Time Series Models for Forecasting Passengers Traffic at Nigeria's Airports in Pre-COVID 19 Era

[1]EJEM EJEM AGWU, [2]IGBOJI MARCELLINUS UCHENNA C.J., [3]AIKOR SHIRGBA TIMOTHY

[1,3]Department of Supply Chain Management
School of Logistics and Innovation Technology
Federal University of Technology, Owerri
NIGERIA.
[2]Department of Logistics and Transport Technology
School of Logistics and Innovation Technology
Federal University of Technology, Owerri
NIGERIA

Abstract: - This paper studied the forecasting of air traffic of passengers at Nigeria airports to address the growth of traffic, evident effects on future airport activity levels for the enabling of airport planning cum decision making and to provide criteria for facility requirements, associated financial planning and funding as part of airport development. As air traffic of passengers experiences considerable growth and changes in increased air travel, year in and year out, the number of various kinds of passengers (e.g. arriving, departing, and transit) influences airport terminal capacity and facility needs. The modelling and forecasting in this paper provided for short and medium out-of-sample forecasts of possible successive monthly and quarterly air traffic of passengers in Nigeria airports collectively for two markets geographical segments: Domestic and International air travel. The following time series models were utilized in this study: Winter's Triple Exponential Smoothing (TESMTH), Autoregressive Integrated Moving Average (ARIMA), AirLine-Model, and Seasonal Autoregressive Integrated Moving Average (SARIMA). The forecast accuracy of each model was assessed using Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE) criteria. It also investigated if merging forecasts from all models improved predicting accuracy. This section of the study was completed using the Combination of Forecasts Technique: Simple Averaging Method. The findings showed that the majority of our models gave accurate projections for the specified market, with MAPE and RMSE errors being less than 10% on average. The study evaluated forecast accuracy to determine the marketability of a model to avoid the traps caused by inaccurate forecast information. Furthermore, the combination of Estimates from Single Models surpassed several of the specific single model forecasts. Finally, these findings should urge the Nigerian government, the Nigerian air transport sector, and academia to address growth and current implications on future airport activity levels for airport planning and decision making.

Keywords: - Airport Planning, Decision making, Winter‘s Triple Exponential Smoothing, ARIMA, SARIMA.

Received: June 12, 2021. Revised: June 16, 2022. Accepted: July 17, 2022. Published: August 31, 2022.

1 Introduction

The number of domestic and international flight passengers in Nigeria increased dramatically between 2003 and 2012. During this time, the number of enplaned (boarded aircraft passengers) and deplaned (disembarked aircraft passengers) air passengers in Nigeria increased from 422,087 to 1,078,078 in the domestic sector (i.e. +155%) and from 154,515 to 438,125 in the international sector (i.e. +184%). (FAAN, 2012). This growth under the same period also took a reflection on the growth of scheduled flights operating in the various Nigerian airports. The increase in passengers and the resultant effect of increased scheduled flights in all ramifications overburden the runways and the operations of Air Traffic Management (ATM) of Airports as almost all individual Nigeria Airports (Domestic or International) utilize one runway for their landings and take-offs. In their research, Mobolaji and Ukpere (2011) discovered that even during the period of their research, most domestic traffic movements have two main peaks, namely morning and evening, although most airlines in Nigeria fly at roughly the same time of day, putting great strains on airport runways and exposing negative effects of delay and queuing of flights waiting for clearances for take-offs and landings, with the headways of queuing aircraft being danged. This increase in passengers could get to the level where airport capacity and level-of-service threshold are exceeded and its result could be adverse. Planning and scheduling for airport development must be based on scenarios that take into account the mix of (future) aircraft types and traffic increase, well before specific level-of-service criteria are exceeded. Transport infrastructures are highly expensive to put in place, and in the scenario of Nigeria, deciding to create one is also quite expensive due to scarcity, and various other aspects of the economy share these limited resources, which must also be considered in wealth distribution (Mobolaji and Ukpere, 2011). However, they also noted that the building of new airports or the expansions of the capacities and facilities of existing airports must first consider if the existing airports and their facilities are fully utilized incapacity.

For this paper, the focus is placed on air traffic of passengers of the Nigeria airports as gathered for the years under study to be evaluated statistically, diagnose findings to buttress hypotheses, analyzed with time series models, forecast upon, conduct Combinations Forecasting and evaluate the forecasts performance accuracy levels of each forecasting method employed. Airport aviation activity forecasts have become an essential aspect of transportation planning. The majority of airport forecasts are created on behalf of airport sponsors and state or regional governments. The kind and manner of forecasting can be heavily influenced by the aim of the prediction. For example, there may be significant differences between estimates used to support a yearly budget and those needed to support a long-term facility expansion. In practice, numerous predictions are prepared in support of the master planning process utilized by the Federal Airport Authority of Nigeria (FAAN) to identify capital projects that may be eligible for money from the agency's Airport Improvement Program. This is the principal government financing vehicle for airport enhancements for public usage.

A combination of (many) predictions reels into play to improve forecast accuracy. Combination Forecasting Techniques provide an additional technique to forecasting from single models. Wong et al. (2007) discovered such strategies for improving individual model forecasting accuracy. These strategies have become widely used in predicting literature over the previous three decades. They have been successfully employed in a variety of sectors, including macroeconomics (Poncela and Senra; 2006, Bjrnland, H., Gerdrup, K., Jore, A., Smith, C., and Thorsrud, L. 2011) and tourism (Shen, S., Li, G., and Song, H., 2008, 2011; Coshall, 2009) - Constantinos Bougas (2013). When considering short and intermediate-term airport aviation activity forecasting, time-series approaches are the most commonly used methods for forecasting traffic demand because it is assumed that market variables believed to influence demand will remain constant or with negligible changes within such a short time frame. These methodologies are limited in their capacity to identify the reasons for market growth and to relate future growth to anticipated developments of causative elements. It may, for example, evaluate the impact of a fare drop, the launch of new aircraft, an economic downturn, or doubts about future regulatory circumstances. Such queries may only be addressed if the forecaster has developed and calibrated a formal model that depicts the effect and interplay of all relevant factors, rather than just one (i.e., time). The time-series method implies that traffic demand has followed a predictable pattern in the past and will continue to do so in the future. While time series models may readily yield quarterly, monthly, weekly, and daily fluctuations, econometric models are better suited for long-term forecasting. Although econometric modelling has the potential to be a highly solid and effective tool, there are numerous ways in which it may go wrong, and it is not always evident how to proceed when statistical tests or data concerns signal a problem.

2 Literature Review

Forecasting is the technique of arranging information about a phenomenon's history to forecast its future. Furthermore, good forecasting may be regarded as a basis of yield management (Prideaux, B., Laws, E., & Faulkner, B.; 2003). In agreement with this definition, Anderson, Sweeney, and Williams (2000) defined a forecast as "a projection or prediction of future values of a time series." Forecast periods might be daily, weekly, monthly, quarterly, annual, and so on. In general, quarterly forecasts are used to plan and predict performance for the following one or two quarters (Hales, 2005). In business, there are two sorts of forecasting approaches: quantitative and qualitative methods. Quantitative approaches use mathematical rules to organize historical data for predictive purposes. Four quantitative generic approaches to airport activity forecasting are highlighted below. These approaches range in statistical complexity from very simple to highly complicated; nevertheless, it is crucial to remember that the application of advanced statistical methods does not always result in superior forecasts (Spitz and Golaszewski; 2007). As previously stated, the majority of real-world airport predictions do not employ the most complex algorithms. Nonetheless, the ideas discussed here represent the most recent best thinking on ways for producing more accurate projections. Market share forecasting, Econometric modelling, Time series modelling, and Simulation modelling are the four basic quantitative forecasting methodologies discussed here.

This list, as discovered by Spitz and Golaszewski (2007), is not complete, but it covers the majority of quantitative forecasting methodologies employed by airport sponsors or managers in industrialized nations. Forecasts of airport aircraft activity have become an essential aspect of global transportation planning. The reason for which the forecast is prepared can have a considerable impact on the kind and technique of forecasting used, and distinctions between short-term/long-term and constrained/unconstrained demand can lead to substantial variances in the related activity projections that are produced. Such distinctions, however, do not imply that one is more right than the other. Most airports, as well as regional and governmental organizations, provide predictions using quite basic methodologies. Data availability and financial restrictions frequently determine whether forecasting approaches are used. Another aspect influencing how airport forecasts are generated is the set of regulations and criteria established by the relevant government's agency authorities for creating airport master and system plans; FAAN in the case of Nigeria. For this research, the time series (extrapolative) methods of quantitative forecasting were employed because that was the ideal method required to obtain short-term and intermediate-range forecasts for the sake of model-fit on data, higher accuracy level and again, our statistical data obtained are in monthly arrangement. Spitz and Golaszewski (2007), in their findings on research, posed that forecasts of airport aviation activity can be utilized for a variety of applications. Typically, projections are not ended goals in and of themselves. Understanding the purpose for which predictions will be utilized is a critical component in their preparation. In economic terms, activity estimates are often intended to represent the demand for aviation services. Forecasts are driven by service demand, which assists airport planners in providing the right supply in terms of infrastructure needed to fulfil demand. In this context, it is critical to remember that observable airport aviation activity is driven not only by demand but also by the interaction between demand for and supply of aviation services (Spitz and Golaszewski; 2007).

Univariate time-series models are just one way of projecting air passenger demand. Many more viable options have emerged throughout the years. This section provides a very basic summary of several of these strategies. The unrestricted parametric functional form of ARIMA models is one of its primary constraints. Important nonlinearities and interactions that have not been explicitly specified may be missed by a priori requirements (Bougas, 2013). Artificial Neural Network (ANN) models can capture them, albeit at the sacrifice of interpretability. According to Bougas (2013), the contribution of each regressor cannot be evaluated separately. For example, Chen et al. (2012) employed back propagation neural networks to uncover the factors that drive air passenger and cargo demand from Japan. They discovered that various factors influence both, but that certain common factors influence both. This enabled them to build models with exceptionally good short- and medium-term forecasting accuracy. Their air passenger demand model, for example, has a MAPE (Mean Absolute Percentage Error) of 0.34%. They did remark, however, that the success of neural network models is strongly dependent on selecting an acceptable training set. Bao et al. (2012) evaluated by comparing the forecasting performance of a Holt-Winters exponential smoothing model, a univariate time series model (ARIMA), and the following Support Vector Machines-based models: single SVM's, Ensemble Empirical Mode Decomposition based Support Vector Machines (EEMD- SVM's), and Ensemble Empirical Mode Decomposition Slope based method Support Vector Machines (EEMD-Slope- SVM's). They achieved this by analyzing monthly air passenger statistics from six American and British airlines, as well as the following performance metrics: Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), Geometric Mean Relative Absolute Error (GMRAE), and Directional Statistic (DS). They concluded that single SVMs beat ARIMA and Holt-Winters, EEMDSVMs exceeded single SVMs, and EEMD-Slope-SVMs were more accurate than EEMD-SVMs (and hence outperformed ARIMA, Holt-Winters, and single SVMs).

Fildes et al. (2011) investigated air traffic flows between the United Kingdom and five additional countries: Germany, Sweden, Italy, the United States, and Canada. They employed the following economic models: An Autoregressive Distributed Lag (ADL) model, a pooled ADL model, a Time-Varying

Parameter (TVP) model, and an automated approach for econometric model specification are all included. They equally analyzed the previous four models with the addition of a world trade explanatory variable (which measures the total trade of all industrial countries). In addition, they used the following (mainly univariate) models: a Vector Autoregressive model (VAR), a vector autoregressive model with the world trade variable, an exponential smoothing model, an autoregressive model of order three (AR (3)), and the Naive I and Naive II benchmark models. Predicting performance was assessed using four criteria: (i) Root Mean Square (Percentage) Error (RMSE), (ii) Geometric Root Mean Square Error (GRMSE), (iii) Mean Absolute Scaled Error (MASE), and (iv) Geometric Mean Relative Absolute Error (GMRAE) (GMRAE). They discovered that ADL models with a world trade variable beat univariate models (exponential smoothing and AR(3) models) overall, but that the difference in predicting performance was generally minimal, but it varied depending on the forecasting performance criterion utilized (usually larger when using RMSE). Grosche et al. (2007) created two gravity models to anticipate air passengers between city pairs. The majority of the variables in both models were geo-economics in nature. The first model excludes city pairs with multiple airports. As a result, it excludes competition. It forecasts travel demand using data such as population, airport distance, average journey time, and money supply index. The second model, on the other hand, contains multi-airport cities as well as factors that account for them (such as the number of competing airports, and the average distance to competing airports). Both models were determined to be statistically valid and well-fitting to the data.

In this study, we adopt a combination strategy that has been frequently used in the forecasting literature: a simple averaging methodology. This method uses a weighted average of single model projections. The simple average technique applies equal weights to each projected value from the single models that are merged. These weights are simple to calculate: they are equal to the inverse of the number of single model forecasts combined. Another forecast combining methodology is variance-covariance (Coshall (2009) and Chu (1998)). They all allocated differing weights to each model forecast being aggregated and considered the forecasting model's historical performance.

Analysis and modelling of the Nigerian Airport Aviation Activity Forecasting on either enplanements - Arrivals and Departures, cargoes or operations on the number of aircraft have not taken a broader approach to model methodology quantitatively. To analyze Nigerian Air Traffic Data, it is typical to employ the classic technique of splitting the series into the traditional components: a secular trend, seasonal movement, and irregular movement. Etuk (2013) went on to change and use extended data that were ninety-six monthly (8 years) totals of Nigerian Air Traffic Data in nearest thousands covering 2004 to 2011 retrieved from the Federal Airways Authority of Nigeria (FAAN) website in his work (A Seasonal Time Series Model For Nigerian Monthly Air Traffic Data). His effort aimed to fit a seasonal ARIMA model to Nigerian Air Traffic Data (NAP) and demonstrate any agreement between the model and the data. Their studies were basically for Mathematics/Computer Science research for fitting models to times series where they happen to choose the Nigeria Air Traffic Data series. Their study wasn't for the benefit of air transportation or any aviation problem yearning for a solution. No form of prediction was associated with their paper.

Other academic researches that have covered fitting time series and econometric models with the Nigeria air traffic time series have done so either to solely test how well regression or forecasting models can fit the time series of a choice to prove the efficiencies of forecasting models to a particular time series using - fitness of model on data‖ as the premise on their researches. Often than not, their works have been geared towards fulfilling requirements for Statistics/Mathematics/Computer Science research rather than proffer forecasts on Nigeria's aviation activities for solutions to airport prevailing problems. They have mostly tested time series for statistical diagnosis, stochastic trend, and deterministic seasonality on data series, normality and autocorrelations (Autocorrelation function and Partial autocorrelation function) of data series and possibly extend the proof of fitness of model used on time series by forecasting out-of-sample into the future. Many of this nature of research even in the developed world were done to prove the efficiency and effectiveness of a model over another and not find an airport or aviation problem to solve through the predictions. On the world scene, many world organizations have enabled certain countries with forecasting their futuristic air traffic demand with Nigeria inclusive to enable their governments and aviation agencies, airports, sponsors and investors to handle efficient and effective decision making. Such work-study was carried out by world organizations such as Airports Council International (ACI) on Global Traffic Forecast (2010-2029) - The Traffic Forecast Report (Statistics and Forecasting Workshop by Harmel-Tourneur in March 2011.

Another is the International Air Transport Association (IATA) has done forecasting for the benefit of many countries exclusively with a country's own air traffic time series and has extended their out-of-sample to the year 2030.

3 Methodology

This study aimed to compare, analyze, and forecast the number of enplaned/deplaned air passengers in Nigeria using the most recent year data available at the Federal Airport Authority of Nigeria (FAAN) statistics database and the National Bureau of Statistics (NBS) statistics database. Winter's Triple Exponential Smoothing Model (Winter's TESMTH) and three common ARMA-based time series models - ARIMA, SARIMA, and Airline-Model - were investigated in the study. Furthermore, this study investigated if merging the forecasts of the aforementioned models aids in the development of more accurate forecasts. Emiray and Rodriguez (2003) separated the time series data into two groups; Constantinos (2013). The first sample contains information from January 2003 to December 2012. It is equivalent to our "Training Data," which is the series utilized to fit the models. The second sample spans the months of January 2013 to December 2014 and is utilized as "Evaluation Data" to assess predicting performance accuracy levels. All investigations were carried out using the NumXL statistical suite (packages) which Spider Financial Corp offers through their website (www.spiderfinancial.com/....,). The version is NumXL Toolbar and the user interface s Add-in version 1.63.41911.1 (SHAMROCK). This NumXL uses the platform of Microsoft Excel where the NumXL functions as an add-in to Microsoft Excel.

The most frequent methods for anticipating traffic demand are time-series approaches. These methodologies are limited in their capacity to identify the reasons for market growth and to relate future growth to anticipated developments of causative elements. They cannot, for example, analyze the impact of a fare drop, the launch of new aircraft, an economic downturn, or uncertainty about future regulatory circumstances. Such inquiries may only be addressed if the forecaster has developed and calibrated a formal model that depicts the effect and interplay of all relevant factors, rather than just one (i.e., time). The time-series technique implies that traffic demand has followed a consistent pattern in the past and will continue to do so in the future. While time series models may readily yield weekly, daily, and hourly fluctuations, econometric models are more suited for long-term forecasting. Time series models are deemed fit for the short-run forecasts because it is presumed that causative or determining factors that affect real-world outcomes would remain unchanging within the period envisaged to be forecasted, therefore, time series modelling is employed for this paper. The data collected for this study are monthly and quarterly time series of enplaned/deplaned air passengers for domestic and international airports traffic, treated and modelled separately by traffic sector for the periods ranging from January 2003 to December 2012 as "training data" for research analyses, modelling, forecasting, and so on, and another January 2013 to December 2014 period catchments on domestic and international air traffic of passengers as "evident data." These market sectors are well-known and used in the Nigerian aviation industry. The domestic sector includes all flights between two airports in Nigeria, whilst the international sector includes flights from/to Nigeria with origins or destinations in another country. Our "training data" are presented below and subsequently have undergone Descriptive analysis modelling and forecasting processes. Subsequent evaluations and appraisals will follow to achieve the desired aims and objectives of this research. The essence of the presence of our evaluation data is for the appraisals of the forecasts from each model considered in this study using Mean Absolute Percentage Error (MAPE) and Root Mean Square (Percentage) Error (RMSE) criteria. Again, the evaluation data will serve for comparisons by charts composing forecasts of models from 2013 to 2014 and evaluation data (Field data) from 2013 to 2014. The charts juxtaposing the forecast and evaluation/field data of the same years will be a systemic and visible way of judging the performance of a forecast from any model and the combination method employed in this research. The monthly traffic data has been transformed on another hand to Quarterly monthly traffics for both "training data" and "evaluation data" but will only be reappearing by forecasts transformation from the monthly forecast traffic.

This paper has taken the monthly traffic for the periods under investigation for major prognoses for results, discussions, investigations and recommendations because the time series monthly traffic is the same (i.e. transformed) for the quarterly traffic of passengers and using quarterly traffic will amount to rigours, complexities and revealing little characteristics of many that revealed in the same monthly traffics. The differences again are that by quarterly, the traffic takes the different structure of season of four (4) in quarters instead of twelve (12) months season, there appears higher concentration of values and then graphically hides the characters of intrigues and manoeuvrings found in the monthly fluctuation of traffics by seasonality. At the end of the forecasts, the research will still provide forecasts for both monthly and quarterly traffics by evaluation.

4 Results and Discussion

4.1 Forecasting

The Winter's forecasts for both the Domestic and International air traffic of passengers are good tracks of the raw data by identifying and modelling out the data characteristics – deterministic trend and stochastic/seasonal movement, and utilizing the embedded and necessary parametric tools to decipher them while at the same time replicated those characteristics in its forecasts. Winter's forecasting technique has proven a good forecasting model that suits data that feature Trends and seasonality. In the ARIMA forecasts for both the domestic and International monthly and quarterly traffics, it is glaring that the ARIMA model could model only the trending feature of the raw traffic data for both sectors (Domestic and International) and ended with extrapolation of values in its forecasts. This is a clear fact that the ARIMA model can do probably well for data that have deterministic trends and little for modelling data that have the feature of seasonality.

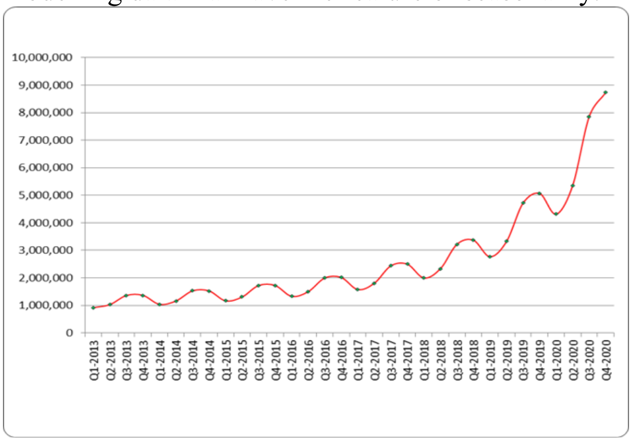

Fig. 1: AirLine-Model-Quarterly Forecasts Chart for International Air Traffic of Passengers

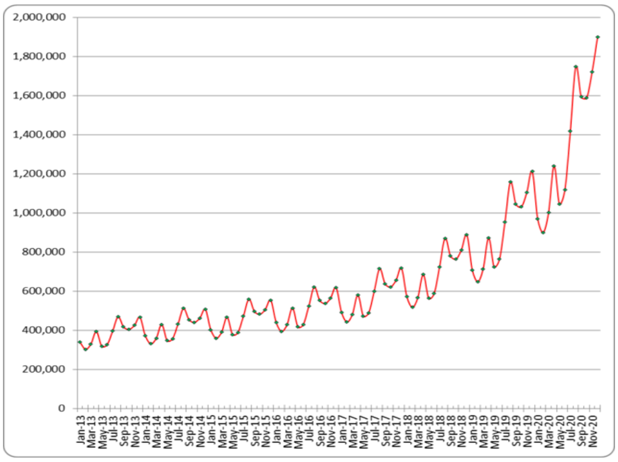

Fig. 2: Combination of Forecasts Chart for International monthly traffic from Winter's versus AirLine-Model International Single Models Forecasts.

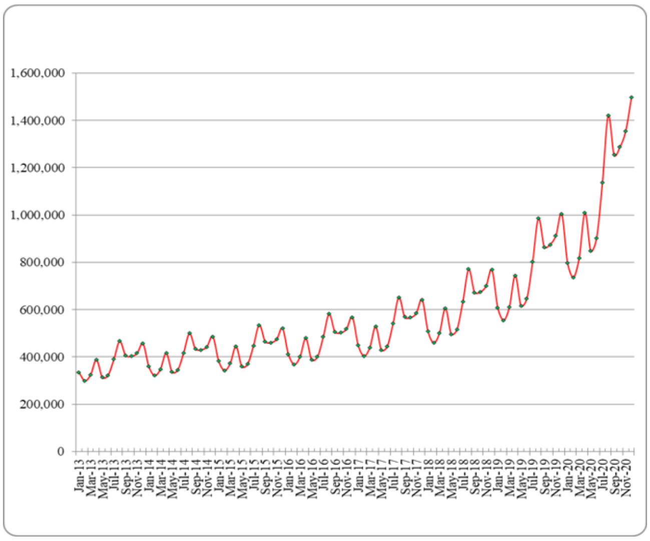

Fig. 3: Combination of Forecasts Chart for International monthly traffic from Winter's versus SARIMA International Single Models Forecasts.

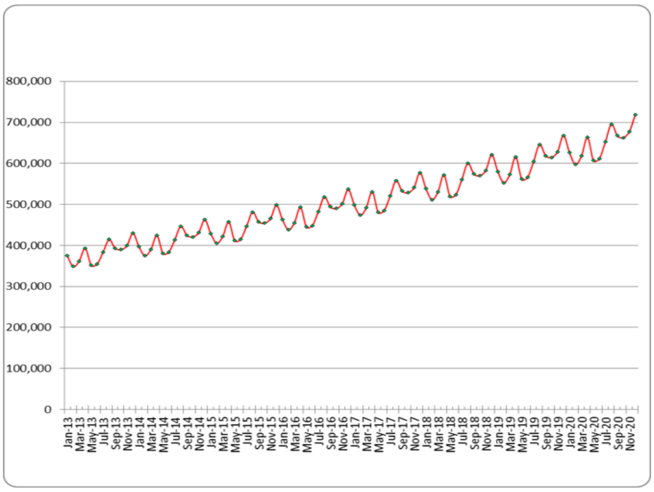

Fig. 4: Combination of Forecasts Chart for International monthly traffic from Winter's versus

ARIMA Models International Single Models Forecasts.

The SARIMA forecasts for both the Domestic and International air traffic of passengers are good tracks of the raw data by identifying and modelling out the data characteristics – deterministic trend and stochastic/seasonal movement, and utilizing the embedded and necessary parametric tools to decipher them while at the same time replicated those characteristics in its forecasts. The SARIMA forecasting model has proven a good forecasting model that suits data that feature Trends and seasonality The AirLine-Model forecasts for both the Domestic and International air traffic are good tracks of the raw data by identifying and modelling out the data characteristics – deterministic trend and stochastic/seasonal movement. The model utilized the embedded and necessary parametric tools to decipher them while at the same time replicating those characteristics in its forecasts afterwards. The AirLine-Model forecasting model has proven a good forecasting model that suits data that feature trends and seasonality. Figures 1 to 4 show pictorially the performances of the models using the international traffic on monthly basis as examples.

4.2 Performance Accuracy Levels of Individual Models on Forecasts

This is the part of the research where this study gives appraisals of models and the forecasting methods employed for this research by evaluating and comparing their forecasting accuracy (performance) level using the Mean Absolute Percentage Error (MAPE) and Root Mean Squared (Percentage) Error (RMSPE) performance criteria. The latter is calculated using input data from the first twenty-four months or first two years (2013 to 2014) period of out-of-sample forecasts for evaluation by juxtaposing them with the "Evaluation data" (Field data) of the same period of 2013 to 2014 for measuring the forecasting performance accuracy level on model forecasts used in this work. The measure for higher accuracy for a model is the closer the MAPE and RMSE percentage errors value tend towards 0% from 10% regarding Chen et al. (2009), that figures below 10% show high predictive power. Firstly, in the monthly traffics of both Domestic and International passengers, some models provide highly accurate forecasts as their MAPE and RMSE results are lower than or at the 10% error benchmark, while some models' forecasts are good as their MAPE and RMSE result values are slightly above or higher than 10% benchmark. The forecasting behaviour of each model depends on the sector considered in some cases.

Table 1: MAPE and RMSPE scaling for single models on Domestic and International monthly air traffic of passengers.

Sector	Winter's	ARIMA	SARIMA	Airline
MAPE				
Domestic	4.71%(1st)	8.94%(2nd)	16.55%(4th)	12.96%(3rd)
International	6.85%(1st)	9.17%(2nd)	10.82%(3rd)	12.19%(4th)
RMSPE				
Domestic	5.89%(1st)	10.02%(2nd)	20.11%(4th)	15.69%(3rd)
International	8.66%(1st)	11.37%(2nd)	12.99%(3rd	15.79%(4th)

() denotes entry on the rank (1st or 2nd or 3rd…) positions of the models in their performance rating for this paper

The Winter's TESMTH model monthly forecasts came best of all models employed for this research as displayed by yardsticks of Mean Absolute Percentage Error (MAPE) and Root Mean Squared (Percentage) Error (RMSE) in scaling the Domestic and International sector monthly series. Winter's model forecasts appraisal performed under MAPE with very high accuracy levels of 95.29% (i.e. 4.71% errors) for the Domestic sector and 93.15% (i.e. 6.85% errors) for the International sector. Under RMSE, Winter's model performed with very high accuracy levels of 94.11 (i.e. 5.89% errors) in the Domestic sector and 91.34% (i.e. 8.66% errors) for the International sector.

The ARIMA model monthly forecasts came second best of all models employed for this research as displayed by yardsticks of Mean Absolute Percentage Error (MAPE) and Root Mean Squared (Percentage) Error (RMSE) in scaling the Domestic and International sector monthly series. The ARIMA model forecasts appraisal performed under MAPE with high accuracy levels of 91.06% (i.e. 8.94% errors) for the Domestic sector and 90.83% (i.e. 9.17% errors) for the International sector. Under RMSE, ARIMA model performed with good accuracy levels of 89.98% (i.e. 10.02% errors) in the Domestic sector and 88.63% (i.e. 11.37% errors) for International sector.

The SARIMA model monthly forecasts under MAPE performed third for the International sector and fourth (fourth out of four) for the Domestic with scaling of 10.82% errors and 16.55% errors respectively showing high accuracy forecasts for the International sector with 89.18% and just good forecast for Domestic sector with 83.45%. The SARIMA model under RMSE performed third in the International sector and performed fourth (Fourth out of four) in the Domestic sector with the scale of RMSE on the International sector yielding good forecasts of 87.01% (i.e. 12.99% errors) and on Domestic yielding forecasts of just 79.89% (i.e. 20.11% errors).

The AirLine-model monthly forecasts came third for the Domestic sector and fourth (Fourth out of four models) for the International Sector under MAPE scaling at 12.96% errors and 12.19% errors respectively showing just good forecasts levels of 87.04% and 87.81% while under RMSE scaling, the AirLine-Model became same third for Domestic and fourth (Fourth out of four) for the International sector with performances at 15.69% errors and 15.79% errors respectively showing little good forecasts of 84.31% and 84.21%.

These results conform with Shen et al. (2011), who discovered that no single model analytically beats all others albeit, Holt-Winters systematically outperforms all others on the scene of both market sectors. This paper found a slight difference in the scaling by MAPE and RMSE criteria when Domestic and International quarterly traffic series are considered for performance appraisals.

4.3 Combinations of Forecasts Techniques

The combination of forecasts takes the phase of using the forecasts of single models to combine them into two or three models with different building structures and generate average outcome values of forecasts to make up the Simple Averaging Method of Forecasting. The ARIMA, SARIMA and AirLine-Model are all derivatives of ARMA models – they all have the same certain fundamental building structures. The study combined forecasts of Winter's Triple Exponential Smoothing (TESMTH) versus SARIMA, Winter's TESMTH versus AirLineModel and Winter's TESMTH versus ARIMA. The combinations covered both Domestic and International traffic each at monthly and quarterly levels. Some combinations of forecasts were previously represented in charts Figures 2 to 4 according to the forecasts of models that were combined.

The combination method of Winter‘s TESMTH versus SARIMA models forecasts is employed in this research, it is evident that the combination method (Simple Averaging Technique) engaged drew out the two features of the single models' forecasts – deterministic trend and stochastic/seasonal movement, as also drawn from the main raw data. The combination forecasts of Winter's TESMTH versus SARIMA models forecasts did a good tracing. The combination method of Winter‘s TESMTH versus AirLine-Model forecasts is evident that the combination method (Simple Averaging Technique) engaged drew out the two features of the single models' forecasts – deterministic trend and stochastic/seasonal movement, as also drawn from the main raw data. The combination forecasts of Winter‘s TESMTH versus AirLine-Model forecasts did a good tracing

The combination method of Winter's TESMTH versus ARIMA models is evident that the combination method (Simple Averaging Technique) engaged drew out the two features of the single models' forecasts – deterministic trend and stochastic/seasonal movement; as also drawn from the main raw data. Although the ARIMA forecasts did not model out seasonality in its forecasts in lining forecasts with those of Winter's TESMTH forecasts, seasonality surfaced in their resultant forecasts. The combination forecasts of Winter's TESMTH versus ARIMA models' forecasts did a good tracing.

4.4 Appraisal of Performance Accuracy Levels for Combination of Forecasts

However, the study bothers next to appraise the performance accuracy levels of each of the combinations of forecasts gotten from merging the single model forecasts. This study came about three different combinations of forecasts notably; Winter's TESMTH forecasts versus ARIMA model forecasts, Winter's TESMTH forecasts versus SARIMA model forecasts and Winter's TESMTH forecasts versus AirLine-Model. The appraisal will be considered also by the yardsticks of both MAPE and RMSE and by matching the evaluation Data to the forecasts of the combination methods. The Evaluation Data only stretches from January 2013 to December 2014 and that limits the length of the combination of forecasts that will match with the same length of evaluation data by period for the input data in MAPE and RMSE. As all combinations of forecasts will be subject to the yardstick of MAPE and RMSE, the presentation here will originate by relating the predicting precision levels of the Winter's TESMTH and ARIMA models to match their combination of forecasts version accuracy levels. The Winter's TESMTH versus SARIMA – to match their combination of forecasts counterpart, will follow suit. The Winter's TESMTH versus AirLine-Model– to match their combination forecasts counterpart, will finally follow suit.

Table 2: Accuracy performance of the combination of forecasts from Winter's TESMTH versus ARIMA models forecasts compared with the accuracy levels of their single-component model's forecasts using the MAPE and RMSE yardsticks.

Sectors	Single Model Forecasts				Combination Forecasts	
	Winter‘s TESMTH		ARIMA		SA	
	MAPE	**RMSE**	**MAPE**	**RMSE**	**MAPE**	**RMSE**
DOMESTIC	4.71 %	5.89 %	8.94 %	10.02%	5.35 %	6.08 %
INTERNATIONAL	6.85 %	8.66 %	9.17 %	11.37%	**6.39 %**	**8.25 %**

BOLD percentage denotes that the Combination of forecasts outperforms the component models forecasts of the same performance criterion by MAPE or RMSE in isolation. SA: Simple average forecasts.

From Table 2, the results there became evident that the forecasts accuracies of combinations of Forecasts of International traffic outperformed the International traffics of Winter's TESMTH and ARIMA individual component models. In that vein, the combinations of forecasts held sway with the accuracy levels of 93.61% (i.e. 6.39% errors) under MAPE and RMSE, held sway with 91.75% (i.e. 8.25% errors) all obtainable on the International traffic. The combination of forecasts (Winter's TESMTH Vs. ARIMA) accuracy levels on the Domestic traffic outperformed its counterpart of the ARIMA forecasts accuracy levels by holding sway of 94.65% (i.e. 5.35% errors) under MAPE and 93.92% (i.e. 6.0% errors) under RMSE, over ARIMA‘s 91.06% (i.e. 8.94% errors) under MAPE and 89.98% (i.e. 10.02% errors) under RMSE. Winter‘s TESMTH accuracy levels took lead on the overall Domestic traffics with 95.29% (i.e. 4.71% errors) under MAPE and 94.11% (i.e. 5.89% errors) under RMSE.

Table 3: Accuracy performance of the combination of forecasts from Winter's TESMTH versus SARIMA models forecasts compared with the accuracy levels of their single-component model's forecasts using the MAPE and RMSE yardsticks.

Sectors	Single Model Forecasts				Combination Forecasts	
	Winter‘s TESMTH		SARIMA		SA	
	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE
DOMESTIC	**4.71 %**	**5.89 %**	16.55%	20.11%	9.05 %	11.22%
INTERNATIONAL	**6.85 %**	**8.66 %**	10.82%	12.99%	7.60 %	9.75 %

BOLD percentage denotes that the Winter's TESMTH forecasts outperform the Combination of forecasts of the same performance criterion by MAPE or RMSE in isolation. SA denotes Simple Average forecasts.

Unfortunately, the combinations of forecasts from Winter's TESMTH versus SARIMA could not outperform the component model forecasts by Winter's TESMTH when compared to their error percentages of MAPE and RMSE. Nonetheless, the combinations of forecasts under MAPE have high forecasts accuracies of 90.95% (i.e. 9.05% errors) for Domestic traffic and 92.4% (i.e. 7.60% errors) for International traffic. Under RMSE, combinations of forecasts have good forecasts accuracies of 88.78% (i.e. 11.22% errors) on Domestic and 90.25% (i.e. 9.75% errors) on International traffic. These accuracy levels of the combination of forecasts performed better than the SARIMA counterparts.

Table 4: Accuracy performance of the combination of forecasts from Winter's TESMTH versus AirLine-Model forecasts compared with the accuracy levels of their single-component model's forecasts using the MAPE and RMSE yardsticks.

Sectors	Single Model Forecasts				Combination Forecasts	
	Winter‘s TESMTH		AirLine-Model		SA	
	MAPE	**RMSE**	**MAPE**	**RMSE**	**MAPE**	**RMSE**
DOMESTIC	**4.71 %**	**5.89 %**	12.96%	15.69%	7.61 %	8.93 %
INTERNATIONAL	**6.85 %**	**8.66 %**	12.19%	15.79%	8.33 %	10.83%

BOLD percentage denotes that the Winter's TESMTH forecasts outperform the combination of forecasts of the same performance criterion by MAPE or RMSE in isolation. SA denotes Simple Average forecasts.

Unfortunately again, the combinations of forecasts from Winter's TESMTH versus AirLine-Model could not outperform the individual component model forecasts of Winter's TESMTH when compared by their error percentages of MAPE and RMSE. Nonetheless, the combinations of forecasts under MAPE have high forecasts accuracies of 92.39% (i.e. 7.61% errors) for Domestic traffic and 91.67% (i.e. 8.33% errors) for International traffic. Under RMSE, combinations of forecasts have good forecasts accuracies of 91.07% (i.e. 8.93% errors) on Domestic traffic and 89.17% (i.e. 10.83% errors) on International traffic. These accuracy levels of the combination of forecasts performed better than their AirLine-Model counterparts. This study observed that by the combination of forecasts and forecasting accuracy performance metrics, the combinations of forecasts have proven more accurate than some accuracy levels found from single nastiest models. This outcome embraces the two market sectors considered. These results differ from the one offered by Wong et al. (2007). These researchers found that there occurs a scarce case where the single nastiest model forecasts were more correct than the combinations of predictions.

Besides, there are indications that the joint forecasts outperformed their single best model equivalent 2 times (out of 12) with each criterion in the International traffic sector when combinations were done between Winter's TESMTH versus ARIMA. They were once occasioned under Mean Absolute Percentage Errors (MAPE) and Root Mean Square Percentage Error (RMSE) performance criterion in isolation on the pane of the Simple Average section. This proposes that the flight segment measured shows a role in whether or not Combinations of forecasts achieve accuracy more than their single model equivalents. The Simple Average Combination Technique outperformed all the ARMA models. Observations are clearer that a combination of forecasts outdo their single best model equivalent when a particular traffic sector is considered along with a particular single model. This held 2 times when considering the MAPE and RMSE criterion performance metrics in line with a traffic sector.

4.5 Discussion of Findings

Of all, Winter's TESMTH held high accuracy levels for both Domestic and International sectors than its counterpart models for the short-run measure of two years on a monthly and quarterly basis. Airport capacity is becoming increasingly limited and must be increased. Following that, the case runways and terminals were expanded with the construction of Terminal 5. In Nigeria, the Murtala Mohammed Airport (MMA) and Port Harcourt Airport have recently expanded their runways. Few industries have expanded and risen as quickly as aviation. However, are the justifications for more capacity acceptable, particularly in poor nations where capacity is frequently underused but vaguely perceived as overutilized? A boost in global income and life expectancy, as well as a relative reduction in global poverty, has increased demand for air transportation during the previous two decades, and Nigeria is no exception. Failure to accommodate the increase anticipated by estimates contained in this study would have major consequences for tourism, the banking industry, and other sectors that rely on global markets. As a result, aviation will continue to play a key part in the future success of both the Nigerian and global economies. However, transportation infrastructure is highly expensive to build.

Indeed, as part of financial planning and forecasting procedures, the choice to create one is also highly expensive since resources are limited and different sectors of the economy share these limited resources, which must also be addressed in resource allocation. Building new airports or expanding existing ones can only be justified if the existing ones' facilities are fully utilized. In terms of resource allocation, air transport will not be a priority sub-sector of the transport sector in a developing economy like Nigeria. As a result, is it reasonable to spend extensively on airports at the expense of road and rail, both of which are the primary modes of transportation for the majority of people? The airport capacity that is currently in place must be fully utilized to maintain relevance for the allotted resources and attract additional. In the twenty-first century, developing countries such as Nigeria face the dual demands of economic expansion and environmental conservation. The forecasts of this research have cast light on the future of possible expected Nigerian airport passengers' traffic demand and give all beneficiaries of this research the connotation to be forearmed. In the short run, the findings will sustain good monthly, quarterly and yearly budgeting and subsequent financial planning and funding for airport development. The forecasts for long-runs would gird and guide airport managements, sponsors, airlines etc., to work on measures to reorganize the scheduling of flights and spread out at airports to improve airport capacity utility and take note of airports where capacity utility is bottlenecked and demanding capacity expansions. Where there is a need for an additional regional airport, studies would prove and direct properly. Where there is a need for overhauling, management research out. The creation of intermodal and interconnected state-of-the-art train systems around the states of Nigeria would also reduce the future domestic airport passengers' demand drastically because, safety, cost and accessibility would make available alternative mode choices for the populace that may want to add to the future aggregate of domestic air passengers.

Estimations of performance accuracy levels of models used in the course of this study were done. The future expected traffics by the predictions and the level of accuracy by the best and second-best models using the Mean Absolute Percentage Error (MAPE) measure of accuracy is considered for display here in this section only. Only models were considered exempting the combinations of Forecasting methods employed. Table 5 holds that Winter's TESMTH model held the highest estimation accuracy in this research with errors terms of 4.71% (95.29% accuracy) and 6.85% (93.15% accuracy) on Domestic and International monthly air traffic of passengers respectively. Table 5 shows the forecasts of Winter‘s TESMTH by the sectors under investigation.

Table 5: Winter's TESMTH forecasts on yearly basis.

Sectors	Years	Predictions
Domestic	2015	11,635,346
	2016	12,373,273
	2017	13,111,200
	2018	13,849,127
	2019	14,587,054
	2020	15,324,981
International	2015	4,994,585
	2016	5,240,992
	2017	5,487,398
	2018	5,733,805
	2019	5,980,211
	2020	6,226,618

Table 6 holds that according to the MAPE performance criterion, the ARIMA model held second best for both Domestic and International monthly air traffic. The ARIMA forecasts were evaluated with accuracy levels of 91.06% (8.94% error term) and 90.83% (9.17% errors) on Domestic and International monthly air traffic of passengers respectively. Table 6 shows the forecasts of the ARIMA model by the sectors under investigation.

Table 6: ARIMA Model forecasts for Domestic and International air traffic of passengers on yearly basis.

Sectors	Years	Predictions
Domestic	2015	12,762,291
	2016	13,767,412
	2017	14,851,693
	2018	16,021,369
	2019	17,283,165
	2020	18,644,337
International	2015	5,693,304
	2016	6,289,736
	2017	6,948,649
	2018	7,676,591
	2019	8,480,791
	2020	9,369,240

The position of the best forecasting model as identified by and for this research alone specifically emanates from the measure of performance accuracy levels done by the Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) criteria/benchmarks, as presented in Table 4. Deducing from Tables 5 and 6 on the performance criterion of models when models have been compared alone, Winter's TESMTH model did best in the forecasting/prediction exhibition for Domestic and International monthly and Quarterly enplaned/deplaned passengers. This is captured considering that the Winter's TESMTH obtained the lowest error prediction levels of 4.71% (95.29% accuracy) and 6.85% (93.15% accuracy) for Domestic and International traffic under MAPE evaluation and the lowest error prediction levels of 5.89% (94.11% accuracy) and 8.66% (91.34% accuracy) for Domestic and International traffic respectively under RMSE appraisal. These in turn represent high levels of accuracy in forecasting performances. When all methods of forecasting are compared together, that brings the combinations of Forecasting methods into play and by that measure, the combinations of Forecasts of Winter's TESMTH versus ARIMA models' forecasts held the best forecasting method as applied and for this research alone on International air traffic with lowest error prediction levels of 6.39% (93.61% accuracy) under MAPE evaluation and 8.25% (91.75% accuracy) under RMSE evaluation for all forecasting methods used. The Winter's TESMTH model (as an individual model) held sway in the Domestic air traffic forecasts under the MAPE and RMSE evaluations for all forecasting methods used. The benchmark is 10%. In the words of Chen et al. (2009), ratios under 10% mirror high predicting precision. There are clear indications to note that our data series under consideration for the Domestic and International air traffic of passengers exhibited deterministic trends and the presence of a unit root (a random walk) which was responsible for seasonality. The presence of these properties excludes our data series from the bases of stationarity. The existence of trend and integration (i.e. unit root) between the observations themselves is the most typical cause of non-stationarity in sample data. A stationary process is a stochastic process whose joint probability distribution remains constant whether time or space is changed. As a result, parameters like the mean and variance, if they exist, do not alter as a result of a change in time or place. The study, on the other hand, used several strategies such as descending, seasonal adjustment and differencing to produce a stationary process in the data set. Finally, the investigation found stationarity in both air traffic sectors.

4 Conclusion

From this research so far, the study can conclude that the models did pretty good on the levels of their forecasting abilities. For the single models, the Winter's TESMTH did best in the forecasting exercise considering the MAPE and RMSE forecasting performance criteria used on the out-of-sample forecasts against the actual field data (Evaluation Data). Winter's TESMTH did best in both Domestic and International sectors under consideration for single models. When all forecasting methods used are compared, the Winter's TESMTH took sway with its Domestic forecasts while the combinations Forecasts of Winter's TESMTH versus ARIMA took sway with its International forecasts.

The ARIMA forecasts did second-best in the Domestic and International forecasts. The Airline-model did third best in domestic forecasting and fourth in International forecasting. SARIMA came third for the International traffic forecasts and fourth on the Domestic traffic forecasts but still has a good level of accuracy as its forecast errors lag a little away from the benchmark of 10% error term. The combination of Forecasts method used in this research is Simple Averaging (SA) which performed wonderfully when Winter's TESMTH versus ARIMA models' forecasts were combined and did great to outperform the single worst model in any of its combinations processes. When Winter's TESMTH was combined with individual ARMA-Based models, Simple Averaging did best based on the International traffic forecasts considered and under both performance criterion schemes (MAPE and RMSE) inclusive. More can be done in the research to obtain more accurate forecasting performance by introducing other Combinations methods on models for the more high level of predictions. This study contributes to the current literature in the following ways: 1. It addresses the most recent Nigerian air passenger series and includes monthly and quarterly projections from 2013 to 2020. 2. It employs, for the first time, a forecasting combination approach using Nigerian air passenger data. The study investigated whether or not the previous studies' results about the performance of these strategies are still true in this scenario. 3. To date, this is the only study that has used Winter's Triple Exponential Smoothing Model to anticipate the number of monthly and quarterly air traffic passengers in Nigeria. Finally, with the advanced techniques of forecasting done for and in this study, there is much provided for researchers to consider and apply or advance from/on in the case of travel demand of Nigeria air traffic of passengers and forecasting per se.

References:

[1] Anderson R., Sweeney J., and Williams (2000). Essentials of Statistics for Business and Economics

[2] Bao, Y., Xiong, T., and Hu, Z. (2012). Forecasting air passenger traffic by support vector machines with ensemble empirical mode decomposition and slope-based method. Discrete Dynamics in Nature and Society, 2012

[3] Bjørnland, H., Gerdrup, K., Jore, A., Smith, C., and Thorsrud, L. (2011). Does forecast combination improve Norges Bank inflation forecasts? Oxford Bulletin of Economics and Statistics, 74(2):163–179.

[4] Bougas, C. (2013). Forecasting Air Passenger Traffic Flows in Canada: An Evaluation of Time Series Models and Combination Methods, MA in Economics Thesis, Québec, Canada. http://www.cms.fss.ulaval.ca/recherche/upload/chaire_aeroportuaire/fichiers/these_bougas_2013.pdf

[5] Chen, C., Chang, Y., and Chang, Y. (2009). Seasonal ARIMA forecasting of inbound air travel arrivals to Taiwan. Transportmetrica, 5(2):125–140.

[6] Chu F. (1998). Forecasting tourism: a combined approach. Tourism Management, 19(6):515–520.

[7] Constantinos B. (2013). Forecasting Air Passenger Traffic Flows in Canada. An Evaluation of Time Series Models and Combination Methods.

[8] Coshall J. (2009). Combining volatility and smoothing forecasts of UK demand for international tourism. Tourism Management, 30(4):495–511

[9] Emiray E. and Rodriguez G. (2003). Evaluating Time Series Models in Short and Long-Term Forecasting of Canadian Air Passenger Data. Department of Economics, University of Ottawa.

[10] Etuk H. E. (2013). A Seasonal Time Series Model for Nigerian Monthly Air Traffic Data. IJRRAS 14 (3).

[11] FAAN (2012). Federal Airport Authority of Nigeria: Annual Operations Reports.

[12] Fildes, R., Wei, Y., and Ismail, S. (2011). Evaluating the forecasting performance of econometric models of air passenger traffic flows using multiple error measures. International Journal of Forecasting, 27(3):902–922.

[13] Grosche, T., Rothlauf, F., and Heinzl, A. (2007). Gravity models for airline passenger volume estimation. Journal of Air Transport Management.

[14] Hales S., Cazelles B., Chavez M., and McMichael A.J. (2005) Nonstationary influence of El Nin˜o on the synchronous dengue epidemics in Thailand.

[15] Mobolaji S. and Wilfred U. (2011). Airport capacity utilization in Nigeria: A performance and efficiency analysis. African Journal of Business Management Vol.5 (27), pp. 11104-11115, 9 November 2011.

[16] Poncela P. and Senra E. (2006). A two-factor model to combine US inflation

forecasts. Applied Economics, 38(18):2191–2197.

[17] Prideaux, B., Laws, E., & Faulkner, B. (2003). Events in Indonesia: exploring the limits to formal tourism trends forecasting methods in complex crisis management. Tourism Management, 24, 475–487.

[18] Shen, S., Li, G., and Song, H. (2008). An assessment of combining tourism demand forecasts over different time horizons. Journal of Travel Research, 47(2):197–207.

[19] Shen, S., Li, G., and Song, H. (2011). Combination forecasts of international tourism demand. Annals of Tourism Research, 38(1):72–89.

[20] Spitz W. and Golaszewski R. (2007). Airport Cooperative Research Program A.C.R.P. Report 76: Addressing Uncertainty about Future Airport Activity Levels in Airport Decision Making.

[21] Wong, K., Song, H., Witt, S., and Wu, D. (2007). Tourism forecasting: to combine or not to combine? Tourism Management, 28(4):1068–1078.