Training Aircraft Selection of the Vietnam People's Air Force Using a Hybrid BWM-Fuzzy TOPSIS Method

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Abstract

Demands that the Vietnam People's Air Force (VPAF) have new modern training aircraft have been growing recently. Although other training aircraft such as the Yak-52 and L-39 have performed well for decades, they are no longer able to perform the full range of training tasks required of them due to an increasing technology gap. In 2016, the United States government lifted a decade-long ban on lethal arms sales for Vietnam. This has created opportunities for Vietnam to access a variety of weapons suppliers from many countries that have a strong, global defence industry. However, one of the most difficult decisions the VPAF must make concerns the type, configuration, and capabilities of future training aircraft. This study therefore proposes a Multi-Criteria Decision Making (MCDM) model by combining the Best Worst Method (BWM) and a Fuzzy Technique for Order of Preference by Similarity to Ideal Solution (Fuzzy TOPSIS) to choose a modern training aircraft that can replicate the characteristics of several fourth-generation or better fighter planes, with the fifth-generation fighters also being able to perform light-attack and reconnaissance duties for VPAF. The case study employing the hybrid BWM-Fuzzy TOPSIS method reveals that the Yak-130 training aircraft is the best selection for VPAF. To validate the robustness of the proposed framework, sensitivity analysis has been conducted with the result compared to Analytic Hierarchy Process (AHP).

Keywords

training aircraft selection, BWM, fuzzy TOPSIS, MCDM, AHP, sensitivity analysis

1 Introduction

The operations of an air force require a large financial and time investment, particularly where training combat pilots is concerned. An experienced combat pilot must be able to adapt to circumstances and make instantaneous judgments. His/her experience has been accumulated in daily and routine training, using both flight simulators and real training aircraft. After passing initial training tasks on propeller-driven training aircraft (including all basic flight programmes), trainees gain the required experience for high-level flight. To shorten the combat training cycle and improve financial savings, beginners can be trained using advanced training aircraft rather than operational jet fighters. Therefore, a sufficiently advanced training aircraft is critical for flight training success while balancing the training system's efficiency.

In recent years, the Vietnam People's Air Force (VPAF) and the Vietnamese Navy have received special attention from the government and the defence force. For the Air Force alone, Vietnam equipped two regiments of modern multi-role fighter-bomber Su-30MK2 aircraft and more modernised military equipment from Russia. This is a strong move by Hanoi to respond to intensifying military threats from the East Sea in recent years. Concurrently, Vietnam also retired all Mig-21bis fighters, which have served for a long time in the VPAF. However, there is a need to upgrade the training aircraft after retiring Mig-21bis and modernising combat aircraft (Tuan, 2019).

The VPAF currently trains pilots on the L-39C and Yak-52: the Yak-52 is a propeller aircraft used to train pilots at the elementary level, while the L-39C, which trains high-class pilots, is suitable for training Mig-21bis aircraft's pilots; however, the L-39C does not replicate the characteristics of the current Su-30MK2 aircraft. This means that pilots have to retrain in the regiment using Su-30MK2 aircraft after graduation, leading to a corresponding increase in the training budget. Therefore, the task facing decision makers is quickly to choose a modern training aircraft that will be able to replicate the

characteristics of fourth-generation fighter planes or better, with the fifth-generation fighters also being able to perform light-attack and reconnaissance duties (Tuan, 2019).

Previously, the only market option for Vietnam was Russia and allied countries and therefore this issue did not arise. However, this issue must be carefully considered now because of the Obama administration's 2016 lifting of the decade-long ban on lethal arms sales for Vietnam. It has created opportunities for Vietnam to access global weapons suppliers. Therefore, the final choice of a training aircraft must be methodically and systematically analysed to ensure a feasible, acceptable, and suitable selection is finalised for the needs of the VPAF.

This study proposes a hybrid BWM (Best Worst Method) and Fuzzy TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) method for supporting the systematic selection of training aircraft in VPAF. The case study is presented with real survey data from experts in Vietnam and offers a practical solution. Furthermore, to validate the robustness of the proposed framework, sensitivity analysis is conducted, and the result is compared to Analytic Hierarchy Process (AHP) (Balaji et al., 2019).

2 Literature review

In the literature, the aircraft selection process has been studied in various ways with a range of criteria and methods applied to choose suitable aircraft in both civilian and military fields as shown in the following studies.

In the civilian field, Bharda (2003) attempted to discover the relationship between the selection of an aircraft and passenger demand, and thereby answer the question: is it possible to derive the selection of aircraft and fleet mix for origin and destination pairs based on the passenger demand for considered destinations? It was revealed that passengers, distance, and types of airport hubs can support the selection of an aircraft quite well. Listes and Dekker (2005) gave a scenario aggregation-based approach to determine fleet composition considering travel demand changes. They deal with this problem from the strategic point of view. Harasani (2006, 2013) introduced a model for the selection of aircraft in the case of a Saudi Arabia airline. Based on aircraft range and payload for a given route network, specific aircraft types were chosen to be considered. As a result of the Excel application created by the author, aircraft efficiency and its contribution to the net profit of the airline were obtained to help planners choose the right aircraft.

Ozdemir et al. (2011) considered both qualitative and quantitative criteria such as time, purchasing, maintenance, operation, etc. as the criteria to solve aircraft selection problems for Turkish Airlines. The focus was middle range, single-aisle aircraft, and the proposed method was Analytic Network Process (ANP). Meanwhile, a two-stage model was proposed by Dožić and Kalić (2013a) to plan an airline fleet. In the first stage, to get a combined fleet in terms of aircraft size (small or medium-sized), input factors were the demand of passenger and distance. As a result, two sets of representative routes covered with small and medium-sized aircraft. Based on the two sets of routes corresponding to those aircraft sizes, the authors divided the planned flights into subsets to solve the problem in two independent fleet sizing problems. They extended their research with aircraft selection as the last stage (Dožić and Kalić, 2013b) and suggested the even swap method as a possible tool to choose the appropriate fleet. Dožić and Kalić (2014) used AHP to solve the aircraft type selection problem for a known route network and forecasted air travel demand.

In the military field, Wang and Chang (2007) proposed a systematic evaluation model to help the Air Force Academy with a selection of an optimal training aircraft in a certain environment mainly focused on technical performance and neglected other characteristics, such as procurement and operation cost, logistics capability, reliability, armament capability, avionic and safety. They utilised a multi-criteria decision-making method to determine the importance weights of evaluation criteria, and TOPSIS to obtain performance ratings of feasible alternatives in linguistic terms described with triangular fuzzy numbers. Wibowo et al. (2016) combined AHP with TOPSIS in a hybrid multi-criteria decision-making methodology to try to select new fighters for the Indonesian Air Force. AHP has also been combined with TOPSIS within a fuzzy environment as a proposed solution to the air combat effectiveness assessment problem by Wang et al. (2008). Ali et al. (2017) used AHP to select a fighter aircraft to improve the effectiveness of air combat in the War on Terror. Paul et al. (2017) approached the assessment alternatives of fighter aircraft based on TOPSIS by considering qualitative and quantitative criteria. This study also showed that cost or price is usually one of the prime criteria, and some measure of quality is ideally another criterion.

Sánchez-Lozano et al. (2015) evaluated military training aircraft through the combination of MCDM with ambiguous logic for the Spanish Air Force Academy. Their

study aimed to attach weight to the criteria using AHP and further evaluated the aircraft using TOPSIS. In 2018, Sánchez-Lozano et al. (2018) once again solved the military training aircraft selection problem for the Spanish Air Force Academy by using a pseudo-Delphi technique combined with a fuzzy AHP methodology. Various criteria information was considered by the experts, with human factors, flying and handling qualities, etc. coexisting with service ceiling, stalling speed, endurance, etc.

Based on the analysis above, it is noteworthy that most studies have originated from developed countries and have specifically focused on civilian applications in which the questions are relatively well-explained. There have been very few studies that were carried out in the context of developing countries (Wibowo et al., 2016; Ali et al., 2017; Paul et al., 2017) and to date, no study has been conducted in the context of Vietnam concerning aircraft selection. Another consideration is that these previous studies have used a variety of methodologies, both individual and integrated for aircraft selection, and they have used AHP, ANP, or TOPSIS for calculating weights of criteria. Another method named BWM has proven its significance to calculate the weights of criteria (Rezaei, 2015), but this has not yet been considered in relation to aircraft selection.

The advantage of BWM and Fuzzy TOPSIS over the other MCDM methods is that while AHP, Multi Criteria Optimisation and Compromise Solution (VIKOR), Decision Making Trial and Evaluation Laboratory (DEMATEL) require numerous pairwise comparison matrices for calculating criteria weights, and these matrices often suffer from the issue of inconsistency due to the large amount of data involved. BWM requires less data (pairwise comparison matrices) and the result obtained is also more consistent, as shown by Rezaei (2015). Rezaei compared the results of AHP and BWM, showing that the result of BWM is more consistent and accurate. Moreover, BWM can also work well with only 4-10 experts as mentioned by Rezaei et al. (2018) in their paper on baggage service quality assessment. For ranking the alternatives, Fuzzy TOPSIS is the most widely employed technique and it is an approach capable of dealing effectively with the inherent imprecision, vagueness, and ambiguity of the human decision-making process with uncertain data. A combination of BWM and Fuzzy TOPSIS is therefore a coherent, consistent, and clear approach.

In fact, the combination of these two methods has been applied in other fields: for instance, supplier selection among small and medium enterprises on the basis of their green innovation ability (Gupta and Barua, 2017) and an evaluation of an organisation's performance on the basis of green human resource management practices (Gupta, 2018), but not aircraft selection. To the best of the authors' knowledge, this study represents the first attempt at using both BWM and Fuzzy TOPSIS methods to overcome some limitations of the other proposed approaches.

3 Methodology
3.1 Research development
In this study, a new three-phase framework is proposed using a hybrid BWM-Fuzzy TOPSIS method for training aircraft selection in Vietnam, as shown in Fig. 1:

- **Phase 1**: Determining the goal and criteria through a review of the extant literature and expert interviews.
- **Phase 2**: Implementing the BWM model. Each criterion and sub-criteria will be determined the weighs by applying BWM.
- **Phase 3**: Ranking the list of training aircraft (alternative) concerning determined criteria and choosing the training aircraft with the highest rank by using Fuzzy TOPSIS.

3.2 Determining criteria
The criteria for considering the selection of aircraft are determined by team of experts and not all the criteria
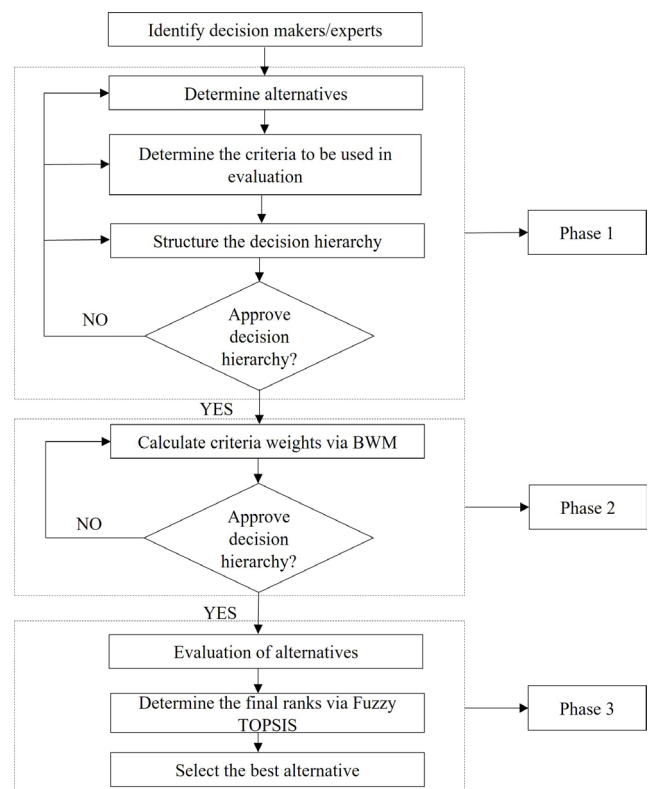

Fig. 1 Proposed framework for phases of methodology

which influence this kind of decision-making problem have the same importance. Additionally, despite decision-making problems that could be similar, the selected criteria depend on the specific context and requirements of each country. Therefore, not only is it important to carry out an appropriate selection of criteria, but also to choose the way of obtaining their weights. The experience and the background of the expert team are utilised in the determination of the criteria and the questionnaire should be answered by each one of the experts.

3.3 Calculating the weights of criteria using BWM

MCDM techniques are utilised in situations of complex problems where decision-makers are assigned a task of selecting the best alternative among many alternatives. A new MCDM method known as BWM had been developed by Rezaei (2015) using an optimisation model to determine the weights of the criteria. This is possible by doing pairwise comparisons. The best criterion compares with other criteria, while other criteria compare to the worst criterion. This technique has been successfully utilised by Rezaei et al. (2016). For this method a linear minmax model is used; the steps which are explained by Rezaei are discussed below:

- **Step 1**: A set of decision criteria are identified that must be used to reach a decision. Decision criteria will be taken and are denoted as $\{c_1, c_2, ..., c_n\}$ for n main criteria.
- **Step 2**: Determination of the best and the worst criterion among main as well as sub-criteria among the available set of criteria by decision makers.
- **Step 3**: The decision maker then carries out pairwise comparisons between the best criterion and other criteria. This is done by determining references using a number between 1 to 9, where "1 = equally important" and "9 = more important". The best criteria over other criteria vector can be written as:

$$A_B = \left(a_{B1}, a_{B2}, ..., a_{Bn}\right), \tag{1}$$

where a_{Bi} represents the rating of the best-selected criteria B over any other criteria j. In this case, $a_{BB} = 1$. The consensus of various experts is taken for finalisation of preference ratings.

- **Step 4**: Similarly using a scale of 1 to 9, calculate the ratings of all other criteria over one worst criterion, the worst criteria is to be determined by experts. The comparison of other criteria to worst criteria can be attributed in the form of a vector as:

$$A_W = \left(a_{1W}, a_{2W}, ..., a_{nW}\right), \tag{2}$$

where a_{iW} represents the rating of any criteria j with the worst selected criteria W. In this case, $a_{WW} = 1$. In this case, also the final value can be arrived by consensus of all the experts involved in decision making.

- **Step 5**: The final step is to optimise the weights of all the criteria $\left(W_1^*, W_2^*, ..., W_n^*\right)$. The objective is to calculate the weights of criteria so that the maximum absolute differences for all j are minimised of the following set $\left\{\left|W_B - a_{Bj}W_j\right|, \left|W_{Bj} - a_{jW}W_W\right|\right\}$ to obtain a unique solution of weights. Following optimization, the model can be formulated thus:

$$\text{Min } \max\left\{\left|W_B - a_{Bj}W_j\right|, \left|W_{Bj} - a_{jw}W_W\right|\right\},$$
$$\text{s.t.}$$
$$\sum_j W_j = 1 \tag{3}$$
$$W_j \geq 0, \text{ for all } j.$$

Eq. (3) can be solved by representing it in the form of a linear model as:

$$\boldsymbol{min}\xi^L,$$
$$\text{s.t.}$$
$$\left|W_B - a_{Bj}W_j\right| \leq \xi^L, \text{ for all } j,$$
$$\left|W_j - a_{jw}W_w\right| \leq \xi^L, \text{ for all } j, \tag{4}$$
$$\sum_j W_j = 1,$$
$$W_j \geq 0, \text{ for all } j.$$

Solving the above Eq. (4), the optimised weights $\left(W_1^*, W_2^*, ..., W_n^*\right)$ and optimal value ξ^L are obtained.

To ensure the rationality of the assessment, two consistency measurements can be calculated: the input-based consistency measurement and the output-based consistency measurement. The output-based consistency ratio CR^O is defined in the original version of BWM (Rezaei, 2015).

$$CR^O = \xi^{L*} / \xi_{max}, \tag{5}$$

where ξ^{L*} is the optimal value ξ^L, and ξ_{max} is the consistency index.

The output-based consistency ratio CR^I is proposed to compliment the output-based CR^O and it is defined as (Liang et al., 2020):

$$CR^I = \max_j CR^I{}_j, \tag{6}$$

where:

$$CR^I_j \begin{cases} \dfrac{|a_{Bj} \times a_{jW} - a_{BW}|}{a_{BW} \times a_{BW} - a_{BW}} & a_{BW} > 1 \\ 0 & a_{BW} = 1 \end{cases}. \quad (7)$$

The thresholds for both output-based and input-based consistency ratios are established in the work of Liang et al. (2020) using Monte-Carlo method.

3.4 Ranking the alternatives using Fuzzy TOPSIS

TOPSIS is a widely used method for solving ranking problems in real-life situations and it was first evolved by Hwang and Yoon (1981). Despite the concept's popularity and simplicity, this method often complains about uncertainty and imprecise results associated with the mapping of the decision maker's perception of crisp values. In the traditional formulation of TOPSIS, personal judgments play an important role and represented with crisp values. However, in various practical circumstances, the human preference model is uncertain and crisp values might be difficult to be accredited to the comparison judgments by decision-makers because of lacking appropriate information (Chan and Kumar, 2007). The reason is that decision-makers usually feel more confident to give interval judgments rather than to use an exact value to express their judgments. Therefore, as some criteria are difficult to measure by crisp values, they are usually ignored during the evaluation. Another reason is these mathematical models that are based on crisp value, so they cannot deal with decision-makers' ambiguities, uncertainties, and vagueness which cannot be handled by crisp values. The use of fuzzy set theory introduced by Zadeh (1965) allows the decision-makers to incorporate incomplete information, unobtainable information, unquantifiable information, and partially ignorant facts into the decision model (Kulak et al., 2005). As a result, Fuzzy TOPSIS and its extensions have been developed to solve ranking and justification problems within a fuzzy environment (Büyüközkan et al., 2008; Chen, 2000; Chen and Tsao, 2008; Kahraman et al., 2007; Önüt and Soner, 2008; Wang and Elhag, 2006; Yang and Hung, 2007; Yong, 2006).

This study uses a triangular fuzzy number for Fuzzy TOPSIS because it is intuitively easy to use and calculate. In addition, in studies using triangular fuzzy numbers by Chang and Yeh (2002), Chang et al. (2007), Kahraman et al. (2004), and Zimmerman (1996) proved the efficiency of the model using triangular fuzzy numbers for solving problems where the information available is imprecise and subjective. In practice, the triangular form is applied most often to represent fuzzy numbers (Ding and Liang, 2005; Kahraman et al., 2004; Karsak and Tolga, 2001; Xu and Chen, 2007). In the following explanation, some basic important definitions of fuzzy sets are given (Chen et al., 2006; Chen, 1996; Cheng and Lin, 2002; Hwang and Yoon, 1981; Xu and Chen, 2007; Zimmerman, 1996). Fuzzy TOPSIS methodology steps can be outlined as follow:

- **Step 1**: Construct a comparison matrix ($\check{k}_{ij}$) of alternatives with different criteria using linguistic variables discussed in Table 1. The linguistic rating mentioned in Table 1 and used in this methodology upholds the property that normalised triangular fuzzy numbers lie in the range [0,1] thus eliminating the need for normalisation (Dağdeviren, et al., 2009).

- **Step 2**: Calculate the weighted normalised fuzzy decision matrix. The weighted normalised value v_{ij} is calculated by Eq. (8) given below:

$$\check{V} = \left[\check{v}_{ij}\right]_{m \times n}, \quad (8)$$

where:

$$i = \{1,2,3,\ldots,m\}, \quad j = \{1,2,3,\ldots,n\}, \quad (9)$$

$$\check{v}_{ij} = \check{k}_{ij} \times w_j. \quad (10)$$

- **Step 3**: Identify FPIS and FNIS where FPIS and FNIS represent the fuzzy positive ideal and the fuzzy negative ideal solution, respectively:

$$A^+ = \{v_1^+, \ldots, v_n^+\}$$

where

$$v_j^+ = \{\max(v_{ij}) \text{ if } j \in J; \min(v_{ij}) \text{ if } j \in J'\}, j = 1 \ldots n, \quad (11)$$

$$A^- = \{v_1^-, \ldots, v_n^-\}$$

where

$$v_j^- = \{\min(v_{ij}) \text{ if } j \in J; \max(v_{ij}) \text{ if } j \in J'\}, j = 1 \ldots n, \quad (12)$$

Table 1 Linguistic scale for alternatives selection

Linguistic variables	Corresponding Fuzzy Numbers
Very Low (VL)	(0, 0, 0.2)
Low (L)	(0, 0.2, 0.4)
Medium (M)	(0.2, 0.4, 0.6)
High (H)	(0.4, 0.6, 0.8)
Very High (VH)	(0.6, 0.8, 1)
Excellent (E)	(0.8, 1, 1)

where J is associated with benefit criteria and J' is associated with cost criteria.

- **Step 4**: Calculate the distance of each alternative from FPIS and FNIS using Eqs. (14) and (15) discussed below:

$$d_i^+ = \sum_{j=1}^{n} d\left(\breve{v}_{ij} - v_j^+\right), \; i=1,\ldots,m; \; j=1,\ldots,n, \qquad (13)$$

$$d_i^- = \sum_{j=1}^{n} d\left(\breve{v}_{ij} - v_j^-\right), \; i=1,\ldots,m; \; j=1,\ldots,n, \qquad (14)$$

where $d\left(\breve{v}_{ij} - v_j^+\right)$ and $d\left(\breve{v}_{ij} - v_j^-\right)$ were calculated by the vertex method for distance between 2 fuzzy triangular number $\breve{v}_{ij}(a_1, a_1, a_1)$ and $v_j^+\left(a_2,b_2,c_2\right)$ or $v_j^-\left(a_2,b_2,c_2\right)$ according to Eqs. (16) and (17).

$$d\left(\breve{v}_{ij} - v_j^+\right) = \left[\frac{1}{3}\left\{\left(a_1 - a_2\right)^2 + \left(b_1 - b_2\right)^2 + \left(c_1 - c_2\right)^2\right\}\right]^{\frac{1}{2}}$$

$$(15)$$

$$d\left(\breve{v}_{ij} - v_j^-\right) = \left[\frac{1}{3}\left\{\left(a_1 - a_2\right)^2 + \left(b_1 - b_2\right)^2 + \left(c_1 - c_2\right)^2\right\}\right]^{\frac{1}{2}}$$

$$(16)$$

- **Step 5**: Calculate closeness coefficient (CC_i) of each alternative by using Eq. (18):

$$CC_i = \frac{d_i^-}{d_i^- + d_i^+}, \; i=1,\ldots,m, \; CC_i \in (0,1). \qquad (17)$$

- **Step 6**: Rank preference order. Choose an alternative with maximum CC_i or rank alternatives according to CC_i in descending order.

4 Case study

The proposed BWM-Fuzzy TOPSIS model is to be applied to a real problem in the VPAF. This study aims to assess possible alternative training aircraft solutions and to help the decision-makers accordingly in terms of user requirements. The high technology weapons make significant improvements in the defence capabilities of the nations. Therefore, selecting the most proper weapon in general and training aircraft in specific is of great importance for the VPAF. But it is hard to choose the most suitable one among the alternatives.

To determine the main features that the candidate training aircraft should have, an expert team was formed from one senior manager of the Air Weapon Department of Air Defense and Air Force High Command Headquarters, three lecturers in the Aviation Weapons Department

of the Air Defense and Air Force Academy, one senior flight instructors of Air Force Officer's College, and one air weapon system manager of an Air Force Regiment. All the experts were chosen because of their vast experience (each with more than 15 years) in the field of operating, using, and studying many kinds of aircraft or in the field of supplier selection and innovations. The criteria to be used in the study were identified by the expert team based on their experience, the demand of VPAF, and the literature review. The application performed is based on the steps provided in the previous section and explained step by step together with the results.

There are four main criteria and 19 sub-criteria to be used for training aircraft selection are established by the expert team through answering the questionnaire. These four main criteria are as follows: General Characteristic (GC), Performance (PF), Price (PR), and Other criteria (OC). These 18 sub-criteria are as follows: Maximum takeoff weight (GC1), Power plant (GC2), Crew (GC3), Maximum speed (PF1), Cruising speed (PF2), Stalling speed (PF3), Range (PF4), Service ceiling (PF5), Climbing rate (PF6), Wing loading (PF7), Thrust/weight (PF8), Maximum G limits (PF9), Acquisition Cost (PZ1), Operating cost (PZ2), Training cost (PZ3), Armament (OC1), Strategic partnership (OC2), Reliability (OC3), Avionics (OC4). Criteria and their definitions of importance are given in Table 2. In those criteria, some new important criteria such as business strategies across countries (OC2) and economic aspects (PZ1, PZ2, PZ3) were first adopted.

Following the determination of the criteria, alternative aircraft were investigated, and the decision-making team determined three suitable training aircraft for the needs are KAI T-50 Golden Eagle, Yakolev Yak-130, and Aero L-159 Alca.

4.1 Calculation of criteria weights using BWM
After finalisation of selection criteria by the experts, the next step is to determine the best and the worst criteria among the main criteria, then determine the preference of the best criteria over all other criteria and preference rating of all the criteria over the worst criteria on a scale of 1–9. To acquire data, the questionnaires were designed and dispatched via email to the expert team. The challenge was finding a method to combine all the questionnaire responses into a single equivalent response. For each comparison between the best criterion to the other criteria and the other criteria to the worst criterion, e.g., between the best main criterion (PZ) and general characteristic (GC), the number of responses was recorded and plotted as shown in Fig. 2.

Table 2 Aircraft evaluation criteria and its definition

Main criteria	Sub criteria	Definition
General Characteristic (GC)	Maximum take-off weight (GC1)	The maximum weight that the aircraft is allowed to take off without causing any damage to the structure, due to structural limit or other limits.
	Power plant (GC2)	To generate the propulsive force directly by increasing the momentum of the airflow through the engine(s).
	Crew (GC3)	Personnel who operate an aircraft while in flight.
Performance (PF)	Maximum speed (PF1)	The aircraft is damaged if the maximum operating speed is exceeded.
	Cruising speed (PF2)	Cruise speed is the precise airspeed that represents the optimal balance between speed & range at which aircraft travels most efficiently.
	Stalling speed (PF3)	The minimum speed at which the wings maintain lift so the plane can fly to maintain level flight.
	Range (PF4)	The maximum distance an aircraft can fly between take-off and landing after a single refuelling.
	Service ceiling (PF5)	The highest operating altitude at which the aircraft can bear the atmosphere and operate efficiently.
	Climbing rate (PF6)	The climb is the increase in aircraft height up to the cruising altitude, and descent means the fall in height from end of cruising until landing. The maximum rate climb allows the aircraft to reach its operating height in the minimum time.
	Wing loading (PF7)	The wing loading is the total weight of an aircraft divided by the area of its wing.
	Thrust/weight (PF8)	Thrust to weight ratio is directly proportional to the acceleration of the aircraft. An aircraft with high acceleration is an aircraft with a high thrust to weight ratio.
	Maximum G limits (PF9)	G (gravity) forces are the acceleration forces that pull on pilots changing the plane of motion. Pilots encounter these forces while engaged in high-speed dogfighting. G forces can be either positive or negative, and both types may be dangerous to a pilot. A pilot's weight increases correspondingly as he or she pulls more Gs. The maximum G limit is the largest positive G force that a pilot can endure. If a pilot is flying straight and pushing the nose of the plane down, then the negative force of gravity reduces his weight. A pilot who pushes too many negative Gs sees the world through bloodshot eyes. The minimum G limit means the strongest negative force of gravity that a pilot can tolerate.
Price (PZ)	Acquisition Cost (PZ1)	The final price of an aircraft including legal costs, transport, and discounts (= money taken off the price), but not including taxes.
	Operating cost (PZ2)	All costs occur when flights are in actual operation, including fuel consumption and maintenance costs, etc.
	Training cost (PZ3)	The cost of all training activities including technical training cost for ground crews and flight training cost for pilots.
Other criteria (OC)	Armament (OC1)	Weapons with can be used.
	Strategic partnership (OC2)	An arrangement between two companies, organisations or countries to help each other or work together, to make it easier for each of them to achieve desired objectives they want to achieve.
	Reliability (OC3)	The extent to which the fuselage, engine, propeller, or all components will perform the required function under specified conditions without failure over a specified period.
	Avionics (OC4)	Avionic systems are the electronic systems used on aircraft including communications, navigation, the display and management of multiple systems, etc.

In this case, the weighted arithmetic mean was calculated to define a scale value for that comparison. Because the weighted arithmetic mean is based on all the observations, and determined for every kind of data, it is least affected by fluctuations of sampling. Only responses are greater than 1 were considered in the computation of the mean. The mean was chosen as a measure of central tendency to eliminate the error due to an incomplete perception of the method by the respondent. The expression to evaluate the mean is stated as follow:

$$\text{Weighted Arithmetic Mean} = \left(\frac{\sum(\text{Scale Value} \times \text{Response Frequency})}{\text{Sum of Acceptable Response Frequency}} \right) \quad (18)$$
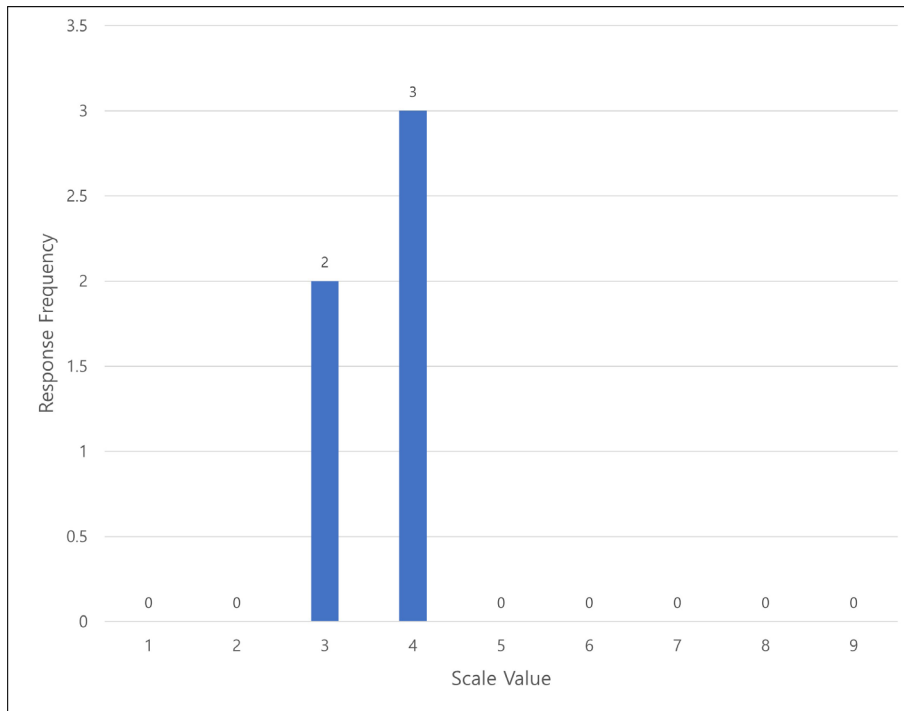
Fig. 2 Comparison between price and general characteristic

For the histogram of comparison between the best main criterion and general characteristic, shown in Fig. 2, the sample calculation is as follow:

$$\text{Weighted Arithmetic Mean} = \left(\frac{(2 \times 3) + (3 \times 4)}{2 + 3} \right) = 4, \quad (19)$$

(to the nearest unit).

This procedure was adopted and applied to all pairwise comparison as the result of the subsequent the best to others rating and others to the worst ratings obtained are represented in Table 3.

As with the pairwise comparison of main criteria, all the sub-criteria are subjected to similar pairwise comparison on a scale of 1 to 9 after identifying their respective best and worst criteria. The pairwise comparison of general characteristics sub-criteria is presented in Table 4.

Similarly, the pairwise comparison of the other sub-criteria is presented in Table 5, Table 6, and Table 7.

After pairwise comparison of all the main criteria and sub-criteria by decision-makers, the next step is to obtain weights of main criteria and subsequently sub-criteria. Using Eq. (4) discussed in step 5. By solving this model in Microsoft excel solver, optimised weights $\left(W_1^*, W_2^*, \ldots, W_n^* \right)$ and ξ^{L*} of main criteria are obtained. Also, the output-based (CR^O) and input-based (CR^I) consistency measurements are calculated. Table 8 shows weights of the main criteria based on responses received from respondents in the questionnaire. Both the output-based (CR^O) and input-based (CR^I) consistency measurements are less than the thresholds suggested by in the work of Liang et al. (2020), and this shows higher consistency among pairwise comparisons.

Like the weights of the main criteria, the weights of sub-criteria are also obtained by formulating the criteria as a linear programming Eq. (4) and solving the equation; the weights obtained are shown in Table 9. By solving Eq. (4)

Table 3 Main criteria comparison

Best to Others	GC	PF	PZ	OC
PZ	4	2	1	7
Others to the worst	OC			
GC	2			
PF	3			
PZ	7			
OC	1			

Table 4 Pairwise comparison for General characteristics sub criteria

Best to others	GC1	GC2	GC3
GC2	6	1	2
Others to the Worst	GC1		
GC1	1		
GC2	6		
GC3	3		

Table 5 Pairwise comparison for performance

Best to others	PF1	PF2	PF3	PF4	PF5	PF6	PF7	PF8	PF9
PF1	1	9	3	4	5	6	8	7	2
Others to the worst	PF2								
PF1	9								
PF2	1								
PF3	3								
PF4	2								
PF5	2								
PF6	2								
PF7	2								
PF8	2								
PF9	5								

Table 6 Pairwise comparison for price

Best to Others	PZ1	PZ2	PZ3
PZ2	3	1	5
Others to the Worst	PZ3		
PZ1	3		
PZ2	5		
PZ3	1		

Table 7 Pairwise comparison for other criteria

Best to others	OC1	OC2	OC3	OC4
OC3	6	5	1	3
Others to the worst	OC1			
OC1	1			
OC2	2			
OC3	6			
OC4	2			

Table 8 Optimal weights for main criteria

Main criteria	Weights	ξ^{L*}	CRO (threshold)	CRI (threshold)
General Characteristic (GC)	0.137			
Performance (PF)	0.255	0.02	0.005 < 0.365	0.023 < 0.268
Price (PZ)	0.529			
Other criteria (OC)	0.078			

for pairwise comparison of all criteria and subsequent sub-criteria, weights of each criterion and sub-criteria are obtained, these weights are used to rank sub-criteria and indicate the importance of each criterion and sub-criteria. Results show Price (PZ) as the most important criterion followed by Performance (PF). Similarly, among sub-criteria, Operating cost has the highest weight followed by Acquisition cost. The next step is to rank the alternative with respect to these criteria by using Fuzzy TOPSIS.

4.2 Ranking the alternatives using Fuzzy TOPSIS
After obtaining weights of all the criteria, the next step is to select the best alternative (training aircraft) with respect to these criteria. Fuzzy TOPSIS as discussed in Phase 3 has been used for obtaining the ranks of alternatives. Decision makers were asked to evaluate all the candidates with respect to criteria using linguistic variables discussed in Table 2. The resultant matrix showing corresponding fuzzy values of linguistic variables for comparison is shown in Table 10.

Table 9 Weights of main and sub criteria

Main criteria	Weights main criteria	Sub criteria	Weights sub criteria	Global weights	Ranking
General Characteristic (GC)	0.137	GC1	0.1	0.014	14
		GC2	0.6	0.082	4
		GC3	0.3	0.041	8
Performance (PF)	0.255	PF1	0.34	0.087	3
		PF2	0.035	0.009	18
		PF3	0.121	0.031	9
		PF4	0.091	0.023	10
		PF5	0.073	0.019	11
		PF6	0.061	0.016	12
		PF7	0.045	0.011	16
		PF8	0.052	0.013	15
		PF9	0.182	0.046	6
Price (PZ)	0.529	PZ1	0.244	0.129	2
		PZ2	0.644	0.341	1
		PZ3	0.111	0.059	5
Other criteria (OC)	0.078	OC1	0.088	0.007	19
		OC2	0.125	0.01	17
		OC3	0.577	0.045	7
		OC4	0.209	0.016	12

To obtain the weighted, normalised fuzzy relation matrix using Eq. (7), the weighted matrix is presented in Table 11. The fuzzy positive-ideal solution FPIS and fuzzy negative-ideal solution FNIS are determined using Eqs. (8) and (9). FPIS (A⁺) and FNIS (A⁻) in this case can be defined as perfect value, $v_j^+ = (1,1,1), v_j^- = (0,0,0)$, as suggested by Chen (2000).

The next step is to obtain the closeness coefficient value CC_i and the final ranking of alternatives using Eqs. (10) and (11). Once the distances of cluster policy

Table 10 Fuzzy comparison matrix for supplier alternatives

	T-50	Yak-130	L-159B	Criteria weights
GC1	(0.6, 0.8, 1)	(0.4, 0.6, 0.8)	(0.2, 0.4, 0.6)	0.014
GC2	(0.6, 0.8, 1)	(0.6, 0.8, 1)	(0.2, 0.4, 0.6)	0.082
GC3	(0.6, 0.8, 1)	(0.6, 0.8, 1)	(0.6, 0.8, 1)	0.041
PF1	(0.8, 1, 1)	(0.4, 0.6, 0.8)	(0.4, 0.6, 0.8)	0.087
PF2	(0.4, 0.6, 0.8)	(0.4, 0.6, 0.8)	(0.4, 0.6, 0.8)	0.009
PF3	(0.4, 0.6, 0.8)	(0.8, 1, 1)	(0.4, 0.6, 0.8)	0.031
PF4	(0.4, 0.6, 0.8)	(0.8, 1, 1)	(0.4, 0.6, 0.8)	0.023
PF5	(0.8, 1, 1)	(0.4, 0.6, 0.8)	(0.4, 0.6, 0.8)	0.019
PF6	(0.8, 1, 1)	(0.2, 0.4, 0.6)	(0.2, 0.4, 0.6)	0.016
PF7	(0.4, 0.6, 0.8)	(0.4, 0.6, 0.8)	(0.4, 0.6, 0.8)	0.011
PF8	(0.6, 0.8, 1)	(0.4, 0.6, 0.8)	(0.4, 0.6, 0.8)	0.013
PF9	(0.4, 0.6, 0.8)	(0.4, 0.6, 0.8)	(0.6, 0.8, 1)	0.046
PZ1	(0.2, 0.4, 0.6)	(0.4, 0.6, 0.8)	(0.6, 0.8, 1)	0.129
PZ2	(0.2, 0.4, 0.6)	(0.6, 0.8, 1)	(0.6, 0.8, 1)	0.341
PZ3	(0.4, 0.6, 0.8)	(0.6, 0.8, 1)	(0.6, 0.8, 1)	0.059
OC1	(0.6, 0.8, 1)	(0.4, 0.6, 0.8)	(0.2, 0.4, 0.6)	0.007
OC2	(0, 0.2, 0.4)	(0.6, 0.8, 1)	(0.6, 0.8, 1)	0.01
OC3	(0.4, 0.6, 0.8)	(0.4, 0.6, 0.8)	(0.4, 0.6, 0.8)	0.045
OC4	(0.8, 1, 1)	(0.6, 0.8, 1)	(0.4, 0.6, 0.8)	0.016

Table 11 Weighted fuzzy evaluation matrix for alternatives

	T-50	Yak-130	L-159B	d_i^+	d_i^-
GC1	(0.0084, 0.0112, 0.014)	(0.0056, 0.0084, 0.0112)	(0.0028, 0.0056, 0.0084)		
GC2	(0.0492, 0.0656, 0.082)	(0.0492, 0.0656, 0.082)	(0.0164, 0.0328, 0.0492)		
GC3	(0.0246, 0.0328, 0.041)	(0.0246, 0.0328, 0.041)	(0.0246, 0.0328, 0.041)		
PF1	(0.0696, 0.087, 0.087)	(0.0348, 0.0522, 0.0696)	(0.0348, 0.0522, 0.0696)		
PF2	(0.0036, 0.0054, 0.0072)	(0.0036, 0.0054, 0.0072)	(0.0036, 0.0054, 0.0072)		
PF3	(0.0124, 0.0186, 0.0248)	(0.0248, 0.031, 0.031)	(0.0124, 0.0186, 0.0248)		
PF4	(0.0092, 0.0138, 0.0184)	(0.0184, 0.023, 0.023)	(0.0092, 0.0138, 0.0184)		
PF5	(0.0152, 0.019, 0.019)	(0.0076, 0.0114, 0.0152)	(0.0076, 0.0114, 0.0152)		
PF6	(0.0128, 0.016, 0.016)	(0.0032, 0.0064, 0.0096)	(0.0032, 0.0064, 0.0096)		
PF7	(0.0044, 0.0066, 0.0088)	(0.0044, 0.0066, 0.0088)	(0.0044, 0.0066, 0.0088)	(1, 1, 1)	(0, 0, 0)
PF8	(0.0078, 0.0104, 0.013)	(0.0052, 0.0078, 0.0104)	(0.0052, 0.0078, 0.0104)		
PF9	(0.0184, 0.0276, 0.0368)	(0.0184, 0.0276, 0.0368)	(0.0276, 0.0368, 0.046)		
PZ1	(0.0258, 0.0516, 0.0774)	(0.0516, 0.0774, 0.1032)	(0.0774, 0.1032, 0.129)		
PZ2	(0.0682, 0.1364, 0.2046)	(0.2046, 0.2728, 0.341)	(0.2046, 0.2728, 0.341)		
PZ3	(0.0236, 0.0354, 0.0472)	(0.0354, 0.0472, 0.059)	(0.0354, 0.0472, 0.059)		
OC1	(0.0042, 0.0056, 0.007)	(0.0028, 0.0042, 0.0056)	(0.0014, 0.0028, 0.0042)		
OC2	(0, 0.002, 0.004)	(0.006, 0.008, 0.01)	(0.006, 0.008, 0.01)		
OC3	(0.018, 0.027, 0.036)	(0.018, 0.027, 0.036)	(0.018, 0.027, 0.036)		
OC4	(0.0128, 0.016, 0,016)	(0.0096, 0.0128, 0.016)	(0.0064, 0.0096, 0.0128)		

from FPIS and FNIS are determined, the closeness coefficient can be obtained with Eq. (14). The index CC_1 of the first alternative is calculated as:

$$CC_1 = \frac{d_1^-}{d_1^- + d_1^+} = \frac{0.605}{0.605 + 18.423} = 0.032. \qquad (20)$$

The CC_i values and ranking of alternatives are shown in Table 12 and Table 13.

From the alternative evaluation results in Table 13, Yak-130 as an optimal training aircraft. This assessment is based on the technical characteristics and economic constraints. Meanwhile, although the T-50 Golden Eagle was better evaluated technically, surprisingly, it ranked third due to economic factors. This table presents a clear view of one that is the most suitable option for the purposes of this study.

5 Discussion and sensitivity analysis
Defence purchases require vast amounts of money and time investment, so it is a process of strategic importance for any country. The procurement or development of aircraft entails huge defence budget expenditures, so the selection of an appropriate aircraft must be carefully evaluated. In the context of the economic and geopolitical challenges related to defence procurement, the opposition between the requirements and constraints need to be dealt with to ensure that a perfect trade-off is made

when approaching the optimal selection. The training aircraft selection for the VPAF was considered in this study. By further considering financial aspects, strategic relationship, and technical characteristics as criteria, various aspects of a training aircraft purchase were evaluated.

The result showed that by using a hybrid BWM and Fuzzy TOPSIS approach for training aircraft selection, the Yak-130 turns out to be the best suitable solution, closely followed by the L-159B. Even though the T-50 Golden Eagle outweighs the technologically superior Yak-130 and L-159B, the Yak-130 and the L-159B outweighs T-50 Golden Eagle in terms of both acquisition and operational cost. Based on the evaluation of decision-makers. The evaluation result is in Table 10. Therefore, the Yak-130 could be considered a more suitable training aircraft in preference to the T-50 since it represents an optimal trade-off between the technological requirements and budget limitations.

In order to validate the robustness of the proposed framework, sensitivity analysis was conducted and the result compared to AHP, another widely used MCDM method, to indicate the effect of varying the priority weights on the evaluation process and ranking of the solution for training aircraft selection. Twenty-three experiments were performed, as shown in Table 14. This was done by replacing the high weight for decision attributes while keeping the other weights constant.

Table 12 Distance of the rating of each alternative from FPIS and FNIS

	T-50		Yak-130		L-159B	
Distance from	A^+	A^-	A^+	A^-	A^+	A^-
GC1	0.989	0.011	0.992	0.009	0.994	0.006
GC2	0.935	0.067	0.094	0.067	0.967	0.035
GC3	0.967	0.034	0.967	0.034	0.967	0.034
PF1	0.919	0.082	0.948	0.054	0.948	0.054
PF2	0.995	0.006	0.995	0.006	0.995	0.006
PF3	0.981	0.019	0.971	0.029	0.981	0.019
PF4	0.986	0.014	0.979	0.022	0.986	0.014
PF5	0.982	0.018	0.988	0.012	0.988	0.012
PF6	0.985	0.015	0.994	0.007	0.994	0.007
PF7	0.993	0.007	0.993	0.007	0.993	0.007
PF8	0.99	0.011	0.992	0.008	0.992	0.008
PF9	0.972	0.029	0.972	0.029	0.963	0.038
PZ1	0.949	0.056	0.935	0.08	0.897	0.105
PZ2	0.865	0.147	0.729	0.278	0.729	0.278
PZ3	0.965	0.037	0.953	0.048	0.953	0.048
OC1	0.994	0.006	0.996	0.004	0.997	0.003
OC2	0.998	0.003	0.992	0.008	0.992	0.008
OC3	0.973	0.028	0.973	0.028	0.973	0.028
OC4	0.985	0.015	0.987	0.013	0.099	0.01
Total	18.423		17.45		17.408	
Total		0.605		0.743		0.72

Table 13 Ranking of alternative according to closeness co-efficient

	Total d_i^+	Total d_i^-	CC_i	Rank
T-50	18.423	0.605	0.032	3
Yak-130	17.45	0.743	0.041	1
L-159B	17.408	0.72	0.04	2

First, sensitivity analysis was conducted for the proposed hybrid method. On the first run, the weight of the main criterion General Characteristic (GC) = 0.4 and weights of all others 3 main criteria = 0.2 while maintaining the weights of sub-criteria. Then CC_i scores are calculated by using Fuzzy TOPSIS method. Again on the second run, the weight of the main criterion Performance (PF) = 0.4 and weights of all others 3 main criteria = 0.2. The weights of sub-criteria are maintained and CC_i values are calculated to get final rank. A similar process is followed until the 4th run. As with the sub-criteria, on the 5th run, the weight of sub-criterion maximum take-off weight (GC1) = 0.4 while GC2 = GC3 = 0.3. On the 8th run PF1 = 0.2 and the other sub-criteria of Performance criteria = 0.1. On the 17th run, PZ1 = 0.5 while PZ2 = PZ3 = 0.25. On

the 20th run, OC1 = 0.4, OC2 = OC2 = OC4 = 0.2. The resultant change in the ranking of criteria and sub-criteria is observed and finally, the alternatives are ranked using Fuzzy TOPSIS. The results of the sensitivity analysis are shown in Table 14 and Fig. 3.

Based on the result, the Yak-130 still maintains the first rank while the ranking of T-50 and L-159B are slightly changed when the main criteria weight is changed. It indicates that the proposed framework is relatively sensitive to the main criteria weights but robustness with any change of sub-criteria weight.

Second, AHP was adopted to solve the problem in the case study and the same sensitivity analysis was conducted. Table 15 presents the ranking of alternatives by sensitivity analysis when the priority vector values are changed, and Fig. 4 presents the result.

Fig. 5 demonstrates the changes among the rankings of three alternative aircraft using BWM-Fuzzy TOPSIS and AHP. This is clearly seen that for rank 1, while the ranking of Yak-130 remains unchanged during the implementation of the proposed method, AHP witnesses 21.74% of adjustment. For rank 2, the ranking of L-159B changed by BWM-Fuzzy TOPSIS and AHP is 17.04% and 34.78%,

Table 14 Ranking of alternative by sensitivity analysis when weight of criteria is changed

	T-50	Yak-130	L-159B
Original	3	1	2
Run 1	2	1	3
Run 2	2	1	3
Run 3	3	1	2
Run 4	2	1	3
Run 5	3	1	2
Run 6	3	1	2
Run 7	3	1	2
Run 8	3	1	2
Run 9	3	1	2
Run 10	3	1	2
Run 11	3	1	2
Run 12	3	1	2
Run 13	3	1	2
Run 14	3	1	2
Run 15	3	1	2
Run 16	3	1	2
Run 17	3	1	1
Run 18	3	1	2
Run 19	3	1	2
Run 20	3	1	2
Run 21	3	1	2
Run 22	3	1	2
Run 23	3	1	2
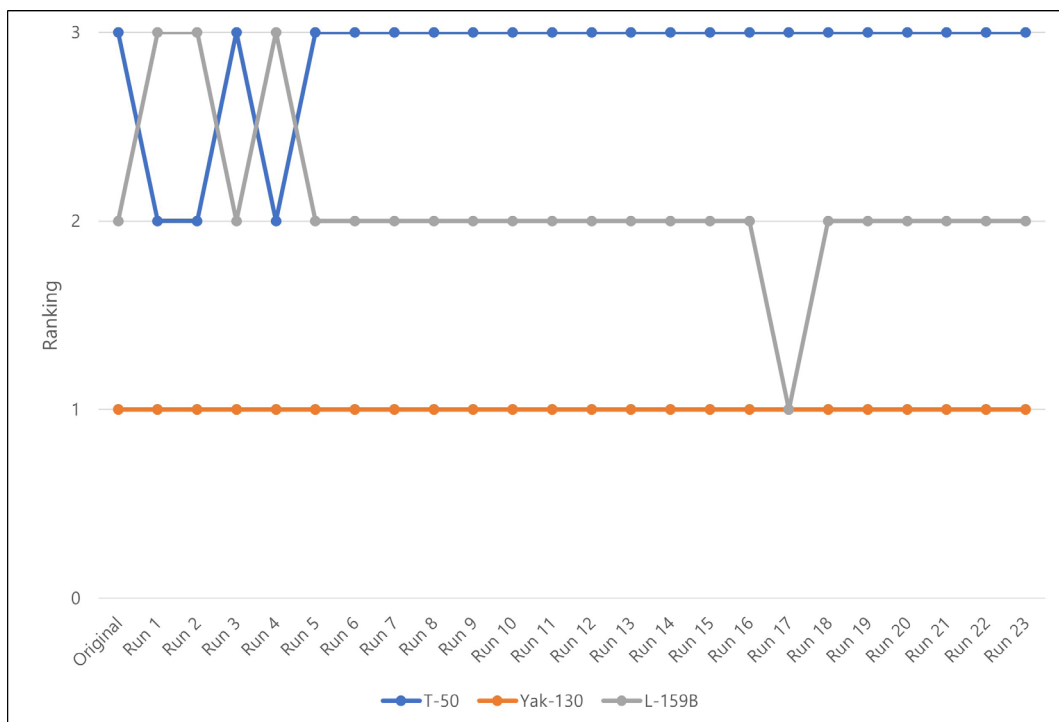
Fig. 3 Result of sensitivity analysis (BWM-Fuzzy TOPSIS)

Table 15 Ranking of alternative by sensitivity analysis when priority vector values is changed

	T-50	Yak-130	L-159B
Original	3	1	2
Run 1	2	1	3
Run 2	2	1	3
Run 3	3	1	2
Run 4	2	1	3
Run 5	3	2	1
Run 6	3	2	1
Run 7	3	2	1
Run 8	3	1	2
Run 9	3	2	1
Run 10	3	1	2
Run 11	3	1	2
Run 12	3	1	2
Run 13	3	1	2
Run 14	3	1	2
Run 15	3	1	2
Run 16	3	1	2
Run 17	3	2	1
Run 18	3	1	2
Run 19	3	1	2
Run 20	3	1	2
Run 21	3	1	2
Run 22	3	1	2
Run 23	3	1	2
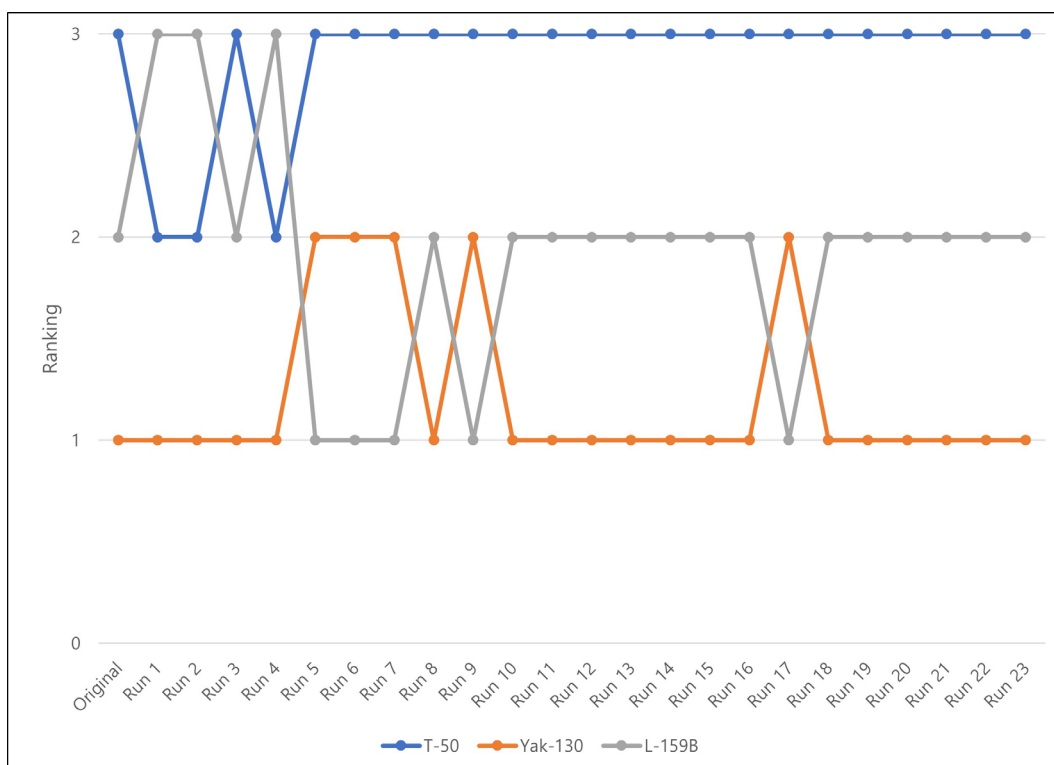
Fig. 4 Result of sensitivity analysis (AHP)
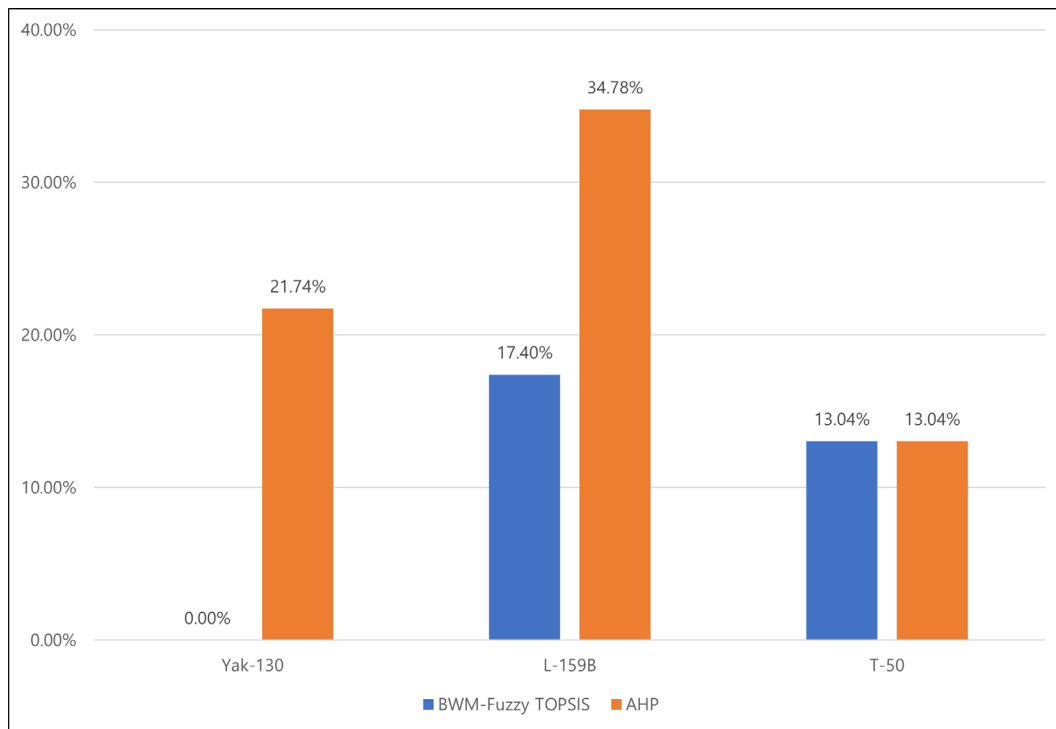
Fig. 5 Comparing the results of BWM-Fuzzy TOPSIS and AHP

relatively. However, rank 3 shows 13.04% of the variation for both methods. It can be concluded that the result obtained by the AHP was sensitive to changes in priority vector values while the proposed hybrid method gives much more reliable results than the AHP method.

6 Conclusions

In this study, a hybrid BWM-Fuzzy TOPSIS method was applied to determine the best training aircraft among a set of alternatives. BWM has advantages over other techniques like AHP, ANP, VIKOR, and DEMATEL because while it requires a lesser number of pairwise comparisons and experts, the result obtained is more consistent. Further, for ranking alternatives, Fuzzy TOPSIS is an approach to effectively dealing with the inherent imprecision, vagueness, and ambiguity of the human decision-making process with uncertain data. Four main criteria and nineteen sub-criteria are used to evaluate the different alternatives. Additionally, important data from an expert team including one senior manager of the Air Weapon Department of Air Defence and Air Force High Command Headquarters, three lecturers in the Aviation Weapons Department of the Air Defence and Air Force Academy, one senior flight instructors of Air Force Officer's College, and one air weapon system manager of an Air Force Regiment was obtained via questionnaires. This information was modelled using triangular fuzzy sets.

With this data, after using the BWM methodology to obtain the weight of the criteria, a formulation of TOPSIS method for fuzzy numbers was applied to get the final ranking of training aircraft with respect to criteria. Sensitivity analysis was conducted, and the result was compared to AHP to validate the robustness of the proposed method. It was shown that the proposed method gives much more reliable results than AHP method. As a result of the process, the Yak-130 turns out to be the best suitable solution, closely followed by L-159B. Even though the T-50 Golden Eagle outweighs the technologically superior Yak-130 and L-159B, the Yak-130 and L-159B outweighs T-50 Golden Eagle in terms of both acquisition and operational cost. Therefore, Yak-130 could be considered a more suitable training aircraft over T-50, since it represents an optimal trade-off between the technological requirements and budget limitations. Based on the evaluation of decision-makers. The evaluation result is in Table 10.

The main contribution of this study is that it presents a hybrid MCDM model for training aircraft selection in VPAF under fuzzy environment condition. This is the first attempt in using BWM and Fuzzy TOPSIS for aircraft selection in the context of VPAF. Moreover, some new important factors, such as business strategies across countries, economic aspects (acquisition, operation costs, and training cost) are also adopted in this study. This research

provides a new flexible and practical approach for decision-makers and a useful guideline for aircraft selection in other developing countries as well as for supplier selection in other fields.

For further studies, this research can also be extended by using the combination of different MCDM techniques such as Multi-Attribute Utility Theory (MAUT), Preference Ranking Organization Method for Enrichment of Evaluations (PROMETHEE), and Elimination and Choice Expressing Reality (ELECTRE) or incorporating additional selection criteria like risk factors.

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