MODELLING AIR PASSENGER TRAFFIC FLOW IN MURTALA MUHAMMAD INTERNATIONAL AIRPORT LAGOS, NIGERIA: A TIME SERIES APPROACH

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**A DISSERTATION SUBMITTED TO THE SCHOOL OF POSTGRADUATE STUDIES, AHMADU BELLO UNIVERSITY, ZARIA,
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DEPARTMENT OF STATISTICS
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DECEMBER, 2016

DECLARATION

I declare that the work in this Dissertation titled "Modelling Air Passenger Traffic Flow in Murtala Muhammad International Airport Lagos, Nigeria: A Time series Approach" has been carried out by me in the Department of Statistics. The information derived from the literature has been duly acknowledged in the text and a list of references provided. No part of this dissertation was previously presented for another degree or diploma at this or any other Institution.

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CERTIFICATION

This dissertation titled "MODELLING AIR PASSENGER TRAFFIC FLOW IN MURTALA MUHAMMAD INTERNATIONAL AIRPORT LAGOS, NIGERIA: A TIME SERIES APPROACH" by FunshoOlalekan OMOLOHUNNU meets the regulations governing the award of the degree of Masters of Science in Statistics of the Ahmadu Bello University, and is approved for its contribution to knowledge and literary presentation.

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DEDICATION

This research work is dedicated to God Almighty. The enablement to complete this research work has come from God.

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ABSTRACT

Aviation is a key sector of the Nigerian economy. Over the years, there have been remarkable influence of aviation on the economy. Murtala Muhammad International Airport (MMIA) Lagos is the busiest airport in Nigeria, accounting for over 60% of the total air passenger and aircraft movement in the country. In such an increasingly competitive aviation sector, it is imperative to make fairly accurate forecast so as to enable long-term planning, short term planning and decision regarding infrastructure development, flight networks and effective management.In this study, Artificial Neural Network (ANN), Seasonal Auto-Regressive Integrated Moving Average (SARIMA) and Holt-Winters Exponential Smoothing (HWES) models are used to model air passenger traffic flow in MMIA.The performances of these proposed models are compared for in-sample and out-of-sample performance by employing static forecast procedure over January 2014 to December 2015 forecast horizon. The best models from the SARIMA, ANN and HWES were selected by employing some performance metrics comprising, Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) and residual diagnostics. The selected models forecasting performances were compared using the statistical loss functions, Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) for the measurement of forecast accuracy. Results show that ANN outperforms the other models in the domestic sector, while the HWES had the best performance in the international sector even though it was outperformed by SARIMA in the domestic sector. ANN yielded the best in-sample performance for domestic and international air passenger traffic. It was concluded that the ANN, which represents a class of non-linear time series model is very efficient in mimicking time series pattern and giving good forecast.

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LIST OF ACRONYMS

ACF	Auto Correlation Function
ADF	Augmented Dickey Fuller
AIC	Akaike Information Criterion
ANN	Artificial Neural Network
ARMA	Auto Regressive Moving Average
ARIMA	Auto Regressive Integrated Moving Average
BIC	Bayesian Information Criterion
CAGR	Compound Annual Growth Rate
HES	Holt Winters Exponential Smoothing
IATA	International Air Transport Association
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
PACF	Partial Auto Correlation Function
RSME	Root Square Mean Error
SARIMA	Seasonal Auto-Regressive Integrated Moving Average

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

Some decades ago, Aviationin Nigeria has been recognized as being a key sector of the economy.It is one of the indices for measuring the development of a country. The importance of this sector to the economy of Nigeria cannot be overemphasized. The effect of this which is typically characterized by business cycles or alternation between periods of economic growth and downturns,brings about our data series exhibiting cyclical patterns or seasonality. Furthermore, every economy is highly susceptible to a variety of shocks of different nature (economic, political, climatic etc), which are likely to modify the past trends and the volatility in thedata (Bougas, 2013).The International Air Transport Association (IATA) released the IATA airline forecast for 2013-2017 showing that airline expect to see a 31% increase in passengers flow between 2012 and 2017. By 2017 the total passenger numbers are expected to rise to 3.91billion- an increase of 930 million passengers over the 2.98billion carried out in 2012.

The IATA airline industry forecast 2013-2017 is a consensus outlook for system-wide passenger growth. Demand is expected to expand by an average of 5.4% Compound Annual Growth Rate (CAGR) between 2013 and 2017. By comparison, global passenger growth expanded by 4.3% CAGR between 2008 and 2012, largely reflecting the negative impact of the 2008 global financial crisis and recession. Of the new passengers, approximately 292 million were carried on international routes and 638 million on domestic routes.

The report further stated that,emerging economies of the Middle-East and Asia Pacific will see the strongest international passenger growth with CAGR of 6.3% and 5.7% followed by Africa and Latin America with CAGR of 5.3% and 4.5%. (IATA, 2013).

Predicting future air passenger traffic flow is important as it allows air transport authorities to adapt necessary infrastructures and offers airline companies the capacity to match the increasing passenger demand for air transportation. There are a great amount of studies, particularly since the 1990's that use time series models to forecast air passenger numbers. The forecasting performance of each model varies depending on the country of the passengers, the type of flight considered (domestic or international), the performance measure and the forecasting horizon (Emiray and Rodriguez, 2003). No methodological approach has been found to always dominate another in terms of forecasting performance (Shen *et al.*, 2011). However, one model that has been successfully used in its various applications is the ANN. The ANN model is a mathematical model inspired by the function of the human brain and its use is mainly motivated by its capability of approximating any Borel-measurable function to any degree of accuracy (Hornik*et al.*,1989). This study provides an evaluation of three time series forecasting models performance based on air passenger traffic movement. These comprise an Autoregressive Moving Average Model known as Seasonal Auto –Regressive Integrated Moving Average (SARIMA), ANN model and the HWES model.

1.2 Description of the Sample Area

Lagos Airport also known as MMIA (renamed in the mid1970s, after a former Nigerian Military Head of state, GeneralMurtalaMuhammed) is an international airport providing worldclass flight services both in Nigeria and elsewhere. MMIA consists of an international and a domestic terminal located at about one kilometer apart from each other. The international terminal was modeled after Amsterdam's Airport Schiphol and was opened officially on 15thMarch 1979.

A new domestic privately funded terminal known as MMA2 has been constructed and was commissioned on 7th April 2007. In 2009 alone the airport served 5,644,572 passengers.

The airport houses the headquarters of the Federal Airport Authority of Nigeria(FAAN) as well as the Head Office of the Accident Investigation Bureau(AIB). The Lagos office of the Nigerian Civil Aviation Authority(NCAA) is located in Aviation House within the airport. MMIAis believed to be the busiest airport in Nigeria rendering services internationally and locally. In recent years, the domestic and overseas passenger traffic has risen steadily at an average of 10% per annum and being the Nation's main gateway, it accounts for over 60% of the total passenger and aircraft movement in the country.

1.3 Motivation for the Study

This research is motivated by the need to comparatively examine the performances of threetime series models (ANN, SARIMA and HWES), in modelling the air passenger traffic flow in MMIA Nigeria.

1.4 Statement of Problem

Over the years, demand for air transportation in Nigeria has greatly increased. This is indicated by increase in air passenger traffic for both domestic and international flights, emergence of more airlines, creation and expansion of terminals. Also, with the rate of increase in passenger traffic and increasing influence of Aviation on the Nigerian economy, it is important that time series models are accurately selected for proper management in the airlines, airports and the Nigerian Airspace.Many researchers adopt the more common time series approach in predicting air passenger traffic. In some cases salient characteristics in the time series data might not be captured due to the simplicity of the adopted models. However, there is a need to apply the conventional methods and compare it with a more robust approach in modelling the air passenger traffic so as to improve forecast accuracy.

1.5 Time Series Models

Presently, there are many time series models used in forecasting, some of which include;ANN, Harmonic Regression (HR), HWES as well as the class of model known as the Auto-Regressive Moving Average (ARMA) model, which consist of the Autoregressive Integrated Moving Average (ARIMA) model, the Seasonal Autoregressive Integrated Moving Average (SARIMA) model and Grey Model among others; theAutoregressive Conditional Heteroscedasticity(ARCH) model(Engle,1982) and all of its extensions is often applied in forecasting of financial time series. As for multivariate models, the Vector Auto-Regressive(VAR) model and the Error Correction Model (ECM) are also common (Artis and Zhang1990).

Forecasting performance of all these time series models vary with the forecasting horizon and depend on the adequate detection of seasonal roots.

1.6 Aim and Objectives of the Study

This study is aimed at comparing the forecast performances of time series models in approximately predicting the air passenger traffic flow in MMIA Lagos, Nigeria. This is achieved through the following objectives; by

(a) fitting three time series models (ANN,SARIMA and HWES);

(b) evaluating the accuracy of the proposed models using some performance criteria comprising Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC) using monthly forecast of air passenger flow at MMIA;

(c)evaluate the out-of-sample forecast performance of these models using some classical loss functions such as MAPE and RMSE and be able to say which among them is better than the others.

1.7 Significance of the Study

Selecting a good time series model is beneficial for an accurate and reliable airport passenger flow prediction.This is an integral component for short-term, long-term planning and decision making regarding airport infrastructure development and flight networks. This research work aims to compare the performances of suitable time series models that can best be used in forecasting air passenger traffic flow in MMIA, Lagos

1.8 Sources of Data

The data to be used for the purpose of this study was collected from the Statistics Department of the Nigerian Airspace Management Agency(NAMA),MMIA, Lagos, an agency responsible for keeping records of the air passengers for both domestic and international flights for the period under study.

1.9 Scope and Limitation of the Study

The empirical study only covers thirteen years, between January 2003 and December 2015,this is due to insufficient data from the primary source to cover the desired number of years for the research work. Only few models will be used for the forecast. Most factors responsible for air passenger traffic flow such as population and economic activities will not be measured hence the analyses will be based on the available data to be obtained from the airport. The study does not exclusively check the evaluation of the models performances on each airline.

1.10 Ethical Considerations

The scope and objective of this research requires that operational data of the MMIA International Airport were used. As such, issues pertaining to data confidentiality and integrity were treated with high ethical regard. All variables that tended to identify and classify individuals, airlines or aircraft involved were discarded. Aircraft registrations and countries of registration were also discarded in compliance with the maintenance of ethics and confidentiality.

CHAPTER TWO

LITERATURE REVIEW

2.1 INTRODUCTION

The aviation sector has been a vital component of the Nigerian economy, contributing immensely to its growth and development. Over the years, the sector has recorded increase in air passenger traffic. Airlines registered in Nigeria carry 6 million passengers and 119,000 tonnes of freight a year, to, from and within Nigeria. These airlines directly employ 7,000 people locally and support, through their supply chain, a further 33,000 jobs and 21,000 jobs supported through household spending of those employed by the airlines and their supply chain, contributing about NGN 29 billion to the Nigerian economy (IATA 2010).

According to the NBS report (2014), the airline sector grew at an average growth rate of 14.3% between 2010 and 2013 and about 50 percent of average total passenger air travel between 2012 and 2013 were via Lagos airports (domestic and international), while about 25% were through Abuja airport.

With the emergence of more airlines, improved safety of the Nigerian airspace and increase of the Nigerian economy, passenger traffic has continued to increase. The steady growth of air passenger traffic was interrupted by the tragic air flight crash in June 2012. Since then, the sector has continued to record increase in air passenger traffic.

Nigeria recorded 68.84 percent domestic travels by air in the first quarter of 2014 out of a total of 3.4 million passengers that used Nigerian Airports, approximately 2.4 million travelled domestically (68.84 percent). According to recent data released by the National Bureau of Statistics (2014).

Nigerian air passenger traffic has been on a steady growth over the years. This could be attributed to the robust economic activities and the rebasing of Nigerian economy making it the largest in Africa in 2014.

Despite interruptions of air passenger traffic as a result of air crashes, hike in air fare, airlines recapitalization etc. The aviation sector has had a remarkable progress evidenced by yearly increase of air passenger traffic, emergence of new airlines and building of additional airports in the country. This has led to the creation of thousands of jobs and immense contribution to the strength of Nigerian economy. The aviation sector supports long run prosperity of the economy supplying benefits which aid the increase in the economy's level of productivity and long term sustainable rate of growth.

Air transport also contributed NGN32.6 billion to Nigeria rebased GDP in 2010, 36.6bn in 2011, NGN42.7bn in 2012 and 48.8bn in 2013 and an average of 0.05 percent of total nominal GDP during the period whilst passenger traffic increased by 1.3 percent between 2012 and 2013 (National Bureau of Statistics, 2014).

Various time series models, univariate or multivariate, have been used in different capacities in modelling and forecasting in the aviation sector. This chapter provides a comprehensive review of previous studies.

2.2 Literature on Time Series Models

A large body of published literature regarding air passenger traffic flow forecast tend to concentrate on three specific regions: the United States, Europe and the Pacific region Andreoni and Postorino (2006). The work of Emiray and Rodriguez (2003) on their long study on Canada, provided monthly forecast of enplane/deplane air passengers flow for three market segments (domestic, international and trans-border flights), based on data covering the period ranging from January 1984 to September 2002. The study considered six time series models (Autoregressive AR(p), AR(p) with seasonal unit roots, Seasonal Autoregressive Integrated Moving Average (SARIMA), Periodic Autoregressive Model (PARM), Structural Time Series Model (STSM) and the seasonal unit roots model). They concluded that forecasting performance depends on two key elements: the market segment considered and the forecasting horizon. They showed that short memory models are better for short term forecasting whereas long memory models are better for long term forecasting.

According to Zhang (2003), ARIMA and SARIMA models are among the most widely used in the air passenger forecasting literature. Their popularity comes from the fact that they are based on very few assumptions. Furthermore, they are easy to specify with the Box- Jenkins methodology.

Coshall (2006) examined the performance of ARIMA and SARIMA models for predicting air passenger traffic flows. The study forecasts air travel from the United Kingdom to twenty destinations using quarterly data of UK outbound air travelers with several models, which include: the Naïve 1, Naïve 2 model, the Holt-Winters model and a variety of ARIMA models. It was concluded that, the Root Mean Square Error (RMSE) suggests that the ARIMA model was almost completely dominant.

Tsui *et al*., (2011) observed in his study of air passenger traffic in Hong Kong International Airport that it is important to check the forecast accuracy of both fitted ARIMA models by evaluating ex-post forecasts. After transforming log-airport passenger traffic to absolute values, it shows the forecasting performance of both fitted models by comparing their actual airport passenger traffic and forecasted values. It was found that the forecasted errors of univariate seasonal ARIMA model are smaller compared to those of Auto-Regressive Integrated Moving Average with Exogenous Input (ARIMAX) model. Another finding is that, for both models, the forecasted error are very accurate within two months forecast horizon, and the forecast error increase remarkably when the forecast horizon gets to three months. This indicates that both models may experience larger forecasting error for longer-term forecast.

Doguwa and Alade (2015), proposed three statistical models in modeling Nigerian external reserves, SARIMA, seasonal autoregressive integrated moving average with an exogenous input (SARIMA-X) and ARDL an autoregressive distributed lag model. Using pseudo-out-of-sample forecasting they concluded that SARIMA model outperformed the other models in three to six months forecast horizon whereas ARDL model performs better in one to two months forecast horizon.

Coshall*et al.,* (2009) generalizes past literature and classified airline passenger traffic forecasting models into four kinds; the first one is judgment prediction which uses the professional judgment to judge the future economic development and revises the predicted passenger flow. The second is trend projection and speculation, which uses statistical model to analyze passenger traffic trend. The third is market analysis, this method predicts regional airline passenger traffic by market share model, and the last one is the econometric modeling method, which is widely used in airline passenger traffic. Econometric model include multi regression model, which uses historical passenger traffic data to predict the future traffic.

Chen *et al,.* (2009) estimated the monthly arrivals to Taiwan from Japan, Hong Kong and United States as well as the total amount of inbound air travels. Interestingly, they divided air arrivals in three categories according to travel purpose: tourism, non-tourism and any other purpose. They considered the following forecasting models: Holt- Winters, SARIMA and Grey forecasting model. SARIMA model was found to outperform all other models when it comes to estimating tourism related arrival to Taiwan. For all purpose and non-tourism arrivals, the SARIMA model outperforms the other two models for arrival from Japan and the United States but not for those from Hong Kong or for total arrival (however, it performs competitively against the others).

The work of Hsu and Wen (1998) applied another approach known as the Grey theory on airline passenger traffic forecasting. The study constructed an improved time series model and show the predicted result of Grey model is more accurate than those predicted by regression model or ARIMA model.

Hsu and Chen (2003),showed that the Grey system theory also known as the Grey analysis published by Deng in 1982, is best used to analyze system in uncertain situation or incompetence data and constructs its predicting model. This model needs little histories data to formulate a predicting model. Therefore it is suitable to predict airline passenger traffic, which data is usually insufficient. Grey topological forecasting model is based on the Grey system theory, and is also called Grey pattern prediction or system trend prediction model.

The combined model of Grey Topology model and Markov-Chain formulated in their research can predict passenger traffic more precisely, and can also predict probability of inaccuracy.

From the base model and scenario development, Chen*et al.,* (2012) summarized that the airfare, level of service impact, gross domestic product (GDP), population, number of flights per day and dwell time play an important roles in determining the air passenger volume, runway utilization and total additional area needed for passenger terminal capacity expansion.

Over the years, many other models and techniques have been developed for forecasting air passenger traffic flow. Some of these methods have proven to have better performance and accuracy in forecasting than the more conventional univariate time series linear models. A priori specification may fail to capture important non-linearity and interaction which has not been explicitly modeled. These can be captured by ANN's model but at the expense of interpretability. The contribution of each regressor cannot be interpreted individually.

Chen *et al.,* (2012) used back propagation neural network as an example to identify the factors that influence air passenger and air cargo demand from Japan to Taiwan. They found that air passenger and air cargo are generally influenced by different factors but that there are some common factors which influence both. This allowed them to construct models which possess very high forecasting accuracy in the short and medium term. However, they noted that the performance of neural network models heavily depends on choosing appropriate training set.

Bao*et al*., (2012) compared the forecasting performance of a HWES model, a univariate time series model (ARIMA) and the following Support Vector Machines Based model: Single Support Vector Machines (SVM'S), Ensemble Empirical Mode Decomposition based Support Vector Machine (EEMD-SVM's) and Ensemble Empirical Mode Decomposition Slope based method Support Vector Machine (EEMD-Slope-SVM's). The monthly passenger data from six American and British airline companies were used and the following performance criteria: Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), Geometric Mean Relative Absolute Error (GMRAE) and Directional Statistic (DS) are used and it was concluded that; Single SVM's outperform ARIMA and HWES,EEMD-SVM's outperform single SVM's,EEMD-Slope- SVM's are more accurate than EEMD-SVM's (and therefore also outperform ARIMA, HWES and single SVM's).

Grosche*et al.*, (2007) developed two gravity models in order to forecast air passenger flow between city pair. Both models include mostly geo-economic variables. The first model includes city-pair which involve multi-airport cities. Hence, it excludes competition. It uses such variables as population, distance between airports, average travel time and buying power index to predict travel demand. On the other hand, the second model includes multi-airport cities as well as variables that take them into account (the number of competing airports, the average distance to competing airports). Both models are found to be statistically valid and fit the data well.

Fildes*et al.,* (2011) made use of a wide variety of multivariate models to study the air passenger traffic flow between the United Kingdom and five countries: Germany, Sweden, Italy, the USA and Canada. They use the following econometric models: an Autoregressive Distributed Lag model (ADL), a pooled ADL, Time –Varying Parameter model (TVP) as well as an automatic method for econometric model specification. They also considered the previous four models augmented by a world trade explanatory variable (which measures the total trade of all industrial countries).

In addition, they applied the following models: Vector Autoregressive model (VAR), Vector Autoregressive model with the world trade variable, Exponential Smoothing model, Autoregressive model of order three (AR(3)) as well as Naïve I and Naïve II benchmark models.

Forecasting combination techniques offer an alternative approach to single models' forecasts. Bates and Granger (1969) were the first to propose such techniques to improve the forecasting accuracy of individual models (Wong *et al.*, 2007). Over the last three decades, these techniques have become highly prevalent in the forecasting literature. They have been applied with success to numerous fields such as: macroeconomics (Bjornland*et al.*, 2011) Meteorology (Brown and Murphy (1996)), Banking (Chan *et al*., 1999) and Tourism (Coshall, 2009).

Some authors have pointed out the reasons for the prevalence of these methods. For instance, Timmermann (2006) observed that, combining forecast allows better aggregate to all relevant information captured in different single model forecasts and they are more robust against a misspecification of the data generating process. Therefore, combined forecasts can improve the forecasting accuracy and they are seen as being more comprehensive. Note that combination forecasts are more likely to improve forecasting performance when each single model forecast being combined is independent of the other (or uncorrelated). Poore (1993) developed a model to test the hypothesis that forecasting of the future demand for air passengers offered by aircraft manufacturers and aviation regulators are reasonable and representative of the trends implicit in experience. He compared forecasts issued by Boeing Airbus Industry and the International Civil Aviation Organization (ICAO) which has actual experience and the results of a baseline model for Revenue Passenger Kilometers (RPKs) demand.

Matthews (1995) conducted a research on measurement and forecasting of peak passenger flow at several airports in the United Kingdom. According to his work, 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 requirement, hourly forecast are almost always based on the forecast of annual passengers flows.

Abed*et al*., (2001) developed a model for forecasting the long-term demand for domestic air passenger in Saudi Arabia. The study utilized several explanatory variables such as total expenditure and population to generate the model. Grosche*et al.*, (2007) in their research observed that, there are some variables that can affect the air passenger flow.

These include; population, gross domestic product (GDP) and buying power index. They considered GDP as representing variable for the level of economic activity.

In summary, most papers on forecast that examined models, have not really been able to come up with a single model which is completely dominant but have been able to establish some facts about the effectiveness of particular models in the sectors considered.

CHAPTER THREE

METHODOLOGY

3.1 Introduction

This chapter discusses more about the models: Box-Jenkings Seasonal Auto-Regressive Integrated Moving Average Model, the Holt-winters Exponential Smoothing model and the Artificial Neural Network approach in modelling the air passenger traffic flow in Murtala Muhammad International Airport for domestic and international flights.The steps employed in the model selection for the SARIMA are elaborated and the procedures for calculating accuracy measures are discussed.

3.2 Data for the Study

The data used in this dissertation are the monthly air passenger traffic flow for international and domestic flights over the period of January 2003 to December 2015. This was obtained from the Nigerian Airspace Management Agency(NAMA).

The domestic air passenger traffic comprises of local passenger arrival and departure to and from Murtala Muhammed International Airport whereas the international air passenger traffic comprises of air passengers from international flights from and to other countries other than Lagos, Nigeria. The data set consists of 156 monthly observations of air passenger traffic flow for domestic flights and 156 monthly observations for international flights.

This study uses the R version 3.2.4(2016), Eviews 9 and Zaitun software for its analysis.

3.3 Normality Test

Various tests for normality have been developed by various statisticians which include the Kolmolgorov Smirnov test, the Lilliefors test, the Cramer-von Mises test, Anderson-Darling test and the Jarque-Bera test among others. In this dissertation, we shall make use of the Jarque-Bera test for normality, developed by Jarque and Bera (1980). The Jarque-Bera test is a simple but powerful normality test that easily matches the skewness and kurtosis to see if the distribution is normal. This test asymptotically has a chi-squared distribution with two degrees of freedom if the data come from a normal distribution.

The Jarque-Bera test statistic is defined as;

$$JB = \frac{n}{6}\left(S^2 + \frac{(K-3)^2}{4} \right) \sim \chi_{(2)}^{2} \qquad (3.1)$$

with S, K, and n denoting the sample skewness,kurtosis and the sample size respectively.

$$\text{Skewness} = \frac{\sum_{i=1}^{n} (x_i - \bar{x})^3}{nS^3} \qquad (3.2)$$

where x_i represents the monthly observation of air passenger traffic in each case for international and domestic air passenger traffic, while $\bar{x}$ signifies the mean, n is the sample size, S is the standard deviation of either international or domestic air passenger as the case may be.

Kurtosis is a measure of flatness (platykurtic) or peakedness (leptokurtic) of the top of a normal distribution.

$$\text{Kurtosis} = \frac{\sum_{i=1}^{n} (x_i - \bar{x})^4}{nS^4} \qquad (3.3)$$

If the random variable is symmetrically distributed then coefficients of skewness and kurtosis will be zero.

The null hypothesis is

H_o: $x_1,..., x_m$ is normally distributed versus $H_{1:}$ $x_1,..., x_m$ is not normally distributed

The test statistic is asymptotically χ^2 distributed with 2 degrees of freedom. We reject H_0if

$JB \geq \chi^{2}_{1-\alpha,2}$

3.4 Concept of Time Series and Models

A time series is defined as a set of quantitative observations arranged in chronological order. It is a set of observations $\{x_t\}$ each one being recorded at a specific time t.

A time series model for the observed data $\{x_t\}$ is a specification of the joint distributions (or possibly only the means and co-variances) of a sequence of random variables $\{x_t\}$ of which $\{x_t\}$ is postulated to be a realization.

In reality, we can only observe the time series at a finite number of times and in that case the underlying sequence of random variables $(x_1, x_2, ..., x_n)$ is just an *n*-dimensional random variable (or random vector). Often, however, it is convenient to allow the number of observations to be infinite. In that case $\{x_t, t = 1,2,......\}$ is called a stochastic process. This will further be elaborated in the following section.

Time series could be discrete or continuous; Discrete time series is one in which the set T_0 at which observations are made is a discrete set. Continuous time series are obtained when observations are recorded continuously over some time interval.

3.5 Stochastic Process

A stochastic process is a collection of random variables $\{x_t\}$ indexed by a set T, i.e. $t \in T$ (Not necessarily independent)

- If T consists of the integers (or a subset), the process iscalled a Discrete Time Stochastic Process.

- If T consists of the real numbers (or a subset), the processis called Continuous Time Stochastic Process.

Similarly, these processes may take on values which are real or restricted to the integers and are called continuous state space or discrete state space accordingly.

A time series is thus a realization or sample function from a certain stochastic process.

3.6 Stationarity

This is the most vital and common assumption in time series analysis. The basic idea of stationarity is that, the probability laws governing the process do not change with time; the process is in statistical equilibrium. Definition of some concept will aid in the definition of the types of stationarity in the sections below.

Definition 3.6.1 (Mean Function)

The mean function of a time series $\{x_t\}$ with $\sum (x_t^2) < \infty$ is

$$\mu_x(t) = \sum (x_t), \quad t \in Z$$

Definition 3.6.2 (covariance function)

The covariance function is defined as: $\gamma_x(r,s) = \text{cov}(x_r, x_s) = \sum [x_r - \mu_x(r))((x_s - \mu_x(s)]$

for all $r, s \in z$

Definition 3.6.3(weak stationarity)

A time series $\{x_t\}_{t \in T}$ is weakly stationary if both the mean $\mu_x(t) = \mu_x$ and for each $h \in z$, the covariance function $\gamma_{x(t+h,t)} = \gamma_{x(h)}$ are independent of time *t*.

Definition 3.6.4(Strict stationarity)

A time series $\{x_t\}$ is said to be strictly stationary if the joint distributions of

$(x_1, \ldots\ldots, x_n)'$ and $(x_{1+h}, \ldots\ldots, x_{n+h})'$ are the same for all $h \in Z$ and $n > 0$.

Definitions 3.6.3 and 3.6.4 imply that, if a time series $\{x_t\}$ is strictly stationary and satisfies the condition $\sum(x_t^2) < \infty$ then $\{x_t\}$ is also weakly stationary. Therefore we assume that $\sum(x_t^2) < \infty$

3.7 Univariate Time Series Models

3.7.1 Autoregressive-Moving Average Model

Three time series model are used in this research, the Seasonal Auto-Regressive Integrated Moving Average model, Holt-Winter Exponential Smoothing model (HW) and the Artificial Neural Network (ANN). The latter captures any non-linearity characteristic of the time series. The Auto-Regressive Integrated Moving Average model ARIMA (Box-Jenkins) methodology has been used widely in the past decades for time series modeling. The models depend on the Box-Jenkins methodology.

The concept of this methodology is that the time series value at a specific time t, denoted by y_t depends on the terms; firstly,the past of the time series (an autoregressive component of order *p*) and secondly the past of the disturbances of the data generation process (a moving average component of order q). This methodology is concerned with iteratively building a parsimonious model that accurately represents the past and future patterns of a time series (Louvieris, 2002). Stationarity is an important concept in ARIMA, differencing process is however employed to transform a non-stationary time series into a stationary one. The general form of an ARMA model is:

$$y_t = \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \varepsilon_t \qquad (3.4)$$

where ϕ_i's $(i = 1, \ldots, p)$ are called the autoregressive parameters, θ_i's $(i = 1, \ldots, q)$ are called the moving average parameters and ε's are white noise error terms.

The ARMA model in equation (3.4) above can be expressed in a more simplified form as given below:

$$\phi(B) y_t = \theta(B) \varepsilon_t \qquad (3.5)$$

where B represents the backward shift operator or the lag operator, $\phi(B)$ is the autoregressive polynomial of order p and $\theta(B)$ is the moving average polynomial of order q.

The two components are expressed below:

$$B^m y_t = y_{t-m} \qquad (3.6a)$$

$$\phi(B) = 1 - \phi_1 B - \ldots\ldots - \phi_p B^p \qquad (3.6b)$$

$$\theta(B) = 1 + \theta_1 B_1 + \ldots\ldots + \theta_q B^q \qquad (3.6c)$$

Equations (3.6b) and (3.6c) give the simplified equation (3.5).

An important characteristic to be considered is determining whether a time series data is stationary orhas a unit root. Let us consider the autoregressive process of order (p), AR (p).

$$y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + ...\phi_p y_{t-p} + \varepsilon_t \qquad (3.7)$$

which is the autoregressive series of order *p*, AR(p) the roots of $\phi_p(B) = 0$ must lie outside the unit circle.

$$\phi_p(B) = 0 \qquad (3.8)$$

AR (1) process is defined as:

$y_t = \phi_1 y_{t-1} + \varepsilon_t \equiv (1 - \phi_1 B) y_t = \varepsilon_t$ (3.9)lets replace the lag operator B by a variable, p, and set to zero $1 - \phi_1 p = 0$, $p = 1/\phi_1$ suppose that $|\phi_1| < 1$ then the root is the value of p that solves the equation. y_t isstationary if the root lies outside the unit circle, thus the AR(1) process from (3.8) is stationary as long as $|\phi_1| < 1$Equation (3.5) has a unit root if at least one of the roots of the equation (3.8) is equal to one (unit root). This generates stochastic non-stationary in (3.5).

Most time series data are not stationary in nature, however, it is important to apply some form of transformation so as to obtain stationarity of the series. Adequate caution should be taken when transforming a time series data so as not to alter the statistical properties of the series thus producing a biased forecast.

There are various tests adopted to determine the type of non-stationarity exhibited by a time series. Such as; Augmented Dickey-Fuller (ADF) test, Elliot –Rothenbery – Stock test, Zivot – Andrews and Kwaitkowski – Phillips – Schmidt – Shin (KPSS) test (Kwiatkowski *et al*., 1992).

In this dissertation we will employ the Augmented Dickey – Fuller test (Dickey & Fuller, 1981). If we difference a series and it becomes stationary after the first difference, it is said to be integrated of order one, often denoted as I(1). In general, the order of integration is the number of differences needed to make the series stationary. This takes us to the ARIMA model.

3.7.2 Autoregressive-Integrated-Moving average model

The autoregressive-integrated-moving average originated from the Autoregressive model (AR), the moving average model (MA) and the combination of the AR and MA, the ARMA models, introduced by Box and Jenkins (1976).

The ARIMA model, denoted as ARIMA (*p, d, q*) contains the additional parameter *d*, which differentiates it from the ARMA (*p, q*) model. This parameter *d* specifies the level of non-seasonal differencing that is required to render a non-stationary time series stationary. The ARIMA (*p, d, q*) model is simply the non-stationary ARMA (*p,q*) model once stationarity is achieved, the series is modeled by the ARMA (*p, q*) model.

The generalized form of the ARIMA (*p, d, q*) model is written as

$$\phi(B)(1-B)^d y_t = \theta(B)\varepsilon_t \Longleftrightarrow \phi(B)\Delta^d y_t = \theta(B)\varepsilon_t \quad d \geq 0 \quad (3.10)$$

where $\Delta^d = (1-B)^d$ denotes the non-seasonal differencing operator.The ARIMA specification in (3.10) captures non-stationarity but it fails to account for the presence of seasonality and shocks in the time series data.

ARIMA models form an important part of the Box-Jenkins approach to time series modeling. It can take different forms depending on the values of the parameter (p, d, q). For example, an integrated (1) model is ARIMA (p, 1, q) and a MA (1) model is ARIMA (0, 0, 1) while an AR (1) model is ARIMA (1, 0, 0,) model.

3.7.3 Seasonal Auto-Regressive-Integrated-Moving Average model (SARIMA)

The seasonal autoregressive-integrated-moving average model is a modified ARIMA (p, d, q) model. We denote it as SARIMA $(p, d, q) \times (P,D,Q)_s$. The ARIMA model proposed byBox and Jenkins (1970) can be used when the time series is stationary and given that there are no missing data. However it does not deal with the seasonality aspect of the time series data.

In this dissertation, the SARIMA $(p, d, q) \times (P,D,Q)_s$ would be employed to model the time series data. Since, in practice, the time series data of air passenger traffic flow are bound to display periodic patterns such as seasonality, it contains periodic behavior and it is non-stationary. The seasonal ARIMA model consists of the seasonal and non-seasonal parts; the seasonal part of the model has its own autoregressive and moving average parameters with orders P and Q while the non-seasonal part has orders p and q (Kulendran& Shan, 2002). The SARIMA model is more flexible and is a short memory model (Bourbonnais and Terraza, 2004). It accounts for any stochastic seasonality in the time series data.

In the SARIMA (*p, d, q*) x (*P,D,Q*) model,*p* represents the number of parameters in the autoregressive model (AR), *d* the degree of non-seasonal differencing, *q* the number of parameters in MA model, *P* the number of parameters in AR seasonal model, *D*is the seasonal differencing degree, *Q*is the number of parameters in MA seasonal model, and *S* the period of seasonality. This is expressed below:

Seasonal autoregressive terms => $\Phi(B^s) = 1 - \Phi_1 B^s - \ldots . \Phi_p B^{PS}$ (3.11a)

Seasonal moving average terms => $\Theta(B^s) = 1 + \Theta_1 B^s + \ldots . + \Theta_Q B^{QS}$ (3.11b)

This gives the SARIMA expression in equation (3.12) below:

SARIMA (*p, d, q*) x (*P, D, Q*)$_s$

$$\phi(B)\Phi(B^s)(1-B)^d(1-B^s)^D y_t = \theta(B)\Theta(B^S)\varepsilon_t \qquad (3.12)$$

$$d, D \geq 0$$

where*s=12* for monthly data and *s=4* for quarterly data.

The above is the generalized seasonal autoregressive integrated moving average.

3.7.4 BOX – JENKINS METHODOLOGY

The Box-Jenkins methodology is aimed at identifying and estimating a statistical model which can be interpreted as having generated the sample data. A method employed in achieving this is through the iterative Box-Jenkins method (1976). This methodology is normally implemented in four steps.

- Identification of SARIMA (*p, d, q*)(*P,D,Q*)$_s$ structure
- Estimating the coefficients of the parameters

- Fitting test on the estimated residuals (diagnostic test)
- Forecasting the future outcomes based on the historical data.

These procedures are shown in the flow chart provided in figure 3.1

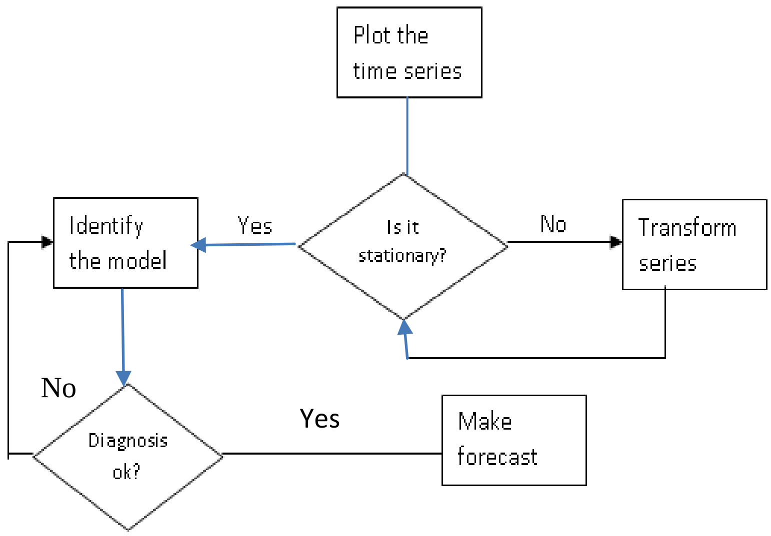


Figure 3. 1Flow chart of ARIMA building model steps Box-Jenkins(1976)

Identification of SARIMA (*p, d, q*)(*P,D,Q)*$_s$ structure

This is a very important step in the iterative procedure. This involves verifying if the time series is stationary and or if it has seasonal patterns and existence of some trend.

Determining the appropriate SARIMA$(p, d, q)(P,D,Q)_s$ model isimportant. A plot of the stationary and de-seasonalised time series data (correlogram) is necessary so as to obtain useful information for determining the appropriate model.

Auto Correlation Functions (ACF), Partial Auto-Correlation Functions (PACF) and descriptive statistics are tools used to identify a tentative ARIMA model (Cuhadar, 2014).

In practice, most time series data are not stationary. They exhibit seasonal patterns and trends with mean and variance not constant. It is important to employ an appropriate method to attain stability.There are different methods used in achieving variance stability, the most common methods for stabilizing the variance are the logarithmic or the Box-Cox transformations. When variance stationarity is achieved, it is important to verify that the series has a constant mean through time. The Augmented dickey-fuller or ADF test, Engle and Granger (1987) will be used in this dissertation, the generalized equation is given below:

$$\Delta y_t = \alpha y_{t-1} + \sum_{i=1}^{p} \beta_i \Delta y_{t-i} + \lambda_t + \gamma + \mu_t \qquad (3.13)$$

$\mu_t \sim IID(0, \delta^2)$

where t is time trend $\Delta y_t = y_t - y_{t-1}$

y_t is the natural logarithm at t, α, β, λ_t and γ are the parameters to be estimated and μ_t is the error.

The hypothesis for testing for stationarity using the Augmented Dickey Fuller test is given as:

H_0:$\alpha = 0$ (exhibits unit root or stochastic trend)

H_i:$\alpha < 0$

The t-statistic of the parameter $\propto$ is evaluated against a critical value at a level of significance. If the ADF test statistic is greater than the critical value, it is concluded that the series has unit root and is said to be non-stationary. The null hypothesis,H_0:$\alpha = 0$, is not rejected.

The selection of the best model is based on model selection criteria such as the AkaikeInformation Criterion (AIC) and Schwarz Bayesian Information Criterion (SBC or BIC) (Hu, 2002).

Estimation (Estimating the co-efficient of the parameters)

This is an important stage in the ARIMA methodology, which involves estimating autoregressive and moving average parameters and in the case of seasonality, the seasonal components. The parameters of the suggested models (candidate models) by visual inspection of the ACF and PACF plots are estimated. The parameters of the models were estimated using the Eviews 9 statistical package.

Fitting test on the estimated residuals (Diagnosis test)

This is the verification phase in which model suitability for prognostic application is verified by testing the residuals, if residuals are not serially correlated and are normally distributed. The estimated model become valid if its errors are uncorrelated and are normally distributed. The Ljung-Box port manteau test (1978)would be employed in test for residuals autocorrelation.

The null hypothesis tests for absence of residual autocorrelations for *h* lags. The test statistics is given thus:

$$Q = n(n+2)\sum_{k=1}^{h}\frac{{\rho_k}^2}{n-k} \qquad (3.15)$$

where:

$$\rho_k = \frac{\sum_k^n \varepsilon_t \varepsilon_{t-k}}{\sum_{t=1}^{n} {\varepsilon_t}^2} \qquad (3.16)$$

ρ_k is the autocorrelation at lag *k*; $\varepsilon's$ are the residuals of the fitted model; *n* is the total number of lags considered.

The Box-Ljung rejects the null hypothesis (indicating that the model has significant lack of fitif $Q > \chi^2_{1-\alpha,d}$

where $\chi^2_{1-\alpha,d}$ is the chi-square distribution table value with *d* degrees of freedom and significance level α . The degrees of freedom has to account for the parameters of the model estimated so that $d = h$. The values of Ljung – Box Q-statistic were obtainedusing the Eviews version 9.0 statistical R package.

Forecasting the future outcomes based on the historical data

The series depends on extrapolation and is generally based on the assumption that past and present characteristics of the series continue. Given a time series y_t the expected value of y_t at time $t+s$, given its past realization is

$$E(y_t / y_t, y_{t-1},......) = \phi_1 E(y_{t+s-1} / y_t, y_{t-1},.....) + ...+ \phi_p E(y_{t+s-p} / y_t, y_{t-1},...) + E(\varepsilon_{t+s} / y_{t,} y_{t-1,}...) - .. \\ - \theta_q E(\varepsilon_{t+s-q} / y_t, y_{t-1},..), \\ s = 1,2...... \qquad (3.17)$$

wherethe expected value of future errors terms $(\varepsilon_{t+j}, j = 1,2,...)$ conditional on the information at time t is 0 and the expected value of future values of the series $(y_{t+j}, j = 1,2..)$ conditional on the information at time *t*, is given by $\hat{y}_{t+j}$.

The equation clearly shows that s period forecast will not only depend on true observation but also on the forecast from time t to time $t+s-1$. After a certain lead time, forecast might be based only on previous forecasts and not true observations (Bresson and Pirotte, 1995).

3.7.5 Holt-Winters Exponential Smoothing Model

The data used in this study consist of trend and seasonal component. It is however appropriate to apply necessary smoothing technique to model the data used.

Smoothing can be seen as a technique to separate the signal and the noise as much as possible and in that a smoother acts as a filter to obtain an "estimate" for the signal (Montgomery *et al*., 2008).

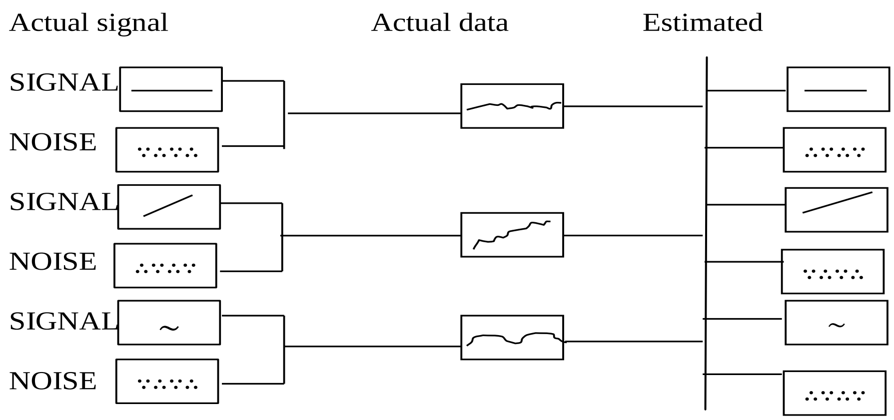


Fig. 3.2 (Montgonery, jenings and Murat, 2008)

From Fig. 3.2 shows the presence of signal and noise in the actual data. The signal represents any pattern caused by the intrinsic dynamics of the process from which the data is collected and it can assume various forms. Exponential Smoothing could be Single Exponential Smoothing, Double Exponential Smoothing and Triple Exponential Smoothing.

3.7.5.1 Single Exponential Smoothing

The single exponential smoothing is also referred to as simple exponential smoothing. It assumes that the data fluctuates around a reasonably stable mean.The model is given below;

$$S_{t+1} = \alpha y_t + (1-\alpha)S_t \quad 0 < \alpha \leq 1, t > 0 \qquad (3.18)$$

Each successive observation in the series that the above is applied to gives each new smoothed value computed as the weighted average of the current observation and the previous smoothed observation.

The weights being applied to get each smoothed value decrease exponentially depending on the value of the parameter ∝. New forecast is previous plus an error adjustment, this can be written as:

$$S_{t+1} = S_t + \alpha\varepsilon_t \qquad (3.19)$$

where ε_t is the forecast error for period t.However single exponential smoothing is not effective when there is a trend. The single parameter ∝ does not accommodate this.

3.7.5.2 Double Exponential Smoothing

The single exponential smoothing has only one constant,∝ as indicated in the equation (3.17) above, which brings about the limitation in handling the presence of trend. However this situation is improved in the double exponential smoothing by the introduction of another equation with additional parameter, a second constant is shown in the equations below

$$S_t = \alpha y_t + (1-\alpha)(S_{t-1} + b_{t-1}) \quad 0 < \alpha < 1 \qquad (3.20)$$

$$b_t = \gamma(S_t - S_{t-1}) + (1-\gamma)b_{t-1} \quad 0 < \gamma < 1 \qquad (3.21)$$

The current value of the series is used to calculate its smoothed value replacement in double exponential smoothing.

There are several methods of setting the initial values for S_t and b_t

S_1 is in general set to y_1. For b_1 the following could be adopted

$$b_1 = y_2 - y_1 \qquad (3.22a)$$

$$b_1 = \frac{[(y_2 - y_1) + (y_3 - y_2) + (y_5 - y_4)]}{3} \qquad (3.22b)$$

$$b_1 = \frac{(y_n - y_1)}{(n-1)} \qquad (3.22c)$$

3.7.5.3 Triple Exponential Smoothing

The previous smoothing in equations (3.20 and 3.21) handle data that have trend by inclusion of the second parameter. However the triple exponential smoothing method is used when the data show trend and seasonality, and a third parameter is added. We introduce a third equation to take care of seasonality. The resulting set of equations is called the "Holt-Winters" (HW) method.

There are two main HW models: additive and multiplicative. In both versions, forecast will depend on the components, level, trend and seasonal co-efficient. The additive version ought to be considered whenever the seasonal pattern of a series has constant amplitude over time (Kalekar, 2004).

This is given below:

$$y_t = a_t + b_t t + s_t + \varepsilon_t \text{ with} \sum_{t=1}^{12} S_t = 0 \qquad (3.23)$$

where a_t represents the level of the series at t, b_t the slope of the series at time t, s_t seasonal coefficients of the series at time t and $s=12$ the periodicity of the series. ε_t's are error with mean 0 and constant variance.

In the case of the multiplicative seasonal model we have:

$$y_t = (a_t + b_t t) s_t \varepsilon_t \text{ with} \sum_{t=1}^{t=s} s_t = s \qquad (3.24)$$

In this dissertation the multiplicative and additive model will be examined, equation 3.25 is used for our forecast.

$$y_{t+h} = (a_t + h b_t) s_{t-12+h} \qquad (3.25)$$

where h represents the forecasting horizon and where a_t, b_t and s_t are estimated with the equations below:

$$a_t = \alpha\left(\frac{y_t}{s_{t-12}}\right) + (1-\alpha)(a_{t-1} + b_{t-1}) \qquad (3.26a)$$

$$b_t = \beta(a_t - a_{t-1}) + (1-\beta) b_{t-1} \qquad (3.26b)$$

$$s_t = \gamma\left(\frac{y_t}{a_t}\right) + (1-\gamma) s_{t-12} \qquad (3.26c)$$

$\propto$, β and γ are smoothing parameters for the level, trend and the seasonal component respectively.

The smoothing constants are estimated by minimizing the Sum of Squared Error (SSE) of the forecast. The value that yields the smallest SSE is selected. The values are from zero to one.

3.7.6 Artificial Neural Network (ANN)

3.7.6.1 Introduction

The Artificial Neural Networks(ANNs) have recently been widely used for variety of works, since 1943, when Warren McCulloh and Walter Pitts presented the first model of artificial neurons. The ANN methodology was inspired in the biology theories of human brain function (Mcclleland and Rumelhart, 1986).

Artificial neural networks are designed to mimic the nervous systems: modeling the way information is processed to give the desired output. This attempt stems from the understanding of the mechanisms for the production and transport of signals from one neuron to the other.

The nervous system involves so many complexities in receiving, processing and giving the necessary output. These complexities are abstracted when designing the Artificial neurons.

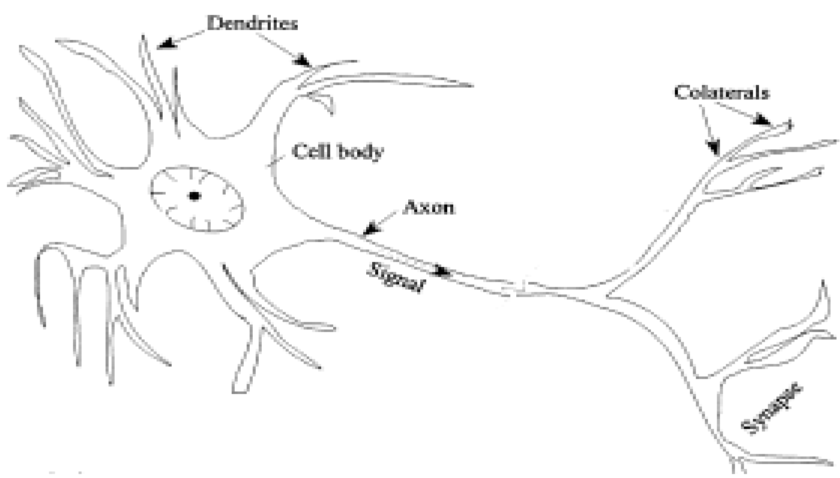


Figure 3. 2:Schematic representation of biological neuron (Basheer andHajmeer 2000)

Natural neurons receive signals through synapses located on the dendrites or membrane of the neuron, these signalsresults in activating the neuron which emits a signal through the axon. This signal might be sent to another synapse which consequently activates other neurons as shown in Fig 3.3.

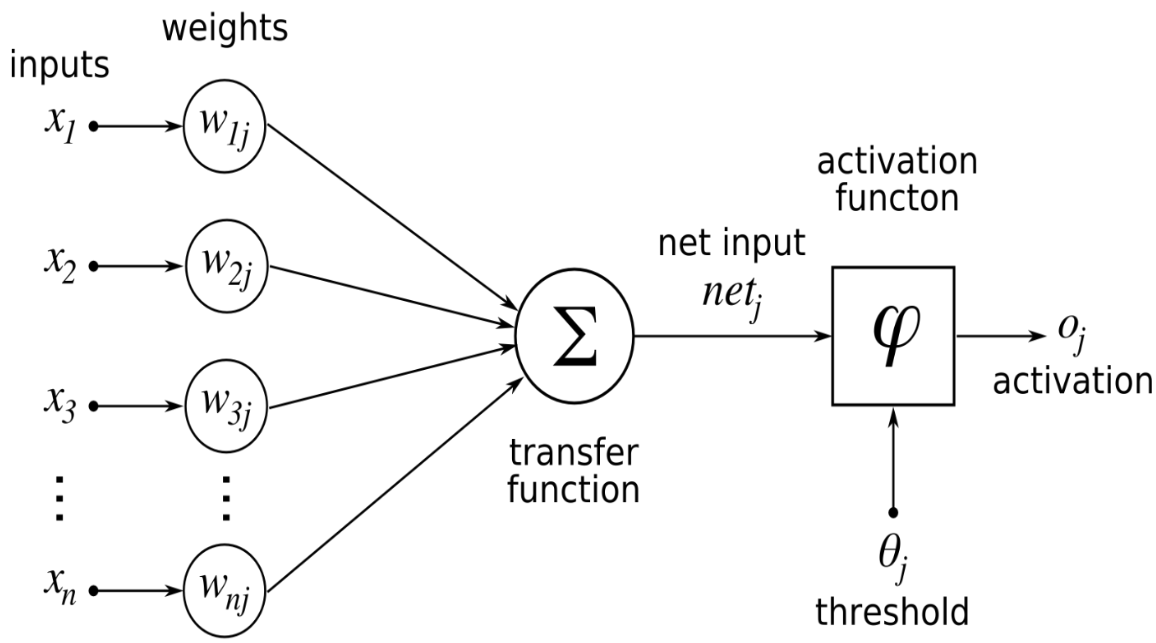


Figure 3. 3Typical Artificial Neural Network Architecture

In Fig 3.4 the inputs $x_1, x_2, x_3,..x_n$ are multiplied by respective weights, $w_{1j}, w_{2j},....w_{nj}$ and then computed by the desired mathematical function which determines the activation of the neuron. The output is generated by another mathematical function.The weights are adjusted depending on the expected output, therefore there is a direct relationship between the weights and the desired outputs of the process.

3.7.6.2 Artificial Neural Network Approach

The main essential features of an ANNs include the neurons, the architecture of the network that connects the neurons and the training algorithm used to find values of the network parameters for performing a particular task. The concept of ANNs has been used in a variety of ways;Business and management, medicine, speech processing, computer vision, control systems,tourism and demand, (Law,2000),in the context of Hydrology, Radar, satellite and meteorology (Koizumi,1999) among many other fields.

The adaptability of ANNs in long and short term forecast gives more flexibility in modeling in various contexts. The ANN has so many advantages over the conventional statistical methods of forecasting, these include; pattern recognition ability and ability to capture non-linearity in the training set.The ANN is however expected to be a more powerful forecasting tool. In the architecture of ANN, the neurons are connected so that the output from one unit can serve as part of the input to another.

Let N be the neurons with outputs $O_j\,(j = 1,......,\ N)$

Input to the next neuron I:

$$I_i = W_{i1} * O_1 + W_{i2} * O_2 .....W_{iN} * O_N = \sum_j W_{ij} * O_j \quad (3.27)$$

Synaptic strength from cell j to cell $i : W_{ij}$,with threshold $O_i = g(I_i + \theta_i)$

The step function is often chosen as transfer function g(.): $g(x) = \begin{cases} 0, & x < 0 \\ 1, & x \geq 0 \end{cases}$

The transfer functions include sign, semi-linear and sigmoid function.

Each connection of the neurons has an associated weight, the weights are the parameters of the model being used by the net to perform specific task. The weights are continually adjusted by comparing the output of the network with the target until the output of the network matches the target. This is achieved when the error is minimized(difference between the target and output).

A typical example of a simplified neural network with three layers is given below;

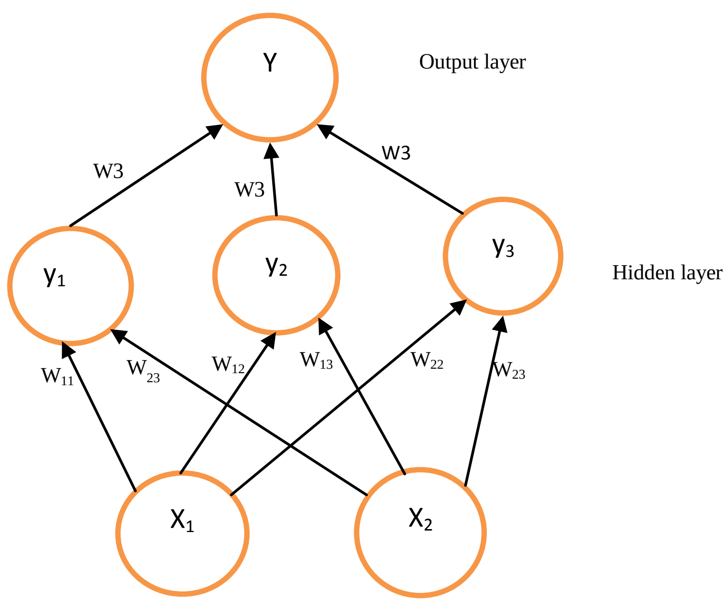


Figure 3. 4A neural network model

In the Fig 3.5 above, each node in the hidden layer computes $y_j \, (j = 1,2,3)$ as indicated in equation 3.25a

$$f_j = \sum_{i=1}^{2} x_i w_{ji} \qquad (3.28a)$$

A sigmoid function (y_j) in equation (3.28b) below will be used to transform the output limited into an acceptable range. The sigmoid function brings the result to the required range, between 0 and 1:

$$y_j = \frac{1}{1+e^{-f_j}} \qquad (3.28b)$$

The sigmoid activation function is usually used for hidden layer because it combines nearly linear behavior, curvilinear behavior and nearly constant behavior depending on the input value (Larose, 2005).

Y, the output layer in fig 3.5 will be obtained by the function in equation 3.28c.

$$Y = \sum_{j=1}^{3} y_j w_j \qquad (3.28c)$$

The process is varied by adjusting the weights, this could be easily done given the small size of the network. In a case where a large network of many neurons is needed, adjusting the weights could become tasking.

Methods of adjusting the weights have however been discovered. In this dissertation the back propagation algorithm employed in the layered feed-forward ANN will be used.

3.7.6.3 The Back Propagation Algorithm

Several methods have been employed for the minimization of the error function, which include standard optimization techniques like conjugate gradient and Newton-type methods. The back propagation algorithm (Rumelhart*et al.*,1988) is most commonly used, it does not involve much difficulty to program.

In this technique, artificial neurons are organized in layers and send their signals forward and then errors are propagated backwards. The network receives inputs by neurons in the input layer and the output of the network is given by the neurons on an output layer.

Training a neural network to learn patterns in the data involves iteratively presenting it with examples of the correct known answers, so as to find the set of weights between the neurons that determine the global minimum of the error function (Kaastraand Boyd, 1996).

The neural network can be trained in batches or incrementally. The latter involves feeding individual pairs one at a time to the network. Output is compared with the target for each input and adjustments of the weights are made using a training algorithm. There are several training algorithms as follows; Quick Prop(QP), Orthogonal Least Square (OLS),Levemberg-Marquart (LM), Back Propagation (BP) and Resilient Propagation (RPROP). The back propagation is, however used in this case.After necessary adjustment has been made to the previous pair the next pair is then fed to the network. In the batch training all the pairs of input and output are fed to the network at the initial stage and the weights are adjusted.

The back propagation algorithm uses the steepest-descent minimization method for the weight adjustment and threshold coefficient.In order to implement the back propagation algorithm, we will make use of the activation function given in the equations below:

$$f_j(\bar{x},\bar{w}) = \sum_{i=0}^{n} x_i w_{ji} \qquad (3.29)$$

where x_i's are the inputs, w_{ji}'s are the respective weights applied.

In this case, activation is only dependent on inputs and respective weights. If the output function is equal to the activation, the neuron is called linear. In that case, we are only trying to make a straight line fit. However we would employ a combination of the linear activation function with sigmoid. There are different types of sigmoidal functions such as, the hyperbolic tangent, logistic sigmoid, bipolar sigmoid function and the Elliot(1993) transfer function. For this dissertation, we will consider the logistic sigmoid function bounded between 0 and 1 and its linearly transformed version, the bipolar sigmoid function bounded between -1 and 1, the one that models the series best will be adopted.

Equations 3.30 and 3.31 represent the sigmoid and bipolar sigmoid functions respectively.

$$y_j(\bar{x},\bar{w}) = \frac{1}{1+e^{-f_j(\bar{x},\bar{w})}} \qquad (3.30)$$

$$y_j(\bar{x},\bar{w}) = \frac{2}{1+e^{-f_j(\bar{x},\bar{w})}} - 1 \Rightarrow \frac{1-e^{-f_j(\bar{x},\bar{w})}}{1+e^{-f_j(\bar{x},\bar{w})}} \qquad (3.31)$$

According to Larose(2005) the sigmoidal activation function combines nearly linear behaviour, curvilinear and nearly constant behaviour depending on the input value. The sigmoid function has non-linear characteristics, monotonically increasing and continuous differentiable.

For the sigmoid activation function, $y_j(\bar{x}, \bar{w})$ we take the range $[0,1]$, this implies that;

As $x_i \rightarrow \infty$, $y_j(\bar{x}, \bar{w}) = 1$ and also as $x_i \rightarrow -\infty$ $y_j(\bar{x}, \bar{w}) = 0$

The bipolar sigmoid function takes the range $[-1,1]$

In the training process, the weights are being adjusted in a way such that the error is minimized. This is achieved by observing the difference between the actual output and the desired output. The error function of each neuron can be defined thus;

$$E_j(\bar{x}, \bar{w}, d) = (y_j(\bar{x}, \bar{w}) - d_j)^2 \quad (3.32)$$

The equation (3.32) gives the error for the individual neuron. The collective error for the entire network is the sum of the individual error of the neurons. This is indicated below in equation (3.33):

$$E(\bar{x}, \bar{w}, \bar{d}) = \sum_j (y_j(\bar{x}, \bar{w}) - d_j)^2 \quad (3.33)$$

In order to adjust the weights appropriately the back propagation will calculate how the errors depend on the outputs, inputs and weights. Thereafter we employ an appropriate method, gradient descendent, to adjust the weight to meet the required target.

The gradient descendent method is indicated below;

$$\Delta w_{ji} = -\lambda \frac{\partial E}{\partial w_{ji}} \quad (3.34)$$

where, Δw_{ji} is the adjustment of each weight, λ is a constant, which is the learning rate, the success of the neural network convergence depends a lot on the learning rate. This is multiplied by the dependence of the previous weight on the error network, the derivative of E in respect to w_{ij}. The equation 3.34 will be implemented until the desired weight with minimal error is obtained. In implementing the back propagation algorithm it is important to know how much the error depends on the output. This is expressed below in equation (3.35).

$$\frac{\partial E}{\partial y_j} = 2(y_j - d_j) \tag{3.35}$$

It is also important to calculate how much the output depends on the activation, which in turn depends on the weights from equations (3.29) and (3.30) or (3.31) depending on the activation function being used.

$$\frac{\partial y_j}{\partial w_{ij}} = \frac{2}{1+e^{-f_j}} - 1 \Rightarrow \frac{(1-e^{-f_j})}{(1+e^{-f_j})}$$

$$= 2(1+e^{-f_j})^2 e^{-f_j}$$

$$= \frac{1}{2}\frac{(4e^{-f_j})}{(1-e^{-f_j})^2}$$

$$= \frac{1}{2}\left[\frac{(1+e^{-f_j})^2 - (1-e^{-f_j})^2}{(1+e^{-f_j})^2}\right]$$

$$= \frac{1}{2}\left[\frac{(1+e^{-f_j})^2}{(1+e^{-f_j})^2} - \frac{(1-e^{-f_j})^2}{(1+e^{-f_j})^2}\right]$$

$$= \frac{1}{2}\left[1 - \frac{(1-e^{-f_j})^2}{(1+e^{-f_j})^2}\right]$$

$$= \frac{1}{2}\left[1 - y_j^{\,2}\right] \tag{3.36a}$$

Equation(3.36) shows the derivative of the bipolar sigmoid function

The derivative of the logistic sigmoid function is simply given as

$$\frac{\partial y_j}{\partial w_{ij}} = \frac{\partial\left(\frac{1}{1+e^{f_j}}\right)}{\partial w_{ij}} = y_j(1-y_j) \qquad (3.36b)$$

$$\frac{\partial y_j}{\partial w_{ij}} = \frac{\partial y_j}{\partial f_j} \times \frac{\partial f_j}{\partial w_{ij}} = \frac{1}{2}\left(1-y_j^{2}\right)x_i \qquad (3.37)$$

From equations (3.35) and (3.36a) we have the resulting equation (3.38) below, using the bipolar activation function.

$$\frac{\partial E}{\partial w_{ji}} = \frac{\partial E}{\partial y_j} \times \frac{\partial y_j}{\partial w_{ji}} = 2(y_j - d_j)\frac{1}{2}(1-y_j^{2})x_i = (y_j - d_j)(1-y_j^{2})x_i \qquad (3.38)$$

Therefore:

$$\Delta w_{ji} = -\lambda(y_j - d_j)(1-y_j^{2})x_i \; (3.39)$$

When applying the logistic sigmoid function the change of weight is given as equation (3.40)

$$\Delta w_{ji} = -2\lambda(y_j - d_j)y_j(1-y_j)x_i \qquad (3.40)$$

The equations (3.39) and (3.40)can be used for ANN with two layers using the bipolar sigmoid function and logistic sigmoid function respectively. However, the iteration is implemented continuously for several layers of the neural network as obtainable in the multi-layer feed forward neural network.

3.7.6.4 Multilayer perceptron

The multilayer perceptron was derived in 1960 and since then it has grown significantly becoming the most widely used neural network topology. The application of the multilayer perceptron involves training and prediction. Weights are applied arbitrarily for the iterations. In such iterations, weights are adjusted with respect to the process that gives the minimum error. It is important to take into consideration the number of nodes and the layers in the network.An insufficient number of hidden nodes in learning data where as an excessive number of hidden nodes might lead to unnecessary training time with marginal improvement in training outcome as well as make the estimation for a suitable set of inter connection weights more difficult (Zealand *et al*., 1999).

The multilayer perceptron is made of a layer and one or more hidden layers, although it has been shown that for most problem it would be sufficient to have only one layer of hidden neurons (Hornik*et al*.,1989). Suppose the input vector or pattern to the neural network is given thus; $X_p : x_{p1},....., x_{pi},....x_{PN}$ then the mathematical representation of the function of the hidden neurons to obtain an output value b_{pj} is defined in equation (3.41)

$$b_{pj} = f_L(\theta_j + \sum_{j=1}^{N} w_{ij}.x_{pi}) \qquad (3.41)$$

where f_L is the activation function of hidden neurons L, θ_j is the threshold of the hidden neuron j, w_{ij} is the weight of the connection between input neuron i and hidden neuron j and finally x_{pi} is the input signal received by input neuron i for pattern p. For the output neurons we define thus;

$$y_{pk} = f_m[\theta_k + \sum_{j=1}^{L} v_{jk} . b_{pj}] \qquad (3.42)$$

where y_{pk} is the output signal provided by output neuron k for pattern p, f_m is the activation function of output neurons m, θ_k is the threshold of output neuron k and finally v_{jk} is the weight of the connection between hidden neuron j and output neuron k. In this work we use the sigmoid and bipolar sigmoid function in the layer neurons and the back propagation algorithm is used for the training.

3.8 Performance Evaluation of proposed models

The models were estimated by making use of the training data set, which represent the monthly air passenger traffic for international and domestic flights over the period of January 2003 to December 2013 (132 observations) were used to estimate the time series models.

The models were used to obtain 24 months ahead forecasts, this was compared with the test set which are the monthly air passenger traffic covering the period of January 2014 to December 2015 (24 observations). The quality of the obtained forecast for 24 months ahead was tested using the Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE).

$$MAPE = \frac{100}{24} \sum_{i=1}^{24} \frac{|y_{it} - \hat{y}_{it}|}{y_{it}} \qquad (3.43)$$

$$RMSE = \sqrt{\frac{1}{24} \left\{ \sum_{i=1}^{24} (y_{it} - \hat{y}_{it})^2 \right\}} \qquad (3.44)$$

Where $y_{it} = y_{1t}, y_{2t}, ... y_{24t}$ represent the natural log of domestic and international air passenger traffic and $\hat{y}_{it} = \hat{y}_{1t}, \hat{y}_{2t}, ... \hat{y}_{24t}$ represent the forecast values for the forecast horizon

$t = 1,2,3,\ldots\ldots 24$. These classical loss functions are used to evaluate the out-sample performance of the models employed.

CHAPTER FOUR

ANALYSIS, RESULTS AND DISCUSSION

4.1 Introduction

The univariate models for modelling the air passenger traffic flow in Murtala Muhammad International Airport are evaluated and the empirical results of the analysis are presented. The time series plot for the air passenger traffic for the types of flights are obtained so as togive a visual representation of the characteristics. Most airline data are seasonal in nature with likely presence of trend and outliers. These characteristics could easily be inferred at times by having a quick glance at the time plot.

Stationarity, which is a key component in time series analysis would be tested before the identification and estimation of the best models for the air passenger traffic.The time series data are log transformed so as to get rid of possible outliers and for variance stationarity. A descriptive statistics of the variables is illustrated before an elaborate analysis of the time series models of concern.

The first model considered is the Box Jenkins Seasonal Auto-Regressive Integrated Moving Average model, there after the Holt-Winter exponential smoothing model then the Artificial Neural Network will be used in modelling the air passenger traffic flow. The accuracy of each model and the forecast performance would be evaluated.

4.2 Descriptive Statistics

It is essential, before estimating the models that an exploration of the data has to be carried out so as to identify the statistical properties of the data and the unforeseen outliers which could impede a good analysis. The JarqueBera test is used to test for normality,the null hypothesis of normality is rejected if $JB \geq \chi^{2}_{1-\alpha,2}$

Table 4. 1: Descriptive Statistics of Air Passenger Traffic Flow

	N	**Mean**	**Median**	**S.Dev**	**1stQu**	**3rdQu**	**Min**	**Max**
Domestic	156	264000	274700	81210.9	191700	337800	100300	441400
International	156	193900	189000	61334.35	136600	243100	85370	311700

Table 4.1 shows a record of raw data on the air passenger traffic for domestic and international flight. The highest recorded passenger movement was obtained from the domestic flight while the lowest air passenger flow record was from international flight. Also, it could be observed from the table that averagely, over the years there have been more air passenger flow domestically than internationally.

Table 4. 2:Descriptive Statistics of Log Transformed Air Passenger Traffic Flow

Statistics	**Skewness**	**Kurtosis**	**JarqueBera**	**P-value**
LDAPT	-0.4140845	2.055372	10.2582	0.005922
LIAPT	-0.3876849	2.111281	9.0416	0.01088

In Table 4.2 **LDAPT** and **LIAPT** represent the log transformed air passenger traffic for domestic flight and international flight respectively.

The international and domestic air passenger data are negatively skewed (skewed to the left), the kurtosis in both cases indicate that the distribution of the data is platykurtic since the computed value is less than 3.

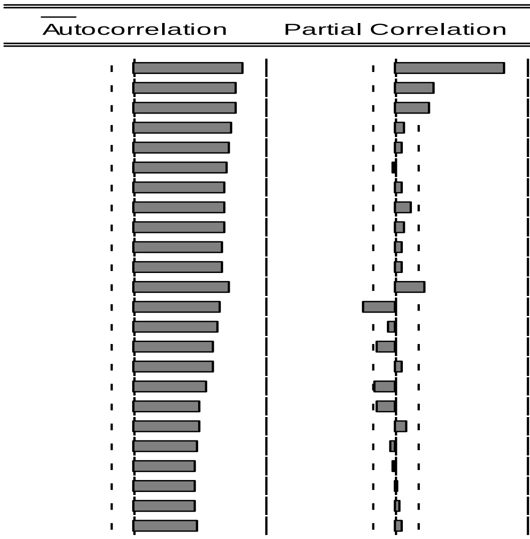
Using the JarqueBera test for normality, the null hypothesis in both cases is rejected since the P-value is less than 0.05 in both cases, the distribution is not normal.

4.3 Graphical Representation

The time plots of the domestic air passenger traffic and international air passenger traffic in **APPENDIX III** show that the time series data sets are not stationary. By visual observation, there is evidence of an upward trend in the air passenger traffic in both cases. It would be necessary to achieve stationarity, through differencing, before embarking on the Box Jenkins methodology.

Looking at the graph for domestic air passenger traffic, a dip in passenger traffic flow could be observed between the year 2005 and 2008. This is a very sad period for the Nigerian aviation sector because it was marked with series of major commercial air crashes and disaster, hence the loss of trust in the sector. The aviation sector experienced major overhaul which immensely affected airlines.After that period it has been a steady increase in air passenger traffic both internationally and locally. Airlines were healthier and new airlines emerged,bringing about healthy competition.

The method of differencing will be applied appropriately to attain stationarity.To further examine the series, the plots of the Auto- Correlation Function (ACF) and Partial Auto-Correlation Function (PACF) were made. The ACF and PACF plots, which are plots of coefficients of correlation and partial correlation coefficients of the time series and lag of itself, of the log transformed series for domestic and international air traffic passenger in **APPENDIX III** show that the time series data is not stationary, evidenced by a slow decay in function.



	AC	PAC	Q-Stat	Prob
1	0.859	0.859	99.593	0.000
2	0.818	0.305	190.57	0.000
3	0.814	0.269	281.46	0.000
4	0.784	0.073	366.48	0.000
5	0.760	0.048	446.92	0.000
6	0.732	-0.01...	522.15	0.000
7	0.720	0.054	595.42	0.000
8	0.725	0.128	670.46	0.000
9	0.719	0.081	744.78	0.000
1...	0.711	0.053	818.06	0.000
1...	0.712	0.058	892.13	0.000
1...	0.749	0.224	974.78	0.000
1...	0.682	-0.25...	1044.0	0.000
1...	0.660	-0.05...	1109.3	0.000
1...	0.634	-0.15...	1170.1	0.000
1...	0.623	0.057	1229.4	0.000
1...	0.578	-0.16...	1280.8	0.000
1...	0.523	-0.14...	1323.3	0.000
1...	0.530	0.084	1367.2	0.000
2...	0.516	-0.03...	1409.2	0.000
2...	0.490	-0.01...	1447.4	0.000
2...	0.485	0.004	1485.2	0.000
2...	0.476	0.037	1522.0	0.000
2...	0.494	0.055	1561.9	0.000

Figure 4. 1:*Correlogram of the Domestic Air Passenger Traffic*

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.853	0.853	98.187	0.000
		2	0.754	0.097	175.48	0.000
		3	0.755	0.341	253.72	0.000
		4	0.748	0.105	331.00	0.000
		5	0.664	-0.15...	392.44	0.000
		6	0.592	-0.06...	441.57	0.000
		7	0.627	0.263	497.23	0.000
		8	0.667	0.190	560.60	0.000
		9	0.640	0.064	619.58	0.000
		1...	0.609	-0.00...	673.42	0.000
		1...	0.669	0.206	738.88	0.000
		1...	0.698	0.006	810.65	0.000
		1...	0.626	-0.15...	868.99	0.000
		1...	0.530	-0.27...	911.07	0.000
		1...	0.521	-0.03...	952.11	0.000
		1...	0.518	0.004	993.10	0.000
		1...	0.438	-0.05...	1022.5	0.000
		1...	0.372	-0.03...	1044.0	0.000
		1...	0.392	0.023	1068.1	0.000
		2...	0.427	0.032	1096.9	0.000
		2...	0.383	-0.06...	1120.3	0.000
		2...	0.364	0.060	1141.6	0.000
		2...	0.403	0.030	1167.9	0.000
		2...	0.431	0.057	1198.3	0.000

Figure 4. 2:Correlogram of the international Air Passenger Traffic

Figures 4.1 and 4.2 show that the time series data for domestic and international air passenger traffic would have to be differenced to attain stationarity. This could be observed with slow decay of ACF up to higher lags.The ACF and PACF plots form the basis for the identification of appropriate models in the Box Jenkins technique.

4.4 Test for Stationarity (Augmented Dickey Fuller test)

As could be observed by a quick glance of the time plots of the data in **APPENDIX III,** there is obvious evidence of non-stationarity. There is presence of trend, seasonality and noise. However it is not enough to draw our conclusion based on that. The Augmented Dickey Fuller test, Dickey and Fuller (1979), was employed to test for stationarity of the original time series data and the differenced time series data for the international air passenger traffic and domestic air passenger traffic. This is displayed in Table 4.5.

Table 4. 3:Unit Root Test using ADF (1979)

Variables	t-statistic	1% level	5% level	10% level	Remark
LDAPT	-1.602388	-3.48162	-2.88393	-2.57879	Non stationary
LIAPT	-1.498611	-3.48162	-2.88393	-2.57879	Non stationary
DLDAPT	-13.24736	-4.03073	-3.44503	-3.14738	Stationary(First Difference)
DLIAPT	-6.989806	-4.03565	-3.44738	-3.14876	Stationary(First Difference)

***LDAPT** represents log of domestic air passenger traffic, **LIAPT** (log of international air passenger traffic), **DLDAPT**(first difference of **LDAPT**) and **DLIAPT**(first difference of **LIAPT**)*

The results in table 4.5 above show that the original time series data for international and domestic air passenger traffic are not stationary but become trend and intercept stationary after first differencing.The plots of the differenced time series data are shown in **APPENDIX III.**

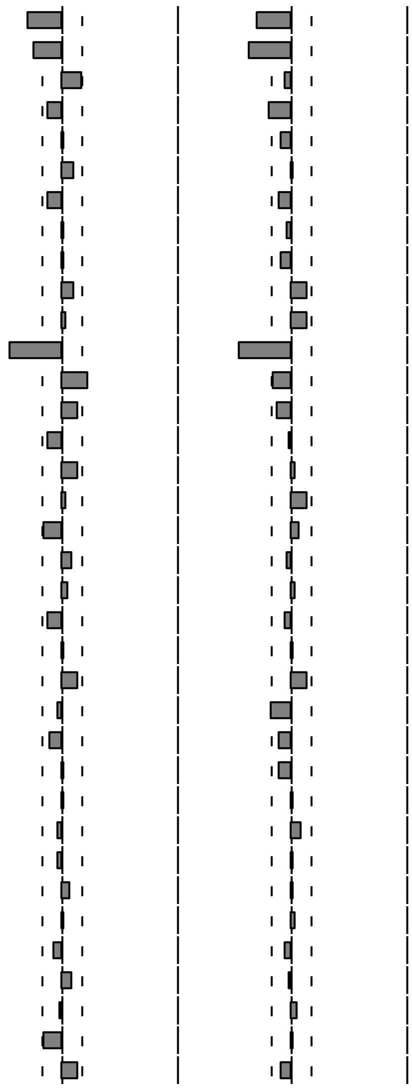
The time series data for the air passenger traffic were also seasonally differenced to take care of the presence of seasonal effect.

4.5 Model identification

In identifying the appropriate seasonal ARIMA model for the time series data, it would be necessary to decide on the non-seasonal and seasonal autoregressive terms, seasonal and non-seasonal differencing and the moving average terms.

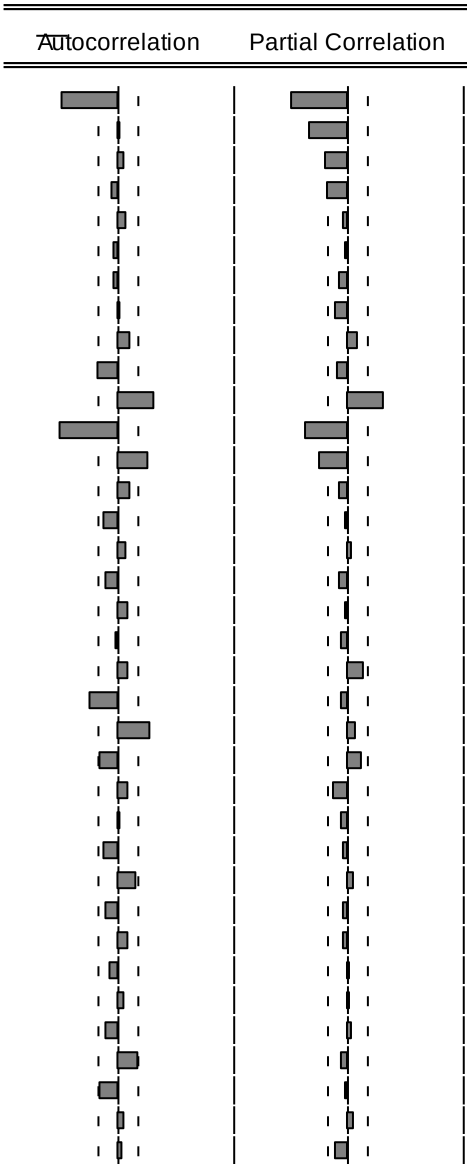
From the time plots, a non-seasonal differencing would be needed, the ADF test in table 4.5 however confirmed that the time series data attained stationarity at order 1.

A glance at the time plots and ACF plots show seasonal pattern. This forms a basis in determining the autoregressive and moving average orders by employing the AIC and BIC information criterion.



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.31...	-0.31...	11.922	0.001
		2	-0.24...	-0.38...	19.436	0.000
		3	0.183	-0.05...	23.580	0.000
		4	-0.11...	-0.19...	25.258	0.000
		5	-0.00...	-0.08...	25.259	0.000
		6	0.111	0.001	26.827	0.000
		7	-0.12...	-0.09...	28.850	0.000
		8	0.017	-0.04...	28.888	0.000
		9	0.013	-0.09...	28.909	0.001
		1...	0.114	0.139	30.612	0.001
		1...	0.025	0.137	30.697	0.001
		1...	-0.47...	-0.47...	60.793	0.000
		1...	0.239	-0.16...	68.566	0.000
		1...	0.143	-0.12...	71.376	0.000
		1...	-0.13...	-0.02...	73.739	0.000
		1...	0.137	0.029	76.367	0.000
		1...	0.034	0.137	76.530	0.000
		1...	-0.16...	0.069	80.451	0.000
		1...	0.096	-0.04...	81.768	0.000
		2...	0.045	0.027	82.059	0.000
		2...	-0.12...	-0.05...	84.439	0.000
		2...	0.011	0.016	84.457	0.000
		2...	0.139	0.151	87.352	0.000
		2...	-0.02...	-0.17...	87.479	0.000
		2...	-0.10...	-0.10...	89.034	0.000
		2...	0.011	-0.11...	89.054	0.000
		2...	0.019	-0.00...	89.108	0.000
		2...	-0.03...	0.091	89.321	0.000
		2...	-0.02...	0.010	89.423	0.000
		3...	0.078	0.009	90.405	0.000
		3...	0.022	0.034	90.481	0.000
		3...	-0.07...	-0.04...	91.430	0.000
		3...	0.098	-0.02...	93.032	0.000
		3...	-0.01...	0.063	93.051	0.000
		3...	-0.17...	0.005	98.082	0.000
		3...	0.152	-0.08...	102.08	0.000

Figure 4. 3:ACF and PACF plot of Δ^{12} LDAPT



	AC	PAC	Q-Stat	Prob
1	-0.51...	-0.51...	31.932	0.000
2	0.004	-0.34...	31.934	0.000
3	0.051	-0.19...	32.261	0.000
4	-0.05...	-0.17...	32.636	0.000
5	0.075	-0.04...	33.338	0.000
6	-0.03...	-0.01...	33.462	0.000
7	-0.04...	-0.07...	33.766	0.000
8	0.015	-0.10...	33.794	0.000
9	0.115	0.091	35.515	0.000
1...	-0.18...	-0.09...	40.002	0.000
1...	0.319	0.320	53.565	0.000
1...	-0.52...	-0.37...	90.892	0.000
1...	0.268	-0.25...	100.63	0.000
1...	0.110	-0.08...	102.29	0.000
1...	-0.13...	-0.02...	104.90	0.000
1...	0.075	0.035	105.69	0.000
1...	-0.10...	-0.08...	107.21	0.000
1...	0.095	-0.02...	108.50	0.000
1...	-0.02...	-0.05...	108.58	0.000
2...	0.086	0.138	109.65	0.000
2...	-0.24...	-0.06...	118.59	0.000
2...	0.290	0.070	131.06	0.000
2...	-0.16...	0.123	135.22	0.000
2...	0.087	-0.13...	136.37	0.000
2...	-0.00...	-0.05...	136.37	0.000
2...	-0.13...	-0.03...	139.27	0.000
2...	0.162	0.044	143.38	0.000
2...	-0.10...	-0.03...	145.15	0.000
2...	0.088	-0.03...	146.39	0.000
3...	-0.08...	0.010	147.41	0.000
3...	0.057	0.004	147.94	0.000
3...	-0.10...	0.030	149.89	0.000
3...	0.175	-0.06...	155.04	0.000
3...	-0.17...	-0.02...	160.02	0.000
3...	0.062	0.044	160.68	0.000
3...	0.030	-0.11...	160.84	0.000

Figure 4. 4: ACF and PACF plot of Δ^{12} LIAPT

Figures 4.3 and 4.4 show the plots of ACF and PACF for both domestic and international air passenger traffic. This gives ample knowledge in identifying the order p, q, Pand Q parameters of the proposed SARIMA models by visual inspection. From Figure 4.1, it is observed that the ACF cuts at q=2 and Q=1 which suggests a moving average parameterof order 2 and a seasonal moving average parameter of order 1. The PACF plot in Figure 4.1, by visual observation suggests AR parameter of order 2 and a Seasonal AR of order 1. Similarly from Figure 4.2, by visual inspection, it is observed that the ACF cuts at q=1and Q=1, while the PACF slightly cuts at p=3(AR parameter of order 3) and P=1(Seasonal AR parameter of order 1). From this inference the best SARIMA models are selected based on error diagnostics,AIC, BIC, RMSE and also keeping in mind parsimony. Based on this,5 SARIMA models were considered each for domestic and international air passenger traffic.

Table 4. 4: Postulated SARIMA models for Domestic Air Passenger Traffic

Model	**AIC**	**BIC**	**RMSE**	**Normality Test**		**Serial Correlation**	
				JB Test	P-value	Q-statistic	P-value
$SARIMA(2,1,1)(0,1,1)_{12}$	-1.222	-1.104	0.129	2.269	0.322	26.027	0.762
$SARIMA(2,1,1)(1,1,1)_{12}$	-1.157	-1.004	0.132	1.066	0.587	23.667	0.587
$SARIMA(1,1,1)(1,1,1)_{12}$	-1.123	-0.997	0.135	1.587	0.452	34.654	0.342
$SARIMA(1,1,1)(0,1,1)_{12}$	-1.203	-1.109	0.130	2.102	0.350	32.940	0.470
$SARIMA(1,1,2)(1,1,1)_{12}$	-1.135	-0.984	0.133	1.172	0.557	29.161	0.561

From Table 4.6, considering the models performance in terms of AIC, BIC and RMSE $SARIMA(2,1,1)(0,1,1)_{12}$ and $SARIMA(1,1,1)(0,1,1)_{12}$ with lower AIC and BIC values performed competitively better than the other SARIMA models. The L-jung Box portmanteau test for residual autocorrelation shows that the residuals are not serially correlatedand theJarque-Bera normality test confirms that the residuals are normal. Both models should be adequate in modelling the domestic air passenger traffic.The $SARIMA(1,1,1)(0,1,1)_{12}$ isthe selected model since it is more parsimonious.

Table 4. 5: Postulated SARIMA models for International Air Passenger Traffic

Model	AIC	BIC	RMSE	Normality Test		Serial Correlation	
				JB Test	P-value	Q-statistic	P-value
$SARIMA(1,1,2)(1,1,1)_{12}$	-1.558	-1.408	0.108	32.600	0.000	23.989	0.811
$SARIMA(3,1,1)(0,1,2)_{12}$	-1.527	-1.361	0.110	13.923	0.009	27.100	0.618
$SARIMA(2,1,2)(2,1,2)_{12}$	-1.841	-1.596	0.092	1.302	0.522	31.495	0.296
$SARIMA(1,1,2)(0,1,1)_{12}$	-1.553	-1.435	0.109	27.881	0.000	25.362	0.791
$SARIMA(3,1,1)(2,1,2)_{12}$	-1.968	-1.721	0.086	4.352	0.114	16.820	0.952

From Table 4.7, $SARIMA(3,1,1)(2,1,2)_{12}$ was selected to be the best model for the international air passenger traffic. Compared to the other proposed SARIMA models, $SARIMA(3,1,1)(2,1,2)_{12}$ has the lowest AIC and BIC, the errors are not serially correlated, errors are normally distributed.

The $SARIMA(2,1,2)(2,1,2)_{12}$ is the SARIMA model that performs closely to the selected model $SARIMA(3,1,1)(2,1,2)_{12}$ but the selected model performs generally better. The other models fail the Jarque-Bera test for normality.

Table 4. 6:Parameter of Estimated SARIMA Models

Domestic air passenger traffic $SARIMA(1,1,1)(0,1,1)_{12}$			**International Air passenger traffic** $SARIMA(3,1,1)(2,1,2)_{12}$		
Variables	**Estimates**	**P-value**	**Variables**	**Estimates**	**P-value**
$AR(1)$	0.133	0.364	$AR(1)$	-0.390	0.085
$MA(1)$	-0.709	0.000	$AR(2)$	-0.324	0.079
$SMA(12)$	0.906	0.000	$AR(3)$	-0.176	0.242
JB Test	2.102	0.350	$SAR(12)$	-0.195	0.029
Q-Test	32.940	0.470	$SAR(24)$	-0.275	0.007
AIC	-1.203		$MA(1)$	-0.459	0.040
BIC	-1.109		$SMA(12)$	-0.665	0.000
			$SMA(24)$	0.872	0.000
			JB Test	4.352	0.113
			Q-Test	16.820	0.952
			AIC	-1.968	
			BIC	-1.721	

Table 4.8 presents the estimated parameters of the seasonal models for both domestic and international air passenger traffic. The diagnostics checks performed indicate that the models should be adequate in modelling the air passenger traffic. The plots of the selected SARIMA models for the air passenger traffic are shown in**APPENDIX V.**The performances of these models were evaluated in comparison with the Holt-winters Exponential smoothing and the performance of the artificial neural network.

4.6 Estimation of the Holt-Winter's Exponential Smoothing Model

The time series data obviously indicate the presence of seasonality as shown in the time plot for both the domestic air passenger and international passenger traffic. The multiplicative and additive Holt-winters exponential smoothing models would be examined on the variables to see which models fit best.

Table 4. 7:Estimates of the Holt-Winters Exponential Smoothing Parameters

Variables	Model	α (Level)	β (Trend)	γ (Seasonal)	BIC	AIC
Domestic	Multiplicative	0.2174	0.0000	0.2032	192.4516	146.3267
Domestic	Additive	0.3300	0.0000	0.0335	166.4400	120.3152
International	Multiplicative	0.3034	0.0253	0.2447	140.8886	94.7637
International	Additive	0.2676	0.0000	0.000	116.9094	70.7846

Estimates of the parameters in the Table 4.6 show that the additive Holt-winters model is best suited for modelling the air passenger traffic for both domestic and the international flight based on AIC and BIC criteria.

The parameters are estimated objectivelyrather than subjectively, by choosing the values that best minimize the sum of squared errors.The value of the parameter β being zero in the models for both domestic and international air passenger traffic, indicates that the slope is relatively constant over time. The values of α and γ show that emphasis is only fairly placed on the recent observation.

The residuals of the best of these models would be examined for presence of non-zero autocorrelations, using the Ljung-Box test and also the forecast performance characteristics.

Table 4. 8:Holt-Winters Model Performance Evaluation

Variables	Model	AIC	BIC	Q-statistic	P-value
Domestic	Additive	120.3152	166.4400	29.7100	0.1946
International	Additive	70.7846	116.9094	20.212	0.6847

From table 4.9 having subjected the models to diagnostics (AIC,BIC&ACF)it could be observed that the Holt-Winters additive models the air passenger traffic better than the multiplicative model does for both domestic and international air passenger traffic. The Ljung-Box test reveals absence of autocorrelation in the residuals of the additive models.

APPENDIX VI shows the plot of the predicted values for both sectors and the ACF plots of the residuals.

4.7 Estimation of the Artificial Neural Network Models

In estimating the ANN model for the air passenger traffic flow, the Feed Forward Neural Network(FFN)is implemented by the back propagation algorithm. Four models, with 3 layers (input layer, hidden layer and output) as expected of most standard neural network architecture were considered. The models with 12 neurons in the input layer, 4 neurons in the hidden layer and one neuron in the output layer(12-4-1), 12 neurons in the input layer, 6 neurons in the hidden layer and 1 neuron in the output layer(12-6-1), 12 neurons in the input layer, 8 neurons in the hidden layer and one neuron in the output layer(12-8-1) and 12 input neurons,12 hidden layer neurons, an input neuron

(12-12-1) were examined.

The Sigmoid and Bipolar Sigmoid activation functions were used in the learning process so as to examine which of these activation functions models the time series data better by observing the mean squared error yielded in each process.

Table 4. 9:Performance of the ANN models for Domestic Air Passenger

Model	**Activation function**	**Iterations**	**MAE**	**MSE**
12-4-1	Sigmoid	20000	0.10098	0.01740
	Bipolar Sigmoid	30000	0.05980	0.00645
12-6-1	Sigmoid	20000	0.10135	0.01754
	Bipolar sigmoid	30000	0.04687	0.00410
12-8-1	Sigmoid	20000	0.10015	0.01733
	Bipolar Sigmoid	30000	0.04020	0.00324
12-12-1	Sigmoid	20000	0.10049	0.01724
	Bipolar Sigmoid	40000	0.01689	0.00079

Table 4. 10: Performance of the ANN models for International Air Passenger

Model	Activation function	Iterations	MAE	MSE
12-4-1	Sigmoid	20000	0.08080	0.01154
	Bipolar Sigmoid	20000	0.05694	0.00538
12-6-1	Sigmoid	20000	0.08173	0.01177
	Bipolar sigmoid	20000	0.03962	0.00277
12-8-1	Sigmoid	20000	0.07998	0.01143
	Bipolar Sigmoid	30000	0.02933	0.00160
12-12-1	Sigmoid	20000	0.07994	0.01150
	Bipolar Sigmoid	30000	0.01028	0.00028

In Tables 4.10 and 4.11 it was observe that in the 4 ANN models that were considered, the best results were obtained when the bipolar sigmoid activation function was used. This was deduced by the measure of accuracy. In each of the cases better results were obtained with the increase in number of neurons in the hidden layer, with the model 12-12-1 using bipolar sigmoid function yielding the best results based on the in-sample measure of error. However, the ANN 12-12-1 model for the international air passenger traffic was not as effective, when checking the out-sample performance separately, it yielded $RMSE = 0.32836$ compared with the other ANN models with fewer neurons in the hidden layer.

ANN 12-4-1 tends to perform averagely better with better out-sample, forecast performance, $RMSE = 0.16185$. For the domestic air passenger traffic, ANN 12-4-1 which has fewer neurons (fewer parameters) and sufficiently good forecast accuracy based on the measure of error would be employed in comparison with the best SARIMA and HWES model.

The input neurons are the lagged series, $y_{t-1,} y_{t-2} .... y_{t-12}$ of the time series data, these are weighted randomly and linearly combined and the results are modified by the bipolar sigmoid function to serve as input to the next layer.

The performance of the ANN best model, 12-4-1, for domestic and international air passenger using the bipolar sigmoid function was compared with the best SARIMA and Holt-Winters exponential smoothing models for the in-sample and out-sample forecast, so as to examine their relative performances based on MAPE and RMSE.

The forecast for the ANN, SARIMA and Holt-Winters model are presented in **Appendix VIII.**

4.8 Performance Comparison of the Models

In evaluating the forecast performance accuracy in each of the models, the training set of data and a test set were used. The training data set contains data from 2003 to 2013, a total of 132 monthly observations in each case, domestic and international air passenger traffic. The test data set contains data from 2014 to 2015, a total of 24 monthly observations in each case. The static out-of-sample forecast is employed in this study. One step ahead forecast,the forecast for the month of January 2014, is made by using the training data set, this estimate is added to the training data set which in turn is used to make forecast for the month of February 2014. The forecast estimate for the month of February 2014 is added to the new training set so as to obtain forecast for March 2014.

The iteration continues until the estimate for the last month, December 2015. This estimates from the static forecast are compared with the actual test data set, using statistical loss functions. Based on this,the values of the MAPE and RMSE for the respective proposed models are compared so as to select the model that has the best out-of-sample performance for the forecast horizon.

The forecast for the ANN, SARIMA and Holt-Winters model are presented in Appendix V.

Table 4. 11:Performance Comparisons of Models for Air Passenger Traffic

Domestic air traffic passenger				
Model	**In-Sample**		**Out-Sample**	
	MAE	**RMSE**	**MAPE**	**RMSE**
SARIMA $(1,1,1)(0,1,1)_{12}$	0.0983	0.1304	0.5291	0.0808
Holt-Winters	0.09183	0.12162	0.6000	0.0932
ANN $(12-4-1)$	0.05896	0.00803	0.40918	0.06364
International air passenger traffic				
Model	**In-Sample**		**Out-Sample**	
	MAE	**RMSE**	**MAPE**	**RMSE**
SARIMA $(3,1,1)(2,1,2)_{12}$	0.0632	0.0864	0.9605	0.1453
Holt-Winters	0.07291	0.10081	0.6435	0.0979
ANN $(12-4-1)$	0.05694	0.07335	0.98190	0.16185

Table 4.10 gives the empirical results of the forecasting performance of the models, ANN, SARIMA and Holt-Winters.All the examined models produced good forecast in the sectors considered, since the MAPE and RMSE are generally low.In modelling the air passenger traffic for both domestic and international flights, the ANN models performed very well in the in-sample forecast. ANN $(12-4-1)$ outperforms the Holt-Winters and SARIMA models for in-sample and

out-sample forecast in the domestic sector. It is observed that the values of MAE, MAPE and RMSE are smaller than the other models.

ANN $(12-4-1)$ model for international air passenger traffic, by comparing the MAPE, MAE and RMSE has a better in-sample performance than the other models but has the least out-sample forecast performance. The effectiveness of the ANN models in this dissertation corroborates emphases made on the flexibility and excellent function approximation capability of the ANN in previous studies byWhite (1989). Though the ANN $(12-4-1)$, in modeling the international air passenger traffic,has the least out sample performance, observing the MAE and RMSE for the training set it is evident that the ANN has a great learning and pattern recognition ability. From the time plot of the international air traffic passenger, theexhibition of a more stable characteristics was obtained compared to the time plot for domestic air passenger traffic. This could be the reason for the better performance of the ANN in modelling the domestic air passenger traffic, since the ANN does very well in capturing some hidden salient characteristics and non-linearity in data.

The Holt-Winters Exponential Smoothing model shows better post forecast accuracy, for international air passenger traffic, than SARIMA $(3,1,1)(2,1,2)_{12}$ and ANN, based on the MAE, RMSE and MAPE. In modelling the domestic air passenger traffic, the ANN had the best in-sample and out-of-sample performance, though SARIMA $(1,1,1)(0,1,1)_{12}$ performed competitively with ANN.

CHAPTER FIVE

SUMMARY, CONCLUSION AND RECOMMENDATIONS

5.1 Introduction

This chapter presents a summary of the procedure undergone to achieve the set objectives of the dissertation. The conclusion and recommendations based on the inference from the results obtained from the 3 models, ANN,SARIMA and Holt-Winters exponential smoothing are discussed.

5.2 Summary

In this dissertation, two sets of time series data from 2003 to 2015, monthly air passenger traffic for domestic and international flight were obtained.

Three time series model were employed in order to achieve the set objectives aimed at employing time series forecasting models to approximately predict air passenger traffic flow in Murtala Muhammad International Airport Lagos, Nigeria.

The data were divided into two sets, training and test sets. The time series models considered were evaluated on these data set so as to measure the accuracy of the models for in-sample and out-sample performance. The time series data were log transformed in order tostabilize the variance,so as to obtain more desirable results in the models considered.

The time plots of the air passenger traffic reveal non-stationarity, presence of trend, seasonality and noise. After first differencing, the Augmented Dickey Fuller test shows that the time series data attained stationarity.

The Jarque-Bera test for normality however reveals that the time series data are not normally distributed.

The Box-Jenkins methodology was employed in building the best SARIMA models for obtaining a fairly good forecast for air passenger traffic flow in Murtala Muhammad international airport.

After the necessary diagnostics using AIC, BIC, error measurements based on in-sample and out-sample forecast performance, SARIMA $(1,1,1)(0,1,1)_{12}$ andSARIMA $(3,1,1)(2,1,2)_{12}$ were selected, as the best SARIMA models for modelling the air passenger traffic for domestic and international respectively.The summary of these models show that, they gave better fit for the air passenger traffic. This was also compared with the other proposed models.

In selecting the best Holt-Winters model, the additive and multiplicative models were considered so as to select the best models. The appropriate smoothing parameters, α , β and γ which best minimize the sum of squared errors for the level, trend and seasonality were used in determining the best Holt-Winters model.In modelling the air passenger traffic, additive model appeared to be the bettermodel based on the AIC and BIC.

The Holt-Winters gave a generally good performance for in and out of sample forecast, it outperforms the SARIMA and ANN in the out-sample forecast in the international sector based on the MAPE and RMSE.

The feed forward neural network, using the back propagation algorithm was used to model the time series data. Eviews 9, Zaitunand R version 3.2.4 software were used to obtain the desired results.

A three layered feed forward neural network was used, with the number of neurons in the hidden layer varied to obtain the neural network architecture that best models the time series data.

ANN(12-4-1),ANN(12-6-1),ANN(12-8-1) and ANN(12-12-1) were considered usingthe sigmoid and bipolar sigmoid functions. ANN(12-12-1) in both domestic and international sector produced the best in-sample performance. However the out-sample performance was least, relative to the other ANN models. ANN(12-4-1) appeared to be the best model for modelling the domesticair passenger traffic, considering the in-sample and out-sample errors. For the international air passenger traffic, ANN(12-4-1) had the least out-sample result.

5.3 Conclusion

Generally, in achieving the aim of this dissertation, three time series models were considered, the seasonal auto-regressive integrated moving average (SARIMA), Holt-Winters Exponential Smoothing model and the Artificial Neural Network. These time series models were tested on the international air passenger and domestic traffic, to evaluate their performances and test the predictive capability of the artificial neural network relative to the other models.

The models were estimated on the training data set which covers the period from January 2003 to December 2013. The test set which covers the period from January 2014 to 2015 December was used to obtain the forecast accuracy measure of these models based on RMSE(Root Mean Squared Error) and MAPE(Mean Absolute Percentage Error).Empirical results show that all the models provide good forecasts of the air passenger traffic for international and domestic.

Comparing results across the models, it was observed that no model completely outperforms the other in all the sectors. However, the ANN model was found to be very efficient and had the best in-sample performance across the two sectors.

In modelling the domestic air passenger, the ANN model was seen to be significantly dominant, while for the international air passenger traffic the ANN also gave the best in-sample accuracy performance but the least out-sample performance. The Holt-Winters exponential smoothing and SARIMA both yielded good results. The Holt-Winters exponential smoothing out-performed the SARIMA and ANN for the out-of-sample forecast of international air passenger traffic while the SARIMA was more dominant than Holt-Winters in the domestic sector.

Conclusively,this study has been able to establish the effectiveness of the ANN in modeling and forecasting time series data and also select time series models that gave fairly accurate forecast of air passenger traffic in Murtala Muhammed International Airport Lagos, Nigeria.

5.4 Recommendations

This section gives a presentation of recommendations inferred from the results obtained from the time series models. The dissertation recommends;

- The time series models considered from the Box-Jenkins methods, Holt-Winters and artificial neural network are appropriate in modelling and forecasting air passenger traffic flow in Murtala Muhammed International Airport Lagos, Nigeria.

- That the artificial neural network representing a class of non-linear time series model, gives a very good in-sample and out-sample forecast accuracy and can be relied on as an alternative to the conventional methods in making forecasts for future plans, policies and decision making.

- The artificial neural network model tends to give a better accuracy of forecast performance in an erratic time series data, due to its non-linear characteristic than the conventional time series model. Time plots show that the domestic sector is more unstable than the international sector. The ANN did well in the domestic than in the international sector which is less volatile. However, it would be recommended that due to the stable nature of international air passenger time series data, less complex conventional time series model could be relied on for better forecast accuracy.

- The common characteristic of the time series data for the domestic and international air passenger is the presence of an obvious upward trend. This indicates increase demands in domestic and international flights. Better measures, policies, accommodation establishment, facilities, enhanced air traffic management have to be put in place to sustain and accommodate the increasing demands.
- Future research on this dissertation could be extended to other types of machine learning, artificial intelligence based forecasting methods, which includes;Adaptive Neuro-Fuzzy Inference System Genetic Algorithm (ANFISGA) &Support Vector Machines (SVMs). Factors affecting the nature of the time series data in both sectors could also be captured using appropriate time series models, including such factors as exogenous input variables.

5.5 Contribution ToKnowledge

- This research work has been able to employ appropriate time series models in modelling the air passenger traffic flow in Murtala Muhammad International Airport Lagos, Nigeria.

- The ANN, compared to the other models considered, was able to mimic the pattern of the time series data more accurately. This establishes the pattern recognition ability of ANN as could be observed from the in sample performance.

- In modelling the International air passenger traffic, which appears to have a simpler time series, ANN had the least out-sample forecast accuracy. This implies that complex models may not necessarily yield the best forecast accuracy in modelling simple time series data

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APPENDICES

Appendix I

Domestic Air passenger traffic

Months	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**
Jan	161645	163852	150174	140080	165941	204186	221483
Feb	145617	156422	166200	126179	112965	168082	219976
Mar	164150	164978	202596	144027	128900	178290	220191
Apr	160866	203629	207928	185424	160854	245760	283973
May	169971	191796	194709	198606	127097	232683	274459
Jun	174640	174209	191216	193153	100335	228898	275248
Jul	155469	207914	188435	214825	193263	204387	300054
Aug	190054	207437	253843	172209	240895	299074	306502
Sep	201486	203535	200968	180919	164213	246329	242736
Oct	194304	170638	179192	209423	204649	248296	368836
Nov	184176	179713	154770	174166	175638	256648	309497
Dec	195480	196445	165873	202656	222596	282287	297148

Months	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**

Jan	274931	320099	245927	285863	298481	339282
Feb	259898	319607	295664	291946	312232	292503
Mar	269129	377105	320561	358642	357858	340895
Apr	322431	286093	333610	305982	379580	328799
May	316723	379245	441437	302146	353975	320474
Jun	315421	337499	345630	311499	356367	321102
Jul	351977	329847	350921	336981	358274	328845
Aug	362430	327116	404423	384775	360772	355739
Sep	325375	336336	348122	357433	350707	330222
Oct	341986	347799	358873	338857	363680	342421
Nov	335089	369056	379968	328504	365933	349081
Dec	389068	397298	366032	338857	352395	379081

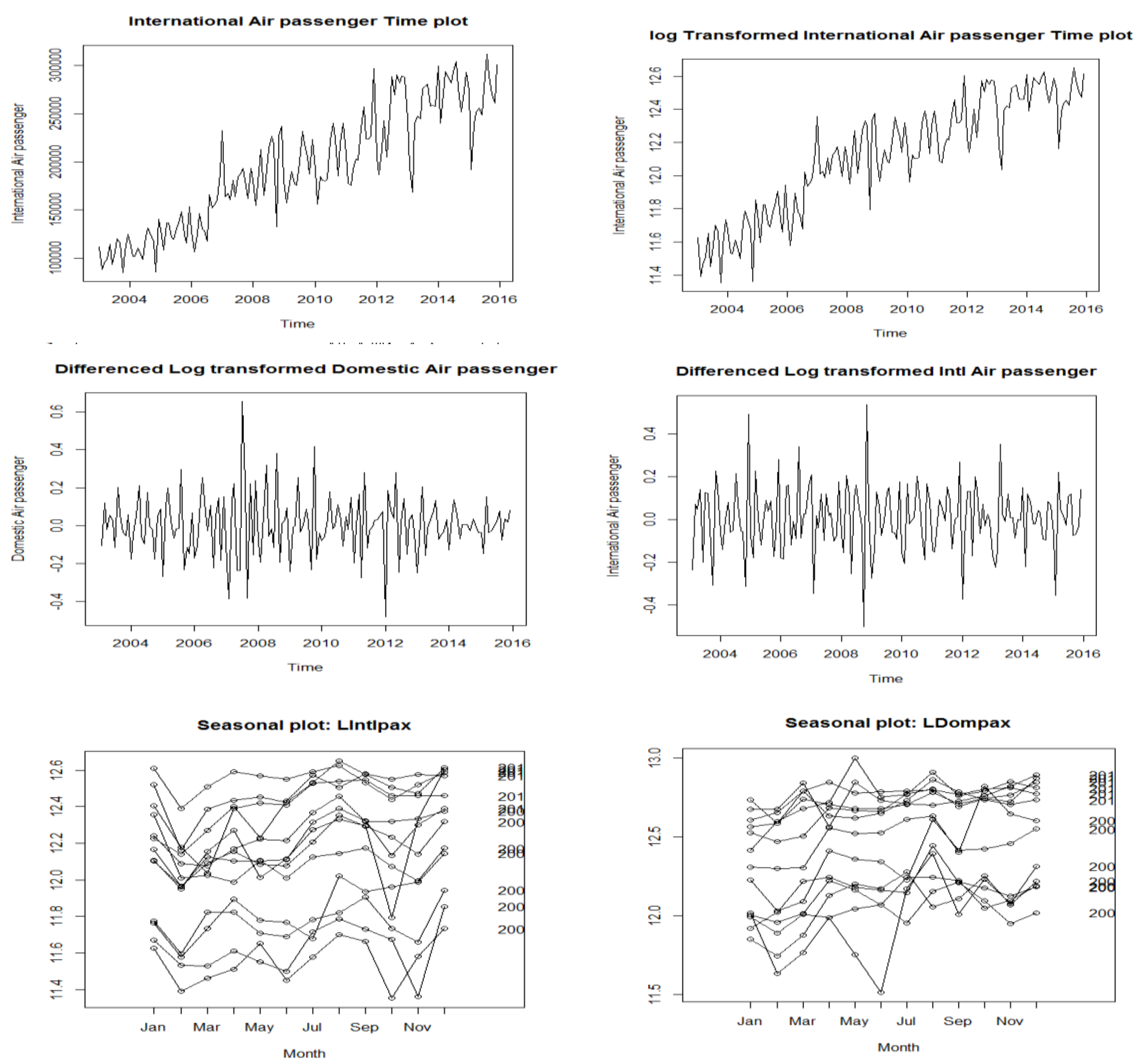
Appendix II

International Air passenger traffic

Months	2003	2004	2005	2006	2007	2008	2009
Jan	111976	117159	130082	128441	232085	180811	180202
Feb	88393	101871	108679	106585	164214	154806	157200
Mar	95083	101779	136350	124617	167039	190062	178612
Apr	99812	110368	136618	146553	160528	212924	190271
May	114782	104068	121368	130161	180793	165081	176775
Jun	93848	98785	119380	128935	164022	182033	175437
Jul	106570	122407	130666	117894	184663	214201	199809
Aug	120627	131187	135784	166104	187897	226598	231805
Sep	116372	124159	148291	152333	193492	218855	218419
Oct	85372	117468	124530	156576	174792	132487	205173
Nov	107189	85767	115925	160947	162112	227027	187258
Dec	124582	140603	153762	187944	193441	237115	223508

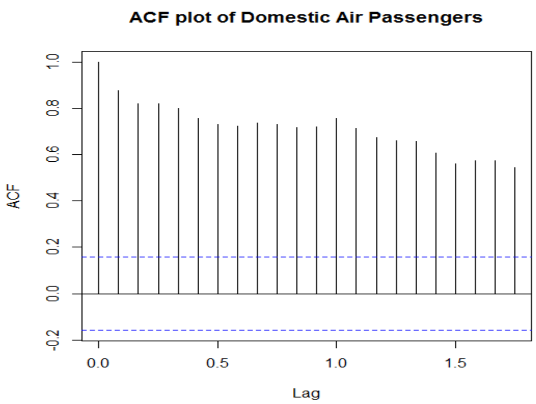
Months	2010	2011	2012	2013	2014	2015
Jan	191869	207351	204307	243513	299507	273897
Feb	156279	177807	186956	194630	240192	191671

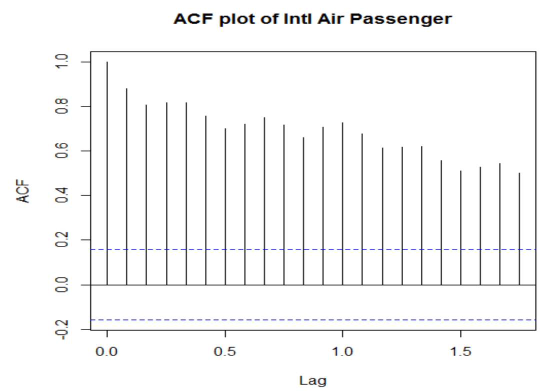
Mar	184559	175486	213106	168773	270528	239484
Apr	180665	192775	242905	240415	293804	251240
May	180560	202995	204705	247210	287505	255596
Jun	181944	201731	250284	244749	281974	248499
Jul	222826	234708	288286	275712	293861	276648
Aug	240335	256808	269616	278630	303774	311726
Sep	224491	224025	290152	280840	276947	289111
Oct	185710	223921	281972	257722	251746	270080
Nov	219478	226883	288989	258111	273573	260974
Dec	240371	296700	287597	257722	293017	300800

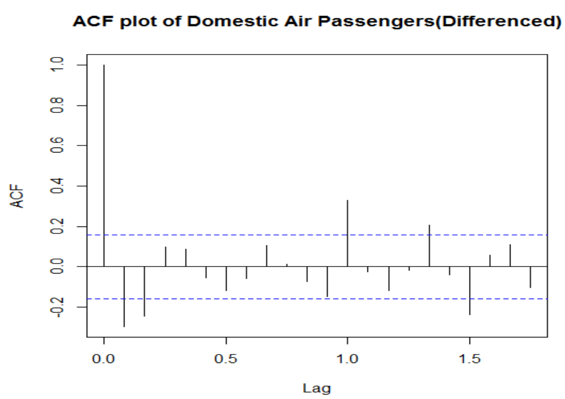


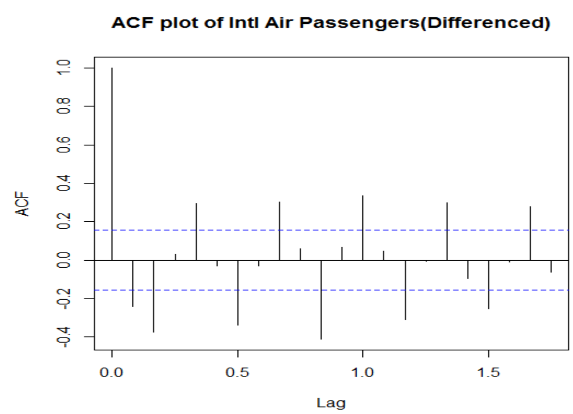
Appendix III: Time plots of the air passenger traffic

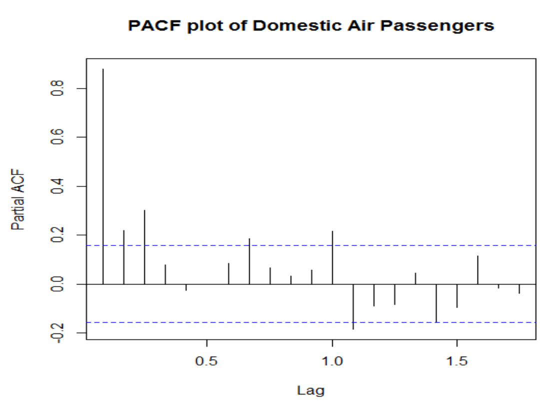
Appendix IV: ACF plots of air passenger traffic

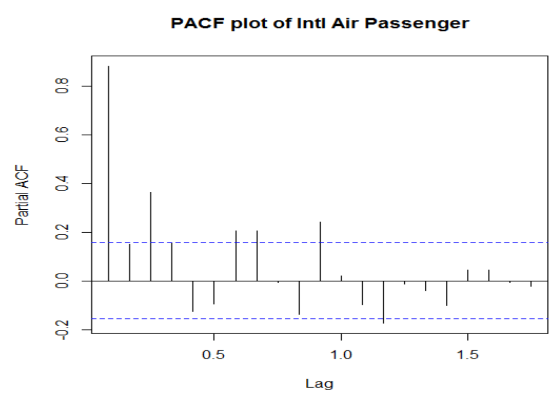


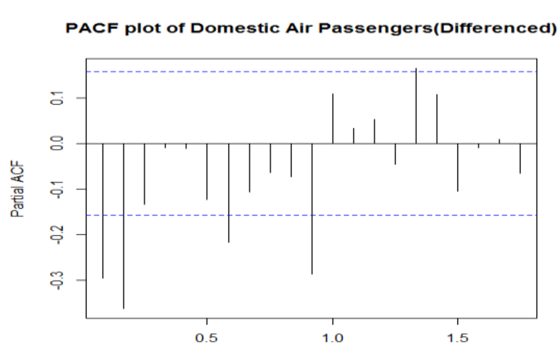




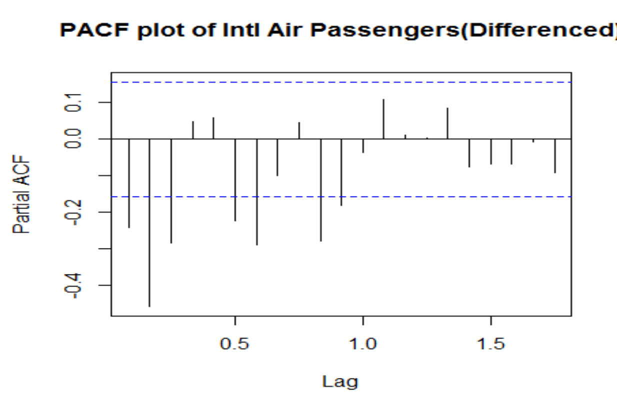


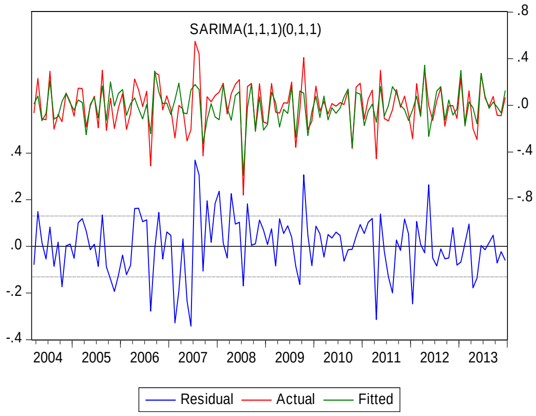


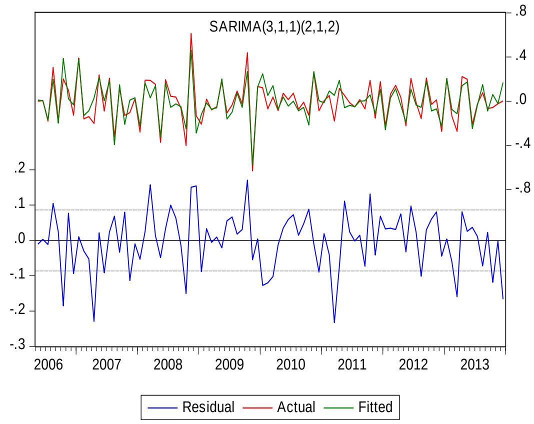


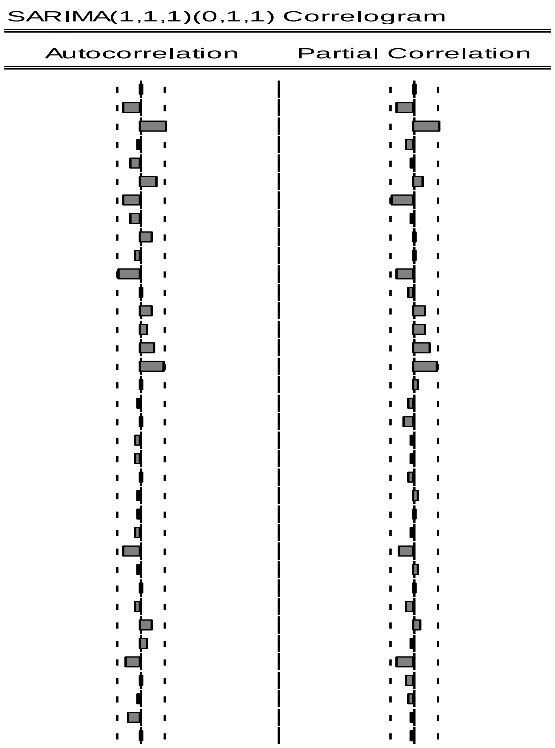


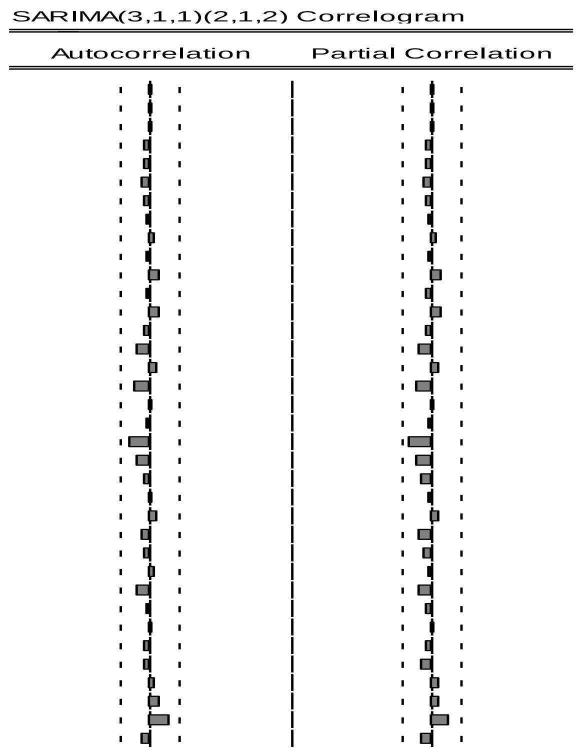
App endi x V: Plot



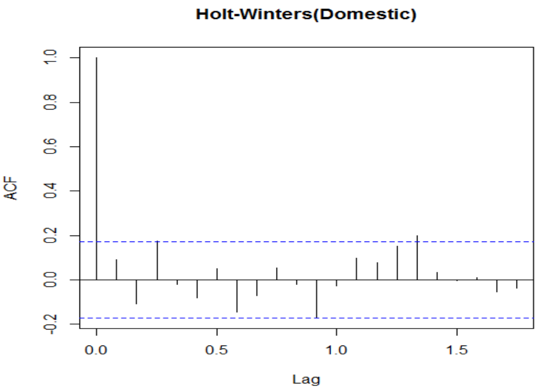

SARIMA(1,1,1)(0,1,1)
.8
.4
.0
-.4
-.8
.4
.2
.0
-.2
-.4
2004 2005 2006 2007 2008 2009 2010 2011 2012 2013
Residual Actual Fitted

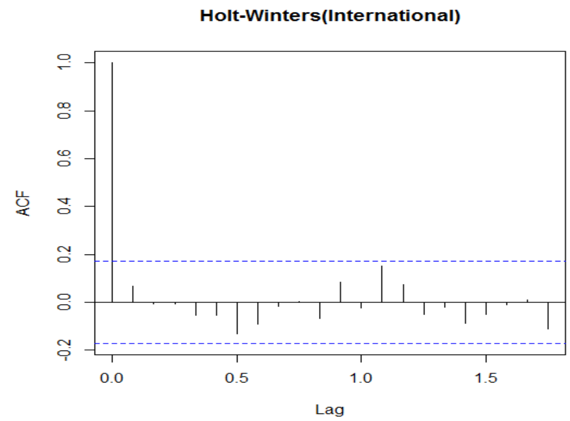

SARIMA(3,1,1)(2,1,2)
.8
.4
.0
-.4
-.8
.2
.1
.0
-.1
-.2
-.3
2006 2007 2008 2009 2010 2011 2012 2013
Residual Actual Fitted

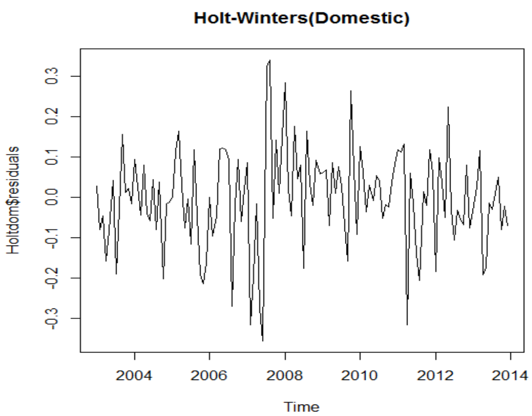

SARIMA(1,1,1)(0,1,1) Correlogram
Autocorrelation
Partial Correlation

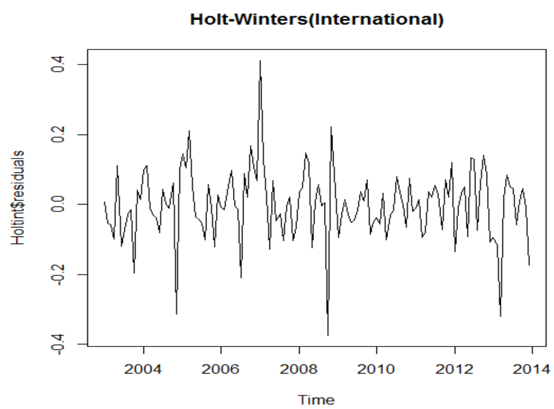

SARIMA(3,1,1)(2,1,2) Correlogram
Autocorrelation
Partial Correlation

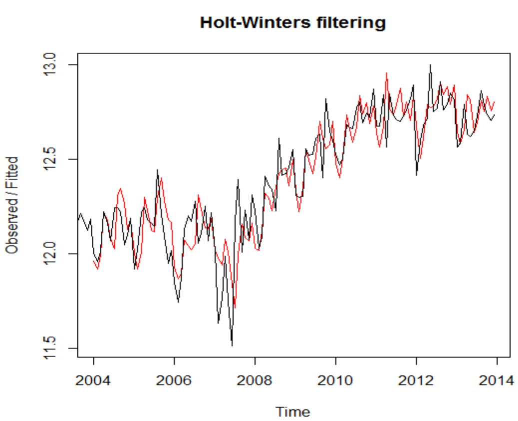
Appendix VI: Plots from HES model for air passenger traffic

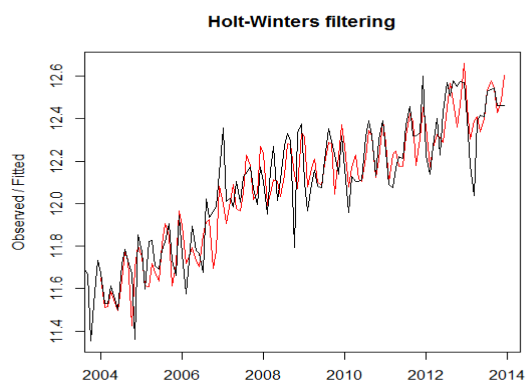


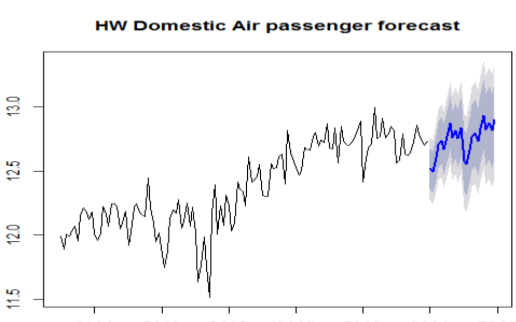


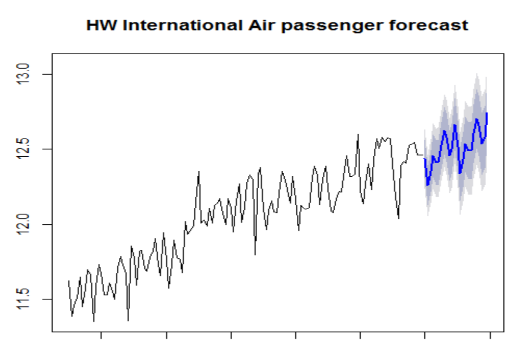


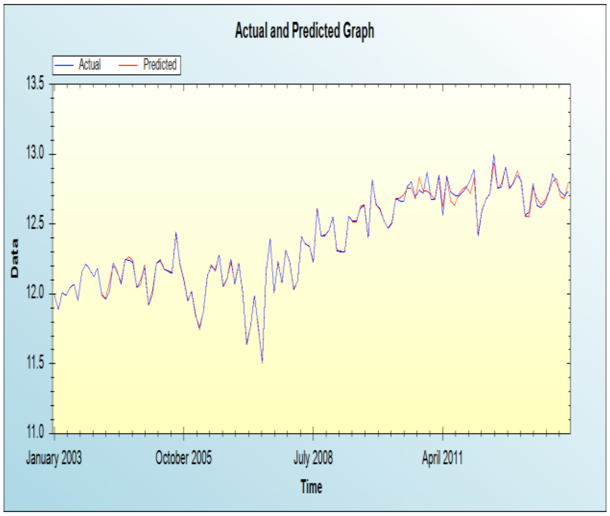


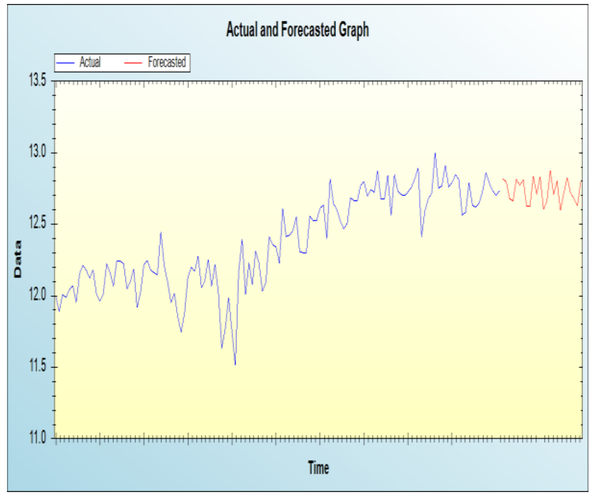


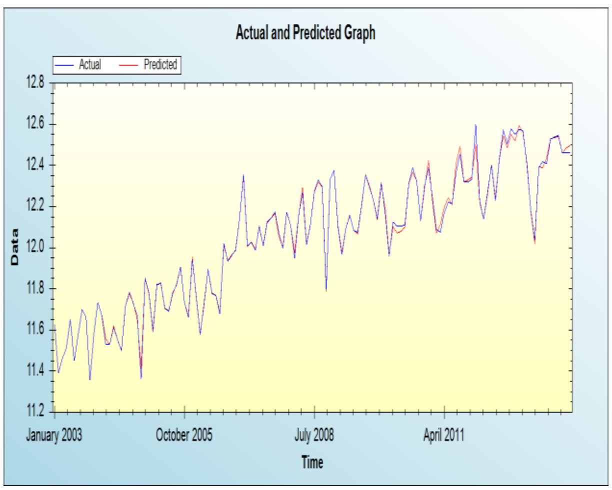


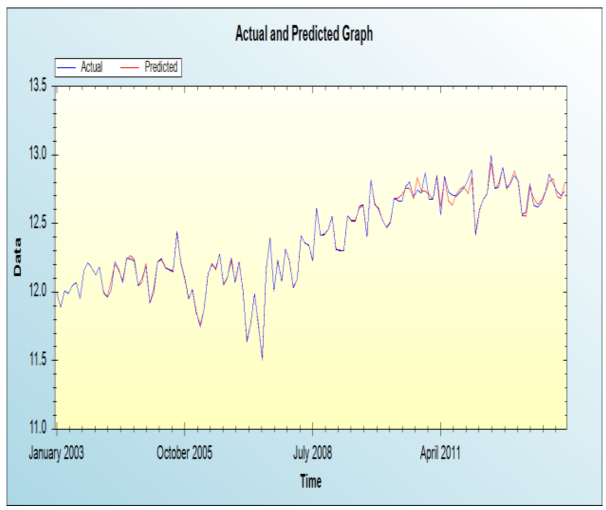






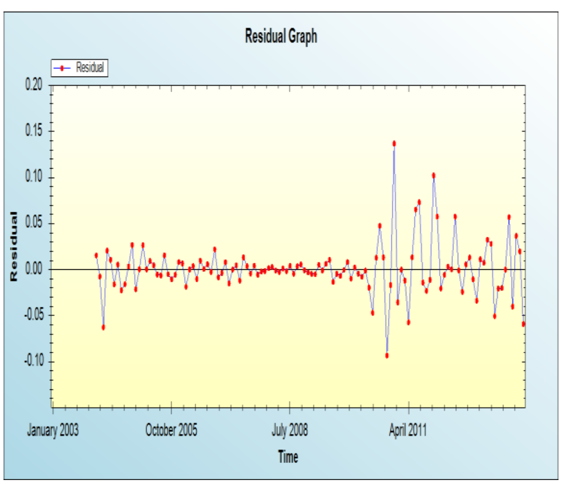


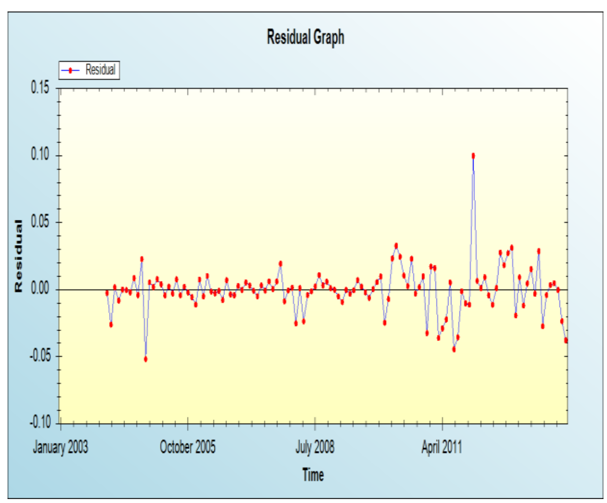




Appendix VII: ANN plots of the actual and predicted air passenger traffic

	SARIMA	Holt-Winters





	2014		2015		2014		2015	
Months	Actual	Predicted	Actual	Predicted	Actual	Predicted	Actual	Predicted
Jan	12.60646	12.54687	12.73459	12.58606	12.60646	12.5183	12.73459	12.5688
Feb	12.6515	12.52049	12.58623	12.5551	12.6515	12.4872	12.58623	12.5510
Mar	12.78789	12.64146	12.73933	12.67534	12.78789	12.5988	12.73933	12.6357
Apr	12.84682	12.69409	12.7032	12.72776	12.84682	12.6826	12.7032	12.7585
May	12.77698	12.71815	12.67756	12.75168	12.77698	12.7238	12.67756	12.7594
Jun	12.78372	12.66293	12.67951	12.69633	12.78372	12.6467	12.67951	12.7024
Jul	12.78905	12.74542	12.70334	12.77869	12.78905	12.7484	12.70334	12.7892
Aug	12.796	12.85482	12.78195	12.88796	12.796	12.8227	12.78195	12.8861
Sep	12.76771	12.74473	12.70752	12.77774	12.76771	12.7391	12.70752	12.7714
Oct	12.80403	12.78137	12.7438	12.81424	12.80403	12.7500	12.7438	12.8106
Nov	12.81021	12.73712	12.76306	12.76986	12.81021	12.7303	12.76306	12.7555
Dec	12.77251	12.80603	12.84551	12.83863	12.77251	12.7857	12.84551	12.847

Appendix VIII: Forecasts in Log fordomestic air passenger traffic

	ANN			
	2014		2015	
Months	Actual	Predicted	Actual	Predicted
Jan	12.60646	12.8154	12.73459	12.6041
Feb	12.6515	12.7967	12.58623	12.6597
Mar	12.78789	12.6788	12.73933	12.8757
Apr	12.84682	12.6631	12.7032	12.7079
May	12.77698	12.8158	12.67756	12.8034
Jun	12.78372	12.7699	12.67951	12.5965
Jul	12.78905	12.812	12.70334	12.718
Aug	12.796	12.6256	12.78195	12.8267
Sep	12.76771	12.6253	12.70752	12.7172
Oct	12.80403	12.8371	12.7438	12.6792
Nov	12.81021	12.7088	12.76306	12.6276
Dec	12.77251	12.8334	12.84551	12.7993

Appendix IX: Forecast in Log for International air passenger traffic

	SARIMA				Holt-Winters			
	2014		2015		2014		2015	
Months	Actual	Predicted	Actual	Predicted	Actual	Predicted	Actual	Predicted
Jan	12.60989	12.39731	12.52051	12.44329	12.60989	12.43653	12.52051	12.50386
Feb	12.38919	12.21811	12.16354	12.25943	12.38919	12.26272	12.16354	12.39035
Mar	12.50813	12.1475	12.38624	12.15926	12.50813	12.35142	12.38624	12.44223
Apr	12.59067	12.34725	12.43416	12.51405	12.59067	12.46137	12.43416	12.54628
May	12.569	12.35924	12.45135	12.42488	12.569	12.43467	12.45135	12.48319
Jun	12.54957	12.45011	12.42319	12.54913	12.54957	12.40834	12.42319	12.48325
Jul	12.59086	12.54522	12.5305	12.63301	12.59086	12.53023	12.5305	12.59945
Aug	12.62404	12.51633	12.64988	12.54069	12.62404	12.60866	12.64988	12.68529
Sep	12.53158	12.52302	12.57457	12.63975	12.53158	12.58025	12.57457	12.64262
Oct	12.43618	12.59102	12.50647	12.5704	12.43618	12.4476	12.50647	12.48983
Nov	12.51932	12.5478	12.47218	12.61931	12.51932	12.48536	12.47218	12.54033
Dec	12.58799	12.62457	12.6142	12.53049	12.58799	12.64527	12.6142	12.69273

	ANN			
	2014		2015	
Months	Actual	Predicted	Actual	Predicted
Jan	12.60989	12.1946	12.52051	12.1523
Feb	12.38919	12.0916	12.16354	12.1093
Mar	12.50813	12.1883	12.38624	12.3823
Apr	12.59067	12.5018	12.43416	12.4817
May	12.569	12.222	12.45135	12.3246
Jun	12.54957	12.5342	12.42319	12.5412
Jul	12.59086	12.4343	12.5305	12.5488
Aug	12.62404	12.5975	12.64988	12.5843
Sep	12.53158	12.4662	12.57457	12.4974
Oct	12.43618	12.5358	12.50647	12.547
Nov	12.51932	12.5127	12.47218	12.4776
Dec	12.58799	12.4282	12.6142	12.2919