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Indeterminacy Fuzzy TOPSIS Framework for Unmanned Stealth Aircraft Selection

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Abstract

Decision-making problems in defense procurement are inherently complex due to multiple conflicting criteria, subjective expert judgments, and pervasive uncertainty. To address these challenges, this study proposes a comprehensive indeterminacy fuzzy TOPSIS (IFS–TOPSIS) framework for the selection of unmanned stealth aircraft in strategic national defense missions. Linguistic evaluations provided by multiple decision makers are modeled using indeterminacy fuzzy sets, allowing the simultaneous representation of truth, indeterminacy, and falsity degrees. Decision-maker importance and criterion weights are determined through indeterminacy fuzzy aggregation, while alternative performances are evaluated via a distance-based ideal solution approach.

The proposed framework is applied to a realistic case study involving three unmanned stealth aircraft alternatives evaluated against five key criteria: stealth capability, payload capacity, communication effectiveness, survivability, and affordability. The results identify the second alternative as the most suitable option, exhibiting the closest proximity to the positive ideal solution. Sensitivity analysis confirms the robustness of the ranking under varying criterion weight scenarios, and a comparative analysis demonstrates the superior discrimination capability of the proposed method over classical TOPSIS. The findings indicate that IFS–TOPSIS provides a robust, transparent, and doctrine-aligned decision-support tool for defense system selection under uncertainty.

1. Introduction

Multiple criteria decision-making (MCDM) has become an indispensable analytical paradigm for addressing complex decision problems involving multiple, often conflicting criteria across diverse application domains. Its importance is particularly pronounced in strategic and high-stakes contexts such as defense acquisition, where decisions entail long-term operational, economic, and security implications (Ardil, 2020; Ardil et al., 2019). The selection of an optimal unmanned stealth aircraft represents a quintessential example of such a complex MCDM problem, as it requires the simultaneous evaluation of heterogeneous criteria spanning technical performance, operational effectiveness, and economic feasibility (Shafiee, 2015).

In unmanned stealth aircraft evaluation, decision criteria typically encompass technical attributes such as speed, operational range, payload capacity, stealth capability, survivability, and communication effectiveness, in addition to logistical and economic factors including maintainability and affordability (Ardil, 2023a). The assessment of these criteria is inherently challenging due to uncertainty, incomplete information, and the subjective nature of expert judgment. These difficulties are further exacerbated by dynamic operational environments, rapid technological evolution, and constraints associated with classified or limited intelligence. Consequently, decision-makers often struggle to articulate their preferences using precise numerical values. Under such conditions, conventional MCDM techniques—particularly classical TOPSIS—are limited in their ability to adequately represent imprecision and ambiguity, as they rely on deterministic and crisp input data (Kaya et al., 2019).

To overcome these limitations, a wide range of extensions to classical MCDM methods has been proposed, incorporating alternative uncertainty modeling frameworks (Kacprzak, 2024). Since the introduction of fuzzy set theory by Zadeh (Zadeh, 1965, 1975), fuzzy-based approaches have played a central role in managing vagueness and imprecision in decision-making processes. Subsequent developments, including interval-valued fuzzy sets (Turksen, 1986; Bustince, 2010), intuitionistic fuzzy sets (Atanassov, 1986, 1989; Atanassov & Gargov, 1989), type-2 fuzzy sets (Mizumoto & Tanaka, 1976), and hesitant fuzzy sets (Torra, 2010), have further enriched uncertainty modeling by capturing hesitation and partial knowledge in expert evaluations. More recently, picture fuzzy sets (Cuong, 2014; Dinh & Thao, 2018) and neutrosophic sets (Smarandache, 2019) have gained increasing attention due to their enhanced capability to model indeterminacy, inconsistency, and incomplete information—phenomena that frequently arise in real-world and defense-related decision environments (Kharal, 2014; Abdel-Basset et al., 2022). Unlike neutrosophic formulations that permit unconstrained information components, the bounded structure of the proposed IFS ensures numerical stability and interpretability, which are essential for operational defense acquisition decisions.

Within this evolving methodological landscape, indeterminacy fuzzy sets have emerged as a practical and expressive extension of classical fuzzy models. Unlike vagueness or hesitation addressed in conventional fuzzy extensions, indeterminacy in defense decision-making primarily arises from conflicting expert evidence, incomplete intelligence, and evolving threat assessments. This feature provides a more flexible and realistic framework for representing epistemic uncertainty, particularly in defense-oriented decision problems where expert assessments are often influenced by conflicting technical evidence, insufficient data, and evolving threat perceptions.

Among available MCDM techniques, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) remains one of the most widely adopted methods due to its conceptual simplicity, intuitive rationale, and computational efficiency (Hwang & Yoon, 1981; Chen, 2000). TOPSIS ranks alternatives based on their relative distances from a positive ideal solution (PIS) and a negative ideal solution (NIS). To improve its applicability in uncertain decision contexts, numerous researchers have extended the classical TOPSIS framework using fuzzy and uncertainty-based representations, including fuzzy TOPSIS (Tüysüz & Kahraman, 2023), intuitionistic fuzzy TOPSIS (Rouyendegh, 2015), interval-valued fuzzy TOPSIS (Lanbaran et al., 2020), hesitant fuzzy TOPSIS (Ambrin et al., 2021), and other generalized fuzzy-based TOPSIS variants (Zeng et al., 2019). However, most existing approaches implicitly treat uncertainty as a byproduct of vagueness or hesitation, without explicitly distinguishing indeterminacy arising from conflicting or insufficient information. This limitation reduces their effectiveness in defense acquisition problems, where indeterminacy often constitutes a dominant source of uncertainty rather than a secondary effect.

In response to these challenges, this study proposes a refined indeterminacy fuzzy set–based TOPSIS (IFS–TOPSIS) framework that explicitly incorporates truth, indeterminacy, and falsity information throughout the decision-making process. By embedding indeterminacy fuzzy representations into the TOPSIS structure, the proposed approach preserves uncertainty semantics across all methodological stages, including decision-maker weighting, aggregation of expert evaluations, normalization, and distance-based ranking. Indeterminacy fuzzy numbers are employed to represent both criterion evaluations and decision-maker importance, thereby capturing the inherent subjectivity, hesitation, and partial confidence present in expert judgments. These assessments are aggregated using an indeterminacy fuzzy weighted averaging (IFWA) operator (Khan et al., 2019), ensuring that heterogeneous expert opinions are combined without information loss.

The methodological novelty of the proposed IFS–TOPSIS framework lies in three key aspects:

(i) the explicit modeling of indeterminacy as an independent informational dimension rather than implicitly absorbing it into membership or non-membership degrees;

(ii) the simultaneous incorporation of indeterminacy fuzzy representations for both criteria evaluations and decision-maker weights; and

(iii) the extension of the classical TOPSIS distance-based ranking mechanism to an indeterminacy fuzzy space.

Compared to classical and existing fuzzy TOPSIS variants, the proposed approach yields more robust, interpretable, and diagnostically informative decision outcomes under uncertainty. Its applicability and effectiveness are demonstrated through a numerical case study focused on unmanned stealth aircraft selection, highlighting its practical relevance for strategic defense decision-support.

The remainder of this paper is organized as follows. Section 2 introduces the fundamental concepts and mathematical properties of indeterminacy fuzzy sets and details the classical TOPSIS and the proposed IFS–TOPSIS methodology. Section 3 presents a numerical application illustrating the effectiveness of the approach in the context of unmanned stealth aircraft selection. Finally, Section 4 concludes the paper by summarizing the main findings, methodological contributions, and potential directions for future research.

2. Methodology

A frequent concern in the fuzzy MCDM literature relates to the conceptual and practical distinction between newly proposed uncertainty frameworks and existing models such as neutrosophic TOPSIS (Bakioğlu, 2025) and picture fuzzy TOPSIS (Jin et al., 2021; Khan et al., 2019). The present study differs from these approaches in several fundamental aspects.

First, unlike neutrosophic TOPSIS, which is often formulated in a highly generalized logical setting and may involve unconstrained truth, indeterminacy, and falsity components, the proposed Indeterminacy Fuzzy Sets (IFS) operate within a strictly bounded and decision-oriented structure. The constraint $0 \leq \mu + \eta + \nu \leq 1$e nsures numerical stability, interpretability, and direct applicability in engineering decision problems, where overly abstract representations may hinder practical adoption.

Second, in comparison with picture fuzzy TOPSIS, indeterminacy in the proposed framework is not treated as a residual or auxiliary membership degree but as an independent and explicitly modeled informational dimension. This distinction is critical in expert-based evaluations where hesitation and incomplete knowledge cannot be adequately captured by positive, neutral, and negative preference degrees alone. As a result, the IFS–TOPSIS framework provides enhanced expressive power while preserving mathematical simplicity.

Third, the novelty of the proposed method lies not only in the uncertainty representation but also in its systematic integration into all stages of the TOPSIS procedure, including decision-maker weighting, criterion aggregation, and distance-based ranking. This end-to-end indeterminacy-aware design distinguishes the approach from many existing fuzzy TOPSIS variants that incorporate uncertainty only at the evaluation stage.

Algorithm. IFS–TOPSIS for Unmanned Stealth Aircraft Selection

Input:

- Set of alternatives $A_i = \{A_1, A_2, \ldots, A_m\}$
- Set of criteria $C_j = \{C_1, C_2, \ldots, C_n\}$
- Set of decision makers $DM_k = \{DM_1, DM_2, \ldots, DM_l\}$
- Linguistic evaluations for criteria and alternatives

Output:

- Ranking of alternatives based on closeness coefficients

2.1. Preliminaries of Indeterminacy Fuzzy Sets (IFS)

Indeterminacy Fuzzy Sets (IFS) extend classical fuzzy constructs by allowing three independent membership degrees: truth (μ), indeterminacy (η), and falsity (ν), each bounded in [0,1] and jointly constrained to ensure informational consistency. This tripartite representation enables the explicit modeling of hesitation, conflict, and incomplete knowledge, which are pervasive in expert-based evaluations.

Arithmetic operations, scalar transformations, and aggregation rules defined over indeterminacy fuzzy numbers preserve mathematical closure and interpretability. In particular, distance measures defined in the indeterminacy space provide the foundation for ranking alternatives within IFS-TOPSIS.

Definition 1. (Ardil, 2024a, 2024b) Let X be a universal set. An indeterminacy fuzzy set A on a universe X is an object of the form

$$A = \{< x, \mu_A(x), \eta_A(x), v_A(x) > | \, x \in X\}$$

where the truth-membership function $\mu_A(\mathrm{x})\text{: X} \to [0,1]$, the indeterminacy-membership function $\eta_A(\mathrm{x})\text{: X} \to [0,1]$, and the falsity-membership function $v_A(\mathrm{x})\text{: X} \to [0,1]$ are three maps in X that satisfy the mathematical constraint condition: $0 \le \mu_A(\mathrm{x}) + \eta_A(\mathrm{x}) + v_A(\mathrm{x}) \le 1 | \, \mathrm{x} \in \mathrm{X}$.

Geometrically, each element of an indeterminacy fuzzy set can be visualized as a point within a three-dimensional unit cube $[0,1]^3$, defined by the membership coordinates (μ,η,ν), which represent the degrees of truth, indeterminacy, and falsity, respectively. The admissible region is bounded by $0 \le \mu_A(x) + \eta_A(x) + v_A(x) \le 1$. Points lying on the plane $\mu_A(x) + \eta_A(x) + v_A(x) = 1$ correspond to cases of complete information, whereas points beneath this plane represent partial or uncertain knowledge.

The indeterminacy fuzzy numbers $\mu_A(x)$, $\eta_A(x)$, and $v_A(x)$ represent the degree of truth, indeterminacy, and falsity of element x to the indeterminacy fuzzy set A, respectively.

Definition 2. Let X be a nonempty set and I be the unit interval [0,1]. An indeterminacy fuzzy set A and B of the form, and $A = \{< x, \mu_A(x), \eta_A(x), v_A(x) > | \, x \in X\}$ and $B = \{< x, \mu_B(x), \eta_B(x), v_B(x) > | \, x \in X\}$. Then

$A \subset B$ if and only if for all $x \in X$

$$\mu_A(x) \le \mu_B(x), \eta_A(x) \le \eta_B(x)$$

or

$$\eta_A(x) \ge \eta_B(x), v_A(x) \ge v_B(x)$$

$$A^C = \{< x, v_A(x), \eta_A(x), \mu_A(x) > | \, x \in X\}$$

$$A \cup B = \left\{\left(x, max(\mu_A(x), \mu_B(x)), min(\eta_A(x), \eta_B(x)\right), min(v_A(x), v_B(x)) | x \in X\right\}$$

$$A \cap B = \{(x, min(\mu_A(x), \mu_B(x)), min(\eta_A(x), \eta_B(x)), max(v_A(x), v_B(x)) | x \in X\}$$

$$A \oplus B = \{(x, \mu_A(x) + \mu_B(x) - \mu_A(x)\mu_B(x), \eta_A(x)\eta_B(x), v_A(x)v_B(x) | x \in X\}$$

$$A \otimes B = \{(x, \mu_A(x)\mu_B(x), \eta_A(x) + \eta_B(x) - \eta_A(x)\eta_B(x), v_A(x) + v_B(x) - v_A(x)v_B(x) | x \in X\}$$

$$O_i^+ = \{< (x, 1,0,0) > | \forall x \in X\}$$

$$O_i^- = \{< (x, 0,0,1) > | \forall x \in X\}$$

Definition 3. The scalar multiplication operation over indeterminacy fuzzy sets A of the universe X is denoted by nA and is defined by

$$nA = \{(x, 1 - (1 - \mu_A(x))^n, (\eta_A(x))^n, (v_A(x))^n | x \in X\}$$

Definition 4. The exponentiation operation over indeterminacy fuzzy sets A of the universe X is denoted by nA and is defined by

$$A^n = \{(x, \mu_A(x))^n, 1 - (1 - \eta_A(x))^n, 1 - (1 - v_A(x))^n | x \in X\}$$

where $n > 0$.

Definition 5. The score s(A), accuracy h(A), and certainty c(A) functions for an indeterminacy fuzzy number $A = (\mu, \eta, v)$ are defined as follows:

$$s(A) = \mu_A - v_A$$

$$h(A) = \mu_A + \eta_A + v_A$$

$$c(A) = \mu_A$$

where $s(A) \in [-1,1]$ and $h(A) \in [0,1]$. For any two indeterminacy fuzzy numbers $A = (\mu_A, \eta_A, v_A)$ and $B = (\mu_B, \eta_B, v_B)$

$$if s(A) > s(B), then (A) > (B)$$

$$if s(A) = s(B), then$$
$$i. if h(A) > h(B) \Rightarrow A > B$$
$$ii. if h(A) = h(B), then\ A \approx B$$

Definition 6. A function $d(A, B)$ is called a distance measure between indeterminacy fuzzy numbers (IFNs) if it satisfies the following properties:

P1. $d(A, B) \geq 0$

P2. $d(A, B) = 0$ if and only if $A = B$ for all $A, B \in IFNs$

P3. $d(A, B) = d(B, A)$ (symmetry)

P4. For all $A, B, C \in IFNs$,

$$d(A, C) \leq d(A, B) + d(B, C)$$

This is the triangle inequality.

Definition 7. Given two indeterminacy fuzzy numbers $A = (\mu_A, \eta_A, v_A)$ and $B = (\mu_B, \eta_B, v_B)$, the Minkowski distance between A and B is defined as

$$d(A, B) = \left[\frac{1}{3n}\sum_{i=1}^{n}(|(\mu_A(x) - \mu_B(x)|^\gamma + |(\eta_A(x) - \eta_B(x)|^\gamma + |(v_A(x) - v_B(x)|^\gamma)\right]^{1/\gamma}, \gamma \geq 1.$$

where $\gamma \geq 1, \infty$. When $\gamma = 1$, the Minkowski distance degenerates to the Hamming distance. When $\gamma = 2$, the Minkowski distance degenerates to the Euclidean distance. When $\gamma = \infty$, the Minkowski distance degenerates to the Chebyshev distance:

$$d_{\gamma_\infty}(A,B) = max(|\mu_A(x) - \mu_B(x)|, |\eta_A(x) - \eta_B(x)|, |v_A(x) - v_B(x)|)$$

2.2. Classical TOPSIS Method

The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method is a valuable approach to multiple criteria decision-making (MCDM). Developing an effective method for solving MCDM problems remains a challenging task. TOPSIS is one such method that has been developed to address this challenge (Hwang & Yoon, 1981).

In general, an MCDM problem aims to assess and rank alternatives, denoted as A_i based on a set of attributes or criteria, denoted as C_j. Each alternative A_i represents a possible choice for the decision-maker, and the goal is to rank these alternatives in order of preference. Each criterion C_j represents a factor that influences the decision-maker's evaluation and ranking of the alternatives. Furthermore, the relative importance or significance of each criterion C_j is often represented by a weight, denoted as ω_j.

The classical TOPSIS method is a distance-based approach that aims to identify the best alternative by determining which one is farthest from the negative ideal solution and closest to the positive ideal solution. In the classical TOPSIS method, decision-makers express their opinions and evaluations by assigning crisp (i.e., precise) values to the alternatives under each criterion. The five steps of the classical TOPSIS method are outlined below (Hwang & Yoon, 1981):

Step 1: The decision matrix X is normalized.

$$Y = \begin{pmatrix} y_{11} & \cdots & y_{1j} \\ \vdots & \ddots & \vdots \\ y_{i1} & \cdots & y_{ij} \end{pmatrix} \tag{1}$$

where y_{ij} is calculated as:

$$y_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{I} x_{ij}^2}} \tag{2}$$

where, x_{ij} denotes the performance of alternative A_i with respect to criterion C_j.

Step 2: Calculate the weighted normalized decision matrix V .

$$V = \begin{pmatrix} v_{11} & \cdots & v_{1j} \\ \vdots & \ddots & \vdots \\ v_{i1} & \cdots & v_{ij} \end{pmatrix} \tag{3}$$

where $v_{ij} = \omega_j y_{ij}$.

Step 3: Obtain the positive ideal solution A^+ and the negative ideal solution A^-.

$$\begin{aligned} A^+ &= [\, v_1^+, v_2^+, \ldots, v_J^+ \,] \\ A^- &= [\, v_1^-, v_2^-, \ldots, v_J^- \,] \end{aligned} \tag{4}$$

where v_j^+ is given by:

$$v_j^+ = \begin{cases} max\, v_{ij}\,, if\, C_j\ is\ a\ beneficial\ criterion \\ min\, v_{ij}\,, if\ C_j\ is\ a\ non-beneficial\ criterion \end{cases} \tag{5}$$

and v_j^- is given by:

$$v_j^- = \begin{cases} min\, v_{ij}\,, if\, C_j\ is\ a\ beneficial\ criterion \\ max\, v_{ij}\,, if\ C_j\ is\ a\ non-beneficial\ criterion \end{cases} \tag{6}$$

Step 4: Compute the separation measures S_i^+ and S_i^- for each alternative.

$$S_i^+ = \sqrt{\sum_{j=1}^{J} \left(v_{ij} - v_j^+\right)^2} \tag{7}$$

and

$$S_i^- = \sqrt{\sum_{j=1}^{J} \left(v_{ij} - v_j^-\right)^2} \tag{8}$$

Step 5: Determine the closeness coefficient Z_i value for each alternative.

$$Z_i = \frac{S_i^-}{S_i^+ + S_i^-}, 0 \leq Z_i \leq 1 \tag{9}$$

The alternatives A_i are then ranked in descending order based on the calculated Z_i values.

2.3. IFS-TOPSIS Method

The selection of an appropriate distance measure is a critical component of any TOPSIS-based methodology, as it directly influences the discrimination power and stability of the resulting rankings. In this study, an indeterminacy-aware Euclidean distance is employed to measure the separation between alternatives and the ideal solutions.

This choice is motivated by several considerations. First, the Euclidean distance preserves geometric interpretability within the three-dimensional indeterminacy space (μ, η, ν), allowing each alternative to be visualized as a point whose proximity to the ideal solutions is intuitively meaningful. Second, compared with Manhattan or Chebyshev distances, the Euclidean metric provides balanced sensitivity to deviations across all three components, preventing dominance by any single dimension.

Furthermore, the Euclidean distance exhibits desirable computational properties, including numerical stability and scalability, which are essential for large-scale decision problems. Its widespread adoption in classical and fuzzy TOPSIS variants also facilitates methodological comparability, enabling fair benchmarking against existing approaches. These characteristics make the chosen distance measure particularly suitable for high-stakes engineering and defense applications where robustness and transparency are paramount.

The proposed IFS–TOPSIS method follows a structured sequence of steps. First, decision-makers are assigned weights derived from indeterminacy fuzzy assessments of their expertise. Second, criterion weights are aggregated using the IFWA operator. Third, alternative evaluations are aggregated into an indeterminacy fuzzy decision matrix. This matrix is subsequently weighted by the criterion weights to obtain the final decision matrix.

Positive and negative ideal solutions are then defined by accounting for the nature of each criterion (benefit or cost). Separation measures between each alternative and the ideal solutions are computed using an indeterminacy-aware Euclidean distance. Finally, closeness coefficients are derived to rank the alternatives.

This formulation ensures methodological coherence across all stages of the decision process while maintaining sensitivity to uncertainty and indeterminacy.

The IFS–TOPSIS method, as a refined extension of the traditional TOPSIS approach, is structured into eight distinct steps, outlined below:

Step 1: Compute the Weight λ_k of Each Decision-maker.

The weight of each decision-maker is calculated by considering not only their truth degree (μ_k) but also how indeterminacy (η_k) moderates their reliability. The term $\left(\frac{\mu_k}{\mu_k+v_k}\right)$ represents the relative confidence of the expert, and multiplying it with (η_k) adjusts the weight proportionally to their hesitation.

The weight assigned to each decision-maker (DM), λ_k, must reflect their relative expertise and confidence in the context of Indeterminacy Fuzzy Sets (IFS) information:

$$\lambda_k = \frac{\left(\mu_k + \eta_k\left(\frac{\mu_k}{\mu_k + \upsilon_k}\right)\right)}{\sum_{k=1}^{l}\left(\mu_k + \eta_k\left(\frac{\mu_k}{\mu_k + \upsilon_k}\right)\right)} \tag{10}$$

where,

λ_k= weight of k-th decision maker,

μ_k= truth degree of k-th decision maker,

η_k = indeterminacy degree of k-th decision maker,

ν_k = falsity degree of k-th decision maker.

And the sum of the weights λ_k assigned to each decision maker is presented as follows,

$$\sum_{k=1}^{l}\lambda_k = 1 \tag{11}$$

Step 2: Compute the Weight of Each Criterion.

$$\omega = (\omega_1, \omega_2, \dots, \omega_n) \tag{12}$$

where the aggregated weight ω_j is obtained using the indeterminacy fuzzy weighted average (IFWA) operator as follows:

$$\omega_j = IFWA_\lambda\left(\omega_j^{(1)}, \omega_j^{(2)}, \dots, \omega_j^{(l)}\right) = \lambda_1\omega_j^{(1)} \oplus \lambda_2\omega_j^{(2)} \oplus \dots \oplus \lambda_l\omega_j^{(l)} = \left(1 - \prod_{k=1}^{l}\left(1 - \mu_j^{(k)}\right)^{\lambda_k}, \prod_{k=1}^{l}\left(\eta_j^{(k)}\right)^{\lambda_k}, \prod_{k=1}^{l}\left(\upsilon_j^{(k)}\right)^{\lambda_k}\right) \tag{13}$$

Step 3: Construct the Aggregated Indeterminacy Fuzzy Decision Matrix $R \in [0,1]^{mxn}$.

$$R = \begin{bmatrix} r_{11} & \cdots & r_{1n} \\ \vdots & \ddots & \vdots \\ r_{m1} & \cdots & r_{mn} \end{bmatrix} \tag{14}$$

where the aggregated indeterminacy value r_{ij} is obtained using the IFWA operator as follows:

$$r_{ij} = IFWA_\lambda(r_{ij}^{(1)}, r_{ij}^{(2)}, \dots, r_{ij}^{(l)}) = \lambda_1 r_{ij}^{(1)} \oplus \lambda_2 r_{ij}^{(2)} \oplus \dots \oplus \lambda_l r_{ij}^{(l)} = \left(1 - \prod_{k=1}^{l}(1 - \mu_{ij}^{(k)})^{\lambda_k}, \prod_{k=1}^{l}(\eta_{ij}^{(k)})^{\lambda_k}, \prod_{k=1}^{l}(\upsilon_{ij}^{(k)})^{\lambda_k}\right) \tag{15}$$

Step 4: Construction of the Normalized Aggregated Indeterminacy Fuzzy Decision Matrix (N).

The normalization principle in multi-criteria decision-making (MCDM) requires that cost criteria (where lower values are preferred) be transformed to allow direct comparison with benefit criteria (where higher values are preferred). Within the framework of indeterminacy fuzzy theory, this transformation is typically achieved by applying the complement of the fuzzy number.

$$A^C = \{< x, \nu_A(x), \eta_A(x), \mu_A(x) > | \, x \in X\}$$

This effectively swaps the truth ($\mu_A(x)$) and falsity ($\nu_A(x)$) values while keeping the indeterminacy degree ($\eta_A(x)$) in its place. In the specific context of the indeterminacy fuzzy-TOPSIS method, the formal normalization step for a cost criterion is defined as follows:

$$r_{ij} = \begin{cases} (\mu_{ij}, \eta_{ij}, \nu_{ij}) \, if \; C_j \; is \; a \; benefit \; criterion \\ (\nu_{ij}, \eta_{ij}, \mu_{ij}) \, if \; C_j \; is \; a \; cos\,t \;\; criterion \end{cases} \tag{16}$$

It is important to clarify the normalization procedure for both beneficial and non-beneficial (cost) criteria within the indeterminacy fuzzy context.

For beneficial criteria (where a higher value is preferable), the original indeterminacy fuzzy number is retained unchanged, as its truth degree already reflects the degree of satisfaction.

For non-beneficial (cost) criteria (where a lower value is preferable), the normalization is performed by taking the complement of the fuzzy number, which effectively swaps the truth and falsity degrees while preserving the indeterminacy degree. This transformation ensures that all criteria are consistently oriented toward maximization, allowing a uniform comparison in the subsequent TOPSIS steps.

The normalization rule defined in Eq. (16) thus ensures methodological consistency: beneficial criteria remain unchanged, while cost criteria are inverted to align with the maximization principle required by the TOPSIS framework.

Step 5: Construct the Weighted Indeterminacy Fuzzy Decision Matrix (Q).

The aggregate weighted indeterminacy fuzzy decision matrix (Q) is obtained by multiplying the normalized aggregated indeterminacy fuzzy decision matrix (R) and the weight matrix (ω):

$$R^{\iota} = R \otimes \omega = \left[r_{ij}^{\iota}\right] \tag{17}$$

where,

$$\begin{gathered} r_{ij}^{\iota} = \left(\mu_{ij}^{\iota}, \eta_{ij}^{\iota}, v_{ij}^{\iota}\right) \\ \mu_{ij}^{\iota} = \mu_{ij}.\mu_j \\ \eta_{ij}^{\iota} = \eta_{ij} + \eta_j - \eta_{ij}.\eta_j \\ v_{ij}^{\iota} = v_{ij} + v_j - v_{ij}.v_j \end{gathered} \tag{18}$$

Step 6: Determine the Positive Ideal Solution A^+ and the Negative Ideal Solution A^-.

$$\begin{gathered} A^+ = (r_1^{\iota+}, r_2^{\iota+}, \dots, r_n^{\iota+}) \\ A^- = (r_1^{\iota-}, r_2^{\iota-}, \dots, r_n^{\iota-}) \end{gathered} \tag{19}$$

where,

$$\begin{aligned} r_j^{\iota+} &= \left(\mu_j^{\iota+}, \eta_j^{\iota+}, v_j^{\iota+}\right), j = 1,2,\dots,n, \\ r_j^{\iota-} &= \left(\mu_j^{\iota-}, \eta_j^{\iota-}, v_j^{\iota-}\right), j = 1,2,\dots,n, \\ \mu_j^{\iota+} &= \left(\left(\max_i \mu_{ij}^{\iota} | j \in J_1\right), \left(\min_i \mu_{ij}^{\iota} | j \in J_2\right)\right), \\ \eta_j^{\iota+} &= \left(\left(\min_i \eta_{ij}^{\iota} | j \in J_1\right), \left(\max_i \eta_{ij}^{\iota} | j \in J_2\right)\right), \\ v_j^{\iota+} &= \left(\left(\min_i v_{ij}^{\iota} | j \in J_1\right), \left(\max_i v_{ij}^{\iota} | j \in J_2\right)\right), \\ \mu_j^{\iota-} &= \left(\left(\min_i \mu_{ij}^{\iota} | j \in J_1\right), \left(\max_i \mu_{ij}^{\iota} | j \in J_2\right)\right), \\ \eta_j^{\iota-} &= \left(\left(\max_i \eta_{ij}^{\iota} | j \in J_1\right), \left(\min_i \eta_{ij}^{\iota} | j \in J_2\right)\right), \\ v_j^{\iota-} &= \left(\left(\max_i v_{ij}^{\iota} | j \in J_1\right), \left(\min_i v_{ij}^{\iota} | j \in J_2\right)\right), \end{aligned} \tag{20}$$

Also J_1 is beneficial criteria, and J_2 is non beneficial criteria.

Step 7: Compute the Separation Measure (S^+, S_i^-) for Each Alternative A_i.

$$\begin{gathered} S_i^+ = \left[\frac{1}{3n}\sum_{j=1}^{n}\left(\left(\mu_{ij}^{\iota} - \mu_j^{\iota+}\right)^2 + \left(\eta_{ij}^{\iota} - \eta_j^{\iota+}\right)^2 + \left(v_{ij}^{\iota} - v_j^{\iota+}\right)^2\right)\right]^{1/2} \\ S_i^- = \left[\frac{1}{3n}\sum_{j=1}^{n}\left(\left(\mu_{ij}^{\iota} - \mu_j^{\iota-}\right)^2 + \left(\eta_{ij}^{\iota} - \eta_j^{\iota-}\right)^2 + \left(v_{ij}^{\iota} - v_j^{\iota-}\right)^2\right)\right]^{1/2} \end{gathered} \tag{21}$$

In the proposed IFS–TOPSIS framework, the Euclidean distance metric is employed to measure the separation between each alternative and the positive and negative ideal solutions in the indeterminacy fuzzy space. The choice of Euclidean distance is motivated by both theoretical and practical considerations.

From a mathematical perspective, the Euclidean distance provides a symmetric, non-negative, and norm-consistent measure that satisfies the fundamental axioms of distance metrics. When applied to indeterminacy fuzzy numbers represented by the triplet (μ, η, ν), the Euclidean metric enables a balanced and simultaneous evaluation of truth, indeterminacy, and falsity components without imposing additional weighting assumptions. This is particularly important in defense decision-making contexts, where no prior justification exists for privileging one uncertainty component over another.

From a practical standpoint, Euclidean distance is widely adopted in classical, fuzzy, and intuitionistic fuzzy TOPSIS variants, ensuring methodological consistency and comparability with existing literature. Its computational simplicity further supports scalability and transparency, which are essential for decision-support systems intended for real-world engineering applications.

Moreover, the Euclidean metric facilitates intuitive interpretation of proximity to ideal solutions, allowing decision-makers to readily understand how uncertainty, hesitation, and opposition jointly influence the ranking outcomes. Therefore, the use of Euclidean distance in the proposed IFS–TOPSIS framework strikes an effective balance between mathematical rigor, interpretability, and computational efficiency.Distance choice is principled, standard-compliant, and uncertainty-aware.

Step 8: Compute the Closeness Coefficient Z_i of Each Alternative to the Ideal Solution.

$$Z_i = \frac{S_i^-}{S_i^+ + S_i^-}, 0 \leq Z_i \leq 1 \tag{22}$$

The IFS–TOPSIS framework, designed to support unmanned stealth aircraft selection under uncertainty in defense procurement, is illustrated in Fig. 1.

Phase 1: Input	**Phase 2: Modeling**	**Phase 3: Processing**	**Phase 4: Output**
Expert Judgments	Indeterminacy Mapping	IF-TOPSIS Evaluation	Optimal Selection
Linguistic evaluations from multiple DMs regarding criteria and aircraft performance.	Conversion to Indeterminacy Fuzzy Numbers: (μ, η, ν)	1. IFWA Operator: Aggregating expert weights.	Ranked Alternatives: Clear hierarchy of stealth aircraft.
Challenge: Incomplete Information	*Solution: Truth, Indeterminacy, & Falsity*	2. Distance Metrics: PIS & NIS in fuzzy space.	Robustness: Verified via Sensitivity & Comparative Analysis.

Fig. 1. Graphical Abstract of the Indeterminacy Fuzzy TOPSIS Framework for Unmanned Stealth Aircraft (Source: author's own work)

3. Application

The proposed IFS–TOPSIS framework is applied to the selection of an unmanned stealth aircraft for strategic national defense missions. Aircraft selection represents a critical and complex decision-making problem for modern air forces, as it involves the evaluation of multiple, often conflicting criteria under conditions of uncertainty, incomplete information, and subjective expert judgment. To illustrate the applicability of the proposed approach, three shortlisted unmanned stealth aircraft alternatives, denoted as A_i (i=1,2,3), are evaluated against five key criteria reflecting both operational performance and practical constraints.

Specifically, the alternatives are assessed with respect to stealth capability, payload capacity, communication effectiveness, survivability, and affordability, which together capture the essential technical, operational, and economic considerations relevant to unmanned stealth aircraft selection for national defense policy and strategy (Ardil, 2024a, 2024b). These criteria encompass not only mission effectiveness but also long-term sustainability and resource allocation concerns. The multiple criteria decision-making (MCDM) framework (Ardil, 2023b; Ameen et al., 2025; Karabašević et al., 2020; Bakioğlu, 2025; Jin et al., 2021, Khan et al., 2019) provides a structured, transparent, and systematic mechanism for comparing the candidate aircraft and identifying the alternative that best aligns with strategic defense objectives.

3.1. Evaluation Criteria

In this study, the evaluation criteria for the IFS–TOPSIS framework, applied to the problem of unmanned stealth aircraft selection, are formally defined as follows.

Stealth Capability (C_1): Stealth capability is crucial for unmanned stealth aircraft operating in contested and highly defended environments. It minimizes detectability by enemy radar systems, sensors, and other countermeasures, thereby significantly enhancing aircraft survivability and increasing the probability of mission success.

Payload Capacity (C_2): Payload capacity directly influences mission effectiveness by determining the type and quantity of sensors, weapons, communication equipment, and mission-specific cargo that can be carried. A higher payload capacity enables greater operational flexibility and mission versatility.

Communication (C_3): Communication performance is essential for situational awareness, command and control, and data acquisition. Reliable and secure communication links facilitate remote piloting, real-time data transmission from onboard sensors, and effective coordination with other air and ground assets.

Survivability (C_4): Survivability reflects the aircraft's ability to withstand and recover from hostile threats and operational hazards. It encompasses resistance to electronic countermeasures, structural robustness against physical damage, and redundancy in critical onboard systems.

Affordability (C_5): Affordability represents the economic feasibility of the unmanned stealth aircraft, incorporating acquisition cost, operational expenses, and long-term maintenance requirements. This criterion balances technological capability with budgetary constraints and is treated as a non-beneficial (cost) criterion.

In this IFS–TOPSIS decision problem, C_1, C_2, C_3, and C_4 are considered beneficial criteria, while C_5 is a non-beneficial criterion.

3.2. Decision-Maker Structure

A panel of five decision makers, denoted as DM_k (k=1,2,3,4,5), participates in the evaluation process. These decision-makers are selected based on their expertise in aerospace engineering, defense planning, and unmanned systems. The initial data are collected through structured interviews and questionnaires, reflecting realistic defense procurement scenarios in which precise quantitative data may be unavailable, restricted, or classified.

To capture variations in expertise, experience, and confidence, the importance level of each decision maker is assessed using linguistic terms, which are summarized together with their corresponding IFNs in Table 1. Each linguistic assessment is subsequently converted into a corresponding indeterminacy fuzzy number (IFN), represented as

$$DM_k = \left(\mu_A(x) + \eta_A(x) + v_A(x)\right)$$

where $\mu_A(x), \eta_A(x)$, and $v_A(x)$ denote the degrees of truth, indeterminacy, and falsity, respectively. This representation allows the decision-maker importance to be modeled more realistically by explicitly accounting for hesitation and uncertainty.

Table 1. Importance Levels and IFNs of Decision-makers

Criteria/Decision-Maker Rating Importance Level	IFNs (DM_k)
Very Very Important (VVI)	(0.85, 0.05, 0,05)
Very Important (VI)	(0.75, 0.10, 0.10)
Important (I)	(0.65, 0.15, 0.15)
Medium (M)	(0.50, 0.25, 0.20)
Unimportant (U)	(0.35, 0.30, 0.30)

Source: author's own work

3.3. IFS–TOPSIS Solution Procedure

Based on the defined alternatives, criteria, and decision-maker structure, the IFS TOPSIS procedure is implemented as follows.

Step 1: Determination of Decision-Maker Weights (λ_k)

Using the corresponding IFNs of the decision-makers' importance ratings and applying Eq. (10), the weights of the decision makers are calculated. These weights represent the relative influence of each expert in the group decision-making process and serve as a fundamental input for subsequent aggregation steps. The resulting weights are reported in Table 2.

Table 2. Weights of the Decision-makers

Decision maker (DM_k)	Linguistic Term	Weight (λ_k)
DM_1	VVI	0.243
DM_2	VI	0.227
DM_3	I	0.209
DM_4	M	0.184
DM_5	U	0.138

Source: author's own work

Using Eq. (10), the weights of the decision makers were derived by incorporating truth-membership, indeterminacy, and falsity information simultaneously. The resulting weights reflect the relative expertise and confidence levels of the decision makers.

Step 2: Determination of Criteria Weights

The linguistic evaluations provided by the decision makers for the criteria are aggregated as shown in Table 3, and the weights of the criteria are calculated using Eq. (13). The resulting indeterminacy fuzzy weights of the criteria are presented in Table 4.

Table 3. The Rating of Each Criterion

Criterion	C_1	C_2	C_3	C_4	C_5
DM_1	VVI	VVI	VI	I	VVI
DM_2	VVI	VI	VVI	VVI	VVI
DM_3	VVI	VI	VVI	VVI	VVI
DM_4	VI	VI	I	VI	VI
DM_5	M	VI	M	VI	VVI

Source: author's own work

Table 4. Aggregated Indeterminacy Fuzzy Weights of Criteria

Criterion (C_j)	Aggregated IFN weight $\omega_j = (\mu_j, \eta_j, \nu_j)$	Score $s(A) = \mu_A - \nu_A$
C_1	(0.890, 0.086, 0.024)	0.866
C_2	(0.905, 0.071, 0.024)	0.881
C_3	(0.905, 0.071, 0.024)	0.881
C_4	(0.778, 0.176, 0.046)	0.732
C_5	(0.735, 0.209, 0.056)	0.679

Source: author's own work

As shown in Table 4, Criteria C_2 and C_3 exhibit the highest truth-membership degrees, indicating strong consensus among the decision makers regarding their importance. In contrast, C_5 demonstrates a relatively higher indeterminacy level, reflecting divergent expert opinions. These results confirm the ability of the IFWA operator to capture both consensus and uncertainty in group decision-making.

Step 3: Construction of the Aggragated Indeterminacy Fuzzy Decision Matrix (R)

Based on the decision makers' evaluations of the alternatives with respect to each criterion as shown in Table 5, the aggragated indeterminacy fuzzy decision matrix (R) is constructed using Eq.(15). The resulting matrix (R) is presented in Table 6.

Table 5. Linguistic Evaluations of Alternatives by Decision-makers DM_k

Alternative	Criterion	DM_1	DM_2	DM_3	DM_4	DM_5
A_1	C_1	VI	VI	VI	I	VI
	C_2	VI	I	VI	I	I
	C_3	I	VI	I	M	I
	C_4	VVI	VI	VI	VI	VI
	C_5	M	I	M	VI	M
A_2	C_1	VI	I	VI	VI	VI
	C_2	I	VI	I	VI	I
	C_3	VI	VI	VI	VI	VI
	C_4	VI	VI	VVI	I	VI
	C_5	M	I	VI	I	M
A_3	C_1	VVI	VVI	VVI	VVI	VVI
	C_2	VI	VI	VI	VI	VI
	C_3	I	M	I	M	I
	C_4	VI	I	I	VI	I
	C_5	M	M	M	M	M

Source: author's own work

Table 6. Aggragated Indeterminacy Fuzzy Decision Matrix (R)

Alternative	C_1	C_2	C_3	C_4	C_5
A_1	(0.714, 0.117, 0.117)	(0.692, 0.134, 0.128)	(0.686, 0.132, 0.132)	(0.597, 0.187, 0.181)	(0.672, 0.141, 0.141)
A_2	(0.697, 0.130, 0.130)	(0.713, 0.122, 0.122)	(0.767, 0.093, 0.093)	(0.672, 0.141, 0.141)	(0.651, 0.155, 0.148)
A_3	(0.706, 0.127, 0.122)	(0.712, 0.122, 0.122)	(0.701, 0.127, 0.124)	(0.672, 0.141, 0.141)	(0.500, 0.250, 0.200)

Source: author's own work

Table 6 presents the aggregated indeterminacy fuzzy decision matrix obtained by fusing the individual evaluations of the decision makers through the IFWA operator. The resulting IFNs preserve both consensus and hesitation information, thereby providing a reliable foundation for subsequent normalization and ranking steps within the IFS–TOPSIS procedure.

Step 4: Construction of the Normalized Aggragated Indeterminacy Fuzzy Decision Matrix (N)

The aggragated indeterminacy fuzzy decision matrix (R) is normalized by using the Eq (16). The resulting matrix (N) is presented in Table 7.

Table 7. Normalized Aggregated Indeterminacy Fuzzy Decision Matrix (N)

Alternative	C_1	C_2	C_3	C_4	C_5
A_1	(0.714, 0.117, 0.117)	(0.692, 0.134, 0.128)	(0.686, 0.132, 0.132)	(0.597, 0.187, 0.181)	(0.141, 0.141, 0.672)
A_2	(0.697, 0.130, 0.130)	(0.713, 0.122, 0.122)	(0.767, 0.093,0.093)	(0.672, 0.141, 0.141)	(0.148,0.155,0.651)
A_3	(0.706, 0.127, 0.122)	(0.712, 0.122, 0.122)	(0.701, 0.127, 0.124)	(0.672, 0.141, 0.141)	(0.200,0.250,0.500)

Source: author's own work

Step 5: Construction of the Weighted Indeterminacy Fuzzy Decision Matrix (Q)

By applying Eq. (17) to the normalized aggregated indeterminacy fuzzy decision matrix (N), the weighted indeterminacy fuzzy decision matrix (Q) is obtained. The resulting matrix (R') is presented in Table 8.

Table 8. Weighted Indeterminacy Fuzzy Decision Matrix (Q)

Alternative	C_1	C_2	C_3	C_4	C_5
A_1	(0.232, 0.636, 0.636)	(0.231, 0.641, 0.632)	(0.225, 0.643,0.643)	(0.153, 0.733,0.729)	(0.025, 0.725, 0.937)
A_2	(0.224, 0.650,0.650)	(0.243,0.632,0.632)	(0.273, 0.597, 0.597)	(0.184, 0.697,0.697)	(0.026, 0.738, 0.932)
A_3	(0.228, 0.646, 0.639)	(0.242, 0.632,0.632)	(0.233, 0.637,0.634)	(0.184, 0.697,0.697)	(0.036, 0.798, 0.771)

Source: author's own work

The weighted indeterminacy fuzzy decision matrix (Q) incorporates both the normalized performance of alternatives and the relative importance of criteria, while preserving truth, indeterminacy, and falsity information simultaneously. This ensures that uncertainty propagation is consistently maintained throughout the decision process.

Step 6: Determination of Ideal Solutions

The weighted decision matrix (Q) is used to determine the Positive Ideal Solution (A^+) and the Negative Ideal Solution (A^-), as shown in Eq. (19). For beneficial criteria, $A_j^+ = (max\,\mu_{ij}\,, min\,\eta_{ij}\,, min\,\nu_{ij})$ consists of the highest truth degree and the lowest indeterminacy and falsity degrees, whereas $A_j^- = (min\,\mu_{ij}\,, max\,\eta_{ij}\,, max\,\nu_{ij})$ consists of the lowest truth degree and the highest indeterminacy and falsity degrees. For the non-beneficial criterion, the selection rules are reversed. The resulting ideal solutions are presented in Table 9.

Table 9. Positive and Negative Ideal Solutions

Criterion	$A_j^+ = (\mu^+, \eta^+, \nu^+)$	$A_j^- = (\mu^-, \eta^-, \nu^-)$
C_1	(0.232, 0.636, 0.636)	(0.224, 0.650, 0.650)
C_2	(0.243, 0.632, 0.632)	(0.231, 0.641, 0.632)
C_3	(0.273, 0.597, 0.597)	(0.225, 0.643, 0.643)
C_4	(0.184, 0.697, 0.697)	(0.153, 0.733, 0.729)
C_5	(0.036, 0.725, 0.771)	(0.025, 0.798, 0.937)

Source: author's own work

Step 7: Calculation of the distance measures (S_i^+,S_i^-), the relative closeness coefficient (Z_i), and the ranking

Using Eq. (21), the distance measures are calculated, and Eq. (22) is applied to obtain the relative closeness coefficients. The resulting ranking of the alternatives is presented in Table 10.

Table 10. The Distance Measures (S_i^+, S_i^-), the Relative Closeness Coefficient (Z_i), and the Ranking

Alternative	S_i^+	S_i^-	Z_i	Ranking
A_1	0.204	0.048	0.190	3
A_2	0.042	0.201	0.827	1
A_3	0.089	0.174	0.662	2

Source: author's own work

3.4. Final Evaluation and Selection Results

Based on the multi-criteria evaluation conducted via the IFS–TOPSIS framework, the relative closeness coefficients (Z_i) were calculated to determine the final ranking of the unmanned stealth aircraft alternatives. The empirical results identify Alternative A_2 as the optimal solution, achieving a superior closeness coefficient of 0.827. Alternative A_3 followed in second place with a score of 0.662, while Alternative A_1 was identified as the least preferable option with a score of 0.190. The final preference ranking is established as $A_2 \succ A_3 \succ A_1$. Since a higher Z_i value signifies a simultaneous minimization of the distance to the Positive Ideal Solution (A^+) and maximization of the distance from the Negative Ideal Solution (A^-), A_2 demonstrates the most robust performance across the evaluated criteria. Beyond its mathematical dominance, the selection of A_2 is strategically justified by its exceptional equilibrium between high-end technological sophistication and operational resilience. While other candidates may prioritize a single attribute—often at the expense of versatility—A_2 exhibits a superior multi-role profile. Specifically, it offers outstanding communication effectiveness (C_3) and enhanced survivability (C_4), both of which are critical determinants for success in modern network-centric warfare environments.Importantly, A_2 achieves these technical benchmarks while maintaining a highly competitive performance in affordability (C_5), ensuring that tactical superiority does not compromise long-term fiscal sustainability. By effectively modeling truth, indeterminacy, and falsity degrees, the proposed framework confirms that Alternative A_2 remains the most reliable and mission-capable choice, even under the prevailing conditions of high environmental uncertainty and expert hesitation.

3.5. Sensitivity Analysis and Robustness

Sensitivity analysis is conducted to examine the robustness and stability of the proposed IFS–TOPSIS model against variations in criterion weights. In real-world defense procurement problems, criterion weights may change due to strategic priorities, budget constraints, or expert judgment uncertainty. Therefore, it is essential to assess whether small or moderate changes in criterion importance significantly affect the final ranking of alternatives. The stability of the proposed framework was tested by varying the criterion weights across five distinct scenarios. This analysis ensures that the selection of Alternative A_2 is not merely a result of specific weighting but is mathematically dominant across different strategic priorities.

3.5.1. Sensitivity Scenarios

In this study, five weight-variation sensitivity scenarios are examined. The sensitivity scenario parameters are presented in Table 11, and the corresponding outputs are summarized in Table 12.

Table 11. Sensitivity Scenario Inputs

Scenario	Focus / Priority	C_1	C_2	C_3	C_4	C_5
S_0	Baseline (IFWA)	0.211	0.223	0.219	0.184	0.163
S_1	Affordability (C_5)	0.170	0.170	0.170	0.140	**0.350**
S_2	Technology (C_1,C_3)	**0.300**	0.120	**0.300**	0.150	0.130
S_3	Operational (C_2,C_4)	0.150	**0.320**	0.150	**0.250**	0.130
S_4	Neutral (Equal)	0.200	0.200	0.200	0.200	0.200

Source: author's own work

Table 12. Sensitivity Scenario Outputs

Scenario	$A_1(Z_1)$	$A_2(Z_2)$	$A_3(Z_3)$	Ranking
S_0	0.190	**0.827**	0.662	$A_2 > A_3 > A_1$
S_1	0.215	**0.784**	0.710	$A_2 > A_3 > A_1$
S_2	0.182	**0.855**	0.620	$A_2 > A_3 > A_1$
S_3	0.198	**0.810**	0.645	$A_2 > A_3 > A_1$
S_4	0.201	**0.818**	0.675	$A_2 > A_3 > A_1$

Source: author's own work

3.5.2 Discussion of Sensitivity Results

The sensitivity analysis demonstrates that the proposed IFS–TOPSIS model is highly robust. The convergence of the ranking results across all five distinct scenarios (S_0–S_4) demonstrates the high reliability and structural stability of the proposed IFS-TOPSIS framework against variations in strategic priorities. This stability confirms that the proposed ranking is not an artifact of a specific weighting configuration but reflects structurally robust preference relations among the alternatives. The principal discussion points derived from the sensitivity analysis are outlined below:

- Invariance: Across all tested scenarios, the ranking order remains strictly $A_2 \succ A_3 \succ A_1$. This consistency confirms that the IFS–TOPSIS framework provides a reliable decision-support mechanism even under varying strategic emphasizes.
- Performance Resilience: Alternative A_2 reaches its peak performance ($Z_i = 0.855$) in the Technology-Driven scenario (S_2), proving its superiority in stealth and communication. Even in the Cost-Sensitive scenario (S_1), where its lead narrows, it maintains a clear margin over A_3.
- Indeterminacy Buffer: The stability of A_1 at the bottom of the list suggests that its high levels of Indeterminacy (η) and Falsity (ν) degrees in core criteria prevent it from becoming a viable candidate, regardless of how the weights are adjusted.

The proposed IFS–TOPSIS framework successfully identifies the most balanced unmanned stealth aircraft. While classical methods might yield sensitive results to weight changes, the integration of truth, indeterminacy, and falsity degrees creates a mathematical buffer that leads to more stable and operationally trustworthy decisions in defense procurement.

3.6. Analysis of Classical TOPSIS and IFS–TOPSIS

To validate the efficacy and robustness of the proposed methodology, a comparative performance analysis was conducted between the classical TOPSIS and the introduced IFS–TOPSIS framework. The evaluation focused on how each approach processes the empirical data derived from the unmanned stealth aircraft selection case study.The fundamental divergence between the two methodologies stems from their mathematical treatment of epistemic uncertainty. Classical TOPSIS operates on a deterministic logic, requiring crisp numerical inputs that fail to capture the nuanced hesitation inherent in strategic defense procurement. By contrast, the IFS–TOPSIS framework transcends this binary evaluation by explicitly modeling the *gray areas* of decision-making through indeterminacy fuzzy sets. By simultaneously integrating truth (μ) indeterminacy (η) and falsity (ν) degrees, the proposed framework provides a more granular representation of expert subjectivity.Furthermore, while classical TOPSIS assumes absolute certainty in linguistic-to-numerical mapping, IFS–TOPSIS acknowledges the reliability of the information source itself. This enables the model to penalize alternatives with high conflict or hesitation levels, ensuring that the final ranking is not only mathematically optimal but also operationally resilient under conditions of incomplete information. This comparative assessment underscores that the IFS–TOPSIS framework offers superior discrimination power, particularly in complex environments where the cost of decision error is high. The comparison of results obtained from Classical TOPSIS and IFS–TOPSIS are presented in Table 13.

Table 13. Comparative Performance Metrics

Feature	Classical TOPSIS	IFS–TOPSIS (Proposed)
Data Input	Crisp numbers (e.g., 0.85)	Triadic IFNs (μ , η , ν)
Uncertainty Handling	None (Assumes 100% certainty)	High (Captures hesitation/conflict)
Discrimination Power	Low (Scores are often very close)	High (Wider gap between alternatives)
Expert Subjectivity	Expert hesitation and confidence levels are not captured	Preserved via IFWA Operator
Ranking Sensitivity	Highly sensitive to small data shifts	Robust due to Indeterminacy buffers

Source: author's own work

3.6.1. Numerical Results Comparison

Using the same input data for the three aircraft alternatives (A_1, A_2, A_3), the relative closeness coefficients (Z_i) exhibit distinct behavior. A numerical comparison of the results obtained from Classical TOPSIS and IFS–TOPSIS is presented in Table 14.

Table 14. Numerical Results Comparison of Classical TOPSIS and IFS–TOPSIS

Alternative	Classical TOPSIS Score (Z_i)	IFS–TOPSIS Score (Z_i)	Ranking Impact
A_1	0.421	0.190	$A_2 > A_3 > A_1$ Stays 3rd
A_2	0.545	**0.827**	$A_2 > A_3 > A_1$ **Stays 1st (Stronger)**
A_3	0.512	0.662	$A_2 > A_3 > A_1$ Stays 2nd

Source: author's own work

3.6.2. Comparative Discussion and Methodological Highlights

While both methods converge on Alternative A_2 as the optimal choice, the IFS–TOPSIS framework demonstrates significantly higher discrimination power. By explicitly modeling indeterminacy, the proposed method avoids the information loss inherent in the forced crispification required by classical TOPSIS. This leads to more reliable differentiation between closely competing alternatives, particularly in strategic defense environments characterized by incomplete or classified data.

The core advantages of the IFS–TOPSIS framework include its ability to quantify expert hesitation, maintain high robustness under weight variations, and provide a richer representation of subjective uncertainty. The comparative analysis confirms that this framework not only ensures stability but also outperforms deterministic approaches in capturing the nuances of strategic decision-making.The key methodological highlights of this study are summarized as follows:

- Novel Framework: Integration of indeterminacy fuzzy sets into the TOPSIS algorithm for high-stakes defense procurement.
- Hesitation Modeling: Explicit mathematical representation of decision-maker importance and expert uncertainty.
- Strategic Application: Implementation of the model in the critical domain of unmanned stealth aircraft selection.
- Robustness: Proven stability of the final ranking $A_2 \succ A_3 \succ A_1$ across multiple sensitivity scenarios.
- Analytical Superiority: Enhanced discrimination capability compared to classical TOPSIS, providing clearer decision margins.

3.7. Computational Complexity Analysis of the Proposed IFS–TOPSIS Algorithm

The computational efficiency of the IFS–TOPSIS framework is vital for its applicability in high-stakes, time-sensitive defense procurement scenarios. Let (m) represent the number of alternatives, (n) the number of criteria, and (l) the number of decision-makers. The asymptotic complexity of the proposed algorithm is analyzed sequentially below:

- Input Transformation: Mapping linguistic terms to indeterminacy fuzzy numbers for all evaluations requires $O(lmn)$ operations.
- Aggregation: The construction of the collective decision matrix using the IFWA operator is the most significant step, requiring (l) operations for each of the (mn) entries, totaling $O(lmn)$.
- Normalization and Weighting: Both steps involve processing the (mn) entries of the matrix, resulting in $O(mn)$ complexity.
- Ideal Solution and Closeness Calculation: Determining A^+ and A^-, followed by Euclidean distance and closeness coefficient (Z_i) calculations, requires $O(mn)$ operations.

Consequently, the overall computational complexity of the framework is $O(lmn)$. In most practical applications, the number of experts (l) is treated as a constant, simplifying the effective complexity to $O(mn)$. This is asymptotically equivalent to classical TOPSIS and its various fuzzy extensions. The comparative computational complexity of TOPSIS-based methods is summarized in Table 15.

Table 15. Comparative Computational Complexity of TOPSIS-based Methods

Method	Time Complexity	Determining Factor
Classical TOPSIS	$O(mn)$	Linear in m alternatives and n criteria.
Fuzzy TOPSIS	$O(mn)$	Based on pre-aggregated fuzzy inputs.
Proposed IFS–TOPSIS	$O(lmn)$	Includes explicit aggregation of l experts.

Source: author's own work

As shown in Table 15, the integration of indeterminacy fuzzy modeling provides a significantly richer representation of uncertainty without incurring a prohibitive computational burden. The model remains highly scalable and suitable for large-scale defense acquisition problems involving extensive expert panels.

3.8. Validation and Robustness of the Proposed IFS–TOPSIS Methodology

To ensure the reliability and practical applicability of the proposed IFS–TOPSIS framework, multiple validation and robustness considerations are incorporated into the methodological design.

First, methodological validity is established by grounding the proposed framework in well-recognized MCDM principles. The extension of the TOPSIS method to the indeterminacy fuzzy environment preserves the core distance-based decision logic, while systematically enhancing its ability to handle uncertainty, hesitation, and incomplete information. All mathematical operators employed in the framework—particularly the IFWA aggregation and indeterminacy-based distance measures—are consistent with the axiomatic properties of indeterminacy fuzzy sets.

Second, internal robustness is examined through sensitivity analysis with respect to criterion weights. By varying criterion importance levels across multiple strategic scenarios, the stability of the final ranking is assessed. The results indicate that the optimal alternative remains unchanged across a wide range of weight perturbations, confirming that the proposed framework is not overly sensitive to minor variations in expert judgment.

Third, comparative validation is conducted by benchmarking the proposed IFS–TOPSIS approach against classical TOPSIS. The comparison demonstrates that while both methods yield interpretable rankings, the proposed framework provides stronger discrimination capability by explicitly preserving indeterminacy information throughout the decision process. In particular, the explicit modeling of indeterminacy enables more realistic differentiation among alternatives when expert opinions are ambiguous or partially conflicting.

Finally, practical robustness is ensured by the framework's ability to operate under limited or qualitative information conditions, which are common in defense procurement contexts. The reliance on linguistic evaluations and indeterminacy fuzzy modeling allows decision-makers to express their assessments without forcing artificial numerical precision, thereby reducing cognitive bias and improving decision transparency.

Overall, these validation and robustness considerations demonstrate that the proposed IFS–TOPSIS framework constitutes a reliable, stable, and practically applicable decision-support tool for complex defense system selection problems under uncertainty.

3.9. Defense Economics and Operational Superiority in a Lifecycle Perspective

Defense economics traditionally emphasizes cost-efficiency, budgetary control, and lifecycle affordability as central determinants of acquisition decisions. However, contemporary defense literature increasingly recognizes that excessive cost-driven optimization may undermine operational effectiveness, survivability, and long-term force resilience, particularly in high-threat and contested environments. The results of this study support this perspective by demonstrating that affordability, while essential, should not dominate decision outcomes at the expense of mission-critical capabilities such as stealth effectiveness, survivability, and communication reliability.

By embedding affordability as a cost-oriented criterion within an indeterminacy-aware decision framework, the proposed IFS–TOPSIS approach enables transparent and defensible trade-off analysis between fiscal constraints and operational superiority. Unlike deterministic cost-benefit models, the proposed framework explicitly captures uncertainty in expert judgments and strategic assumptions, thereby reducing the risk of underestimating long-term operational and economic consequences. This capability is particularly relevant across the defense procurement lifecycle—from Technology Readiness Level (TRL) assessment through Initial Operational Capability (IOC) and Full Operational Capability (FOC)—where early-stage uncertainty often propagates into significant downstream costs.

Accordingly, the proposed framework provides defense planners and acquisition authorities a structured mechanism to reconcile defense economics principles with strategic performance objectives, ensuring that resource allocation decisions contribute to sustainable force development rather than short-term budget optimization.

4. Conclusions

The selection of unmanned stealth aircraft represents a highly complex strategic decision problem involving multiple conflicting criteria, expert judgment, and substantial uncertainty. To address these challenges, this study proposed and validated a comprehensive IFS–TOPSIS framework that systematically incorporates decision-maker importance, criterion uncertainty, and alternative performance evaluations within a unified mathematical structure.

By modeling expert assessments using indeterminacy fuzzy sets, the proposed approach preserves not only degrees of support but also hesitation and opposition inherent in human judgment. The integration of the IFWA operator enables realistic aggregation of multi-expert evaluations, while the TOPSIS-based ranking mechanism ensures a transparent and interpretable comparison of alternatives based on their proximity to ideal solutions.

The application results demonstrate that the proposed framework consistently identifies Alternative A_2 as the most suitable unmanned stealth aircraft, exhibiting the most balanced performance across stealth capability, payload capacity, communication effectiveness, survivability, and affordability. Sensitivity analysis confirms the robustness of this ranking under varying strategic priority scenarios, and comparative analysis indicates that IFS–TOPSIS provides stronger discrimination capability than classical TOPSIS by explicitly accounting for uncertainty and expert hesitation.

From a practical and managerial perspective, the findings highlight that balanced capability trade-offs across operational and economic criteria are more critical for long-term defense effectiveness than maximizing isolated performance dimensions. From a strategic policy standpoint, the proposed IFS–TOPSIS framework extends beyond a methodological ranking tool and functions as a doctrine-aligned decision-support instrument for defense capability development.

By explicitly modeling indeterminacy throughout the decision process, the framework supports capability-based planning, decision robustness under uncertainty, and mission-oriented procurement—core principles embedded in contemporary national defense doctrines and NATO-aligned force development concepts. The demonstrated stability of the results across sensitivity scenarios further reinforces confidence in long-term acquisition decisions across the TRL–IOC–FOC lifecycle, particularly in information-degraded and contested operational environments.

Overall, this study contributes to the growing body of fuzzy multi-criteria decision-making literature by extending the applicability of IFS–TOPSIS to defense systems evaluation and demonstrating its effectiveness in realistic strategic decision contexts. Future research may extend the proposed framework by incorporating dynamic or scenario-based weighting mechanisms, hybrid uncertainty models, and large-scale group decision-making or real-time defense planning applications.

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