Artigo submetido a 27 de Julho 2021; versão final aceite a 23 de Maio de 2022 Paper submitted on July 27, 2021; final version accepted on May 23, 2022 DOI: https://doi.org/10.59072/rper.vi64.50

# The Importance and Centrality of Brazilian Airports in the Regular Passenger Traffic<sup>1</sup>

## A Importância e Centralidade dos Aeroportos Brasileiros no Tráfego Regular de Passageiros

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## Abstract

The Brazilian airport network underwent significant changes from 2000 onwards. There were changes in the structure of ownership, management, and operation, highlighting the process of airport concessions. The network has a flexible structure and is subject to interference from external factors. The importance and centrality of airports varied in the 2000-2020 period. The study applies the reliability indicator, analysing the impacts of the Covid-19 pandemic. The indicator is based on the centrality of airports and allows them to be classified in relation to operational continuity (critical, worrying, and suitable contexts). The results confirm the indicator as a tool that allows a preliminary analysis of airport networks in the regular domestic segment.

Keywords: Airports, Centrality, Network Reliability, Air Transport

JEL Code: H540, R420

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<sup>&</sup>lt;sup>1</sup> Funding: This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

#### Resumo

A rede aeroportuária brasileira passou por alterações significativas a partir de 2000. Houve mudanças na estrutura de propriedade, gestão e operação, destacando-se o processo de concessões aeroportuárias. A rede possui uma estrutura flexível e sujeita à interferência de fatores externos. A importância e centralidade dos aeroportos sofreram variações no período 2000-2020. O estudo aplica o indicador de confiabilidade, analisando os impactos da pandemia Covid-19. O indicador tem como base a centralidade dos aeroportos e permite classificar os mesmos em relação à continuidade operacional (contextos crítico, preocupante e adequado). Os resultados confirmam o indicador como ferramenta que permite uma análise preliminar de redes aeroportuárias, no segmento doméstico regular.

Palavras-chaves: Aeroportos, Centralidade, Confiabilidade da Rede, Transporte Aéreo

Código JEL: H540, R420

#### 1. INTRODUCTION

The period 2000-2020 can be considered as a time of significant changes in air transport in Brazil. In this regard, the creation of the National Civil Aviation Agency (Agência Nacional de Aviação Civil – ANAC) in 2005, which marked the liberalization of the market, stands out. There was also a strong expansion in demand, reflecting the growth and diversification of the Brazilian economy in the period 2000-2015. Regarding the airport network, it is worth highlighting the beginning of a set of investments related to the expansion of capacity, which was mainly aimed at meeting the needs related to two major international sporting events: the FIFA World Cup, in 2014, and the Olympic Games in 2016. There were also changes in the structure of ownership, management, and operation of the airport infrastructure, highlighting in this regard the concession process. Twenty-two airports were granted in the period 2011-2019.

The centrality measures are network theory metrics and indicate how much an airport (node) is connected to other airports (nodes), which are the most central, measuring the quality of airport connections, that is, how significant they are, regardless of the number of passengers that were transported. The airports that have the greatest influence on the network are those that have the highest centrality. Airports with lower centrality have less influence, and as observed over the period 2000-2020 and observed by Brito, Baltazar and Silva (2021), they can interrupt the operation of regular flights (failures). It is important to measure and monitor the centrality of airports, as well as the factors that influence them.

According to Grubesic et al. (2008), failures can cause unscheduled loss of service resources within a network, resulting in costly repairs and service interruptions, especially for infrastructure. According to the authors, connectivity issues are fundamental for any network, since its purpose is to establish and maintain connectivity between the set of elements to facilitate the movement of valuable goods and services through a system.

The study aims to analyse the centrality of Brazilian airports in the regular domestic segment and apply the operational continuity indicator developed by Brito, Baltazar and Silva (2021), extending the study period from 2000-2018 to 2000-2020, comparing the results found and observing the effects of the Covid-19 pandemic on the indicator and on the Brazilian network.

#### 2. LITERATURE REVIEW

Air transport has been approached from different perspectives, including regulation and privatization, planning and management of airlines, airports, and air traffic, among others. The number of authors is expressive, and the approaches presented allowed to broaden knowledge in relation to operational, geographic, economic, and political aspects. About airport systems, the methodologies discussed allow analysing the infrastructure from different perspectives: effects of deregulation and governance, concentration and spatial evolution of traffic, changes in the structure of routes and

their quantities, among others.

About the use of network theory for the study of air transport, Buonova (2009) states that its application was made possible due to the availability of data and the easy representation of airport systems. According to Newman (2010), centrality metrics in network analysis have different concepts of importance, being very useful to identify and classify the most important nodes or edges in the network.

Among the authors who used the theory of networks applied to air transport, Rocha (2009) investigated the structure and evolution of the airport network in Brazil from 1995 to 2006 in terms of routes, connections, passengers, and cargo. The analysis revealed a dynamic structure, with airports and routes changing in importance. The results indicate that the network shrank in the number of routes but grew in the number of passengers and cargo volume.

Zhang et al. (2010) studied the Chinese airport network using the theory of complex networks. According to the authors, the tool is useful, since airports can be represented by nodes and flights by edges. The results showed that the network topology remained stable during the period 2002-2009, although there were significant changes regarding the degree of importance, addition and removal of airports and airlines from the network.

Lordan et al. (2014) presented a methodology for identifying critical airports using the centrality of intermediation. The study aims to help develop contingency plans for an adequate response to the closure of an airport in the global Air Transport Network (ATN) in the event of an attack. Through the study, it is possible to identify the airports, whose isolation would cause the greatest losses in network connectivity.

Wong et al. (2017) analysed the global air transport network using traffic volume and topological metrics. The authors developed the Airport Centrality Index (ACI). Wong et al. (2019) examined the narrative that Low-Cost Carriers (LCCs) tend to focus their activities on secondary airports. airports from the ACI created by Wong et al (2017) The study by Mazzarisi et al (2020) focused on centrality and causality metrics. The authors measured the importance of a node and the propagation of disturbances throughout. The authors also proposed generalizations of these metrics, proving that they are suitable for ATM applications.

About reliability, this theme has been discussed in several studies. Grubesic et al. (2008) reviewed and compared some approaches that assessed the importance of infrastructure and the vulnerability of networks. The authors highlighted the significant differences between measures of infrastructure importance and network performance, as well as the need for a clear understanding of interdiction risks and critical infrastructure vulnerability assessment.

Burbidge (2016) complemented Eurocontrol's analysis regarding operational and business risks at an airport. The author considered the potential consequences of climate change, highlighting the need to develop resilience to these risks.

Yang (2020) applied multiple linear regression to identify factors that contribute to the perception of the risk of aircraft noise pollution among residents near the international airports of Taoyuan and Kaohsiung, in Taiwan.

Brito, Baltazar and Silva (2021) presented a methodology to estimate the reliability of the Brazilian airport network, based on the centrality of airports. The results allowed us to classify the network into three groups of airports (suitable, worrisome, and critical contexts), indicating those that could stop operating regular domestic traffic in Brazil.

The articles reinforce the importance of the research theme and validate the understanding of the effectiveness of network theory and risk analysis as analysis tools in studies on air transport. The different approaches allowed to broaden the insights about the different possibilities and forms of applications to the study of airport networks.

#### 3. METHODOLOGY

The study applies Network Theory and reliability the methodologies, the first being used as basis for the second. The concept of the network was associated with the group of airports that operate regular domestic passenger traffic in Brazil. The data were obtained from the ANAC, the sector's regulatory agency in the Country, and cover the period 2000-2020. The data used were the totals passengers transported by airport each year. When preparing the data, some inconsistencies were found (unproductive flights, origin and destination domestic registered as international and

vice versa, equal origin and destination, unknown origin and destination). These records were extracted manually during the process of cleaning and analysing the database. The network was classified as non-directed, due to the use of the total number of passengers in the connections (boarding and landing). The airports were Identified by the International Civil Aviation Organization (ICAO) code.

The Open Graph Viz (Gephi) platform was used. The software was used by Jimenez, Claro, and Sousa (2012) when studying Portuguese aviation networks (airlines and airports) through visual analysis, representing them spatially. The Gephi platform allows analysing the relationships between the components of a network through a set of metrics. It is possible to emphasize aspects such as network growth and centrality. Centrality was measured by calculating the Eigenvector Centrality (EC), which indicates the most central airports in the network. The concept of centrality was introduced by Bonacich in 1972 (Equation 1). EC values can range from 0 to 1. The closer to 1 the EC of an airport, the closer to the central region of the network it will be located. The closer the EC is to 0, the further the airport is from the central region of the network.

$$EC(i) = \mu_1(i) = \frac{1}{\lambda_1} A \mu_1 = \frac{1}{\lambda_1} \sum_{j=1}^n a_{ij} \mu_1(j)$$
 (1)

Where  $\mu_1(i)$  is the set of neighbours of airport i.  $\lambda_1$  is the largest eigenvalue. A is the adjacency matrix  $a_{ij}$ . n is the number of airports (nodes) and  $a_{ij}$  of the adjacency matrix represents the connections from airport i to airport j (1 < i < n; 1 < j < n). A given airport will have a high EC if it is connected to other airports with central positions in the network. After calculating the EC, the airports were distributed into five classes, according to their centrality and importance in the network (Table 1).

**Table 1. Eigenvector Centrality Class** 

Eigenvector Centrality	Class
0.000 F 0.200	Ultra-peripherals
0.200 F 0.400	Peripherals
0.400	Intermediaries
0.600 ₺ 0.800	Central
0.800 F 1.000	Main Hubs

Source: authors' elaboration

The research focuses on the application of EC, as it measures the quality of connections at airports, that is, how significant the connections are, regardless of the number of passengers transported. A higher EC indicates that the airport is connected to other airports with more relevant positions in the network, reducing the possibility of no longer operating regular traffic. A low EC indicates that the airport's connections are of little relevance, increasing the possibility of no longer operating regular traffic. The interruption of the operation of regular flights mainly affects regions where access by other means of transport is limited or difficult, either due to distance or regional characteristics.

Brito, Baltazar and Silva (2021) applied the concepts of reliability based on the study by Fogliatto and Ribeiro (2009), which in its broadest sense is associated with the successful operation of a product or system, with the absence of breaks or failures within a period and under environmental conditions of use of the item. Fogliatto and Ribeiro (2009) state in their study that the risk function h(t), also known as the failure rate or risk rate, is one of the most used reliability measures and can be interpreted as the amount of risk associated with a unit (component or system) at time t. Still following the authors, the risk function is very useful in analysing the risk to which a unit is exposed over time, serving as a basis for comparison between units with different characteristics. In this study, the estimator for h(t) for large samples will be applied:

$$\hat{h}(t) = \frac{\bar{N}(t) - \bar{N}(t + \Delta t)}{\bar{N}(t)\Delta t}$$
 (2)

Where  $\hat{h}(t)$  is the hazard ratio to be calculated for each class interval and  $\bar{N}(t)$  is the number of

surviving units at time t.  $\Delta t$  is the class interval and  $\overline{N}(t+\Delta t)$  is the number of failures at time  $t+\Delta t$ . N is the sum of failures at time t. The risk function was adapted to the study of the airport network, about operational continuity, where  $\hat{h}(t)$  is the risk rate of an airport that may stop operating regular domestic traffic. This is calculated for each EC class interval of the airports that stopped operating in the network in the period under study, that is, in time t.

In the current study, time t comprises the period 2000-2020. N is the number of airports that stopped operating regular domestic traffic in time t.  $\overline{N}(t)$  is the number of airports that continued to operate regular domestic traffic in time t.  $\Delta t$  is the EC class interval.  $\overline{N}(t+\Delta t)$  is the number of airports that stopped operating regular domestic traffic at time  $t+\Delta t$ . The authors observed a deviation in amplitude between the values of the variables  $\overline{N}(t)$ ,  $\overline{N}(t+\Delta t)$  and N and EC values of the airports (difference between the maximum and minimum numbers). To get around the situation, the authors transformed the variables into logarithmic values, when calculating the risk rate  $\hat{h}(t)$ , the values of the variables  $\overline{N}(t)$ ,  $\overline{N}(t+\Delta t)$  and N were transformed into EC from airports. The same principle was adopted by Brito, Baltazar and Silva (2021).

According to Brito, Baltazar and Silva (2021), the risk of an airport not operating regular traffic does not increase over time and the risk function is decreasing. The higher the EC, the lower the risk of the airport ceasing to operate regular traffic. The authors adapted the Pareto ABC Curve principle to the operational continuity risk curve of airports (Figure 1). Thus, it was possible to categorize the airports into three context groups: i) Suitable – EC at time t above 100% of the maximum EC of airports that stopped operating during the study period; ii) Worrisome – EC at time t above 80% but below 100%; and iii) Critical – EC at time t below 80%. Percentages can be adjusted according to each study.

Eigenvector Centrality maximum of airports that stopped operating regular traffic during the study period.

Critical Worrisome Suitable

80% Eigenvector máx 100% Eigenvector máx

Figure 1. Illustration of an airport operating continuity risk curve - regular traffic

Source: Brito, Baltazar, Silva (2021)

#### 4. RESULTS AND DISCUSSIONS

#### 4.1. Airport concessions

In relation to changes in the structure of ownership, management and operation of airport infrastructure, concessions were the most relevant. During the period 2011-2019, twenty-two airports were granted to the private sector (Table 2).

**Table 2: Airports granted** 

Year	Airports
2011	São Gonçado do Amarante - Natal (SBSG)
2012	Brasília (SBBR), Guarulhos (SBGR) e Viracopos (SBKP)
2013	Confins (SBCF) e Galeão (SBGL)
2017	Florianópolis (SBFL), Fortaleza (SBFZ), Porto Alegre (SBPA) e Salvador (SBSV)
2018	Northeast block: Recife (SBRF), Maceió (SBMO), João Pessoa (SBJP), Aracaju (SBAR), Campina Grande (SBKG) e Juazeiro do Norte (SBJU)
	Southeast block: Vitória (SBVT) e Macaé (SBME)
2019	Midwest Block: Cuiabá (SBCY), Sinop (SWSI), Rondonópolis (SWRD) e Alta Floresta (SBAT)

Source of data: ANAC (2021a) / Elaboration: authors

The process began in 2011, with the concession for the construction and operation of the new airport in the city of Natal: São Gonçalo do Amarante Airport. In 2012 and 2013 the concessions of the Brasilia, Guarulhos, Viracopos, Galeão and Confins Airports took place. At the time, these concentrated 38.4% of the connections and 39.4% of the number of passengers in regular domestic traffic.

In the period 2011-2014, investments in airport infrastructure generated works at several airports, especially those located in cities that hosted the 2014 FIFA World Cup games. During this period, due to the works, the number of connections in the domestic segment decreased, contrasting with the growth in the number of passengers.

The enthusiasm for implementing the freedom of routes and fares has passed, with more mature and profitable connections remaining, where airlines have better rates of utilization on flights. Tables 3A, 3B and 3C show the evolution of the number of connections and passengers in the post-concession period (2013-2020).

Table 3A: Number of air connections and passengers - regular traffic

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SBBR, SBCF, SBGL, SBGR, SBKP Top five airports awarded	2013	2014	2015	2016	2017	2018	2019	2020			
•											
Nº connections - domestic	273	265	284	274	258	255	257	249			
Nº passengers - domestic	35105555	37203522	37266388	33612243	33792848	35883010	36062881	18383720			
Nº connections - international	115	133	136	125	102	125	126	113			
Nº passengers - international	17172487	18252627	18572524	18233606	18922412	20519963	20821829	5720697			

Source of data: ANAC (2021b) / Elaboration: authors

Table 3B: Number of air connections and passengers - regular traffic

All twenty-two airports gran- ted	2013	2014	2015	2016	2017	2018	2019	2020					
Nº connections - domestic	573	548	558	545	517	515	518	505					
Nº passengers - domestic	57260452	60051615	60132201	54501664	55264231	58730342	58715441	29442061					
Nº connections - international	152	174	180	170	154	189	193	166					
Nº passengers - international	18619923	19790940	20099195	19565700	20505878	22605470	23144294	6349782					

Note: There were 22 airports granted, but only 15 have international traffic. Source of data: ANAC (2021b) / Elaboration: authors

Source of data: ANAC (2021b) / Elaboration: authors

Table 3C: Number of air connections and passengers - - regular traffic

Brazil	2013	2014	2015	2016	2017	2018	2019	2020
Nº connections - domestic	1420	1247	1310	1239	1148	1207	1241	1158
Nº passengers - domestic	89433040	94256530	94873627	86901491	88421752	93092872	93879238	44149170
Nº connections - international	168	195	200	191	179	222	216	186
Nº passengers - international	19010049	20330055	20614570	19954802	20896736	23175700	23635327	6463362

Source of data: ANAC (2021b) / Elaboration: authors

Observing Table 3B, in the period 2013-2019, it can be seen a reduction of 55 connections in the domestic segment (9.6%), contrasting with an increase of 41 connections in the international

segment (27.0%). Considering the period 2013-2020, there was a reduction of 68 connections in the domestic segment (11.9%), contrasting with an increase of 14 connections in the international segment (9.2%). It is noteworthy that the values for the period 2013-2020 reflect the negative impacts of the Covid-19 pandemic in 2020, which can lead to biased analyses and conclusions. However, in both periods, data show that airport concessions benefited international connections, to the detriment of domestic connections.

## 4.2. Eigenvector Centrality (EC)

After calculating the EC, the airports were distributed into five groups: ultra-peripheral, peripheral, intermediate, central, and main hubs (Table 1). A similar classification was used by Guimera et al (2005) and Buonova (2009). It can be seen in Figure 2 that the EC of the airports had considerable variability during the study period, indicating that a significant part of the airports was in the ultra-peripheral and peripheral classes, that is, far from the central area of the network.

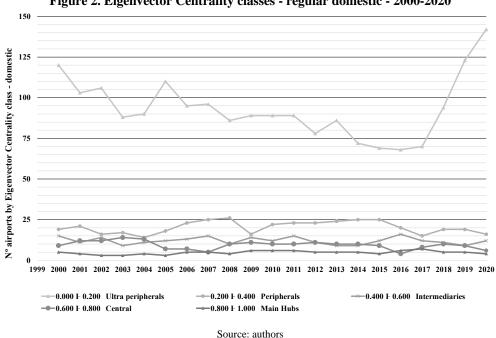


Figure 2. Eigenvector Centrality classes - regular domestic - 2000-2020

Airports located in the peripheral and ultra-peripheral classes are those where connections have little relevance in the network and, consequently, may no longer operate regular traffic. Variations in these two classes are the most significant. Figure 3 is the spatial representation of the Brazilian airport network, making it possible to analyse the years visually and comparatively 2000 and 2020. The Map of Countries and Geo Layout distributions of the Gephi platform were applied since they allow to visualize the network according to the geographic position and the Eigenvector Centrality class. The fundamental issue is not the number of airports that change classification over the years. The data confirm an inconsistency in the peripheral and ultra-peripheral classes of the network.

There are difficulties in maintaining regular flights in a significant part of the airports that are located mainly in the ultra-peripheral class. In some, the operation of regular traffic started and was suspended more than once in the period 2000-2020. It was observed that, of the airports located in the ultra-peripheral class, those that maintained regular operation throughout the period were those that have connections with airports located in the central and/or intermediate classes of the network.

2000 Midwest Southeast 2020 North South 0.000 F 0.200 Ultra-peripheral 0.200 F 0.400 Peripheral 0.400 F 0.600 Intermediate 0.600 F 0.800 Central 0.800 F 1.000 Main Hub

Figure 3: Eigenvector Centrality class of airports – 2000 e 2020

Note: There was a small gap between airports to avoid overlapping from geographical positioning Source: authors

## 4.3. Operational context

In their study, Grubesic et al. (2008) state that obstructions are important to assess the robustness of a network and that reaching the widest possible "image" of the damage that can occur allows for an understanding of the consequences of failures. The authors mention that when evaluating the vulnerability of a network, the aim is to answer two points related to importance: how robust is the network in relation to failures in nodes and/or arcs and what are the essential nodes and/or arcs of the network. In their study, Brito, Baltazar and Silva (2021) reversed the meaning of the node's importance in the network, focusing on airports with less centrality and relating failures to the continued operation of regular flights at these airports. The authors identified 226 failures in the period 2000-2018. In the current study period (2000-2020), 256 failures were identified. Table 4 presents the hazard ratio values for each class.

Table 4. Airport Operational Continuity Risk Rate - Regular Domestic - 2000-2020

Classes	Failure	s in time t (2000- 2020)	Risk Rate	Surviving units at time t	Failures in time t+Δt
		N	ĥ(t)	$ar{\it N}(t)$	$\bar{N}(t + \Delta t)$
$0.0000 < EC \le 0.0890$	225 (87,9%)		4.28	256	31
$0.0890 < EC \le 0.1779$	25 (9,8%)		0.34	31	231
$0.1779 < EC \le 0.2669$	5 (2,0%)		0.12	6	251
$0.2669 < EC \le 0.3558$	1 (0,4%)		0.02	1	255
$\sum N$		256			

Source: Authors / adapted from Brito, Baltazar and Silva (2021)

The Pareto ABC Curve principle was adapted to the operational continuity risk curve of airports (Figure 4), which are categorized into three groups: i) Suitable – EC at time t above 0.3558; ii) Worrisome - EC at time t above 0.1779 and below or equal to 0.3558; and iii) Critical – EC at time t less than or equal to 0.1779. The percentage values of the Pareto Curve (80-20) were adjusted to better suit the current study.

When comparing the results of the curves 2000-2018 and 2000-2020, there is a displacement of the same in the current study, generating a considerable increase in the area of critical and worrying contexts (Figure 5). In the 2000-2018 curve, the minimum EC was 0.0019 and the maximum 0.2054. In the 2000-2020 curve, the minimum EC was 0.0008 and the maximum EC 0.3558. The maximum EC of airports that stopped operating regular domestic traffic went from 0.2054 in the 2000-2018 period to 0.3558 in the 2000-2020 period. The displacement indicates an aggravation of the situation of the airports, which, in order to be in the proper context, need to have an EC higher than 0.3558. The displacement of the maximum EC can be explained by two reasons: i) 58 new airports started operating regular traffic in the period 2018-2020 (all were in the ultra-peripheral region of the network) and of these 58 airports, only 16 continued to operate regular traffic in the first quarter of 2021; and ii) the impact of the Covid-19 pandemic in 2020, which drastically reduced air operations worldwide. In 2020, 180 airports operate regular domestic traffic in Brazil. Of these 180 airports, 50 stopped carrying out regular operations in the first quarter of 2021 (27.8%).

4,50 4,00 Eigenvector Centrality maximum of airports that stopped Airports operational continuity risk rate - regular domestic operating regular traffic during the study period. 3,50 3,00 2,50 2,00 Critical Worrisome Suitable 1.50 0.50 0.17790.2669 0.3558 0.0500 0.3500 0,4000 0.0000 0.1000 0.1500 0.2000 0.3000 Eigenvector Centrality - Risk Rate 2000-2020

Figure 4: Airports operational continuity risk curve - 2000-2020

Source: authors

5.00 Airports operational continuity risk rate - regular domestic Eigenvector Centrality maximum of airports that stopped 4,50 4.00 3,50 3,00 Critica 2,50 2,00 Suitable 1,00 0,1027 0.50 0,1779 0.2669 0.1540 0,00 0,1500 0.0500 0.2500 0.3500 0.4000 0,1000 Eigenvector Centrality Risk Rate 2000-2018 (Brito, Baltazar and Silva, 2021) Risk Rate 2000-2020

Figure 5: Airports operational continuity risk curve – 2000-2018 and 2000-2020

Source: authors

The displacement of the curve does not indicate an inaccuracy in the indicator. It demonstrates that it is flexible, adapting to different situations and exceptions. Thus, it can be applied to other domestic and/or regional networks. The possibility of the indicator being adapted in relation to the study time and the number of network failures is positive. By extending the study period, failures, and events between 2018-2020, such as the construction and operation of new airports, new airport concessions and pandemics with different consequences, served as inputs to calibrate the indicator, making it more robust and embracing. In other words, they served to improve values and, consequently, context classifications. Thus, the 2000-2020 curve shows itself as an improvement of the 2000-2018 curve.

Based on the 2000-2020 curve, airports were categorized according to context: suitable, worrisome, or critical (Tables 5A and 5B) over the period of the current study.

Table 5A. Number of airports in operation according to the context in Time T

Context in Time T	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
In Operation	168	151	151	131	132	150	143	146	136	136	139
- Suitable	32	33	29	28	30	27	30	29	29	32	32
- Worrisome	46	47	48	45	45	53	40	48	51	43	44
- Critical	90	71	74	58	57	70	73	69	56	61	63

Source: authors / adapted from Brito, Baltazar and Silva (2021)

Table 5B. Number of airports in operation according to the context in Time T

-,	ioic cb.	11411100		01 05 111	operation	ii accor	unig to	me come	C210 111 1		
Context in Time T	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	1° Trim 2021
In Operation	143	128	134	120	119	114	112	139	165	180	131
- Suitable	32	33	31	29	28	30	31	28	25	25	24
- Worrisome	49	49	53	43	45	40	38	39	42	46	38
- Critical	62	46	50	48	46	44	43	72	98	109	69

Source: authors / adapted from Brito, Baltazar and Silva (2021)

Observing Tables 5A and 5B, it was possible to observe variations in the number of airports in each context, with those in the critical context being the most significant. However, what stands out is not the number of airports that change category over the years. The data show an inconstancy, that is, there are difficulties in maintaining regular flights in a considerable part of the airports that

are located, mainly, in the ultra-peripheral area of the network. There are cases where the operation of regular traffic started and stopped more than once in the period 2000-2020.

Tables 6A and 6B show the number of airports at time t+1, for example, how many airports at time t were in the suitable context and which time t+1 remained in the same context, or moved to the contexts of worrisome, critical, or even ceased to operate regular domestic traffic.

Table 6A. Context of Airports in Time T + 1

Context in	Context in Tin 1	ne T +										
Time T		2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
In operation			168	151	151	131	132	150	143	146	136	136
- Suitable			32	33	29	28	30	27	30	29	29	32
	- Suitable		29	27	27	28	25	25	27	27	29	32
	- Worrisome		3	6	2		5	2	3	2		
	- Critical											
	- Inoporative											
- Worrisome			46	47	48	45	45	53	40	48	51	43
	- Suitable		3	2	1	2	2	5	2	2	3	
	- Worrisome		37	35	32	34	37	34	34	39	38	33
	- Critical		5	6	10	7	4	11	3	3	9	9
	- Inoporative		1	4	5	2	2	3	1	4	1	1
- Critical			90	71	74	58	57	70	73	69	56	61
	- Suitable											
	- Worrisome		5	4	7	9	9	1	11	8	5	9
	- Critical		61	54	43	37	39	58	42	52	43	48
	- Inoporative		24	13	24	12	9	11	20	9	8	4

Source: authors / adapted from Brito, Baltazar and Silva (2021)

Table 6B. Context of Airports in Time T + 1

Context in	Context in Ti	ne T + 1										
Time T		2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
In opera- tion		139	143	128	134	120	119	114	112	139	165	180
- Suitable		32	32	33	31	29	28	30	31	28	25	25
	- Suitable	32	32	30	27	27	25	28	28	23	24	22
	- Worrisome			3	3	2	3	2	3	5	1	3
	- Critical											
	- Inoporative				1							
- Worri- some		44	49	49	53	43	45	40	38	39	42	46
	- Suitable		1	1	2	1	5	3		2	1	2
	- Worrisome	39	44	42	36	37	35	33	33	31	38	35
	- Critical	4	3	5	13	5	4	3	5	6	3	9
	- Inoporative	1	1	1	2		1	1				
- Critical		63	62	46	50	48	46	44	43	72	98	109
	- Suitable											
	- Worrisome	8	4	7	4	5	2	2	2	5	7	
	- Critical	47	42	36	31	33	35	39	41	56	75	59
	- Inoporative	8	16	3	15	10	9	3		11	16	50

(\*) 1st Quarter 2021

Source: authors / adapted from Brito, Baltazar and Silva (2021)

To complement the analysis of the data presented in Tables 5 and 6 (parts A and B), Figure 6 shows the spatial representation of the Brazilian airport network. The Gephi Map of Countries and Geo Layout distributions were applied to allow a visual and comparative analysis between 2000 and 2020, based on the context and geographic position of the airports.

Although airports are evenly distributed across the Brazilian territory, the construction of part of the airport network did not consider the need to integrate areas inaccessible by other modes of transport or demand studies. The location and construction were influenced by political and historical factors. As consequence, there is inconstancy in the operation of regular domestic flights and the variations in the category of airports, as observed in this study.



Figure 6. Context of airports – 2000 and 2020

Note: There was a small gap between airports to avoid overlapping from geographical positioning Source: authors

## 5. CONCLUSIONS

A 20-year cycle allows for very comprehensive analyses. In the Brazilian case, the period 2000-2020 was the period of the greatest transformation of air transport, encompassing regulatory aspects, demand, airport infrastructure and air navigation, among others. During this period 2000-2020, events that can also be considered atypical occurred, such as the beginning of the operation of regular flights in 50 new airports in the domestic segment in just two years (2018-2020) and two pandemics with totally different negative impacts (H1N1 in 2009 and Covid-19 in 2020).

The events between 2018-2020 have led to a considerable shift in the curve. However, this shift does not indicate an inaccuracy in the indicator. It demonstrates that it is flexible, adapting to different situations and exceptions. Thus, it can be applied to other domestic and/or regional networks. The fact that the indicator can be adapted in relation to the time and number of network failures is positive. By extending the study period, failures, and events between 2018-2020 served as inputs to calibrate the indicator, making it more robust and comprehensive. In other words, they served to improve values and, consequently, context classifications. Thus, the 2000-2020 curve shows itself as an improvement of the 2000-2018 curve. The results confirm the indicator as a tool that allows a preliminary analysis of airport networks in the regular domestic segment.

It is noteworthy that the current study does not belittle or invalidate the results found by Brito, Baltazar and Silva (2021). This study supports the methodology as a preliminary analysis tool of domestic and/or regional passenger airport networks.

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