5}$$

$$\alpha^{\gamma} = ((\mu_s(x))^{\gamma}, 1 - (1 - (v_s(x))^{\gamma})) \tag{6}$$

Definition 5
Let there be n intuitive fuzzy numbers:$\alpha_i = (\mu_{si}, v_{si}, \pi_{si})$, (i=1,2,….,n) and w = ($w_1, w_2, \dots, w_n$) are the weight vectors of these fuzzy numbers. The arithmetic mean is defined as equality 7.

$$\text{Average} = (\alpha_1, \alpha_2, \dots, \alpha_n) = (1- \prod_{i=1}^{n}(1-\mu_i)^{wi}, \prod_{i=1}^{n}(v_i)^{wi}) \tag{7}$$

4.2. Gray Relational Analysis (GRA)

GRA was developed as part of Grey System Theory (GST), which was proposed by mathematician Deng in 1989 [30]. GRA is a decision-making method with grading and ranking capabilities that is used when the sample set or the judgment sets on which the sample is evaluated are small, since the distribution of the sample is unknown [31]. GRA is a frequently used technique to assist in the decision-making process of systems with mixed hierarchical structure. For this reason, multi-criteria decision-making techniques are used either simply or integrated with other methods in solving problems that require application [32]. In GRA, the method steps start with determining the data set and creating the decision matrix. In the data set to be prepared, if i is expressed as alternatives and j is expressed as the values of the alternatives while evaluating the criteria, the decision matrix consisting of x_{ij}'s is created as shown below.

$$X = \begin{bmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{bmatrix} (m \times n)$$

After the decision matrix is created, the reference series and comparison matrix need to be created. To perform this operation, the smallest or largest values in the data set are used. Then, the comparison matrix is created by adding the determined reference series to the top row of the X matrix.

The next step after obtaining the comparison matrix is the normalization step, which is necessary to convert the data used in the GRA method into the same unit. This process is also called gray formation in gray system theory [33]. Benefit, cost and optimality situations are considered for the normalization process. The formulas used for these cases are given in Equation (8), Equation (9) and Equation (10), respectively.

$$x_i^* = \frac{\text{xi (j)} - \text{minj } x_i \text{ (j)}}{maxj\ x_i(j) - \text{minj } x_i \text{ (j)}} \tag{8}$$

$$x_i^* = \frac{\text{maxj } x_i \text{ (j)} - \text{xi (j)}}{maxjx_i(j) - \text{minj } x_i \text{ (j)}} \tag{9}$$

$$x_i^* = \frac{|\, x_i \text{ (j)} - x_{0b} \text{ (j)}|}{maxjx_i(j) - x_{0b} \text{ (j)}} \tag{10}$$

As a result of calculating these values, the normalization matrix is obtained. All values take values in the range 0-1. The general representation of the normalization matrix is made as shown in the matrix named X* below.

$$X^* = \begin{bmatrix} x *_{11} & \cdots & x *_{1n} \\ \vdots & \ddots & \vdots \\ x *_{m1} & \cdots & x *_{mn} \end{bmatrix}$$

The Δ matrix is obtained with the values obtained by subtracting the X* matrix from the reference series. The formula for the calculations in the matrix is given in Equation (11).

$$\Delta_{ij} = |x^*_{0j} - x^*_{ij}| \quad (11)$$

The general representation of the Δ absolute value matrix is given as follows.

$$\Delta_{0i} = \begin{bmatrix} \Delta_{11} & \cdots & \Delta_{1n} \\ \vdots & \ddots & \vdots \\ \Delta_{m1} & \cdots & \Delta_{mn} \end{bmatrix}$$

After this step is completed, gray relational coefficients are found. The formula used to calculate the coefficients is given in Equation (12).

$$\gamma_{0i}(j) = \frac{\Delta\min + \zeta\,\Delta\max}{\Delta_{0i}(j) + \zeta\,\Delta\max} \quad (12)$$

Δ_{max} and Δ_{min} used in the formula express the largest and smallest values obtained in the absolute difference matrix. The expression ζ is defined as the separation coefficient. It can take values in the range of 0-1. The general acceptance used in the literature is to take the value 0.5. [24]. The last processing step in GRA is the calculation of gray relational degrees using gray relational coefficients. The concept referred to as gray relational degree is the multiplication of gray relational coefficients with criterion weights. When it comes to this point, two issues arise. The first situation is that the criterion weights have equal importance. If the problem is designed this way, equation (13) is used as the formula. If there are criterion weights (w_i) obtained with the help of different multi-criteria decision-making methods, equation (14) is used as the formula.

$$\Gamma_{0i} = \frac{1}{n}\sum_{j=1}^{n}\gamma_{0i}(j) \quad (13)$$

$$\Gamma_{0i} = \sum_{j=1}^{n}[w_i(j).\gamma_{0i}(j) \quad (14)$$

After calculating the gray relational degrees, the mathematical scores obtained are sorted from largest to smallest. The alternative with the highest score value can be suggested to decision makers as the best alternative to solve the problem.

5. Application and Results

In many cases, decision-makers involved in the decision-making process are not on an equal footing. Some decision-makers are more influential due to factors such as experience, position, etc. Linguistic variables that can be used to determine the importance level of decision-makers and the corresponding fuzzy numbers are given in Table 2.

Table 2. Intuitionistic Fuzzy Linguistic Variables

Linguistic Variables	**μ**	**v**	**π**
Very Important (VI)	0.9	0.1	0
Important (I)	0.75	0.2	0.05
Medium (M)	0.5	0.4	0.1
Low Important (LI)	0.35	0.6	0.05
Very Low Important (VLI)	0.1	0.9	0

The evaluations made by decision-makers using the data from Table 2 are presented in Table 3.

Table 3. Evaluations for Criteria

Criteria	**Decision Maker**	
	d_1	**d_2**
C_1	VVI	VVI
C_2	M	I
C_3	I	VI
C_4	VI	VI
C_5	L	I
C_6	VVL	VL
C_7	M	VL

To determine the criteria weights, each decision-maker evaluates the criteria using the variables given in Table 2 and their corresponding fuzzy numbers. Subsequently, entropy values and entropy weights are calculated using equations 15 and 16 respectively. [34]

$$H_j = \frac{1}{n\,ln2}\sum_{d=1}^{l}\left[\mu_{dj}\ln_{\mu dj} + v_{dj}\ln_{vdj} - \left(1-\pi_{dj}\right)\ln(1-\pi_{dj}) - \pi_{dj}\ln 3\right] \tag{15}$$

$$w_j = \frac{1-Hj}{n-\sum_{j=1}^{n} H_j} \quad j=1,2,\ ....,n \tag{16}$$

The entropy values and entropy weights for the criteria are provided in Table 4. The rankings of the weights are shown in Figure 1.

Table 4. Entropy Values and Weights of Criteria

Criteria	**Entropy Values**	**Entropy Weights**
C_1	0.051	0.160
C_2	0.200	0.134
C_3	0.146	0.138
C_4	0.106	0.145
C_5	0.198	0.130
C_6	0.143	0.138
C_7	0.216	0.216

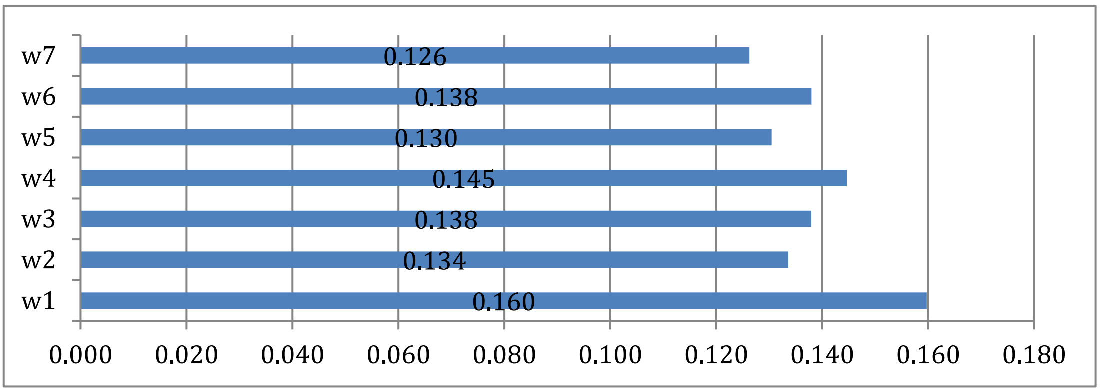

Figure 1. Weights of Criteria

The results reveal first the importance of OLI, second the effectiveness of the ammunition used, and third the importance of performance and lifetime criteria.

Decision-makers evaluate alternatives for each criterion using linguistic expressions shown in Table 5. Each decision-maker's evaluation is then aggregated into an intuitionistic fuzzy decision matrix. All decision-makers' matrices are transformed into an integrated intuitive decision matrix using the Induced Generalized Intuitionistic Fuzzy Ordered Weighted Average (IG-IFOWA) operator.

Table 5. Evaluations Alternatives

Linguistic Variables	**μ**	**v**	**π**
Critical Important (CDI)	1	0	0
Very Very Important (VVI)	0.95	0.05	0
Very Important (VI)	0.85	0.1	0.05
Important (I)	0.7	0.2	0.1
Medium (M)	0.5	0.35	0.15
Low (L)	0.35	0.55	0.1
Very Low (VL)	0.25	0.7	0.05
Very Very Low (VVL)	0.1	0.9	0

IG-IFOWA is defined as [35-37]:

$$\text{IG-IFOWA}(\{u_1, \alpha_1\}, \{u_2, \alpha_2\}, \ldots, \{u_l, \alpha_l\}) = (w_1(\alpha_{\beta(1)})^{\lambda} + w_2(\alpha_{\beta(2)})^{\lambda} + \ldots w_l(\alpha_{\beta(l)})^{\lambda} = \left(\left(1 - \prod_{d=1}^{l}\left(1 - (\mu_{\alpha^{\beta}(d)})^{\lambda}\right)\delta d\right)^{1/\lambda}, 1\text{-}(1\text{-}\prod_{d=1}^{l}\left(1 - (1 - (v_{\alpha^{\beta}(d)})^{\lambda}\right)\delta d\right)^{1/\lambda}\right) \quad (17)$$

Here;

$\lambda \in (-\infty, +\infty)$

$\alpha^{\beta}(d)$: The value of the u_d, α_d IFOWA pair with the largest u_d value with rank d

u_d: u_d, α_d Induced variable in IFOWA pair

α_d: intuitionistic fuzzy number matrix value

δ: $(\delta_1, \delta_2, \ldots, \delta_l)^T$

Decision-makers have evaluated the alternatives for each criterion using the linguistic variables in Table 3. The evaluations obtained are shown in Tables 6 and 7. These evaluations have been incorporated into calculations using the quantitative values in Table 5.

Table 6. Intuitionistic fuzzy decision matrix of d1 Decision Maker

	c_1	**c_2**	**c_3**	**c_4**	**c_5**	**c_6**	**c_7**
x_1	I	I	L	M	L	M	I
x_2	M	L	L	VI	L	VI	VL
x_3	M	VI	VI	I	M	VI	VI

Table 7. Intuitionistic fuzzy decision matrix of d2 Decision Maker

	c_1	**c_2**	**c_3**	**c_4**	**c_5**	**c_6**	**c_7**
x_1	VI	VI	VL	L	VL	I	VI
x_2	M	I	I	VL	M	VL	VI
x_3	M	I	VI	VI	I	I	VI

The integrated intuitive fuzzy decision matrix was obtained using equation 17 with $\lambda=2$ and $\delta=(0.618, 0.382)^T$ via the IG-IFOWA (Induced Generalized Intuitionistic Fuzzy Ordered Weighted Average) operator, resulting in Table 8.

Table 8. Integrated Intuitionistic Fuzzy Decision Matrix

	c_1			**c_2**			**c_3**			**c_4**			**c_5**			**c_6**			**c_7**		
x_1	0.796	0.142	0.062	0.634	0.142	0.224	0.095	0.613	0.291	0.193	0.430	0.376	0.095	0.613	0.291	0.390	0.264	0.346	0.634	0.142	0.224
x_2	0.506	0.350	0.144	0.339	0.323	0.338	0.339	0.323	0.338	0.499	0.230	0.271	0.193	0.436	0.371	0.499	0.230	0.271	0.499	0.242	0.259
x_3	0.506	0.350	0.144	0.634	0.139	0.227	0.732	0.100	0.168	0.634	0.142	0.224	0.390	0.264	0.346	0.634	0.139	0.227	0.732	0.100	0.168

The reference series is constructed based on the best values obtained by the criterion. For benefit criteria, $\alpha^+=(1,0,0)$ and for cost criteria, $\alpha^-=(1,0,0)$ are taken.

Equation 12 is utilized for calculating grey relational coefficients. Hamming distance is used for the distance matrix. After computing the absolute difference between membership and non-membership degrees as shown in Table 9, the distance matrix is determined with a compromise criterion of 0.5, resulting in grey relational coefficients calculated in Table 10.

Table 9. Distance Matrix

	c_1	**c_2**	**c_3**	**c_4**	**c_5**	**c_6**	**c_7**
x_1	0.346	0.508	1.518	1.237	1.518	0.875	0.508
x_2	0.844	0.985	0.985	0.730	1.242	0.730	0.742
x_3	0.844	0.505	0.368	0.508	0.875	0.505	0.368

Table 10. Gray Correlation Coefficient Matrix

	c_1	**c_2**	**c_3**	**c_4**	**c_5**	**c_6**	**c_7**
x_1	1.000	0.872	0.485	0.553	0.485	0.676	0.872
x_2	0.689	0.634	0.634	0.742	0.552	0.742	0.736
x_3	0.689	0.874	0.981	0.872	0.676	0.874	0.981

Grey relational coefficients are transformed into grey relational degrees using equations 13 and 14, and these degrees are presented in Figure 2.

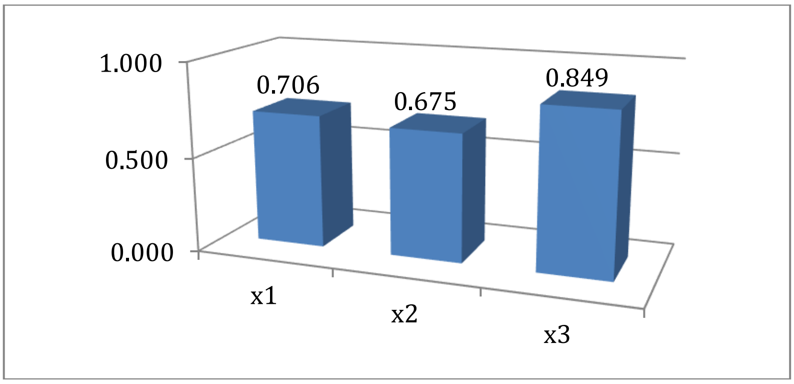

Figure 2. Gray Relationship Degrees

The alternative with the highest grey relational degree is considered the best. Therefore, the ranking based on this would be $A_3 > A_1 > A_2$.

With the results obtained, 3 different self-propelled artillery systems were listed. However, the analysis was not limited to this and a computer assisted military experiment was conducted on ammunition in a completely generic scenario.

Computer assisted military experiments play a significant role in modern warfare. These experiments enable the testing of military strategies and tactics through simulations. Computer modeling and simulation techniques help military leaders better understand and optimize their decision-making processes. Moreover, they allow for the evaluation of various scenarios without risking real-world conditions. These experiments support the planning and execution of military operations, providing strategic advantages and ensuring preparedness and effectiveness of military forces [38].

The importance of computer- assisted military experiments extends to the development of defense technologies and training of military personnel. Integration of new technologies such as artificial intelligence and big data analytics enhances the efficiency of military experiments and facilitates a better understanding of more complex scenarios. Additionally, these experiments can contribute to reducing the costs of military operations and improving the efficient use of resources. In conclusion, computer assisted military experiments remain a critical tool in shaping modern warfare and security strategies [39].

In this context, a computer assisted military experiment was conducted on the Joint Conflict and Tactical Simulation (JCATS) program on 155mm high explosive (HE) ammunition on different targets for A_3, which was determined to be the best weapon system. The results obtained are shared in Table 11. A generic image of the JCATS program is given in Figure 3 [40-41].

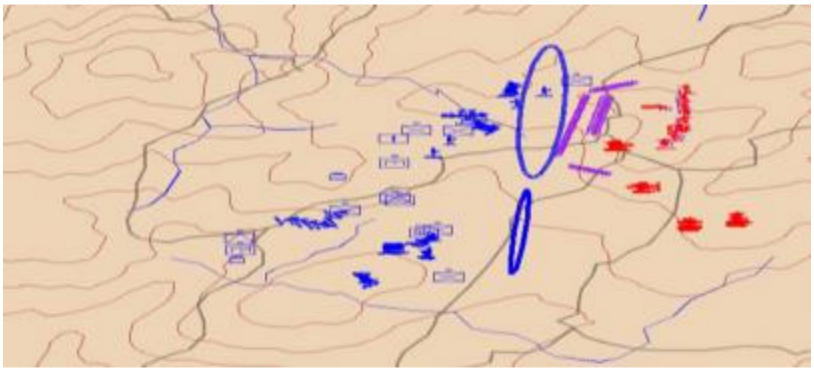

Figure 3. A Partial JCATS Interface for A Simulation Scenario

Table 11. Simulation Results (%)

Vulnerability Category	Mobility Kill	Fire Power Kill	Mobility and Fire Power Kill	Kill
Fixed Wing	25	0	0	75
Helicopter	25	0	0	75
Armored Vehicle	0	50	0	50
Soft Skinned	50	0	0	50
Tank	0	0	0	100

It shows the probability values of the effects that occur on different targets as a result of the use of 155mm HE ammunition by the A_3 alternative in the JCATS program. Probability values resulting from a generic scenario prove that the targets are largely completely destroyed.

6. Conclusions

The nature of warfare has evolved into a new era where weapon systems are also considered capabilities. Traditional front-line battles have given way to complex and multifaceted conflicts, where technological advancements and strategic intelligence have become paramount. Modern battlefields have expanded with new dimensions such as information technologies, cyber security, and psychological operations. This shift underscores that in warfare, along with weapon systems, capabilities like leadership, quick decision-making, teamwork, and technological proficiency are decisive factors. For instance, gathering accurate intelligence and analyzing it effectively can enhance the efficiency of weapon systems in military operations. Furthermore, understanding the political, economic, and social impacts of warfare and making strategic decisions are crucial. In conclusion, contemporary conflicts are won not only with weapon systems but also with human capabilities, highlighting the increasing importance of capability-based analyses.

Capability-based analyses play a crucial role in determining the superiority of weapon systems on modern battlefields. Analytical methods can objectively evaluate the effectiveness of weapon systems and provide valuable insights in the strategic decision-making process. For instance, the performance of a weapon system can be assessed based on factors such as target hit rates, cost-effectiveness analyses, and availability, revealing its strengths and weaknesses. Furthermore, detailed analyses of the technical specifications and operational capabilities of weapon systems contribute significantly to the development of warfare strategies and identification of enemy vulnerabilities. Therefore, capability-based analyses are indispensable tools for the development, modernization, and effective deployment of weapon systems in combat arenas. In conclusion, evaluating weapon systems through analytical methods holds vital importance in gaining strategic advantages within the dynamics of warfare and will remain a pivotal factor in shaping future defense and security policies. In this study, utilizing criteria identified through a literature review, three different self-propelled artillery systems were evaluated by military experts.

In military decision-making, problems are often complex and uncertain; therefore, methods such as multi-criteria decision-making and fuzzy sets provide significant advantages in improving the decision-making process. Multi-criteria decision-making considers multiple criteria to make decisions more comprehensive and balanced, thus ensuring decisions are more accurate and consistent. On the other hand, the fuzzy sets method is effective in dealing with uncertainty and imprecise information, as it can better model real-world situations and aid military strategies in becoming more adaptable. These methods provide military leaders with the tools necessary to make more effective decisions in variable and dynamic environments, thereby enhancing operational success and achieving strategic objectives more effectively. Considering these advantages, in the study, the IG-IFOWA operator was integrated with GRA to determine the best alternative. The integration of IG-IFOWA with GRA in WSSP problems distinguishes this study as pioneering. Moreover, conducting a generic simulation experiment on different targets was chosen over actual testing of this weapon system due to its high cost and non-effectiveness. Additionally, integrating computer-assisted military experiments with FMCDM introduces a novel approach to the literature. It should be noted that more experiments and field applications are needed to validate this complex military decision problem. The types of weapon systems and the results regarding the simulation scenario do not reflect a real event, they were created purely to present a methodological example.

Instead of the GRA method applied in the study, distance-based MCDM methods such as TOPSIS, CODAS, ARAS can also be used. The reasons for the differences in the rankings for different applications and which method is more useful can be analyzed by comparing the results obtained from these methods.

Conflicts of Interest

The author declare no conflicts of interest.

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