The Netherlands Press

Journal of Airline Operations and Aviation Management

Article

Aeronautical Infrastructure Optimization to Enhance the Strategic and Operational Business Performance of Small Airports

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DOI: https://doi.org/10.56801/jaoam.v3i1.3

Abstract.

Airport business management literature commonly evaluates the performance of these organizations based on the number of passengers and cargo processed, aircraft movements, number of runways, number of employees, and passengers' terminal dimension, among other factors concerning commercial aviation, commonly applied to large structures, with gaps being identified in the literature of small airports. The identification and analysis of the main factors that interfere with the performance of airport business, and the strategic and operational management of small public airports have been analyzed from 24 small Brazilian airports. The study employed the Data Envelopment Analysis method based on the Charnes, Cooper, and Rhodes model, as well as the Banker, Charnes, and Cooper model, adapted for Visual Basic Analysis. The main results demonstrate that infrastructural characteristics, such as runway width, pavement classification number, runway length, buldings' age, maximum take-off weight of the critical aircraft, passenger terminal size, and air cargo and passengers processed, show significant relevance to the operational performance of small airports. The main theoretical implications of the study are the definition of strategic and operational parameters that impact the performance of small airports, which can be used as a reference by air transport decision-makers.

Keywords: Air Transport; Airport business; Operations; Linear regression.

Journal of Airline Operations and Aviation Management Volume 3 Issue 1

Received Date 05 March 2024
Revised Date 02 April 2024
Accepted Date 10 April 2024

1. Introduction

Efficient management of small airports necessitates identifying factors influencing their strategic and operational performance, and many studies in the literature have proposed different approaches to measuring airport performance [1-5]. Despite the existence of numerous studies on airport efficiency, it is evident that few of them have specifically focused on analyzing the business aspects of small airports, even with their relevance in regional development and their role in aggregating demand for airlines [6-9]. It can be noted that the business management literature commonly evaluates the performance of airport companies based on the number of passengers and cargo processed, aircraft movements, and aeronautical and non-aeronautical revenues, among other factors related to commercial aviation, applicable to large structures, with gaps being identified in the literature related to the study of small airports.

The identification of factors associated with airport performance can be found in Jacquillat and Odoni's study [10], which focuses on analyzing the impact of demand and the airport's ability to predict and manage congestion on its overall operational performance. The authors highlight factors, such as the number of runways and their configuration for efficient multi-runway operations, as well as operational considerations concerning the separation of aircraft operations during take-off and landing procedures, aircraft types, weather conditions, and other factors influencing ground handling processes. The study emphasizes that proposals to enhance passenger and air cargo performance should consider the size of the airport infrastructure. Zuidberg [11], for instance, from an econometric analysis of 125 airports in Europe, the United States, Canada, Australia, and New Zealand, shows a quadratic relationship between seasonality and profitability, indicating that seasonal fluctuations in demand harm profitability due to periods of low passenger movement under a great and expensive structure. However, in the case of small airports, seasonality can contribute to profitability, as small and clean structures experience higher passenger flows during peak tourist seasons when they are situated in popular seasonal destinations [12].

Efficiency analysis of small airport operations considers many infrastructural characteristics, such as runway length, passenger processing capacity [3], building size and age, and technical equipment [13]. Other studies highlight the network of factors influencing airport performance, including socio-economic aspects [14-16], planning, management, and operations [10]. Suau-Sanches and Voltes-Dorta [3], for instance, employ the zero-inflated Poisson model to identify small airports with favorable conditions for airlines to increase regular passenger traffic and stimulate socio-economic development. Christensen et al. [15], considering Greenland as a case study, demonstrate that airports with shorter runways are less attractive to airlines due to limitations on aircraft types, which affects the profitability of both the airline and the airport.

In non-tourist destinations, small airports may experience uneven distribution of activities throughout the year. To maintain revenues, these airports need to supplement aeronautical income with non-aeronautical sources [17, 18]. In the analysis of small airports and low-cost carriers (LCC) performance, Červinka [13] considers the earnings before interest, taxes, depreciation, and amortization (EBITDA) indicator. This indicator allows for relative comparisons of airport performance and the financial outcomes of passengers and employees every month. The study reveals the significant potential of air cargo to enhance the financial results of small airports.

Considering the limitations in the state of the art associated with small airport organizations, this study endeavors to contribute to the existing literature on airport performance by providing comprehensive insights and analysis, with a particular focus on small airports, in the sense of maximizing passenger and air cargo processing in terms of limited infrastructure and operations management.

2. Method

In identifying the main factors associated with the business performance of small airports, it is necessary to identify strategic, operational, and infrastructural factors associated with the movement of aircraft and passengers and their impacts on the airport's efficiency. Subsequently, data collection was conducted to develop a mathematical model for evaluating the performance of these airports. According to the National Civil Aviation Agency [19], Brazil witnessed a total of 831,000 regular and non-scheduled flights, transporting approximately 98 million domestic and international passengers throughout 2022. Brazil boasts a total of 3,426 aerodromes, comprising 495 public and 2,931 private facilities, of which approximately 120 serve commercial aviation [20]. For this study, 24 small Brazilian airports, representing around 20% of the nation's airports dedicated to commercial aviation, were considered. The airports were classified based on the methodology of the Federal Aviation Administration (FAA), which categorizes them according to their share of total national boardings, ranging from 0.05% to 0.25%.

To analyze the airport infrastructure, management reports data generated by the Ministry of Infrastructure [21] and ANAC (2020) were utilized. Different factors were considered, including the number of passengers processed, air cargo volume, pavement classification number (PCN), passenger terminal size (TPS), runway width, runway length, buildings' age, structure depreciation coefficient, and maximum take-off weight of the critical aircraft (MTOW). The independent variables in the analysis were passengers and cargo processed, while the remaining variables were treated as dependent variables. Table 1 displays the main characteristics of these airports, with their respective locations provided in Appendix A.

The operational efficiency analysis of the small Brazilian airports, listed in Table 1, was conducted using multiple linear regression and Data Envelopment Analysis (DEA) in Visual Basic Analysis (VBA). The efficiency values generated by these models were compared to assess their performance. Table 1 also presents the depreciation coefficient, calculated using the straight-line method. This coefficient was included as one of the variables in the multiple linear regression analysis.

Table 1. List of selected small airports data.

ICAO Code	Passengers boarded (n)	Air cargo (kg)	PCN	TPS (m^2)	Runway width (m)	Runway length (m)	Buildings' age (years)	Structure depreciation coefficient	MTOW (tons)
SBAE	135,851	135,851	42	2,140	45	2010	15	0.14	79.01
SBBV	187,191	178,318	38	4,798	45	2700	48	0.602	79.01
SBCA	112,347	85,660	48	839.5	30	2063	42	0.518	6.6
SBCH	223,958	207,220	45	1173	45	1670	32	0.378	75.5
SBCJ	65,858	181,092	41	833.45	45	1800	46	0.574	79.01
SBCX	103,655	132,519	45	183	30	2000	39	0.476	79.01
SBDN	155,090	118,146	38	172	35	2158	21	0.224	79.01
SBFN	150,894	64,219	30	1,035	45	2100	82	1.078	75.5
SBIL	232,967	1,380,346	35	3,400	45	1577	82	1.078	15.55
SBIZ	164,923	138,735	50	2,164	45	1798	39	0.476	79.01
SBJA	65,817	56,877	57	143	30	2499	7	0.028	75.5
SBJU	236,402	230,335	45	1,050	45	1540	48	0.602	75.5
SBJV	278,846	1,116,706	51	4,000	45	1940	66	0.854	6.6
SBKG	64,297	98,977	50	2,500	45	1615	51	0.644	15.55
SBMA	138,063	186,778	40	1,011	45	2000	85	1.12	79.01
SBMK	110,731	106,310	34	733	45	2100	81	1.064	75.5
SBMQ	296,530	359,558	48	2,913	45	1600	57	0.728	79.01
SBPF	78,992	105,242	29	135	30	1700	64	0.826	3.69
SBPL	179,167	2,596,716	80	3,093	45	3250	39	0.476	79.01
SBRB	170,771	523,710	78	4,292	45	1630	13	0.112	79.01
SBSI	79,790	66,763	66	30	36	2100	51	0.644	79.01
SBSN	237,321	546,815	48	131,96	45	2400	43	0.532	79.01
SBVC	149,475	52,522	44	234	45	2525	66	0.854	79.01
SBZM	76,086	4,882	66	323	45	1845	87	1.148	15.55

3. Results

Analysis of the results demonstrates the relevance of elements that can be used as a basis for developing complementary key performance indicators for airports [22]. To establish the variables for the multiple linear regression model of passengers and annual cargo processed, the Pearson coefficient was employed, as shown in Equation 1. This coefficient was utilized as input for the logistic regression model, as the coefficient values were below 0.7, indicating a moderate correlation.

$$\rho = \frac{\sum_{i=0}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{[\sum_{i=1}^{n}(x_i - \bar{x})][\sum_{i=1}^{n}(y_i - \bar{y})]}} \quad (1)$$

Equation 1, ρ takes on values ranging from -1 to 1. In Equation 1, the variable x_i represents the values of the dependent variable, $\bar{x}$ denotes the average of the dependent variable values, y_i represents the values of the independent variable, and $\bar{y}$ signifies the mean of the independent variable values. The corresponding coefficients are presented in Table 2.

Table 2. Pearson's coefficient concerning passengers and annual cargo, processed in 2019.

	Passengers	Air Cargo
Passengers	*	0.428172
Air cargo	0.428172	*
PCN	-0.03396	0.418354
TPS	0.503977	0.491884
Runway width	0.470638	0.263567
Runway length	-0.08141	0.393282
Buildings' age	0.051155	0.020293
Depreciation coefficient	0.051155	0.020293
MTOW	0.108315	-0.09168

By examining the Pearson coefficients presented in Table 2, it was observed that the values for the TPS displayed higher consistency with both passenger and air cargo processed variables when compared to other independent variables. This underscores the significance of optimizing terminal infrastructure in small airports, as proposed by Christensen et al. [15], for the overall development of the country, as well as highlights the potential contribution of small airports in bolstering airline businesses [8].

On the other hand, the highest negative values were associated with MTOW, indicating a negative correlation with air cargo processed. This suggests the possibility of utilizing multipurpose passenger aircraft for cargo transportation at small airports. It is worth noting that dedicated cargo aircraft typically prefer airports with more extensive infrastructure, even if it results in longer ground travel times for cargo from their region of origin to larger airports, as discussed by Lotti and Caetano [23] when they consider the costs and travel time to the international cargo dispatch airport as selection criteria.

The data were further analyzed through multiple linear regression, conducted separately for the independent variable of passengers processed and the independent variable of air cargo processed. The results of these analyses are presented in Table 3.

Table 3. Regression statistics for passengers and air cargo processed.

	Passengers	Air cargo
Multiple R	0.695317	0.78036
R-Square	0.483465	0.60896
Adjusted R-square	0.257482	0.43788
Standard error	59713.92	436097
Comments	24	24

Based on the findings presented in Table 3, it is evident that the correlation between the dependent and independent variables yielded a moderate R-Square value for passengers (0.483465). Conversely, the air cargo analysis demonstrated the highest R-Square value (0.60896), indicating the potential suitability of the small airports considered for cargo transport operations based on the variables under consideration. This information can be significant in optimizing aeronautical infrastructure projects [24].

To assess the efficiency values of DMUs, DEA was performed in VBA using two input-oriented models: the Charnes, Cooper, and Rhodes (CCR) model, and the Banker, Charnes, and Cooper (BCC) model. The CCR and BCC models differ in their approach to maximizing and minimizing inputs. The CCR model, as proposed by Charnes, Cooper, and Rhodes [25] in Equation 2, was employed to analyze the super-efficiency of the DMUs, resulting in the identification of 13 efficient DMUs [26].

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{l=1}^{m} v_i x_{ij} \leq 0, j = 1, 2, \ldots, n, j \neq 0 \qquad (2)$$

where for the DMU with 100% efficiency, values greater than 1 can be assumed, as denoted by j≠o.

In the BCC model, a total of 18 efficient DMUs were identified. The efficiency of these DMUs, was determined using Equation 3, based on the maximization approach proposed by Banker, Charnes, and Cooper [27], where Co represents a free parameter known as the scale factor.

$$Wo = \max \sum_{r=1}^{s} u_r . y_{r0} + C_0 \qquad (3)$$

The efficiency analysis of airports was conducted using DEA, also employed by Ennen and Batool [1]. This approach was applied to the data of the 24 small airports considered in this study, as presented in Table 4. The table ranks the airports based on their efficiency scores in both the BCC and CCR Super-efficiency models.

Table 4. DEA data in ranking.

ICAO Code	BCC Efficiency %	CCR Super-efficiency %	Ranking
SBSN	100	393	1
SBPL	100	327	2
SBPF	100	316	3
SBJV	100	245	4
SBRB	100	160	5
SBIL	100	154	6
SBSI	100	148	7
SBMQ	100	124	8
SBJA	100	124	9
SBDN	100	122	10
SBCH	100	118	11
SBJU	100	115	12
SBCA	100	114	13
SBFN	100	89	14
SBAE	100	81	15
SBBV	97	79	16
SBCX	100	73	17
SBVC	84	68	18
SBIZ	100	68	19
SBZM	91	67	20
SBMA	83	64	21
SBMK	87	61	22
SBKG	100	48	23
SBCJ	95	32	24

According to Table 4, the super-efficient CCR method excludes the DMU under evaluation from the reference set, allowing a DMU classified as extremely efficient to obtain an efficiency index, generally greater than 1, thus being designated as super-efficient. However, the BCC model assumes variable values for the scale, variables between increasing, constant, and decreasing, with the maximum efficiency index equal to 100%. The models were analyzed according to the values assigned to the outputs surveyed in this study. The CCR super-efficient method excludes the DMU being evaluated from the reference set. This allows a DMU classified as extremely efficient to obtain an efficiency index, typically greater than 1, and be designated as super-efficient. On the other hand, the BCC model considers variable values for the scale, including increasing, constant, and decreasing scales, with the maximum efficiency index capped at 100%. The models are analyzed based on the values assigned to the outputs examined in this study.

To compare different small airports and rank them, considering both models simultaneously, the International Airport of Santarém - Maestro Wilson Fonseca (SBSN), presented in Figures 1 and 2, emerges as the most efficient airport in both the BCC and CCR models. Until the period in which this research was carried out, the SBSN was administered by the public company Infraero and, since November 27, 2023, its management has been under concession to the private sector, since then it has been administered by Aena Brasil. This concession is part of a contract along with 14 other airports, including prominent ones such as São Paulo – Congonhas Airport (SBSP) and Campo Grande Airport (SBCG) [28].

Figure 1. Airside of SBSN.

Source: Aena Brasil [29].

Figure 2. Passenger terminal of SBSN.

Source: Aena Brasil [29].

Situated 14.5 km from downtown Santarém, SBSN serves as a crucial transportation hub, employing 456 individuals directly and indirectly. As of 2023, the airport handles daily approximately 1,200 passengers and 7,000 kg of air cargo, and it accommodates operations by the airlines Azul, Gol, and LATAM, as well as from general aviation [30].

The assignments for the analyzed data were solved using the LP Simplex solution method in VBA's Solver tool, following the procedures outlined in Table 5. The constraints were taken into account with an entry index of 1.

Table 5. Procedures outlined.

$Private\ Sub\ CommandButton1\_Click()$
$For\ n\ =\ 1\ to\ 24$
$Range("M1")\ =\ n$
$solversolve\ Userfinish{:}=True$
$Range("N"\ \&\ 6\ +\ n)\ =\ Range("M2")$
$Next\ n$
$End\ Sub$

The DEA analysis in VBA for the BCC and CCR models, as shown in Table 5, involved the calculation of individual values for the weighted output using the range M2. This calculation was performed automatically by VBA. The range structure was responsible for selecting the cell range or cell to be analyzed. To determine the variables with the most significant relevance, an analysis of the weights assigned to the DMUs was conducted. Consequently, the previous code was updated and adapted to reflect the respective positions of the weights assigned to variables in VBA. The procedures outlined in Table 6 were followed to perform this analysis.

Table 6 . Procedures for variable relevance.

$Private\ Sub\ CommandButton1\_Click(\ )$
$For\ n\ =\ 1\ to\ 24$
$Range("M1")\ =\ n$
$solversolve\ Userfinish{:}=True$
$Range("N"\ \&\ 6\ +\ n)\ =\ Range("M2")$
$Range("C"\ \&\ n\ +\ 32\ \&\ ":J"\ \&\ n\ +\ 32).Value\ =\ Range("C3{:}J3").Value$
$Next\ n$
$End\ Sub$

The DMUs analyzed were subsequently classified into dummy variables to assess the significance of inputs and outputs for each DMU. The results of this classification are presented in Figure 3, in increasing order of relevance, both in the BCC and CCR super-efficiency models.

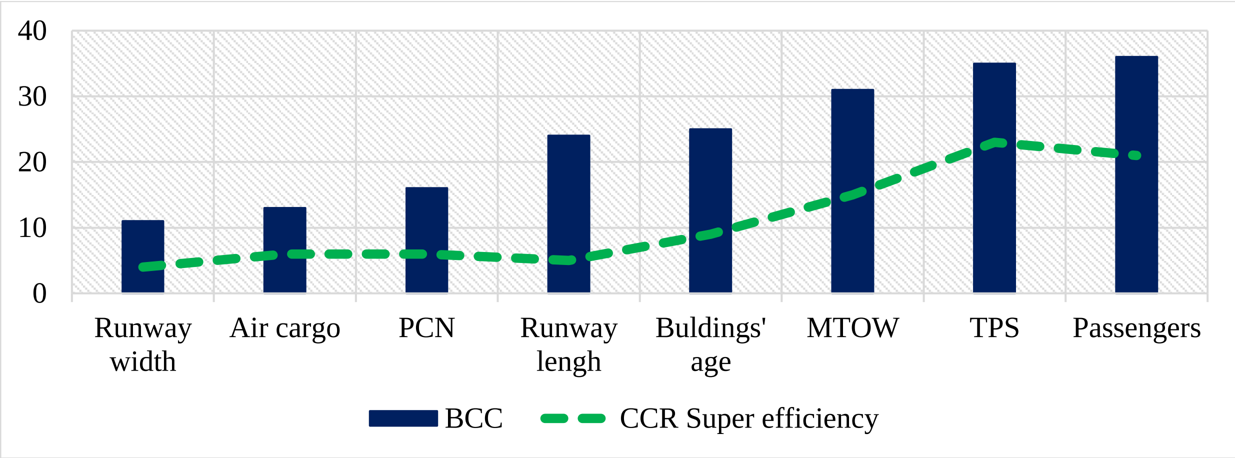

Figure 3. Data from DEA analysis for relevant input and output variables.

Figure 3 represents the sums of relevance for the variables analyzed, in percentage, being the data compared between the BCC and the CCR super-efficiency model. The runway dimensions (transversal, thickness, and longitudinal) appear among the least relevant, also accompanied by air cargo, despite significatives. In the case of this last variable, this result contrasts the findings from Uludağ [4] about the productivity of airports with movements below 1 million annual passengers, or even with Yu and Rakshit [5], as the authors show great weight to this variable. About physical conditions, complementing the author, here the dimensions of the runway were considered, and not just their quantity.

These results complement those proposed by Caetano et al. [14], who also identify little relevance to the physical dimensions of the runway compared to the number of cities and towns served by the airport, GDP/capita, formal jobs in the municipality, and population when prioritizing aerodromes for investments. On the other hand, variables such as passenger terminal size (TPS) and maximum take-off weight of the aircraft in operation (MTOW), as well as passenger movement, have a high level of relevance, which demonstrates characteristics of interest in small airports that are different from those commonly considered in the literature [31, 32].

In the BCC model, the DMUs are considered efficient, whereas in the CCR model, efficiency is not achieved for all DMUs. This suggests that the data used in the BCC model provide a more robust basis for the analysis. Figure 1 also reveals that the variables with the highest relevance are passengers, TPS, and MTOW. This indicates that these variables, as stressed by Boiral et al. [6], maybe more strongly associated with regional sustainable development from small airports.

4. Conclusion

This study focused on identifying the key aeronautical infrastructure characteristics associated with passenger and cargo transport in small airports. Efficiency analyses were conducted using the BCC and CCR super-efficiency mathematical models.

From the presented results, it is noticeable that the Pearson coefficients exhibit average correlation values between processed passenger variables and annual processed cargo, with the variable TPS showing a significant coefficient for both analyzed variables. While the runway width variable shows a more significant correlation in processed passengers, the runway length variable is more significant to annual processed cargo. The PCN variable shows the least significant correlation for processed passengers. However, conversely, it exhibits a significant correlation with the annual processed cargo variable.

The results also revealed that for passenger transport, the TPS, runway width, and MTOW were the most significant factors. Regarding air cargo transport, the TPS, PCN, and runway length emerged as the main characteristics with notable relevance. These findings provide valuable insights into the efficient management of small airport operations. Moreover, the BCC model was found to be particularly relevant for this analysis, offering a robust framework for assessing airport efficiency. Infrastructure characteristics identified as efficient with better index are related to runway length, age of buildings, maximum take-off weight of critical aircraft, and additionally, the number of processed passengers, with the BCC model considered the most relevant for the analyses. It is observed that the correlation between dependent variables and the independent passenger variable, the coefficient of determination R-squared, presented a medium value. In contrast, the independent variable of annual processed cargo showed the maximum value for R-squared.

The study's theoretical implications, which define strategic and operational parameters affecting small airport performance, can serve as a valuable reference for air transport decision-makers.

The main limitations of the study are related to the availability of data limitations regarding aerodromes, which complicates the analysis and requires the estimation of values for certain variables, such as the physical dimensions of passenger terminals. Further analysis is required to mathematically establish the correlation between variables characterizing the analyzed infrastructures and airport performance. Therefore, the suggestion for future research involves the development of mathematical models that compensate for the absence of specific data, often challenging for researchers to access. Another suggestion is to develop mathematical models incorporating machine learning techniques and real-time data analytics, as the power of this tool is to assist small airport businesses in implementing more effective and efficient strategies in real-time.

Acknowledgments

Conselho Nacional de Desenvolvimento Científico e Tecnológico – CNPq, Brasil (National Council for Scientific and Technological Development – CNPq), Brazil.

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Appendix A

Names of airports considered in the study

ICAO Code	Airport name	City	State
SBAE	Bauru/Arealva	Bauru	SP
SBBV	Atlas Brasil Cantanhede	Boa Vista	RR
SBCA	Coronel Adalberto Mendes da Silva	Cascavel	PR
SBCH	Serafin Enoss Bertaso	Chapecó	SC
SBCJ	Carajás	Parauapebas	PA
SBCX	Hugo Cantergiani	Caxias do Sul	RS
SBDN	Presidente Prudente	Presidente Prudente	SP
SBFN	Fernando de Noronha	Fernando de Noronha	PE
SBIL	Bahia - Jorge Amado	Ilhéus	BA
SBIZ	Prefeito Renato Moreira	Imperatriz	MA
SBJA	Regional Sul	Jaguaruna	SC
SBJU	Orlando Bezerra de Menezes	Juazeiro do Norte	CE
SBJV	Lauro Carneiro de Loyola	Joinville	SC
SBKG	Presidente João Suassuna	Campina Grande	PB
SBMA	João Correa da Rocha	Marabá	PA
SBMK	Mário Ribeiro	Montes Claros	MG
SBMQ	Alberto Alcolumbre	Macapá	AP
SBPF	Lauro Kurtz	Passo fundo	RS
SBPL	Senador Nilo Coelho	Petrolina	PE
SBRB	Plácido de Castro	Rio branco	AC
SBSI	Presidente joão Batista Figueire	Sinop	MT
SBSN	Maestro Wilson Fonseca	Santarém	PA
SBVC	Glauber de Andrade Rocha	Vitória da Conquista	BA
SBZM	Presidente Itamar Franco	Goianá	MG