An innovative multicriteria decision-making framework for assessing India's airport operating efficiency

Surinder Kaur [*1], Javalkar D. Kumar [2], Gopal Chaudhary[3]

[1] Lingaya's Vidyapeeth, Haryana, India, and Bharati Vidyapeeth's College of Engineering, New Delhi, India;
[2] Lingaya's Vidyapeeth, Haryana, India;
[3] Bharati Vidyapeeth's College of Engineering, Delhi, India;

Emails**:** kaur.surinder@bharatividyapeeth.edu; dineshjavalkar@lingayasvidyapeeth.edu.in;
gopal.bvcoe@bharatividyapeeth.edu

* Correspondence: kaur.surinder@bharatividyapeeth.edu

Abstract

Global air transport operations have risen dramatically, which has led to new airport developments, requiring an in-depth effectiveness study of these investment projects, as is the case here. 6 Indian civil airports' operating efficiency between 2015 and 2018 are examined in this research. These sources were evaluated and assessed using an integrated Shannon's entropy MCDM technique. Using Shannon's entropy approach and the fuzzy WSM method, the weights of decision criteria are determined, and airports are prioritized. As a result, it is capable of dealing with the trepidation and uncertainty that accompany the subjective appraisal of input and outcome components. The findings also show that airports in touristic locations are more efficient than those in less popular places. The more convenient the airport is to the city Centre, the more passengers arrive, and the more money the airport makes. As a result, efficiency ratings are influenced by both of these elements. Airport operators and policymakers will benefit from the study's innovative efficiency analysis approach.

Keywords: Multi-Criteria Decision-Making; Evaluation criteria; MCDM; decision making; Shannon's Entropy; Trapezoidal fuzzy; airports; WSM

1. Introduction

An important part of the global economy, the air transportation sector connects countries and acts as a stimulus for international commerce. Travelers and cargo traveling among airports all over the world rely on the industry's well-oiled machinery to keep them secure. In this context, airports need to provide rising, secure, and human- and environmental infrastructure to travelers, carriers, and other consumers to deliver efficient operational services at worldwide standards.

DOI: https://doi.org/10.54216/FPA.040204
Received: March 11, 2020 Accepted: July 03, 2021

In light of the complexity of airports, authority is required to respond to changing worldwide circumstances and manage expensive operational operations to maximize efficiency in machine parks, human capital, slot privileges, and power consumption [1], [2] promptly. Because of this, governments have adopted a variety of strategies, such as reinvesting in the main terminal or partnering with the private market to administer terminals, maintain revenue and provide clients with the highest service quality possible.

The growing influence of airport companies in air transportation is another noteworthy development. Airports' profitability is the primary consideration for the private sector, ignoring social and demographic considerations in favor of their scale and worldwide appeal.

Because of this, evaluating airport efficiency is critical, especially for publicly owned airports, to identify areas that may be improved with new rules. In several European nations, airports and airspace operations are managed by centralized civil aviation [3]. For general populace partnership (BOT) contracts, TGDSA manages TGDSA.

Like many other nations, it places a high value on the performance of its ports because of their strategic significance. Air passenger transportation in 2018 grew at an average rate of 6.4%, as per the World Airports Traffic Report, 2019. Over the next decade, airports are expected to manage over 7.2 billion people and 122 million tonnes of air cargo, seeing an 8.8 percent increase in travelers and air freight [4]. In addition, the World Tourism Organization estimates that in 2019, 52 million visitors generated 34.5 billion dollars in income. To maintain this growth rate, airport efficiency regulations must be implemented.

The effectiveness of airports has been the subject of several research projects, including operational, technological, and scalability studies [5]–[12]. Many factors are considered when assessing efficiency, including seating capacity, low-cost commercial airplane pathways, airline traffic control, the detectors of the best support runaway, condition monitoring and managed services, managerial ambiguity staff, scale, and enhancement for airport entrance assignments, among many others.

In published studies, airport performance is also measured using a variety of methods. The most often used models are those based on DEA and related hybrids. Various input and output measurements [13]–[16] are used to assess the airports' operating efficiency. As a result, current studies adopt a two-step approach to evaluating airport efficiency. Shannon's entropy weight approach is used in the first phase to assess each airport's efficiency and compute the weights of the criteria. Second, using WSM to rank alternatives [17], [18].

The following is the structure of this document. A complete assessment of the current literature is provided in Section 2. Methodology and variables are discussed in Section 3, followed by the empirical findings and a full explanation of them in Section 4. Lastly, Section 5 wraps up the project and suggests further study avenues.

2. Literature Review

In the last several years, a slew of research has examined the effectiveness of airports, highlighting their growing significance in long-term growth [19]–[23]. With the fast expansion of air transportation in emerging nations, this issue has become more relevant.

Many of these studies show that airports' overall productivity and financial performance are greatly improved by improvements in efficiency[24], [25].

Capacity has an important impact on the effectiveness of 40 Spanish airports, according to research[26]. [27]examined the effectiveness of 35 Brazilian airports using DEA. Similar to[28], a similar DEA technique was used to analyze the relative efficiency of Japanese airports, especially addressing the problem of overinvestment. There were further significant characteristics that affected the efficiency ratings of Greek airports obtained using DEA, which were identified using DEA and truncated built from scratch regression (tbr). Efficiencies were shown to be strongly influenced by factors such as site selection, building size, and day-to-day operations. [29]examined the effectiveness of 41 airports in China. It was shown that airports situated near major cities are more efficient than those in rural areas when using the double bootstrap DEA approach. Another research on Chinese airports was done in[30], which looked at 20 major Chinese airports between 2006 and 2009 and rated their performance. They came to the same conclusion as before: International airports outperformed smaller airports by a wide margin.

To evaluate 24 international airports, an innovative technique was developed in[31], combining AHP, DEA, and Assurance Region (AR).

They argued that the DEA-AR mixture had a greater ability to distinguish across groups than the traditional DEA method. Additionally, an investigation on the factors that influence DEA's technical and scalability efficiency

DOI: https://doi.org/10.54216/FPA.040204
Received: March 11, 2020 Accepted: July 03, 2021

ratings over 10 years, from 2006 to 2016, has been conducted in Italy[32]. There is little doubt that airport size, low-cost airline presence, and cargo traffic are critical determinants, according to the authors. At Pakistan's largest airports, Ennen and Batool [33] found that overstaffing and overinvestment in capacity led to cost inefficiencies, based on DEA data for 2012. According to Olariaga and Moreno[34], major Colombian airports run by the private sector were more efficient than those controlled by the public sector. Stichhauerova and Pelloneova [35]used DEA-CCR (Charnes, Cooper, and Rhodes) and BCC (Banker, Charnes, and Cooper) methods to examine the efficiency of 27 German airports in 2016.
Thirteen airports were found to be operating at peak efficiency thanks to their adherence to industry best practices. New Zealand airports were evaluated by Ngo and Tsui using DEA-Window analysis, which relied on slack-based metrics for 11 of them. Tourists, private airports, and low-cost airlines have a favorable impact on efficiency, according to a study published in the Journal Transportation Research Part B. In a two-stage approach, Huynh et al. [36] analyzed the performance of Southeastern Asia's airports and found that decentralizing authority tended to boost efficiency. When Liu conducted a similar analysis, he found that airport productivity was favorably impacted by the airlines serviced and locations[37].

Efforts to uncover factors of productivity from a variety of viewpoints have gained traction in recent years. For example, a High-Speed Rail network that serves an airport significantly helps the overall efficiency of the transportation system, in which the authors found an improvement of 0.15 percent for every 1 percent rise in the Logistic Performance Index. 12 Polish airports' human capital and efficiency ratings were investigated to show that management experience earned at a single airport is important. Stochastic frontier analysis with temporal variation was employed by the authors. Another focus of recent study has been to identify the operational determinants of efficiency. By using DEA, I figured out how efficient major international airports' facilities and flight convergence were. A quantitative study of airports that have previously performed well was used to extract the efficiency drivers. A new fuzzy double-frontier network DEA was used to examine the sustainable efficiency of major Euroasian airports, taking into account both desired and unwanted outputs. Private engagement has a favorable influence on the outcomes, as shown by these findings.

As a whole, this research provides light on how airports may be evaluated using a broad range of input and output metrics. As a result of the discretionary skewed data collection and processing step, there is no one set of criteria. As a result, the current study's suggestion of fuzzy Shannon's entropy, a systematic strategy that can deal with subjectivity, is quite helpful. These researches also show that the anomaly research did not get the focus it needed. The WSM method is used to compute the rank of alternatives.

3. Trapezoidal Fuzzy Shannon's entropy and WSM

There are many forms to address the basic operations of trapezoidal fuzzy numbers.

Example: a $y = (a, b, c, d)$ can be defined as a trapezoidal number and can compute the membership function as:

$$M_F(x) = \begin{cases} \dfrac{x-a}{b-a} & x \in (a, b) \\ 1 & x \in (b, c) \\ \dfrac{d-x}{d-c} & x \in (c, d) \\ 0, & otherwise \end{cases}$$

There are operations of two trapezoidal numbers $y_1 = (a_1, b_1, c_1, d_1)$ and $y_2 = (a_2, b_2, c_2, d_2)$

$$y_1 \oplus y_2 = (a_1 + a_2, b_1 + b_2, c_1 + c_2, d_1 + d_2)$$

$$y_1 \ominus y_2 = (a_1 - d_2, b_1 - c_2, c_1 - b_2, d_1 - a_2)$$

$$y_1 \odot y_2 = (a_1 \cdot a_2, b_1 \cdot b_2, c_1 \cdot c_2, d_1 \cdot d_2)$$

DOI: https://doi.org/10.54216/FPA.040204
Received: March 11, 2020 Accepted: July 03, 2021

$$y_1 \oslash y_2 = \left(\frac{a_1}{d_2}, \frac{b_1}{c_2}, \frac{c_1}{b_2}, \frac{d_1}{a_2}\right)$$

$$Ty_1 = (Ta_1, T\,b_1, Tc_1, Td_1)$$

Choosing the best airport operations in India is critical and challenging because multi-aspect decision-making is a challenge.

Prioritizing and ranking attributes and alternatives using the MCDM approach begins with identifying criteria and sub-criteria connected to a goal, as well as assigning numerical measurements to assess their value.
Decision criteria are weighted according to Shannon's entropy approach, and WSM is used to prioritize airport operations options in this research. In 1947, Shannon and Weaver came up with the idea.
It was used by Shannon and Weaver to address information issues.
Additional information is accessible if the entropy value is lower, per the theory of entropy. Due to the ability to assess using positivist and interpretive expert viewpoints, Shannon's notion is used to determine criterion weights.

Using Lee and Chang's [38] work, the equations are altered for the subsequent steps. The score and scale of variables are as in [39]. Figure 1 shows the proposed framework of this study.

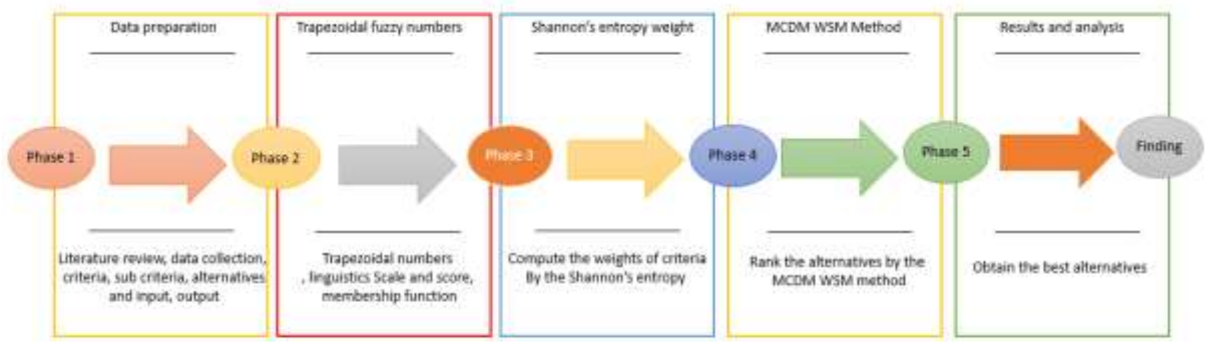

Figure 1: The framework of this study.

Step 1: Creating a consistency matrix by the opinions of a group of decision-makers. Then aggregate these values by the average method.
Step 2: Normalize the aggregated consistency matrix.

$$nor_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}}$$

Where $i = 1,2,3, \ldots\ldots, m$

Step 3: By every column, the entropy is calculated

$$e_j = -K \sum_{i=1}^{m} nor_{ij}.\ln nor_{ij}$$

DOI: https://doi.org/10.54216/FPA.040204
Received: March 11, 2020 Accepted: July 03, 2021

Where $j = 1,2,3 \ldots..n$

$$K = -\frac{1}{\ln m}$$

Where k is definite as a constant of entropy

Step 4: For every column, the diversification index is computed as:

$$d_j = 1 - e_j$$

Step 5: The normalized weight vector can be calculated as:

$$W_j = \frac{d_j}{\sum_{j=1}^{n} d_j}$$

Where $j = 1,2,.3 \ldots \ldots n$

MCDM's WSM technique is among the most straightforward and extensively utilized. The simple weighted additive approach is another name for it. All criteria are multiplied by their respective sub-criterion levels to get weighted normalized results. Preference scores may be calculated by adding the weighted normalized values of every airport option together. Rank the airport options according to the preferred score. The ranking is based on preference scores.

$$A_i^{WSM} = \sum_{j=1}^{n} W_j x_{ij}$$

when A_i^{WSM} is weighted, the normalized matrix has W_j weight for each criterion and x_{ij} the efficiency score of an option for that sub-criterion.

4. Case Study

We examined data from 6 Indian airports. Three of the country's 6 airports are operated by the commercial sector, while the rest are run by the public sector. Because no evidence is accessible for the newest airports, they were excluded from our analysis.

Selecting variables came next, after the selection of samples. Following an exhaustive literature search, we derived the most often used performance metrics. Shannon's entropy approach was used to analyze 9 inputs and 4 outputs, and 13 criteria, which included capacity, financial, and service parameters as below.

DOI: https://doi.org/10.54216/FPA.040204
Received: March 11, 2020 Accepted: July 03, 2021

Main criteria	Alternatives
Number of percentage EAC1	EAA1
Cargo volume EAC2	EAA2
Number of flights EAC3	EAA3
Total revenue EAC4	EAA4
Terminal capacity EAC5	EAA5
Runaway capacity EAC6	EAA6
Total expenditures EAC7	
Connection to the city center EAC8	
Number of employees EAC9	
Number of gates EAC10	
Flight capacity per year EAC11	
Number of counter EAC12	
Passenger capacity per year EAC13	

Step 1: Tables 1,2,3 show the consistency matrix by three decision-makers who have expertise in this field to evaluate the decision matrix. Then aggregate their opinions in table 4.

Table 1: The decision matrix by the first decision-makers.

	EAC_1	EAC_2	EAC_3	EAC_4	EAC_5	EAC_6	EAC_7	EAC_8	EAC_9	EAC_{10}	EAC_{11}	EAC_{12}	EAC_{13}
EAA_1	6	5	3	6	6	8	5	6	5	5	6	5	5
EAA_2	8	8	6	5	6	8	3	6	6	5	8	5	3
EAA_3	6	3	8	6	5	8	3	8	6	6	8	6	3

DOI: https://doi.org/10.54216/FPA.040204
Received: March 11, 2020 Accepted: July 03, 2021

	EAC_1	EAC_2	EAC_3	EAC_4	EAC_5	EAC_6	EAC_7	EAC_8	EAC_9	EAC_{10}	EAC_{11}	EAC_{12}	EAC_{13}
EAA_4	3	6	8	3	6	6	1.25	8	8	8	8	3	8
EAA_5	6	8	3	6	3	6	6	6	8	8	6	1.25	6
EAA_6	8	6	3	3	3	5	3	3	6	6	3	3	3

Table 2: The decision matrix by the second decision-makers.

	EAC_1	EAC_2	EAC_3	EAC_4	EAC_5	EAC_6	EAC_7	EAC_8	EAC_9	EAC_{10}	EAC_{11}	EAC_{12}	EAC_{13}
EAA_1	8	3	1.25	5	8	6	6	5	3	3	5	6	3
EAA_2	6	6	5	6	8	6	6	8	1.25	5	8	5	3
EAA_3	5	1.25	5	5	6	5	8	5	1.25	8	5	8	6
EAA_4	1.25	8	6	6	8	5	3	3	6	8	6	3	8
EAA_5	8	5	8	5	5	3	8	6	6	5	6	8	6
EAA_6	8	8	3	1.25	5	3	3	1.25	5	6	3	3	3

DOI: https://doi.org/10.54216/FPA.040204
Received: March 11, 2020 Accepted: July 03, 2021

Table 3: The decision matrix by the third decision-makers.

	EAC_1	EAC_2	EAC_3	EAC_4	EAC_5	EAC_6	EAC_7	EAC_8	EAC_9	EAC_{10}	EAC_{11}	EAC_{12}	EAC_{13}
EAA_1	5	5	3	8	5	1.25	8	6	5	1.25	6	8	1.25
EAA_2	8	8	3	8	6	3	8	6	3	5	6	6	5
EAA_3	3	6	1.25	5	6	6	6	3	3	8	3	6	8
EAA_4	3	8	8	3	6	8	5	1.25	5	6	1.25	5	6
EAA_5	8	5	6	1.25	5	3	6	1.25	6	3	1.25	6	5
EAA_6	5	5	1.25	1.25	8	5	5	1.25	5	8	5	1.25	3

Table 4: The aggregated decision matrix.

	EAC_1	EAC_2	EAC_3	EAC_4	EAC_5	EAC_6	EAC_7	EAC_8	EAC_9	EAC_{10}	EAC_{11}	EAC_{12}	EAC_{13}
EAA_1	6.333333	4.333333	2.416667	6.333333	6.333333	5.083333	6.333333	5.666667	4.333333	3.083333	5.666667	6.333333	3.083333

DOI: https://doi.org/10.54216/FPA.040204
Received: March 11, 2020 Accepted: July 03, 2021

EAA_2	EAA_3	EAA_4	EAA_5	EAA_6
7.333333	4.666667	2.416667	7.333333	7
7.333333	3.416667	7.333333	6	6.333333
4.666667	4.75	7.333333	5.666667	2.416667
6.333333	5.333333	4	4.083333	1.833333
6.666667	5.666667	6.666667	4.333333	5.333333
5.666667	6.333333	6.333333	4	4.333333
5.666667	5.666667	3.083333	6.666667	3.666667
6.666667	5.333333	4.083333	4.416667	1.833333
3.416667	3.416667	6.333333	6.666667	5.333333
5	7.333333	7.333333	5.333333	6.666667
7.333333	5.333333	5.083333	4.416667	3.666667
5.333333	6.666667	3.666667	5.083333	2.416667
3.666667	5.666667	7.333333	5.666667	3

Step 2: The aggregated decision matrix is normalized in table 5.

Table 5: The normalized aggregated decision matrix.

	EAA_1	EAA_2	EAA_3
EAC_1	0.180523	0.209026	0.133017
EAC_2	0.1247	0.211031	0.098321
EAC_3	0.088685	0.171254	0.174312
EAC_4	0.226866	0.226866	0.191045
EAC_5	0.180952	0.190476	0.161905
EAC_6	0.160105	0.178478	0.199475
EAC_7	0.203753	0.182306	0.182306
EAC_8	0.202381	0.238095	0.190476
EAC_9	0.146893	0.115819	0.115819
EAC_{10}	0.088729	0.143885	0.211031
EAC_{11}	0.179894	0.232804	0.169312
EAC_{12}	0.214689	0.180791	0.225989
EAC_{13}	0.108504	0.129032	0.199413

DOI: https://doi.org/10.54216/FPA.040204
Received: March 11, 2020 Accepted: July 03, 2021

EAA_4	0.068884	0.211031	0.269113	0.143284	0.190476	0.199475	0.099196	0.145833	0.214689	0.211031	0.161376	0.124294	0.258065
EAA_5	0.209026	0.172662	0.207951	0.146269	0.12381	0.125984	0.214477	0.157738	0.225989	0.153477	0.140212	0.172316	0.199413
EAA_6	0.199525	0.182254	0.088685	0.065672	0.152381	0.136483	0.117962	0.065476	0.180791	0.191847	0.116402	0.081921	0.105572

Step 3: The entropy is computed $e_1 = 0.969789, e_2 = 0.981055, e_3 = 0.957848, e_4 = 0.964239, e_5 = 0.994084, e_6 = 0.991654, e_7 = 0.980194, e_8 = 0.966336, e_9 = 0.980457, e_{10} = 0.979424, e_{11} = 0.98717, e_{12} = 0.972666, e_{13} = 0.968425$

Step 4: the diversification index is computed

$$d_1 = 0.030211, d_2 = 0.018945, d_3 = 0.042152, d_4 = 0.035761, d_5 = 0.005916, d_6 = 0.008346, d_7 = 0.019806, d_8 = 0.033664, d_9 = 0.019543, d_{10} = 0.020576, d_{11} = 0.012829, d_{12} = 0.027334, d_{13} = 0.031575$$

Step 5: The normalized weight vector is calculated in figure 2.

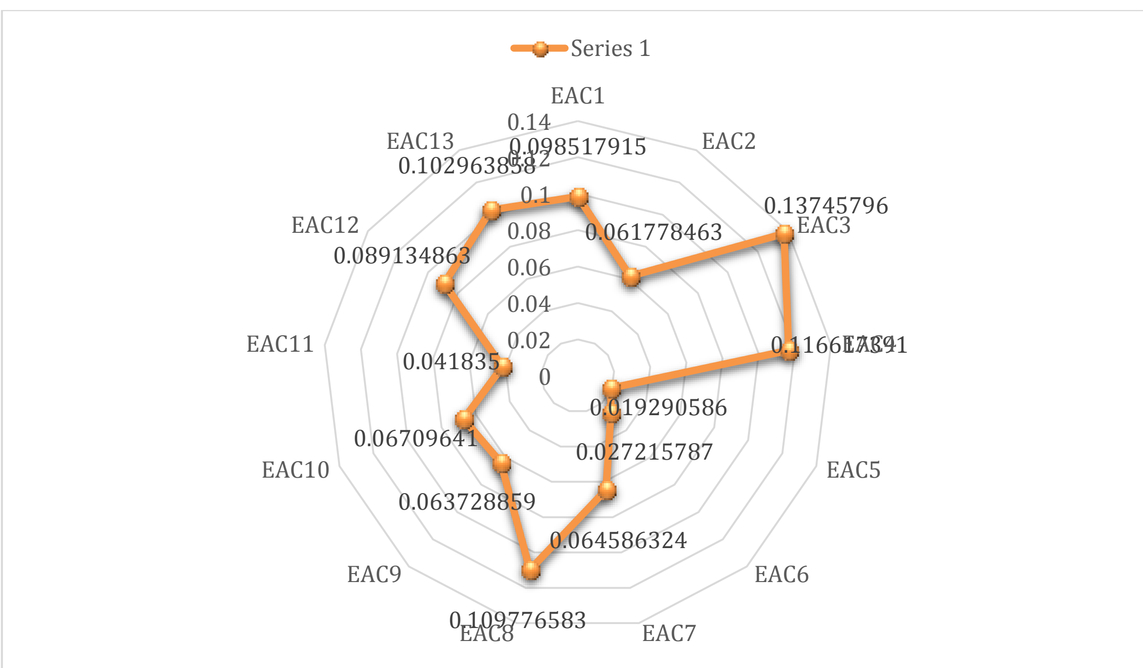

Figure 2: The weights of the criteria

DOI: https://doi.org/10.54216/FPA.040204
Received: March 11, 2020 Accepted: July 03, 2021

Step 6: we multiply the weights of criteria by the aggregated decision matrix in table 6 and compute the sum of every row to compute the rank of alternatives in figure 3.

Table 6: The values of the WSM method.

	EAA_1	EAA_2	EAA_3	EAA_4	EAA_5	EAA_6
EAC_1	0.623947	0.722465	0.45975	0.238085	0.722465	0.689625
EAC_2	0.267707	0.453042	0.211076	0.453042	0.370671	0.391264
EAC_3	0.33219	0.64147	0.652925	1.008025	0.778928	0.33219
EAC_4	0.738577	0.738577	0.621959	0.46647	0.476188	0.213799
EAC_5	0.122174	0.128604	0.109313	0.128604	0.083593	0.102883
EAC_6	0.138347	0.154223	0.172367	0.172367	0.108863	0.117935
EAC_7	0.409047	0.365989	0.365989	0.199141	0.430575	0.236817
EAC_8	0.622067	0.731844	0.585475	0.448254	0.484847	0.201257
EAC_9	0.276158	0.21774	0.21774	0.403616	0.424859	0.339887
EAC_{10}	0.206881	0.335482	0.49204	0.49204	0.357848	0.447309
EAC_{11}	0.237065	0.30679	0.22312	0.212661	0.184771	0.153395
EAC_{12}	0.564521	0.475386	0.594232	0.326828	0.453102	0.215409
EAC_{13}	0.317472	0.377534	0.583462	0.755068	0.583462	0.308892

DOI: https://doi.org/10.54216/FPA.040204
Received: March 11, 2020 Accepted: July 03, 2021

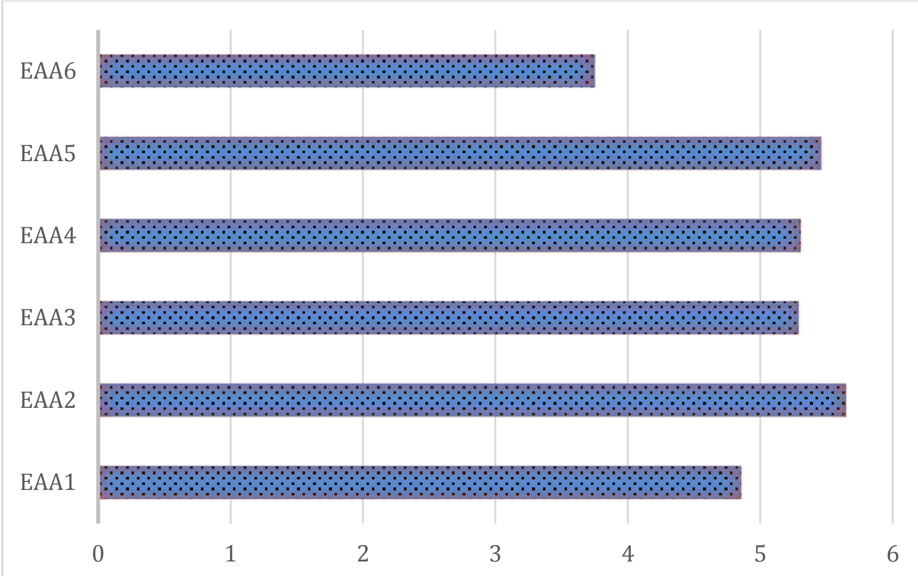

Figure 3: The rank of alternatives

5. Conclusion

Because of the enormous number of people passing through and the potential for fast expansion, airports are essential for economic development and international commerce. As a result, travelers, airline businesses, and other consumers are anticipated to get accurate and scalable services. As a result, aviation officials should work to improve airport performance. Trapezoidal fuzzy Shannon's entropy and WSM model were used to analyze the efficiency of 6 Indian airports from 2015 to 2018. Shannon's entropy was utilized in the first phase to estimate airport efficiency and compute the weights of criteria, and WSM was used in the second phase to investigate the influence of explanatory factors on airport efficiency and rank the alternatives. The weights of the various attributes and sub-attributes are calculated using Shannon's entropy approach.

A. The study Implications

Airport officials and management may use the findings to make better decisions. According to the results of Shannon's entropy study, the total passengers, net income, and cargo quantity were also emphasized as outputs and airport capability, runway ability, and total expenses. The uniqueness of our technique was to use trapezoidal fuzzy numbers to represent the underlying subjectiveness of the inlet and outlet screening process. Central and local governments must invest in underperforming airports to boost their economic impact on the area. In addition to Low-Cost Carriers' contributions to the expansion of small airports, airport police should consider. They must try to get additional airlines to fly into smaller locations to boost tourism and investment prospects, but the well of the local population. Whether it's the high population density or the burgeoning economy, these cities stand out. Another factor contributing to airport efficiency gains is the city's growing tourist potential.

References

[1] A. Graham, *Managing airports: An international perspective*. Routledge, 2018.
[2] M. K. Akyüz, H. Kafalı, and Ö. Altuntaş, "An analysis on energy performance indicator and GWP at Airports; a case study," *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects*, vol. 43, no. 19, pp. 2402–2418, 2021.

DOI: https://doi.org/10.54216/FPA.040204
Received: March 11, 2020 Accepted: July 03, 2021

[3] T. Ülkü, “A comparative efficiency analysis of Spanish and Turkish airports,” *Journal of Air Transport Management*, vol. 46, pp. 56–68, 2015.
[4] M. E. Dursun, J. F. O’Connell, Z. Lei, and D. Warnock-Smith, “The transformation of a legacy carrier–A case study of Turkish Airlines,” *Journal of air transport management*, vol. 40, pp. 106–118, 2014.
[5] H. Dinçer, Ü. Hacıoğlu, and S. Yüksel, “Balanced scorecard based performance measurement of European airlines using a hybrid multicriteria decision making approach under the fuzzy environment,” *Journal of Air Transport Management*, vol. 63, pp. 17–33, 2017.
[6] S.-J. Hong and M. Jeon, “The technical efficiency of French regional airports and low-cost carrier terminals,” *Sustainability*, vol. 11, no. 18, p. 5107, 2019.
[7] M. Noruzoliaee and B. Zou, “Airfield infrastructure management using network-level optimization and stochastic duration modeling,” *Infrastructures*, vol. 4, no. 1, p. 2, 2019.
[8] Á. Rodríguez-Sanz, F. Gómez Comendador, R. Arnaldo Valdés, J. M. Cordero García, and M. Bagamanova, “Uncertainty management at the airport transit view,” *Aerospace*, vol. 5, no. 2, p. 59, 2018.
[9] Z. Turskis, J. Antuchevičienė, V. Keršulienė, and G. Gaidukas, “Hybrid group MCDM model to select the most effective alternative of the second runway of the airport,” *Symmetry*, vol. 11, no. 6, p. 792, 2019.
[10] D. Wei and C. Liu, “Fuzzy model and optimization for airport gate assignment problem,” in *2009 IEEE International Conference on Intelligent Computing and Intelligent Systems*, 2009, vol. 2, pp. 828–832.
[11] E. Zu, S.-Y. Liu, B.-M. Hsu, Y.-C. Wang, and E. M Lau, “An Analysis of the Success Factors for Passenger Boarding Enthusiasm for Low-Cost Regional Airline Routes,” *Sustainability*, vol. 12, no. 16, p. 6600, 2020.
[12] C. Zuniga and G. Boosten, “a practical approach to monitor capacity under the CDM approach,” *Aerospace*, vol. 7, no. 7, p. 101, 2020.
[13] D. C. Ferreira, R. C. Marques, and M. I. Pedro, “Comparing efficiency of holding business model and individual management model of airports,” *Journal of Air Transport Management*, vol. 57, pp. 168–183, 2016.
[14] V. Liebert and H.-M. Niemeier, “A survey of empirical research on the productivity and efficiency measurement of airports,” *Journal of Transport Economics and Policy (JTEP)*, vol. 47, no. 2, pp. 157–189, 2013.
[15] D. Parker, “The performance of BAA before and after privatisation: A DEA study,” *Journal of Transport Economics and policy*, pp. 133–145, 1999.
[16] E. Pels, P. Nijkamp, and P. Rietveld, “Inefficiencies and scale economies of European airport operations,” *Transportation Research Part E: Logistics and Transportation Review*, vol. 39, no. 5, pp. 341–361, 2003.
[17] A. Fragoudaki and D. Giokas, “Airport efficiency in the dawn of privatization: The case of Greece,” *Journal of Air Transport Management*, vol. 86, p. 101821, 2020.
[18] T. Ngo and K. W. H. Tsui, “A data-driven approach for estimating airport efficiency under endogeneity: An application to New Zealand airports,” *Research in Transportation Business & Management*, vol. 34, p. 100412, 2020.
[19] V. S. Özsoy and H. H. Örkcü, “Structural and operational management of Turkish airports: a bootstrap data envelopment analysis of efficiency,” *Utilities Policy*, vol. 69, p. 101180, 2021.
[20] A. E. Ripoll-Zarraga and S. Huderek-Glapska, “Airports’ managerial human capital, ownership, and efficiency,” *Journal of Air Transport Management*, vol. 92, p. 102035, 2021.
[21] X. L. Fernández, J. Gundelfinger, and P. Coto-Millán, “The impact of logistics and intermodality on airport efficiency,” *Transport Policy*, 2021.
[22] S. Güner, H. İ. Cebeci, J. J. M. Antunes, and P. F. Wanke, “Sustainable efficiency drivers in Eurasian airports: Fuzzy NDEA approach based on Shannon’s entropy,” *Journal of Air Transport Management*, vol. 92, p. 102039, 2021.
[23] T. M. Huynh, G. Kim, and H.-K. Ha, “Comparative analysis of efficiency for major Southeast Asia airports: A two-stage approach,” *Journal of Air Transport Management*, vol. 89, p. 101898, 2020.
[24] M. F. Bongo and L. A. Ocampo, “A hybrid fuzzy MCDM approach for mitigating airport congestion: A case in Ninoy Aquino International Airport,” *Journal of Air Transport Management*, vol. 63, pp. 1–16, 2017.
[25] Z. Wang and W.-K. Song, “Sustainable airport development with performance evaluation forecasts: A case study of 12 Asian airports,” *Journal of Air Transport Management*, vol. 89, p. 101925, 2020.
[26] R. R. Martín-Cejas, “An approximation to the productive efficiency of the Spanish airports network through a deterministic cost frontier,” *Journal of Air Transport Management*, vol. 8, no. 4, pp. 233–238, 2002.
[27] E. Fernandes and R. R. Pacheco, “Efficient use of airport capacity,” *Transportation research part A: Policy and practice*, vol. 36, no. 3, pp. 225–238, 2002.

DOI: https://doi.org/10.54216/FPA.040204
Received: March 11, 2020 Accepted: July 03, 2021

[28] Y. Yoshida and H. Fujimoto, "Japanese-airport benchmarking with the DEA and endogenous-weight TFP methods: testing the criticism of overinvestment in Japanese regional airports," *Transportation Research Part E: Logistics and Transportation Review*, vol. 40, no. 6, pp. 533–546, 2004.
[29] T. Tsekeris, "Greek airports: Efficiency measurement and analysis of determinants," *Journal of Air Transport Management*, vol. 17, no. 2, pp. 140–142, 2011.
[30] Y.-C. Chang, M.-M. Yu, and P.-C. Chen, "Evaluating the performance of Chinese airports," *Journal of Air Transport Management*, vol. 31, pp. 19–21, 2013.
[31] L. W. Fan, F. Wu, and P. Zhou, "Efficiency measurement of Chinese airports with flight delays by directional distance function," *Journal of Air Transport Management*, vol. 34, pp. 140–145, 2014.
[32] P. Lai, A. Potter, M. Beynon, and A. Beresford, "Evaluating the efficiency performance of airports using an integrated AHP/DEA-AR technique," *Transport Policy*, vol. 42, pp. 75–85, 2015.
[33] D. Ennen and I. Batool, "Airport efficiency in Pakistan-A Data Envelopment Analysis with weight restrictions," *Journal of Air Transport Management*, vol. 69, pp. 205–212, 2018.
[34] O. D. Olariaga and L. P. Moreno, "Measurement of airport efficiency. The case of Colombia," *Transport and Telecommunication*, vol. 20, no. 1, pp. 40–51, 2019.
[35] E. Stichhauerova and N. Pelloneova, "An efficiency assessment of selected German airports using the DEA model," *Journal of Competitiveness*, vol. 11, no. 1, pp. 135–151, 2019.
[36] R. D. Banker, A. Charnes, and W. W. Cooper, "Some models for estimating technical and scale inefficiencies in data envelopment analysis," *Management science*, vol. 30, no. 9, pp. 1078–1092, 1984.
[37] D. Liu, "Measuring aeronautical service efficiency and commercial service efficiency of East Asia airport companies: An application of Network Data Envelopment Analysis," *Journal of air transport management*, vol. 52, pp. 11–22, 2016.
[38] H.-C. Lee and C.-T. Chang, "Comparative analysis of MCDM methods for ranking renewable energy sources in Taiwan," *Renewable and Sustainable Energy Reviews*, vol. 92, pp. 883–896, 2018.
[39] M. R. Milošević, D. M. Milošević, A. D. Stanojević, D. M. Stević, and D. J. Simjanović, "Fuzzy and interval AHP approaches in sustainable management for the architectural heritage in smart cities," *Mathematics*, vol. 9, no. 4, p. 304, 2021.

DOI: https://doi.org/10.54216/FPA.040204
Received: March 11, 2020 Accepted: July 03, 2021