Innovations

Geometric Based MCDM Methods for Performance Evaluation and Ranking of Drone Propeller Materials in Intuitionistic Fuzzy Environment

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Abstract: *The rapid expansion of drone technology across areas such as creative industries, crop management, ecological surveillances, and facilities inspection has underlined the relevance of fundamental elements in influencing complete system effectiveness. Among these, aerodynamic lift, propulsion, steadiness, navigational control, and functional effectiveness are all strongly influenced by the propeller. Accordingly, the choice of suitable materials for drone propellers is crucial for achieving optimal performance, durability, and cost-effectiveness. This study gives a systematic examination of critical parameters for material selection, including cost, stiffness, durability, strength, sustainability, manufacturability, density, and strength-to-weight ratio. The most appropriate propeller materials are found using advanced multi-criteria decision-making (MCDM) methodologies, namely RAMS and RATMI. Additionally, these techniques feature an intuitionistic fuzzy extension that uses fuzzy logic and the Trace Similarity Median Index to account for uncertainty in traditional assessment procedures. The results indicate that a composite methodology, which includes the relative value of material features, offers the most consistent and reliable rankings. The suggested approach not only supports informed material selection by maximizing performance, cost, and operational parameters but also provides a sophisticated decision-support tool for boosting drone efficiency across varied applications.*

Keywords: *Drone Propeller, Geometric based methods, RAMS, RATMI, Intuitionist fuzzy sets, Correlation Analysis, Ranking Consistency Index and Trace.*

1. Introduction

A drone is a type of unmanned aircraft. Drones are also known as unmanned aerial vehicles (UAVs) or unmanned aircraft systems (UAS). A drone is essentially a flying machine that can be remotely controlled or remotely controlled by utilizing operating system flight plans in its integrated system works in conjunction with onboard sensors and GPS.

The rapid growth of drone technology has led to its widespread use in sectors like agriculture, logistics, surveillance, and entertainment. Among the key components of a drone, the propeller plays a crucial role in determining thrust, stability, fuel efficiency, and overall performance. Therefore, selecting the right material for drone propellers is essential to improve performance, durability, and reliability. Traditional methods for evaluating propeller materials often focus on mechanical properties, but they may not fully capture material behavior under diverse operational conditions. To overcome this, advanced frameworks like Ranking Alternative by Medium Similarities (RAMS) and Ranking Alternative by Treces Medium Indexes (RATMI) offer a more comprehensive approach. RAMS helps rank materials based on factors like reliability and safety, while RATMI adds depth by using Treces medium indexes for material analysis. The integration of intuitionistic fuzzy logic further refines the evaluation by accounting for uncertainties and expert opinions. This study combines these methods to help manufacturers make informed decisions for selecting materials that optimize drone propeller performance and durability.

Multi-Criteria Decision-Making (MCDM) approaches have progressed greatly, particularly in handling uncertainty through intuitionistic fuzzy sets (IFS). Early works by Liu and Wang [1], Lin et al. [2], and Chen [3] presented fuzzy-based evaluation functions and scoring systems to reflect alternative satisfaction and criteria relevance. Subsequent work, notably Wang and Zhang [4] and Venkatesan & Sriram [5], increased aggregation and algebraic features of intuitionistic fuzzy matrices for robust decision-making. Material-specific applications for drones were examined by Suchat et al. [6] and Mohamed et al. [7], focusing on composites and carbon materials, while Farhadinia [8] and others [9–14] merged MCDM with fuzzy and entropy-based techniques for reliable weight determination and ranking. New MCDM tools, such as RAMS, RATMI, RAPS, and MCRAT, have been introduced recently [15–30]. These tools have shown exceptional performance in a variety of engineering applications, ranging from industrial and logistical optimization to UAV components. These methods, particularly RAMS and RATMI, efficiently handle uncertainty, incorporate expert judgment, and allow multi-criteria evaluation, establishing a strong framework for selecting optimal drone propeller materials.

2. Geometric Based MCDM Methods

Geometric-based multi-criteria decision-making (MCDM) approaches evaluate and rank alternatives by studying their geometric correlations within a multi-dimensional decision space. Instead of relying exclusively on weighted aggregations or pair wise comparisons, these strategies measure distances, similarities, or geometric indices to determine how well each alternative matches with an ideal or reference answer. Common approaches include distance-based algorithms (e.g., TOPSIS), similarity-based models, and geometric aggregation measures that capture the geographic distribution of criteria values. These techniques are especially useful because they can show trade-offs, represent complicated decision contexts, and offer natural interpretations based on similarity or proximity. They handle both qualitative and quantitative criteria and are extremely adaptable to varied applications such as engineering design, materials selection, supply chain optimization, and risk assessment. All things considered, geometric-based MCDM frameworks provide a solid and comprehensible foundation for determining the best options in multi-criteria decision situations.

This study proposed the most recent MCDM techniques, RAMS, and RATMI, proposed new multi-criteria decision-making tools, Ranking by Median Similarity (RAMS) and Ranking Alternatives by Trace to Median Index (RATMI), which extends the perimeter similarity method (RAPS). Reda M. S. Abdulaal, Nguyen et al. [16] (2024), Baraily et al. [17] (2024), Bui et al. [18] (2024) and Omer A. Bafail [9] (2022) Illustrated through a case study on brake booster valve materials and also extended in this paper and the proposed methods are discussed below.

Geometric based MCDM methods such as RAMS, and RATMI offer a systematic and objective approach to materials selection for drone propeller. By considering multiple criteria and objectives, these methods help decision-makers identify the most suitable materials based on a balanced assessment of various factors. In the paper, eight sub-criteria are considered for evaluation and ranking of materials for drone propeller through proposed methods in Intuitionistic fuzzy environment.

2.1 Intuitionistic Fuzzy Sets: IFSs, propounded by Atanassov [1] in 1986, are an improvement to the traditional fuzzy sets, presented by Zadeh [11]. IFSs enhance the ability of fuzzy sets to take into account the degree of uncertainty associated with the data by proposing a degree of hesitancy for each element. According to the IFS theory, we may define an IFS $\tilde{A}$ within a finite domain X, consisting of a degree of hesitation coupled with the membership degree and non-membership degree as per the traditional fuzzy set theory as:

$$\tilde{A}= \{\langle x, \mu\tilde{A}(x), \nu\tilde{A}(x)\rangle \mid x \in X\} \quad (1)$$

Where the membership degree, $\mu\tilde{A}(x){:}X\to[0,1]$, represents a measure of belongingness of an element x to IFS $\tilde{A}$, and the non-membership degree is given by $\nu\tilde{A}(x){:}X\to[0,1]$, following the relationship $0\le\mu\tilde{A}(x)+\nu\tilde{A}(x)\le1$. The hesitancy degree, $\pi\tilde{A}(x)$, accounts for the indecision or scepticism associated with an element defined as shown below:

$$\pi\tilde{A}(x)=1-\mu\tilde{A}(x)-\nu\tilde{A}(x) \tag{2}$$

According to fuzzy sets, $\nu\tilde{A}(x)=1-\mu\tilde{A}(x)$ and hence, they fail to account for the hesitation associated with any decision-making process. Therefore, IFSs are better equipped to model practical decision-making scenarios, where the decision-making experts have a degree of hesitancy associated with their evaluation. Assume $\tilde{A}=\langle\mu\tilde{A},\nu\tilde{A}\rangle$ and $\tilde{B}=\langle\mu\tilde{B},\nu\tilde{B}\rangle$ are intuitionistic fuzzy numbers (IFNs). The standard mathematical operations performed on $\tilde{A}$ and $\tilde{B}$ may be defined, as shown below:

$$\tilde{A}\oplus\tilde{B}=\{\mu\tilde{A}+\mu\tilde{B}-\mu\tilde{A}\mu\tilde{B},\ \nu\tilde{A}\nu\tilde{B}\} \tag{3}$$

$$\tilde{A}\otimes\tilde{B}=\{\mu\tilde{A}\mu\tilde{B},\ \nu\tilde{A}+\nu\tilde{B}-\nu\tilde{A}\nu\tilde{B}\} \tag{4}$$

$$\lambda\tilde{A}=\{1-(1-\mu\tilde{A})\ \lambda,\ \nu\tilde{A}\lambda\} \tag{5}$$

$$\tilde{A}\lambda=\{\mu\tilde{A}\lambda,\ 1-(1-\nu\tilde{A})\ \lambda\} \tag{6}$$

In MCDM applications, it is often necessary to rank IFNs in an order of preference. For this purpose, the corresponding score function is defined such that the IFN with a higher score function is considered greater. The score function of an IFN can be computed as:

$$(\tilde{A})=\frac{\mu\tilde{A}-\nu\tilde{A}+12}{2};\ (\tilde{A})\in[0,1] \tag{7}$$

2.2 | IF-RAMS

The RAMS method, proposed by Abdula aland Bafail [15], is a modification of the newly developed RAPS method. The RAPS method de composes each alternative into two components by separating the beneficial and non-beneficial evaluation criteria. Subsequently, the beneficial and non-beneficial parts, referred to as the max and min components, are treated to be at ninety-degree angles, forming a right-angled triangle, for each alternative. The RAPS approach evaluates the similarity between the perimeter of the triangles created by the decomposed components of all alternatives and the optimal one and ranks them based on a perimeter similarity index, defined as the ratio of the individual and optimal perimeters. As an extension to this theory, the RAMS method assigns a rank to the alternatives based on the similarity between the median of the triangle between the decomposed max-min components of every alternative to that of the ideal one. The RAMS approach in an IF environment (IF-RAMS) evaluates the efficacy of the available alternatives against the responses and represents the evaluations as IFNs.

A typical MCDM problem consists of a finite number of alternatives, say $A= [A1, A2, \ldots \ldots,\ ]$ and a finite set of criteria $C=[C1,C2,\ldots,Cn]$. The mathematical steps involved in ranking of the alternatives utilizing the given criteria according to the IF-RAMS approach are outlined below:

Step 1: Evaluate available alternatives in relation to each criterion using linguistic variables.

Step 2: Transform the above-mentioned linguistic variables into their corresponding IFNs and obtain the initial IF decision matrix.

$$\tilde{X}= [\tilde{x}_{ij}]_{m\times n};\ i=1,2,\ldots,;\ = 1,2,\ldots,n \tag{8}$$

Where, the IFN $\tilde{x}_{ij}= \{\mu_{ij}, \nu_{ij}\}$ represents the evaluation of alternative i against criterion j.

Step 3: Formulate the weighted IF decision matrix as the product of the IFN-based performance evaluation of every alternative with the corresponding IF criteria weights.

$$\tilde{U}= [\tilde{u}_{ij}]_{m\times n};\ \tilde{u}_{ij}=\tilde{w}_j\otimes\tilde{x}_{ij} \tag{9}$$

Step 4: Find the optimal alternative for each criterion (response).

$$\bar{Q} = [\tilde{q}_j]_{1\times n};\ \tilde{q}_j= \{\mu\tilde{q}_j,\nu\tilde{q}_j\} \tag{10}$$

$$\mu\tilde{q}_j = max_i\ \mu_{ij};\ \nu\tilde{q}_j = min_i\ \nu_{ij} \tag{11}$$

Step 5: Separate the optimal alternative into the corresponding max (beneficial) and min (non-beneficial) components of the criteria set.

$$\bar{Q} = \bar{Q}^{max} \cup \bar{Q}^{min} \tag{12}$$

$$\bar{Q} = \{\tilde{q}_1, \tilde{q}_2,\ldots \tilde{q}_k\}\cup\{\tilde{q}_1, \tilde{q}_2,.\ \tilde{q}_h\};\ \mathrm{k}+h = n \tag{13}$$

Where k denotes the count of beneficial criteria and h symbolizes the number of non-beneficial criteria.

Step 6: Decompose the available alternatives into their constituent max and min components.

$$\tilde{U}_i= \tilde{U}i^{max} \cup \tilde{U}i^{min} \tag{14}$$

$$\tilde{U}_i = \{\tilde{u}_{i1}, \tilde{u}_{i2}\ldots \tilde{u}_{ik}\} \cup \{\tilde{u}_{i1}, \tilde{u}_{i2}\ldots \tilde{u}_{ih}\} \tag{15}$$

Step 7: Evaluate the magnitude of max and min components for all alternatives, including the optimal alternative, using the following equations:

$$\tilde{U}i_{\mathrm{k}} = \{\tilde{u}^2_{i1}\oplus\tilde{u}^2_{i2}\oplus\ldots\oplus\tilde{u}^2_{ik}\}^{1/2} \tag{16}$$

$$\tilde{U}i_{\mathrm{h}} = \{\tilde{u}^2_{i1}\oplus\tilde{u}^2_{i2}\oplus\ldots\oplus\tilde{u}^2_{i\mathrm{h}}\}^{1/2} \tag{17}$$

$$\bar{Q}_k = \{\tilde{q}_1^2\oplus\tilde{q}_2^2\oplus\ldots\oplus\tilde{q}_k^2\}^{1/2} \tag{18}$$

$$\bar{Q}_h = \{\tilde{q}_1^2 \oplus \tilde{q}_2^2 \oplus \ldots \oplus \tilde{q}_h^2\}^{1/2} \quad (19)$$

Step 8: Obtain the median for the optimal alternative.

$$\widetilde{M} = \frac{\left(\bar{Q}_k^2 \oplus \bar{Q}_h^2\right)^{1/2}}{2} \quad (20)$$

Step 9: Compute the median for each alternative.

$$\widetilde{M} = \frac{\left(\tilde{U}_{ik}^2 \oplus \tilde{U}_{ih}^2\right)^{1/2}}{2} \quad (21)$$

Step 10: Determine the median similarity for every alternative as shown below:

$$MS_i = \frac{S(\tilde{M}i)}{S(\tilde{M})} \quad (22)$$

Higher value of MSi is an indication of the median for the corresponding alternative being closer to the median for the optimal alternative. Therefore, the alternatives can be ranked in descending order of MSi to ensure alternatives with the higher MSi values receive a better rank.

2.3 IF-RATMI

The RATMI is a combination of RAMS and MCRAT methods, proposed by Reda M. S. Abdulaal [15]. It integrates the median similarity index with the trace of the matrix of the max and min components to obtain an aggregate measure, referred to as the majority index. The IF-RATMI approach utilizes IFNs to represent performance of the alternatives against the considered evaluation criteria. To derive ranking of the alternatives using the IF-RATMI approach, the IF-RAMS method must be executed first and then, the following mathematical calculations are employed:

Step 1: Formulate a diagonal matrix (F) consisting of the magnitude of the max and min components of the optimal alternative. Similarly, develop diagonal matrixes (Gi) consisting of the magnitude of the components of each alternative.

$$\mathrm{F} = \begin{bmatrix} \tilde{Q}_k & 0 \\ 0 & \tilde{Q}_h \end{bmatrix} \quad (23)$$

$$G_j = \begin{bmatrix} \widetilde{U}_{ik} & 0 \\ 0 & \widetilde{U}_{ih} \end{bmatrix}, \forall i = [1,2,\ldots\ldots,m] \quad (24)$$

Step 2: Compute the product of matrixes F and Gi for each alternative and subsequently, estimate the trace (tri) of the product matrix (Ti).

$$\mathrm{T_i} = \mathrm{F} \times G_j = \begin{bmatrix} \tilde{t}_{11j} & 0 \\ 0 & \tilde{t}_{22j} \end{bmatrix}, \forall i = [1,2,\ldots\ldots,m] \quad (25)$$

$$t_{ri} = (\tilde{t}_{11} \oplus \tilde{t}_{22}) \quad (26)$$

Step 3: Calculate the majority index (E_i) for each alternative as the weighted sum of RAMS strategies.

$$E_i = \omega\frac{(tr_i - tr^*)}{(tr^- - tr^*)} + (1-\omega)\frac{(MS_i - MS^*)}{(MS^- - MS^*)} \tag{27}$$

$tr^* = \max_i (tr_i), \quad \forall i = [1,2, \ldots \ldots . \ldots .., m]$
$tr^- = \min_i (tr_i), \quad \forall i = [1,2, \ldots \ldots \ldots .., m]$
$MS^- = \min_i (MS_i), \forall i = [1,2, \ldots \ldots . \ .., m]$
$MS^* = \max_i (MS_i), \ \forall i = [1,2, \ldots . . \ldots .., m]$

Where ω is the importance assigned to MCRAT approach, while $(1-\omega)$ is the weight allotted to RAMS method.

Step 4: Arrange the available alternatives in a decreasing order of the majority index (Ei).

3. Critical attributes of evaluations of Drone propeller Materials

To evaluate the quality of responses more systematically, linguistic scores are converted into Intuitionistic Fuzzy Numbers (IFNs). By giving each linguistic term three parameters the degree of membership (μ), the degree of non-membership (v), and the degree of hesitation (π), IFNs enable the depiction of doubt. Compared to conventional sharp scales, this method offers a more flexible and realistic assessment. The IFNs that correspond to the linguistic characteristics used to rate the responses are shown in table 1.

Table 1. IFNs for linguistic rating of the responses for the rating matrix

Numerical	Linguistic variable	IFN		
		Mew(μ)	New(v)	Pie(π)
1	VP	0.05	0.75	0.2
2	P	0.08	0.88	0.04
3	BA	0.35	0.6	0.05
4	A	0.5	0.45	0.05
5	AA	0.65	0.3	0.05
6	G	0.75	0.2	0.05
7	VG	0.9	0.05	0.05
8	E	0.95	0.05	0.0

The IFNs indicated in Table 1 serve as the quantitative basis for converting language assessments into a measurable form. These values are then utilized to form the intuitionistic fuzzy rating matrix for later research.

To incorporate perspectives from multiple expert groups, each stakeholder provides linguistic ratings for the selected properties. The table 2 summarizes these evaluations given by the decision makers (DMs), serving as input for further intuitionistic fuzzy analysis.

Table 2. Linguistic evaluation of the responses by different stakeholders

S.No.	Stake holders	DMs	Properties							
			X1	X2	X3	X4	X5	X6	X7	X8
1	Engineers & Designers	DM1	P	E	AA	G	VP	A	VG	BA
2	Manufacturers	DM2	E	AA	G	VG	P	BA	A	E
3	Material Scientists	DM3	AA	G	VG	E	A	AA	G	VG
4	Environmental Experts	DM4	BA	A	AA	BA	E	G	P	A
5	Marketing & Sales	DM5	VG	G	G	AA	BA	A	AA	G
6	Regulatory Bodies	DM6	AA	G	VG	G	E	AA	A	BA
7	End users	DM7	G	VG	E	G	AA	A	AA	BA
8	Investors & Financial Analysts	DM8	E	AA	A	G	BA	A	G	AA

The linguistic assessments in Table 2 provide the qualitative foundation for the evaluation process. These inputs will be converted into their corresponding IFNs to construct the intuitionistic fuzzy rating matrix for further analysis.

After converting the stakeholders' linguistic evaluations into IFNs, the individual assessments are aggregated to obtain representative response weights for each property. The table 3 presents these aggregated intuitionistic fuzzy values, reflecting the overall consensus across all decision makers.

Table 3. Aggregated IF response weights

Properties	Mew(μ)	New(ν)	Pie(π)
X1	0.785	0.182	0.033
X2	0.784	0.173	0.043
X3	0.807	0.146	0.047
X4	0.786	0.171	0.044
X5	0.567	0.308	0.028
X6	0.567	0.381	0.052
X7	0.661	0.274	0.065
X8	0.703	0.249	0.048

The aggregated IFNs in table 3 represent the combined judgment of all stakeholders for each property. These values form the basis for further analysis, such as ranking or decision-making using intuitionistic fuzzy methods.

To evaluate material selection for drone propellers using new MCDM methods of IF-RAMS and IF-RATMI, to assign the linguistic variables to critical properties like cost-effectiveness(X1), stiffness(X2), durability(X3), strength(X4), sustainability(X5), manufacturability(X6), density (X7) and weight to strength ratio (X8) as shown the table 1, it apply intuitionistic fuzzy logic for fuzzy rankings. It define beneficial (higher is better) and non-beneficial (lower is better) criteria. Linguistic ratings like Linguistic ratings like "Extremely Good (EG)" to "Very Very Bad (VVB)" are assigned based on measured responses for each property rating scale as shown in the table 4.

Table 4.Scale for linguistic evaluation of the responses for different properties

Linguistic Variable	Properties							
	X1	X2	X3	X4	X5	X6	X7	X8
Extremely Good (EG)	9	9	9	9	9	9	1	1
Very Very Good (VVG)	8	8	8	8	8	8	2	2
Very Good (VG)	7	7	7	7	7	7	3	3
Good (G)	6	6	6	6	6	6	4	4
Medium Good (MG)	5	5	5	5	5	5	5	5
Medium (M)	4	4	4	4	4	4	6	6
Medium Bad (MB)	3	3	3	3	3	3	7	7
Bad (B)	3	3	3	3	3	3	8	8
Very Bad (VB)	2	2	2	2	2	2	9	9
Very Very Bad (VVB)	1	1	1	1	1	1	10	10

The scale in Table 4 provides a standardized way to convert qualitative linguistic evaluations into quantitative scores. These numerical values enable consistent comparison and aggregation of responses across all properties.

To evaluate materials using intuitionistic fuzzy logic, linguistic terms are represented as Intuitionistic Fuzzy Numbers (IFNs). Table 5 presents the IFN scale, assigning membership (μ), non-membership (ν), and hesitation (π) values to each linguistic variable.

Table 5. IFN scale for evaluation of material as linguistic variables

Numerical	Linguistic variable	IFN		
		Mew(μ)	New(ν)	Pie(π)
1	EP	0.1	0.9	0.0
2	VP	0.2	0.6	0.2
3	P	0.35	0.6	0.05
4	MP	0.5	0.4	0.1
5	MG	0.6	0.2	0.2
6	G	0.75	0.2	0.05
7	VG	0.8	0.1	0.1
8	EG	0.9	0.1	0.0

The IFN scale in Table 5 provides a standardized framework for translating qualitative material evaluations into quantitative intuitionistic fuzzy values. These values serve as the basis for further aggregation and analysis in the decision-making process.

Table 6 presents the initial Intuitionistic Fuzzy (IF) decision matrix constructed for the material selection problem. Each alternative material (A1–A18) is evaluated with respect to the eight decision criteria (X1–X8) using intuitionistic fuzzy numbers. For every criterion, the assessment is expressed through the membership (μ), non-membership (ν), and hesitation (π) degrees, reflecting the extent to which an alternative satisfies, does not satisfy, or remains uncertain with respect to the criterion. These values were obtained from expert judgments based on the predefined linguistic scales. The maximum and minimum IF values for each criterion, shown in the final two rows, serve as reference bounds and are utilized in subsequent normalization and weighting procedures within the IF-RAMS framework.

Table 6.Initial IF decision matrix

Alternative Materials	X1			X2			X3			X4			X5			X6			X7			X8		
	μ	ν	π	μ	ν	π	μ	ν	π	μ	ν	π	μ	ν	π	μ	ν	π	μ	ν	π	μ	ν	π
A1	0.2	0.05	0.75	0.2	0.05	0.75	0.2	0.05	0.75	0.2	0.05	0.75	0.2	0.05	0.75	0.2	0.05	0.75	0.2	0.05	0.2	0.05	0.75	0.2
A2	0.1	0	0.9	0.1	0	0.9	0.1	0	0.9	0.1	0	0.9	0.1	0	0.9	0.1	0	0.9	0.1	0	0.1	0	0.9	0.1
A3	0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.2	0.2	0.2	0.6	0.2
A4	0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.6	0.2	0.2	0.6
A5	0.6	0.05	0.35	0.6	0.05	0.35	0.6	0.05	0.35	0.6	0.05	0.35	0.6	0.05	0.35	0.6	0.05	0.35	0.6	0.05	0.6	0.05	0.35	0.6
A6	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1	0.1	0.1	0.8	0.1
A7	0.1	0	0.9	0.1	0	0.9	0.1	0	0.9	0.1	0	0.9	0.1	0	0.9	0.1	0	0.9	0.1	0	0.1	0	0.9	0.1
A8	0.4	0.1	0.5	0.4	0.1	0.5	0.4	0.1	0.5	0.4	0.1	0.5	0.4	0.1	0.5	0.4	0.1	0.5	0.4	0.1	0.4	0.1	0.5	0.4
A9	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1	0.1	0.1	0.8	0.1
A10	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1	0.1	0.1	0.8	0.1
A11	0.1	0	0.9	0.1	0	0.9	0.1	0	0.9	0.1	0	0.9	0.1	0	0.9	0.1	0	0.9	0.1	0	0.1	0	0.9	0.1

A12	0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.2	0.2	0.2	0.6	0.2
A13	0.4	0.1	0.5	0.4	0.1	0.5	0.4	0.1	0.5	0.4	0.1	0.5	0.4	0.1	0.5	0.4	0.1	0.5	0.4	0.1	0.4	0.1	0.5	0.4
A14	0.6	0.05	0.35	0.6	0.05	0.35	0.6	0.05	0.35	0.6	0.05	0.35	0.6	0.05	0.35	0.6	0.05	0.35	0.6	0.05	0.6	0.05	0.35	0.6
A15	0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.6	0.2	0.2	0.6
A16	0.2	0.05	0.75	0.2	0.05	0.75	0.2	0.05	0.75	0.2	0.05	0.75	0.2	0.05	0.75	0.2	0.05	0.75	0.2	0.05	0.2	0.05	0.75	0.2
A17	0.4	0.1	0.5	0.4	0.1	0.5	0.4	0.1	0.5	0.4	0.1	0.5	0.4	0.1	0.5	0.4	0.1	0.5	0.4	0.1	0.4	0.1	0.5	0.4
A18	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1	0.1	0.1	0.8	0.1
MAX	0.60	0.20	0.90	0.60	0.20	0.90	0.60	0.20	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.60	0.20	0.90	0.60	0.20	0.60	0.20	0.90	0.60
MIN	0.10	0.00	0.20	0.10	0.00	0.20	0.10	0.00	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.10	0.00	0.20	0.10	0.00	0.10	0.00	0.20	0.10

Based on the initial IF decision matrix in Table 6, the intuitionistic fuzzy evaluations for all alternatives and criteria are organized for further processing within the IF-RAMS framework. These raw IF assessments form the foundation for the next stages of analysis, where they are combined with the aggregated IF criteria weights to generate the weighted IF decision matrix. This weighting step incorporates the relative importance of each criterion and allows the performance of the alternative materials to be compared on a unified fuzzy scale. The weighted evaluations are then used to determine the optimal IF values for each response and to carry out subsequent benefit–cost decomposition in the later phases of the method.

Since these six criteria are classified as beneficial, they collectively form the maximum component for each alternative. In contrast, the minimum component is constructed from the non-beneficial criteria density (X7) and weight-to-strength ratio (X8). The IF operations applied to these two criteria generate the intuitionistic fuzzy value that reflects the material's non-beneficial performance. After determining the magnitudes of both components, they are used to estimate the median value of the optimal alternative in accordance with the IF-RAMS framework. The same procedure is then applied to compute the median IF value for each material. In the first experiment, combining the maximum and minimum components produces the composite intuitionistic fuzzy evaluation for Material 1. This composite value is subsequently transformed using the appropriate IF rules to obtain the final intuitionistic fuzzy representation of its median performance.

The table 7 presents the weighted Intuitionistic Fuzzy (IF) decision matrix, obtained by integrating the initial IF evaluations with the aggregated criteria weights. This step reflects the relative importance of each criterion and produces a refined set of IF values membership, non-membership, and hesitation for all alternative materials across the eight performance responses. The table also includes the maximum and minimum weighted IF values identified for each criterion, which serve as reference points in determining the optimal alternative. Based on these bounds, the optimal IF values for each criterion are derived, forming the benchmark against which the performances of all materials are subsequently compared within the IF-RAMS framework.

Table 7.Weighted IF decision matrix and optimal alternative

Alternative Materials	X1			X2			X3			X4			X5			X6			X7			X8		
	μ	ν	π	μ	ν	π	μ	ν	π	μ	ν	π	μ	ν	π	μ	ν	π	μ	ν	π	μ	ν	π
A1	0.589	0.345	0.066	0.588	0.339	0.074	0.605	0.317	0.078	0.589	0.337	0.074	0.057	0.931	0.013	0.423	0.474	0.103	0.495	0.419	0.085	0.527	0.399	0.074
A2	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.

	706	264	030	705	256	039	726	231	042	707	254	039	142	723	135	482	443	076	595	347	059	633	324	043
A3	0.471	0.345	0.184	0.470	0.339	0.191	0.484	0.317	0.199	0.471	0.337	0.192	0.057	0.931	0.013	0.567	0.381	0.052	0.396	0.419	0.184	0.422	0.399	0.179
A4	0.157	0.673	0.170	0.157	0.669	0.174	0.161	0.658	0.180	0.157	0.668	0.175	0.142	0.723	0.135	0.567	0.381	0.052	0.132	0.710	0.158	0.141	0.699	0.160
A5	0.275	0.673	0.053	0.274	0.669	0.056	0.282	0.658	0.059	0.275	0.668	0.057	0.057	0.931	0.013	0.283	0.629	0.088	0.231	0.710	0.059	0.246	0.699	0.054
A6	0.628	0.264	0.109	0.627	0.256	0.117	0.646	0.231	0.123	0.629	0.254	0.118	0.142	0.723	0.135	0.567	0.381	0.052	0.528	0.347	0.125	0.563	0.324	0.114
A7	0.706	0.264	0.030	0.705	0.256	0.039	0.726	0.231	0.042	0.707	0.254	0.039	0.057	0.931	0.013	0.057	0.938	0.005	0.595	0.347	0.059	0.633	0.324	0.043
A8	0.392	0.509	0.099	0.392	0.504	0.104	0.404	0.487	0.109	0.393	0.502	0.105	0.142	0.723	0.135	0.482	0.443	0.076	0.330	0.565	0.105	0.352	0.549	0.099
A9	0.628	0.264	0.109	0.627	0.256	0.117	0.646	0.231	0.123	0.629	0.254	0.118	0.057	0.931	0.013	0.340	0.567	0.093	0.528	0.347	0.125	0.563	0.324	0.114
A10	0.628	0.264	0.109	0.627	0.256	0.117	0.646	0.231	0.123	0.629	0.254	0.118	0.142	0.723	0.135	0.567	0.381	0.052	0.528	0.347	0.125	0.563	0.324	0.114
A11	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.

	706	264	030	705	256	039	726	231	042	707	254	039	057	931	013	227	690	083	595	347	059	633	324	043
A12	0.471	0.345	0.184	0.470	0.339	0.191	0.484	0.317	0.199	0.471	0.337	0.192	0.142	0.723	0.135	0.567	0.381	0.052	0.396	0.419	0.184	0.422	0.399	0.179
A13	0.392	0.509	0.099	0.392	0.504	0.104	0.404	0.487	0.109	0.393	0.502	0.105	0.057	0.931	0.013	0.000	0.381	0.619	0.330	0.565	0.105	0.352	0.549	0.099
A14	0.275	0.673	0.053	0.274	0.669	0.056	0.282	0.658	0.059	0.275	0.668	0.057	0.142	0.723	0.135	0.397	0.505	0.099	0.231	0.710	0.059	0.246	0.699	0.054
A15	0.157	0.673	0.170	0.157	0.669	0.174	0.161	0.658	0.180	0.157	0.668	0.175	0.057	0.931	0.013	0.340	0.567	0.093	0.132	0.710	0.158	0.141	0.699	0.160
A16	0.589	0.345	0.066	0.588	0.339	0.074	0.605	0.317	0.078	0.589	0.337	0.074	0.142	0.723	0.135	0.057	0.845	0.098	0.495	0.419	0.085	0.527	0.399	0.074
A17	0.392	0.509	0.099	0.392	0.504	0.104	0.404	0.487	0.109	0.393	0.502	0.105	0.057	0.931	0.013	0.340	0.845	-0.185	0.330	0.565	0.105	0.352	0.549	0.099
A18	0.628	0.264	0.109	0.627	0.256	0.117	0.646	0.231	0.123	0.629	0.254	0.118	0.142	0.723	0.135	0.057	0.845	0.098	0.528	0.347	0.125	0.563	0.324	0.114
MAX	0.706	0.673	0.184	0.705	0.669	0.191	0.726	0.658	0.199	0.707	0.668	0.192	0.669	0.191	0.135	0.705	0.669	0.619	0.595	0.710	0.184	0.633	0.699	0.179

MIN	0.157	0.264	0.030	0.157	0.256	0.039	0.161	0.231	0.042	0.157	0.254	0.039	0.030	0.030	0.013	0.030	0.030	-0.185	0.132	0.347	0.059	0.141	0.324	0.043
Optimal	0.706	0.264	0.030	0.705	0.256	0.039	0.726	0.231	0.042	0.707	0.254	0.039	0.567	0.308	0.126	0.567	0.381	0.052	0.595	0.347	0.059	0.141	0.324	0.536

Following the construction of the weighted IF decision matrix in Table 7, the weighted evaluations is analyzed to identify the optimal performance levels for each criterion. These optimal intuitionistic fuzzy values represent the best achievable membership, non-membership, and hesitation degrees across all alternatives and are used as reference points for subsequent computations. Using these optimal values, the next stage of the IF-RAMS procedure involves decomposing each alternative's weighted evaluations into their corresponding maximum (beneficial) and minimum (non-beneficial) components. This decomposition enables a more precise assessment of each material's performance relative to the optimal benchmark, and forms the basis for calculating the component magnitudes and median values in the later stages of the analysis.

The table 8 presents the magnitudes of the decomposed components obtained after separating each alternative's weighted IF evaluation into its beneficial (maximum) and non-beneficial (minimum) parts. These components, denoted as U_{ik} and U_{ih}, capture the contribution of each material to the beneficial and non-beneficial criteria, respectively. Using the IF aggregation procedures outlined earlier, the squared magnitudes of these components and their combined values are computed for all alternatives. These results are presented in table 8, and then used to derive the median value and the material score for each alternative, to obtain for the final ranking. The table 8 shows the complete set of magnitudes, median values, scores, and corresponding ranks, enabling a comprehensive comparison of material performance within the IF-RAMS framework.

Table 8. Magnitude of the decomposed components

Alternative Materials	U_{ik}			U_{ih}			$U_{ik}^2 + U_{ih}^2$			Mi				MSi	Rank
	μ	ν	π	μ	ν	π	μ	ν	π	μ	ν	π			
A1	0.588	0.339	0.074	0.989	0.007	0.06	0.977	0.008	0.015	0.799	0.062	0.139	0.533	0.847	**8**
A2	0.705	0.256	0.039	0.908	0.002	0.02	0.831	0.002	0.002	0.907	0.028	0.066	0.604	0.961	**1**
A3	0.470	0.339	0.191	0.856	0.005	0.11	0.773	0.006	0.072	0.702	0.055	0.242	0.468	0.745	**11**
A4	0.157	0.669	0.174	0.949	0.058	0.30	0.904	0.100	0.164	0.407	0.227	0.366	0.272	0.432	**16**
A5	0.274	0.669	0.056	0.935	0.123	0.28	0.876	0.205	0.052	0.398	0.330	0.272	0.266	0.422	**17**
A6	0.627	0.256	0.117	0.982	0.001	0.03	0.964	0.001	0.015	0.853	0.026	0.121	0.569	0.905	**4**
A7	0.705	0.256	0.039	0.935	0.005	0.02	0.887	0.004	0.003	0.893	0.046	0.062	0.595	0.946	**3**
A8	0.392	0.504	0.104	0.800	0.023	0.17	0.748	0.034	0.062	0.597	0.130	0.272	0.398	0.633	**13**
A9	0.627	0.256	0.117	0.980	0.003	0.04	0.960	0.003	0.019	0.831	0.035	0.133	0.554	0.881	**6**
A10	0.627	0.256	0.117	0.890	0.001	0.03	0.813	0.001	0.015	0.853	0.026	0.121	0.569	0.905	**4**
A11	0.705	0.256	0.039	0.786	0.003	0.02	0.733	0.003	0.003	0.895	0.039	0.065	0.597	0.949	**2**
A12	0.470	0.339	0.191	0.870	0.004	0.11	0.852	0.005	0.071	0.705	0.049	0.246	0.470	0.747	**10**
A13	0.392	0.504	0.104	0.967	0.025	0.15	0.936	0.037	0.054	0.620	0.137	0.243	0.413	0.657	**12**
A14	0.274	0.669	0.056	0.956	0.077	0.27	0.914	0.131	0.052	0.437	0.261	0.303	0.291	0.463	**15**
A15	0.157	0.669	0.174	0.899	0.111	0.43	0.893	0.186	0.213	0.281	0.313	0.406	0.187	0.297	**18**
A16	0.588	0.339	0.074	0.782	0.009	0.07	0.850	0.011	0.018	0.780	0.073	0.147	0.520	0.827	**9**
A17	0.392	0.504	0.104	0.633	0.055	0.18	0.493	0.081	0.064	0.561	0.204	0.236	0.374	0.594	**14**
A18	0.627	0.256	0.117	0.887	0.003	0.05	0.870	0.003	0.021	0.822	0.038	0.140	0.548	0.871	**7**
Optimal	**0.705**	**0.256**	**0.039**	**0.993**	**0.027**	**-0.02**	**0.995**	**0.024**	**0.003**	**0.943**	**0.109**	**0.053**	**0.629**	**1.000**	

The results in Table 8 provide a detailed comparison of the beneficial and non-beneficial performance magnitudes for each material alternative. By combining these decomposed components, the median intuitionistic fuzzy values and overall material scores are obtained, allowing the alternatives to be ranked according to their aggregated performance. The ranking reveals the relative suitability of each material within the IF-RAMS framework, highlighting those that most closely align with the optimal intuitionistic fuzzy characteristics. These rankings form the basis for identifying the most appropriate material choices for drone propeller fabrication in the subsequent analysis and discussion.

The table 9 presents the final ranking of 18 alternative materials using the IF-RATMI approach, which combines fuzzy-rough and multi-criteria evaluation methods. The table lists key material parameters (T_i, tr_i, MS_i), calculates an overall evaluation score (E_i), and assigns a final rank to each material.

Table 9. Final ranks of material using IF-RATMI approach

Alternative Materials	Ti			t_{ri}	MS_i	E_i	Ranks
	μ	v	π				
A1	0.416	0.017	0.567	0.278	0.847	0.807	**8**
A2	0.498	0.013	0.489	0.332	0.961	1.000	**1**
A3	0.337	0.016	0.647	0.224	0.745	0.625	**11**
A4	0.117	0.064	0.820	0.078	0.432	0.101	**17**
A5	0.195	0.113	0.692	0.130	0.422	0.197	**16**
A6	0.445	0.013	0.543	0.297	0.905	0.887	**4**
A7	0.498	0.014	0.488	0.332	0.946	0.989	**3**
A8	0.279	0.031	0.690	0.186	0.633	0.466	**13**
A9	0.445	0.013	0.542	0.297	0.881	0.869	**6**
A10	0.445	0.013	0.543	0.297	0.905	0.887	**4**
A11	0.498	0.014	0.488	0.332	0.949	0.991	**2**
A12	0.337	0.016	0.648	0.224	0.747	0.627	**10**
A13	0.279	0.033	0.688	0.186	0.657	0.484	**12**
A14	0.195	0.078	0.727	0.130	0.463	0.228	**15**
A15	0.117	0.104	0.780	0.078	0.297	0.000	**18**
A16	0.416	0.018	0.565	0.278	0.827	0.792	**9**
A17	0.279	0.052	0.669	0.186	0.594	0.437	**14**
A18	0.445	0.013	0.542	0.297	0.871	0.862	**7**

The results in Table 9 highlight the effectiveness of the IF-RATMI approach in differentiating and ranking the alternative materials based on multiple criteria. The ranking clearly identifies the most suitable materials (A2, A11, and A7) for potential application, while also showing which materials (A15, A4, A5) are less favorable. This systematic evaluation facilitates informed decision-making by providing a clear comparison of material performance, considering both their individual properties and overall suit ability.

The Table 10 compares the final rankings of 18 alternative materials using two evaluation methods: IF-RAMS and IF-RATMI. It presents the material scores (MSi), intermediate criteria (tri), overall evaluation scores (Ei), and the corresponding ranks from both methods. This table provides a direct comparison, showing how the two approaches assess material suitability and highlighting consistencies or differences in ranking outcomes across the evaluated alternatives.

Table 10. Comparison of ranking of the materials IF-RAMS and IF-RATMI

Alternative Materials	MSi	IF RAMS	t_{ri}	E_i	IF RATMI
A1	0.85	8	0.28	0.81	8
A2	0.96	1	0.33	1.00	1
A3	0.74	11	0.22	0.63	11
A4	0.43	16	0.08	0.10	17
A5	0.42	17	0.13	0.20	16
A6	0.90	4	0.30	0.89	4
A7	0.95	3	0.33	0.99	3
A8	0.63	13	0.19	0.47	13
A9	0.88	6	0.30	0.87	6
A10	0.90	4	0.30	0.89	4
A11	0.95	2	0.33	0.99	2
A12	0.75	10	0.22	0.63	10
A13	0.66	12	0.19	0.48	12
A14	0.46	15	0.13	0.23	15
A15	0.30	18	0.08	0.00	18
A16	0.83	9	0.28	0.79	9
A17	0.59	14	0.19	0.44	14
A18	0.87	7	0.30	0.86	7

The comparison in Table 10 demonstrates that both IF-RAMS and IF-RATMI approaches produce largely consistent material rankings, with top-performing materials such as A2, A11, and A7 maintaining high ranks in both methods. Minor differences in intermediate scores and rankings reflect the distinct evaluation criteria and weighting mechanisms of each method. Overall, the table confirms the reliability of these fuzzy-based multi-criteria approaches in systematically identifying the most suitable materials for the intended application.

3.1 Aggregation of Ranks by Proposed Geometric Based MCDM Methods

Aggregating ranks obtained through RAMS, and RATMI in intuitionistic fuzzy environment to obtain more comprehensive and robust evaluation of alternatives. The algorithm proposed by Mohammadi and Jafar Rezaei (2020), is adopted to obtain aggregate ranking. Final ranking obtained through aggregation of ranks of the alternatives materials for drone propeller is presented in table 11.

Alternative Materials	**IF RAMS Rank**	**IF RATMI Ranks**	**Aggregation rank**
A1	8	8	**8**
A2	1	1	**1**
A3	11	11	**11**
A4	16	17	**16**
A5	17	16	**16**
A6	4	4	**4**
A7	3	3	**3**
A8	13	13	**13**
A9	6	6	**6**
A10	4	4	**4**
A11	2	2	**2**
A12	10	10	**10**
A13	12	12	**12**
A14	15	15	**15**
A15	18	18	**18**
A16	9	9	**9**
A17	14	14	**14**
A18	7	7	**7**

The results clearly show a strong consistency between the IF-RAMS and IF-RATMI methods, with all materials receiving identical ranks across both approaches. This stability indicates high reliability in the evaluation process. Material A2 emerges as the best overall choice, securing Rank 1 in every method, followed closely by A11 and A7, which consistently hold the 2nd and 3rd positions. Materials such as A6, A10, A1, A18, and A9 fall within a moderate performance range, suggesting they may be acceptable depending on secondary design priorities. A group of materials including A3, A12, A13, and A8 consistently occupy middle-lower positions, showing limited suitability. The lowest-ranked materials A4, A5, A14, A17, and especially A15 demonstrate weaker performance across all criteria and are not recommended. Overall, the strong agreement between the two methods and the aggregated results increases confidence in the final ranking, confirming A2 as the optimal material alternative, with A11, A7, and A6/A10 as reliable secondary options.

5. Correlation analysis of proposed methods:

In this context, there's a need for metrics to assess the similarity and dissimilarity of ranked lists. Three popular methodologies in this regard are the Kendall's Tau, Pearson's correlation coefficient, and Rank-Biased Overlap (RBO). Each offers a unique lens to view and evaluate rank similarity.

5.1 Kendall's Tau: Measures the consistency between two rankings by comparing the number of pairs that are in the same order to the number that are in a different order.

5.2 Spearman's Rank Correlation Coefficient: Measures the strength and direction of the association between two ranked variables.

5.3 Rank-Biased Overlap (RBO): RBO provides a measure that combines the evaluation of top-ranked items with a gradual consideration of the items' depth in the rank

5.1.1 Correlation Analysis: Correlation coefficients of the proposed methods are determined through Pearson's Coefficient method and presented in the table 12.

Table 12: Correlation Coefficients

Pearson's Coefficient method		
Methods	RAMS	RATMI
RAMS	1.000	0.998
RATMI	0.998	1.000

The table provided shows Pearson's coefficient of correlation between different methods: MCRAT, RAMS, RATMI, and RAPS. The values are close to 1, which indicates a strong positive correlation between each pair of methods. This suggests that as the scores from one method increase, the scores from the others also tend to increase, indicating that they may be measuring similar or related constructs.
Overall, these methods are closely aligned in terms of their outcomes, suggesting they may be suitable for interchangeable use depending on specific requirements or constraints of a study. However, the slight variations might point to subtle differences in what each method measures or how sensitive they are to different aspects of the data.
5.1.2 Kendall’s index: Kendall’s index of the proposed methods are determined through Mat-lab code and presented in the table 13.

Table 13: Kendal index values

Kendall coefficient		
Methods	RAMS	RATMI
RAMS	1.000	0.987
RATMI	0.987	1.000

The results highlight that RAMS, and RATMI have strong ordinal associations with each other, consistently ranking data in a similar way. RAMS, however, while still showing good agreement, has somewhat less correlation with the other methods. This could suggest that RAMS might be more sensitive to different types of data or might interpret certain ordinal rankings differently than the other methods. This difference can be beneficial in studies looking for a nuanced analysis where subtle variations in data are critical.
5.1.3 RBO index: In this method the overlap of ranking depth is determined through Mat-lab code to arrive the RBO Index and the results are presented in table 14.

Table 14: RBO Index Values

RBO Index Values		
Methods	RAMS	RATMI
RAMS	1.000	0.995
RATMI	0.995	1.000

The provided table shows the results for the Rank-Biased Overlap (RBO) method, a similarity measure used to compare the agreement of different ranking methods over a set of items, taking into account the positions in which items are ranked.
Overall, the RBO results indicate that while MCRAT, RATMI, and RAPS have relatively similar ranking behaviors, particularly for items ranked higher, RAMS appears to be the outlier, often ranking items in a significantly different order. This divergence could be useful in applications where diverse perspectives on ranking are desired to capture a broader range of criteria or viewpoints.

5.1.4 Average Ranking Consistency Index: Average consistency index of each MCDM method, is determined by averaging the values in the i^{th} row and the j^{th} column (excluding the diagonal element which will always be 1 as it's the comparison of the method with itself). Average Consistency index values are presented in the table 15.

Table 15: Average Consistency index values

MCDM Method	**Consistency Method**			**Average**
Methods	**Pearson's Correlation**	**Kendall's Coefficient**	**RBO**	
RAMS	0.998	0.987	0.995	0.9933
RATMI	0.998	0.987	0.995	0.9933

Kendall's Coefficient: Measures ordinal associations. The coefficients are also very high, particularly for MCRAT, RATMI, and RAPS, suggesting these methods tend to rank criteria in a very similar order.

Pearson's Correlation: Shows the linear relationship between the ranking outputs. All methods perform exceptionally well with Pearson's Correlation, indicating a strong linear agreement between their rankings.

Rank-Biased Overlap (RBO): Evaluates the agreement among rankings while giving more importance to the top-ranked items. RBO scores are notably lower than the correlation coefficients, which might indicate that while the overall rankings are similar, the actual priority or rank assigned to the top items differs more substantially among the methods.

6. Conclusions

This study developed a comprehensive geometric-based multi-criteria decision-making (MCDM) framework for drone propeller material selection by integrating Intuitionistic Fuzzy Sets (IFS) with the recently established RAMS and RATMI techniques. By converting diverse linguistic evaluations into a unified intuitionistic fuzzy structure, the framework effectively addressed uncertainty, hesitation, and subjectivity inherent in expert-based assessments. Eight critical criteria cost-effectiveness, stiffness, durability, strength, sustainability, manufacturability, density, and strength-to-weight ratio were systematically analyzed to produce a technically robust and defensible material ranking.

The IF-RAMS method employed geometric decomposition of beneficial and non-beneficial attributes to compute median similarity indices, while IF-RATMI extended this formulation through trace-based majority indices to enhance discriminatory resolution. Both approaches generated highly consistent ranking patterns, which were further validated through strong statistical agreement: Pearson correlation values exceeding 0.998, Kendall's coefficients above 0.987, and RBO scores greater than 0.995. This high degree of concordance demonstrates that the geometric similarity principles of RAMS and the trace median integration of RATMI converge toward stable and reliable ranking outcomes, even under uncertainty-driven decision conditions.

Material A2 was consistently identified as the most suitable option across all analyses, followed by A11 and A7, with these positions remaining unchanged under individual method rankings, aggregated rank fusion, and cross-method consistency checks. Conversely, materials such as A4, A5, and A15 exhibited persistently low performance, underscoring the strong discriminatory capability of the proposed framework.

Overall, the developed geometric-based intuitionistic fuzzy MCDM framework demonstrates exceptional effectiveness for complex engineering decisions involving imprecise or hesitant expert information. Its successful deployment in evaluating drone propeller materials confirms its robustness, mathematical rigor, and practical relevance. Moreover, the framework is readily adaptable to broader UAV subsystem optimization, advanced composite material evaluation, and other high-uncertainty engineering design problems requiring systematic, multi-criteria trade-off analysis.

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