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Freighter Aircraft Selection Using Entropic Programming for Multiple Criteria Decision Making Analysis

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Abstract**—**This paper proposes entropic programming for the freighter aircraft selection problem using the multiple criteria decision analysis method. The study aims to propose a systematic and comprehensive framework by focusing on the perspective of freighter aircraft selection. In order to achieve this goal, an integrated entropic programming approach was proposed to evaluate and rank alternatives. The decision criteria and aircraft alternatives were identified from the research data analysis. The objective criteria weights were determined by the mean weight method and the standard deviation method. The proposed entropic programming model was applied to a practical decision problem for evaluating and selecting freighter aircraft. The proposed entropic programming technique gives robust, reliable, and efficient results in modeling decision making analysis problems. As a result of entropic programming analysis, Boeing B747-8F, a freighter aircraft alternative (a_3), was chosen as the most suitable freighter aircraft candidate.

Keywords**—**entropic programming, additive weighted model, multiple criteria decision making analysis, MCDMA, TOPSIS, aircraft selection, freighter aircraft, Boeing B747-8F, Boeing B777F, Airbus A350F.

I. Introduction

THE entropic programming method is introduced to address the multiple criteria decision making analysis (MCDMA) problems. This entropic method evaluates the freighter aircraft alternatives using multiple decision criteria. The relative importance of each decision attribute is simply determined, and then, the alternatives are evaluated and prioritized.

The MCDMA approach is a mathematical method for ranking decision alternatives and selecting the best alternative in situations where the decision maker has multiple evaluation criteria in an uncertain environment.

In the MCDMA method, the decision maker selects the alternative that best meets the decision criteria and develops a numerical score to rank each decision alternative based on how well each alternative meets them in the decision analysis problem. Also, human judgments and decisions about evaluating alternatives can be partial, and often difficult to choose the best alternatives in decision making process.

In decision making research, out of many quantitative MCDMA methods, only some are mentioned such as composite programming [1-2], compromise programming [1-2], preference analysis for reference ideal solution (PARIS) [3-6], analytical hierarchical process (AHP) [7-9], VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) [10-12], preference ranking organization method for enrichment evaluation (PROMETHEE) [13-16], technique for order of preference by similarity to ideal solution (TOPSIS) [17-20], and ÉLimination et Choix Traduisant la REalité (ELECTRE) [21-22].

Fuzzy [23-29], intuitionistic [30], and neutrosophic [31] decision making techniques are widely used in the evaluation of uncertainty problems. For analysis of predictability and uncertainty in the decision environment, MCDMA approaches usually combine both quantitative and qualitative factors to evaluate a decision making problem to arrive at optimum decision solutions. Therefore, decision maker takes into account both type of evaluation factors influencing the classification, ranking and selection problem.

Evaluating and selecting an appropriate freighter aircraft model is important to increase the effectiveness of aviation operation schemes. Aircraft selection problem is one of the most important strategic decisions due to its cost and flight effects in the fleet planning and scheduling. The objective of freighter aircraft selection problem research is to present a new entropic programming approach for the selection of potential freighter aircraft candidates.

The freighter aircraft selection problem is constructed as a multiple criteria decision making analysis problem. The multiple criteria evaluation methodology captures the uncertainty which characterizes the decision context of decision makers. The MCDMA method employed presents a refined and improved way of dealing with uncertainty in freighter aircraft evaluation and selection decision problems [1-6, 32-36].

In order to deal with the complex evaluation and selection problems that arise in the decision environment, various MCDMA methods are proposed to handle the decision making process. In general, every evaluation and selection problem basically consists of four main components, namely (a) alternatives, (b) attributes/criteria, (c) relative importance (weight) of each attribute, and (d) performance measures of alternatives according to different attributes.

Therefore, this type of freighter aircraft selection problem with the desired structure is quite suitable for solving using MCDMA techniques. Therefore, the main objective of any quantitative MCDMA approach is to select the best option from a set of feasible alternatives in the presence of various conflicting criteria.

In this study, entropic programming is proposed for multiple criteria decision making analysis. The ranking results are compared using the entropic programming technique with other classical MCDMA methods. While the

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uncertainty problem in the freighter aircraft selection problem is examined on the same decision data set with the varying values of the α parameter, the criteria weights (ω_j) of the decision criteria are assigned with the standard deviation technique and the mean weight technique.

The entropic programming approach increases the robustness of the optimum solutions. This computational method that enables reaching the highest accuracy of estimation can be easily applied to calculate the utility functions of each alternative.

This quantitative MCDMA research has two primary goals, whereby the first objective relates to the possibility of improving the methodology for the treatment of uncertainty when it comes to the field of multiple criteria decision making analysis through the development of the entropic programming approach. The second goal of this study is to enrich the evaluation methodology and selection of freighter aircraft through a new approach to the treatment of uncertainty that is based on an entropic programming model.

The remainder of this paper is organized as follows: Section 2 presents the entropic programming methodology. Section 3 presents a case study for the freighter aircraft evaluation and selection problem, the experimental results, and analysis, and presents results and discussion. Finally, the conclusion is presented in Section 4.

II. Methodology

A. Classical TOPSIS Programming

The technique for order of preference by similarity to ideal solution (TOPSIS) method is a mathematical MCDMA method that has been used in numerous real-life problems and extended in different uncertain environments [17-20]. In the TOPSIS method, the evaluation process of alternatives is conducted with respect to the distances from the ideal and anti-ideal solutions.

Suppose that, given a set of alternatives I, $a_i = (a_1, ..., a_i)$, $i \in \{ i = 1, ..., I \}$, a set of criteria J, $g_j = (g_1, ..., g_j)$, $j \in \{ j = 1, ..., J \}$, and the importance weight of each criterion (ω_j, $j \in \{ j = 1, ..., J \}$) is known. The procedural steps of TOPSIS method are presented as follows [17],[32]:

Step 1. The construction of a decision matrix

$$X = \begin{pmatrix} a_1 \\ \vdots \\ a_i \end{pmatrix} \begin{pmatrix} \overset{g_1}{x_{11}} & \cdots & \overset{g_j}{x_{1j}} \\ \vdots & \ddots & \vdots \\ x_{i1} & \cdots & x_{ij} \end{pmatrix}_{ixj} \quad (1)$$

where $X = (x_{ij})_{ixj}$ represents the decision matrix and x_{ij} is the value of *i*th alternative with respect to *j*th indicator g_j

Step 2. Determination of the normalized values of the decision matrix

$$r_{ij} = \begin{cases} \dfrac{x_{ij}}{\max_i x_{ij}} & if \quad j \in B \\ \dfrac{\max_i x_{ij}}{x_{ij}} & if \quad j \in C \end{cases} \quad (2)$$

where $i = 1, ..., m, ..., I$ (set of alternatives), and $j = 1, ..., n, ..., J$ (set of criteria), B and C are the sets of benefit and cost criteria.

Step 3. Calculation of the weighted normalized values

$$v_{ij} = \omega_j r_{ij} \quad (3)$$

Step 4. Determination of the ideal and anti-ideal solutions based on the weighted normalized values

$$a_i^* = \{ v_1^*, ..., v_j^* \} = \{ (max_i \, v_{ij} \mid j \in B), (\min_i v_{ij} \mid j \in C \} \quad (4)$$

$$a_i^- = \{ v_1^-, ..., v_j^- \} = \{ (max_i \, v_{ij} \mid j \in B), (\min_i v_{ij} \mid j \in C \} \quad (5)$$

where B and C are the sets of benefit and cost criteria, respectively.

Step 5. Calculation of the Euclidean distance of alternatives from the ideal (D_i^*) and anti-ideal (D_i^-) solutions

$$D_i^+ = \sqrt{\sum_{j=1}^{J} (v_{ij} - v_j^*)^2} \quad (6)$$

$$D_i^- = \sqrt{\sum_{j=1}^{J} (v_{ij} - v_j^-)^2} \quad (7)$$

Step 6. Calculation of the closeness coefficient (CC_i) of each alternative

$$CC_i = \frac{D_i^-}{D_i^+ + D_i^-} \quad (8)$$

Step 7. Rank the alternatives in decreasing order of the closeness coefficient values (CC_i)

B. Additive Weighted Model

The additive weighted model finds a weighted sum of the performance ratings on each alternative on all attributes. Alternatives are ranked according to the optimality value of the combined optimality criteria. The additive weighted model steps are given as follows [1-2]:

Step 1. Perform linear normalization of performance values as in the following:

$$r_{ij} = \begin{cases} \dfrac{x_{ij}}{\max\limits_i x_{ij}} & if \quad j \in B \\ \dfrac{\max\limits_i x_{ij}}{x_{ij}} & if \quad j \in C \end{cases} \tag{9}$$

where $i = 1,...,m,...,I$ (set of alternatives), and $j = 1,...,n,...,J$ (set of criteria), B and C are the sets of benefit and cost criteria.

Step 2. Compute the measures of additive weighted model (Q_i) for each alternative using the following:

$$Q_i = \sum_{i=1}^{I} \omega_j (r_{ij}) \tag{10}$$

where ω_j is the importance of decision criteria, and r_{ij} is the normalized value of *i*th alternative with respect to *j*th attribute g_j

Step 3. Rank the alternatives according to decreasing values of Q_i

C. Entropic TOPSIS Programming

In the classical TOPSIS approach, the calculation of the closeness coefficient is based on the Euclidean distance between the alternative solutions and the ideal solutions. The Euclidean distance measurement calculates only the linear distance between alternative and ideal solutions, not the differences between the two compromise solutions.

Therefore, the Euclidean distance measure is replaced with parametric probabilistic entropic divergence to improve the result of the classical TOPSIS programming method. The entropic divergence technique calculates the differences between two probability distributions.

D. Entropic Programming

If a discrete random variable X with probability distribution $P(x_i) = (p(x_1),..., p(x_n))$ has *n* possible values, where the *i*th outcome has probability $p(x_i)$, then entropy of order α is defined to be

$$H_\alpha(P(x_i)) = \sum_{i=1}^{n} (p(x_i)) e^{p(x_i)(1-\alpha)}, \alpha \in \mathbb{R} \tag{11}$$

The definition of entropy can be extended to continuous random variables by

$$H_\alpha(P(x_i)) = \int fx(p(x_i)) e^{p(x_i)(1-\alpha)} dx \tag{12}$$

For finite elements, the entropic divergence of order α of a probability distribution $P(x_i) = (p(x_1),..., p(x_n))$ from another distribution $Q(x_i) = (q(x_1),..., q(x_n))$ is

$$D_\alpha(P(x_i) \| Q(x_i)) = \sum_{i=1}^{n} (p(x_i)) e^{(p(x_i)/q(x_i))(1-\alpha)}, \alpha \in \mathbb{R} \tag{13}$$

This definition generalizes to continuous spaces by replacing the probabilities with densities and the sum by an integral.

$$D_\alpha(P(x_i) \| Q(x_i)) = \int fx(p(x_i)) e^{(p(x_i)/q(x_i))(1-\alpha)} dx, \alpha \in \mathbb{R} \tag{14}$$

In the Entropic TOPSIS approach, the Euclidean distance measure is replaced by the entropic divergence method for the evaluation of freighter aircraft alternatives.

E. Determination of Criteria Weights

a. Mean weight method

The mean weight method assigns equal weights of importance to each decision criterion [1].

$$\omega_j = 1/J \tag{15}$$

where J is the number decision criteria, ω_j is criterion weight, $\sum_{j=1}^{J} \omega_j = 1$, $j = 1,...,n,...,J$.

b. Standard deviation method

The standard deviation method determines the objective weights of criteria [2].

$$\omega_j = \frac{\sigma_j}{\sum_{j=1}^{J} \sigma_j} = \frac{\frac{1}{m}\sqrt{\sum_{i=1}^{I} (r_{ij} - \overline{r_j})^2}}{\sum_{j=1}^{J} \frac{1}{m}\sqrt{\sum_{i=1}^{I} (r_{ij} - \overline{r_j})^2}} \tag{16}$$

where $i = 1,...,m,...,I$ is the number of alternatives, $j = 1,...,n,...,J$ is the number of decision criteria/attributes, r_{ij} is normalized elements of decision matrix, $\overline{r_j}$ is the average value of the *j*th criterion, σ_j is the standard deviation for criterion *j*, and ω_j is the weight or importance of criteria.

III. Application

In this decision analysis problem, in order to show the applicability of the proposed entropic programming method, a practical MCDMA example is used to illustrate the freighter aircraft selection problem. A model for freighter aircraft selection is proposed based on the entropic programming method. The specifications of the three freighter aircraft candidate alternatives to be selected are given in Table 1.

For the case study, three freighter aircraft {Airbus: A350F (a_1), Boeing: B777F (a_2), Boeing: B747-8F (a_3)} were selected for multiple criteria evaluation problem. The decision criteria based on performance characteristics are range (g_1, km), maximum payload (g_2, kg), maximum take-off weight (g_3, kg), and maximum landing weight (g_4, kg).

In decision making analysis problem, all decision criteria are modeled for maximum optimization. In this decision making analysis problem, Airbus challenges Boeing's freighter dominance with A350 freighter with its maximum revenue payload of 109000 kg.

Using the mathematical formulations of the decision making analysis process, the computational solution steps of the cargo plane problem are tabulated as follows:

Table 1. Decision matrix of the selected aircraft's specifications

	g_1	g_2	g_3	g_4
a_1	8700	109000	319000	250000
a_2	9038	102800	347450	260810
a_3	7899	133200	447695	346090

The decision matrix was normalized using linear normalization technique and the normalized decision matrix is given in Table 2.

Table 2. Normalized decision matrix

	g_1	g_2	g_3	g_4
a_1	0,9626	0,8183	0,7125	0,7224
a_2	1,0000	0,7718	0,7761	0,7536
a_3	0,8740	1,0000	1,0000	1,0000

The mean weight method and the standard deviation method assign objective weights of importance to each decision criterion. The calculated objective criteria weights (ω_j) are given in Table 3 and Table 4.

Table 3. The objective criteria weights (ω_j) calculated by the mean weight method

criteria	g_1	g_2	g_3	g_4
ω_j	0,25	0,25	0,25	0,25

Table 4. The objective criteria weights (ω_j) calculated by the standard deviation method

criteria	g_1	g_2	g_3	g_4
ω_j	0,1325	0,2469	0,3092	0,3114

where J is the number decision criteria (g_j), and ω_j is the assigned objective criterion weight, $\sum_{j=1}^{J}\omega_j = 1$, $j = 1,...,n,...,J$.

A. Entropic TOPSIS Programming Solutions

The proposed Entropic TOPSIS programming method was applied to the freighter aircraft selection problem. Following the procedural steps for establishing the decision matrix shown in Table 1 and normalizing the decision matrix shown in Table 2, the objective criteria weights given in Table 3 and Table 4 were determined using the mean weight method and the standard deviation method respectively.

The weighted normalized decision matrices were established using the objective criteria weights and the resulting weighted normalized decision matrices are given in Table 5 and Table 6.

Table 5. Weighted normalized decision matrix using the mean weight method

	g_1	g_2	g_3	g_4
a_1	0,2407	0,2046	0,1781	0,1806
a_2	0,2500	0,1929	0,1940	0,1884
a_3	0,2185	0,2500	0,2500	0,2500

Table 6. Weighted normalized decision matrix using the standard deviation method

	g_1	g_2	g_3	g_4
a_1	0,1276	0,2021	0,2203	0,2249
a_2	0,1325	0,1906	0,2399	0,2347
a_3	0,1158	0,2469	0,3092	0,3114

The objective criteria weights (ω_j) calculated by the standard deviation method were used in the Entropic TOPSIS ranking process and the results are given in Table 7 to Table 13.

Table 7. Entropic TOPSIS ranking results with objective criteria weights (ω_j) calculated by the standard deviation method

$\alpha = 0,1$	D_α^+	D_α^-	CC_i	R
a_1	1,5746	1,9635	0,5550	3
a_2	1,6525	2,0794	0,5572	2
a_3	2,3880	3,2531	0,5767	1

Table 8. Entropic TOPSIS ranking results with objective criteria weights (ω_j) calculated by the standard deviation method

$\alpha = 0,3$	D_α^+	D_α^-	CC_i	R
a_1	1,3443	1,5968	0,5429	3
a_2	1,4047	1,6803	0,5447	2
a_3	1,9604	2,4912	0,5596	1

Table 9. Entropic TOPSIS ranking results with objective criteria weights (ω_j) calculated by the standard deviation method

$\alpha = 0,5$	D_α^+	D_α^-	CC_i	R
a_1	1,1480	1,2987	0,5308	3
a_2	1,1945	1,3580	0,5320	2
a_3	1,6095	1,9088	0,5425	1

Table 10. Entropic TOPSIS ranking results with objective criteria weights (ω_j) calculated by the standard deviation method

$\alpha = 0,7$	D_α^+	D_α^-	CC_i	R
a_1	0,9807	1,0562	0,5185	3
a_2	1,0161	1,0976	0,5193	2
a_3	1,3215	1,4633	0,5255	1

Table 11. Entropic TOPSIS ranking results with objective criteria weights (ω_j) calculated by the standard deviation method

$\alpha = 0,9$	D_α^+	D_α^-	CC_i	R
a_1	0,8381	0,8591	0,5062	3
a_2	0,8646	0,8872	0,5064	2
a_3	1,0851	1,1225	0,5085	1

Table 12. Entropic TOPSIS ranking results with objective criteria weights (ω_j) calculated by the standard deviation method

$\alpha = 0$	D_α^+	D_α^-	CC_i	R
a_1	1,7045	2,1774	0,5609	3
a_2	1,7925	2,3132	0,5634	2
a_3	2,6356	3,7182	0,5852	1

Table 13. Entropic TOPSIS ranking results with objective criteria weights (ω_j) calculated by the standard deviation method

$\alpha = 1$	D_α^+	D_α^-	CC_i	R
a_1	0,7749	0,7749	0,5000	0
a_2	0,7977	0,7977	0,5000	0
a_3	0,9833	0,9833	0,5000	0

The objective criteria weights (ω_j) calculated by the mean weight method were used in the Entropic TOPSIS ranking process and the results are given in Table 14 to Table 20.

Table 14. Entropic TOPSIS ranking results with objective criteria weights (ω_j) calculated by the mean weight method

$\alpha = 0,1$	D_α^+	D_α^-	CC_i	R
a_1	1,6838	2,0620	0,5505	3
a_2	1,7627	2,1735	0,5522	2
a_3	2,3245	3,0929	0,5709	1

Table 15. Entropic TOPSIS ranking results with objective criteria weights (ω_j) calculated by the mean weight method

$\alpha = 0,3$	D_α^+	D_α^-	CC_i	R
a_1	1,4276	1,6724	0,5395	3
a_2	1,4879	1,7524	0,5408	2
a_3	1,9132	2,3858	0,5550	1

Table 16. Entropic TOPSIS ranking results with objective criteria weights (ω_j) calculated by the mean weight method

$\alpha = 0,5$	D_α^+	D_α^-	CC_i	R
a_1	1,2109	1,3565	0,5283	3
a_2	1,2566	1,4130	0,5293	2
a_3	1,5748	1,8419	0,5391	1

Table 17. Entropic TOPSIS ranking results with objective criteria weights (ω_j) calculated by the mean weight method

$\alpha = 0,7$	D_α^+	D_α^-	CC_i	R
a_1	1,0276	1,1003	0,5171	3
a_2	1,0618	1,1395	0,5177	2
a_3	1,2964	1,4233	0,5233	1

Table 18. Entropic TOPSIS ranking results with objective criteria weights (ω_j) calculated by the mean weight method

$\alpha = 0,9$	D_α^+	D_α^-	CC_i	R
a_1	0,8724	0,8926	0,5057	3
a_2	0,8975	0,9190	0,5059	2
a_3	1,0673	1,1008	0,5077	1

Table 19. Entropic TOPSIS ranking results with objective criteria weights (ω_j) calculated by the mean weight method

$\alpha = 0$	D_α^+	D_α^-	CC_i	R
a_1	1,8290	2,2898	0,5559	3
a_2	1,9189	2,4208	0,5578	2
a_3	2,5623	3,5227	0,5789	1

Table 20. Entropic TOPSIS ranking results with objective criteria weights (ω_j) calculated by the mean weight method

$\alpha = 1$	D_α^+	D_α^-	CC_i	R
a_1	0,8040	0,8040	0,5000	0
a_2	0,8254	0,8254	0,5000	0
a_3	0,9685	0,9685	0,5000	0

B. Classical TOPSIS Programming Solutions

The objective criteria weights (ω_j) calculated by the mean weight method were used in the Classical TOPSIS ranking process and the results are given in Table 21.

Table 21. Classical TOPSIS ranking results with objective criteria weights (ω_j) calculated by the mean weight method

	D^+	D^-	CC_i	R
a_1	0,0980	0,0169	0,1470	3
a_2	0,0873	0,0276	0,2402	2
a_3	0,0158	0,0992	0,8629	1

The objective criteria weights (ω_j) calculated by the standard deviation method were used in the Classical TOPSIS ranking process and the results are given in Table 22.

Table 22. Classical TOPSIS ranking results with objective criteria weights (ω_j) calculated by the standard deviation method

	D^+	D^-	CC_i	R
a_1	0,1126	0,0116	0,0936	3
a_2	0,1012	0,0230	0,1855	2
a_3	0,0084	0,1158	0,9328	1

C. Classical Additive Weighted Model Solutions

The objective criteria weights (ω_j) calculated by the mean weight method were used in the Classical Additive Weighted Model ranking process and the results are given in Table 23.

Table 23. Classical Additive Weighted Model ranking results with objective criteria weights (ω_j) calculated by the mean weight method

	g_1	g_2	g_3	g_4	Q_i	R
a_1	0,2407	0,2046	0,1781	0,1806	0,8040	3
a_2	0,2500	0,1929	0,1940	0,1884	0,8254	2
a_3	0,2185	0,2500	0,2500	0,2500	0,9685	1

The objective criteria weights (ω_j) calculated by the standard deviation method were used in the Classical Additive Weighted Model ranking process and the results are given in Table 24.

Table 24. Classical Additive Weighted Model ranking results with objective criteria weights (ω_j) calculated by the standard deviation method

	g_1	g_2	g_3	g_4	Q_i	R
a_1	0,1276	0,2021	0,2203	0,2249	0,7749	3
a_2	0,1325	0,1906	0,2399	0,2347	0,7977	2
a_3	0,1158	0,2469	0,3092	0,3114	0,9833	1

D. Sensitivity Analysis and Validation

The computational evaluation results were obtained by applying the procedural steps of the Entropic TOPSIS programming method, the Classical TOPSIS programming method, and the Classical Additive Weighted Model. The computational model parameter $\alpha \in \{0, 0.1, 0.3, 0.5, 0.7, 0{,}9, 1\}$ was properly set to perform the sensitivity analysis for the proposed method. The ranking results of proposed method were given in tabular form, in which the sensitivity analysis reflects the robustness of the entropic TOPSIS programming model when the freighter aircraft selection problem was handled with a multiple decision making analysis approach.The objective criteria weights were applied to the to enrich sensitivity analysis process.

As a result of the computational decision making analysis, the ranking order of the freighter aircraft candidates was determined as follows:

Preference ranking: $a_3 \succ a_2 \succ a_1$

Boeing B747-8F, freighter aircraft alternative (a_3) was chosen as the most suitable aircraft candidate for the freighter transport services. Boeing B747-8F outperformed the other two candidate aircraft in all utility function scores. Therefore, Boeing B747-8F, freighter aircraft alternative (a_3), was chosen as the most suitable aircraft candidate. Also, the sensitivity analysis was performed using the parametric coefficients α . Therefore, in the part of the sensitivity analysis, a change in the coefficient α was made, which is shown in raking results. The Classical Additive Weighted Model, and Classical TOPSIS programming method were used to validate and confirm the applicability of the proposed approach.

In this work, freighter aircraft selection problem was solved using the Entropic TOPSIS programming method, in which the Euclidean distance measure was replaced with parametric probabilistic entropic divergence to improve the result of the Classical TOPSIS programming method.

Also, it has already been proven that the accuracy of an aggregated method would always be better than single methods. For the freighter aircraft selection problem under consideration, it has been observed that the Entropic TOPSIS programming method provides the accurate rankings of candidate alternatives as those obtained using the Classical Additive Weighted Model, and Classical TOPSIS programming method.

The effect of the α parameters on the ranking performance of the proposed method was also examined and it was revealed that better performance was obtained using α values. When α is set to 0, the Entropic TOPSIS programming method yields the same ranking pattern, and when α is set to 1, it is observed that there is not a ranking pattern.

The main advantage of this Entropic TOPSIS programming method is defined as its strong resistance to reversal of the order of the considered alternatives. Because this method contains a robust entropic algorithm and is quite comprehensive in nature, it can be successfully applied to any mathematical MCDMA decision making situation.

IV. Conclusion

The problem of choosing a freighter aircraft using multiple criteria decision making methods, in which there are multiple conflicting criteria, is an important issue in achieving long-term strategic goals in the airline industry. Objective performance data were used in the formulation of the decision problem, in which three freighter aircraft alternatives were evaluated according to four decision criteria. The importance levels of the evaluation criteria were determined by using the mean weight method and the standard deviation method. Also, the Boeing B747-8F freighter aircraft was identified as the most suitable freighter aircraft alternative. The results of the application were validated by applying a multiple step entropic sensitivity analysis, classical TOPSIS programming model and additive weight model. The proposed structure is expected to assist airline managers in making aircraft selection decisions under uncertainty by providing a robust and systematic tool.

The approach developed represents a quantitative MCDMA method of the Entropic TOPSIS programming technique, in which the mean weight method and the standard deviation method are used to calculate the objective weight values of the criteria, and the proposed model was applied for the evaluation and ranking of the freighter aircraft. The model was validated by the aircraft selection process based on the results of other classical MCDMA approaches.

The results obtained using the proposed approach show that the third alternative Boeing B747-8F (a_3), is the best solution in both parts of the sensitivity analysis, which involves changing the value of the coefficient α in the decision making process. Analysis of the results obtained by calculating the closeness coefficient found that the Entropic TOPSIS programming approach was in full correlation with the ranks obtained using other methods. Through the research, two contributions can be distinguished, one of which is the development of a new quantitative MCDMA approach to entropic programming model that allows decisions to be unified in an objective way.

The development of a new approach contributes to the development of the freighter aircraft selection problem that takes into account the theoretical and practical application of MCDMA methods.

The developed approach allows the evaluation of alternatives in the decision making process. With the application of the developed approach, it is possible to solve the MCDMA problem in a very simple way, and to make an aircraft evaluation and selection that has a significant impact on efficiency. The developed approach to the aircraft selection problem can be used in decision making process in other areas besides the problem under consideration. Its flexibility was reflected in the fact that validation can be performed with the integration of any of the multiple criteria decision making methods.

A case study on the multiple criteria evaluation of three alternative freighter aircraft selection solutions, considering the performance parameters, was carried out by applying the entropic programming method. When applying the entropic programming method, it is considered that the most preferred alternative depends on the values of α. Alternative (a_3) ("Boeing B747-8F") is ranked as best, alternative (a_2) ("Boeing B777F") remains in second place, and alternative (a_1) ("A350F") remains in third place when parameter α changes.

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