Langit Biru: Jurnal Ilmiah Aviasi Vol.18 No.2 June 2025 Page. 94 : 102
ISSN (p) 1979-1534 ISSN (e) 2745-8695

MULTI-CRITERIA DECISION ANALYSIS FOR FIRE PATROL HELICOPTERS SELECTION USING AHP-ENTROPY-TOPSIS

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Received :	Revised :	Accepted :
15 January 2025	01 May 2025	12 June 2025

Abstract: Forest fires pose a significant threat both locally and globally, with indirect impacts including global air pollution and human health issues. Aerial patrols using helicopters are a crucial measure in wildfire management. However, selecting the appropriate helicopter model involves multiple factors. Poor decision-making can lead to increased operational costs, accidents, and mission failure. To address this, operators must choose the most suitable helicopter for fire patrol operations. This study aims to enhance the decision-making process by integrating subjective and objective weighting methods in Multi-Criteria Decision Making (MCDM). Subjective weights are determined using the Analytic Hierarchy Process (AHP), while objective weights are derived from the Entropy method. The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is applied to identify the optimal helicopter model. By analyzing the combined weighting results, this study provides a robust decision-support tool, ensuring the selection of the most efficient and effective helicopter for wildfire patrols.

Keywords: Helicopter Selection, MCDM, AHP, Entropy, TOPSIS, Aviation, Subjective and Objective Weighting

Introduction

Wildfires pose a serious environmental and public health threat, both locally and globally. The immediate impacts are felt at the site of the incident, including vegetation degradation, biodiversity loss, property damage, and even casualties (Herawati & Santoso, 2011). Beyond these direct consequences, wildfires also generate smoke and carbon emissions, leading to global air pollution and human health issues (Abdul Kadir et al., 2022). According to the annual report of the Indonesian National Disaster Management Agency (BNPB), there were 2,051 forest and land fires in Indonesia in 2023, accounting for 37.98% of total disasters and making it the most frequent natural disaster of the year (Badan Nasional Penanggulangan Bencana, 2024). This highlights the urgent need for effective infrastructure to combat wildfires.

Aerial firefighting, particularly through helicopter patrols and water bombing operations, plays a crucial role in wildfire mitigation. Helicopters offer extensive coverage, rapid response, and the ability to reach remote areas such as mountainous regions and vast tropical forests in Indonesia. However, the high operational costs, along with various technical and non-technical criteria that must be considered, make helicopter selection a critical aspect of wildfire management. The success of a mission depends not only on speed and coverage but also on cost efficiency, maneuverability in difficult terrains, and endurance in extreme environmental conditions. Therefore, an in-depth study is needed to determine the optimal helicopter for wildfire patrol operations.

DOI: https://doi.org/10.54147/langitbiru.v18i02

Multi-Criteria Decision Making (MCDM) is widely used for selecting aircraft based on multiple evaluation criteria (Nila & Roy, 2023). The aviation industry has applied MCDM in aircraft selection processes, considering factors such as technical specifications, economic efficiency, safety, and operational performance (Dožić, 2019; Singh & Pant, 2021). A key challenge in MCDM is determining the appropriate weighting method, as different approaches can significantly impact the decision-making process.

There are two primary weighting approaches in MCDM: subjective weighting, which relies on expert judgment, and objective weighting, which is derived from mathematical optimization (Alemi-Ardakani et al., 2016). Subjective weighting methods, such as those applied in selecting police helicopters for aerial patrol, assign importance to criteria based on expert evaluations (de Assis et al., 2023). However, expert-based assessments are prone to biases and may not fully reflect real-world data (Alemi-Ardakani et al., 2016). On the other hand, objective weighting, such as the variance-based method used in military helicopter selection (C. Ardil, 2022), calculates weights based on statistical variation across alternatives. While objective weighting eliminates expert bias, it lacks sensitivity to contextual priorities and decision-specific requirements.

To address these limitations, some studies have integrated subjective and objective weighting methods, such as in impact optimization of composites, where a hybrid approach improved decision accuracy and reliability(Alemi-Ardakani et al., 2016). Despite the growing use of MCDM for helicopter selection, previous studies have largely treated subjective and objective weighting separately. So far, no research has specifically applied a hybrid weighting approach for wildfire patrol helicopter selection, either in civil or military contexts.

This research gap presents an opportunity to develop a hybrid weighting framework, integrating subjective and objective weighting to enhance decision-making reliability. This study employs Analytic Hierarchy Process (AHP) for subjective weighting and Entropy for objective weighting. The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is then applied to determine the optimal helicopter model based on proximity to the ideal solution (Chakraborty, 2022). By combining these methods, this study aims to provide a robust decision-making tool for helicopter selection in wildfire patrol operations, balancing expert judgment with data-driven optimization.

Method

This study employs an integrated AHP-Entropy-TOPSIS approach to systematically determine the most suitable fire patrol helicopter by combining subjective (expert-based) and objective (data-driven) weighting methods. The methodology consists of three main stages: AHP for subjective weighting, Entropy for objective weighting, and TOPSIS for ranking alternatives.

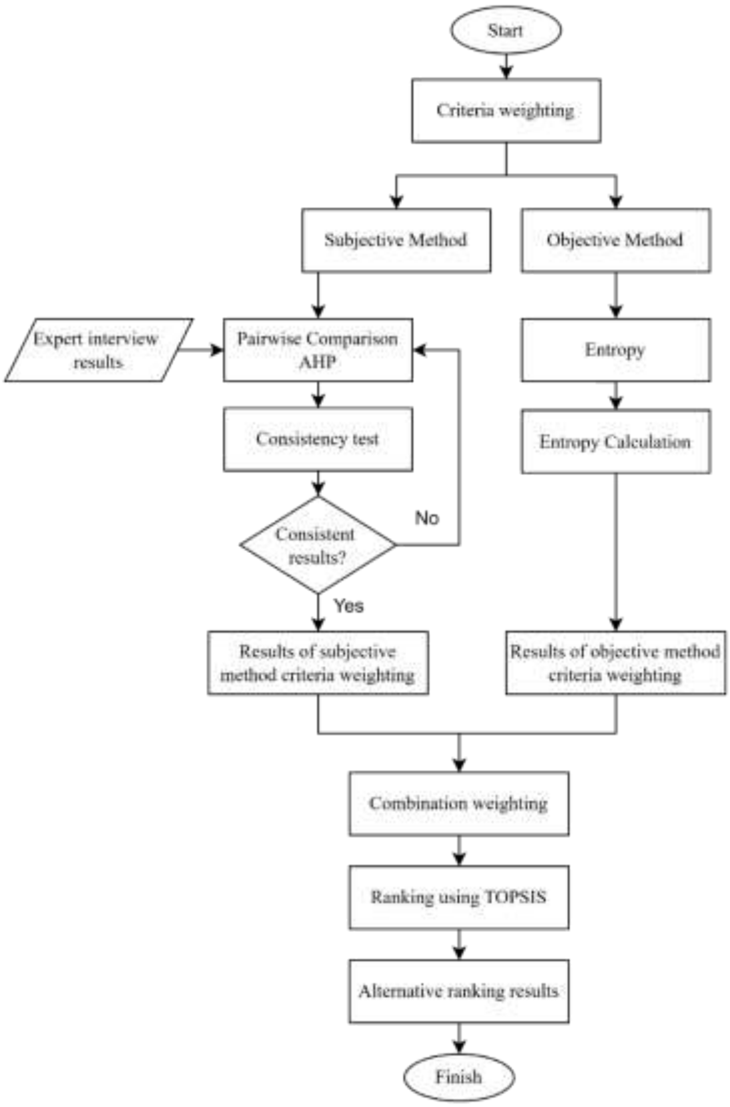

Figure 1. Research Flowchart

1. Criteria and Data Collection

A literature review was conducted to identify key selection criteria for fire patrol helicopters. These criteria were validated through expert consultation, ensuring their relevance to operational, technical, economic, and safety aspects. The study utilizes both primary and secondary data. Primary data were obtained through structured questionnaires and expert interviews, specifically targeting professionals with experience in helicopter operations for fire patrol missions. The experts evaluated and ranked the importance of selection criteria. Secondary data, including helicopter specifications, cost data, and operational performance metrics, were gathered from official sources such as the Indonesian National Disaster Management Agency (BNPB), manufacturers, and previous studies (C. Ardil, 2022; de Assis et al., 2023; Rodrigues et al., 2024).

Table 1. Criteria and Sub-criteria

Criteria	Sub-Criteria	Code
Economic	Maintenance Cost (USD)	C1
	Operating Cost (USD)	C2
	Price of Aircraft (USD)	C3
	BNPB Selling Price (USD/hour)	C4
Safety	Number of Engines	C5
	Number of Crew	C6
	OEM Support	C7
Technical	Range (NM)	C8
	Endurance (Hour)	C9
	Fuel Capacity (usable) (Lbs)	C10
	Dimension (m)	C11
	Fuel Consumption (Gal/Hour)	C12
	Payload (lbs)	C13

Table 2. Alternatives

Helicopter Model	Manufacturer
Bell 206	Bell Helicopter Textron
Bell 505	Bell Helicopter Textron
AW 109	AgustaWestland
AS 350 B	Airbus Helicopters
EC 155 B1	Airbus Helicopters
AS 365 N2	Airbus Helicopters

2. AHP

Step 1: Constructing the Pairwise Comparison Matrix. Experts provided judgments using Saaty's scale (Saaty, 2008), ranging from 1 (equally important) to 9 (extremely more important) for each criterion. The pairwise comparison matrix is denoted as follows:

$$A = \begin{bmatrix} 1 & a & \cdots & a_{1n} \\ \frac{1}{a_{12}} & 1 & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{1}{a_{1n}} & \frac{1}{a_{2n}} & \cdots & 1 \end{bmatrix} \quad (1)$$

Where a_{ij}represent the relative importance of criterion i compared to criterion j, and follows the reciprocal property:

$$a_{ji} = \frac{1}{a_{ij}} \quad (2)$$

Step 2: Combining Expert Judgement and Normalizing the Pairwise Comparison Matrix. When multiple experts provide input, their pairwise comparison matrices need to be aggregated. Each element in the matrix is normalized (A') by dividing it by the sum of its respective column (Setiawan et al., 2020)

$$Geometric\ Mean = \sqrt[1/n]{(A_1 A_2 \ldots A_n)} \quad (3)$$

$$A'_{ij} = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}} \quad (4)$$

Step 3: At this point, the priority (relative) weights for each criterion are determined. These weights are obtained by averaging the preference values from expert evaluations within the comparison matrix. The calculation adheres to a normalization process, ensuring that the total of all weights sums to 1. The normalization of the comparison matrix is performed by dividing each matrix element by the column sum of matrix A, ensuring that the total value becomes 1. To compute the relative weights (eigenvector), the eigenvalue λ_{max} and eigenvector W^A of the normalized matrix are calculated(Kumar et al., 2017).

Step 4: Consistency Test. In AHP, the consistency test is an essential process that assesses the degree of consistency or inconsistency in the decision matrix by using the Consistency Ratio (CR). If the CR is below 0.10 (10%), the judgment is considered consistent. However, if it exceeds this value, a re-evaluation of expert judgments is required. The Consistency Index (CI) is calculated using the following equation (Boonsothonsatit et al., 2024).

$$CI = \frac{\lambda_{max-n}}{n-1} \qquad (5)$$

3. Entropy (Objective Weighting)

To complement the AHP-based subjective weights, the Entropy method is employed to determine objective weights based on data variability. The entropy method assigns higher weights to criteria with greater variation across alternatives.

Step 1: Normalization of the Decision Matrix. Before applying entropy, the decision matrix must be normalized to ensure comparability across different measurement scales.

$$r_{ij} = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}} \qquad (5)$$

Step 2: Computing Entropy Values. The entropy measure quantifies the degree of uncertainty or randomness associated with each criterion. If a criterion has little variation across alternatives, its entropy value will be high, meaning it provides less useful information for decision-making. Conversely, criteria with significant variability will have lower entropy values, indicating higher relevance in distinguishing between alternatives. The entropy value (e_j) for each criterion is calculated as follows (Chen, 2019):

$$e_j = -\frac{1}{\ln m}\sum_{i=1}^{m} r_{ij}\ln(r_{ij}) \qquad (6)$$

This step ensures that each criterion’s contribution to the final decision is determined by the distribution of its values across alternatives rather than subjective assessments.

Step 3 : Calculating the Degree of Diversification. The degree of diversification (d_j) measures how much a criterion contributes to differentiation among alternatives. It is computed as(Jozi et al., 2012):

$$d_j = 1 - e_j \qquad (7)$$

A higher degree of diversification means the criterion plays a more significant role in distinguishing among the available alternatives, making it a more influential factor in decision-making.

Step 4: Computing the Objective Weights. After determining the degree of diversification (W^E), the final objective weights for each criterion are calculated using(Lotfi & Fallahnejad, 2010):

$$W_j^E = \frac{d_j}{\sum_{i=1}^{n} d_j} \qquad (8)$$

This formula ensures that criteria with greater variability in decision alternatives receive higher importance, while those with low differentiation are assigned lower weights. Unlike subjective weighting methods that rely on expert judgment, the entropy method ensures that weights are derived purely from data, reducing bias and enhancing decision objectivity.

4. Combination Weighting

To achieve a balanced approach between subjective and objective perspectives, the final combined weight of each criterion is determined using a weighted combination $\left(w_j^C\right)$ of the AHP-derived subjective weights (w_j^A) and Entropy-derived objective weights (w_j^E) (Al-Aomar, 2010; Mohamadi et al., 2017)

$$W_j^C = \frac{(w_j^A)(w_j^E)}{\sum_j^n (w_j^A)(w_j^E)} \qquad (9)$$

5. TOPSIS

Once the combined AHP-Entropy weights are determined, the TOPSIS method is used to rank the helicopter alternatives. TOPSIS operates on the principle that the optimal alternative is the one with the shortest distance from the positive ideal solution and the greatest distance from the negative ideal solution. This improved methodology provides a thorough and reliable decision-making framework, combining expert opinions and objective data analysis to choose the most appropriate fire patrol helicopter. (Rodrigues et al., 2024).

Discussion

The discussion presents the data and research results and arranged in the form of tables, figures, photos, or diagrams

1. Weight results

The weighting results from AHP and Entropy methods reveal significant variations in how different criteria influence the selection process (see Table 3). The AHP method, which relies on expert judgment, assigned the highest weight to aircraft price (C3) at 0.322, followed by fuel consumption (C10) at 0.141 and maintenance cost (C1) at 0.127. These findings indicate that experts prioritize economic factors in selecting helicopters, likely due to the high operational costs associated with aerial fire patrols.

Conversely, the Entropy method, which is based on the variability of data across alternatives, assigned the highest weight to OEM support (C7) at 0.273, followed by engine count (C5) at 0.128 and maintenance cost (C1) at 0.125. This suggests that criteria with greater variation across different helicopter models are more influential in an objective assessment.

The combination of AHP and Entropy weights produced a more balanced set of weights, ensuring that both subjective and objective factors contribute to the decision. The combined weights reflect the importance of economic feasibility, operational reliability, and technical performance in helicopter selection.

Table 3. The weight calculation value of three methods

Weighting Method	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13
AHP	0.127	0.084	0.322	0.038	0.069	0.069	0.001	0.021	0.012	0.141	0.005	0.078	0.034
Entropy	0.125	0.160	0.028	0.076	0.128	0.034	0.273	0.020	0.087	0.009	0.015	0.038	0.005
Combinations	0.271	0.229	0.153	0.048	0.151	0.041	0.004	0.007	0.018	0.022	0.001	0.051	0.003

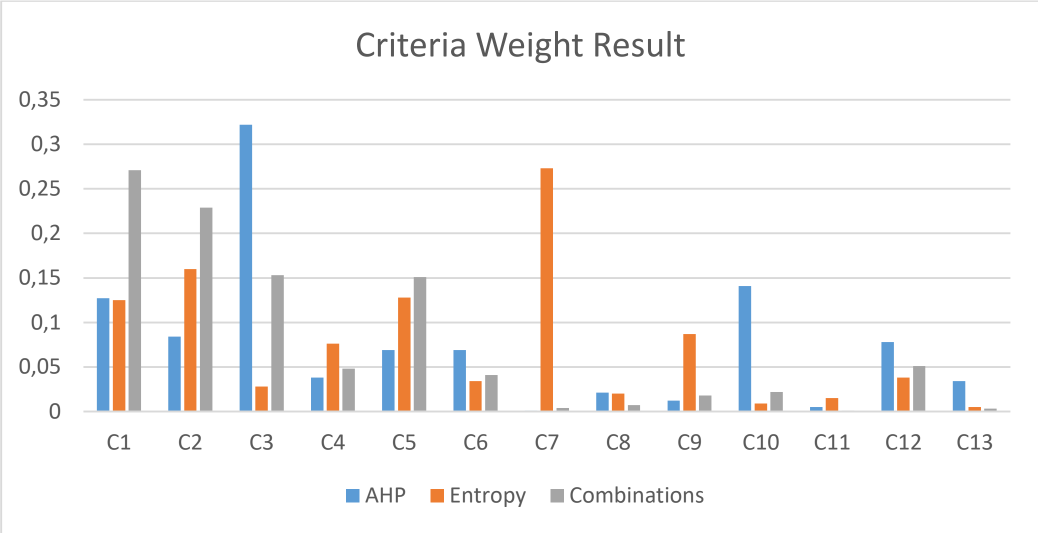

Figure 2. The weight result of three methods

2. Calculation result of TOPSIS

Using the combined AHP-Entropy weights, the TOPSIS method was employed to rank the six helicopter alternatives. The results indicate that the Bell 505 ranked the highest, followed by the Bell 206 and AS 350 B. The ranking is determined by the relative closeness coefficient (CCi). The Relative Closeness Coefficient (CCi) is a value used in the TOPSIS method in multi-criteria decision making. It measures how close an alternative is to the ideal (best) solution and how far it is from the negative ideal (worst) solution. The CCi value ranges between 0 and 1, where a value closer to 1 indicates that the alternative is more desirable or better, while a value closer to 0 means it is less preferable. Essentially, CCi helps rank alternatives based on their proximity to the optimal solution.

The high ranking of Bell 505 suggests that this model offers the best balance between cost efficiency, fuel consumption, and technical capabilities, making it the most suitable choice for fire patrol operations. Bell 206, which secured the second position, performed well in terms of economic feasibility but was slightly outperformed by Bell 505 in operational and technical parameters. AS 350 B, in third place, demonstrated strong technical performance but was less favorable in economic factors.

On the other hand, EC 155 B1 ranked lowest, indicating that its attributes do not align well with the prioritized criteria. In the TOPSIS method, Di+ represents the distance of an alternative from the ideal (best) solution, while Di- represents the distance from the negative ideal (worst) solution. An alternative with a low Di+ value is closer to the ideal solution, indicating better performance. Conversely, a high Di- value means the alternative is far from the worst solution, which is also desirable. Therefore, the best alternatives are those with the smallest Di+ and the largest Di-, as they are closest to the ideal conditions and farthest from the worst ones. The high Di+ and low Di- suggest that EC 155 B1 may have higher costs or lower operational efficiency, making it less suitable for wildfire patrol missions.

Table 4. Distance each Alternative from positive and negative ideal solution

Alternative	Di+ (Positive Ideal Solution)	Di- (Negative Ideal Solution)
Bell 206	0.042622138	0.176707

Bell 505	0.042888165	0.178446
AW 109	0.081579006	0.10821
AS 350 B	0.045590053	0.165789
EC 155 B1	0.178411635	0.043367
AS 365 N2	0.119175177	0.110555

Table 5. Alternative Rank

Rank	Helicopter Model
1	Bell 505
2	Bell 206
3	AS 350 B
4	AW 109
5	AS 365 N2
6	EC 155 B1

Conclusion

The findings highlight the significance of integrating subjective and objective weighting approaches in helicopter selection. The AHP method captures expert knowledge and operational experience, while the Entropy method ensures data-driven objectivity by reducing bias in weight allocation. By combining these approaches, the AHP-Entropy-TOPSIS framework provides a robust and transparent decision-support tool. Moreover, the application of MCDM methods in this study demonstrates their potential for improving decision-making processes in the aviation sector. Future research could explore sensitivity analysis to assess the stability of rankings under different weighting schemes or extend the approach to other types of aircraft selection problems.

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