AIR TRAFFIC PREDICTION FOR PLANNING AIR TRAFFIC CONTROL OPERATIONS AT BRAZILLIAN AIR NAVEGATE MANAGEMENT CENTER

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ABSTRACT

With the System Wide Information Management and other innovations for Air Traffic Flux Monitoring, the strategic and tactical procedures will be increasingly collaborative with stakeholders. Meanwhile, there is no methodology at Brazilian Air Force instructions about on long-term demand prediction to adequate the optimal aeronautical infrastructure and human resources. This study presents a five years prediction of aircraft demand, using a macro and microeconomic conditional and an unconditional estimative for Brazilian Flight Information Region's origin and destination matrix. The condition estimative shows a strong statistical indicative that the regressions are nor spurious, and the estimated average grow rate is 2,81% per year for an optimistic scenario.

Keywords: Air Traffic Control, Air Traffic Movement, CGNA, SISCEAB.

1. INTRODUCTION

For a strategic framework to air traffic modernization project, ICAO (2010) suggest the following assessment performance list: updating safety needs, environment impacts, workload impact on flight crews and controllers, effect on capacity, on training requirements and feedback to participants.

Subordinate to Department of Airspace Control (DECEA), the Air Navigation Management Center (CGNA) is responsible for Air Traffic Flow Management (ATFM) and Air Space Management (ASM), at strategic (at least 1 day before flight), pre-tactical (24 hours before flight) and tactical planning (for 6 hours before flight until the operational phase) (Brazil, 2010). It is the Air Traffic Control (ATC) positions, e.g. Air Control Center (ACC), Tower (TWR) and others, those responsible for providing the Air Traffic Services (ATS).

In the military environment, the strategic and tactical logistical planning provides the necessary means to ensure the conduct of their combined activities (Pitz *et al.*, 2017). Differently from the concept used by Ballou (2006), which says that strategic planning is long term (at least 1 year) and tactical planning has an intermediate time horizon.

At Brazil (2010, 2017a, 2017b, 2016c), there is no methodology about aircraft demand prediction. This is important to assist the assessment performance list provided by ICAO (2010).

With the CGNA, was possible to implement the concept of Communication, Navigation and Surveillance/Air Traffic Monitoring (CNS/ATM), now the air navigation is based on performance. As a result, many operational restrictions have come into existence, and the objective of the Air Traffic Flow Management Unit (ATFMU) is to ensure maximum capacity of the aeronautical infrastructure, to ensure that declared capacity is not exceeded and to evaluate the adoption of measures of management from Decision and Coordination Cell (DCC). The ATFMU and the DCC are tactical and strategic planning sections, respectively inside the CGNA.

With the CNS/ATM, the ATFM is meso and micro management, but for that the operational data must be shared between the stakeholders, and the Airport Collaborative Decision Making (A-CDM) is an example of what can be made by a robust System Wide Information Management (SWIM) concept (ACI-EU, 2017).

The SWIM is been developing by Brazilian Air Force, universities and stakeholders. Meanwhile, using Brazilian Civil Aviation Authority (ANAC)'s data. Air traffic movement was predicted by Flight Information Region (FIR) for the next 5 years by using a macroeconomic conditional estimative. In addition, there is a discussion about Brazilian air capacity model, with an empirical equation to predicted demand at one ATC sector and based on operational restrictions.

FIR is an airspace macroregion with defined dimension, where are provided Flight Information Service (FIS) and Alert Service (AS). At Brazilian Air Space there are 5 FIRs: Amazonia, Brasília, Curitiba, Recife and Atlantic.

From 2008 to 2017, the highest growth in aircraft movements was between the Recife and Amazon Regions, with an average of 16.9% per year. Within the Curitiba FIR, there was an average reduction of 4.28% per year in the aircraft movement, being the only region with a movement retraction. On average, air traffic in Brazil grew by an average of 5.6% per year (ANAC, 2018).

The increase in air transportation demand causes congestion, one of the central issues in air traffic management (ATM) systems, problems in safety, workload and to reduce airport congestion delays, where the incoming and outgoing traffic is concentrated (Hong *et al*., 2018). A strategic planning for the next 5 years, might be helpful to adequate the optimal aeronautical infrastructure and human resources.

2. LITERATURE REVIEW

2.1 Air traffic demand forecast

The air traffic demand analysis is part of airport and air space planning, which indicates its capacity to use. It is also important for the development of infrastructure and for reducing operational risk. In addition, peak demand periods require particular management to meet

the atypical demand, such as terminal capacity and runway utilization. Air traffic demand can be affected by internal factors and external factors (Lynesis, 2000), which are essential for business decisions. As external factors, there are the GDP and the population, while the fare represents an internal factor, for example.

Rolim *et al*. (2016) developed an empirical model of passenger demand for airports routes to investigate the privatization process impact over traffic. They perform an econometric analysis employing a regression-based methodology for fixed effects, using price endogeneity in a sample. The objective was to identify patterns of demand at privatization and post-privatization, that could interfere in the airport governance. Recent Brazilian privatization was analysed and recognized an overall increase in demand produced by the privatization. They aimed to fill the literature gap of the *ceteris* paribus privatization impact on demand.

The presence of low cost carrier (LCC) is an important case for demand, as well as price. They nominate as key drivers of long run impact on passenger demand, the airport capacity, airport regulation and its efficiency. Monthly data of all domestic routes from January 2003 to December 2013 were used. The parameters used were daily passenger (PAX), the product of the gross domestic product (GPD) per capita of origin and destination cities; product of population of origin and destination cities, yield, presence of LCC, privatization stage as a dummy variable (Rolim *et al.*, 2016).

Escobari (2014) found that the consumers' purchasing behaviour changes near the departure date. Therefore, they become more price sensitive. The model used captures sales during and specific period relative to the aircraft size, number of days prior to departure and posted fare.

Escobari (2009) shows that carriers charge higher fares in periods of known peak demand, using empirical support to estimate a congestion premium. The variables were fare, a dummy variable for thanksgiving period, ratio of occupied aircraft seats, number of days between the departure and the day the fare was recorded, and another dummy variable to flights on Tuesdays.

Suryani *et al*. (2010) discussed ways to model PAX demand forecasting and evaluate some politics scenarios for runway expansion and terminal capacity. In this way, a dynamic network system was used in a scenario modeling, since it represents physical and information flows. Thus, important characteristics are found in the volume of passengers, such as the impact of airfare, service level, gross domestic product (GDP), population, number of flights per day and length of stay. In addition, the demand can also interfere in the level of the runway use and additional area for the passenger terminal.

The population scale is determinant in air traffic demand (Jifeng *et al.*, 2008). Miller and Clarke (2007) consider the impact of tariff and service level as internal variables, using concepts of elasticity of time and price.

Bafail *et al*. (2000) developed a model to predict long-term future demand. The variables used in this study were: total expenditures and population using data from Saudi Arabia. Population data was also used by Grosche *et al*. (2007), besides used other variables such as GDP and purchasing power index.

While Yamaguchi *et al*. (2001) analyzed the economic impact of airport deregulation expansion in the domestic market in Japan. In this sense, the expansion of airport capacity was expanded to attend the increase in demand.

Alves *et al*. (2011) sought to find in Brazil the relationship between demand for air tickets with prices, fuel prices and GDP, based on data from companies that carry at least 85% of the passengers, evidencing the high concentration in this sector.

They conclude that economic growth is a key factor to pressure airport capacity. Therefore, the predominance of passengers in business in domestic transportation makes the price variable less significant when making long-term projections. For this, a vector model with error correction (VECM) was used, adding time series to obtain the relations between the variables under study and to use the elasticities to predict the demand.

Meyn (2002) present the use of probabilistic methods to forecast demand. The usual methods are deterministic for utilizing location predictions of each aircraft, as precise values. So, the Monte Carlo simulations demonstrate that this method produce 15% to 20% lower standard deviations then the results of deterministic methods. To achieve this reduction,

the uncertainty in arrival-time prediction should be reduced in 25 to 35%.

To forecast demand at the Rhodes Airport, Profillidis (2000) used econometric and fuzzy methods. A priori, it was analyzed the relationship between the economic activity and the economic activity, and then using of appropriate models for the tourist's seasonal demand.

In addition, survey results and statistical methods were used. Forecasting demand is essential for long-term planning. In general, there are three main biases for demand forecasting: market surveys, trend projections and econometric relationships. Recently linear fuzzy or nonlinear regression has been used also.

Samagaio & Wolters (2010) evaluated official passenger forecasts for Lisbon, using auto-regression models and exponential smoothing models. From this, he concludes that the official government forecasts are overly optimistic and consider only the final forecast time.

In this way, the objective was to obtain a more realistic from 2008 to 2020, using non-causal models. To find trend and seasonal characteristics the Holt-Winters model was used. Then, this index was included in a linear model.

Another variable related to the demand can be credit concessions. Miranda and Oliveira (2016) investigated the relationship between the increase in air transport demand and the credit concessions in Brazil through their correlation.

It resulted a positive impact on the number of trips, mainly the "credit card" mode. The study included six types of credit for individuals and eleven for legal entities, adding up the values of the different types of fees. Note that credit has a greater influence on demand than the average ticket price itself.

3. METHODOLOGY

The present model uses the technique of Generalizes Method of Moments (GMM) to estimate the unknown parameter at air traffic demand predication and an unconditional analysis, both by a Flight Information Region's Origin/Destination matrix. This method tends to produce more informative about the aleatory variance at instrumental variables.

3.1. Model description

The model consists in predict the number of aircraft (A), endogenous variable, correlated with operational (W) and economic (Z) exogenous variables. The GMM was applied using the Two-Stage Least Squares to estimating the weighting matrix and Ordinary Covariance weighting matrix as a default adjustment.

$$A_{ij} = \beta_0 + \beta_1 W_{\dots} + \beta_{\dots} Z_{\dots} + \varepsilon \quad (1)$$

The t-test verifies the probability of there being differences between the degrees of freedom of the variables. For the application of this test in a simple regression, the formula of the difference between variables with the average divided by the standard error of this group is used. For multiple regressions, this test is found from the difference between the variables with the mean divided by the root of the variance of that group. The closer to 1 is the result, the better the similarity between the groups of regression variables (WOOLDRIDGE, 2010).

The p-value is the probability that the statistical hypotheses are repeated in the extreme values of the t-test, if the errors are normally distributed. This indicator is used to verify whether a hypothesis can be accepted or rejected within a level of significance (WOOLDRIDGE, 2010).

The coefficient of determination R-square (R^2) demonstrates how one variable adjusts according to another. The R^2-adjusted ($R^{-}\wedge 2$) indicates how reliable the model is if more variables are added within the regression function, if these new variables are not explanatory to the model (HILL et al., 2010).

The Durbin-Watson Statistics indicator measures the autocorrelations in the regression residuals. The scale of this parameter ranges from 0 to 4 and to be accepted it must be greater than R^2, and if less than 2, the better the evidence of a positive correlation (WOOLDRIDGE, 2010).

For the unconditional analysis, the logarithm function (2), the power function (3) and the exponential function (4) are used to predict these variables. The method consists in comparing the projections with the actual values, and can make three scenarios (optimistic,

weighted and pessimistic) according to the dispersion of the results. Or the projection closest to the real can be used as the response parameter

$$Y = a + x * \ln b \quad (2)$$
$$Y = a * x\hat{}b \quad (3)$$
$$Y = a * \exp(b * x) \quad (4)$$

Where: *Y*: dependent variable (demand);
x: series count;
a: linear coefficient (intercept); e
b: angular coefficient.

4. APLICATION

4.1. Data acquisition

The economic, financial and operational values were organized monthly. The table with the data used for this application can be found at the following address:

https://goo.gl/82TrEc

From the literature review, was selected the monthly GDP (BRL millions), BRL to US$ and the airline ticket price (ANAC, 2018; BCB, 2018). ANAC data informs the airline ticket prices (TKT) and the number of seats sold, by origin and destination, in one month. Other table with the name ICAO Airport codes and the FIR where the airport is located, was linked to a new query at MS Access™. After that, was used the Power Pivot, an extension for MS Excel™ to find the weighted average price for each route by month. The data has been organized into an origin and destination matrix.

The same process to link the name ICAO Airport codes and the FIR where the airport is located, was made to find Aircraft (A) movement and PAX in an O/D matrix.

With O/D movement in Brazil, there the FIRs to SBAZ, SBBS, SBCW and SBRE. The data nomenclature at database for Aircraft (A), PAX, TCKT and FIR is VARIABLE_ORIGIN_DESTINATION.

For statistic application, was used the IHS EViews® 9.

4.2. Results

The Table 1 shows the results of the conditional estimative finds by GMM. Only for A_SBAZ_SBAZ, is a good correlation, for the others the R^2 is considered as very good, as well for R^2-Adjusted were in all results are very close to the R^2.

All angular coefficients for the average price of airline ticket are negative, indicating that there is a reduction in passenger demand as the price increases.

The estimated linear coefficients (t-test) are scattered from 1, also given by the large difference between the coefficients and the standard error. Next to 0,5, are the variables A_SBAZ_SBRE, A_SBRE_SBAZ, A_SBRE_SBBR and SBRE_SBCW.

The p-value is closer to 0 for the majority dependent variables, showing that is possible to occur again the given event. The null hypothesis is rejected for A_SBAZ_SBRE and A_SBRE_SBAZ.

The Durbin-Watson is smaller than the R^2 in A_SBAZ_SBAZ, A_SBAZ_SBBS, A_SBBS_SBBS and A_SBAZ_SBRE, for these the regression results are spurious. For others, the results are closer to 1, that shows a correlation next to the real condition.

The angular coefficient for PIB is negative between the FIRs A_SBBS_SBBS, SBBS_SBCW, A_SBBS_SBCW, A_SBCW_SBBS, A_SBCW_SBCW and A_SBRE_SBRE, shows that there may be a growth in the movement of aircraft even with the fall in GDP.

The Table 2 shows the unconditional estimative, using the exponential, logarithm and power analysis. The first one, results in a pessimistic scenario, with the average grow rate of 0,66% per year. In this scenario, the movement might decrease at A_SBAZ_SBAZ (-0,01%) and A_SBCW_SBCW (-0,05%). The highest grow rate in this case is at A_SBAZ_SBRE (1,05%). At second scenario, conservative, the average grow rate is 0,82% per year, with a decrease at movement at the same areas as in the first scenario. In the last scenario, optimistic, the average grow rate is 2,81% per year.

Table 1: Air traffic prediction using GMM

Dependent variable	Coefficient					R^2	R^2 Adj.	Durbin-Watson
	C	PAX_	GDP	TKT_	US$			
	Std. Err	Std. Err	Std. Err	Std. Err	Std. Err			
A_SBAZ_SBAZ	5962.412^{+++}	0.005196^{+++}	0.003074^{+++}	-4.720429^{+++}	-1005.076^{+++}	0.61	0.59	0.37
	855.9371***	0.001236***	0.001569***	2.541540***	202.6835***			
A_SBAZ_SBBS	660.7449^{+++}	0.007724^{+++}	0.000282^{+++}	-0.358905^{+++}	-101.5678^{+++}	0.90	0.90	0.80
	57.21149***	0.000357***	0.000223**	0.152026***	18.57202***			
A_SBAZ_SBCW	523.9162^{+++}	0.005218^{+++}	0.000783^{+++}	-0.323267^{+++}	-106.7544^{+++}	0.76	0.75	1.13
	84.12445***	0.000525***	0.000263***	0.126126***	25.19234***			
A_SBAZ_SBRE	5.452015^{+}	0.007555^{+++}	0.000366^{+++}	-0.044087^{+}	-23.46037^{+++}	0.89	0.89	0.94
	30.50463*	0.000333***	0.000009***	0.085979*	9.736237***			
A_SBBS_SBAZ	698.1688^{+++}	0.007633^{+++}	0.000513^{+++}	-0.566406^{+++}	-109.0015^{+++}	0.88	0.88	1.02
	66.00892***	0.000437***	0.000266***	0.176783***	20.97117***			
A_SBBS_SBBS	5316.944^{+++}	0.011601^{+++}	-0.007519^{+++}	-7.263936^{+++}	305.3208^{+++}	0.85	0.84	0.68
	278.5139***	0.000816***	0.001437***	1.112735***	131.7820***			
A_SBBS_SBCW	3646.147^{+++}	0.010492^{+++}	-0.006894^{+++}	-3.824182^{+++}	223.6960^{+++}	0.95	0.95	1.56
	246.8192***	0.000276***	0.000626***	0.610166***	65.07593***			
A_SBBS_SBRE	1705.858^{+++}	0.007345^{+++}	-0.000149^{++}	-1.376315^{+++}	-168.7397^{+++}	0.94	0.94	1.21
	92.25724***	0.000239***	0.000293*	0.202300***	29.69941***			
A_SBCW_SBAZ	604.1386^{+++}	0.005541^{+++}	0.000600^{+++}	-0.424787^{+++}	-100.8126^{+++}	0.63	0.61	1.68
	117.5105***	0.000836***	0.000384**	0.170057***	34.43379***			
A_SBCW_SBBS	34.11661^{+++}	0.010030^{+++}	-0.005432^{+++}	-3.686532^{+++}	179.4401^{+++}	0.95	0.95	1.75
	283.9562***	0.000256***	0.000595***	0.690941***	67.99316***			
A_SBCW_SBCW	15425.32^{+++}	0.008993^{+++}	-0.022719^{+++}	-6.123153^{+++}	-344.0223^{+++}	0.94	0.94	1.35
	786.2222***	0.000225***	0.001456***	1.827716***	167.6915***			
A_SBCW_SBRE	2273.010^{+++}	0.005424^{+++}	0.000054^{+}	-0.921840^{+++}	-200.7582^{+++}	0.90	0.90	1.39
	170.4414***	0.000185***	0.000425*	0.292001***	50.54940***			
A_SBRE_SBAZ	-15.05461^{+}	0.008389^{+++}	0.000181^{+++}	0.046449^{+}	-11.65954^{+++}	0.91	0.91	1.36
	38.08617*	0.000291***	0.00009*	0.107375**	10.79630**			
A_SBRE_SBBS	1489.194^{++}	0.006455^{+++}	0.001217^{+++}	-1.210575^{+++}	-219.1780^{+++}	0.89	0.89	1.28
	139.1820***	0.000327***	0.000388***	0.323352***	41.18352***			
A_SBRE_SBCW	2126.474^{++}	0.005202^{+++}	0.000856^{+}	-0.923502^{+++}	-227.7368^{+++}	0.87	0.87	1.36
	207.1334***	0.000216***	0.000479***	0.368761***	57.34558***			
A_SBRE_SBRE	6694.627^{+++}	0.005618^{+++}	-0.000245^{+}	-9.447744^{+++}	-476.7592^{+++}	0.76	0.75	0.68
	407.1155***	0.000701***	0.000889**	1.331995***	98.78072***			

$^{+}$ t-test < 0,5; $^{++}$ t-test ≅ 1; $^{+++}$ t-test > 1,5, *p-value < 1; **p-value < 0,5; ***p-value < 0,1; positive and negative values.

Table 2: Air traffic prediction using unconditional analysis.

Dependent variable	Pessimistic	R^2	Conversative	R^2	Optimistic	R^2
	Equation		Equation		Equation	
A_SBAZ_SBAZ	-0,01%	0,00	-0,11%	0,00	2,43%	0,08
	y = -3,89739ln(x) + 4.754,82727		y = 4.908,91048x-0,01569		y = 5.217,61346e-0,002x	
A_SBAZ_SBBS	1%	0,46	1,09%	0,48	4,24%	0,32
	y = 232,01527ln(x) + 714,20445		y = 859,30208x0,15725		y = 1.269,79401e0,00346x	
A_SBAZ_SBCW	0,85%	0,4	1,14%	0,5	4,30%	0,23
	y = 166,72161ln(x) + 491,98986		y = 588,81425x0,16440		y= 891,46414e0,00351x	
A_SBAZ_SBRE	1,05%	0,25	1,35%	0,29	6,08%	0,26
	y = 80,55460ln(x) + 116,00920		y = 190,72564x0,19423		y = 297,17442e0,00492x	
A_SBBS_SBAZ	0,91%	0,52	1,22%	0,58	5,03%	0,43
	y = 258,49174ln(x) + 631,29401		y = 810,91419x0,17517		y = 1.235,07325e0,00409x	
A_SBBS_SBBS	0,69%	0,2	0,89%	0,22	1,80%	0,04
	y = 652,24644ln(x) + 3.144,57084		y = 3.345,20834x0,12853		y = 4.991,83768e0,00149x	
A_SBBS_SBCW	0,71%	0,29	0,90%	0,28	2,27%	0,07
	y = 890,05802ln(x) + 4.057,31177		y = 4.422,51912x0,13040		y = 6.495,23738e0,00187x	
A_SBBS_SBRE	0,87%	0,45	1,22%	0,53	4,35%	0,30
	y = 445,68164ln(x) + 1.256,60354		y = 1.478,69118x0,17545		y = 2.329,54739e0,00355x	
A_SBCW_SBAZ	0,87%	0,36	1,09%	0,24	3,73%	0,12
	y = 169,46968ln(x) + 481,43068		y = 599,85621x0,15644		y = 905,76527e0,00305x	
A_SBCW_SBBS	0,68%	0,23	0,83%	0,2	1,66%	0,03
	y = 831,17158ln(x) + 4.220,05294		y = 4.560,94224x0,11927		y = 6.617,71212e0,00137x	
A_SBCW_SBCW	-0,05%	0	-0,20%	0,01	-3,16%	0,12
	y = -124,04838ln(x) + 19.630,84902		y = 20.866,92863x-0,02944		y = 21.932,29024e-0,00268x	
A_SBCW_SBRE	0,49%	0,16	0,52%	0,1	1,07%	0,02
	y = 363,56540ln(x) + 3.236,13548		y = 3.404,60288x0,07487		y = 4.292,06961e0,00089x	
A_SBRE_SBAZ	1,06%	0,17	1,21%	0,2	5,62%	0,19
	y = 84,80836ln(x) + 117,93070		y = 211,57200x0,17440		y = 312,29288e0,00456x	
A_SBRE_SBBS	0,90%	0,5	1,27%	0,57	4,79%	0,35
	y = 473,41983ln(x) + 1.184,49616		y = 1.450,07397x0,18346		y = 2.306,74918e0,00390x	
A_SBRE_SBCW	0,53%	0,2	0,60%	0,18	1,62%	0,05
	y = 395,02772ln(x) + 3.135,26179		y = 3.286,51027x0,08613		y = 4.210,64004e0,00134x	
A_SBRE_SBRE	0,18%	0,02	0,17%	0,01	-0,94%	0,02
	y = 143,13924ln(x) + 4.609,85071		y = 4.620,52825x0,02463		y = 5.325,08800e-0,00079x	

5. CONCLUSION

A consistent forecast demand can contribute for planning, strategically, the air navigation procedures, as described at Brazil (2017). With the estimated number of aircraft, the optimal financial and human resources might be allocated, to attend the required or increase the safety level.

The proposed model applied in this paper, using the GMM found different equations for each origin and destinations FIRs. There is a significative statistic result, where the p-values are closer to 0 and the null hypothesis were rejected.

For unconditional estimative, for the most FIRs at O/D matrix, the R^2 is very low. The estimated average grow rate for the next 5 years is 0,66, 0,92% and 2,81% per year for a pessimistic, conservative and optimistic scenario, respectively.

The prediction by FIR is an innovative prediction and could be used to explain the meso and macro-economic scenario in Brazil. In the matrix of origin and destination, it is possible to identify that the Regions of Flight Information that historically have greater demands, are with less flights, on the other hand, in the regions of flight information of the north and northeast of the country are busier. A correlation with the number of aircraft for domestic flight could be made to verify if they are new aircraft or whether there has been a reallocation in the airline network.

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