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Forecasting airline demand in Brazil: performance of models

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Abstract

This paper aims to analyze the effectiveness of domestic airline passenger demand forecasting methods for three of the most important airports in Brazil. For this purpose, univariate models are tested, which serve as benchmarks for the analysis, including naïve forecasts, autoregressive integrated moving average (ARIMA) with the seasonal component, and Holt-Winters (HW) exponential smoothing. More recent approaches are also considered, such as autoregressive neural networks (ARNN), Bootstrap aggregation (bagging), and model combination techniques. The data cover the period from January 2000 to January 2014 with monthly frequency. To capture the dynamics of the Brazilian economy and the supply-side factors for the airline industry, an autoregressive distributed lag model (ARDL) is used. The results indicate that all models provide accurate forecasts, but there was no winning method with consistent results for all different airports or forecast horizons in this study, which aligns with the forecasting literature.

Keywords: Forecasting, Machine Learning, Econometrics, Airline forecasts.

JEL Classification: C13, C45, C53, C82.

1. Introduction

The number of air passengers in Brazil has increased steadily during the last decade as a consequence of the consolidation and competition of airline companies, an increase in family income, and access to credit. In this context, accurate airport traffic demand forecasts serve as essential information for planning on expanding infrastructure investments of airport capacity, economic viability of new airports, planning, and development of existing airports, and for tourism prediction.

Several studies use time series models to forecast air passenger flow. Emiray & Rodriguez (2003), Oh & Morzuch (2005) and Chu (2009) argue that the forecasting performance of each model varies depending on the location of the airport, the nature of the flight (domestic or international), the performance measure used, and the forecasting horizon. A stylized fact in the literature states that no methodological approach has proved to be dominant in terms of forecasting performance out-of-sample.

Most tourism forecasting studies apply univariate models due to the lack of understanding of the exogenous factor associated with the problem. Song & Li (2008) argue that autoregressive integrated moving averages with a seasonal component, naïve approaches, and exponential smoothing are popular time series analysis methods. However, given that air transportation demand is highly linked to economic activity, which is typically characterized by business cycles that could likely modify past trends and bring volatility in the data, causal models are of particular interest as well. This is a characteristic of the Brazilian economy, especially after 2015 when the worst

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economic recession in the country's history started, undoubtedly affecting the seasonal patterns and short-term trends.

Jiao & Chen (2019) reviewed 72 studies in tourism demand forecasting during the period from 2008 to 2017, covering econometric, time series, and artificial intelligence (AI) models. The Authors argue that due to the increasing attention to the importance of tourism forecasting, many empirical works focus on developing forecasting techniques to improve forecasting accuracy.

Gilliland (2020) explores the impact of machine learning methods on forecasting and discusses the contributions of competition to the development of new approaches. The author states that for over 50 years, there is been uncertainty about whether technological and methodological advances have delivered any value for forecasting. He argues that under certain circumstances, simpler methods are still competitive with sophisticated ones, mostly related to the low level of computational time required compared to AI methods.

Hyndman (2020) reviews the history of forecasting competitions and discusses their contributions. The author comments on the Makridakis competition, the most renowned one, from its first edition in 1979 to the latest (M4 competition) in 2018. Hyndman (2020) presents the methodological evolution in terms of winner models from simple exponential smoothing variations in the first competition to more sophisticated techniques that include the combination of models and AI ones.

In terms of performance evaluation, combination forecasting techniques have become popular in the forecasting literature to improve forecasting performance and to control for the uncertainty of relying exclusively on a single model. In the tourism forecasting literature, Shen et al. (2008), Coshall (2009), and Shen et al. (2011) state that single model combinations are generally found to outperform the specific models being combined, independently of the time horizon considered. However, these results are sensitive to the combination technique as well as other regional characteristics. Wong et al. (2007) state that the best performance is likely to be achieved by combining two or three single forecasts at most.

Thus, this paper seeks to measure the efficiency of forecasting models for Brazilian air passengers at the three most important airports in the country, located in the states of São Paulo, Rio de Janeiro, and the Federal District. Various univariate models like Seasonal Autoregressive Integrated Moving Average (SARIMA), exponential smoothing, and naïve approaches are performed as benchmarks. We include a causal model to evaluate the impact of selected macroeconomic variables in the passenger's prediction problem in addition to including an analysis of an auto-regressive neural network model, following the steps of Hyndman (2018), and a bagging (bootstrap) approach.

All models were estimated using 14 years of monthly data. Mean absolute percentage error (MAPE) and root mean squared error (RMSE) are used as measures of forecast accuracy in post-sample forecasts. Our results indicate that all models provide accurate forecasts, and most of the models adequately passed the specification tests (for parametric methods) and captured the main statistical characteristics of the domestic passenger series.

In addition to this introduction, the work has four more sections, where section 2 presents the methods used in the methodology, section 3 explains the database considered and presents the results, and, finally, section 4 concludes.

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2. Methodology

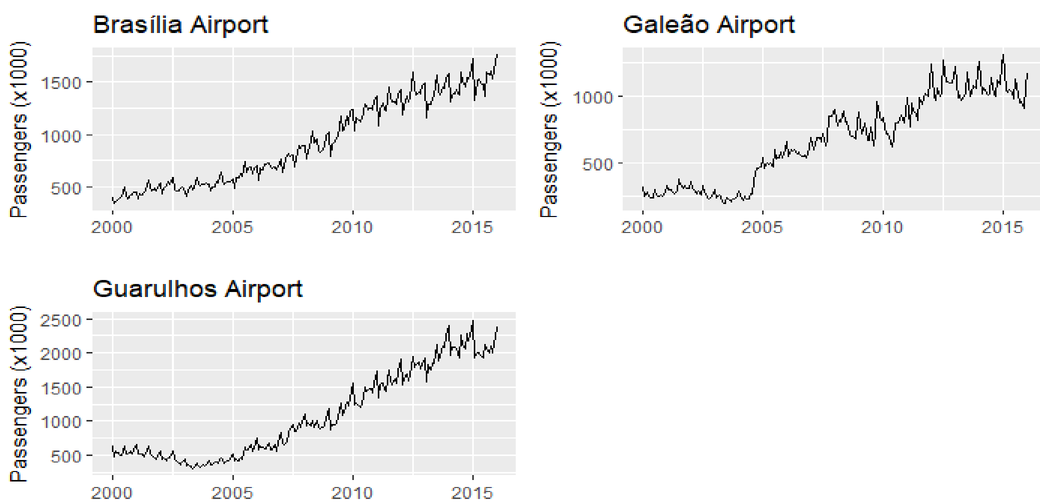
2.1 Data

Historical data for the Brasilia, Galeão, and Guarulhos airports were collected from the Brazilian civil agency Agência Nacional de Aviação Civil – ANAC and includes monthly passenger traffic as presented in Figure 1. All models were estimated on the training set from January 2003 to July 2014, summing up 163 observations. We saved the last 18 observations for a (pseudo) out-of-sample test set to measure the accuracy in post-sample forecasts for the period August 2014 to January 2016.

Figure 4 presents the passenger flow in each of the airports analyzed measured in level units. Seasonal analysis in Figure 5 shows expected patterns with an increase in demand in the winter and summer (school vacations). To smooth the seasonal variation with no information loss, we log-transformed the data for all modeling processes. To assess the forecasting performance, we compare several methods in terms of their passenger traffic forecasting performance, including the season naïve method.

The naïve methods are simple approaches to assess estimates through the replication of last observations, mostly used as a benchmark for other modeling strategies. The seasonal naïve variation uses the same last seasonal observation as an estimate of the forecasting value, which means that for monthly seasonality, the next estimate will be the observation from the same month of last year.

Figure 4. Monthly passenger flow for selected airports for domestic flights in Brazil



Source: Elaborated by authors.

To compare the predictive accuracy of the various combination methods, I make use of two forecasting performance criteria: MAPE (Mean Absolute Percentage Error) and RMSE (Root Mean Squared Error). These two criteria are widely used in the air passenger and tourism forecasting literature. Both error measures are based on the forecast error and have the advantage of being easy to interpret. They are calculated using the following formulas:

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(\hat{y}_t - y_t)^2}{n}} \quad (18)$$

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{y_t - \hat{y}_t}{y_t}\right| \quad (19)$$

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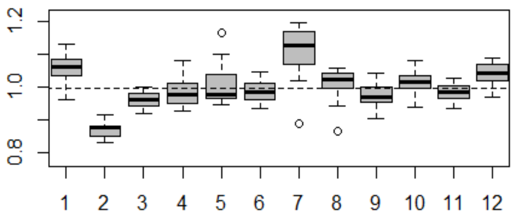
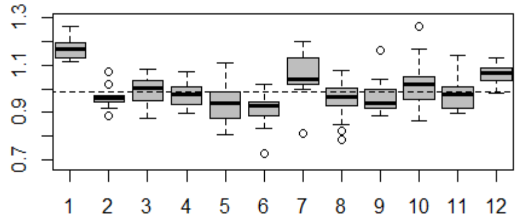
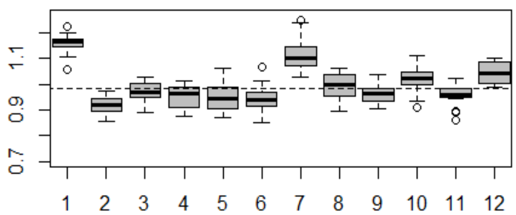
Figure 5. Seasonal patterns for airline demand



a) Brasília airport



b) Galeão airport



c) Guarulhos airport

Source: Elaborated by authors.

2.2 Forecasting methods

To forecast the monthly passenger flow, we estimated univariate models for forecasting the number of air passengers departing from three Brazilian domestic airports. The estimations were treated individually, and no distinction was made regarding the origin or destination at each airport. To evaluate the forecasts, this study uses 24 monthly observations from February 2014 until January 2016 that were treated as unknown and used to compare the point predictions with the actual values.

As a forecasting strategy, we use seasonal Naïve estimations and the seasonal ARIMA model known as the Airline model, which is a (0,1,1)(0,1,1) Arima model as benchmarks for the accuracy of other models described in the following section.

2.1 Seasonal Auto-Regressive Integrated Moving Average (SARIMA)

Auto-Regressive Integrated Moving Average (ARIMA) has become one of the conventional parametric forecasting approaches since the 1970s with the influential work of Box and Jenkins (1970). Also, with the characteristics of seasonality and trends in traffic data, some researchers use seasonal ARIMA to predict traffic flow (Williams, Hoel 2003; Tan et al. 2009) and international air passenger flow (Faraway and Chatfield 1993; Lim and McAleer 2002; Chen et al. 2009).

Like the widely used ARIMA model, the seasonal autoregressive-integrated-moving average model, SARIMA, is a more flexible model that accounts for stochastic seasonality. Such seasonality is present when the seasonal pattern of a time series changes over time. In such a case, the time series will contain a seasonal unit root and will need to be seasonally differentiated. This will be done through the seasonal difference parameter. If this parameter equals zero, then the seasonal pattern exhibited by the time series is relatively stable over time and can be modeled uniquely through the seasonal autoregressive and moving average terms.

The generalized multiplicative SARIMA model for a series Y_t can be written as:

$$\phi(L)\,\Phi(L^s)\,\Delta^d\,\Delta_s^D\,Y_t = \theta(L)\,\Theta(L^s)\,\varepsilon_t \quad (1)$$

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Where:

$$\phi(L) = 1 - \phi_1 L - \phi_2 L^2 \ldots - \phi_p L^p \tag{2}$$

$$\Phi(L^s) = 1 - \Phi_1 L^s - \Phi_2 L^{2s} \ldots - \Phi_P L^{Ps} \tag{3}$$

are, respectively, the non-seasonal and seasonal AR polynomial terms of order *p* and *P*.

$$\theta(L) = 1 + \theta_1 L + \theta_2 L^2 \ldots + \theta_q L^q \tag{4}$$

$$\Theta(L^s) = 1 + \Theta_1 L^s + \Theta_2 L^{2s} \ldots + \Theta_Q L^{Qs} \tag{5}$$

are the non-seasonal and seasonal Moving Average (MA) parts of order *q* and *Q*, respectively:

L : is the backward shift operator

$\Delta^d = (1 - L)^d$: is the non-seasonal differencing operator

$\Delta_s^D = (1 - L^s)^D$: is the seasonal differencing operator

$d \ and \ D$: are the non-seasonal and seasonal orders of differences, respectively. The order d is used to eliminate polynomial stochastic trends and the order *D is* used to eliminate seasonal patterns.

ε_t: is a white noise sequence; $E(\varepsilon_t) = 0$; $Var(\varepsilon_t) = \sigma^2$ and $cov(\varepsilon_t, \varepsilon_\tau) = 0$ for all t and $t \neq \tau$.

The seasonal ARIMA model is usually abbreviated as $SARIMA\ (p, d, q)(P, D, Q)s$ where the lowercase notation (p, d, q) represents the part non-seasonal of the model and the uppercase notation (P, D, Q) for the seasonal parts of the model and s is the length of the periodicity (seasonality). When there is no seasonal effect $s = 0$, and so $\Phi(L^s) = 1$ and $\Theta(L^s) = 1$. In this case, a SARIMA model reduces to pure ARIMA (p, d, q). When the time series dataset is stationary $d = 0$ and a pure ARIMA reduces to ARMA(p,q).

2.2.1 Holt-Winters Exponential Smoothing

The Holt-Winters (HW) method is a recursive procedure of a broad class of exponential smoothing techniques that have become particularly useful due to the fluctuation reduction on the irregular component in the observed time series, as presented by Lim & Mcaleer (2001). HW is an easy approach for forecasting by decomposing the series in level, trend, and seasonal pattern, and there are two main versions for the procedure, considering the additive or multiplicative pattern of the seasonal component. Coshall (2009) argues that the main question is to address the weight to be attributed to past observations, with the likelihood being that more recent readings have more influence on future forecasts.

Following Kalekar (2004), the additive version is preferred when the seasonal component has a constant amplitude over time, and the series can be written as:

$$y_{t+h} = a_t + b_t t + s_{t-m+h_m^+} \tag{6}$$

Where a represents the level of the series, b the slope, s the seasonal coefficient of the series at time t. In the expression, h represents the forecasting horizon, m denotes the frequency of the seasonality (12 for monthly data) and $h_m^+ = [(h - 1) \bmod m]$. The parameters can be computed following the expressions:

$$a_t = \alpha(y_t - s_{t-m}) + (1 - \alpha)(a_{t-1} + b_{t-1}) \tag{7}$$

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$$b_t = \beta(a_t - a_{t-1}) + (1-\beta)b_{t-1} \tag{8}$$

$$s_t = \gamma(y_t - a_{t-1} - b_{t-1}) + (1-\gamma)s_{t-m}$$

The multiplicative approach has better results when the seasonal pattern presents a varying amplitude. In such a case, the series can be represented as follows:

$$y_t = (a_t + b_t t)s_{t-m+h_m^+} \tag{9}$$

$$a_t = \alpha \frac{y_t}{s_{t-m}} + (1-\alpha)(a_{t-1} + b_{t-1}) \tag{10}$$

$$b_t = \beta(a_t - a_{t-1}) + (1-\beta)b_{t-1} \tag{11}$$

$$s_t = \gamma \frac{y_t}{a_{t-1} - b_{t-1}} + (1-\gamma)s_{t-m} \tag{12}$$

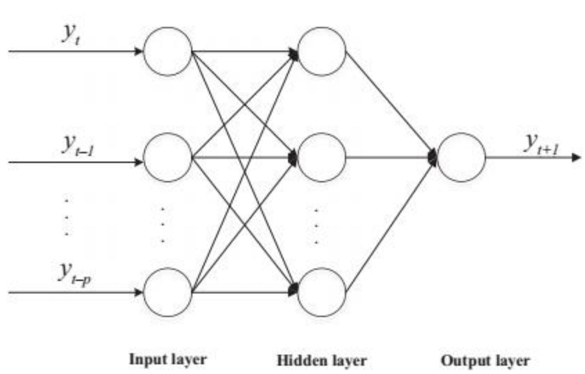
Parameters α, β and γ are smoothing parameters (weights) for the level, trend, and seasonal components respectively. All three parameters lie in [0,1] intervals and can be interpreted as discounting factors: the closer to 1, the larger the weight of the recent. Cho (2003) also mentions that the closer the parameter is to 0, the more the related component is constant over time. Optimal values for the three parameters are obtained by minimizing the squared one-step ahead forecast errors.

2.2.2 Auto Regressive Neural Networks (ARNN)

Neural Networks (NN) models with hidden layers are a class of general function approximations capable of modeling nonlinearity for a variety of practical applications. This approach has gained popularity as an emerging computational method to explore the dynamics and complexity of data.

Since these networks contain many interacting nonlinear neurons in the multiple layers, the networks can capture relatively complex relationships and phenomena. For a univariate time series forecasting problem, the networks' inputs are the past lagged observations of the data series and the outputs are the future forecasted values. Each input vector has a moving window of fixed length along with the sample datasets, as presented in Figure 1.

Figure 1. Structure of Auto-Regressive Neural Networks



Source: Elaborated by authors.

The nonlinear relationship between the series output (y_t) and the auto-regressive inputs

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$(y_{t-1}, y_{t-2}, \dots, y_{t-p})$ has the following representation:

$$y_t = \alpha_0 + \sum_{j=1}^{q} \alpha_j g\left(\beta_{0j} + \sum_{i=1}^{p} \beta_{ij} y_{t-i}\right) + \varepsilon_t \qquad (13)$$

Where α_j and β_{ij} are the connection weight p is the number of input nodes and q is the number of hidden nodes. The logistic function is often used as the hidden layer transfer function g(.), as follows:

$$g(x) = \frac{1}{1 + \exp(-x)} \qquad (14)$$

To address the overfitting specification effect that commonly appears in neural network models, Zhang (2001) points out that a small number of hidden nodes is preferred for forecasting purposes, avoiding an excessive number of parameters estimation that can lead to a good fit in the training sample, but a poor performance for out-of-sample data.

I use the Hyndman (2018) specification for seasonal problems denoted by $\mathrm{NNAR}(\mathrm{p}, \mathrm{P}, \mathrm{k})_{12}$, which uses one hidden layer with k nodes, p lagged inputs for the level component and P lagged inputs for the seasonal component. The author exemplifies that an $\mathrm{NNAR}(3,1,2)_{12}$ model has as inputs $(y_{t-1}, y_{t-2}, y_{t-3})$, and (y_{t-12}), and two neurons in the hidden layer. The default values are $p = 1$ and p is chosen from the optimal linear model fitted to the seasonally adjusted data.

2.2.3 Auto Regressive Distributed Lag (ARDL)

General-to-specific modeling technique to specify reduced ARDL has been used commonly because it does not make many a priori assumptions on the model specifications. This approach involves creating a general demand model that has several explanatory variables, plus the lagged dependent and lagged explanatory variables.

Shrestha & Bhatta (2017) explain that an ARDL model is an ordinary least square (OLS) base model that is applicable for both non-stationary time series as well as for times series with mixed order of integration.

Then, ARDL models require the use of sufficient numbers of lags to capture the data-generating process in a general-to-specific modeling framework. Some examples in tourism demand forecasting include Dritsakis and Athanasiadis (2000), Ismail, Iverson, and Cai (2000), Song, Wong, and Chon (2003), Lim (2004), and Croes and Venegas (2005). The general model can be written as:

$$y_t = \alpha_0 + \sum_{i=1}^{p} \gamma_i \, y_{t-1} + \sum_{j=1}^{k} \sum_{i=0}^{q_j} \beta_{ji} \, x_{j,t-i} + \epsilon_t \qquad (15)$$

This study uses standard model specification $\mathrm{ARDL}(p, q_1, q_2, \dots, q_k)$, where p is the number of lags of the dependent variable, q_1 is the number of lags of the first explanatory variable, and q_k is the number of lags of the k-th explanatory variable. Several variables might influence the number of airline passengers and recent literature explores different aspects of geographic, economic, social, market, and regulatory factors.

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Looking for a parsimonious domestic airline model, we choose jet fuel price, exchange rate, and monthly GDP proxy (Brazilian Central Bank real activity index, IBC-BR index) as variables to explain the airline demand. GDP is a proxy for economic activity and credit conditions on the demand side. On the supply side, jet fuel prices (strongly correlated with oil barrel prices) and the exchange rate relate to the cost structure of airline companies. I also include monthly dummies to deal with the seasonality presented in the data. Considering the research interest in short-term forecasting, I do not further investigate the long-run (cointegrating) interactions between variables.

2.2.4 Bootstrap with Aggregation (Bagging)

Bootstrap aggregation (bagging) is a technique to reduce variance without increasing the bias of predictions to achieve more accurate predictions. In bagging, bootstrapped versions of the original data are generated (resampling the original data) and predictions for new data are achieved by averaging individual results. Put in simple terms, instead of having one single set of forecasts, bagging generates larger numbers of sets of forecasts from a model.

The main advantage of the use of Bagging is related to its simplicity and the increase in accuracy without the need for other explanatory variables. In this sense, all the arguments for the use of univariate models can be extended to the bagging approach, with all the benefits of the increase in the testing sample.

In this work, I follow the procedure proposed by Petropoulos et al (2018) where new versions of a series can be obtained by fitting an Exponential Smoothing or an Arima model to the series, and then generating new bootstrapped residuals to combine its original components of trend and seasonality. The procedure is shown in Figure 3.2.

In the first step, a Box-Cox transformation is applied to the data to stabilize the variance and to ensure that components of the time series are additive. The parameter λ of the transformation is chosen automatically and then a decomposition procedure is applied to the series

Finally, a bootstrapping procedure is applied to the remainder component to reconstruct a new series as a composition of previous components (trend, seasonal, and resampling random remainders. A simple but more formal description of the procedure is described by Athanasopoulos et al. (2018). Figure 2 shows a flowchart for generating bootstrapped series as described by Bergmeir et al. (2016) apud Petropoulos et al (2018).

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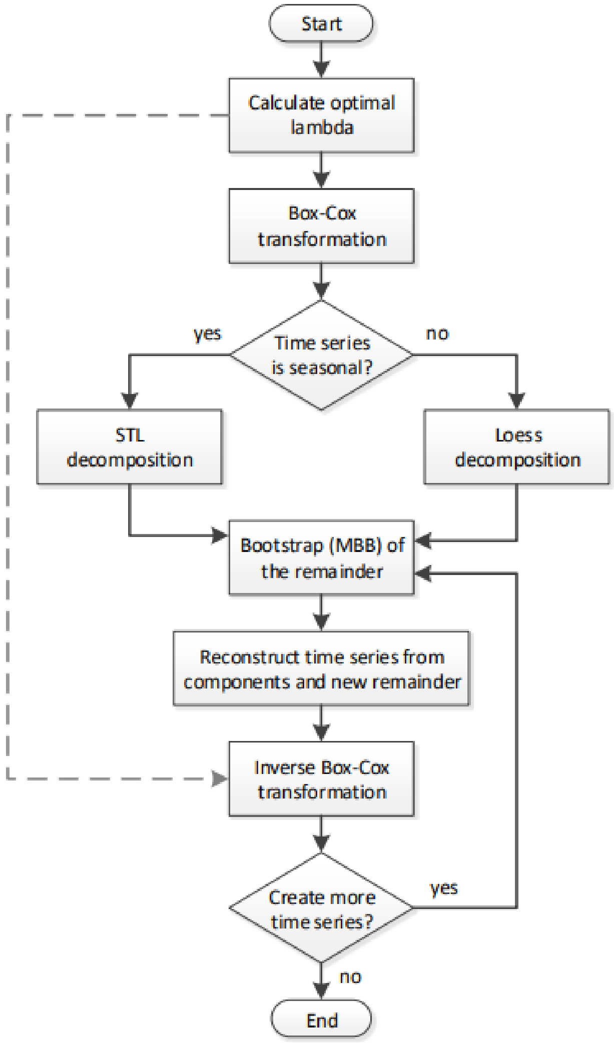
Figure 2. Flowchart for generating bootstrapped



Source: Elaborated by authors.

Figure 3 shows an example of a new series generated from the original passenger flow for the Brasilia airport. In this study, considering the forecasting purpose of the analysis and following other studies mentioned, we generated 100 new time series for each airport passenger flow to obtain a more accurate forecasting value for different time horizons.

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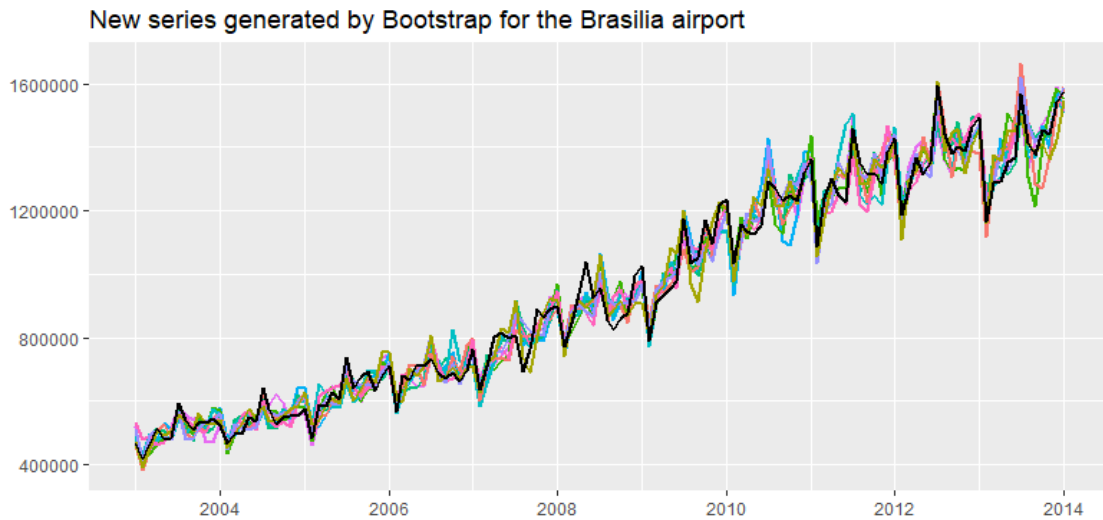
Figure 3. Example of new series generated by Bagging procedure for the Brasilia airport.



Source: Elaborated by authors.

2.2.5 Forecast Combination

In addition to the previous forecasting models presented, the use of forecasting combination techniques in tourism demand forecasting is common to utilize the specific advantages of various forecasting models. The combination forecasting technique is an effective forecasting method, following the seminal work of Bates & Granger (1969). Armstrong (2001) and Yu (2005) state that a combination forecasting model could generate a better forecast than a single one, considering some circumstances. The core idea of the combination forecasting methods is to combine various individual forecasts from multiple single forecasting models and then achieve a better-combined forecast.

Rapach et. Al (2010) recognizes the better results from model combinations and explores their advantages compared to the bagging approach. In the short-term tourism demand forecasting literature, Oh and Morzuch (2005) showed that the combined forecasts (based on the simple average) of four competing single time series models always outperformed the poorest individual forecast, and sometimes even performed better than the best individual forecast.

The combined forecast can be written in function on a weighted of the k models considered as:

$$y_t = w_1 f_{t(1)} + w_2 f_{t(2)} + \cdots + w_k f_{t(k)} = \sum_{i=1}^{k} w_i f_{t(i)} \tag{16}$$

Where w_i represents the following weight of each forecasting model and k represents the number of models.

2.2.5.1 Arithmetic mean

A simple arithmetic mean is the obvious choice when it comes to combining different model estimates. The Combined forecast uses, therefore, equal weights for all models considered. We define this approach as the Combination 1 method.

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2.2.5.2 Inverse of the mean square error

A weighting scheme based on the individual performance of each of the k forecast methods can be computed using the mean squared distance between the actual value and forecast value for the training sample. The forecast weights are then obtained as:

$$w_i = \frac{1/MSE_i}{\sum_{i=1}^{k} 1/MSE_i} \tag{17}$$

This method is one of the methods mentioned in the seminal paper by Bates and Granger (1969). This method is just named the Combination 2 method from here on.

3. Results

As an initial procedure to perform model identification, we checked the stationarity of all series by performing Augmented Dickey-Fuller (ADF), Kwiatkowski-Phillips-Schmidt-Shin (KPSS), and Phillips-Perron (PP) Unit Root tests for variations of model specifications, including intercept and trend combinations. Table 1 summarizes the tests, indicating that all series present a unit root in the level component.

By visually inspecting the series, we decided not to evaluate structural breaks for Brasília and Guarulhos airports. For the Galeão airport, we followed Zeileis (2003) through the endogenous analysis, concluding that October 2004 could be considered a breakpoint. In this context, we confirm the series stationarity in the first difference by performing the Zivot-Andrews (1992) unit root test as well.

We included a dummy variable in the SARIMA model to incorporate the effects of the structural break. After investigating this episode, the conclusion is that the sudden increase in the demand in Galeão is explained by the reduced capacity of the Santos Dumont (second Rio de Janeiro airport, concentrated on domestic flights only) airport during its renovation, which led to some flight transfers. Table 1 shows unit root tests.

Table 1. Unit Root tests for airline demand in different airports in Brazil

Serie	ADF test t-statistic	PP test t-statistic	KPSS test t-statistic	Results
y = log(Brasília)	-0,453	-0,588	1,636***	Non-stationary
y = d(log(Brasília))	-18,792***	-81,314***	0,164	Stationary
y = log(Galeão)	-0,774	-0,524	1,496***	Non-stationary
y = d(log(Galeão))	-16,899***	-18,713***	0,094	Stationary
y = log(Guarulhos)	0,220	0,024	1,478***	Non-stationary
y = d(log(Guarulhos))	-19,197***	-27,181***	0,325	Stationary

Note: All equations with intercept. Rejection of null hypothesis at the levels of significance: *, **, *** represent 10%, 5%, and 1%, respectively.
Source: Elaborated by authors.

To assess the forecasting accuracy of the models, we estimate model coefficients for the training set, using RMSE and MAPE as performance indicators. For the specification of the SARIMA models, this work follows Hyndman & Khandakar's (2008) procedure, searching for variations of lagged auto-regressive and moving average terms for the level and seasonal components. The final models are presented in Table 2.

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Table 2. SARIMA model specification and coefficients

Airport	Model (1)	Coefficients					AIC	RMSE	MAPE
Brasília	(1,1,1)(0,1,1)12	AR(1)	MA(1)	SMA(1)			-496,6	0,044	0,233
		0,56	-0,83	-0,829					
Guarulhos	(1,1,2)(0,1,1)12	AR(1)	MA(1)	MA(2)	SMA(1)		-424,4	0,056	0,312
		-0,212	0,111	-0,166	-0,812				
Galeão	(0,1,0)(2,0,0)12	SMA(1)	SMA(2)			Break (1)	-322,4	0,088	0,493
		0,31	0,414			-0,079			

Source: Elaborated by authors.

Except for Galeão, other airports presented a seasonal unit root after the Hegy test analysis, following the Hyndman & Khandakar (2008) procedure. To inspect residuals for SARIMA models, we make use of Arch LM to check homoscedasticity, Correlogram analysis for serial correlation, and Jarque-Bera for Normality. During residuals analysis, we found that all airports passed Arch-LM and Serial Correlation tests, but Galeão presented some histogram outliers (breakpoints) that were captured in the Jarque-Bera test.

Results for the Holt-Winters method are shown in Table 3 and present similar performance for the in-sample training set in comparison with SARIMA models. The additive method had better performance, but we decided to include the multiplicative version in the out-of-sample analysis as an alternative model that could be incorporated into the forecast combinations methods. Table 3 shows Holt-Winter parameters.

Table 3. Holt-Winters smoothing parameters

Airport	Holt Winters Additive					Holt Winters Multiplicative				
	α	β	γ	RMSE	MAPE	α	β	γ	RMSE	MAPE
Brasília	0,3266	0	0,1685	0,0489	0,2775	0,0658	0,0234	0,0692	0,0631	0,381
Galeão	0,9879	0,0531	0	0,0564	0,3324	0,2266	0,0809	0,0302	0,0859	0,5011
Guarulhos	0,5653	0,1386	0	0,0749	0,4193	0,1541	0,0384	0	0,1047	0,622

Source: Elaborated by authors.

The results and specifications for ARNN models are presented in Table 4, with performance at the same levels as the previous models for the in-sample dataset. The idea of incorporating a non-linear model was to investigate the performance of these models in classic forecasting problems, even considering that recent applications in economics suggest that they perform well in the presence of a very long observation sample, which was not the case here. Even in this adverse environment, the results for the out-of-sample set show that these models can be very competitive even for smaller samples.

Table 4. Auto-Regressive Neural Network (ARNN) model specification

Airport	Model (1) (2)	RMSE (3)	MAPE (3)
Brasília	(1,1,2)12	0,0604	0,3445
Galeão	(1,1,2)12	0,1016	0,5927
Guarulhos	(1,1,2)12	0,094	0,5429

(1) The NNAR method uses a single hidden layer.

(2) Follows the NNAR (p,P,K)representation, where p is the number of lagged inputs for the level component. P is the number of lagged inputs for the seasonal component. K is the number of nodes of the hidden layer

(3) Computed for the in-sample training set.

Source: Elaborated by authors.

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The ARDL models are selected on AIC criteria and were incorporated to capture some economic rationale in the specification of airline demand, following the tourism and forecasting literature. Table 5 presents the specifications for each airport.

Table 5. ARDL model specifications

Airport (1) (2)	Brasília	Galeão	Guarulhos
ARDL Model	(3,5,4,0)	(2,4,4,2)	(2,5,3,2)
Δy_{t-1}	-0.231***	-0.0182	-0.1450
Δy_{t-2}	-0.242***	-0.2185**	-0.2222*
Δy_{t-3}	-0.152*	-	-
Δy_{t-4}	-	-	-
Δx_{1t}	-0.717	-1.1923	-0.7299
Δx_{1t-1}	-0.006	0.5980	-0.9619
Δx_{1t-2}	0.177	0.7124	1.365*
Δx_{1t-3}	-1.202**	-2.2519**	-1.5674**
Δx_{1t-4}	1.206**	1.2544	0.4852
Δx_{1t-5}	1.507***	-	1.6659**
Δx_{2t}	0.059	-0.0429	-0.0200
Δx_{2t-1}	-0.080	-0.1417	0.0098
Δx_{2t-2}	-0.078	0.0379	-0.1423*
Δx_{2t-3}	-0.104**	-0.1540	-0.1827**
Δx_{2t-4}	-0.093**	0.1840*	-
Δx_{2t-5}	-	-	-
Δx_{3t}	-0.177*	-0.2426	-0.1492
Δx_{3t-1}	-	-0.2310	-0.2211*
Δx_{3t-2}		0.1693	-0.1600
AIC	-3.325	-2.5014	-2.952
R^2	0,848	0.7356	0.8587
LM Breusch-Godfrey (Serial Correlation)	0.105	0.7073	0.8189
Jarque-Bera (Normality)	0,388	0.1781	0.2489
Breush-Pagan-Godfrey (Heteroskesdaticity)	0.968	0.0947	0.8009

Notes: (1) x_1, x_2, x_3 represent the IBC-BR index (Brazilian Central Bank proxy for GDP), Jet fuel prices, and Exchange Rate from Brazilian Real to US Dollar, respectively.
(2) All variables are log-transformed.
(3) Serial Correlation, Normality and Heteroskedacity tests show p-values
(4) Galeão and Guarulhos were estimated from 2005m01 to 2014m08 to deal with some outliers on the sample. Brasilia was estimated from 2003m01 to 2014m08.

Source: Elaborated by authors.

The economic activity and its effect on the airline demand were captured by the Brazilian Central Bank activity index with a mainly 3 to 5-month lag. We deliberately added jet fuel prices and exchange rates to capture the supply-side dynamics of the market, but the coefficients were not all significant for Galeão and Guarulhos but could explain a relevant part of the airline demand variation.

Table 6 presents the performance of all models for the out-of-sample set. ARDL models show better results in a broad perspective, but there was no winner model for all situations. This result is in line with stylized facts in the forecasting literature, considering differences in the characteristics of the airports, forecast horizons, and seasonal patterns, among other factors. By comparing the performance of different models, it can be pointed out that all models performed very well, even the seasonal naïve. The Holt-Winter multiplicative method outperformed the additive one in almost all situations.

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Table 6. Ex Post Out-of-Sample forecasting Performance of rival models (1) (2) (3)

Airport	Forecast Model	h=1		h=3		h=6		h=12		h=18		Rank	
		RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
Brasília	Univariate Benchmark	0,0137	0,0948	0,0218	0,1280	0,0678	0,4536	0,0901	0,4705	0,0745	0,4028	6	6
	Auto Arima	0,0008	0,0054	0,0201	0,0889	0,0879	0,5260	0,0969	0,4878	0,0673	0,2543	5	2
	NNAR	0,0374	0,2602	0,0398	0,2640	0,0484	0,3133	0,0557	0,2876	0,0646	0,3879	4	5
	Combination Model 1	0,0100	0,0699	0,0160	0,1017	0,0682	0,4524	0,0818	0,3632	0,0612	0,2756	1	3
	Combination Model 2	0,0089	0,0617	0,0167	0,0976	0,0762	0,5101	0,0896	0,4172	0,0612	0,2444	1	1
	ARDL	0,0551	0,3491	0,0932	0,4107	0,2241	1,5539	0,0957	0,6740	0,0899	0,5464	7	7
	Bagging Model	0,0661	0,4596	0,0482	0,2923	0,0521	0,3392	0,0853	0,3474	0,0640	0,2870	3	4
Galeão	Univariate Benchmark	0,0823	0,5889	0,1332	0,9153	0,1318	0,8529	0,1561	0,9775	0,1249	0,7240	7	7
	Auto Arima	0,0413	0,2954	0,0444	0,2677	0,0935	0,5659	0,1207	0,7549	0,0629	0,3724	1	1
	NNAR	0,0134	0,0962	0,0815	0,5186	0,1232	0,8077	0,1005	0,6188	0,0923	0,5365	3	3
	Combination Model 1	0,0398	0,2846	0,0951	0,6220	0,1233	0,7927	0,1469	0,9195	0,1024	0,5528	4	4
	Combination Model 2	0,0168	0,1199	0,0732	0,4356	0,1224	0,7857	0,1529	0,9690	0,1046	0,5656	6	5
	ARDL	0,0566	0,4052	0,051	0,3149	0,1205	0,7497	0,1551	0,9817	0,1038	0,5789	5	6
	Bagging Model	0,0584	0,4177	0,0650	0,3631	0,1251	0,8011	0,1395	0,8832	0,0813	0,4369	2	2
Guarulhos	Univariate Benchmark	0,0412	0,2804	0,0335	0,2114	0,0350	0,1938	0,1291	0,8391	0,1352	0,8005	5	6
	Auto Arima	0,0040	0,0274	0,0282	0,1899	0,0306	0,1708	0,1380	0,8977	0,1316	0,7554	4	4
	NNAR	0,0225	0,1531	0,0507	0,2603	0,0666	0,3932	0,1132	0,7590	0,1175	0,7028	2	2
	Combination Model 1	0,0321	0,2188	0,0220	0,1386	0,0215	0,1311	0,1298	0,8508	0,1244	0,7115	3	3
	Combination Model 2	0,0294	0,2000	0,0188	0,1278	0,0210	0,1322	0,1431	0,9371	0,1369	0,7778	6	5
	ARDL	0,0115	0,0786	0,0160	0,1019	0,0949	0,6464	0,1065	0,6652	0,0712	0,3854	1	1
	Bagging Model	0,0172	0,1171	0,0253	0,1527	0,0311	0,1694	0,1431	0,9372	0,1483	0,8508	7	7

Notes: (1) ARDL models were not included in the combination models to compare univariate and multivariate approaches. (2) Performance criteria are computed as an average of all forecasting estimates until period h. Ex. For h=6, we compute six observations of MAPE and RMSE and then average them. (3) Rank represents results for h=18. (4) Univariate Benchmark based on the average Accuracy measures of Seasonal Naïve, Auto Arima, Holt-Winters Additive, and Holt-Winters Multiplicative. (5) Combination 1 e 2 refer, respectively, to the composition of the average and weighted combination of the prediction from Seasonal Naïve, Airline Arima, Auto Arima, and HW.
Source: Elaborated by authors.

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These findings indicate that the use of univariate time series can be a great starting point for modeling purposes or can even be considered a competitive and more flexible alternative to other methods, following the findings of Fildes et al. (2011). In this context, Athanasopoulos et al. (2011) also point out that univariate models should be the first method to be considered in this modeling problem, and the results corroborate this hypothesis by showing that more sophisticated models present marginal performance gains.

Neural networks have recently gained a lot of attention in economic modeling with machine learning applications. They are relatively simple to implement, have the advantage of having no requirements in terms of model specifications, and have performed well and were able to capture the seasonality of the series. The forecasting competition shows that more sophisticated models are emerging, but the computational costs for larger databases still present some challenges for their implementation.

There is some consensus in the forecasting literature that the use of combination methods is a great way to increase the accuracy of single forecast models. In this study, the results confirm this conclusion and are in line with the seminal work of Winkler & Makridakis (1983). We used two combination methods that worked as a reference for univariate models and in a comprehensive evaluation, they performed better than individual univariate models and showed the simplicity of the application.

4. Conclusion

This paper aimed to measure the efficiency of air demand forecasting models. To this end, several econometric models were specified to generate passenger number forecasts for three of the largest Brazilian airports for domestic flights from 2014 to 2016. They include an ARDL specification and several univariate models such as Seasonal ARIMA, Holt-Winters, ARNN, Bagging approach, and two combination methods.

The error measures of the different methods produced different results in the forecast evaluations, and no winning method could be presented as the best approach for the different airports or time horizons. The results are evidenced in a dynamic window forecast for a horizon period of 1 to 18 months, which means that, once a model was calibrated, there was no update of its parameters in the test dataset.

The findings indicate that all models provided specifically are accurate, but there is no single method that stands out from the rest across all forecast horizons and different airports. In line with the scientific literature investigating forecasting methods, the combination of models also proved to be efficient in forecasting Brazilian air demand.

Therefore, these results contribute to the forecasting literature by providing empirical evidence on the use of forecasting models in the airline industry, and future research could incorporate structural autoregressive vectors that consider additional explanatory variables that could contribute to better forecasting.

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