AIR PASSENGER DEMAND MODEL ESTIMATED BASED ON BIG DATA FROM MOBILE PHONE NETWORKS: THE CASE OF BRAZILIAN DOMESTIC MARKET

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Abstract: The purpose of this research is to develop a model for the demand of air passengers using the data of the Brazilian domestic origin-destination (OD) matrix generated by mobile phone networks. The methodology includes: the forecast and the distribution of the domestic demand throughout the Brazilian territory and the assignment of the estimated demand to predefined airports. Based on the OD matrix, we generate real catchment areas of airports. With these areas, we can determine the relevant value of economic variables and, therefore – along with other indicators at airport level – to estimate the distribution of demand by airport. Our simulated results provide a tool to evaluate trending demand growth for existing airports and to assess competing effects brought about prospective new airport infrastructure.

Keywords: Big Data; OD Matrix; Passenger forecast; Gravitational model

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1. INTRODUCTION

Commercial aviation in Brazil has experienced significant growth in recent years. According to World Bank (2021), air passenger throughput grew 128% from 2010 to 2019. In recent years, the air transport sector in Brazil has increasingly experienced an airport concession process. With the sixth round of concessions in the year 2021, a total of 43 airports are now under private operation. According to ANAC (2021), that represents 77% of the movement of passengers in 2019. In addition to expansion of the domestic network, regional aviation operations are spreading out to less densely populated regions and new entrant airlines are coming into the market. All of this corroborates to improve the service to the population and allows the continuation of a scenario of growth in the demand for air transport in the country.

One of the main goals of the National Airway Plan – PAN (Brazil, 2018), the Brazilian civil aviation masterplan, is to improve safety, accessibility, connectivity, efficiency and development of the Brazilian transport network. In 2020, the disclosure of the domestic origin-destination (OD) matrix generated by mobile phone networks (Brazil, 2020) has made possible the access to a more accurate data base for real origins and destinations of travel and the areas of influence of airports in the network, setting up a major data reference for research on transportation and trade.

This paper summarizes the work carried out within the Department of Planning and Management of the National Secretariat of Civil Aviation of the Ministry of Infrastructure, which deals with two main activities: the update of air demand projection (based on previous work by De Paula et al, 2019) and the support to develop a 2021 version of the National Airway Plan – PAN 2021.

Therefore, the purpose of this research is to develop a model for the demand of air passengers using the data of the Brazilian OD matrix, generated by mobile phone networks. The paper is divided in 5 sections, including this introduction. Section 2 presents the domestic OD matrix developed by mobile phone data and describes the Territorial Planning Units (UTP). Session 3 discusses the methodological aspects and development of the demand projection model, session 4 discusses the results, presenting the distribution of demand in different scenarios for the composition of the domestic network, and session five brings the main conclusions of the study.

2. BRAZILIAN DOMESTIC OD MATRIX

The OD matrix (Brazil, 2020) was obtained from the database provided by Telefônica mobile phone company, extracted through the Luca platform, which includes trips made between the 780 UTPs defined by SAC/MInfra, through air or not air. The base was developed from the supply of aggregated data in displacement volumes based on the records of mobile phone users in the Radio Base Stations (ERBs) network. Using this information, it was possible to identify the displacements and classify the mode of transport used in air or non-air (or land), through some considered criteria. When classified as air, the cities of origin and destination of passengers were also identified, as well as the departure and arrival airports.

According to Ortúzar and Willumsen (2011), advances, especially in telecommunication devices and GPS, are changing the way travel data is collected. This type of data collection offers specific advantages in tracking movements over long periods of time.

According to Alexander et al. (2015), the ubiquity of mobile phones, along with the advancement of technology, has facilitated the storage of usage records that contain date and time coordinates from anonymous customers, providing spatiotemporal information about users' movement patterns. In addition, location data offers “digital footprints” on a scale that can hardly be obtained through interview surveys.

This survey of data by mobile telephony has already accumulated many studies in the area of transport, Hemmings and Goves (2016) describe the study carried out in the European project BigData4ATM, which aimed to obtain displacement information (door to door) between the cities of Madrid and Barcelona by road, rail – via the High Speed Train (HST) – and air transport modes.

According to the study by Wang et al. (2013), understanding the origin/destination traffic flow and the travel demand between cities is an essential and primordial task for strategic planning and management. In this study, a case study in Kansas City is approached, where many people who live in adjacent cities work. In addition, some government employees work in Topeka but live near Lawrence or Kansas City, and these three cities are known to form a traffic corridor known as: Metro Corridor Kansas. For this reason, the implementation of an intercity transport system was considered to reduce the impact of this traffic.

Returning to Alexander et al. (2015), the study aimed to analyze, through mobile data, the origin/destination and departure time of trips in the main cities of the United States. As for the methodology, the research seeks to evidence an O/D matrix mapping cell signals; locations are inferred, such as: home, work and others, depending on the observation of the frequency of travel, day of the week and time of day, in order to represent the O/D matrix.

2.1. Territorial Planning Units (UTP)

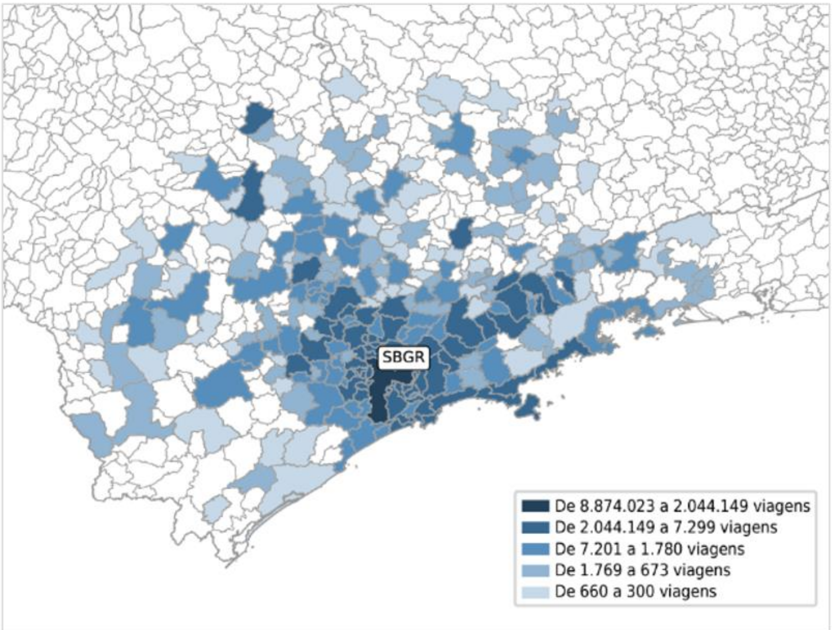
To perform the extraction of the mobile telephony database, some premises or business rules were listed. One of them was the delimitation of pre-defined areas called UTP throughout the entire Brazilian territory, whose trips were beginning to be identified from the observation of displacements between these territories. The definition of UTPs had the objective of representing regions of population concentration and, thus, of the greatest potential demand for air transport. According to the then SAC/MTPA (2017), the results of the origin/destination survey carried out by SAC with the Planning and Logistics Company (EPL) identified that around 84% of airport demand is part of the population of urban agglomerations immediately next to them. Thus, based on the hypothesis that most of the demand for air transport is present in urban agglomerations where there is an installed airport infrastructure, the definition of UTPs was also based on information from the study by the Brazilian Institute of Geography and Statistics (IBGE) entitled Arrangements populations and urban concentrations (IBGE, 2016).

2.2. Results of the OD Matrix

The data sample from mobile phone records is the direct observation of over 219 million trips and over 26.5 million unique users. Finally, 77 million trips were identified by air mode and 1.8 billion trips in land mode, also called not air mode (road, rail, waterway).

The information contained in the O-D matrix includes the real origin and the real destination of each travel, the passenger mode decision, and, consequently, each airport catchment area (Figure *1*). Based on the latter, we can generate desire line maps, to analyze airport competition.

Figure 1 – Catchment area of Guarulhos Airport (SBGR) - Municipalities with more them 300 trips by year



Fonte: Brazil (2020); Website Hórus [Data Base].

The data represents an original and unprecedent strategy in transport planning in Brazil. Developing a real O-D matrix, capturing the passenger real mode choice, allows us to build up a realistic model for air or land transportation planning. The results not only are nation-wide in terms of infrastructure, but mainly they deal with the impact of different airport services and also with the competition between flights and road modes.

3. MATERIAL AND METHODS

In order to generate a model for the demand of air passengers based on big data from mobile phone networks, a sequential procedure with three steps was developed:

- **Air transportation demand forecasting** aims to forecast the future demand in three distinct scenarios – baseline, optimistic and pessimistic. We use a panel-data model to estimate the equation and forecast the domestic demand.
- **Demand distribution** aims to distribute the domestic demand throughout the Brazilian territory. In this step we estimate a model using catchment areas of airports obtained from the OD matrix.
- **Airport demand assignment** aims to assign the demand to a predefined airport network. This step uses a gravitational model and provides the demand for new and existing airports.

3.1. Air transportation demand forecasting

We use an econometric panel-data model to estimate the equation to forecast the domestic air passenger demand. Equation 1 shows the model for estimating the Brazilian domestic passenger demand. We estimate a total passenger demand based on annual data from airport of origin (i) to airport of destination (j).

$$\mathrm{Pass}_{i,j,t} = \alpha_{1i,j} + \alpha_2 \mathrm{Pass}_{i,j,t-1} + \alpha_2 GDP_{i,t} + \alpha_3 GDP_{j,t} + \alpha_4 \mathrm{Dist}_{i,j,t} + \alpha_5 \mathrm{Yield}_{i,j,t} + \alpha_6 \mathrm{PreçoComb}_t + \alpha_7 \mathrm{DummiesAtrat}_{i,j} + \varepsilon_{i,j,t} \quad \text{Equation 1}$$

$$Yield_{i,j,t} = f(number\ of\ airlines\ and\ flights) \quad \text{Equation 2}$$

Where:

$Pass_{i,j,t}$ is the number of passengers transported from origin airport i to destination airport j, in year t;

$Pass_{i,j,t-1}$ is the number of passengers transported from origin airport i to destination airport j, in the previous year t;

$GDP_{i,t}$ is the gross domestic product (GDP) of the catchment area of the origin airport (i), in year t;

$GDP_{j,t}$ is the gross domestic product (GDP) of the catchment area of the destination airport (i), in year t;

$Dist_{i,j,t}$ distance between the origin airport (i) to the destination airport (j);

$Yield_{i,j,t}$ is the average fare per kilometer-passenger from the origin airport (i) to the destination airport (j) in year t;

$Fuel_t$ is the jet fuel price, in year t;

$TouristicDummies_{i,j}$ is a dummy variable for the touristic airport cities.

The data for passenger demand $Pass_{i,j,t}$ was obtained from the statistical database of the National Civil Aviation Agency (ANAC, 2021). The $GDP_{i,t}$ and $GDP_{j,t}$ are the sum of the GDP of each city in the airport catchment area in the OD Matrix. The cities GDP were obtained from the Brazilian Institute of Geography and Statistics (IBGE, 2021).

The variable $Yield_{i,j,t}$ is calculated using data from the Domestic Passenger Air Transport Fares database (ANAC, 2019). This database has information about the fares and number of sold seats per origin and destination. To calculate the average fare per kilometer-passenger we also use the distance between the origin airport and destination airport. We use this variable to capture the effect of the price-elasticity of passenger demand. This variable is endogenously and is directly proportional to the number of airlines operating at the airport and the number of flights (Equation 2).

The jet fuel price ($Fuel_t$) was obtained from the JetFuelPrice – Index Mundi (2021) platform, which provides the annual price of jet fuel in dollars (USD). We converted this price into Brazilian Real (BRL) to capture the fluctuation effects in the exchange rate in the national market.

The $TouristicDummies_{i,j}$ was collect from the Brazilian Tourism Map by the Brazilian Ministry of Tourism (Brazil, 2021). This map informs the tourism classification of all 5570 Brazilian cities. This variable is used to capture the touristic elasticity, which is not capture by the GDP.

To forecast the air passenger demand, we created three forecasting scenarios. We vary the GDP and the number of airlines and flights according to Table 1. The number of airlines and flights impact the variable Yield (Equation 3).

Table 1 - Forecasting scenarios

Scenario	**GDP average annual growth**	**Number of airlines (Yield impact)**
Baseline	2.2% p.a.	Growing slowly and returning to current levels in 2030
Optimistic	3.5% p.a	Grows quickly
Pessimistic	Negative standard deviation in relation to the baseline scenario	Remains constant

3.2. Demand distribution

The objective of this step is distributing the demand throughout the territory. In other words, we distribute the demand to their real origins and destinations. We estimate a cross-section model (Equation 3) for each catchment area of airports from the OD matrix.

$$\mathrm{Pass}_{i,j} = \alpha_1 + \alpha_2 \mathrm{GDP}_j + \alpha_3 \mathrm{Dist}_{i,j} + \varepsilon_{i,j} \qquad \text{Equation 3}$$

Where:

$\mathrm{Pass}_{i,j}$ is the number of passengers from UTP (j) who arrives or departures at airport (i);

GDP_j is the GDP from UTP (j);

$Dist_{i,j}$ is the distance between airport (i) and UTP (j);

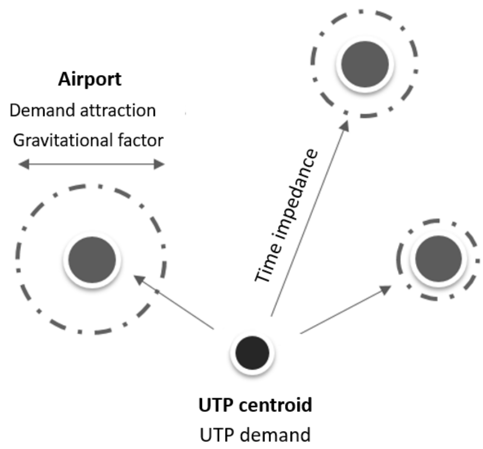
A UTP (j) is a group of cities that was defined in Section 2. The dependent variable $\mathrm{Pass}_{i,j}$ is obtained from the OD Matrix.

From the estimated Equation 3, we calculate the demand percentual of each UTP in the airport's catchment area, also considering the forecasted variation of GDP_j. We use this percentual to distribute the forecasted demand from step one to each UTP.

3.3. Airport demand assignment

This step refers to the simulation of the behavior of passengers when they are choosing the airport to travel. We modeled the way this choice is influenced by supply variables. The objective is transferring the UTP demand from step two to the airports. Figure *2* shows the concept of the implemented model. In general, each airport in the network has a gravitational factor defined by multiple supply variables. Those airports that have a greater gravitational factor tend to attract a greater amount of demand from the territory that surround them.

Figure 2 – Concept of the implemented model



Equation 4 is used to calculate how many passengers from the UTP (i) use the airport (j).

$$Pass_{ij} = k \,.\frac{P_i . E_j}{d_{ij^{\beta}}}$$ Equation 4

Where:

$\mathrm{Pass}_{i,j}$ is the number of passengers from UTP (i) who arrives or departures at airport (j);

*Pi is the t*otal of passengers of UTP i;

Ej is the gravitational factor from airport *j*, according to Equation 5;

dij is the travel time between UTP i and airport j;

β is a constant defined in the calibration (section 3.3.1);

k is a constant defined in the calibration (section 3.3.1);.

The dependent variable $\mathrm{Pass}_{i,j}$ is obtained from the OD Matrix. The gravitational factor (Ej) is defined in Equation 6.

$$E_j = \alpha_1 . Y_j + \alpha_2 . NA_j + \alpha_3 . NV_j + \alpha_4 . NE_j + \alpha_5 . ND_j + \alpha_6 . CT_j$$ Equation 5

Where:

Ej is the gravitational factor from airport j

Yj is is the average fare per kilometer-passenger of the airport (j)

NAj *is the* number of travel seats offered from the airport (j)

NVj is the number of flights of the airport (j)

NEj is the number of airlines operating in the airport (j)

NDj is the number of unique destinations of the airport (j)

CTj is the touristic score from the city of the airport (j)

$\alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5, \alpha_6$ are weight of each variable defined in the calibration (section 3.3.1);.

All variables from Equation 5 must be normalized. The variable *Yj* was calculated utilizing data from the Domestic Passenger Air Transport Fares database (ANAC, 2021). *NAj, NVj, NEj, NDj* were obtained from statistical database of the National Civil Aviation Agency (ANAC, 2020). *CTj* was collect from the Brazilian Tourism Map by the Brazilian Ministry of Tourism (Brazil, 2021).

3.3.1. Model calibration

Before using the model from Equation 4, it is necessary to calibrate it. We must make sure, that the model results are as close as possible to the demand observed in the OD Matrix.

We use a Genetic Algorithm (GA) to maximize the calibration results, consequently, we define β and k (Equation 4) and the weights $\alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5, \alpha_6$ (Equation 5). GA is a search algorithm, widely used in optimization problems. Individuals (list of possible solutions) are represented by chromosomes (list of variables) and they compete for resources and possibility of reproduction. The individuals who are more successful (with higher fitness) will propagate the genes (variables) to the next generation of individuals (Goldberg, 1989).

In our problem, the objective is maximizing the calibration fit of the regression defined in Equation 8. We defined, therefore, for our GA:

- Population: list of chromosomes (list of possible solutions);
- Chromosome: [$\alpha 1, \alpha 2, \alpha 3, \alpha 4, \alpha 5, \alpha 6$] from Equation 5;
- Genetic operators: simple reproduction and simple mutation (Goldberg, 1989).
- Fitness: r-squared of the regression model (Equation 6);

$$\log(G_{ij}) = \log(k) - \beta . \log(d_{ij}) \qquad \text{Equation 6}$$

$$G_{ij} = \frac{Pass_{ij}}{P_i . E_j} = \frac{k}{d_{ij^\beta}} \qquad \text{Equation 7}$$

Where:

G_{ij} is defined by Equation 7, which is a math shortcut of Equation 4;
β is a constant defined in the calibration;
k is a constant defined in the calibration;
d_{ij}: is the travel time between UTP i and airport j;

It is possible to calculate G_{ij} with the information of each chromosome and fit a linear regression (Equation 8) to obtain the constants k and β and the Fitness (r-squared). At each generation, the fitness of all chromosomes is calculated. The best chromosomes are transferred to the next generation of the population. After a predefined number of generations, the best chromosome defines the values of α1, α2, α3, α4, α5 and α6.

After the calibration we can use Equation 4 to calculate the airport's demand in the assignment step.

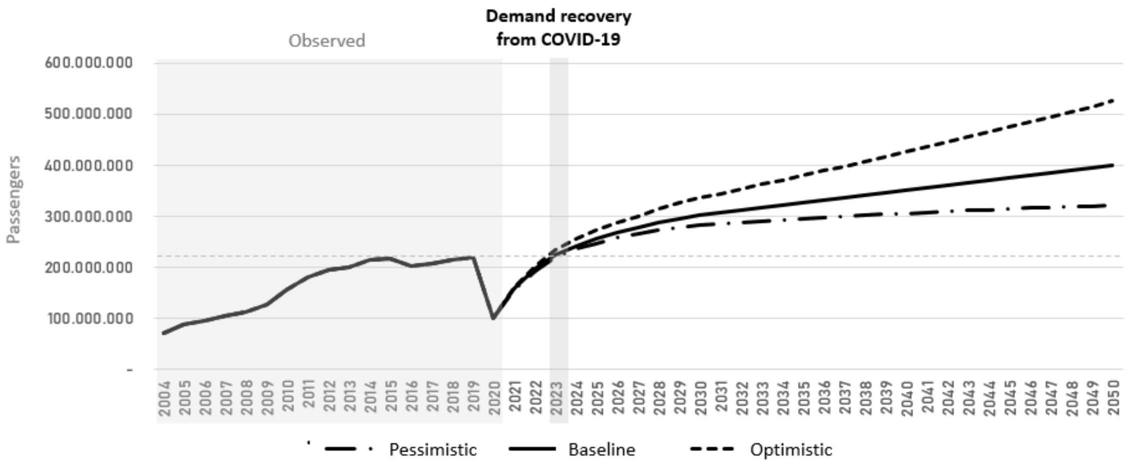
4. RESULTS

In this section, we present the application of the model to Brazil, considering the data from Equation 1 (Forecasting step), Equation 4 (Distribution step) and Equation 7 (Assignment step) for the period 2004–2020.

4.1. Forecasting results

The Brazilian demand forecast estimated from Equation 1 and scenarios from Table 1 is plotted in Graph 1. Our forecast model predicts that the domestic demand recovers from COVID-19 crisis between 2023 (optimistic or baseline scenarios) and 2024 (pessimistic scenario). The forecasted number of domestic passengers for 2023 will be about 223 million in the baseline scenario.

Graph 1 - Brazilian demand forecast

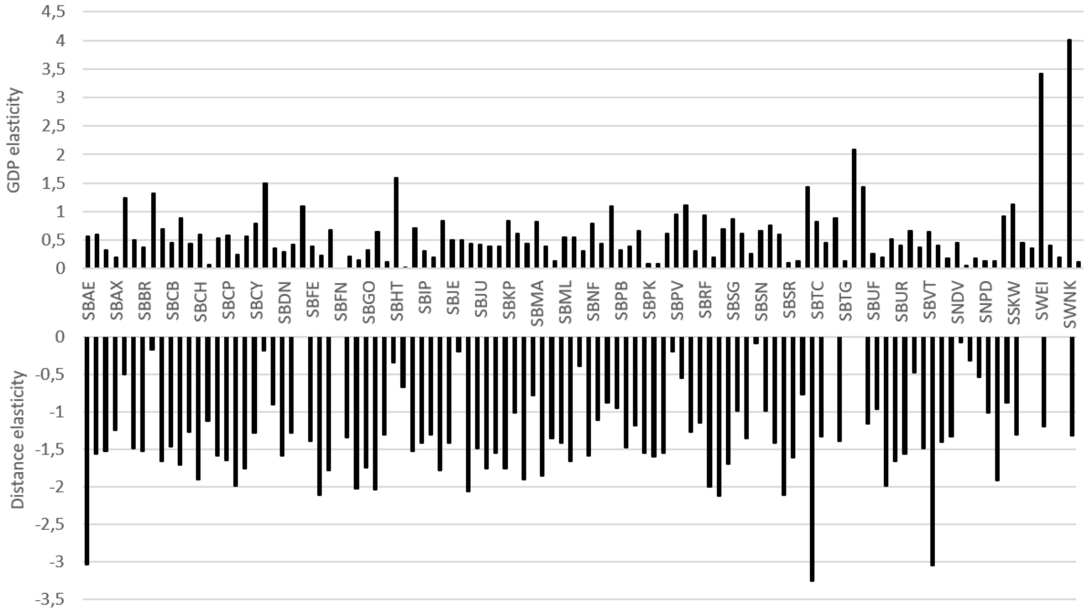


It is important to remember that the forecast result from Graph 1 is the sum of forecasted passengers of each airport ($\mathrm{Pass}_{i,j,t}$) from Equation 1. Thus, each airport has its forecasting. In the next distribution step, we distribute the forecasting of each airport to the UTPs.

4.2. Distribution results

To distribute the forecasted demand to the UTPs, we estimate one model (from Equation 3) for each airport in the OD Matrix. In total, there were 108 unique models. Graph 2 shows the estimated GDP and Distance elasticities of each model.

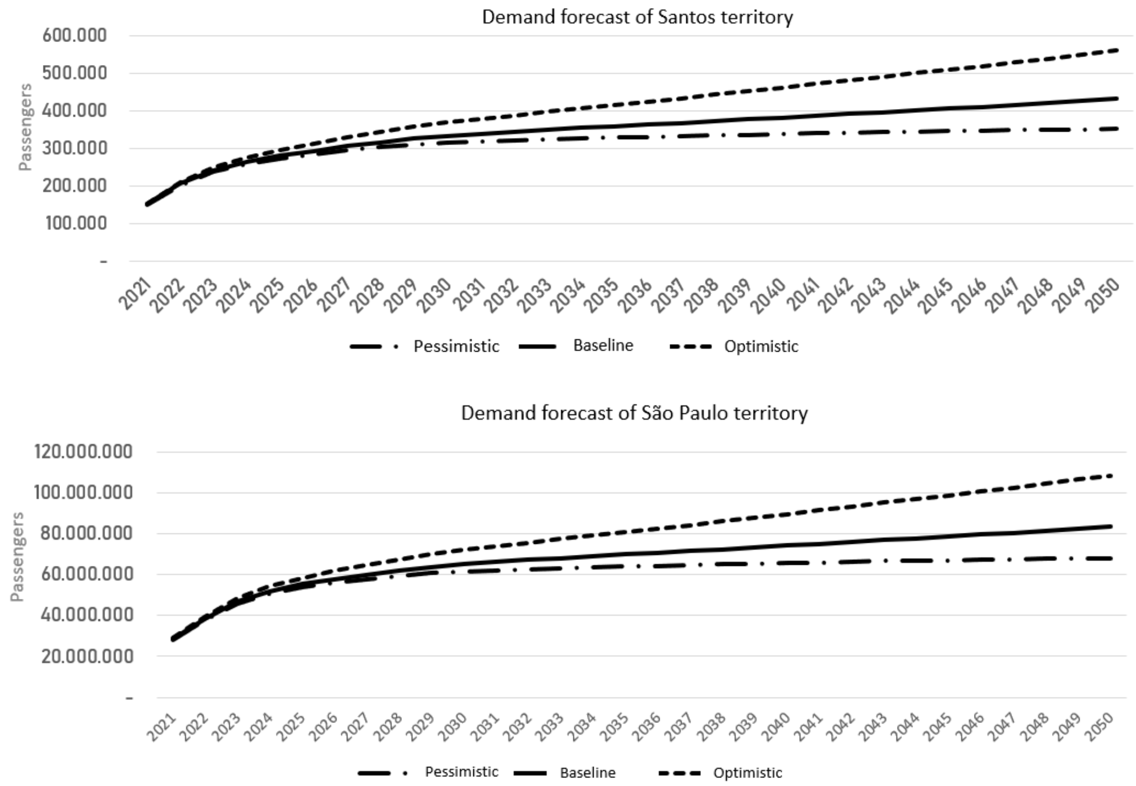
Graph 2- Estimated GDP and Distance elasticities of each model



With the GDP and Distance elasticities we distribute $\mathrm{Pass}_{i,j,t}$ to the UTPs of airport 's catchment areas. It is possible there are UTPs that belong to two or more catchment areas. In such cases, the UTP demand is the sum of distributed $\mathrm{Pass}_{i,j,t}$ of each airport.

Then we calculate the demand of 780 UTPs. To illustrate results, Graph 3 shows the demand of the UTPs of Santos and São Paulo.

Graph 3 – Forecasted demand of the UTPs of Santos and São Paulo



4.3. Assignment Calibration results

We calibrate our model using data from year 2017 and the OD matrix (Section 2). We carried out several tests to calibrate the assignment model. In the beginning, we tried to implement a single model for the entire country. The second attempt was performed based on the calibration of separated models for each federation state. Finally, we calibrated a separate model for each category defined by IBGE (2018). IBGE classifies Brazilian cities by urban hierarchy and socioeconomics characteristics. Table *2* shows the IBGE categories, the number of UTPs, the percentual of the total demand for each category, as well as the estimated values (from Equation 6) of k, β and R^2.

Table 2 – Estimated values for each IBGE category

IBGE category	**Number of UTPs**	**Percentual of the total demand**	**R^2**	**k**	**β**
National metropolis	3	48,92%	0,77	2,70E-07	1,33
Metropolis	11	28,99%	0,83	1,30E-06	1,17
Regional Capital A	9	6,81%	0,77	1,90E-05	0,94
Regional Capital B	24	5,07%	0,54	3,50E-05	0,96
Regional Capital C	62	4,87%	0,47	1,00E-04	0,92
Sub-Regional Center A	85	2,05%	0,27	8,40E-05	1,01
Sub-Regional Center B	165	1,47%	0,23	1,50E-04	1,12
Zone Center A	66	0,18%	0,15	2,00E-04	1,15
Zone Center B	64	0,10%	0,11	2,70E-04	0,75
Local Center	256	1,54%	0,07	2,30E-04	0,56

Table 3 indicates results of α1, α2, α3, α4, α5 and α6 (from Equation 5). α1 is expressive in the categories Metropolis, National Metropolis, Regional Capital A and Regional Capital B. The results indicate that in such UTPs the passenger can choose the airport considering the ticket's price. On the other hand, α1 is not expressive in categories below Regional Capital B. That means the passenger probably does not have the possibility to choose airports with more attractive ticket's price.

Table 3 – Results of α1, α2, α3, α4, α5 and α6

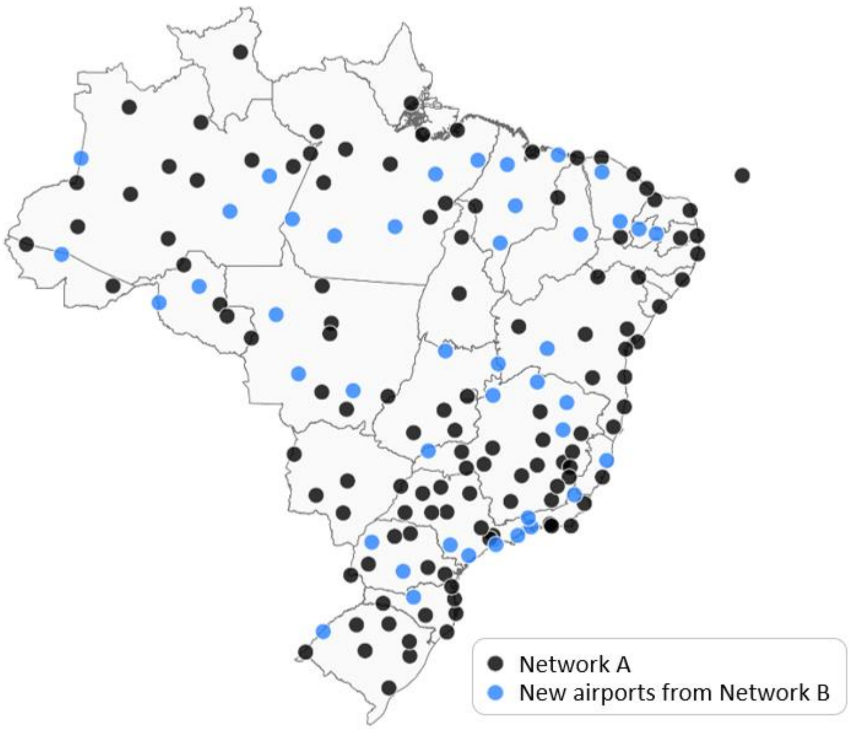
IBGE category	$\alpha_1\ (Y_j)$	$\alpha_2\ (NA_j)$	$\alpha_3\ (NV_j)$	$\alpha_4\ (NE_j)$	$\alpha_5.\ (ND_j)$	$\alpha_6 (CT_j)$
Metropolis	0,305	0,108	0,122	0,230	0,030	0,206
National metropolis	0,373	0,058	0,030	0,035	0,067	0,436
Regional Capital A	0,092	0,342	0,244	0,034	0,285	0,004
Regional Capital B	0,082	0,450	0,059	0,021	0,359	0,029
Regional Capital C	0,039	0,124	0,218	0,030	0,579	0,011
Sub-Regional Center A	0,010	0,105	0,139	0,348	0,319	0,080
Sub-Regional Center B	0,026	0,102	0,132	0,340	0,316	0,084
Zone Center A	0,018	0,323	0,015	0,024	0,303	0,317
Zone Center B	0,041	0,174	0,189	0,243	0,047	0,305
Local Center	0,000	0,317	0,072	0,345	0,163	0,102

4.4. Assignment results

With the demand of each UTP (section 4.2) and the calibrated values to each IBGE category of UTPs (section 4.3), it is possible to apply Equation 4 to calculate the airport's demand of a network. We apply the model in two different networks (Figure 3):

- **Network A:** a set of 124 airports currently operating commercial flights.
- **Network B:** a set of 163 airports including airports that do not have commercial flights and new planned airports. The two cases are more likely to receive investments from Federal Government.

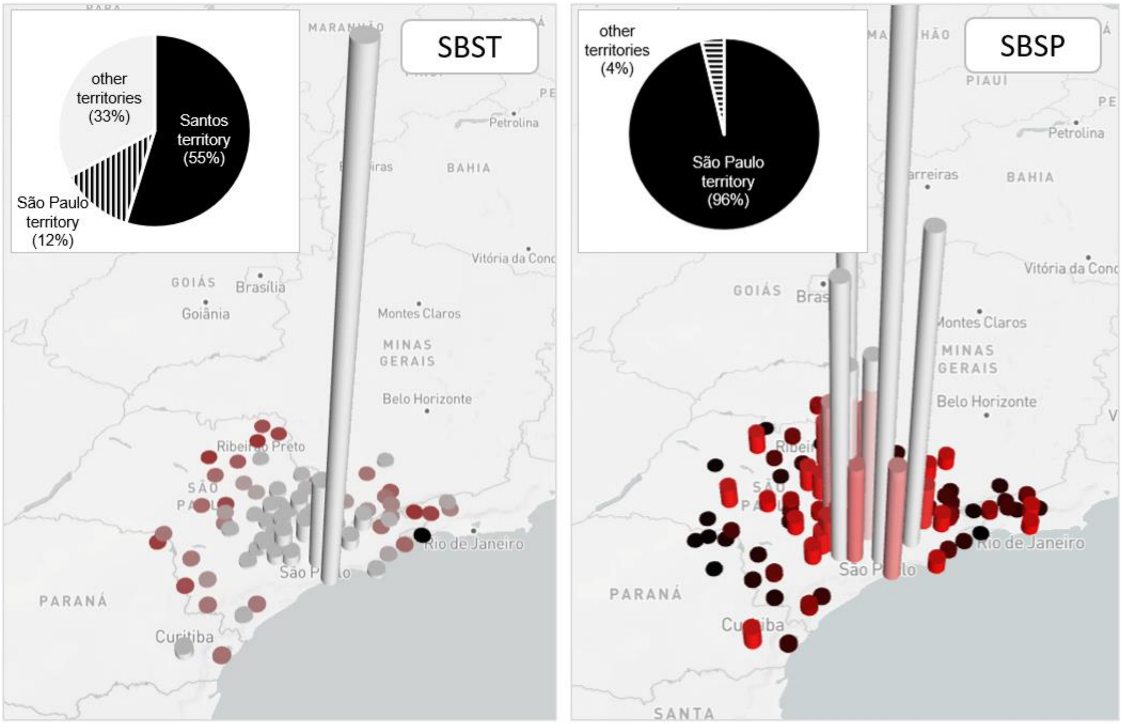
Figure 3 – Networks used in the model application.



The assignment step (Section 3.3) allows the demand estimation of all airports on the network and at the same time. However, to illustrate a possible outcome, we present the result of an airport introduction in the city of Santos in Network B. Santos is a coastal city of Brazilian's state São Paulo with a population of 433,656 inhabitants (IBGE, 2020). Santos is an important transport hub, and the Port of Santos is the biggest seaport in Latin America. The city has only an Air Force Base that does not operate commercial flights.

Figure *4* shows the catchment areas of the new Santos Airport (SBST) and of the São Paulo Congonhas Airport (SBSP). The forecasted number of passengers of SBST is about 214 thousand passengers in the year 2023, 55% of the demand comes from Santos's UTP, 12% comes from São Paulo's UTP and the other 33% comes from other UTPs. For SBSP, the forecasted number of passengers is about 31 million, most of the demand comes from São Paulo's UTP and only 4% comes from other UTPs.

Figure 4 – Catchment areas of Santos Airport (SBST) and São Paulo Congonhas Airport (SBSP) – Network B



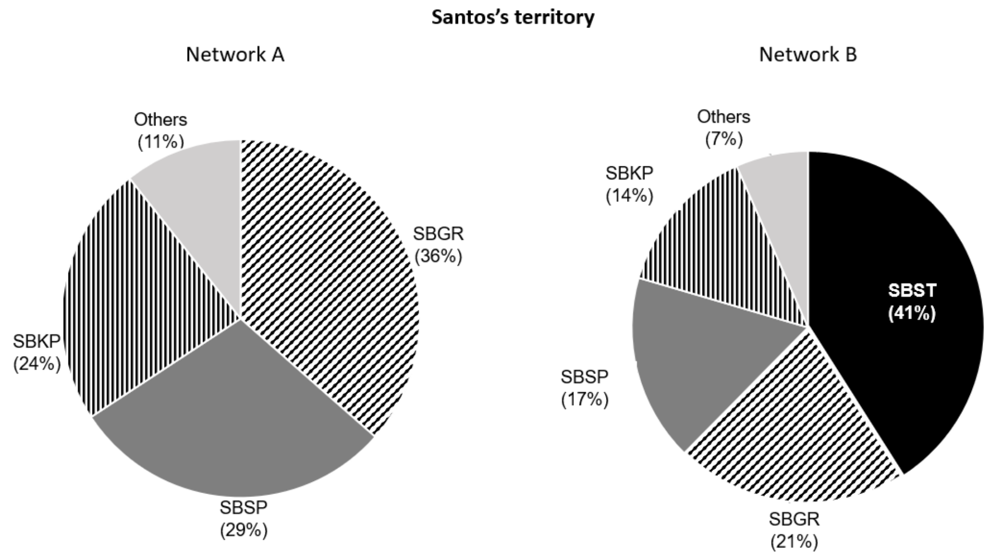
SBSP attracts much more passengers (about 1,2 million) than SBST (about 97 thousand) from secondary UTPs. That is because the values from the gravitational factor (E_j, from Equation 6) are greater in SBSP than in simulated SBST. Table 4 presents the gravitational variables from SBST and SBSP used in Network B. Increase the values from SBST impacts in how much SBST attract from the UTPs around it.

Table 4 – Gravitational variables (Equation 6) from SBST and SBSP

Airport	NA_j	NV_j	CT_j	ND_j	NEj	Y_j
SBST (simulated)	30,000	200	1	6	2	0,3
SBSP (observed)	9,348,419	59,164	1	47	4	0,54

For comparative purposes, Graph 4 shows the demand assignment results of Santos's UTP in Network A and Network B. In Network A, without SBST, the demand of Santos's UTP is assigned to SBGR (36%), SBSP (29%), SBKP (24%) and other airports (11%). In Network B, SBST captures 41% from Santos's UTP demand. The remaining is assigned to SBGR (21%), SBSP (17%), SBKP (14%) and other airports (7%).

Graph 4 - Demand assignment results of Santos's UTP in Network A (without SBST) and Network B (with SBST)



Therefore, the results show the expected impact of new airports on the existing network. Any inclusion of a new airport affects the results of the whole network. Thus, any airport in the network impact on the other airports of the region.

5. CONCLUSIONS

We present in this article an air passenger demand model for airports that was estimated based on an OD Matrix obtained from mobile phone networks. From this source, we obtained the real catchment area of the airports, that is, the main information to calibrate the model.

The model was applied in the case of Brazilian domestic market. Forecasted scenarios, with new airports in the network, can be evaluated in terms of cost-benefit analysis. Therefore, our simulated results provide a tool to evaluate trending demand growth for existing airports and to assess competing effects brought about prospective new airport infrastructure. This information is important to help future policies and to prioritize investments, especially in regional airports.

The main difference between our model and the model from De Paula et. al. (2019) is: the model from De Paula et. al (2019) has two types of demand, the primary demand and the secondary demand. An airport in a specific territory captures all the primary demand from this territory and competes for the secondary demand from the other territories. On the other hand, our model does not have the two types of demand. All demand is assigned to the airports throughout the assignment model (section 3.3), calibrated using the data of the OD Matrix.

With the implemented model, the decision-makers can evaluate the impact of a new airport on the network operation also how much of the demand this airport captures from other airports that already operate. Moreover, it is possible to decide where and when to invest in an airport, helping to evaluate the viability of a new airport and the calculation of the necessary infrastructure to absorb the potential demand. In other words, is possible to simulate, closer to reality, the effects of a new airport, airlines, routes or externalities as a gravitational model that influences the market all the time, which affects the decision of governments or private companies.

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