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Research Article

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Modelling and Forecasting of Air Traffic Passengers of Yola International Airport

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Abstract Forecast is vital to every business organization or government and for every significant management decision. Decisions can be improved if more is known about the future events. In this paper, we discussed a better forecasting model that will predict the passenger traffic at Yola Airport. We used the Box-Jenkins Autoregressive Integrated Moving Average (ARIMA) methodology to build the ARIMA model for forecasting airport passenger traffic for Yola Airport. Yola airport's future passenger traffic is predicted to maintain a growth trend for the ember month the following year, although a slight downward trend is seen from the forecast. This downward trend may not be unconnected to the case of insurgency (Boko Haram activities that was going on at the time of this research) in Adamawa state.

Keywords Air traffic passengers, ARIMA, Forecasting

1. Introduction

Despite all the challenges facing air transport in Nigeria, an average Nigerian still prefer to travel by air. It is now obvious that airports and airlines have witnessed an increase in the volume of passenger. Convenience and the current insecurity situation may be the leading factor that causes increase in air transport. As a result of this increase, passengers are disappointed in the way services are been rendered, FAAN workers are over worked and sometimes the airport is congested. The challenge right now at hand is how they will cope with the volume of the anticipated passenger traffic.

According to International Civil Aviation Organization, ICAO the availability of data required for airport forecasting and planning varies considerably from case to case, the airport facilities to be considered and the nature of the planning decisions to be taken will determine the range of items to be forecast. This research intends to build a forecasting model that can accurately predict airport passenger traffic at Yola International Airport in order to help managers plan effectively in line with the anticipated volume of passengers. And also to help managers to understand the variation associated with passengers' patronage. The next section contains a brief review of extant literature while we present the method of data analysis in section 2 together with the result. We finally conclude this study with section 4.

2. Air Passenger Forecast

The level at which firms, organizations or governments operate depends on how well they predict the future. Forecast is vital to every business organization or government and for every significant management decision. Forecast is an attempt to determine what is going to happen before it happens. Decisions can be improved if more is known about the future events. If firm, organization and government have some ideas about what is going to happen, they could utilize their resources much more efficiently.

Stoner and Freeman [1], consider forecast as a statement about the future. Markland [2] defined forecasting to be the extrapolation of past data into the future using some scientific or statistical method. Monks [3] defined forecast as estimate of occurrence, timing or magnitude of future events. Krajcwski and Ritzman [4] see forecast as a prediction of future events used for planning purposes and this is needed to aid in determining what resources are needed, scheduling existing resources and acquiring additional resources [5].

Forecasting is at the heart of planning and design process at airports to adequately meet the needs of air passengers. Airport terminals, runways, freight storage facilities, parking lots, and even the roadway network to and from an airport are all based on the anticipation. Andreoni and Postorino [6] expressly put forward that forecast of air transport demand has a great influence on the development of airport master plans with respect both to airside (runways, taxiways, aprons, technological devices) and landside (boarding/landing area, waiting rooms, etc.). Forecasts of passenger volumes are translated to space requirements for the terminal building facilities, while forecasts of aircraft movements are translated to the runway, taxiway, and apron needs, as well as to the need for air traffic control systems.

When planning and designing airport terminal there is a significant number of traffic characteristics that must be forecasted: total number of passengers for the design period, domestic, commuter and international passenger ratios at peak hours, seasonal variations in demand, volumes of transfer and/or transit passengers for each type of traffic, number of passengers, bags and well-wishers, distribution of dwelling times of passengers, and sometimes origin and destination of flights for immigration, customs, and health control purposes. These forecasts are used to determine the space requirement for new terminals or the expansion of existing facilities.

Forecasting process is avital factor and needed to be considered in the development of any airport. Mistakes made in this phase of the process can be very costly and damaging for local economies. Underestimating demand can lead to increased congestion, delay, and lack of storage facilities. While on the other hand, Overestimating demand could also create significant problems. Errors in the forecasting process can lead to long delays or to empty terminals: both these cases can cause significant damage to the economy of an airport's hinterland that depends on the successful operation of that airport.

An accurate and reliable airport passenger demand forecasting is an integral component for short-term and long-term planning and decision making regarding airport infrastructure development and flight networks [7]. Suryani et al. [8] developed model to analyze and to forecast air passenger demand in the future related with runway and passenger terminal capacity to support long-term growth. Poore [9] attempted to test the hypothesis that forecasts of the future demand for air transportation offered by aircraft manufacturers and aviation regulators are reasonable and representative of the trends implicit in actual experience.

Matthews [10] worked on the measurement and forecasting of peak passenger flow at several airports in the United Kingdom. According to his research, annual passenger traffic demand can be seen as the fundamental starting point, driven by economic factors and forecasting. While forecasts of hourly flows are needed for long-term planning related with infrastructure requirements. Hourly forecasts are almost always based on forecasts of annual flows. In forecasting highly seasonal demand in regional airports in Corfu, Greece where peak flows approach airport capacity, Matthew [11], proposed a modeling combination of dynamic Tobit models with GARCH disturbances. His finding reveals that improved demand model specifications are an invaluable tool in obtaining more accurate demand estimates.

Bafail et al [12] have developed a model for forecasting the long-term demand for domestic air travel in Saudi Arabia. They utilized several explanatory variables such as total expenditures and population to generate model formulation. Karlaftis [13] have proposed a modeling combination, dynamic Tobit models with GARCH disturbances, which are able to capture many of the shortcomings of most traditional models. The Models are calibrated using monthly passenger and flight data for a 20 year period for the airport of Corfu in Greece, where traffic over the summer approaches airport capacity and seasonal fluctuations in demand are very intense.

One of the first published causal modeling efforts concerned with airport-specific forecasting was by Jacobson [14]. His linear regression based model predicted the trips generated at an airport (dependent variable) based only on the average airfare per mile for all routes in the United States, and the total income per capita for the airport catchment area. The model was calibrated with eighteen years of data from the airports of Virginia.

Sivrikaya and Tunç [15] applied semi-logarithmic regression model for the estimation of domestic passenger volume between domestic cities in Turkey. Using cross sectional calibration data, their model is particularly applicable to city-pairs where no air service exists, no historical data are available, or factors describing the current service level of air transportation are not available. Their findings among other things reveals all the quantitative relationships among the independent variables, which are helpful for airlines or other relevant aviation companies to understand the consequences of changes in their decision variables or adjustment of their routing structures as well as helpful for related authority to quantify the benefits of airport capacity expansion or to predict potential air travel demand for a new airport.

Yukun, Xiong and Hu [16] used Support Vector Machines with Ensemble Empirical Mode Decomposition and Slope-Based Method to model real monthly air passenger traffic series including six selected airlines in USA and UK. Priyadarshana and Fernando [17] developed demand model to capture terrorist activity, economic growth and air fare impact as explanatory variables modelled air passenger demand in Bandaranaike International Airport. They note that developing economies [like Nigeria] experience higher growth rates in air passenger traffic and modeling passenger demand is essential for designing and strategic planning of facilities in the airports.

Le [18] looked at the demand management at congested airports with demonstration of the existence of profitable flight schedules that improve the public goals for LaGuardia airport. He took a novel approach in modeling a profit-seeking, single benevolent airline, to develop an airline flight scheduling and fleet assignment model to simulate scheduling decisions. His approach explicitly accounts for the interaction of demand and supply through price. Sivrikaya and Tunç [15] observed that accuracy in the estimation of air transport demand is a key element while an aviation company is planning its short term or long term business plan regardless of its status, being an incumbent or a startup company.

Hess, Ryley, Davison and Adler [19] considered improving the quality of demand forecasts through cross nested logit. Their finding shows not only significant gains in model performance in estimation when moving to this more advanced nesting structure, but the more appropriate cross-elasticity assumptions also lead to more intuitively correct substitution patterns in forecasting examples.

Tsui et al. [7] in their research, Forecasting airport passenger traffic have employs the Box-Jenkins Autoregressive Integrated Moving Average (ARIMA) methodology to build and estimate the univariate seasonal ARIMA model and the ARIMX model with explanatory variables for forecasting airport passenger traffic for Hong Kong, and projecting its future growth trend from 2011to 2015. Both fitted models are found to have the lower Mean Absolute Percentage Error (MAPE) figures, and then the models are used to obtain ex-post forecasts with accurate forecasting results. More importantly, both ARIMA models predict a growth in future airport passenger traffic at Hong Kong.

Time series models have been widely used, especially; simple autoregressive time series models [6] for modeling and forecasting of air transport demand. Andreoni and Postorino [6] employed multivariate arima model to forecast air transport demand levels about Reggio Calabria regional airport. They conclusively pointed that the comparison between univariate and ARIMAX models shows that both models provide satisfactory results, even though the univariate models fit better than the ARIMAX model when there are some peaks. Hence the choice of univeriate ARIMA for this study

3. Methodology and Data Analysis

Daily passenger traffic from February 2012 to December 2014 is used in this research. This amounts to 1057 observations. Theoretically, Box-Jenkins ARIMA models are built empirically from the observed time series relying on three underlying process components.

The objective of B–J [Box–Jenkins] is to identify and estimate a statistical model which can be interpreted as having generated the sample data. If this estimated model is then to be used for forecasting we must assume that the features of this model are constant through time, and particularly over future time periods. Thus the simple reason for requiring stationary data is that any model which is inferred from these data can itself be interpreted as stationary or stable, therefore providing valid basis for forecasting.

A general ARIMA model is in the form:

$$x_t = z + \varphi_1 x_{t-1} + \varphi_2 x_{t-2} + \ldots + \varphi_p x_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \ldots - \theta_q \varepsilon_{t-q}$$

With $(p+q+2)$ unknown parameters $\left(\mu; \varphi_1, \varphi_2 \ldots, \varphi_p; \theta_1, \theta_2, \ldots, \theta_q; \sigma_\varepsilon^2\right)$

where x_t is the numerical value of an observation

t is the period time

φ_i is the autoregressive parameters for $i = 1,2, \ldots, p$

θ_j are the moving average parameters for $j = 1,2, \ldots, q$

Other than the constant term z these models are equivalent to the ARMA in the disturbances formulation estimated by ARIMA, though the latter are more flexible and allow at least four classes of models. Using lag operator notation ARIMA can be expressed as

$$\Phi(B)x_t = z + \Theta(B)\varepsilon_t$$

$$(1 - \varphi_1\beta - \varphi_2\beta^2 - \ldots - \varphi_p\beta^p)x_t = z + (1 - \theta_1\beta - \theta_2\beta^2 - \ldots - \theta_q\beta^q)\varepsilon_t$$

Where

$$\Theta(\mathrm{B}) = (1 - \theta_1\beta - \theta_2\beta^2 - \ldots - \theta_q\beta^q)$$

and

$$\Phi(\mathrm{B}) = (1 - \varphi_1\beta - \varphi_2\beta^2 - \ldots - \varphi_p\beta^p)$$

Before estimating departure-airport passenger traffic time series, we checked whether the time series data was stationary. From preliminary investigation using time plot, the series seems to be stationary as indicated by the time plot of figure I. this is further confirmed by the formal unit root test (shown in table 1) as proposed by Dickey-Fuller which strongly reject the unit root hypothesis even at 1% level of significance.. Thus, further differencing process were not required.

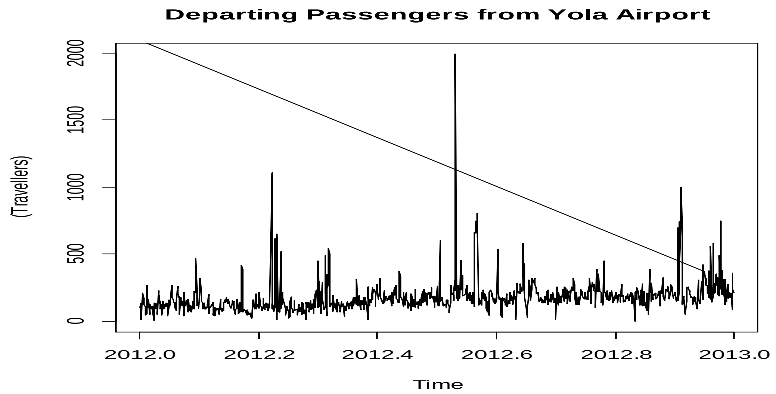

Figure 1: Time plot

Table 1: Dickey-Fuller unit root test

Test Statistics Z(t)	1% Critical Value	5% Critical Value	10% Critical Value
-21.708	-3.430	-2.860	-2.570

Moreover, the correlograms of Autocorrelation (ACF) and Partial Autocorrelation (PACF) indicate that the time series have some autoregressive and moving average processes as it can be seen in figure 2 below. This suggests the use of the ARIMA model. The correlogram suggest an ARMA(3,0,0) process. This is further confirmed by the information criterion presented in Table 2where the least value of BIC=9.405799, corresponds to AR(3) and MA(0)

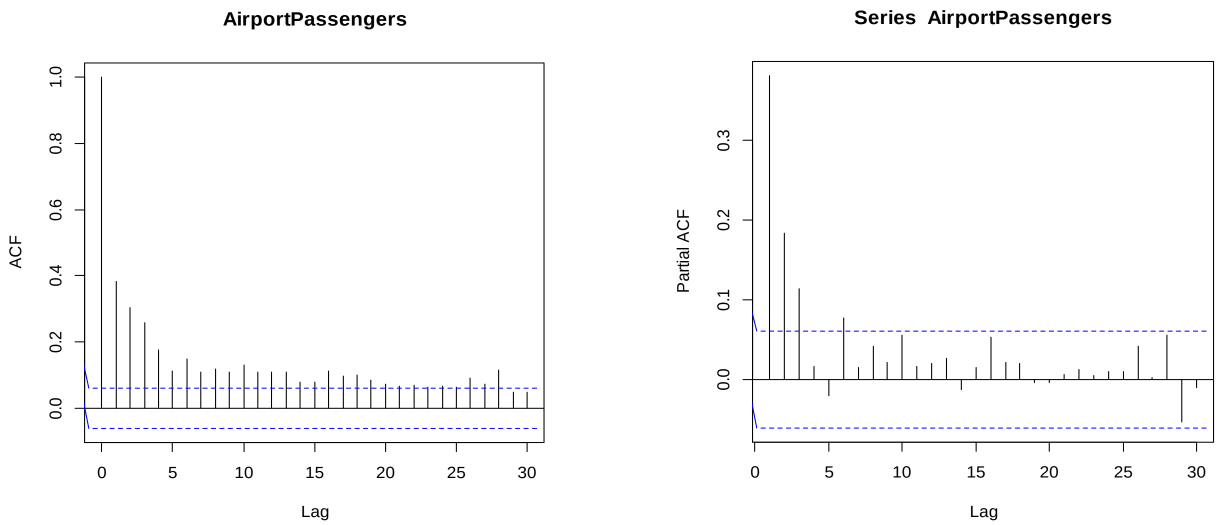

Figure 2: Air Passengers correlogram

Table 2: Minimum information criterion

lags	MA0	MA1	MA2	MA3	MA4	MA5
AR 0	9.588438	9.530578	9.4908	9.456171	9.446731	9.451107
AR 1	9.438729	9.406083	9.412484	9.417636	9.424577	9.426714
AR 2	9.411484	9.414242	9.416618	9.422127	9.429357	9.427
AR 3	9.405799	9.415074	9.421165	9.427511	9.434835	9.433286
AR 4	9.412531	9.421221	9.427547	9.433946	9.440649	9.439655
AR 5	9.41846	9.426666	9.430502	9.432383	9.437766	9.444833

Minimum Table Value: BIC (3,0)=9.405799

Figure 3 is the standardized residuals, ACF residual and Ljung-Box statistic of the fitted model. The standardized residuals and ACF residual are shown to be white noise (purely random). The P-value for Ljung-Box statistic is not significantly different from zero which indicates that the residuals are independently distributed. The same can be said of the standardized residuals and ACF residuals. We also provided actual series and forecast plot on figure 4.

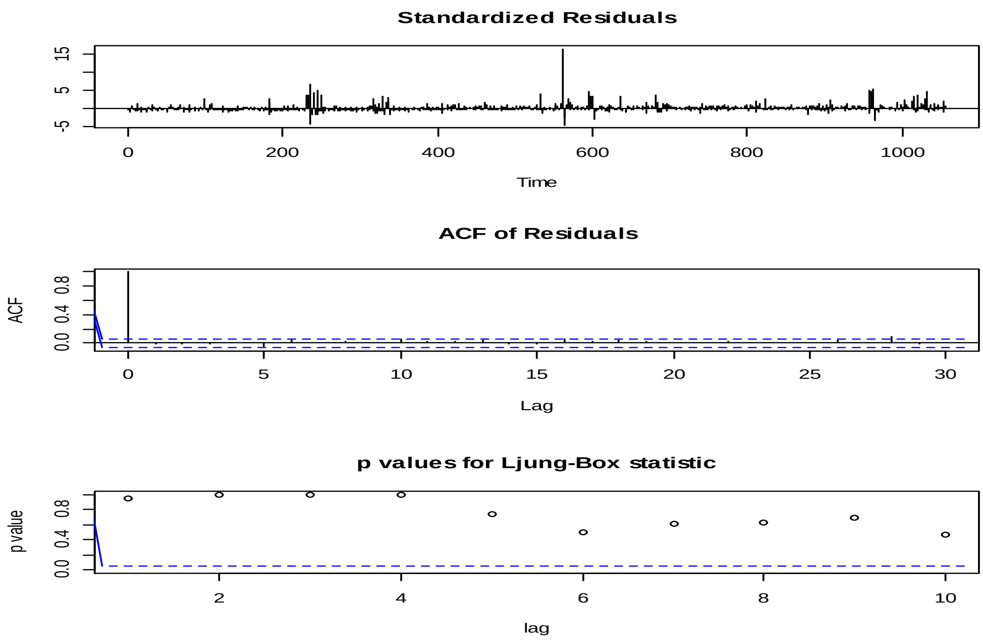

Figure 3: Diagnostic Plot

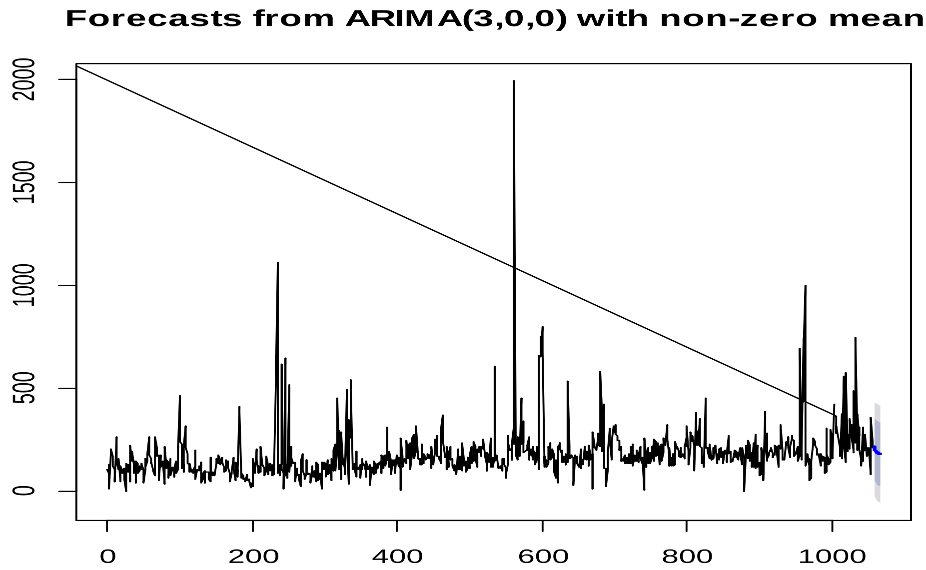

Figure 4: Forecast Plot

4. Conclusion

The goal of this study was to examine and analyze the demand for, and the ability to, forecast passenger traffic of Yola airports. In this study we proposed a Box-Jenkins ARIMA model. The best-fit Box-Jenkins ARIMA model is built for predicting airport passenger traffic for Yola airport. Yola airport's future passenger traffic is predicted to maintain a growth trend for the ember month the following year, although a slight downward trend is seen from the forecast. this reflect the findings of Andreoni and Postorino [6] "the air demand is continuously increasing, despite some negative peaks due to political and/or market driven events that reduce the user willingness to travel". This downward trend may not be unconnected to the case of insurgency (Boko Haram activities that was going on at the time of this research) in Adamawa state.

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