Evaluation of drone propeller materials through geometrics components using multi criteria decision making methods

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Abstract. Drones are widely used many different industries like Defence, Agriculture, Entertainment, Infrastructures inspections and monitoring of environmental etc. In these applications Drone's lift the propulsion, stability, maneuverability, and overall efficiency is great depends on its drone propeller. The choice of material for the drone propellers significantly affects the performance, durability, and efficiency. This study assess the important criteria while choosing the propeller materials such as stiffness, strength, durability, cost effectiveness, manufacturability, sustainability, density, and strength- to- weight ratio. The study presented and applied different multi criteria decision making (MCDM) techniques are MEREC, CRITIC, FUCOM, SWARA, and Entropy to evaluate these criteria. Further the study expands it evaluation to determine optimal materials for drone propellers using geometric based MCDM methods which are RAPS, RAMS, RATMI, and MCRAT. The results indicate that while each method has its owen strengths and weaknesses, a composite approach incorporating relative importance of the properties materials proves to the most effective. This comprehensive analysis offers valuable insights for selecting the most suitable material for enhancing drone performance across various applications. This study also examined the correlation among four multi criteria assessment techniques like RAPS, RAMS, MCRAT and RATMI. The relationships between variable were assessed using Pearson's correlation coefficient values, Kendall's Tau and Rank-Biased Overlap (RBO). Strong positive correlations were found among MCRAT, RATMI and RAPS, while RAMS displayed notable divergence. These results are suggested that, even though general methodologies are interchangeable, their subtle differences should be considered for specific research applications.

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1 Introduction

The unmanned aerial vehicles(UAVs) or unmanned aircraft systems(UAS) is know as Drone and it is also called as remotely operated flying robots, It is capable of performing very precise and repeated works without deviation through Embedded flight plans supported by onboard sensors and GPS navigation. Drones applications are Defence Entertainment, Agriculture, Environnemental Monitoring, Logistics, and Infrastructure inspection. The propeller is the most critical component in the drone, among the all other components, it is directly controls lift, thrust, maneuverabilty and efficiency. Hence, the material selection for drone propeller becomes crucial for achieving optimal performance, durability, and sustainability.

Many researchers have investigated composites and polymeric materials to enhance propeller performance in the recent years. The Suchat et al. (2020) evaluated epoxidized natural rubber nano silica composites for propeller blades and they also discovered significant improvements in tensile strength after UVs exposure. Mohamed et al. (2020) used FTIR, EDX, and LIBS to characterize carbon composite materials for UAV applications. Anand et al. (2022) examined additive manufacturing materials and high-performance alloys for UAVs, highlighting the trade-offs between cost, manufacturability, and stiffness etc. All of these research emphasize that the best propeller materials must strike a compromise between cost-effectiveness, weight reduction, and mechanical performance.

Due to their capacity to incorporate several competing criteria, Multi-Criteria Decision-Making (MCDM) procedures have emerged as a key component for material selection in tandem with materials research. For the evaluation of engineering materials in UAV and mechanical design research, objective and hybrid weighing techniques as MEREC (Keshavarz et al., 2021), CRITIC (Thakkar et al., 2021), SWARA, FUCOM, and Entropy have been widely used. These techniques reduce subjectivity and allow for the methodical prioritization of qualities like strength, sustainability, and manufacturability. In order to increase decision dependability, recent studies like those by Bennani et al. (2022), Ritu et al. (2023), and Altaie et al. (2023) show the increasing trend toward incorporating fuzzy or entropy-based hybrid weighing frameworks.

The majority of conventional MCDM frameworks handle criteria relationships linearly, missing the geometric interpretation of similarity between alternatives, even if these techniques improve quantitative robustness. Geometric component-based MCDM techniques, such as RAPS (Ranking by Alternatives Perimeter Similarity), RAMS (Ranking by Alternatives Median Similarity), MCRAT (Multi-Criteria Ranking and Analysis Technique), and RATMI (Ranking by Alternatives Trace-to-Median Index), have been developed recently to overcome this limitation. These techniques analyze alternatives using geometric constructs like perimeter, median, and trace values (Urosevic et al., 2024; Abdulaal & Bafail, 2022; Chatterjee & Chakraborty, 2025). These methods improve ranking stability and interpretive depth by capturing nonlinear interactions between criteria.

1.1 Research gap and novelty

Geometric component-based MCDM techniques have not been used in any previous study to assess and rank propeller materials, despite a great deal of work on drone material selection and the widespread use of MCDM methodologies. Previous research has mostly concentrated on using traditional ratio-based decision models or weighting criteria. By combining well-known objective weighing methods (MEREC, CRITIC, FUCOM, SWARA, Entropy) with geometric component-based analysis (RAPS, RAMS, MCRAT, and RATMI), the current study uniquely fill this gap, by converting abstract choice

matrices into geometric representations that uncover underlying structural links among performance criteria, this integrated framework makes it possible to compare materials in multiple dimensions. Therefore, the study offers a methodological novelty as well as a useful contribution to the design and selection of sustainable, high-performance drone propeller materials.

2 Identification and prioritization of critical properties of materials for drone propeller

The performance and efficiency of drones are strongly affected by the design and choice of material for the respective propellers. Propeller is a important main component for producing thrust, lift, and propulsion, which has a directly impact the drone stability, and overall operational effectiveness. Therefore, the appropriate material selection for the drone propellers are the crucial task, it included systematic analysis of various criteria are cost - effectiveness(X1), stiffness(X2), durability(X3), strength(X4), sustainability(X5), manufacturing capability(X6), density(7), and strength-to-weight ratio(X8). The perspective stake holders are considered Designers & Engineers (DM1), Manufacturer (DM2), Material Scientists (DM3), Environmental Experts (DM4), Marketing & Sales (DM5), Regulatory Bodies (DM6), End Users(DM7) and Investors & Financial Analysts. Multi-Criteria Decision-Making (MCDM) methods are presented in a systematic frame work for such complex decision-making process to enabling for systematic assessment and ordering of multiple factors, rgular conflicting criteria. Traditional methods for material choice may not fully address the specific requirements of drone propeller materials, including the balance between structural integrity and low weight with high stiffness and manufacturing feasibility.

In this work, investigated advanced applications of multi criteria decision-making process to identify, analyse the critical properties of materials which is suitable for drone propellers. We applied multiple MCDM techniques, such as MEREC (Measurement of Relative Entropy for Criteria), CRITIC (Criteria Importance through Intercriteria Correlation), FUCOM (Full Consistency Method), SWARA (Stepwise Weight Assessment Ratio Analysis), and Entropy, to assess the relative importance for various properties of material.

2.1 Explanation for choice of the proposed methods

The study's objective weighing techniques were choosen is based on their methodological diversity and complementary analytical strengths. Each method reflect different facets of decision information. MEREC (Measurement of Relative Entropy for Criteria) objectively determines the importance of criteria by evaluating the impact of removing each criterion, ensuring stability and robustness in complex datasets. CRITIC (Criteria Importance through Intercriteria Correlation) considers both the contrast intensity and inter-criterion correlation, offering a balanced view of variability and redundancy among material properties. FUCOM (Full Consistency Method) emphasizes pairwise consistency and logical coherence in derived weights, minimizing inconsistencies in expert judgments. SWARA (Stepwise Weight Assessment Ratio Analysis) allows sequential adjustment of criterion importance based on expert preference, introducing structured flexibility. Finally, Entropy weighting quantifies the degree of uncertainty or dispersion in the evaluation matrix, providing a purely data-driven perspective on criteria significance.

Combined these five methods provide a comprehensive and cross - verified through weighted framework, where the variance-based methods are integrated (CRITIC), entropy-

based (MEREC, Entropy), and consistency based (FUCOM, SWARA) approach improve reliability and minimise systematic error. Their integration ensures that both objective data dispersion and decision-maker priorities are effectively captured, resulting in a more comprehensive and defensible weighting structure for subsequent material ranking. By applying these methods, the aim to explain complete evaluation of the criteria that are very critical for selecting high-performance drone propeller materials. This approach not only improves the objectivity and accuracy of material selection but also contibute important analysis to optimizing drone construction and functionality. MCDM methods are discussed below.

3 Selection of materials for drone propeller

This study presents the advancement of recently developed multi criteria methods are RAPS, RAMS, MCRAT and RATMI, proposed new multi-criteria decision-making methods, Ranking by Median Similarity (RAMS) and Ranking Alternatives by Trace to Median Index (RATMI), which extends a perimeter similarity method (RAPS). Reda M. S. Abdulaal, Nguyen et al. [2024], Baraily et al. [2024], Bui et al. [2024], Omer A. Bafail [2022] Illustrated through a case study on brake booster valve materials, these methods were validated against seven established MCDM techniques and extended in this paper and the proposed methods are discussed with flow diagram of Figure 1 as shown below.

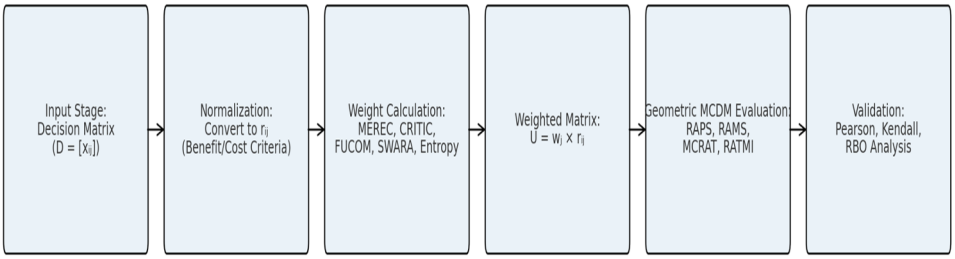

Fig. 1. Flow diagram for proposed methods.

Step1: Formulating data for problem (D): Formulate problem data as decision matrix (Xij) for use decision making process :

$$D = [x_{ij}]_{max} = \begin{bmatrix} A/C & C_1 & C_2 & \dots & C_n \\ A_1 & x_{11} & x_{12} & \dots & x_{1n} \\ A_2 & x_{21} & x_{22} & \dots & x_{2n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ A_m & x_{m1} & x_{m2} & \dots & x_{mn} \end{bmatrix}$$

where D: Decision matrix, A: Set of alternatives $[A_1, A_2, \dots, A_m]$ specified series of options, where m represents a number of available options, C: Set of criteria $[C_1, C_2, \dots, C_m]$ is specified series of criteria and where n represents a count for available criteria, Xij: Evaluation of alternative Ai in relation to criterion Cj and the evaluation involve s both benefit criteria (to be maximized) and cost criteria (to be minimized).

Step2: Transform problem data to Normalization form (R): The problem data involves multiple dimensions, for every dimension represents a different criterions, which complicates the decision making process. To overcome the these difficulties it is very much essential to transform it multidimensional decision space to a one dimensional solution space. Normalization for maximisation criteria is evaluated by using the following process:

$$r_{ij} = \frac{x_{ij}}{\max_i(x_{ij})}, \forall i \in [1,2,\dots,m] \Lambda j \in S_{max} \quad (1)$$

Where Criteria to be minimized

$$r_{ij} = \frac{\min_i(x_{ij})}{x_{ij}}, \forall i \in [1,2,\ldots.,m] \Lambda j \in S_{max} \quad (2)$$

Where r_{ij}: Normalized value of$x_{ij,}$ s_{max}: series of criteria to be maximized, s_{min}: Set of criteria to be minimized and R: Normalized decision matrix

According to the normalized decision matrix is represented in the following form x_{ij}

$$R = [r_{ij}]_{max} = \begin{bmatrix} A/C & C_1 & C_2 & \ldots & C_n \\ A_1 & r_{11} & r_{12} & \ldots & r_{1n} \\ A_2 & r_{21} & r_{22} & \ldots & r_{2n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ A_m & r_{m1} & r_{m2} & \ldots & r_{mn} \end{bmatrix}$$

Step3: Weighted data normalization (U): Execute the weighted normalization for all normalized evaluations for following these process r_{ij}

$$u_{ij} = w_i r_{ij,} \forall i \in [1,2,..,m], \forall j \in [1,2,\ldots,n] \quad (3)$$

In which u_{ij} : Weighted normalized value, w_j: significance of criterion C_j, and U: Weighted normalization matrix, Indicate importance of criterion j which could be obtained through an advisery experts or by employing a MCDM method. The weights must have total value of one: $\sum w_j = 1$. Subsequentely, the weighted matrix for normalized decision matrix is stated below:

$$U = [u_{ij}]\ max = \begin{bmatrix} A/C & C_1 & C_2 & \ldots & C_n \\ A_1 & u_{11} & u_{12} & \ldots & u_{1n} \\ A_2 & u_{21} & u_{22} & \ldots & u_{2n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ A_m & u_{m1} & u_{m2} & \ldots & u_{mn} \end{bmatrix}$$

Step4: Identification Optimal alternative (Q): The elements of the optimal alternatives are identified through the follows procedure:

$$q_j = \max\left(u_{ij} \middle| 1 \le j \le n\right), \forall i \in [1,2,\ldots,m] \quad (4)$$

A most suitable alternatives are determined using the set detauled below:

$$Q = \{q_{1,}q_{2,} \ldots\ldots, q_j\}, (j = 1, 2\ldots\ n) \quad (5)$$

Where q_j: Elements of the optimal alternative, Q: Set of optimal alternatives

Step5: Dissection of the optimal alternative: Decompose the optimal alternative into two separate components or sets,

$$Q = Q^{max} \cup Q^{min}, \forall i \in [1,2,\ldots,m] \quad (6)$$

$$Q = \{q_{1,}q_{2,} \ldots\ldots, q_k\} \cup \{q_{1,}q_{2,} \ldots\ldots, q_h\};\ k + h = j \quad (7)$$

In which Q_{max}: Group of components which need to be maximized, Q_{min}: Group of components which need to be minimized and where k denotes the total count of criteria to be maximized and where h denotes the total count of criteria to be minimized.

Step6: Dissection of the alternative similarly, to step5: Dissection of the optimal alternative

$$U_i = U_i^{max} \cup U_i^{min}, \forall i \in [1, 2, \dots, m] \quad (8)$$

$$U_i = \{u_{i1}, u_{i2}, \dots \dots, u_{ik}\} \cup \{u_{i1}, u_{i2}, \dots \dots, u_{ih}\}; \forall i = [1, 2, \dots, m] \quad (9)$$

Here U_i^{max}: Maximum component set for the alternativeA_i, U_i^{min}: Minimum component set for the alternative A_i

Step7: Magnitude of component: Determine the magnitude corresponding to every element of the most suitable choice, by following definition.

$$Q_k = \sqrt{q_1{}^2 + q_2{}^2 + \cdots . + q_k{}^2} \quad (10)$$

$$Q_h = \sqrt{q_1{}^2 + q_2{}^2 + \cdots . + q_h{}^2} \quad (11)$$

The same procedure is repeated for all alternatives.

$$U_{ik} = \sqrt{u_{i1}{}^2 + u_{i2}{}^2 + \cdots + u_{ik}{}^2}, \quad \forall i = [1, 2, \dots, m] \quad (12)$$

$$U_{ih} = \sqrt{u_{i1}{}^2 + u_{i2}{}^2 + \cdots + u_{ih}{}^2}, \qquad \forall i = [1, 2, \dots, m] \quad (13)$$

Where Q_k: Magnitude of components to be maximized, Q_h : Magnitude of components to be minimized, Q_{ik}: Magnitude of components to be maximized for alternative A_i, Q_{ih}: Magnitude of components to be minimized for alternative A_i,

3.1 Ranking by alternatives perimeter similarity (RAPS)

In this method, the most preferred alternative represented by a right angled triangle defined base Q_k and Q_h . The perimeter of this reference triangle serves as a benchmark against which the perimeters of other alternatives are compared.

Step 1: Calculate Perimeter (P): Calculate Perimeter form the following formula

$$P = Q_k + Q_h + \sqrt{Q_k^2 + Q_h^2} \quad (14)$$

Where P is Perimeter of the most preferred alternative

Step 2: Calculate Perimeter for Each Alternative: Calculate a Perimeter of each alternative from the below equation

$$P_i = U_{ik} + U_{ih} + \sqrt{U_{ik}^2 + U_{ih}^2} \quad (15)$$

Here P_i is Perimeter of each alternative

Step3: Calculate Perimeter Similarity (PS_i): Calculate the Perimeter Similarity form the following formula

$$PS_i = \frac{P_i}{P}, \forall i = [1, 2, \dots ., m] \quad (16)$$

Here PS_i is Perimeter Similarity for each alternative.

Step4: Rank the Alternatives: Rank the Alternatives as per the descending order for Perimeter Similarity

3.2 Ranking by alternatives median similarity (RAMS)

RAMS provides a systematic approach examine and rank the alternative with respect to their median similarity of an optimal reference by calculating and comparing median values. The use of RAMS technique by calculating median value as per following steps.

Step1: Determine Median(M): Calculate a Median as per the formula

$$\mathrm{M} = \sqrt{({Q_k}^2 + {Q_h}^2)/2} \tag{17}$$

Here M is Median of the optimal alternative

Step2: Determine a Median for each alternative: Calculate the Median of each alternative from following formula

$$\mathrm{M}_i = \frac{\left(\sqrt{{\mathrm{U_{ik}}}^2 + {U_{ih}}^2}\right)}{2} \tag{18}$$

Here M_i is Median of each alternative

*Step3: Determine Median Similarity (MS_i)***:** Calculate the Median Similarity from the following formula

$$MS_i = \frac{\boldsymbol{M_i}}{\boldsymbol{M}}, \forall \boldsymbol{i} = [\mathbf{1}, \mathbf{2}, \ldots., \boldsymbol{m}] \tag{19}$$

Here $\mathrm{MS_i}$ is Median Similarity for each alternative

Step4: Rank the Alternatives: Rank the Alternatives as per the descending order for Median Similarity.

3.3 Ranking by alternatives trace (MCRAT)

The Multi-Criteria Ranking and Analysis Technique (MCRAT) that serves as a benchmark for evaluating alternatives, it encapsulates the optimal performances and is essential for the subsequent steps in the MCRAT methodology.

Step1 Construct matrix F using components for optimal alternative: Calculate the components for the optimal alternatives from the following matrix

$$\mathrm{F} = \begin{bmatrix} Q_k & 0 \\ 0 & Q_h \end{bmatrix}$$

Where F is matrix of optimal alternative components.

Step2Construct matrix G_j using components of optimal alternative: Determine the composed of optimal alternative components from the following matrix

$$\mathrm{G_j} = \begin{bmatrix} U_{ik} & 0 \\ 0 & U_{ih} \end{bmatrix}, \forall i = [1,2, \ldots., m] \tag{20}$$

Here $\mathrm{G_j}$ is Matrix of components for each alternative

Step3 Create the matrix G_j composed of optimal alternative components: Determine the components of the optimal alternatives from the following matrix

$$\text{Ti=F x } G_j = \begin{bmatrix} t_{11j} & 0 \\ 0 & t_{22j} \end{bmatrix}, \forall i = [1,2,\ldots\ldots,m] \quad (21)$$

Where Ti is product of matrix F and matrix $\mathbf{G_j}$

Step4: Rank the Alternatives: Rank the Alternatives as per the descending order of alternatives traces.

3.4 Ranking the alternatives using the trace to median index (RATMI)

The RATMI method provides a systematic framework for evaluating and ranking alternatives based on multiple criteria. Assume that v represents the importance of MCRAT's strategy and (1 – v) is a importance of RAMS's strategy, prefrence index (E_i) between the two strategies are calculated and explained below.

Step1 Define Weights for Strategies: Define and assign the strategies as following
Define and assign weights, Where 'v' indicates the weight for the MCRAT's strategy and '(1 – v)' represents the weight for RAMS's strategy.

Step2 Determine Majority Index (E_i): Determine the value of major index from the following formula

$$\text{E}_\text{i} = \text{v } \frac{(tr_i - tr^*)}{(tr^- - tr^*)} + (1-v)\frac{(MS_i - MS^*)}{(MS^- - MS^*)} \quad (22)$$

In which

tr_i = tr (T_i), $\forall i = [1,2,\ldots\ldots\ldots\ldots,m]$
tr^* = min ($tr_{i)}$, $\forall i = [1,2,\ldots\ldots\ldots\ldots,m]$
tr^- = max ($tr_{i)}$, $\forall i = [1,2,\ldots\ldots\ldots\ldots,m]$
MS^- = max (MS_i), $\forall i = [1,2,\ldots\ldots\ldots,m]$
MS^* = min (MS_i), $\forall i = [1,2,\ldots\ldots\ldots\ldots,m]$

Here *v* is a value between 0 and 1, in this case *v*= 0.5.

Step3: Rank the Alternatives: Rank the Alternatives as per the descending order for alternatives traces, alternatives median and alternatives perimeter.

4 Results and discussion

4.1 Prioritization of properties of drone materials

In this regard, the properties namely (X1) Cost-Effectiveness, (X2) Stiffness , (X3) Durability, (X4) Strength , (X5) Sustainability, (X6) Manufacturing Capability, (X7) Density and (X8) Strength-to-Weight Ratio are considered and Relative rating of the Properties are Stakeholders related Designing, Manufacturing, material selection, Marketing & Sales, Regulatory bodies, end users and Investors are considered for rating of drone propeller material properties. Rating matrix indicated in this table 1.

Table 1. Rating matrix.

Stake holders	DMs	Criteria							
		X1	X2	X3	X4	X5	X6	X7	X8
Engineers & Designers	DM1	2	8	5	6	1	4	7	3
Manufacturers	DM2	8	5	6	7	2	3	4	8
Material Scientists	DM3	5	6	7	8	4	5	6	7
Environmental Experts	DM4	3	4	5	3	8	6	2	4
Marketing & Sales	DM5	7	6	6	5	3	4	5	6
Regulatory Bodies	DM6	5	6	7	6	8	5	4	3
End Users	DM7	6	7	8	6	5	4	5	3
Investors & Financial Analysts	DM8	8	5	4	6	3	4	6	5

Prioritization of Properties through the proposed methods: In this paper, MEREC, CRITIC, FUCOM, SWARA and Entropy methods are implemented to determine the relative weights of the properties. Table 2 shows the assessment for the relative weights are derived with the proposed techniques.

4.2 Relatives weights are derived from the proposed methods

Relative weights for proposed methods and expected relative weights for the properties were provided in table 2.

Table 2. Expected relative weights.

Main Criteria	Relative Weights					Expected Weight
	MEREC	CRITIC	SWARA	FUCOM	Entropy	
Cost-Effectiveness (X1)	0.1759	0.1347	0.1313	0.1190	0.1071	0.1345
Stiffness (X2)	0.0704	0.0959	0.1397	0.1037	0.1081	0.1027
Durability(X3)	0.0719	0.0806	0.1426	0.1017	0.1083	0.1018
Strength (X4)	0.1219	0.1033	0.1397	0.1051	0.0764	0.1075
Sustainability (X5)	0.2493	0.1779	0.1040	0.1702	0.1434	0.1693
Manufacturing Capability(X6)	0.0695	0.1098	0.1069	0.1391	0.1059	0.1042
Density (X7)	0.1629	0.1322	0.1179	0.1297	0.0831	0.1229
Weight to Strength Ratio(X8)	0.0783	0.1655	0.1179	0.1315	0.2677	0.1571

Consensus Weight:

The consensus weight vector was obtained as the three-point estimate of the normalized weights from the five objective methods (MEREC, CRITIC, SWARA, FUCOM, and Entropy). A resampling-based robustness check, which recomputed the consensus after removing one method at a time. It evaluates how sensitive a model or result is to the influence of individual components.

4.3. Analysis

The results indicate relative weights assigned for different methods to evaluating key criteria related to material performance. Every methodology like MEREC, CRITIC, SWARA, FUCOM, and Entropy provide separate findings regarding the significances for several factors.

Cost-Effectivités (X1): The weights vary between 0.0164 (Entropy) to 0.1493 (SWARA), reflecting it various approach for weigh cost-effectiveness in divers way. SWARA position is a formost consideration, indicating it values this criterion substantially in the decision-making process.

Stiffness (X2): The weighting for stiffness differs notably, with MEREC indicating 0.1328, where as SWARA indicationg 0.0574. This demanstrates how material choice impact the significance of stiffness in material analysis.

Durability (X3): The weights are comparatively low across all methods, the FUCOM indicates 0.1073. This may shows that durability is important, it is not prioritized as highly as other criteria like strength.

Strength (X4): Strength is significantly importance, in MEREC (0.3482) and CRITIC (0.0998), it showing that strength is a critical factor in evaluating materials.

Sustainability (X5): Sustainability weights vary, with CRITIC (0.1759) showing it the highest importance, it show rise trend in prioritizing environmentally friendly materials.

Manufacturing Capability (X6): Significant the weights are vary, with CRITIC (0.1456) emphasizing this criterion showing that manufacturing considerations are importance in some methodologies, potentially indicating the feasibility of production.

Density (X7): The highest density weight in SWARA (0.2240), shows that this method significantly factors density into its evaluation criteria, its importance in applications where weight is critical.

Weight to Strength Ratio (X8): The weights are high across all methods, with MEREC and SWARA both assigning 0.1522. This shows that this ratio is important in choosing of materials, in structural applications where optimizing weight and strength is essential.

The analysis indicates substantial diversity in comparative importance for every respective parameter to evaluate by respective methodology. Such as MEREC tend to prioritize strength and cost-effectiveness, while others like CRITIC emphasize sustainability and manufacturing capability. The differences in weights indicates the required for thoughtful avaluation. when choosing a methodology to evaluation of material, as it can significantly affects the considered weights of different properties. These refinement enables decision-makers to adapt their analysis frame works to fit with particular objectives and critical issues.

4.4 Drone propeller materials

The Eighteen materials are choosen for producing drone propellers in drone industry. Here selected as important materials in this study. Polycarbonate(PC), Polypropylene(PP), Acrylonitrile Butadiene Styrene(ABS), Nylon (Polyamide), Carbone Fiber Reinforced Plastics(CFRP), Fiberglass Reinforced Plastics(FRP), Wood(W), Aluminum(AL), Thermoplastic Elastometers (TPE), Polystere(PS), Polylactic Acids(PLA), Polyether Ether Ketone (PEEK), Polyetherimide (PEI/ULTEM), Carbon Fiber Filled Filaments(CFFF), Carbon Fiber (CF), Glass Fiber Filled Filaments(GFFF), Ti-6Al-4V5 and Ti-6Al-4VELI Grade 23 are taken into consideration. In this study, RAPS, RAMS, MCRAT and RATMI

methods are applied for identication of UA propeller materials is evaluated and methodology is presented.

4.5 Relative rating of the materials

Decision Rating Matrix : Stakeholders related Designing, Manufacturing, material selection, Marketing & Sales, Regulatory bodies, end users and Investors are considered for rating of drone propeller material properties. The matrix of size an n x m, where n corresponding to the series of Alternatives (A) and m is corresponding to the series of properties (X). All criteria are benefit hence components are considered as benefit only. The problem data, structured as a decision-making matrix as described in step 1 of section 3 and presented in table 3.

Table 3. Decision making matrix.

S.No.	Alternative Materials	Criteria							
		X1	X2	X3	X4	X5	X6	X7	X8
1	Polycarbonate(PC)	6	3	3	3	3	6	3	2
2	Polypropylene (PP)	8	5	5	4	4	8	8	7
3	Acrylonitrile Butadiene Styrene(ABS)	5	4	6	5	3	7	4	6
4	Nylon (Polyamide)	2	6	2	2	4	5	8	1
5	Carbone Fiber Reinforced Plastics(CFRP)	3	1	8	8	4	4	2	8
6	Fiberglass Reinforced Plastics(FRP)	7	6	7	6	4	5	3	5
7	Wood	8	2	3	2	1	2	7	1
8	Aluminum	4	6	6	6	5	2	5	6
9	Thermoplastic Elastometers (TPE)	7	4	2	7	4	3	2	4
10	Polystere(PS)	7	2	1	3	4	2	2	4
11	Polylactic Acids(PLA)	8	3	2	2	8	6	2	2
12	Polyether Ether Ketone(PEEK)	5	1	6	5	4	4	5	4
13	Polyetherimide(PEI/ULTEM)	4	3	1	2	4	5	6	3
14	Carbon Fiber Filled Filaments	3	8	3	8	7	3	7	8
15	Carbon Fiber	2	8	8	8	7	3	5	8
16	Glass Fiber Filled Filaments	6	7	7	6	3	1	4	6
17	Ti-6Al-4V(5)	4	2	5	3	5	2	1	1
18	Ti-6Al-4VELI(Grade 23)	7	2	5	3	5	2	1	1

Relative priority of material for Drone Propeller: in this study, according to the relative weights for the critical properties, relative priority of material for drone propeller is explores through RAPS, RAMS, MCRAT and RATMI. The ranks of the alternate material

for drone propeller obtained by the proposed methods are compared and shown in Table 4. Expected rank is also determined and observations are summarized.

Table 4. Expected rank.

S.No	Materials	Methods				
		RAPS	RAMS	RATMI	MCRAT	Expected rank
1	Polycarbonate(PC)	17	17	17	17	17
2	Polypropylene (PP)	3	3	3	3	3
3	Acrylonitrile Butadiene Styrene(ABS)	9	9	9	9	9
4	Nylon (Polyamide)	15	14	15	15	15
5	Carbone Fiber Reinforced Plastics(CFRP)	4	4	4	4	4
6	Fiberglass Reinforced Plastics(FRP)	7	7	6	6	6
7	Wood(W)	16	15	16	16	16
8	Aluminum(AL)	6	6	7	8	10
9	Thermoplastic Elastomers (TPE)	10	10	10	10	10
10	Polystyrene(PS)	12	12	12	12	12
11	Polylactic Acids(PLA)	5	5	5	5	5
12	Polyether Ether Ketone(PEEK)	11	11	11	11	11
13	Polyetherimide(PEI/ULTEM)	14	14	14	14	14
14	Carbon Fiber Filled Filaments(CFFF)	1	1	1	1	1
15	Carbon Fiber (CF)	2	2	2	2	2
16	Glass Fiber Filled Filaments(GFFF)	8	8	8	7	8
17	Ti-6Al-4V(5)	18	18	18	18	18
18	Ti-6Al-4VELI(Grade 23)	13	13	13	13	13

The results are exhibited clear consistency, leading to the selection of the most suitable materials for drone propellers. The most appropriate drone propeller material is identified that Carbon Fiber Filled Filaments (CFFF), this material exhibit high mechanical strength, excellent dimensional stability and robust process reliability. The leading to the consistent product performance, outstanding quality control and stringent specification adherence along with the recyclable. The second highest ranked material is Carbon Fiber (CF). Relative ranking of the proposed materials are shown Figure 2 of histogram with embedded lines as shown below.

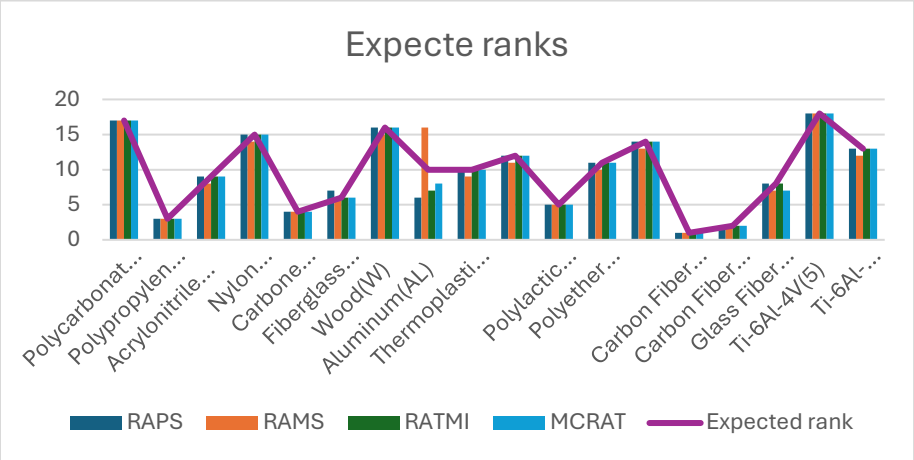

Fig. 2. Comparison of rankings by proposed methods.

4.6 Discussion of results

The comparative ranking outcomes derived from RAPS, RAMS, MCRAT, and RATMI are closely aligned with the intrinsic mechanical and physical properties of the evaluated materials. Carbon Fiber Filled Filaments (CFFF) secured the highest rating predominantly because of the materials high tensile strength-to-weight ratio, which is about the range of 590 MPa to 700MPa in density close to 1.6 g/cm³ and structural stability that confirm maximum lifting performance and resistance to the oscillation during the UAV uses. In addition to ability to recycled and suitable for 3D printing to enhances for better eco friendly and fabrication rating.

The material in second highest rank is Carbon Fiber (CF), shows equivalent strength advantages, however reduced the processing flexibility and more expenses, some what reducing the it score, near affordable and manufacturing capacity . CFRP (Carbon Fiber Reinforced Plastics) and PLA (Polylactic Acid) placed in subsequently. Since it providing a best trade-off in medium range tensile capacity of 65 – 80MPa, reduced mass density range is 1.2 – 1.6 gm/cc, good formability and rendering them into desired low weight drone propeller model, in which economical and sustainability concern are crucial consideration.

In the polymeric base materials, PP and ABS showed the significant performance because of the low material density, deformability and manufacturability, even though reduced their structured stiffness and endurance limit for high thrust drone propeller models. Altrantively metal based choice such as aluminium alloys and titanium alloys(Ti-6A1-4V) & (Ti-6A1-4V ELI) are showed high mechanical performances but experienced higher density of 2.6 – 4.5 gm/cc which reduced the performances and also reducing geometric similarity rating as per RAPS and RAMS studies. Whole combined specific materials strength, stiffness, light weight and recyclability shown in the carbon based composites, repeatedly obtained best scores and rankings in all geometric multi criteria decision making methods. The results confirm the model's effectiveness to capture the engineering and technical conditions of the drone propeller performances, validating that geometric similarity indices that integrated performance and sustainability in material choosing process.

It is evident, that the results show strong consistency. The most appropriate material for the drone propeller is identified that Carbon Fiber Filled Filaments(CFFF), this material provide high strength along with very good dimensional stability and process stability. This material ensures reliable performance in challenging environment. The result leads to

consistently reliable product performance, it is produce excellent quality control, adheres to strict product specifications and fully recyclable. The Carbon Fiber (CF) material hold the second rank, it is the most preferred material for this application.

5 Correlation analysis for proposed methods

In this framework, metrics are required to evaluate the similarity and dissimilarity between the ranked lists. Three prominent methodologies are applied in this context, the Pearson's correlation coefficient values, Kendall's Tau and rank-biased overlap (RBO). Each provide a unique approach for evaluating similarity in ranking.

5.1 Spearman's Rank Correlation Coefficient

Determine the magnitude and the trend correlation for the two variables in ranked order

5.2 Kendall's Tau

Evaluate the ranking consistency by comparing how many pairs are in the same order to those that are in a different order.

5.3 Rank-Biased Overlap (RBO)

RBO gives a similarity measures that emphasize the evaluation of highly ranked items, while progressively integrating the influences of items' depth within the ranking.

5.1.1 Pearson's correlation analysis

Pearson's method is applied to calculate the correlation coefficient values of the proposed methods and illustrated in table 5.

Table 5. Correlation coefficients.

Pearson's Coefficient method				
Methods	**MCRAT**	**RAMS**	**RATMI**	**RAPS**
MCRAT	1.000	0.968	0.982	0.962
RAMS	0.968	1.000	0.991	0.997
RATMI	0.982	0.991	1.000	0.988
RAPS	0.962	0.997	0.988	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 rank correlations

Kendall rank correlation's values are computed with MAT Lab programming and presented in table 6.

Table 6. Kendal index values.

Kendall coefficient				
Method	**MCRAT**	**RAMS**	**RATMI**	**RAPS**
MCRAT	1.0000	0.8954	0.9869	0.9739
RAMS	0.8954	1.0000	0.8824	0.8693
RATMI	0.9869	0.8824	1.0000	0.9869
RAPS	0.9739	0.8693	0.9869	1.0000

The table illustrated the Kendal correlation values, further correlation of measure of it indicators, corresponding the RAPS, RAMS, RATMI, and MCRAT. The Kendal values are evaluated for strength and direction of the correlations are observed between given two variables analyzed via ordinal or continuous scales. In this method highly beneficial for analyzing.

The outcomes emphasize that RAPS, RATMI, and MCRAT possess significant correlation among themselves. The systematic arranging data in the consisting way. The RAMS on the other side, though continuing to display good consistency. It also presents slightly weaker correlation comparing to the other MCDM methods. That reflects that RAMS could be greater sensitivity to diverse sets of data or may analyzes particular ranking orders differently relatively to the other techniques. This divergence may helpful in research studies for subtle in the analytical nuance where small data variations are crucial.

5.1.3 Ranked biased overlap values

This approach establishes depth wise ranking overlap with MAT Lab software to generate RBO values. The RBO technique aim to quantify the the comparable between two ranked order sets while placing higher priority elements. The results for the Rank-Biased Overlap (RBO) method are represented in table 7.

Table 7. RBO index values.

RBO Index Values				
Method	**MCRAT**	**RAMS**	**RATMI**	**RAPS**
MCRAT	1.0000	0.4962	0.5810	0.5693
RAMS	0.4962	1.0000	0.4743	0.4626
RATMI	0.5810	0.4743	1.0000	0.5911
RAPS	0.5693	0.4626	0.5911	1.0000

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

For each MCDM method, Average consistency index are calculated by averaging the values in the i^{th} row and column (excluding the diagonal element, which is always 1 since it compares the method to itself). The Consistency score mean levels are displayed in table 8.

Table 8. Average consistency index values.

Index Values	Consistency Method			Average
MCDM Method	**Correlation**	**Kendall's**	**RBO**	
MCRAT	0.9707	0.9521	0.5488	0.8239
RAMS	0.9853	0.8824	0.4777	0.7818
RATMI	0.9870	0.9521	0.5488	0.8293
RAPS	0.9823	0.9434	0.5410	0.8222

***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.
***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.
***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.

Profit and cost factors were clearly specified and standardised to maintain uniform directional coherence of rating values. Minor divergence observed in the RAMS method (Average = 0.7818) compared to RAPS, MCRAT, and RATMI (Average ≈ 0.82) originates from RAMS's median-based smoothing behaviour, which moderates the influence of extreme performance values. Importantly, all methods preserved the same top-ranked alternatives (CFFF, CF), demonstrating high inter-method reliability and methodological robustness of the geometric component based framework. Quantitative comparison clarifies the decision-makers' rankings. Typical carbon-fiber-filled filaments (CFFF) exhibit density ≈ 1.6 g cm^{-3}, modulus 50 GPa, and tensile strength 800 MPa, closely matching continuous carbon fiber (70 GPa, 1000 MPa) but with superior manufacturability. CFRP composites, though strong (≈ 900 MPa), show reduced specific stiffness due to the polymer matrix. Under equal-stiffness sizing, CF and CFRP props would weigh ≈ 10 % and 5 % less than CFFF respectively differences small relative to their processing and sustainability penalties, justifying CFFF's top rank.

5.1.5 Sensitivity analysis

Twelve runs are simulated through Taguchi design with L12 model with eight factors maintained at two levels (+/-10% variation and +/- 20%) variation in the base weight structure and rank stability is observed. Top rank stability. Weight structure of the runs is presented in table 9.

Table 9. Weight structure for sensitivity analysis

Run	WX1	WX2	WX3	WX4	WX5	WX6	WX7	WX8
1	0.1345	0.1027	0.1018	0.1075	0.1693	0.1042	0.1229	0.1571
2	0.1128	0.0862	0.0854	0.0902	0.1420	0.1311	0.1546	0.1977
3	0.1131	0.0864	0.1284	0.1356	0.2135	0.0876	0.1033	0.1321
4	0.1011	0.1158	0.0766	0.1213	0.1910	0.0784	0.1386	0.1772
5	0.1021	0.1169	0.1159	0.0816	0.1927	0.1186	0.0933	0.1789
6	0.1059	0.1213	0.1203	0.1270	0.1334	0.1231	0.1452	0.1237
7	0.1538	0.0783	0.1164	0.1229	0.1290	0.0794	0.1405	0.1796
8	0.1533	0.0780	0.1160	0.0817	0.1929	0.1187	0.1400	0.1193
9	0.1510	0.0769	0.0762	0.1207	0.1900	0.1170	0.0920	0.1763
10	0.1617	0.1234	0.1224	0.0861	0.1357	0.0835	0.0985	0.1888
11	0.1648	0.1258	0.0831	0.1317	0.1383	0.1276	0.1004	0.1283
12	0.1595	0.1218	0.0805	0.0850	0.2008	0.0824	0.1458	0.1242

Ranking of material under 12 scenarios is presented below table 10.

Table 10. Ranking of material under 12 scenerios.

S. No.	Alternative Materials	Scenarios												Overall ranks
		1	2	3	4	5	6	7	8	9	10	11	12	
1	Polycarbonate(PC)	17	16	17	17	17	15	17	17	15	15	14	17	17
2	Polypropylene (PP)	3	1	3	3	3	3	1	1	3	2	1	3	3
3	Acrylonitrile Butadiene Styrene(ABS)	9	5	9	9	9	8	8	9	9	8	8	12	9
4	Nylon (Polyamide)	12	10	13	11	11	10	14	13	17	16	16	11	12
5	Carbone Fiber Reinforced Plastics(CFRP)	4	4	4	4	4	4	4	6	5	7	8	4	4
6	Fiberglass Reinforced Plastics(FRP)	6	7	6	8	8	5	5	5	6	6	4	5	5
7	Wood	13	14	18	15	15	12	13	11	14	12	11	10	13
8	Alumin	8	6	7	5	5	7	7	7	7	7	9	6	7

	um													
9	Thermo plastic Elastom eters (TPE)	10	12	10	10	10	12	10	12	10	10	10	9	10
10	Polyster e(PS)	15	15	15	14	14	17	13	16	12	13	15	15	15
11	Polylact ic Acids(P LA)	5	9	5	6	6	9	9	4	4	9	5	4	5
12	Polyethe r Ether Ketone(PEEK)	11	11	11	12	12	11	11	10	11	11	12	14	11
13	Polyethe rimide(P EI/ULT EM)	16	13	16	13	13	14	16	15	16	17	17	16	16
14	Carbon Fiber Filled Filamen ts	2	2	1	1	1	2	2	2	1	1	2	1	1
15	Carbon Fiber	1	3	2	2	2	1	3	3	2	3	3	2	2
16	Glass Fiber Filled Filamen ts	7	8	8	7	7	6	6	8	8	5	6	7	8
17	Ti-6Al-4V(5)	18	18	14	18	18	18	18	18	18	18	18	18	18
18	Ti-6Al-4VELI(Grade 23)	14	17	12	16	16	16	14	14	13	14	13	13	14

The evaluation of material ranking in twelve scenarios indicates that carbon fiber filled filaments material (CFFF) consistently appear as highest performing material, immediately succeeded by the carbon fiber (CF) and polypropylene(PP), showing their excellent combination of mechanical strength, weight optimization and ease of production. CFRP and FRP shows steady performance, rendering them as reliable options for top performance and eco friendly design frame work. PLA shows the satisfactory results because of its sustainable characteristics, whereas aluminium and GFFF are hold in intermediate ranking positions. The alternative materials are PC, PEI/ULTEM, PS and titanium alloys have exhibits steadily low performance rankings, mostly because of high expensive, dense nature or restricted flexibility under various parameters. Whole composite and polymer based materials are excelling over the metals and standard materials indicating their significant importance in modern lightweight and green manufacturing practices.

Coherence across the scenarios is established because the correlation values are close to one (Greater than 0.9). Therefore, ranking consistency is achieved.

6 Conclusion

The present study emphasizes the crucial importance of rigorous choice of materials for UAV propellers which is very much necessary for performance and efficiency optimization by applying sophisticated MCDM techniques such as MEREC, CRITIC, FUCOM, SWARA, and Entropy methods. This study established systematic methods for evaluating important properties of prospective materials. The combinations of correlation matrices for determining criteria significances to strengthen the study and enabling in depth of understanding of materials properties from a multiple stakeholders perspective including designers, manufacturers and end users. The work outcomes not only provides valuable insights for the choice of material decision making and also basis for future studies aimed at optimizing drone design and performance, the systematic approach is illustrated in this work. Enable the decision makers to make knowledgeable choices that achieve equilibrium among the performance, expenses and eco friendliness thereby supporting the progressive improvements of drone systems.

Furthermore, the comprehensive analysis with RAPS, RAMS, RATMI, and MCRAT emphasize the importance priorities assigned by MCDM techniques to critical properties, including economic efficiency, stiffness, durability, mechanical strength, density, manufacturability, and strength to weight ratio, highlighting carbon fiber filled filaments(CFFF) is the optimal choice based on its exceptional strength, structural stability, recyclability, and environmentally friendly characteristics. Validating the importance of a structured methodology in choosing materials, CFFF provides balanced options with printability, lighter than CF, and higher stiffness/strength than PP, at the cost of some CF performance. The performance comparisons justify the order: CFFF rank1, CF rank2, and PP rank3.

The correlation evaluations also confirm the consistency of the proposed methods, demonstrating robust correlations according to Pearson's and Kendall's values. Furthermore Rank Biased Overlap (RBO) evaluations shows that fine grained deviations can provide customized specific purposes and applications.

Broadly, this study emphasizes a flexible approach for choosing drone propeller materials, it facilitating the decision makers to synchronize strategies with project requirements, while taking into account the heterogeneous concern of the stakeholders. Established a robust frame work for future investigation focused on drone design enhancement and performance improvement through strategic materials selection, there by supporting the development of UAV amide rapid innovation.

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