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Aircraft Selection Using Multiple Criteria Decision Making Analysis Method with Different Data Normalization Techniques

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Abstract**—**This paper presents an original application of multiple criteria decision making analysis theory to the evaluation of aircraft selection problem. The selection of an optimal, efficient and reliable fleet, network and operations planning policy is one of the most important factors in aircraft selection problem. Given that decision making in aircraft selection involves the consideration of a number of opposite criteria and possible solutions, such a selection can be considered as a multiple criteria decision making analysis problem. This study presents a new integrated approach to decision making by considering the multiple criteria utility theory and the maximal regret minimization theory methods as well as aircraft technical, economical, and environmental aspects.

Multiple criteria decision making analysis method uses different normalization techniques to allow criteria to be aggregated with qualitative and quantitative data of the decision problem. Therefore, selecting a suitable normalization technique for the model is also a challenge to provide data aggregation for the aircraft selection problem. To compare the impact of different normalization techniques on the decision problem, the vector, linear (sum), linear (max), and linear (max-min) data normalization techniques were identified to evaluate aircraft selection problem.

As a logical implication of the proposed approach, it enhances the decision making process through enabling the decision maker to: (i) use higher level knowledge regarding the selection of criteria weights and the proposed technique, (ii) estimate the ranking of an alternative, under different data normalization techniques and integrated criteria weights after a posteriori analysis of the final rankings of alternatives. A set of commercial passenger aircraft were considered in order to illustrate the proposed approach. The obtained results of the proposed approach were compared using Spearman's rho tests. An analysis of the final rank stability with respect to the changes in criteria weights was also performed so as to assess the sensitivity of the alternative rankings obtained by the application of different data normalization techniques and the proposed approach.

Keywords**—**Normalization Techniques, Aircraft Selection, Multiple Criteria Decision Making, Multiple Criteria Decision Making Analysis, MCDMA.

I. Introduction

MULTIPLE criteria decision making analysis method (MCDMA) aims to rate and prioritize a set of alternatives that best satisfy a given set of criteria in decision analysis problems [38-41]. The proposed approach is focused to choose the appropriate alternative among the several alternatives, shortly it means evaluation, ordering and choosing. Decision criteria is a set of principles, guidelines, and requirements that an analyst or organization uses to make a mathematical decision. Also, decision criteria are a set of requirements or independent attributes that must be satisfied by a set of alternatives. The decision analysis process may be described as the choice made from a set of alternatives by using at least two decision criteria.

Each decision criterion may be measured in different units such as degrees, kilograms or meters; but dimensionless classifications to allow aggregation in a final rating, i.e. all must be normalized to obtain a common numerical scale. Therefore, data normalization is an essential part of any decision making analysis process as it allows the use of decision making methods to rate and rank a set of alternatives by transforming the input data into numerical and comparable data.

The basic procedural steps of decision making methods are as [38-41]: (1) to determine the evaluation criteria of the decision problem, (2) to determine the alternatives, (3) to determine the weights of evaluation criteria, (4) to evaluate the alternatives according to the decision criteria, (5) to apply the decision analysis technique, and (6) to choose an optimal alternative according to the essentials of the decision making method.

When making a choice among a set of alternatives, it is rather difficult to choose the best alternative. Moreover, there are decision problems that are related to select the most suitable alternative among the challenging alternatives, thereof a lot of decision analysts employ the decision analysis. In order to solve the problem of aircraft selection, different multiple criteria analysis techniques have been applied in the literature, and one of the mathematical methods that have been applied is the MCDMA technique. The MCDMA approach provides a methodical approach that simultaneously employs decision criteria both benefit and cost information and the views of decision makers in selecting optimum alternative from a set of alternatives. Generally, the multiple criteria decision making analysis methods may be categorized as compensatory (AHP, CP, MAUT, WSM, WPM, TOPSIS, VIKOR, and fuzzy applications) and noncompensatory approaches (ELECTRE, PROMETHEE, and fuzzy applications) [17-18]. The decision making analysis tools rank alternatives with reference to decision criteria which generally have different units of measurement. The MCDMA approach is the most employed approach for decision analysis problems [19]. The use of the multiple criteria analysis technique significantly improves decision making in decision problems involving multiple conflicting decision criteria.

The purpose of this study, therefore, is to compare different

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data normalization techniques with respect to the use of MCDMA methods in addressing problem of aircraft selection. The motivation to undertake this study also includes significant issues: a) the importance of data normalization in decision problems where it is required to aggregate data to obtain a final rating per alternative; b) the low number of research studies available on the aircraft selection topic; c) continuation of previous studies on the suitability of data normalization techniques for decision making methods; d) contribute to advances in aircraft selection research, where it is necessary to aggregate vast amounts of available data [5].

Specifically, the MCDMA approach using the integrated weights of the mean weights and the standard deviation weights is presented for the evaluation of decision making analysis problems. Considering the contrast among the conflicting decision criteria in the decision analysis problem, it is aimed to make an optimal decision.

In this study, it is aimed to analyze a set of aircraft alternatives over decision criteria by using different data normalization techniques suitable for decision making analysis problems. Sensitivity analysis is also performed to demonstrate the stability and validity of the ranking results using integrated weights of the mean weights and the standard deviation weights.

The remaining parts of this paper is organized as follows: Section 2 presents the methodology of the decision analysis problem. Section 3 indicates application of different data normalization techniques to the MCDMA decision problem. Finally, conclusions and future directions are presented in section 4.

II. Methodology

A. Multiple Criteria Analysis

Multiple criteria decision making analysis (MCDMA) method is considered as a complex decision making tool involving both quantitative and qualitative factors. The approach is generally applied in arriving at an optimum decision when faced with multiple alternatives having multiple conflicting and noncommensurable decision criteria [17-18]. The MCDMA technique is a mathematical decision analysis tool for solving complex real-life problems due to its intrinsic ability to judge diverse alternatives with reference to various decision criteria in order to choose to best alternative [38-41]. The MCDMA procedural steps are enlisted as below:

Step 1: Determine the decision matrix with the multiple criteria $g_j = (g_1, g_2, ..., g_n)$, $j = 1,...,n$, and the set of possible alternatives $a_i = (a_1, a_2, ..., a_m)$, $i = 1,...,m$.

$$X = \begin{pmatrix} a_1 \\ \vdots \\ a_m \end{pmatrix} \begin{array}{c} \begin{matrix} g_1 & & g_n \end{matrix} \\ \begin{pmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{pmatrix}_{mxn} \end{array} \quad (1)$$

.

Step 2: Normalize the decision matrix, $Y = (x_{ij})_{mxn}$. Calculate the normalized decision matrix. The vector (N1), linear (sum) (N2), linear (max) (N3), and linear (max-min) (N4) data normalization techniques are used for normalization of the decision matrix [33-34].

a. Vector Normalization (N1):

If g_j is a benefit criteria, then

$$y_{ij} = \frac{x_{ij}}{\left(\sum_{i=1}^{m} x_{ij}^{2}\right)^{1/2}} \quad (2)$$

If g_j is a cost criteria, then

$$y_{ij} = 1 - \frac{x_{ij}}{\left(\sum_{i=1}^{m} x_{ij}^{2}\right)^{1/2}} \quad (3)$$

b. Linear (Sum) Normalization (N2):

If g_j is a benefit criteria, then

$$y_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \quad (4)$$

If g_j is a cost criteria, then

$$y_{ij} = \frac{1/x_{ij}}{\sum_{i=1}^{m} 1/x_{ij}} \quad (5)$$

c. Linear (Max) Normalization (N3):

If g_j is a benefit criteria, then

$$y_{ij} = \frac{x_{ij}}{x_{ij}^{\max}} \quad (6)$$

If g_j is a cost criteria, then

$$y_{ij} = \frac{x_{ij}^{\min}}{x_{ij}} \quad (7)$$

d. Linear (Max-Min) Normalization (N4):

If g_j is a benefit criteria, then

$$y_{ij} = \frac{[x_{ij} - \min_j(x_{ij})]}{[\max_j(x_{ij}) - \min_j(x_{ij})]} \tag{8}$$

If g_j is a cost criteria, then

$$y_{ij} = \frac{[\max_j(x_{ij}) - x_{ij}]}{[\max_j(x_{ij}) - \min_j(x_{ij})]} \tag{9}$$

where x_{ij} are the evaluation indices and $i = 1,...,m$, number of alternatives, and number of criteria, $j = 1,...,n$.

$$\max_j x_{ij} = \max_j \left\{x_{1j}, x_{2j},..., x_{mj}\right\},$$
$$\min_j x_{ij} = \min_j \left\{x_{1j}, x_{2j},..., x_{mj}\right\}$$

Upon normalizing criteria of the decision matrix, all elements x_{ij} are reduced to interval values [0, 1], so all criteria have the same commensurate metrics.

Step 3: Determine the weight ω_j of the criteria.

The standard deviation (SD) measures the dispersion or variation of the values of a variable around its mean value. The standard deviation is the average distance from the mean value of all values in a set of data. In the SD preference method, the determination of objective criteria weights $\omega_j = (\omega_1, \omega_2,..., \omega_n)$ is based on the contrast intensity and the conflicting character of the evaluation criteria. For decision criteria $g_j = (g_1, g_2,..., g_n)$ in the normalized decision matrix, the standard deviation σ_j is calculated, and σ_j represents the measure of deviation of values of alternatives for the given criterion of average value.

To calculate the standard deviation, if n number of observations ($x_i = (x_1, x_2,..., x_n)$, $i = 1,...,n$) is given, then the standard deviation is determined by

$$\sigma = \left(\frac{\sum_{i=1}^{n} (x_i - \mu)^2}{n-1} \right)^{1/2} \tag{10}$$

$$\mu = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{11}$$

where μ corresponds to the mean of the data. x_j is one sample value, and n is the sample size. Criteria weights ω_j are determined based on values of standard vector deviation σ_j.

$$\omega_j = \frac{\sigma_j}{\sum_{k=1}^{m} \sigma_k} \tag{12}$$

$$\begin{cases} \omega_j > 0 \\ \sum_{l=1}^{n} \omega_j = 1 \\ j, k = 1, 2, ..., n \end{cases} \tag{13}$$

where ω_j is the objective weight of *j*th criterion. The higher the importance weight, the more important the criterion.

The quantity of information inherent in the *j*th criteria is calculated.

$$C_j = \sigma_j \sum_{j=1}^{n} (1 - \rho_{jk}) \tag{14}$$

where σ_j is standard deviation of the *j*th criterion, and ρ_{jk} is the correlation coefficient between the two criteria.

$$\rho_{jk} = \frac{\sum_{i=1}^{m} (y_{ij} - \overline{y_j})(y_{ik} - \overline{y_k})}{\left(\sum_{i=1}^{m} (y_{ij} - \overline{r_j})^2 \sum_{i=1}^{m} (y_{ik} - \overline{y_k})^2 \right)^{1/2}} \tag{15}$$

Intercriteria correlation weights are calculated to obtain objective weights [22].

$$\omega_j = \frac{\sigma_j}{\sum_{k=1}^{m} C_{jk}} \tag{16}$$

where ω_j is the intercriteria correlation weights, and n is the number criteria.

Step 4: Determine the weighted normalized decision matrix. Multiple criteria utility theory takes into consideration the decision maker's preferences in the form of utility functions defined over a set of tangible and intangible criteria [30]. The weighted normalized performance values u_{ij} of a weighted normalized decision matrix are calculated by

$$u_{ij}(a_i) = \omega_j y_{ij}(a_i) \tag{17}$$

The aggregated performance values $P_i(a_i)$ are calculated by aggregation operator [28].

$$P_i(a_i) = \sum_{j=1}^{n} \omega_j y_{ij}(a_i) \tag{18}$$

Select a_i^* such that $P_i^*(a_i) = \max \sum_{j=1}^{n} \omega_j y_{ij}(a_i)$ (19)

The alternative $P_i(a_i)$ selected must maximize the utility function.

Step 5: Minimize the maximal regret. Maximal regret minimization theory proposes that when facing a decision, the decision makers might anticipate regret and thus incorporate in their choice their desire to eliminate or reduce this possibility [31]. Minimization of the maximal regret $R_i(a_i)$ is calculated from the normalized matrix.

a. For each g_j calculate $C_j = \max_i(c_{ij})$ (20)

b. For each pair a_i and g_i calculate $r_{ij} = C_j - c_{ij}$ (21)

c. For each a_i calculate $R_i(a_i) = \sum_{j=1}^{n} \omega_l r_{ij}(a_i)$ (22)

d. Select a_{i*} such that $R_{i*}(a_i) = \min \sum_{j=1}^{n} \omega_j r_{ij}(a_i)$ (23)

Step 6: Rank the alternatives according to the decreasing values of assessment scores $0 \le P_i(a_i) \le 1$ and $0 \le R_i(a_i) \le 1$. The alternative with the highest $P_i(a_i)$, and the alternative with the lowest $R_i(a_i)$, is the best choice among the alternatives.

Step 7: Calculate sensitivity analysis. Sensitivity analysis determines how target variables are affected based on changes in input variables.

a. Integrating the values of the weights of the criteria

The weights of criteria can be considered as random values.The objective weights of the criteria assess the structure of the data array, i.e., the decision matrix. The weights of the criteria, as well as the probabilities of the random values, range from 0 to 1. Bayes' theorem applied to criteria weights may be interpreted as the need to recalculate these weights when different criteria weights are obtained using other evaluation methods.The criteria weights may be considered as a number of random values, making a complete set. In fact, the sum of the criteria weights' values is equal to one: $\sum_{l=1}^{n} \omega_j = 1$.

The criteria weights are recalculated by the Bayes' equation [32] .

$$\omega(g_j / x) = \frac{\omega(g_j)\omega(x / g_j)}{\sum_{j=1}^{n} \omega(g_j)\omega(x / g_j)} \quad (24)$$

where $\omega(g_j) = \omega_j^k$ is the initial weight of the *j*th criterion g_j ; x denotes the event, when new criteria weights are obtained; $\omega(x / g_j) = \omega_j^l$ denotes new weights of the criteria calculated by a different method. Then, the integrated weights of the criteria are calculated by

$$\alpha_j = \frac{\omega_j^k \omega_j^l}{\sum_{j=1}^{n} \omega_j^k \omega_j^l} \quad (25)$$

where α_j denotes the recalculated weights of the criteria.

b. Spearman's rank-order correlation (ρ)

There are two methods to calculate Spearman's correlation depending on whether: data does not have tied ranks or data has tied ranks.

The Spearman's correlation ρ is calculated when there are no tied ranks:

$$\rho = 1 - \frac{6\sum_{i=1}^{n} d_i^2}{n(n^2 - 1)} \quad (26)$$

where $d_i = r_{1i} - r_{2i}$ is difference in paired ranks, r_{1i} is the rank of *i* in the first set of data, r_{2i} is the rank of *i* in the second set of data, and *n* is number of pair of observations.

The Spearman's correlation ρ is calculated when there are tied ranks. The Spearman rank correlation coefficient is the sample Pearson product-moment correlation of the ranks of the observations (x_i, y_i), $i \in \{1,...,n\}$.

$$\rho = \frac{\sum_{i=1}^{n} (x_i - \bar{x})(y_i - \bar{y})}{\left(\sum_{i=1}^{n} (x_i - \bar{x})^2 \sum_{i=1}^{n} (y_i - \bar{y})^2 \right)^{1/2}} \quad (27)$$

where $\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$ and $\bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i$ are sample means of ranks.

B. Aircraft Selection Problem

a. Criteria

In this study, the four selected civil aircraft are ranked based on the following decision criteria:

- Price of Aircraft ($, ($g_1$), min): This criterion includes costs of average market price of aircraft in million dollars ($).
- Fuel Efficiency per Seat (L/100 km, (g_2), min): Fuel efficiency per seat produces a double dividend effect with simultaneous benefits on economy and environmental quality.
- Aircraft Range (km, (g_3), max): Range is the total distance measured with respect to ground traversed by the aircraft on a full tank of fuel.

- Aircraft Seat Capacity (#, (g_4), max): The aircraft with the highest number of seats is preferred.
- Maximum Takeoff Weight (kg, (g_5), max): The maximum gross weight due to design or operational limitations at which an aircraft is permitted to take off.
- Maximum Payload (kg, (g_6), max): Maximum payload capacity means the maximum certificated takeoff weight of an aircraft less the empty weight.

b. Alternatives

In this study, aircraft selection problem is considered to determine the most suitable short-medium range aircraft. Thus, a set of alternative commercial passenger aircraft, [Airbus family {(A320neo (a_1), A321neo (a_2)}; Boeing family{ B737 MAX8 (a_3), B737 MAX9 (a_4)}], are identified for multiple criteria evaluation using six decision criteria for the aircraft selection problem as shown in Table 1.

Table 1. Decision Matrix for Aircraft Selection Problem

	Economic Aspect	Environmental Eco. Aspect	Technical Aspect	Technical Aspect	Technical Aspect	Technical Aspect
	min	min	max	max	max	max
	g_1	g_2	g_3	g_4	g_5	g_6
a_1	110,6	2,25	6300	180	79400	15100
a_2	129,5	2,19	7400	210	97400	24100
a_3	121,6	2,28	6575	178	82190	16239
a_4	128,9	2,28	6575	193	88314	17327

III. Application

In this section, the MCDMAM methodology is applied to aircraft selection problem. A set of candidate aircraft from Airbus and Boeing are handled as the alternatives as shown in Table 1. The evaluation criteria affecting the aircraft selection problem are determined from the literature [1-16], [42-44].

A. *Application of the MCDMAM Methodology*

The MCDMAM methodology, which uses the multiple criteria utility theory and the maximal regret minimization theory, is applied to select the best aircraft among the alternatives and is explained in phases as follows.

Phase 1: Define the decision criteria and alternatives for the aircraft selection problem: The aim of the aircraft selection problem is to find the best aircraft for the airlines. During the selection and evaluation process, the literature was reviewed, and a set of aircraft types were selected as candidates for multiple criteria analysis. Thus, six decision criteria affecting the selection process were determined. The criteria for the price of aircraft (g_1) and fuel efficiency per seat (g_2), are defined as cost criteria. Other criteria, aircraft range (g_3), aircraft seat capacity (g_4), maximum takeoff weight (g_5), and maximum payload (g_6) are defined as benefit criteria in the decision matrix structure (1).

Phase 2: Normalize the decision criteria and determine the objective criteria weights using the standard deviation. Then, the weighted normalized decision matrix is calculated through equations (2)-(14). The utility function values $P_i(a_i)$ and minimization of the maximal regret values $R_i(a_i)$ are calculated and the rankings of alternatives are listed using equations (15)-(23) in Table 2-Table 17.

Phase 3:Sensitivity analysis is performed, after the integrated criteria weights α_j are determined using equations (24)-(25), the weighted normalized decision matrix is calculated.

Phase 4:The utility function values $P_i(a_i)$ and minimization of the maximal regret values $R_i(a_i)$ are calculated and the rankings of alternatives are listed using equations (15)-(23) in Table 18-Table 29.

B. *Aircraft Selection Using the Standard Deviation Weights*

a. Vector Normalization (N1):

Table 2. Normalized Decision Matrix (N1)

	g_1	g_2	g_3	g_4	g_5	g_6
a_1	0,5500	0,5001	0,4684	0,4720	0,4558	0,4076
a_2	0,4731	0,5134	0,5502	0,5507	0,5591	0,6505
a_3	0,5052	0,4934	0,4888	0,4668	0,4718	0,4383
a_4	0,4755	0,4934	0,4888	0,5061	0,5070	0,4677
μ	0,5010	0,5001	0,4991	0,4989	0,4984	0,4910
σ	0,0358	0,0094	0,0354	0,0387	0,0458	0,1091
ω_j	0,1306	0,0344	0,1292	0,1411	0,1669	0,3979

Table 3. Weighted Normalized Multiple Criteria Utility Theory $P_i(a_i)$ Decision Matrix (N1)

	g_1	g_2	g_3	g_4	g_5	g_6
a_1	0,0718	0,0172	0,0605	0,0666	0,0761	0,1622
a_2	0,0618	0,0177	0,0711	0,0777	0,0933	0,2588
a_3	0,0660	0,0170	0,0631	0,0658	0,0787	0,1744
a_4	0,0621	0,0170	0,0631	0,0714	0,0846	0,1861

Table 4. Weighted Normalized Minimization of Maximal Regret Theory $R_i(a_i)$ Decision Matrix (N1)

	g_1	g_2	g_3	g_4	g_5	g_6
a_1	0,0000	0,0005	0,0106	0,0111	0,0172	0,0967
a_2	0,0100	0,0000	0,0000	0,0000	0,0000	0,0000
a_3	0,0058	0,0007	0,0079	0,0118	0,0146	0,0844
a_4	0,0097	0,0007	0,0079	0,0063	0,0087	0,0727

Table 5. Ranking Alternatives (N1)

	$P_i(a_i)$	R	$R_i(a_i)$	R
a_1	0,4543	4	0,1360	4
a_2	0,5803	1	0,0100	1
a_3	0,4651	3	0,1253	3
a_4	0,4843	2	0,1061	2

b. Linear (Sum) Normalization (N2):

Table 6. Normalized Decision Matrix (N2)

	g_1	g_2	g_3	g_4	g_5	g_6
a_1	0,2761	0,2499	0,2346	0,2365	0,2286	0,2075
a_2	0,2358	0,2568	0,2756	0,2760	0,2804	0,3312
a_3	0,2511	0,2466	0,2449	0,2339	0,2367	0,2232
a_4	0,2369	0,2466	0,2449	0,2536	0,2543	0,2381
μ	0,25	0,25	0,25	0,25	0,25	0,25
σ	0,0188	0,0048	0,0177	0,0194	0,0230	0,0556
ω_j	0,1348	0,0343	0,1275	0,1393	0,1649	0,3992

Table 7. Weighted Normalized Multiple Criteria Utility Theory $P_i(a_i)$ Decision Matrix (N2)

	g_1	g_2	g_3	g_4	g_5	g_6
a_1	0,0372	0,0086	0,0299	0,0329	0,0377	0,0828
a_2	0,0318	0,0088	0,0351	0,0384	0,0463	0,1322
a_3	0,0339	0,0085	0,0312	0,0326	0,0390	0,0891
a_4	0,0319	0,0085	0,0312	0,0353	0,0419	0,0951

Table 8. Weighted Normalized Minimization of Maximal Regret Theory $R_i(a_i)$ Decision Matrix (N2)

	g_1	g_2	g_3	g_4	g_5	g_6
a_1	0,0000	0,0002	0,0052	0,0055	0,0085	0,0494
a_2	0,0054	0,0000	0,0000	0,0000	0,0000	0,0000
a_3	0,0034	0,0003	0,0039	0,0059	0,0072	0,0431
a_4	0,0053	0,0003	0,0039	0,0031	0,0043	0,0372

Table 9. Ranking Alternatives (N2)

	$P_i(a_i)$	R	$R_i(a_i)$	R
a_1	0,2292	4	0,0689	4
a_2	0,2926	1	0,0054	1
a_3	0,2342	3	0,0638	3
a_4	0,2439	2	0,0541	2

c. Linear (Max) Normalization (N3):

Table 10. Normalized Decision Matrix (N3)

	g_1	g_2	g_3	g_4	g_5	g_6
a_1	1	0,9733	0,8514	0,8571	0,8152	0,6266
a_2	0,8541	1	1	1	1	1
a_3	0,9095	0,9605	0,8885	0,8476	0,8438	0,6738
a_4	0,8580	0,9605	0,8885	0,9190	0,9067	0,7190
μ	0,9054	0,9736	0,9071	0,9060	0,8914	0,7548
σ	0,0679	0,0186	0,0644	0,0702	0,0818	0,1677
ω_j	0,1443	0,0395	0,1367	0,1492	0,1739	0,3563

Table 11. Weighted Normalized Multiple Criteria Utility Theory $P_i(a_i)$ Decision Matrix (N3)

	g_1	g_2	g_3	g_4	g_5	g_6
a_1	0,1443	0,0385	0,1164	0,1279	0,1417	0,2233
a_2	0,1233	0,0395	0,1367	0,1492	0,1739	0,3563
a_3	0,1313	0,0380	0,1215	0,1265	0,1467	0,2401
a_4	0,1238	0,0380	0,1215	0,1371	0,1577	0,2562

Table 12. Weighted Normalized Minimization of Maximal Regret Theory $R_i(a_i)$ Decision Matrix (N3)

	g_1	g_2	g_3	g_4	g_5	g_6
a_1	0,0000	0,0011	0,0203	0,0213	0,0321	0,1331
a_2	0,0211	0,0000	0,0000	0,0000	0,0000	0,0000
a_3	0,0131	0,0016	0,0152	0,0227	0,0272	0,1162
a_4	0,0205	0,0016	0,0152	0,0121	0,0162	0,1001

Table 13. Ranking Alternatives (N3)

	$P_i(a_i)$	R	$R_i(a_i)$	R
a_1	0,7921	4	0,2079	4
a_2	0,9789	1	0,0211	1
a_3	0,8040	3	0,1960	3
a_4	0,8343	2	0,1657	2

d. Linear (Max-Min) Normalization (N4):

Table 14. Normalized Decision Matrix (N4)

	g_1	g_2	g_3	g_4	g_5	g_6
a_1	1,0000	0,3333	0,0000	0,0625	0,0000	0,0000
a_2	0,0000	1,0000	1,0000	1,0000	1,0000	1,0000
a_3	0,4180	0,0000	0,2500	0,0000	0,1550	0,1266
a_4	0,0317	0,0000	0,2500	0,4688	0,4952	0,2474
μ	0,3624	0,3333	0,3750	0,3828	0,4126	0,3435
σ	0,4656	0,4714	0,4330	0,4610	0,4429	0,4492
ω_j	0,1710	0,1731	0,1590	0,1693	0,1626	0,1650

Table 15. Weighted Normalized Multiple Criteria Utility Theory $P_i(a_i)$ Decision Matrix (N4)

	g_1	g_2	g_3	g_4	g_5	g_6
a_1	0,1710	0,0577	0,0000	0,0106	0,0000	0,0000
a_2	0,0000	0,1731	0,1590	0,1693	0,1626	0,1650
a_3	0,0715	0,0000	0,0398	0,0000	0,0252	0,0209
a_4	0,0054	0,0000	0,0398	0,0794	0,0805	0,0408

Table 16. Weighted Normalized Minimization of Maximal Regret Theory Decision Matrix $R_i(a_i)$ (N4)

	g_1	g_2	g_3	g_4	g_5	g_6
a_1	0,0000	0,1154	0,1590	0,1587	0,1626	0,1650
a_2	0,1710	0,0000	0,0000	0,0000	0,0000	0,0000
a_3	0,0995	0,1731	0,1193	0,1693	0,1374	0,1441
a_4	0,1656	0,1731	0,1193	0,0899	0,0821	0,1241

Table 17. Ranking Alternatives (N4)

	$P_i(a_i)$	R	$R_i(a_i)$	R
a_1	0,2393	4	0,9257	4
a_2	0,8290	1	0,1710	1
a_3	0,1573	3	0,8427	3
a_4	0,2459	2	0,7541	2

C. Aircraft Selection Using the Integrated Criteria Weights

A. Sensitivity Analysis

Sensitivity analysis is structured with the integrated criteria weights generated by the intercriteria correlation method and the standard deviation method using equations (24)-(25).

Table 18. α_j Weighted Normalized Decision Matrix (N1) - Multiple Criteria Utility Theory $P_i(a_i)$

	g_1	g_2	g_3	g_4	g_5	g_6
a_1	0,2068	0,0124	0,0436	0,0496	0,0595	0,1103
a_2	0,1779	0,0127	0,0512	0,0578	0,0730	0,1760
a_3	0,1900	0,0123	0,0455	0,0490	0,0616	0,1186
a_4	0,1788	0,0123	0,0455	0,0531	0,0662	0,1266
α_j	0,3761	0,0248	0,0930	0,1050	0,1305	0,2706

Table 19. α_j Weighted Normalized Minimization of Maximal Regret Theory $R_i(a_i)$ Decision Matrix (N1)

	g_1	g_2	g_3	g_4	g_5	g_6
a_1	0,0000	0,0003	0,0076	0,0083	0,0135	0,0657
a_2	0,0289	0,0000	0,0000	0,0000	0,0000	0,0000
a_3	0,0168	0,0005	0,0057	0,0088	0,0114	0,0574
a_4	0,0280	0,0005	0,0057	0,0047	0,0068	0,0495
α_j	0,3761	0,0248	0,0930	0,1050	0,1305	0,2706

Table 20. α_j Weighted Ranking Alternatives (N1)

	$P_i(a_i)$	R	$R_i(a_i)$	R
a_1	0,4822	3	0,0954	3
a_2	0,5486	1	0,0289	1
a_3	0,4769	4	0,1007	4
a_4	0,4824	2	0,0952	2

Table 21. α_j Weighted Normalized Multiple Criteria Utility Theory $P_i(a_i)$ Decision Matrix (N2)

	g_1	g_2	g_3	g_4	g_5	g_6
a_1	0,1064	0,0061	0,0214	0,0242	0,0292	0,0558
a_2	0,0908	0,0063	0,0252	0,0282	0,0358	0,0891
a_3	0,0967	0,0060	0,0224	0,0239	0,0302	0,0600
a_4	0,0913	0,0060	0,0224	0,0260	0,0325	0,0641
α_j	0,3852	0,0244	0,0913	0,1023	0,1278	0,2690

Table 22. α_j Weighted Normalized Minimization of Maximal Regret Theory $R_i(a_i)$ Decision Matrix (N2)

	g_1	g_2	g_3	g_4	g_5	g_6
a_1	0,0000	0,0002	0,0037	0,0040	0,0066	0,0333
a_2	0,0155	0,0000	0,0000	0,0000	0,0000	0,0000
a_3	0,0096	0,0002	0,0028	0,0043	0,0056	0,0291
a_4	0,0151	0,0002	0,0028	0,0023	0,0033	0,0250
α_j	0,3852	0,0244	0,0913	0,1023	0,1278	0,2690

Table 23. α_j Weighted Ranking Alternatives (N2)

	$P_i(a_i)$	R	$R_i(a_i)$	R
a_1	0,2431	2	0,0478	2
a_2	0,2754	1	0,0155	1
a_3	0,2393	4	0,0516	4
a_4	0,2421	3	0,0488	3

Table 24. α_j Weighted Normalized Multiple Criteria Utility Theory $P_i(a_i)$ Decision Matrix (N3)

	g_1	g_2	g_3	g_4	g_5	g_6
a_1	0,4032	0,0267	0,0814	0,0919	0,1074	0,1471
a_2	0,3444	0,0274	0,0956	0,1073	0,1317	0,2348
a_3	0,3667	0,0263	0,0849	0,0909	0,1112	0,1582
a_4	0,3460	0,0263	0,0849	0,0986	0,1194	0,1688
α_j	0,4032	0,0274	0,0956	0,1073	0,1317	0,2348

Table 25. α_j Weighted Normalized Minimization of Maximal Regret Theory $R_i(a_i)$ Decision Matrix (N3)

	g_1	g_2	g_3	g_4	g_5	g_6
a_1	0	0,0267	0,1486	0,1429	0,1848	0,3734
a_2	0,1459	0	0	0	0	0
a_3	0,0905	0,0395	0,1115	0,1524	0,1562	0,3262
a_4	0,142	0,0395	0,1115	0,081	0,0933	0,281
α_j	0,4816	0,1071	0,1062	0,1000	0,1025	0,1026

Table 26. α_j Weighted Ranking Alternatives (N3)

	$P_i(a_i)$	R	$R_i(a_i)$	R
a_1	0,8577	2	0,1423	2
a_2	0,9412	1	0,0588	1
a_3	0,8383	4	0,1617	4
a_4	0,8441	3	0,1559	3

Table 27. α_j Weighted Normalized Multiple Criteria Utility Theory $P_i(a_i)$ Decision Matrix (N4)

	g_1	g_2	g_3	g_4	g_5	g_6
a_1	0,4816	0,0357	0,0000	0,0062	0,0000	0,0000
a_2	0,0000	0,1071	0,1062	0,1000	0,1025	0,1026
a_3	0,2013	0,0000	0,0265	0,0000	0,0159	0,0130
a_4	0,0153	0,0000	0,0265	0,0469	0,0507	0,0254
α_j	0,4816	0,1071	0,1062	0,1000	0,1025	0,1026

Table 28. α_j Weighted Normalized Minimization of Maximal Regret Theory $R_i(a_i)$ Decision Matrix (N4)

	g_1	g_2	g_3	g_4	g_5	g_6
a_1	0,0000	0,0714	0,1062	0,0937	0,1025	0,1026
a_2	0,4816	0,0000	0,0000	0,0000	0,0000	0,0000
a_3	0,2803	0,1071	0,0796	0,1000	0,0866	0,0896
a_4	0,4664	0,1071	0,0796	0,0531	0,0517	0,0772
α_j	0,4816	0,1071	0,1062	0,1000	0,1025	0,1026

Table 29. α_j Weighted Ranking Alternatives (N4)

	$P_i(a_i)$	R	$R_i(a_i)$	R
a_1	0,5236	1	0,4764	1
a_2	0,5184	2	0,4816	2
a_3	0,2567	3	0,7433	3
a_4	0,1648	4	0,8352	4

B. *Decision Analysis*

A sensitivity analysis was performed to demonstrate the stability and validity of the ranking results from different data normalization techniques. Furthermore, the ranking results of the proposed methodology were evaluated with comparative values of the $P_i(a_i)$ and $R_i(a_i)$ listings. The mathematical decision results show that the presented methodology is efficient and stable for solving aircraft selection problems, except the rank reversal observation after the sensitivity analysis was applied to the data normalization techniques.

The Spearman rank correlation coefficient (ρ) was calculated between paired ranks when sensitivity analysis was performed using integrated criteria weights (α_j). There was not a rank discordance between the paired ranks when the standard deviation weights were used for the ranking of alternatives. But, when the sensitivity analysis was performed using the integrated criteria weights (α_j), there was a rank discordance between the paired ranks. Therefore, the Spearman rank correlation coefficients (ρ) were calculated between the paired ranks (Table 17 - Table 20, ρ =0,80), (Table 17 - Table 23, ρ =0,40), (Table 17 - Table 29, ρ = -0,40), (Table 20 - Table 23, ρ =0,80), (Table 20 - Table 29, ρ =0,00), and (Table 23 - Table 29, ρ =0,60) respectively.

However, the alternative (a_2) was selected as the best aircraft in all ranking results from the data normalization techniques [N1, N2, N3, N4] before the sensitivity analysis was applied.

Results of the spearman correlation (ρ) indicated that there is a significant very large positive relationship between the data normalization techniques [N1, N2, N3] and the data normalization technique [N4] under the integrated criteria weights α_j.

Table 30. The standard deviation weights (ω_j) for the data normalization techniques [N1, N2, N3, N4]

	g_1	g_2	g_3	g_4	g_5	g_6
N1	0,1306	0,0344	0,1292	0,1411	0,1669	0,3979
N2	0,1348	0,0343	0,1275	0,1393	0,1649	0,3992
N3	0,1443	0,0395	0,1367	0,1492	0,1739	0,3563
N4	0,171	0,1731	0,159	0,1693	0,1626	0,165

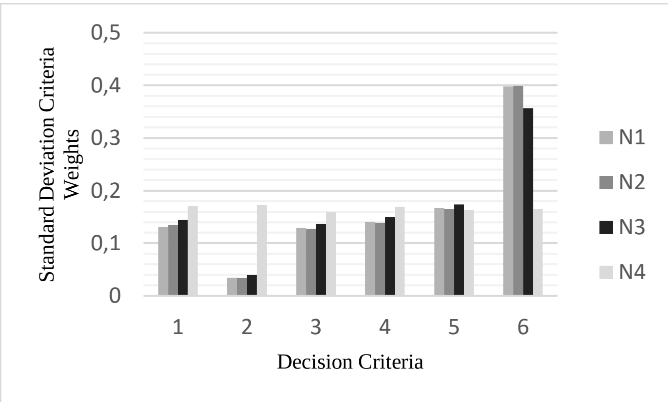

Fig. 1 Standard deviation criteria weights (ω_j) for the data normalization techniques [N1, N2, N3, N4]

Table 31. The integrated criteria weights (α_j) for the data normalization techniques [N1, N2, N3, N4]

	g_1	g_2	g_3	g_4	g_5	g_6
N1	0,1306	0,0344	0,1292	0,1411	0,1669	0,3979
N2	0,3852	0,0244	0,0913	0,1023	0,1278	0,2690
N3	0,4032	0,0274	0,0956	0,1073	0,1317	0,2348
N4	0,4737	0,1041	0,1123	0,0993	0,106	0,1046

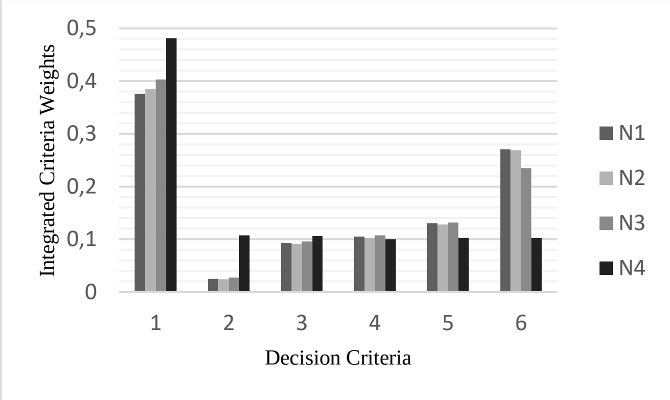

Fig. 2 Integrated criteria weights (α_j) for the data normalization techniques [N1, N2, N3, N4]

IV. Conclusion

The proposed MCDMA approach enables airlines to effectively use their limited resources when considering technical, economic, and environmental factors. The Network, fleet and schedule planning, and the selection of appropriate aircraft are critical decision making processes for airlines. The selection of suitable aircraft can increase airlines' profits and reduce their costs.

A number of mathematical decision methods are used for multiple criteria evaluation, and the selection of aircraft using the proposed methodology offers airlines a satisfactory solution to this decision analysis problem. For this reason, airlines should consider the results obtained by multiple criteria methods to gain a competitive advantage in the industry and increase their gains in choosing the appropriate aircraft. Using this proposed model, airlines can select aircraft suitable for their fleet and network operations, considering economic, technical, and environmental aspects. Also, different types and sizes of aircraft can be selected by changing the criteria and criteria weights in the model.

This proposed model can be used not only in the selection of wide and narrow body commercial passenger aircraft, but also in the selection of trainer aircraft, cargo aircraft and military trainer aircraft. Therefore, decision makers in fleet planning and network operations can use this model to add different decision criteria, and evaluate the aircraft alternatives according to their institutional interests. Also, in the aviation industry, which is extremely uncertain, it is very important for decision makers to make the right decisions. In addition to using this method in aircraft selection, the presented model can be used for route selection, network design, airline service quality assessment, risk analysis, and project planning.

In this study, a mathematical decision model for aircraft evaluation is proposed. The model includes six decision criteria; price of aircraft, fuel efficiency per seat, aircraft range, maximum takeoff weight, aircraft seat capacity, and maximum payload. The model framework is based on a hybrid approach that uses both the multiple criteria utility theory and the maximal regret minimization theory. The hybrid method offers a more specific solution as it helps decision makers make more accurate decisions for aircraft selection in an increasingly uncertain environment.

Unlike other studies in the literature, this study focuses on the selection of commercial passenger aircraft by utilizing the multiple criteria utility theory and the maximal regret minimization theory. In the first stage, the decision criteria related to aircraft selection were identified by reviewing previous studies in the literature. In the second stage, the appropriate importance criteria were determined using the standard deviation method and weighted these decision criteria.

The objective of this study is to propose a mathematical decision method to determine the most eligible commercial passenger aircraft for the airlines. The aircraft selection problem is usually very complex in nature because a set of important multiple criteria must be considered, and the selection procedure needs to be error-free and reliable. The proposed method in this study is a hybrid approach including multiple criteria utility theory and minimization of maximal regret theory.

This approach is unique for the solution of such real-life problems. The proposed approach evaluated the alternatives and produced acceptable possible solutions to a decision problem. In decision problems, the decision criteria values and the objective weights are usually characterized by crisp numbers and fuzzy numbers, which brings flexibility in decision making. The application of different data normalization techniques contributed to the proposed model by adding a pivotal dimension to the multiple criteria assessment process. The final decision was significantly influenced by the incorporated different data normalization techniques. All decision ranking orders were the same under the vector (N1), linear (sum) (N2), linear (max) normalization (N3) techniques, except only the linear (Max-Min) normalization technique (N4) yielded different ranking orders when integrated criteria weights were applied in sensitivity analysis. The results of the proposed model clearly indicate the preference score of each alternative. With these evaluation scores, the final ranking of the alternatives is presented so that decision makers can easily eliminate a candidate alternative or a group of candidate alternatives that fall short of the set of alternatives. Thus a decision support system might be developed to improve the efficiency of the decision making process for selecting aircraft. The contributions of the study can be summarized as follows:

1. The multiple criteria utility theory and the maximal regret minimization theory provide mathematical solutions for the selection of the appropriate alternative, and the ranking of different alternatives by integrating objective weighting procedures to determine the decision criteria. However, these multiple criteria decision analysis methods have not been used in aircraft type selection problem before.

2.The multiple criteria utility theory and the maximal regret minimization theory were used to rank a set of aircraft alternatives. The decision criteria and the aircraft alternatives were determined from the literature review. The aircraft alternatives, were evaluated in terms of technical, economic, and environmental aspects in multiple dimensions.

3.The standard deviation method was used when determining the decision criteria set for the aircraft selection problem.

4.The application of different data normalization techniques added a pivotal dimension to the comparative results in multiple criteria assessment process.

5.The Bayes theorem was used to combine the mean weights and the standard deviation weights when determining the integrated criteria weights.

6.The multiple criteria utility theory and the maximal regret minimization theory methods are used for decision making under uncertainty, the model provides stable results to the aircraft selection problem.

7. The aviation industry can exploit the proposed methodology for the aircraft selection process. In this way, the industry can choose the most suitable aircraft for their fleets, networks, and operational planning policies.

8.This model can also be used in future aircraft selection studies. By changing the decision criteria in the model, commercial passenger aircraft, cargo aircraft, and military aircraft can be selected from a predetermined set of alternatives.

Evaluating and selecting the most suitable aircraft among the alternatives is very important for airlines. Appropriate aircraft selection is important for airlines' competitive strategies, and appropriate aircraft selection can provide an effective competitive advantage correspondingly. Therefore, airlines should determine a useful mathematical evaluation method for aircraft selection. Considering the decision making process followed, and the MCDMA methods used in the structuring of this study, it is expected to make significant contributions to the airlines in the selection of the appropriate aircraft. In addition, the proposed MCDMA methodology can easily be adapted for use in other industries and sectors. Finally, it is recommended that the proposed MCDMA methodology in this study should be preferred in future ranking and selection studies.

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APPENDIX

Table 32. Multiple criteria decision making analysis methods for aircraft selection problem

Authors	Methodologies	Criteria	Alternatives
See,T.-K., Gurnani, A., Lewis, K. E. (2004)[1]	Weighted Sum Method, Hypothetical Equivalents and Inequivalents Method	Speed, Max. Range, Number of passengers	Comparison of 4 aircraft types B747, B777, A340, B747
Wang, T. C., Chang, T. H. (2007)[2]	Fuzzy Technique for Order Preference by Similarity to Ideal Situation	Fuel capacity, Power plant, Service ceiling, Maximum G limits, Minimum G limits, Maximum operating speed, Econ cruising speed, Maximum speed with landing gears down, Maximum speed with flaps down, Stalling speed: flameout, Maximum cruising speed, Maximum climbing rate at sea level, Take-off distance, Landing distance, Take-off to 50 feet, Landing from 50 to full stop	Comparison of 7 aircraft types T-34, PC-7, PC-9, PC-7 MK2, T-6A, KT-1, T-27
Ozdemir, Y., Basligil, H., Karaca, M. (2011) [3]	Analytic Network Process	Cost, Time, Physical Attributes and Others: Maintenance cost, Operation and spare cost, Purchasing cost, Salvage cost, Dimensions, Reliability, Security, Suitability for service quality, Delivery time, Useful life	Comparison of 3 aircraft types A319, A320, B737
Gomes, L. F. A. M., Fernandes, J. E. d. M., Soares de Mello, J. C. C. B.(2012) [4]	Novel Approach to Imprecise Assessment and Decision Environments (NAIADE Method)	Financial, Logistics, Quality :Acquisition cost, Liquidity, Operating costs, Range, Flexibility, Cruising speed, Replacement parts availability, Landing and take-off distance, Comfort, Avionics availability, Safety	Comparison of 8 aircraft types Cessna 208, De Havilland DHC-6, LET 410, Fairchild Metro, Beechcraft 1900, Embraer EMB 110, Dornier 228, CASA 212
Dožić,S., Kalić, M. (2014)[5]	Analytic Hierarchy Process	Seat capacity, Price of aircraft, Total baggage, Maximum take-off weight (MTOW), Payment conditions, Total cost per available seat miles (TCASM)	Comparison of 7 aircraft types AT72-500, AT72-600, ERJ190, Q400, NG CRJ700, CRJ900, CRJ1000
Teoh, L. E., Khoo, H. L. (2015)[6]	Analytic Hierarchy Process	Load factor, Passengers carried, Revenue passenger kilometers (RPK), Available seat kilometers (ASK), Fuel efficiency	Comparison of 3 aircraft types A320-200, A330-300, B747-800
Sánchez-Lozano, J.M., Serna,J., Dolón-Payán, A.(2015)[7]	Fuzzy Analytic Hierarchy Process, Fuzzy Technique for Order Preference by Similarity to Ideal Solution	Service ceiling, Cruising speed, Stalling speed, Endurance, Positive Limit Load Factor, Negative Limit Load Factor, Take-off distance, Landing distance, Human factors, Flying and handling qualities, Security systems, Tactical capability	Comparison of 5 aircraft types Pilatus PC-21, Beechcraft T-6C, PZL-130 Orlik (TC-II), KT1 – Basic Trainer, CASA C-101 Aviojet
Dožić, S., Kalić, M. (2015)[8]	Analytic Hierarchy Process, Even Swaps Method	Seat capacity, Price of aircraft, Total baggage, Maximum take-off weight (MTOW), Payment conditions, Total cost per available seat miles (TCASM)	Comparison of 7 aircraft types ATR 72-500, ATR 72-600, ERJ 190, Q400 NG, CRJ 700, CRJ 900, CRJ 1000
Ozdemir, Y., Basligil, H. (2016)[9]	Fuzzy Analytic Network Process, Choquet Integral Method , Fuzzy Analytic Hierarchy Process,	Cost, Time, Physical Attributes and Others : Maintenance cost, Operation and spare cost, Purchasing cost, Salvage cost, Dimensions, Reliability, Security, Suitability for service quality, Delivery time, Useful life	Comparison of 3 aircraft types Hypothetic A, B, C aircraft
Golec, A., Gurbuz, F., Senyigit, E. (2016)[10]:	Analytic Hierarchy Process, Weighted Sum Method, Elimination and Choice Expressing the Reality (ELimination Et Choix Traduisant la REalité), Technique for Order Preference by Similarity to Ideal Solution	The country's share in the project, Maintainability of aircraft, Maintenance easiness, Cost effectiveness, Operational effectiveness	Comparison of 3 aircraft types Hypothetic A, B, C aircraft
Silva, M. A., Eller, R. d. A. G., Alves, C. J. P., Caetano, M. (2016)[11]	Analytic Hierarchy Process	Price, Number of seats, Payload, Maximum take-off weight (MTOW), Range	Comparison of 3 aircraft types Embraer 195, SSJ 100, CRJ 900

Ali,Y., Muzzaffar, A. A., Muhammad, N., Salman, A. (2017)[12]	Analytic Hierarchy Process, Cost Benefit Analysis	Service Ceiling, Maximum takeoff weight (MTOW), Precision target capability (PTC), Combat radius, Cruising speed, Maneuverability, Acquisition cost, Operation cost, Maintainability, Availability	Comparison of 6 aircraft types Dassault Rafale, Saab JAS 39 Gripen, Mikoyan Mig-35, Sukhoi Su-35, Chengdu J-10, PAC JF-17 Thunder
Dozic,S., Lutovac,T., Kalic, M. (2018)[13]	Fuzzy Analytic Hierarchy Process	Aircraft characteristics (Aircraft seat capacity, Maximal take-off mass (MTOM), Aircraft range), Costs (Purchasing cost, Maintenance costs, Total cost per available seat miles (TCASM)), Added value indicators (Delivery time, Payment conditions, Fleet commonality, Comfort)	Comparison of 7 aircraft types ATR 72-500, ATR 72-600, ERJ 190, Q400 NG, CRJ 700, CRJ 900, CRJ 1000
Kiraci, K., Bakir, M. (2018)[14]	Analytic Hierarchy Process, Complex Proportional Assessment of Alternatives, Multi-Objective Optimization By Ratio Analysis	Range, Price, Speed, Seating capacity, Fuel consumption, Maximum payload, Amount of greenhouse gas release	Comparison of 4 aircraft types A320, A321, B737-800, B737-900ER
Kiraci, K., Bakir, M. (2018)[15]	Technique for Order Preference by Similarity to Ideal Solution	Range, Price, Speed, Seating capacity, Fuel consumption	Comparison of 4 aircraft types A320, A321, B737-800, B737-900ER
Ilgin, M. A. (2019)[16]	Linear Physical Programming	Price, Fuel consumption, Range, Number of seats, Luggage volume	Comparison of 6 aircraft types A319(neo), A320(neo), A321(neo), B737(MAX7), B737(MAX8), B737(MAX9)