Statistical Analysis of Road Traffic Accident in Addis Ababa: Application of SARIMA and SETAR model

By: Hirko Beyene Gerbi

Main Advisor:- Agatamudi Lakshmana Rao (PhD)

Co-Advisor:- Dechasa Bedada (Assistant Professor, MSc.)

A Thesis Submitted to Jimma University College of Natural Sciences Department of Statistics in Partial Fulfillment of the Requirements for the Degree of Masters of Science in Biostatistics

February, 2020

Jimma, Ethiopia

Approval Sheet

Jimma University

School Of Graduate Studies, Department Of Statistics

As thesis research advisors, we her by certify that we have read the thesis prepared by Hirko Beyene under our guidance, which is entitled **"Statistical Analysis of Road Traffic Accident in Addis Ababa: Application of SARIMA and SETAR model "** has been approved for submission to the Graduate Programs of Jimma University in partial fulfillment of the requirements for the award of the Degree of Master of Science in Statistics (Biostatistics) assembles with the regulations of the University and meets the accepted standards with respect to originality and quality.

Name of Advisors	**Signature**	**Date**
Agatamudi Lakishmana Rao (PhD)	_________	_________________
Dechasa Bedada (Assistant Professor,MSc.)	_________	_________________

As the members of the board of examiners of MSc. thesis open defense examination. We certify that we have read and evaluated the thesis and examined the candidate. We recommend that the thesis be accepted as it fulfills the requirements for the degree of Master of Science in Biostatistics.

______________________________ _________________ _________________

Name of chairman **Signature** **Date**

______________________________ __________________________________

Name of Internal Examiner **Signature** **Date**

______________________________ __________________________________

Name of External Examiner **Signature** **Date**

Acknowledgements

First and for most, I would like to extend my unshared thanks to the almighty God for providing me the opportunity for what I have achieved and for his mercy.

I would also like to thank my advisors Dr. Agatamudi Lakshmana Rao and Mr. Dechasa Bedada for their expertise, efforts, and unreserved support in making this thesis successful. The value of their dedication, kind and untiring guidance and warm hearted advice throughout the execution of this thesis is not only difficult to estimate but also very hard to express adequately by the usual terms of acknowledgement. Their comments and suggestions immensely enriched the content of this work.

I am also grateful to the entire staff and faculty of Jimma University's College of Natural Sciences Department of Statistics. Finally, I would like to express my gratitude to the Addis Ababa Traffic Police Commission for their assistance in providing me data for this study.

Table of Contents

List of Tables

List of Figures

List of Abbreviations

AATPC	Addis Ababa Traffic Police Commission
ACF	Autocorrelation Function
ADF	Augmented Dickey-Fuller
AIC	Akaikes Information Criterion
AR(p)	Auto regression model of order p
WHO	World Health Organization
BIC	Bayesian Information Criterion
GC	Gregorian Calendar
TAR	Threshold Autoregressive
SETAR	Self-Excited Threshold Autoregressive
MA	Moving Average
MAE	Mean Absolute Error.
MAPE	Mean Absolute percentage Error
MSE	Mean Square Error
RMSE	Mean Absolute Error
PACF	Partial Autocorrelation Function
RTA	Road Traffic Accident
SARIMA	Seasonal Autoregressive Integrated Moving Average
CSA	Central Statistical Agency

Abstract

Road traffic accidents are one of the leading causes of injuries and death in both developed and developing countries. According to WHO, 1.35 million people die each year as a result of road traffic accidents globally. Ethiopia is one of the developing countries and at least 114 people die for every 10,000 vehicle accidents annually. Moreover, road traffic accident the capital city, Addis Ababa resulting in thousands of physical injuries and costing the economy in millions of dollars. Hence, time series analysis related to the road traffic accident has a very important place in revealing the future trends of the accident and decision making process. Therefore, this study focuses on statistical analysis of road traffic accident using Seasonal Autoregressive Integrated Moving Average (SARIMA) and Self-Excited Threshold Autoregressive (SETAR) time series models. Data were obtained from Addis Ababa Traffic Police Commission and temporally aggregated from January 2004 to December 2018 for analysis purpose. Data analyses were performed using R and S-plus statistical software. The estimated trend component of RTA showed a rising trend from 2010 to 2016 G.C .Furthermore, road traffic accident most frequently occurs during the rainy seasons (June, July and August) of Ethiopia. The two regime SETAR model was adopted to accommodate non linearity and linear SARIMA model was fitted as a benchmark for comparative analysis. The model was nominated from SARIMA and SETAR models based on the selection criteria and model comparison was made between the selected models. Nonlinear SETAR(2,8,8) outperformed forecast than linear SARIMA$(1,1,1)(1,1,2)_{12}$ model for road traffic accident of Addis Ababa. The out sample forecasted value indicates that, road traffic accident has an increasing trend over the forecasted period.

Keywords: Regime, unit root, invertible, stationary, nonlinearity

1. Introduction

1.1. Background

Road traffic accident is a major public health problem worldwide. It includes collisions between vehicles and animals, vehicles and pedestrians, vehicles and fixed objects or vehicles and vehicles (Bereket et al., 2016).According to WHO (2018) report, there are 1.35 million deaths per year and road traffic accident is the eighth leading cause of death for all age groups globally.

WHO (2018) investigated the risk of dying in a road traffic accident by continent and Africa is the leading with the chance of 26.6 followed by south east Asia (20.7).Even though the numbers show the large prevalence rate in road traffic accident in developing countries specifically in Africa (including Ethiopia), the issue is still under reported and neglected to be studied and interventions are needed urgently (Samuel *et al*., 2012).

Abegaz *et al*. (2019) reveals that, road accident related injuries and fatalities are exceptionally high in Ethiopia and there is paucity of evidence regarding of the accident. Further, the available estimates based on official reports are likely to underestimate the extent of the problem. Abdi *et al.*(2017) showed that, road traffic accident in Addis Ababa resulting in thousands of physical injuries and costing the economy in millions of dollars. Moreover, the finding of Teferi (2019) emphasis that, road traffic accident continue to be a significant for morbidity and mortality problem in Addis Ababa and requiring urgent attention. Similarly, road traffic deaths and injuries affect the livelihood of community and the economy of the country unless effective measures are taken to control the problem (Fesseha *et al*., 2014).

Unless the trend is detained, the social and economic problem of road traffic accident will become more and more serious as the number of vehicle increases. And, access to the information about road traffic accident in a given context is significant to generate evidence to contribute to the prevention and control of context-specific accidents (Cherati *et al*., 2012).Time series models are very useful to enhance one's understanding on traffic accident trends (Bossche *et al*., 2004).

The cases of accident being a timely occurrence can be modeled using Box and Jenkins approach to time series modeling developed by two mathematicians, George Box and Gwilym Jenkins (1970). The Box-Jenkins model requires the data to be stationary, and differencing was used to make the data stationary if it is not stationary. When seasonality is contained in the series, the seasonal components are incorporated into the ARIMA model to make the seasonality not to die out .This leads to Seasonal Autoregressive Integrated Moving Average (SARIMA) model (Eze *et al*.,2018).

Nonlinear threshold model was introduced by Tong (1978) and Self-Exciting Threshold Autoregressive (SETAR) model was a special case of the TAR model which accommodates structural changes in regimes of the data. Moreover, Clements et al. (2004) reviewed, the current state of this model ranging from estimation, evaluation and selection of forecasting models. Due to the shortcomings of linear and nonlinear models, the hybrid forecasting approach has come to the forefront over the past decade (Gulay, 2019).According to Zhang (2019) finding, the combined linear and nonlinear time series model can be an effective way to improve forecasting accuracy achieved by either of the models used separately. Therefore, this study was focused on the application of SARIMA and SETAR model for analyzing road traffic accident of Addis Ababa.

1.2. Statement of the problem

In Ethiopia, the rate of road traffic accidents is very high and at least 114 people die for every 10,000 vehicle accidents annually. The real figure may be higher due to underreporting. In addition, the country is experiencing highest rate of such accidents resulting in fatalities and the capital city, Addis Ababa shares 65% of the total accident in the country (NRSCO, 2008).

Tesema (2005) conducted a research on road traffic accident data comprising a dataset of 4,658 accident records at Addis Ababa traffic police commission to investigate the application of data mining technology for accident severity using classification of algorithms .Also, Guyu (2013) studied, spatial distribution of the severity of road traffic accident among the 10 sub-cities of Addis Ababa and the study identified 125 hazardous black-spots in all sub-cities of Addis Ababa.

Hordofa *et al*. (2018) investigated the prevalence of fatality and associated factors of road traffic accidents using bivariate and multivariate analyses. Subsequently, Kebede (2015) examined the factors contributing to the mortality related to road traffic accidents and the cause of the accident was analyzed using descriptive statistics.

Hence, previous researchers were used descriptive statistics, spatial distribution, bivariate, multivariate, classification of algorithm and data mining model for analyzing road traffic accidents. Though, to inform police traffic commission about the estimates of road traffic accident in the future, time series analysis related to the road traffic accident has a very important place in revealing the trends and decision making process. It has a major impact in the development of appropriate solutions to combat this phenomenon, and can provide important information in road accident trends. This future trend can help in identifying the feature of road accidents whether it tends to increase or decrease so that preventive measures can be taken. Therefore, the objective of this research was to analyze road traffic accident in Addis Ababa using SARIMA and SETAR models. The key questions that was addressed in this research were:

- What is the pattern of road traffic accident in Addis Ababa?
- In which season does road traffic accident most frequently occurs over time span of the data?
- Which SARIMA and SETAR model is appropriate for modeling and forecasting road traffic accident in the study area?

1.3. Objectives of the study

1.3.1. General objective

The general objective of this study is to analyze road traffic accident in Addis Ababa using SARIMA and SETAR model. The results of this study can provide information that could be useful to reduce road traffic related morbidity and mortality in the study area.

1.3.2. Specific objectives

The specific objectives are:

- ➢ To assess the pattern of road traffic accident in Addis Ababa
- ➢ To investigate the season in which road traffic accident mostly frequently occurs over the time span of the data
- ➢ To identify appropriate model from SARIMA and SETAR for modeling and forecasting road traffic accident in the study area

1.4. Significance of the Study

Road traffic accident have been increasing from time to time and become fear of society. Hence, identifying the current trend and forecasting magnitude of road traffic accident was an important step to guide future course of action for describing its economic implications and saving the lives. Therefore, the study could be used to assist in designing strategy to policymakers, transport authorities, road engineers, and other concerned bodies to prevent accidents and number of deaths due to it in the upcoming years.

1.5. Limitation of the study

This study mainly uses the information collected from Addis Ababa traffic police commission that is available from 15 years accident records which is from 2004 to 2018 G.C. Though, there was seven daily observation and twenty four recorded data in hourly basis per one year. Hence, there were no documented data in monthly basis. Due to poor handling and recording of road traffic accidents data, temporal aggregation was employed for analysis purpose.

1.6. Organization of the study

This thesis was organized into the following chapters. Chapter one was introduction of the thesis. This chapter briefly addresses the research objectives, statement of problem, significance of the study, limitation and background of the study. Chapter 2 reviews the literature with emphasis on road traffic accident and the statistical tools relevant on the application of SARIMA and SETAR models. Chapter 3 explains the methodology applied in building SARIMA and SETAR models and estimating their parameters. Chapter 4 presents the result and discussions. Chapter 5 was conclusions and recommendations.

2. Literature Review

2.1. Overall burden of road traffic accident

Road accident is one of the causes for the death of people and has been ranked as one of the top leading causes of death in the world. Over millions of people are killed each year. Every day, thousands of people are killed and injured on road by traffic accident. It is the leading cause of death, disabilities and hospitalization, sever socioeconomic costs, across the world. According to (WHO, 2018), it has been estimated that Road Traffic Accident takes the live of over 1.35 million each year. In addition, when considered in the context of the increasing global population and rapid motorization that has taken place over the same period, this suggests that existing road safety efforts may have mitigated the situation from getting worse. However, it also indicates that progress to realize Sustainable Development Goal (SDG) target 3.6 which calls for a 50% reduction in the number of road traffic deaths by 2020 remains far from sufficient.

Road traffic accident is the series issue in Africa and it is from most killer disease. The numbers of road traffic injuries and deaths have been increasing from time to time. African Region had the highest rate of fatalities from road traffic injuries worldwide at 26.6 per 100 000 population. The increased burden from road traffic injuries and deaths is partly due to economic development, which has led to an increased number of vehicles on the road. Given that air and rail transport are either expensive or unavailable in many African countries, the only widely available and affordable means of mobility in the region is road transport. However, the road infrastructure has not improved to the same level to accommodate the increased number of commuters and ensure their safety and as such many people are exposed daily to an unsafe road environment (Abegaz *et al.*, 2014).

Various studies have addressed the different aspects of road traffic with most focusing on predicting or establishing the critical factors influencing injury severity (Chong *et al.*, 2005). Numerous data mining-related studies have been undertaken to analyze RTA data locally and globally, with results frequently varying depending on the socio-economic conditions and infrastructure of a given location

Ossenbruggen, Pendharkar *et al*. (2001) used a logistic regression model to identify the prediction factors of crashes and crash-related injuries, using models to perform a risk assessment of a given region. These models included attributes describing a site by its land use activity, roadside design, use of traffic control devices, and traffic exposure. Their study illustrated that village sites were less hazardous than residential or shopping sites.

Tibebe (2005) analyzed historical RTA data, including 4,658 accident records at the Addis Ababa Traffic Office, to investigate the application of data mining technology to the analysis of accident severity in Addis Ababa, Ethiopia. Using the decision tree technique and applying data mining tool, the developed model classified accident severity into four classes: fatal injury, serious injury, slight injury, and property-damage. Accident cause, accident type, road condition, vehicle type, light condition, road surface type, and driver age were the basic determinant variables for injury severity level. The classification accuracy of this decision tree classifier was reported to be 87.47%.

2.2. Empirical literature on road traffic accident using SARIMA model

Yousefzadeh-Chabok *et.al*. (2016) studied a time series model for assessing the trend and forecasting the road traffic accident mortality Zanjan Province, Iran in the period 2007 to 2013.The logarithmic transformation was used to remove the non-stationary condition in variance. Then, seasonality variation was removed by seasonality differencing with lag 12. SARIMA model used to analyze the data and the model was identified through ACF and PACF plots. The study showed a decreasing trend over the past and the next four years in Iran.

Eke *et al*. (2000) studied the seasonal effect on road traffic accident using data collected form university of Port Harcourt Teaching Hospital (UPTH) from January 1986 to December 1995 found that most of the accident in Port Harcourt, Nigeria occurred during the rainy seasons (June, July and August).In addition, Manikandan *et.al*. (2018) forecasted road traffic accident deaths in India using SARIMA model from January 2001 to December 2012 (144 months). The trend of RTA deaths in India showed a seasonal pattern and to stabilize the mean and variance, first order of difference of historical time series data was considered. Subsequently, the tentative SARIMA model was selected as SARIMA (1,0,0) $(2,1,0)_{12}$ using the smallest value of AIC and BIC.

Nanga (2016) investigated time series analysis of road accidents in Ghana using SARIMA model. The Box Jenkins method was applied for a 20 year period from 1991-2010.A model was subsequently developed to fit the time series data. SARIMA (1,1,0) × (0,1,1)12 was found to be the best model for road accident cases with a maximum log likelihood value of 245.48, and least AIC value of 5.892 and RMSE value of 17.930 .The rate of road accidents is expected to increase at least for the next years 10 years.

Favour *et al*. (2016) investigated that statistical analysis of pattern on monthly reported road accidents in Nigeria. The data used for this paper was monthly data collected for a period of 2004 to 2014. Autoregressive Moving average model were fitted to the data and the best order was choosing using AIC. The order = c (1, 1, 2), seasonal =c (1, 1, 2)) gives the best description of the data with minimum (AIC). The time plot plotted showed that, the graphs maintain a constant movement from 2004 to 2008 but increases abnormally in 2010 and later drop again maintaining appreciable downward movement as the year progresses.

Balogun *et al*. (2014) analyzed a data set collected from Nigerian traffic accidents using time series approach. The data collected spanned the period between 1989 to 2008. The study reveals that, the best model was AR (1) for annual data. Moreover, Mutangi (2015) analyzed the data of traffic accidents in Zimbabwe using three ARIMA tentative models which were suggested based on the ACF and PACF plots of the differenced series. These were ARIMA(0,1,0), ARIMA(1,1,0) and ARIMA(1,1,1) and he decided that ARIMA (0,1,0) was the best model for the Zimbabwe annual traffic accidents data.

Foroutaghe *et al*. (2019) studied time trends in gender specific incidence rates of road traffic injuries in Iran. The seasonal auto-regressive integrated moving average method (SARIMA) was employed to predict road traffic incidence time series. The final model was selected from various SARIMA models based on the Akaike information criterion (AIC) and Bayesian information criterion (BIC). To examine whether the residuals were white noise, the Ljung-Box test and residuals plots were used with respective for no correlation and zero mean stationarity. The sample auto-correlation function (ACF) and the partial autocorrelation function (PACF) with 20 lags were employed to determine the order of models and to ascertain if the residuals of the model were uncorrelated

2.3. Empirical studies using SETAR model in several time series analysis

Non-linear time series modelling has attracted much attention in recent years. The threshold autoregressive (TAR) model proposed by Tong and Lim (1978) is one of the popular non-linear time series models that shows wide application in many areas. An important special case of TAR was Self-exciting Threshold Autoregressive (SETAR) model. Similar economics study by Sjoberg (2010), compared the forecast performance of ARIMA, and SETAR models using monthly Swedish industrial production from 28 branches over the period January1990 to December 2008.

Tong's (1978) threshold autoregressive (TAR) model has been a useful and popular tool in nonlinear time series modeling. The threshold approach is a natural approach as nonlinearity can be well approximated by a piecewise linear structure which can be created by a regime dependent linear model. The basic idea of threshold models is the introduction of regimes via thresholds. The principle allows the analysis of a complex stochastic system by decomposing it into simpler subsystems (Li, 2006).

Akeyede *et al*. (2015) compared different forecasting methods proposed in existing literature to obtain h-step ahead forecast. Multi step forecast performance of linear and nonlinear time series model was compared and the finding reveals that SETAR model was best in terms of its prediction ability. Likewise, Badawi *et al*. (2016) in an unpublished master's thesis, compared the forecast performance between SARIMA and SETAR models using data on pneumonia cases in the northern region of Ghana. The data was obtained from the Tamale Teaching Hospital over the period January, 2000 to October, 2015 based on the forecast values from the two models, the SETAR model was adjudged the best in terms of its MSE, RMSE and Diebold and Marino test also performed to check whether there is exist a difference in forecasting abilities of the two models.

Clements *et al*. (2001) evaluated forecasts from SETAR models of exchange rates and compared them with traditional random walk measures. Caner *et al*. (2001) used Chow test in testing unknown structural change timing. Boero *et al*. (2003) studied the out of sample forecast performance of SETAR models in Euro effective exchange rate. The SETAR models were specified with two and three regimes, and their performance was assessed against that of a simple linear AR model .

Aidoo (2010) forecast the performance of Ghana Inflation rates using SARIMA models and SETAR model. Based on the in-sample forecast assessment from the linear SARIMA and the nonlinear SETAR models, the forecast measure Mean Absolute Error (MAE) and Residuals Mean Square Error (RMSE) suggest that the nonlinear SETAR model outperform the linear SARIMA model. Also, using multi-step-ahead forecast method the researcher was predicted and compared the out-of-sample forecast of the linear SARIMA and the nonlinear SETAR models over the forecast horizon of 12 months. The results as suggested by MAE and RMSE, the forecast performance of the nonlinear SETAR models was superior to that of the linear SARIMA model in forecasting Ghana inflation rate.

Nafisah (2018) studied comparative analysis of forecast performance between SARIMA and SETAR models using macroeconomic variables in Ghana. Keenan and Tsay-F tests showed the datasets were threshold nonlinear with two regime SETAR model. Accordingly, the performance between the SARIMA and SETAR models were compared for inflation by employing forecast measures RMSE and MAE and the nonlinear SETAR model outperformed than linear SARIMA model for inflation rate of Ghana.

Analyzing structural changes in the Taiwan stock market, Hsu *et al*. (2010) found the SETAR model to better examine the out of sample forecast of the non-linear time series. Employing monthly data from January 2005 to December 2009, the best model was chosen by performing a unit root test and comparing the out of sample forecast between the standard linear ARIMA model and the nonlinear SETAR model. A graphical view of their results showed that the structural change in the time series occurred in the month of June 2008. Thereby they built a 2 regime SETAR model. In conclusion the nonlinear SETAR model was found to be superior in forecasting to the linear ARIMA model in the Taiwan stock market.

Desaling Germay (2016) dealt with modeling the unemployment rate in Sweden is using univariate time series SARIMA and SETAR models. The combined modeling process showed that unemployment rate was non stationary and nonlinear. The rate also has stationary seasonal nature. The predictive accuracy performance of model was measured based on RMSE, MAE as well as Diebold and Marino test. And, the study showed that SETAR model was better forecasting performance than SARIMA model.

3. Research Methodology

3.1. Study Area

Addis Ababa, the capital city of the Federal Democratic Republic of Ethiopia, is located in the center of the country .The city has a total of 54,000 hectares and 4,725,816 population. The city is the country‘s political and economic center, the seat of head offices of African union and united nations economic commission for Africa. It also accommodates many international aid and development organization and more than 100 embassies. Addis Ababa is exhibiting high social, economic, structural and change is found to be a fast growing city. More than 70% of registered vehicles in the country are found in Addis Ababa.

For administration purposes, Addis Ababa is divided into 10 sub cities, Akaki Kaliti, Nefas Silk, Kolfe Keraniyo, Gulele, Ledeta, Kerkos, Arada, Addis Ketema, Bole and Yeka. Over the past years, the city of Addis Ababa has witnessed with an amazing expansion in size. The rapid increase in urban population with an annual growth rate of 3.8 percent per year has not been provided with an equal growth in provisions of road infrastructures, urban transportation, and other infrastructures. The road length envisaged by the Addis Ababa 2003 was 800 km. As of April 2010, constructed road and pedestrian walkway was 620km and 423km respectively. Currently the road coverage of the built area is 11.3% and it is envisioned to have the road network coverage about 20% by the year 2020. Mobility has been improved; but the total number of road traffic accident has also gone up (Helen, 2018).

3.2. Sources of Data

Data for this study were obtained from the Addis Ababa traffic police commission. The site was chosen due to availability of relatively long series of road traffic accident data. Even though, the data were recorded in total hourly (24 hrs) per in each year .The hourly data of road traffic accident were aggregated to monthly for statistical analysis.

An aggregation process consists of deriving a low frequency representation of the process from a high frequency formulation; this derivation can be exerted through time. Aggregation across time, also called temporal aggregation, refers to the process by which a low frequency time series is derived from a high frequency time series (Nikolopoulos, 2011).

After the data aggregated from total hourly to January 2004 to December 2018, the model forecast performance was conducted by splitting a given data set into in-sample period which were used for initial parameter estimation and model selection; and out sample period which were used to evaluate forecast performance. Yet, there are no broadly accepted guidelines as to how to select the sample split (Peter, 2012).Instead, researchers adopt a variety of practical approaches (Hansen et al., 2012). In this study, the in sample period was runs from January 2004 to December 2016 (156 observation). And, this was used to model selection and estimation. Whereas, the out-of-sample period runs from January 2017 to December 2018 (24 observation) for evaluation of forecasting purpose.

3.3. Statistical Model

3.3.1. The concept of stationary

The concept of stationary of a stochastic process can be visualized as a form of statistical equilibrium. The statistical properties such as mean and variance of a stationary process do not depend upon time. Usually time series showing trend or seasonal patterns are non-stationary in nature. In such cases, differencing was used to remove the trend and to make the series stationary. A unit root test was used verify stationary of the data.

3.3.2. Unit Root Test

In statistics, a unit root test examines whether a time series is stationary or not, using an autoregressive model. The widely used unit-root tests were Augmented Dickey Fuller (ADF) and Phillips-Perron (PP) tests. The following discussion outlines the basic features of unit root tests.

3.3.2.1. The Augmented Dickey Fuller (ADF) Test

The augmented Dickey-Fuller (1979) test was used to determine if a time-series is stationary by checking for unit roots. This was important when applying an SARIMA model to determine if the data needs to be differentiated. Hence, the autoregressive order one is given as

$$y_t = \phi y_{t-1} + \varepsilon_t \quad \text{[1]}$$

Where ϕ is a parameter to be estimated, and ε_t is assumed to be white noise. If $|\phi| \geq 1$, y_t is a non-stationary series and the variance of y increases with time and approaches infinity. On the other hand, if $|\phi| \leq 1$ y_t is stationary series. Therefore, the hypothesis of stationary was evaluated by testing whether the value of ϕ is strictly less than one. The hypotheses are:

H_0: $\phi = 1$ (the series is not stationary) vs H_a: $\phi < 1$ (the series is stationary)

Dickey Fuller model can be expressed as:

$$\Delta y_t = \tau y_{t-1} + \varepsilon_t \quad \text{……………………………………………………………………………[2]}$$

Where $\tau = \phi - 1 \quad and \quad \Delta y_t = y_t - y_{t-1}$

The null and alternative hypothesis may be rewritten as: Ho: $\tau = 0$ vs Ha: $\tau < 0$

The test statistic is the conventional t-ratio for τ ; $t(\tau) = \dfrac{\hat{\tau}}{se(\hat{\tau})}$ ……………..…………………[3]

Where $\hat{\tau}$ is the OLS estimate of τ and $se(\hat{\tau})$ is the standard error of $\hat{\tau}$.

3.3.2.2. The Phillips-Perron (PP) Test

Phillips and Perron (1988) developed a number of unit-root test and received much attention in analysis of most time series data. This unit root test is quite different from the Augmented Dickey Fuller (ADF) test in terms of their approach in dealing with errors arising from serial correlation and heteroscedasticity. Also, this test unlike the ADF test, makes use of non-parametric procedures in their test regression. The test regression for the PP tests can be written as follows;

$$\Delta y_t = \beta D_t + \tau y_{t-1} + \varepsilon_t \text{.. [4]}$$

Where, Δ is a difference operator, β is a constant, D_t is a time trend, τ is the dickey fuller test statistic and ε_t is an error term. The hypothesis is:

H_0: $\tau = 0$ (non-stationary) vs H1: Not H_0

On the other hand, the Phillips- Perron test was built on the same principles as the Augmented Dickey Fuller test. But, it ignores any serial correlation in the regression used for the test and adds a correction to the t- test statistic and produces the following test statistic:

$$C = \left(\frac{\hat{\sigma}^2}{\hat{\lambda}^2}\right)^{\frac{1}{2}} t(\tau = 0) - \frac{1}{2}\left(\frac{\hat{\lambda}^2 - \hat{\sigma}^2}{\hat{\lambda}^2}\right)\left(\frac{T.SE(\hat{\theta})}{\hat{\sigma}^2}\right) \ldots\ldots [5]$$

Where, $T = \frac{\hat{\pi}}{se(\hat{\pi})}$, $t(\tau = 0) = \frac{\hat{\tau}}{se(\hat{\tau})}$, $\hat{\sigma}^2$ and $\hat{\lambda}^2$ are the consistent estimates of the variance parameters.

$$\sigma^2 = \lim_{T \to \infty} T^{-1} \sum_{i=1}^{T} E(\varepsilon_t)$$

$$\lambda^2 = \lim_{T \to \infty} T^{-1} \sum_{i=1}^{T} E\left[T^{-1}\left(\sum_{i=1}^{T} \varepsilon_t\right)^2\right]$$

3.3.3. Moving Average (MA) process

Moving average models accounts for the possibilities of a relationship between a variable and a residuals from a previous period. The jth order MA process can be expressed as;

$$y_t = \varepsilon_t + \mu + \theta_1\varepsilon_{t-1} + \theta_2\varepsilon_{t-2} + \ldots + \theta_q\varepsilon_{t-q} = \mu + \sum_{j=1}^{q} \theta_i\, \varepsilon_{t-j} + \varepsilon_t \ldots\ldots [6]$$

Where, ε_t and ε_{t-j} are the current disturbance terms and previous white noise disturbance term respectively , θ_i is the MA parameters which describes the effect of the past error on y_t .So that y_t depends on the current and previous values of a white noise disturbance term.

3.3.4. Autoregressive (AR) Process

Autoregressive models are models in which the value of the variable in one period is related to its value in previous period. A time series y_t is an autoregressive process with order p if each observation of AR (p) process can be denoted as the following equation:

$$y_t = \mu + \phi_1 y_{t-1} + \phi_2 y_{t-2} + ... + \phi_p y_{t-p} + \varepsilon_t = \mu + \sum_{i=1}^{p} \phi_i y_{t-i} + \varepsilon_t \text{ ....[7]}$$

Where, μ is constant, ε_t is a white noise term and ϕ_i is the coefficients of lagged variable in time t-p. y_{t-i} is the value and $t-i$ periods ago. The only special thing is the regressor is the dependent variable's own lagged terms.

3.3.5. Autoregressive Moving Average process (ARMA)

Autoregressive of order p and Moving Average of order q were combined to obtain a very flexible class of ARMA processes. Its specific subset of univariate modeling in which a time series was expressed in terms of past values of itself plus current and lagged values of a white noise error term. ARMA (p, q) was given by:

$$y_t = \mu + \varepsilon_t + \{\phi_1 y_{t-1} + \phi_2 y_{t-2} + ... + \phi_p y_{t-p}\} + \{\theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + ... + \theta_q \varepsilon_{t-q}\}$$

$$= \mu + \varepsilon_t + \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} \text{ ....[8]}$$

Where y_t was the value of traffic accident at time t,μ is constant mean , $\phi_1, \phi_2, ..., \phi_p$ are autoregressive parameters, $\varepsilon_t, \varepsilon_{t-1}, \ldots, \varepsilon_{t-p}$ are white noise error with mean zero and variance $\sigma^2{}_t$ and $\theta_1, \theta_2, \ldots, \theta_q$ are moving average parameters.

3.3.6. The Seasonal ARIMA Model

The seasonal autoregressive integrated moving average (SARIMA) model, of Box and Jenkins (1976) was given by

$$\varphi(B^s)\,\phi(B)\,\nabla_s{}^D\,\nabla^d x_t = \theta(B^s)\Theta(B)\,w_t \text{ ....[9]}$$

The general model was denoted as SARIMA (p, d, q) × (P, D, Q)S. The non-seasonal autoregressive and moving average component are represented by polynomials $\phi(B)$ and $\theta(B)$ of the order p and q ,respectively and the seasonal autoregressive and moving average component by

$\varphi(B^s)$ and $\theta(B^s)$ of orders P and Q and non-seasonal and seasonal difference components by $\nabla^d = (1-B)^d$ and $\nabla_s{}^D = (1-B^s)^D$

Where,

- p, d and q are the order of non-seasonal AR, differencing and MA respectively.
- P, D and Q is the order of seasonal AR, differencing and MA respectively.
- x_t Represents time series data at period t.
- w_t Represents Gaussian white noise process (random shock) at period t.
- B, represents backward shift operator ($B^k x_t = x_{t-k}$)
- $\nabla_s{}^D$, represents seasonal difference
- ∇^d, represents non-seasonal difference
- S, represent seasonal order (s= 12 for monthly data).

3.3.7. Building Seasonal ARIMA Models

There were a few basic steps to fitting Seasonal ARIMA models to time series data. These steps involve plotting the data, possibly transform the data, identifying the appropriate model, parameter estimation, model diagnosis and forecasting. The original Box-Jenkins modeling procedure involves an iterative three-stage process of model selection, parameter estimation and diagnostic checking. But, further explanations of the process by Makridakis et al. (1998) often add a preliminary stage of data preparation and a final stage of forecasting and evaluation of the forecast performance measure.

3.3.7.1. Model Identification

The purpose of the identification stage is to determine the differencing required to achieve stationarity and also the order of both the seasonal and the non- seasonal autoregressive and moving average operators.

3.3.7.1.1. Autocorrelation Functions

Autocorrelation function is a very useful in order to identify a time series model. It measures the linear dependence or the correlation between y_t and y_{t-k} .

$$\rho_k = \frac{Cov(y_t, y_{t-k})}{\sqrt{\operatorname{var}(y_t)\operatorname{var}(y_{t-k})}} = \frac{Cov(y_t, y_{t-k})}{\operatorname{var}(y_t)} \quad \text{[10]}$$

The order of moving average was determined by the number of significant auto correlation.

3.3.7.1.2. Partial Autocorrelation Function

The correlation between y_t and y_{t-k} after removing the effect of the intervening variables y_{t-1}, $y_{t-2}, y_{t-3}, \ldots, y_{t-k-1}$ denoted by ϕ_{kk}

$$\phi_{kk} = corr(y_t, y_{t-k} \mid y_{t-1}, y_{t-2}, \ldots, y_{t-k+1})$$

$$\phi_{kk} = \frac{\rho_k - \sum_{j=1}^{k-1} \phi_{k-1,j}\,\rho_{k-j}}{1 - \sum_{j=1}^{k-1} \phi_{k-1,j}\,\rho_j} \quad \text{[11]}$$

$$where, \phi_{jk} = \phi_{k-1,} j - \phi_{kk}\ \phi_{k-1,k-1,} k = 2,3,\ldots, j = 1,2,\ldots k-1, \phi_{00} = 1, \phi_{11} = \rho_1.$$

When the stationarity condition of the data was satisfied, the order of the model which AR, MA, seasonal AR and MA terms were determined with the help of the ACF and the PACF plot of the stationary series. The ACF gives information about the internal correlation between observations in a time series at different distances apart, usually expressed as a function of the time lag between observations. These ACF and PACF plots suggest the model should be built and the researcher was look at both seasonal and non-seasonal lags. Usually the ACF and the PACF has spikes at lag k and cuts off after lag k at the non-seasonal level. Also, the ACF and the PACF has spikes at lag ks and cuts off after lag ks at the seasonal(s) level. The number of significant spikes suggests the order of the model. Table 3.1 and 3.2 below describes the behavior of the ACF and PACF for both seasonal and the non-seasonal series (Shumway and Stoffer, 2006).

Table 3.1: Behavior of ACF and PACF for Non-seasonal ARMA (p, q)

	AR(p)	**MA(q)**	**ARMA(p, q)**
ACF	Tails off at lag k, k=1, 2, 3…	Cuts off after lag q	Tails off
PACF	Cuts off after lag p	Tails off at lags k, k=1, 2, 3…	Tails off

Table 3.2: Behavior of ACF and PACF for pure Seasonal ARMA (P, Q)S

	AR(P)s	**MA(Q)s**	**ARMA(P,Q)s**
ACF	Tails off at lag ks k=1, 2,3,…..	Cuts off after lag Qs	Tails off at lag ks
PACF	Cuts off after lag Ps	Tails off at lags ks, k=1, 2,3,……	Tails off at lag ks

3.3.7.2. Model Selection with the HK-algorithm

Hyndman and Khandakar (2008) developed the Hyndman-Khandakar (HK) algorithm and can be applied in R with the function auto.arima in the forecast package. They suggest an iterative time-saving procedure where the model with the smallest value of AIC and BIC.To derive these information criterions, the first thing that is needed was the likelihood function $L(\tilde{\varphi})$, where $\tilde{\varphi}$ is the maximum likelihood estimates of the parameters for the SARIMA with k=p+q+P+Q+1 parameters and sample size n. The criterions are then derived by the following equations.

$$AIC = 2k + n\log\left(\frac{RSS}{n}\right) \quad \ldots\ldots[12]$$

$$BIC = \log(\sigma^2{}_e) + \frac{k}{n}\log(n) \quad \ldots\ldots[13]$$

Where:

- k is the number of parameters in the statistical model, (p+q+P+Q+1).
- RSS is the residual sum of squares of the estimated model.

- n is the number of observation, or equivalently, the sample size.
- σ^2_e is the error variance.

The HK-algorithm then performs an iterative procedure to select the model that minimizes the value of each criterion.

3.3.7.3. Parameter Estimation

Parameter estimation of SARIMA model was achieved using maximum likelihood estimation. At this stage precise estimates of the coefficients of the chosen model was estimated. If the tentative model has significant parameters, whose values lie within the bounds of stationary and inevitability and was not highly correlated, then the researcher was proceed to the last stage, diagnostic checking. If not, the researcher was return to the identification stage and formulate an alternate model based on the information gained at the estimation stage.

3.3.7.4. Model Diagnostics

Once a model has been identified and the parameters estimated, diagnostic checks was applied to the fitted model. In model diagnostics the researcher was examine standardized residuals, ACF of residuals and the formal test of serial correlation. If the model fits well, the standardized residuals should behave as an identically and independently distributed with zero mean and unit variance. Also, the ACF plot of the residuals must show no significant autocorrelations at any lag order. One might expect approximately 1 lag in every 20 lags to be statistically significant by chance alone for a 95% confidence limit test.

3.3.7.4.1. Ljung-Box Test

Ljung and Box (1978), described this test as a diagnostic tool used to check for the presence or absence of serial correlations in the residuals of a fitted model. Thus, a time series with any specified lag orders, say order m examines autocorrelations in the residuals. Instead of testing randomness at each distinct lag, usually it tests the overall randomness based on a number of specified lags. The test procedure is given as follows; the hypothesis was given as follows;

H_0: There is no autocorrelation

H_1: not H_0

The test statistic is;

$$Q_m = n(n+2)\sum_{k=1}^{m}\frac{\rho_k^{\ 2}}{n-k} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots[14]$$

Where, $\rho_k^{\ 2} = \dfrac{\sum_{t=k+1}^{n}(y_t-\bar{y})(y_{t-k}-\bar{y})}{\sum_{t=1}^{n}(y_t-\bar{y})^2}$, $k = 1,2,\ldots m.$ m is the number lags being tested, n is the number of residuals.

3.3.7.5. Forecasting From Seasonal ARIMA Models

The last step in Box-Jenkins model building approach was forecasting. After a model was passed the entire diagnostic test, it becomes adequate for forecasting. For given Seasonal ARIMA model we can forecast the next step which is given by (Cryer, 2008)

$$y_t - y_{t-1} = \phi(y_{t-12} - y_{t-13}) + \varepsilon_t - \theta\varepsilon_{t-1} - \Theta\varepsilon_{t-12} + \theta\Theta\varepsilon_{t-13}$$

$$y_t = y_{t-1} + \phi y_{t-12} - \phi y_{t-13} + \varepsilon_t - \theta\varepsilon_{t-1} - \Theta\varepsilon_{t-12} + \theta\Theta\varepsilon_{t-13} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots[15]$$

The one step ahead forecast from the origin t is given by

$$\hat{y}_{t+1} = y_t + \phi y_{t-11} - \phi y_{t-12} - \theta\varepsilon_t - \Theta\varepsilon_{t-11} + \theta\Theta\varepsilon_{t-12} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots[16]$$

The next step is

$$\hat{y}_{t+2} = \hat{y}_{t=1} + \phi y_{t-10} - \phi y_{t-11} - \Theta\varepsilon_{t-10} + \theta\Theta\varepsilon_{t-11} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots[17]$$

And so forth. The noise terms $\varepsilon_{13,}\ \varepsilon_{12}, \varepsilon_{11}, \varepsilon_{10}, \ldots, \varepsilon_1$ (as residuals) was enter into the forecasts for lead times l=1,2,….,13,but for l>13 the autoregressive part of the model takes over and we have

$$\hat{y}_{t+l} = \hat{y}_{t=l-1} + \phi y_{t+l-12} - \phi y_{t+l-13} \quad for\ l > 13 \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots[18]$$

3.3.8. SETAR model

Self-Excited Threshold Autoregressive (SETAR) model is a class of the Threshold Autoregressive (TAR) model proposed by Tong (1978) and further studied in Tong and Lim(1980). The SETAR model is a set of different linear AR models, changing according to the value of the threshold variable which is the lagged values of the series. The process was linear in each regime, but the movement from one regime to the other makes the entire process nonlinear. The two regime SETAR model order (2; $P_{(1)}$, $P_{(2)}$) was given as:

$$y_t = \begin{cases} \phi_0^{(1)} + \sum_{i=1}^{P(1)} \phi_i^{(1)} y_{t-i} + \varepsilon_t^{(1)} & \text{if } y_{t-d} \le \tau \\ \phi_0^{(2)} + \sum_{i=1}^{P(2)} \phi_i^{(2)} y_{t-i} + \varepsilon_t^{(2)} & \text{if } y_{t-d} > \tau \end{cases} \quad \text{..[19]}$$

Where $\phi_i^{(1)}$ and $\phi_i^{(2)}$ are the coefficient in lower and higher regime respectively which needs to be estimated; τ is the threshold value; $P_{(1)}$, and $P_{(2)}$ are the order of the linear AR model in low and high regime respectively. y_{t-d} is the threshold variable that governs the transition between the two regimes, d is the delayed parameter which is a positive integer (d≤ p); $\varepsilon_t^{(1)}$ and $\varepsilon_t^{(2)}$ are a sequence of independently and identically distributed random variables with zero mean and constant variance.

3.3.8.1. Test of non-linearity

This was done using graphical method, Keenan test, Tsay test and likelihood ratio test for threshold nonlinearity.

3.3.8.1.1. Graphical method

This method basically gives a clue. If the regression lines were all straight in lagged scatter plots and the density of the plots decrease from the center suggests that the underlying process could be linear. If on the other hand, there were curved regression lines and there exists a hole in the center, then it was suggested that the data could fitted with nonlinear time series model (Cryer and Chan, 2008).

3.3.8.1.2. Keenan's One-Degree Test for Nonlinearity

For an observable time series yt, the SETAR model was only be applied if the series under consideration is found to be nonlinear or irregular in nature under the hypothesis:

H0: linearity exists

H1: nonlinearity exists

Beyond testing for nonlinearity, Keenan test suggests the working order (p) of the AR process. This was determined by minimizing the AIC through the AR function. However, where the working order (p) of the AR was known, it can be added in the Keenan test function through the order argument. The partial autocorrelation graph can also suggest the working order (p) of the AR process.

According to Cryer and Chan (2008), Keenan's test was motivated by approximating a nonlinear stationary time series by a second-order Volterra expansion. This can be represented in equation

$$y_t = \mu + \sum_{u=-\infty}^{\infty} \theta_u \, \varepsilon_{t-u} + \sum_{v=-\infty}^{\infty} \sum_{u=-\infty}^{\infty} \theta_{uv} \, \varepsilon_{t-u} \, \varepsilon_{t-v} \quad \text{[20]}$$

Where, μ is the mean level of nonlinear observation yt , with the error terms ε_{t-u} and ε_{t-v} . ε_t is a sequence of independent and identically distributed with zero-mean random variable. The process yt is linear if the double sum of the right-hand side of (25) does not exist (i.e. $\sum_{v=-\infty}^{\infty} \sum_{u=-\infty}^{\infty} \theta_{uv}\varepsilon_{t-u}\,\varepsilon_{t-v} = 0$) Thus, the researcher was test linearity of the time series by testing whether or not the double sum of (25) was zero. The Keenan's test is equivalent to testing if η=0 in the multiple regression model

$$y_t = \theta_0 + \phi_1 y_{t-1} + \ldots + \phi_m y_{t-m} + \eta \, \hat{y}_t^{\,2} + \varepsilon_t \quad \text{[21]}$$

The Keenan's test statistic for the null hypothesis of linearity (H0: η =0) was given as;

$$\hat{F} = \frac{\eta^2 (n - 2m - 2)}{RSS - \eta^2} \quad \text{[22]}$$

Where, m is lag order of the linear autoregressive process, n is same size considered, RSS: the residual sum of squares from the AR(m) process. The null hypothesis of linearity was rejected if the p-value associated with $\hat{F}$ was small (p– value< α).

3.3.8.1.3. Tsay's F -test

Tsay (1989) introduced the Tsay test for detecting nonlinearity in an observable time series after improving on the power of the Keenan (1985) test in 1986. Tsay's (Tsay, 1986) linearity test was based on recursive auto regression and destructive term estimators .firstly, the recursive auto regressions were established starting from b observation value in return for the p and the relevant d values with AR level, h is max(1, p+1-d), $\hat{e}_t$ is the estimated residual and then the model was established between the $\hat{e}_t$ values and $(1, y_{t-1}, y_{t-2}, \ldots, y_{t-p})$ .Then, the following test was obtained among the inclusions of the model formed with $\hat{e}_t$

$$\hat{F}(p,d) = \frac{\left(\sum \hat{e}_t - \sum \hat{e}_t^{\,2}\right) / (p+1)}{\sum \hat{e}_t^{\,2} / (n-d-b-p-h)} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [23]$$

In the F test of Tsay, the hypothesis was tested as;

H_0: linear AR(p) model vs H_1: non-linear threshold model

3.3.8.1.4. Threshold Nonlinearity (Likelihood Ratio) Test

This helps to handle the weakness of Keenan test in detecting threshold nonlinearity (Chan, 1991; and Tong, 1990). Therefore, it becomes important to consider a likelihood ratio test with the threshold model as the specific alternative. The hypothesis of threshold nonlinearity test was given as follows;

H_0: Model is an autoregressive process AR (p) vs

H_1: Model is two-regime TAR model of order p and with constant noise variance

The likelihood ratio test statistic was given by:

$$T_n = (n-p)\log\left\{\frac{\hat{\sigma}^2(H_0)}{\hat{\sigma}^2(H_1)}\right\} \qquad [24]$$

Where n-p is the effective sample size, $\hat{\sigma}^2(H_0)$ is the maximum likelihood estimator of the noise variance from the linear AR (p) fit and $\hat{\sigma}^2(H_1)$ from the TAR fit with threshold searched over some finite interval.

3.3.8.2. Choosing the Threshold Variable and Delay Parameter

Tsay (1989) describe a method of selecting the threshold variable. In context of SETAR model for a given time series y the threshold variable was taken as its own lag value yt−d for some positive integer d called delay parameter providing that d ε{1, 2,. . . , d∗}, where d∗ was the upper bound. The estimated optimal value of d was chosen in such a way that it provides the maximum F-values. Tsay suggests to select an estimate of the delay parameter, such that

$$d = \arg\max_{d \le p} \hat{F}(p, d_p) \qquad [25]$$

Where, $\hat{F}(p, d_p)$ was given in equation (28) the F-statistic value, the estimate of d depends on p. The delay value that gives the highest test of F value for the relevant p-value was selected from the threshold variables and it was suspected to be the delayed parameter for the SETAR model.

3.3.8.3. Model Selection

The SETAR model has two different AR processes in the two regimes defined by the threshold variable y_{t-d} and threshold value (τ). One important issue in fitting the SETAR model was to select the best subset model. In other words, we need an efficient way to identify values of d and subsets of $\phi_i^{(k)}$,k=1,2 and k=0,…, $P_{(i)}$ that were important , given the maximum AR orders of $P_{(1)}$ and $P_{(2)}$ for the two regimes. Mike et al. (2003) reveals that identification problem can be highly complicated because it involves a very large number of possible models and there were $d_0 \times 2^{P_1+P_2+2}$ models to consider, where d_0 the maximum possible delay parameter. The grid search method was used to find the potential threshold in the series by minimizing the residual sum of square of as follows:

$$\hat{\theta} = \arg \min_{\theta} \; Rss(\theta) \qquad \text{[26]}$$

Where θ is threshold parameter. The model which have the smallest residual sum of squares was the most consistent estimate of the delay parameter. Therefore, a threshold value corresponding to the smallest sum square of residuals was efficient. The orders of SETAR models were commonly identified by considering the Akaike information criterion (AIC). For each possible delay parameter, Tong and Lim (1980) use the AIC to estimate threshold value and find suitable autoregressive orders in both regimes of the threshold model.

$$AIC(p_1, p_2) = n_1 \ln(\hat{\sigma}_1{}^2) + n_2 \ln(\hat{\sigma}_2{}^2) + 2(p_1 + 1) + 2(p_2 + 1) \qquad \text{[27]}$$

Where, n_j , $j = 1,2$ is the number of observations in the j[th] regimes and

$\hat{\sigma}^2{}_j$, $j = 1,2$ is the variance of the residuals in the j[th] regimes p_1 and p_2 are the selected lags order in regime 1 and 2 respectively for which the information criterion is minimized.

3.3.8.4. Parametric Estimation

After the desired model was selected, the next step is to estimate the parameters of the selected model. The parameters were estimated using a sequential conditional least square method. According to Franses and van Dijk (2000), by using this method the resulting estimates were equivalent to maximum likelihood estimates under the additional assumption that the residuals are normally distributed.

3.3.8.5. Model Diagnostics

After carefully selecting tentative models to be used for forecasting, the residuals of the models were checked. This step is paramount to making any meaningful inferences with the models. So, plot of residual versus time, test of normality and Ljung-Box test of serial correlation were employed in this study.

3.3.8.5.1. Time Plot of the Residuals

Time plot of the standardized residuals should not show any structure. It must indicate no trend in the residuals and no changing variance across time.

3.3.8.5.2. Normality of the residuals

To investigate whether or not the residuals of the fitted model were normally distributed, the Jarque-Bera test and Q-Q plot were applied. Q-Q plot was a normal probability plot of a plot based on estimated quantiles. The normal Q-Q plots provide a quick way to visually inspect to what extent the pattern of data follows a normal distribution.

3.3.8.5.4. Test for Serial Correlation

Ljung and Box (1978), described this test as a diagnostic tool used to check for the presence or absence of serial correlations in the residuals of a fitted model. The test procedure was given as follows; The hypothesis to be tested is;

H_0 : Residuals are uncorrelated up to order k

H_1: Residuals are correlated up to order k

The test statistic is

$$Q_k = n(n+2)\sum_{d=1}^{k}\frac{\hat{\rho}_d^{\,2}}{n-d} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots[28]$$

Where, $\hat{\rho}_d^{\,2}$ represents residual autocorrelations of the series at lag k, k is the number lags being tested, n is the number of residuals. The model was considered adequate when the p-value associated with Qk is large; otherwise the whole estimation process has to be repeated again in order to get the most adequate model.

3.3.8.6. Forecasting From SETAR Model

The important aim of considering nonlinear type of model such as SETAR as compare to the linear counterpart was to adequately describe the dynamic behavior of the observable series under consideration and also to produce adequate forecast values .The optimal one step-ahead forecast from the origin is given by:

$$\hat{y}_{t+1|t} = E\left[y_{t+1}|\Omega_t\right] = E\left[F(x_{t+1};\phi)|\,\Omega_t\right] \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots[29]$$

Where $\hat{y}_{t+1}$ is the forecast value for the time (t+1), and Ω_t is the history of the time series up to and including the observation at time t. $F(x_t;\phi)$ is the nonlinear function that represent the SETAR model. The next optimal step-ahead forecast is given by:

$$\hat{y}_{t+2|t} = E\left[y_{t+2}|\Omega_t\right] = E\left[F(x_{t+2};\phi)|\,\Omega_t\right] \quad [30]$$

In general, the linear conditional expectation operator E cannot be interchanged with the nonlinear operator F, that is

$$E[F(.)] \neq F(E[.]) \quad [31]$$

Put differently, the expected value of a nonlinear function is not equal to the function evaluated at the expected value of its argument. Hence,

$$E\left[F\left(y_{t+1};\phi\right)|\,\Omega_t\right] \neq F\left(E\left[y_{t+1}|\,\Omega_t\right];\phi\right) = F\left(\hat{y}_{t+h|t};\phi\right) \quad [32]$$

The optimal h-step-ahead forecast can be obtained as

$$\hat{y}_{t+h|t} = E\left[y_{t+h}|\Omega_t\right] = F(x_{t+h-1};\phi) \quad [33]$$

3.3.8.7. Comparison of forecasting performance between SARIMA and SETAR model

A good model for forecasting can be described as a model that produces minimum forecast errors as compare to other competing models. And to choose a final model for forecasting the accuracy of the model should be higher than that of other competing model. The accuracy for each model was checked to determine how the model performed in terms of both in-sample and out-of-sample forecast. In this study, the accuracy of the models was compared using Mean Error (ME), Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) .A model with a minimum of ME, MAE and RMSE was considered to be the better for forecasting. In mathematical notation it was defined as follows;

$$ME = \frac{1}{T}\sum_{t=1}^{T}\varepsilon_t \quad [34]$$

$$MAE = \frac{\sum_{t=1}^{T} |\hat{y}_t - y_t|}{T} = \frac{\sum_{t=1}^{n} |\varepsilon_t|}{T} \quad \text{[35]}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{T} (\hat{y}_t - y_t)^2}{T}} = \sqrt{\frac{\sum_{t=1}^{n} \varepsilon_t^{\ 2}}{T}} \quad \text{[36]}$$

Where y_t is the actual observation, $\hat{y}_t$ is the forecasted value and T is the sample size.

3.3.8.7.1. Diebold-Mariano (DM) test

A test suggested by Diebold and Mariano (1995) was also used to compare the forecasting performance of models. The test checks for the existence of significant differences between the forecasting accuracy of two models. The DM test has the null hypothesis of no difference between the forecast accuracy of the two models.

In competing forecasts $y_{(i)+\frac{h}{t}}$ from two models $i = 1,2$, the corresponding forecast errors was computed as $\varepsilon_{(i)+\frac{h}{t}} = y_{t+h} - y_{(i)\ t+\frac{h}{t}}$ the h - steps forecasts were computed for $t = t_1, \ldots, T$ producing a series of forecast errors $\left\{\ \varepsilon_{(i)+\frac{h}{t}}\right\}_{t1}^{T}$ which was also be serially correlated because of the overlapping data used to compute the forecasts.

The accuracy of each forecast is measured using a loss function $L(y_{t+h}\,, y_{(i)t+\frac{h}{t}}) = L(\varepsilon_{(i)t++\frac{h}{t}})$ which was in most cases taken as the squared errors or absolute errors. The Diebold -Mariano test with the null hypothesis of equal forecast accuracy between the models has the following loss function and test statistic:

Loss function: $d_t = L\left(\varepsilon_{(1)t+\frac{h}{t}}\right) - L\left(\varepsilon_{(2)t+\frac{h}{t}}\right)$ ………………………………………………... [37]

Null hypothesis: $E\left[L\left(\varepsilon_{(1)t+\frac{h}{t}}\right)\right] = E\left[L\left(\varepsilon_{(2)t+\frac{h}{t}}\right)\right]$ ……………………………………………… [38]

Alternative hypothesis: $E\left[L\left(\varepsilon_{(1)t+\frac{h}{t}}\right)\right] \neq E\left[L\left(\varepsilon_{(2)t+\frac{h}{t}}\right)\right]$…………………………………….… [39]

The Diebold-Mariano test statistic: $S = \frac{\bar{d}}{(LRV_{\bar{d}} / T)^{1/2}}$ ………………..……………………...…..… [40]

Where $\bar{d} = \frac{\sum_{i=0}^{T} d_i}{T}$ and $LRV_{\bar{d}} = \text{cov}(d_t, d_{t-j})$

4. Result and discussion

4.1. Data summary

The data employed in this study comprise of 180 total monthly aggregated observations of road traffic accidents of Addis Ababa spanning from January 2004 to December 2018.The data was divided into two parts, one was for model estimation and another was for evaluation of forecasting road traffic accident .The first part which is called in sample data set with 156 observations varying from the total accident of January 2004 to December 2016 was used to estimate the models. Meanwhile, the second part which is called out-sample data set with 24 observations varies from January 2017 to December 2018 for evaluation of forecasting purpose. The below Table 4.1 was the summary of data description.

Table 4.1: summary of road traffic accident data

Skewness	Kurtosis	Jarque-Bera (p-value)
0.768	-0.1254	0.0004

The above Table 4.1 shows that, the skweness is 0.0768 which implies that the distribution has a long right tail than normal distribution (positively skewed). Hence, the kurtosis is -0.125 which is smaller than normal distribution of kurtosis of 3 and it reveals that the data was platykurtic in nature. The Jarque-Bera test of normality was used to confirm the asymmetric nature of the road traffic accident. At 5% significance level, the test confirmed that the data was not normally distributed as its p-value (0.0004).

4.2. Features and Stationarity of Accident Series

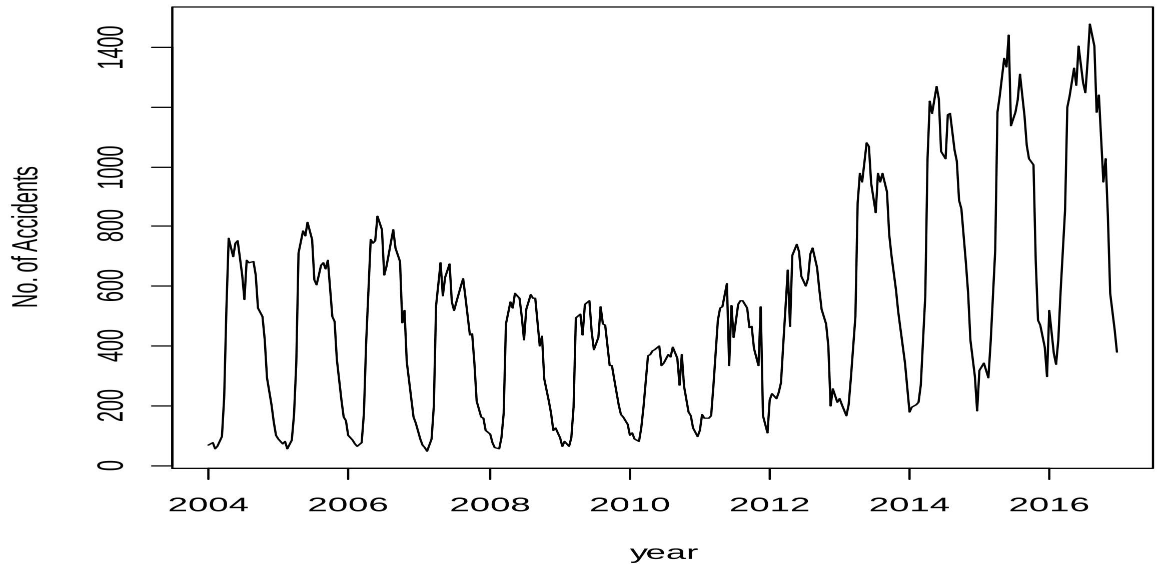


Figure 4.1: Plot of road traffic accident data

The above Figure 4.1, reveals both increasing and decreasing pattern in road traffic accident overtime. The plot shows the existence of seasonal fluctuations. This series varies randomly over time and there was a general trend and seasonal fluctuations. From Figure 4.1, it is evident that unconditional mean and variance were changing over time. The seasonal fluctuations were roughly constant in size over time and do not seem to depend on the level of the time series. Since the random fluctuations in the data were roughly constant in size over time, time series was described using an additive model.

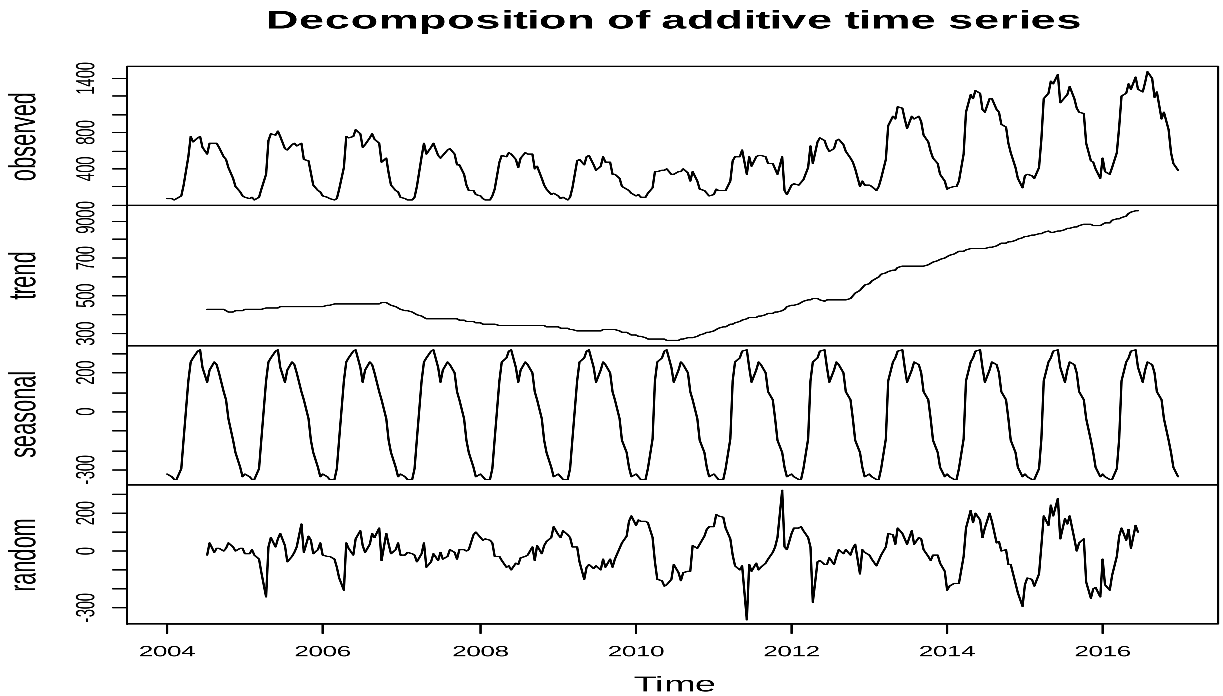


Figure 4.2: Decomposition of time series data into trend, seasonal and random.

The above Figure 4.2 shows, the original time series (top), the estimated trend component (second from top), the estimated seasonal component (third from top), and the estimated random component (bottom). Here, it was clearly observed that the estimated trend component shows a constant movement from 2004 to 2006 and steady decrease from 2007 to 2010 then showing indications of a rising trend in from 2010 to 2016 G.C. It appears that road traffic accidents in the Addis Ababa were highly seasonal. There was a gradual increase at the start of every year and minor drop early and midway followed by a sharp drop at the end of each year. Moreover, the seasonal subseries plot of monthly road traffic accident was shown on the Figure 4.3 below.

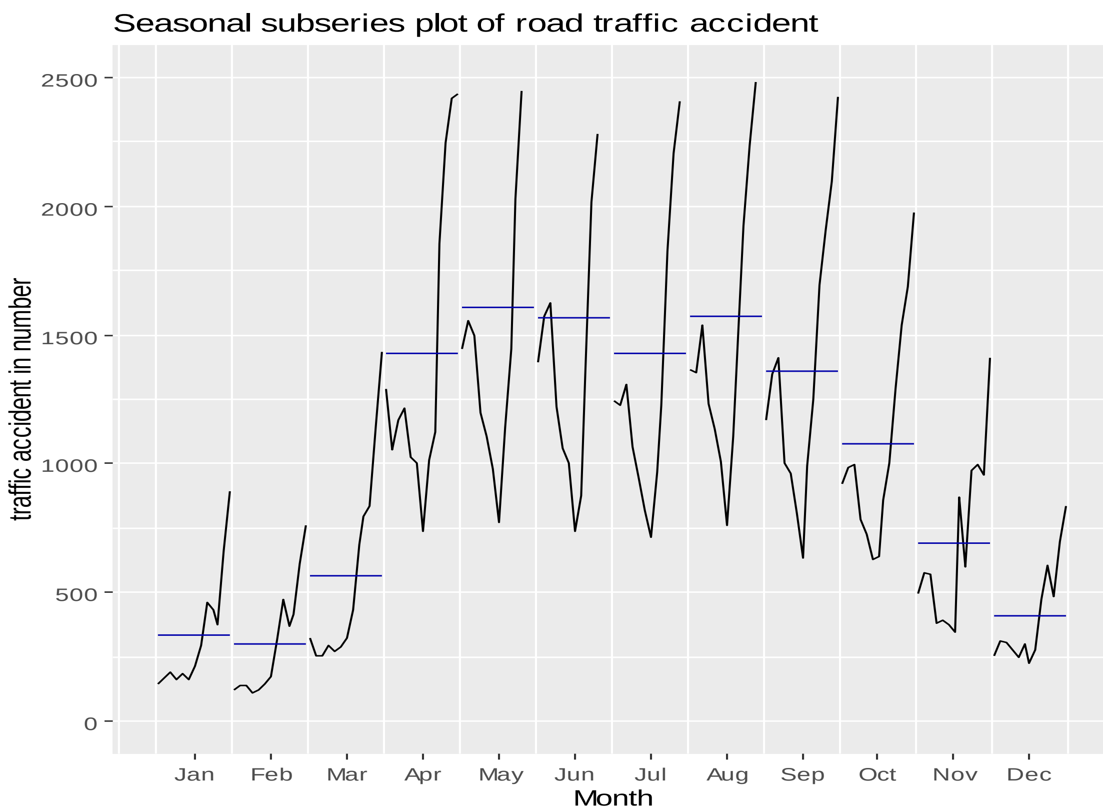


Figure 4.3: Seasonal subseries plot of road traffic accident in Addis Ababa.

In the above Figure 4.3, the horizontal lines indicate the mean of traffic accident for each months during the year. This form of plot enables the underlying seasonal pattern to be seen clearly, and also shows the changes in seasonality over time .It was shown that during a period, the highest values were observed in the month of May, June, July and August and lower in other months. Hence, from the above seasonal subseries plot, most of road traffic accident occurs during the months of June, July and August, the rainy season in Ethiopia. So, there was a seasonal effect on the number of accident, which in the raining seasons the trend increased as compared to other months.

4.3. ACF and PACF plot of road traffic accident data

To identify the stationarity feature of the series, analysis of ACF and PACF plots were a useful and very informative method. It is known that for a stationary time series, the ACF drops to zero relatively quickly, while the ACF of non-stationary time series decreases slowly.

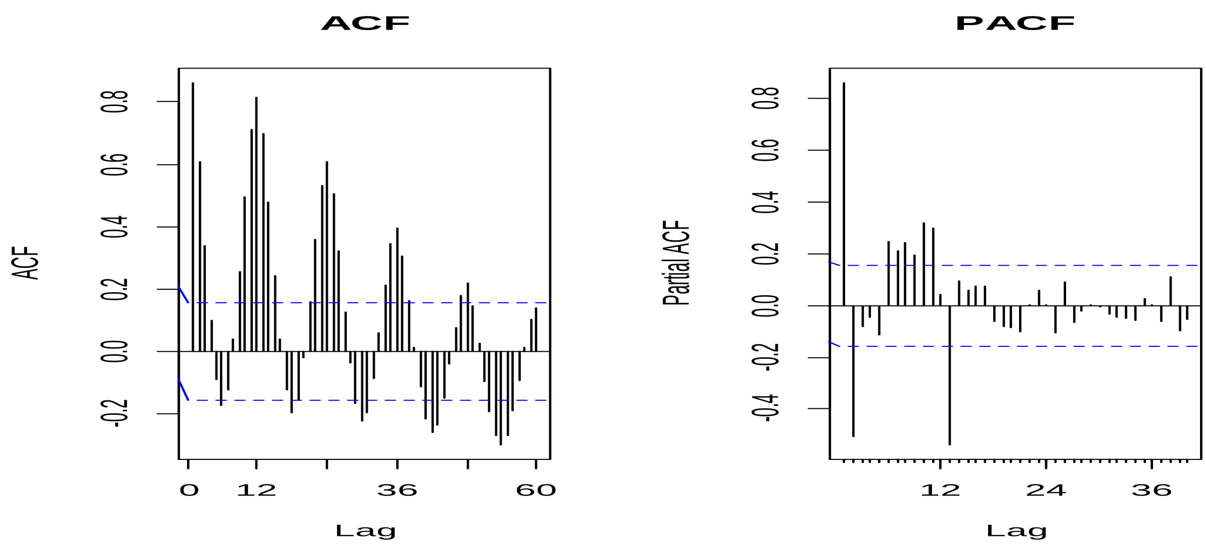


Figure 4.4: ACF and PACF plot of road traffic accident data of Addis Ababa

The above Figure 4.4 demonstrates, upside down progress with clear evidence of regularly repeating patterns after every 12 lags. This reveals that non stationary of the series, with the presence of seasonality and trend components. Also, it show that, the time series was non-stationary and requires some preprocessing steps to make it stationary. At the beginning, the log transformation was performed. This was used to stabilize the variance of the series, but it wasn't enough to make it stationary (Robert Nau, 2017).

To stabilize the mean of the series, seasonal and non-seasonal differencing were performed. The non-seasonal differencing was achieved to eliminate the trend from the series, but there were still remained seasonal patterns in the plot of ACF, repeating after every 12 lags. However, the simple non-seasonal differencing cannot deal with strong seasonality effect. Therefore, after one non-seasonal differencing, seasonal differencing with lag = 12 was performed. Hence, a seasonal ARIMA process was a form of SARIMA (p, 1, q) (P, 1, Q) $_{12.}$ The estimated order of the model parameters p, q, P and Q were identified by visual inspection of ACF and PACF of the stationary process.

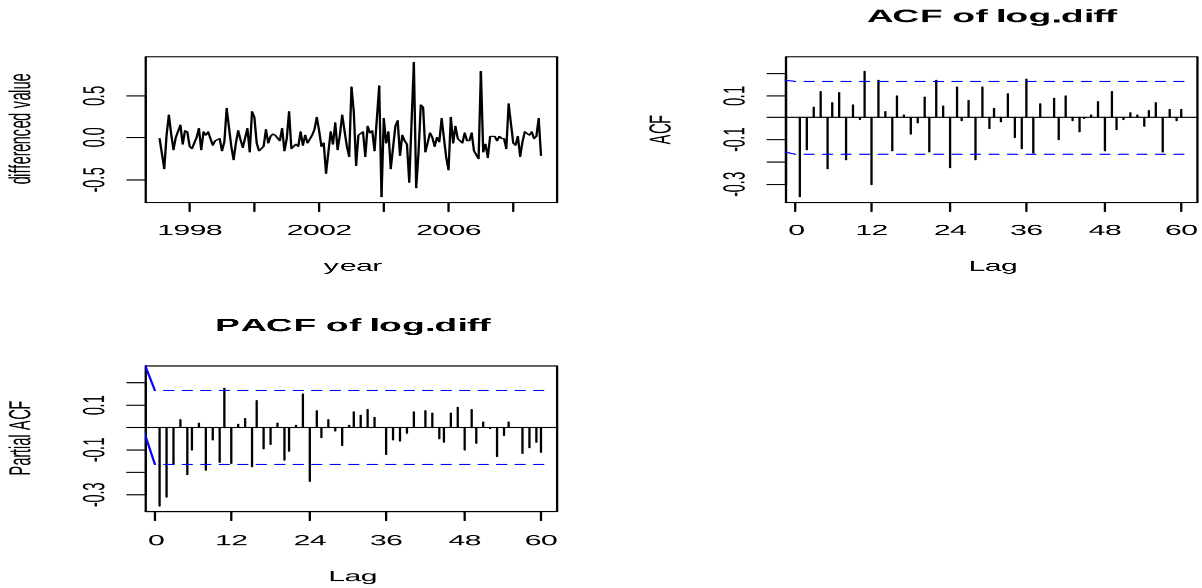


Figure 4.5: The ACF and PACF plot of monthly road traffic accident data after log transformation, one non-seasonal and seasonal differencing with lag=12.

The ACF and PACF plots of the preprocessed time series data demonstrate signs of stationarity. This was also confirmed by the ADF and PP test. The results of the two tests were shown in below Table 4.2

Table 4.2: The ADF and PP test after taking the first and seasonal difference of log original data

Test	**P-value**
ADF	0.01
PP	0.01

From the above Table 4.2, the p-value of both ADF and PP test were 0.01, which is less than 0.05, suggesting stationarity and no other differencing was needed.

4.4. Seasonal ARIMA Model

In this section the researcher fit SARIMA model and forecast monthly road traffic accident of Addis Ababa. In the modeling cycle, the researcher was illustrate the steps in the methodology though model identification, estimation, diagnostic checking, forecasting and measuring the accuracy of the forecast were adopted.

4.4.1. Model Identification

Identification of the model was concerned with deciding the appropriate values of (p,d,q) (P,D,Q). It was done by ACF and PACF plots. The ACF helps in choosing the appropriate values for ordering of moving average terms (MA) and PACF for those autoregressive terms (AR). The seasonal part of the time series was handed separately from the non-seasonal trend. It means that identifying P, D, Q for the seasonal component and p, d, q for the non-seasonal part. Notice that capital letters are used to denote the seasonal autoregressive (P), differencing (D), and moving average (Q) orders.

The ACF and PACF plots were employed to get a preliminary model from Seasonal ARIMA models. The ACF and PACF plot of monthly road traffic accident data after log transformation, one non-seasonal differencing and one seasonal differencing with lag=12 was plotted in the above Figures 4.5. To determine the non-seasonal AR terms, we look at the PACF, which shows clear spikes at lags 1, 2. Thus, the non-seasonal AR terms were determined to be of order 2. There were two spikes at lags 1, 5 in ACF, so we have two non-seasonal MA terms. Now for the seasonal part of the model, we have to look at lag 12, 24, 36, and 48 for both ACF and PACF plot. For both ACF and PACF plot, there were two significant spikes at lags 12 and 24; thus, the order of the seasonal AR and MA was two.

4.4.2. Model Selection

As discussed in the methodology part, a model with small AIC and BIC is preferable. Based on these selection criteria, SARIMA(1,1,1)(1,1,2)12 is found to be the best model that fits the data and all suggested SARIMA models were displayed in Table A1(appendix).Hence, as described in equation (9) methodology part. This model have p=1,q=1,d=1 and P=1,D=1,Q=2,S=12.For this the general model can be written as :

$$(1-\varphi_1 B)(1-\phi_1 B^{12})(1-B)(1-B)\,X_t = (1-\Theta_1 B)(1-\theta_1 B^{12})\,(1-\theta_2 B^{24})w_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots[4.1]$$

4.4.3. Model estimation

Model estimation was the process of estimating the model parameters after selecting an appropriate model. From the above model selection, the model that have the lowest value of AIC and BIC was SARIMA(1,1,1)(1,1,2)$_{12}$. The maximum likelihood estimation method was used to estimate the parameters of the model. The results of estimation are given in Table 4.3 below:

Table 4.3: Maximum Likelihood Estimates for parameters

Coefficients	Estimates	Standard error	p-value
ar1	0.467	0.102792	<0.01
ma1	-0.882	0.049396	<0.01
sar1	-0.642	0.260291	0.01368
sma1	0.321	0.265771	0.22687
sma2	-0.438	0.110747	<0.01

As described on the above equation 4.1, the corresponding parameter values from the Table 4.3 above were; $\varphi_1 = 0.467$, $\phi_1 = -0.641$, $\Theta_1 = -0.882$, $\theta_1 = 0.321$, $\theta_2 = -0.438$.and, the final fitted model was written as follows:

$$(1-0.467B)(1+0.641B^{12})(1-B)(1-B)\,X_t = (1+0.882B)(1-0.321B^{12})\,(1+0.4358B^{24})w_t \ldots.[4.2]$$

4.4.4. Diagnostic Checking of SARIMA (1, 1, 1)(1,1,2)$_{12}$ Model

Model diagnostics were concerned with assessing the quality of the model that was specified and estimated in model estimation. It was concerned with testing the goodness of fit of a model. In time series modelling, the selection of model to the data was directly related to whether residual analysis was performed well. Accordingly, Ljung-Box test and ACF plot of residuals were used to check the adequacy of the model.

4.4.4.1. Ljung-Box Test

The Ljung–Box test was used to check whether or not the residuals from an SARIMA model appear to be white noise. The shown in below Table 4.4, the p-value was higher than 0.05. This leads to the conclusion that we cannot reject the null hypothesis that the autocorrelation is zero. Therefore, the selected model was an appropriate one for forecasting monthly road traffic accident of Addis Ababa.

Table 4.4: Box-Pierce test for SARIMA (1,1,1)(1,1,2)12 model

Box-Ljung test	X-squared	Df	p-value
	0.0020134	1	0.9642

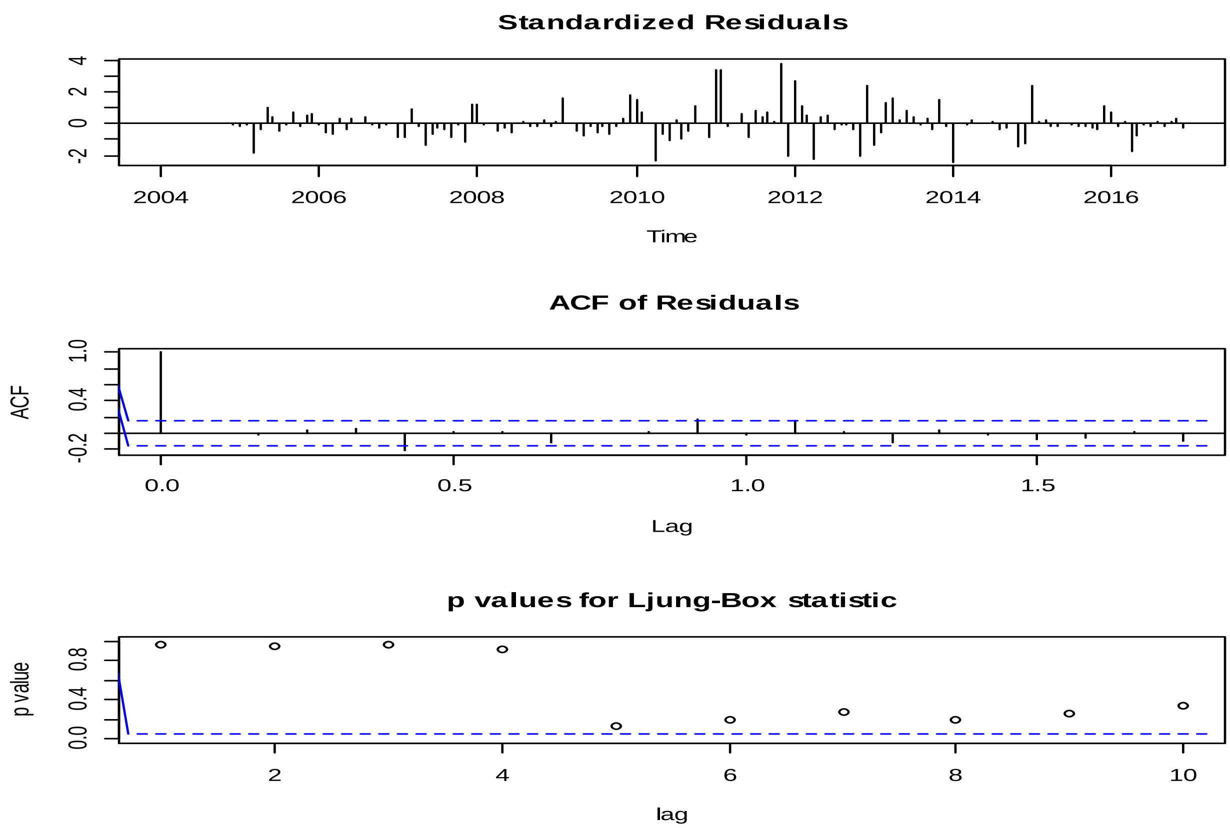


Figure 4.6: Residual graphics and Ljung-Box p-values for SARIMA(1,1,1)(1,1,2)12 model

The top box of Figure 4.6 contains the time plot of the standardized residuals of the model .It shows that no obvious pattern and looks like an independent identical distribution sequence with mean zero. There was no trend in the residuals and no changing variance across time. The middle part is the ACF plot of the residuals. The plotted ACF of residuals versus lag lies within the confidence interval and the residuals shows no significant autocorrelations except at lag 1 which was a good result. The bottom plot displays the p-values of the Ljung-Box test for various values of horizontal line and the p-values for the Ljung-Box test are above 0.05% for all lag orders showing there is no significant departure from white noise for the residuals. The Ljung-Box p-value plot also suggests that SARIMA $(1, 1,1)(1,1,2)_{12}$ capture the data well enough.

4.4.5. Forecasting of SARIMA (1, 1, 1) (1, 1, 2)$_{12}$ model

From below Table 4.5, the out-of-sample forecast was performed from January 2017 to December 2018 which consists 24 observations. The out-of-sample forecast graph was also displayed in Figure A1 (Appendix) and it show that increasing trend of monthly road traffic accident of Addis Ababa over the forecast period from January 2017 to December 2018.

Table 4.5: The actual and fitted values of RTA (January, 2017-December, 2018)

Month	Out of sample observed value	Forecast Value	Month	Out of sample observed value	Forecast Value
Jan 2017	777	907	Jan 2018	1575	1069
Feb 2017	948	837	Feb 2018	1630	980
Mar 2017	1551	1575	Mar 2018	2146	1846
Apr 2017	2768	2874	Apr 2018	3236	3724
May 2017	3124	3192	May 2018	3347	4068
Jun 2017	3165	3221	Jun 2018	3196	4016
Jul 2017	3089	3096	Jul 2018	2973	3823
Aug 2017	3280	3364	Aug 2018	2819	4115
Sep 2017	3051	2829	Sep 2018	2607	3502
Oct 2017	2382	2353	Oct 2018	2142	2825
Nov 2017	1677	1450	Nov 2018	1605	1897
Dec 2017	1125	901	Dec 2018	1085	1165

4.5. SETAR Model

4.5.1. Detection of nonlinearity graphically

In case of SARIMA model, monthly aggregated road traffic accident data were one non-seasonal and seasonal differenced with lag=12 after log transformation. This was done to obtain stationarity feature of linear SARIMA model. However, SETAR model can capture nonlinearity in data. Therefore, the data was not seasonally differenced for SETAR model. Hence, nonlinearity was checked by plotting the scatter diagram of yt against yt_{-1} or y_{t-2} or y_{t-3} and so on. The relationships between the first differenced log of monthly road traffic accident data and its lags were captured in Figure A2 (Appendix) and it shows that a fitted nonparametric regression lines on each scatter diagram. As shown in Figure A2 (In the appendix), the scatter diagrams, especially lag 1 up to 8 have holes in the center. This suggests that the process was nonlinear. In addition, the plots of the non-parametric regression function estimates appear to be strongly nonlinear for lags 1 to 8. This supports the first deference of logarithm of Addis Ababa monthly road traffic accident data were a nonlinear behavior. Additionally, nonlinearity feature of the data could be checked using the formal tests.

4.5.2. Formal test of nonlinearity

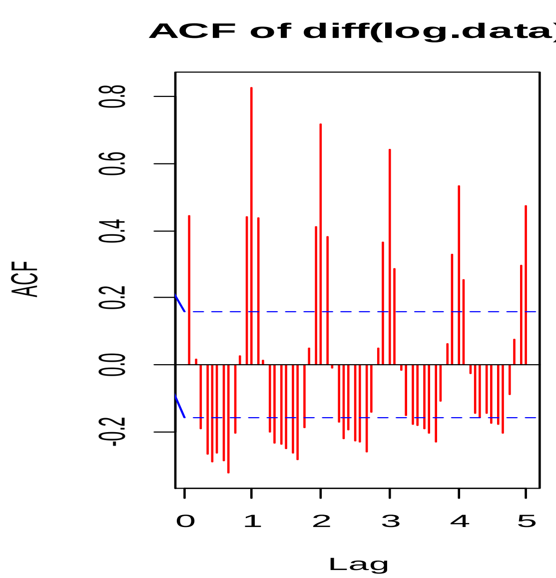
In modeling road traffic accident with the SETAR model, the data should first satisfy the condition of nonlinearity. So, the nonlinearity was checked in this series by specifying the order of the linear AR(p) model. The order of the linear AR(p) was chosen as the AR(p) model based on the maximum lag order with the least value of AIC. The summary of the linearity tests were given in the following Table 4.6;

Table 4.6: Linearity test for first differenced log road traffic accident data

Test	Test statistic	P- value	Order	Decision
Keenan Test	10.60241	0.00144	12	Reject Linearity
Tsay Test	3.296	0.0000	12	No threshold nonlinearity rejected
Likelihood Ratio Test	3.42983	0.00025	12	The model is SETAR with two regimes

From the above Table 4.6, Keenan and Tsay tests suggest that the working order, p could be 12 using Akaki Information Criterion. The Keenan test statistic (10.60241) was significant with p-value (0.00144), and Tsay test statistic (3.296) was significant with p-value (0.000). As a result, the null hypothesis was rejected with conclusion that first differenced log road traffic accident data follows a nonlinear process. In addition, the p-value of likelihood ratio test is 0.0025. So, we reject the null hypothesis that the time series follows some AR process and concluded that data follows a two-regime SETAR model of order p with constant noise variance.

4.5.3. Selection of the lag order and nonlinearity test



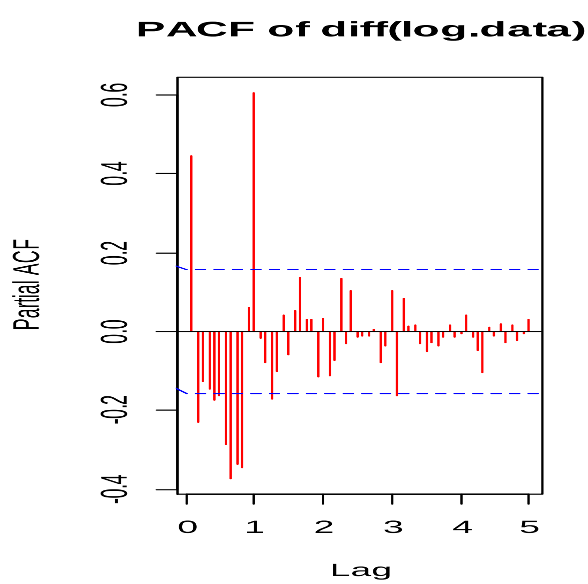


Figure 4.7: ACF and PACF of first order differenced logarithm of monthly road traffic accident data of Addis Ababa

The above Figure 4.7 reveals that, the autocorrelation function and partial autocorrelation function were the indication of linear dependence existing between the lags. The structure of the lags indicate the presence of a strong and persistent cycle in the data. From the above Figure 4.7, there was significant large spike at seasonal lags (12, 24, 36, etc.) revealing that, there was seasonality in the first order differenced logarithm of monthly road traffic accident data of Addis Ababa. The researcher notice a non-seasonal lag cut at lag1 and a seasonal lag cut at lag12 suggesting an AR parameter of order 12 (p=12).This also confirmed by Keenan and Tsay tests from the Table 4.6. This suggests that, an AR model with each individual lag order from 1 to 12 should be tested using Tsay's F test for threshold nonlinearity.

Table 4.7: Nonlinearity test (p=12)

Delay (d)	**F-value**	**P-value**
1	**3.6002**	**0.0001***
2	**3.3464**	**0.0003***
3	**3.3005**	**0.0003***
4	1.3898	0.1769
5	1.1934	0.2947
6	1.6188	0.0917
7	**2.6682**	**0.0029***
8	**2.5099**	**0.0050***
9	**2.4310**	**0.0066***
10	1.5563	0.1103
11	**2.4720**	**0.00l57***
12	**1.8786**	**0.0411***

The above Table 4.7 shows that, all tests suggest nonlinearity for d=1,2,3,7,8,9,11 and 12 at the 5% level .However, The p-values of delayed 4, 5,6 and 10 were greater than 0.05. That means, we do not reject the null hypothesis of no threshold nonlinearity for all chosen delay parameter. Then, the researcher tried lower the lag order (p) to 8 by avoiding a non-significant delayed parameters as adopted in (Zivot, E. and Wang, J., 2005). Subsequently, nonlinearity for lag order (p=8) was tested. The summary of the result was given in the following Table 4.8.

Table 4.8: Nonlinearity test when p=8

Delay(d)	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
F-value	5.2409	8.5895	4.8626	9.4523	10.7204	5.3914	4.1018	4.3857
P-value	0.000	0.000	0.000	0.000	0.000	0.000	0.0001	0.0001

The above Table 4.8 show that, the tests for all delays (d) have a p-values less than 0.05. The null hypothesis of no threshold nonlinearity was actually rejected for all delayed parameters. The optional argument p specifies the AR order to use in the arranged auto regression, and the optional argument d was used to select the delay parameters from 1 to 8. The output was give the F statistics and their corresponding p-values for all chosen values of delayed parameter (d), and shows that the evidence for threshold nonlinearity was strong with the AR(8) specification **.**

4.5.4. Selection of the delayed parameter

For a given AR order p, Tsay suggests to select an estimate of the delay parameter, such that $d = \arg\max_{d \le p} \hat{F}(p, d_p)$ .Where, $\hat{F}(p, d_p)$ was the F-statistic value, the estimate of d depends on p. From above Table 4.9, when d=1, F=5.2409, when d=2, F=8.5895, when d=3, F=4.8626, when d=4, F=9.4523, when d=5, F=10.7204, when d=6, F=5.3914 , when d=7, F=4.1018 , when d=8, F= 4.3857 .The largest test statistic value occurred at d = 5. Consequently, 5 is suspected to be the delayed parameter for the SETAR model.

4.5.5. Model Selection

After confirming that the data were threshold nonlinear with 5 delayed parameter, the specific SETAR model that fit the data was identified. This was done by determining the autoregressive lag order (p) in each regime and the threshold variable y_{t-d} .Where, d represent the delayed parameter. The researcher choose the model with lag order (p) for both regimes and threshold variable with the minimal AIC by performing a grid search on all possible combinations of SETAR models. The selected model using grid search from all possible models combinations were illustrated in Table 4.10.

Thus, from below Table 4.9, the grid search using delay (d=5) with order of lower regime 8 and order of upper regime 8 with -0.2564485 threshold value have the smallest AIC value. Accordingly, SETAR (2, 8, 8) model with no serial correlation is found to be the selected model that fits road traffic accident data.

Table 4.9: Grid search for SETAR model using d=5

Grid search for the model using (p=8)						
Threshold delayed (d)	Rank	Order of lower regime	order of upper regime	Threshold Value	AIC	Serial correlation
d=5	**1**	**8**	**8**	**-0.2564485**	**-396.9006**	**No**
	2	8	8	-0.2674560	-395.6086	No
	3	8	8	-0.2244672	-394.1635	No
	4	5	8	-0.2718599	-393.6719	Yes

4.5.6. Model Estimation

Table 4.10: Maximum likelihood estimates of SETAR (2, 8, 8) model

	Low Regime				High Regime			
Coefficient	Estimate	Std Error	t- value	p-value	Estimate	Std Error	t- value	p-value
Constant	0.220	0.207	1.059	0.291	0.136	0.033	4.141	0.000
ϕ_1	-0.964	0.206	-4.682	0.000	0.387	0.086	4.490	0.000
ϕ_2	-0.887	0.143	-6.189	0.000	0.169	0.098	1.730	0.085
ϕ_3	-1.122	0.175	-6.399	0.000	-0.211	0.089	-2.364	0.019
ϕ_4	-0.771	0.159	-4.845	0.000	-0.254	0.077	-3.276	0.001
ϕ_5	-0.692	0.196	-3.522	0.000	-0.208	0.071	-2.892	0.004
ϕ_6	-0.806	0.376	-2.143	0.033	-0.310	0.075	-4.107	0.000
ϕ_7	-0.986	0.378	-2.607	0.010	-0.135	0.0621	-2.189	0.030
ϕ_8	-1.351	0.277	-4.8685	0.000	-0.391	0.0619	-6.317	0.000
	Threshold value = -0.2564							
Proportion	25.17%				74.83%			

As indicated in Table 4.10, the numbers of data falling in lower and upper regimes are 25.17% and 74.83% respectively. Hence, the final SETAR (2, 8, 8) model using the estimated value of above Table 4.11 was written as follows;

$$y_t = \begin{cases} 0.22 - 0.94y_{t-1} - 0.89y_{t-2} - 1.12y_{t-3} - 0.77y_{t-4} - 0.69y_{t-5} - 0.81y_{t-6} - 0.97y_{t-7} - 1.35y_{t-8}, y_{t-5} \le -0.2564 \\ 0.14 + 0.39y_{t-1} + 0.10y_{t-2} + 0.09y_{t-3} + 0.08y_{t-4} + 0.07y_{t-5} + 0.81y_{t-6} + 0.06y_{t-7} + 0.062y_{t-8}, y_{t-5} > -0.2564 \end{cases}$$

Figure A3 (in appendix) depicts the nature of the regimes. And, it reveals which data value falls in which regime in the first differenced logarithm of monthly road traffic accident data. Data falling in the lower regime was drawn as black line while high regime was drawn by red line .The estimated threshold was -0.2564 as estimated in the above Table 4.11.This threshold value was not close to the minimum or the maximum observation . It was the break point of the data.

4.5.8. Forecasting of SETAR (2, 8, 8) Model

The below Table 4.11 show that the out-of-sample forecasted value from January 2017 to December 2018 which consists 24 observations.

Table 4.11: Actual and forecasted values of the series using SETAR (2, 8,8)

Month	Out of sample observed value	Forecast Value	Month	Out of sample observed value	Forecast Value
Jan 2017	777	578	Jan 2018	1575	808
Feb 2017	948	1003	Feb 2018	1630	1254
Mar 2017	1551	1347	Mar 2018	2146	1688
Apr 2017	2768	2489	Apr 2018	3236	2946
May 2017	3124	4703	May 2018	3347	3725
Jun 2017	3165	4203	Jun 2018	3196	3621
Jul 2017	3089	4285	Jul 2018	2973	3335
Aug 2017	3280	2704	Aug 2018	2819	2604
Sep 2017	3051	2456	Sep 2018	2607	2509
Oct 2017	2382	1928	Oct 2018	2142	1845
Nov 2017	1677	1214	Nov 2018	1605	1375
Dec 2017	1125	1000	Dec 2018	1085	1194

4.5.9. Model diagnosis

After carefully selecting tentative models to be used for forecasting, the researcher check the residuals of the models to ensure that, the model satisfy the assumptions.

4.5.9.1. Time plot of the SETAR (2,8,8) model residuals

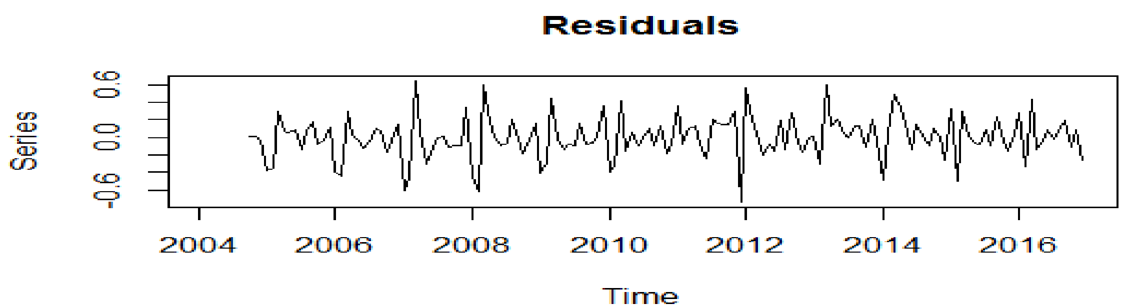


Figure 4.8: Time plot of the SETAR (2,8,8) model residuals.

As shown in above Figure 4.8, the standardized residuals plot shows no obvious pattern and looks like an identically and independently distributed of mean zero.

4.5.9.2. Test of Normality

To investigate whether or not the residuals of the fitted model are normally distributed, the Jarque-Bera test was applied. The test have a null hypothesis that the residual follows a normal distribution and therefore a rejection of the null hypothesis suggests that the residual does not follow a normal distribution.

Table 4.12: Jarque Bera test for SETAR (2,8,8) model residuals

	X-squared	Df	p-value
Jarque Bera Test	1.1787	2	0.5547

As shown in above Table 4.12, the p-value for the test was 0.5547 which was greater than 0.05. So, we do not reject the null hypothesis. This test was provide evidence of normality for the standardized residuals. In addition, Figure A4 (Appendix) show that the histogram and QQ plot of SETAR (2,8,8) model residuals. The histogram features provide strong indications of the proper distributional of the model for the data. Also, the QQ-normal plot seem to follow a straight line especially in the extreme values.

4.5.9.3. Test for Serial Correlation

Ljung and Box (1978), described this test as a diagnostic tool used to check for the presence or absence of serial correlations in the residuals of a fitted model.

Table 4.13: Box-Pierce test for SETAR (2,8,8) model

Box-Ljung test	X-squared	Df	p-value
	0.051991	1	0.8196

The above Table 4.13 shows that the p-value was higher than 0.05. This leads to the conclusion that we don't reject the null hypothesis of no autocorrelation. Therefore, the selected model is an appropriate one for forecasting road traffic accident of Addis Ababa.

4.6. Comparison between SARIMA and SETAR models

The researcher compare between two methodologies for building time series models and using the models for forecasting. Error measurement play a critical role in tracking forecast accuracy, and benchmarking forecasting process .The forecasting performance of SARIMA(1,1,1)(1,1,2)$_{12}$ and SETAR (2, 8, 8) model were compared based on ME, MAE,RMSE and Diebold and Marino test

Table 4.14: Comparison of forecasting accuracy between SETAR (2, 8, 8) and SARIMA (1, 1, 1)(1,1,2)12

Forecast Performance	SETAR (2, 8, 8)	SARIMA$(1,1,1)(1,1,2)_{12}$
ME	0.0008	0.0057
MAE	0.090	0.1018
RMSE	0.113	0.1618
Diebold and Marino test		
Model	DM-test statistics	p-value
SARIMA vs SETAR	2.7236	0.003599

From above Table 4.14, the two-tailed Diebold and Marino test was performed to examine whether there was any predictive accuracy difference between the models. The p-value of Diebold and Marino test was 0.003599 which was less than (p=0.05) and it reveals that there were enough evidence to reject the null hypothesis of equal predictive accuracy of SETAR and SARIMA models. Also, the result of ME, MAE and RMSE of SETAR (2, 8, 8) model was relatively minimum with compared to SARIMA $(1,1,1)(1,1,2)_{12}$ model. Since, A model with a minimum of forecasting error was considered to be the better, SETAR (2, 8, 8) model performs better than SARIMA $(1, 1,1)(1,1,2)_{12}$ model in forecasting road traffic accident of Addis Ababa.

4.7. Discussion

This study emphasized on application of SARIMA and SETAR models on road traffic accident of Addis Ababa. Several studies also applied time series model to predict road traffic accidents (Eze et al.,2018; Foroutaghe et al.,2019;Nanga,2016).The finding of this research indicated that the trend of road traffic accident showed a constant movement from 2004 to 2006 , steady decrease from 2007 to 2010 and then showing indications of a rising trend from 2010 to 2016 G.C. Despite of this finding, the pattern on monthly reported road accidents in Nigeria reveals that, a constant movement from 2004 to 2008 and increased abnormally in 2010 and then downward movement as the year progresses. Accidents can occur at any time and at any place. Hence, how do road traffic accidents occur was varies from time to time and from place to place depending on the intensity of the interaction and places of importance.

This study followed 12-monthly seasonal pattern of road traffic accident of Addis Ababa and the accident was most frequently occurred in rainy season of Ethiopia (June, July and August). In agreement with this study, Eke et al. (2000) collected road traffic accident data from Port Harcourt university of Nigeria from January 1986 to December 1995 and found that, road traffic accident most frequently occurs during the rainy seasons (June, July and August). Moreover, Parshant et al. (2018) studied the impact of rain on road transport of India and the study showed that, high number of road traffic accident occurs in a rainy season due to widening of potholes and cracks.

Beside of comparative analysis of SARIMA and SETAR models, the result obtained from this study reveals that SETAR (2, 8, 8) model performs better than SARIMA$(1,1,1)(1,1,2)_{12}$ model in forecasting road traffic accident of Addis Ababa. And, this was consistent with the study of Nafisah (2018) on comparative analysis of forecast performance between SARIMA and SETAR models using macroeconomic variables in Ghana. Keenan and Tsay-F tests showed the datasets were threshold nonlinear with two regime SETAR model. Accordingly, the performance between the SARIMA and SETAR models were compared for inflation by employing forecast measures RMSE and MAE and the nonlinear SETAR model outperformed than linear SARIMA model for inflation rate of Ghana.

5. Conclusion and recommendation

5.1. Conclusion

This study examined statistical analysis of road traffic accident in Addis Ababa using SARIMA and SETAR models. The estimated trend component showed that, a constant movement from 2004 to 2006, steady decrease from 2007 to 2010 and then showing indications of a rising trend from 2010 to 2016 G.C. In addition, road traffic accident most frequently occurs during the rainy seasons (June, July and August) of Ethiopia. In the case of SARIMA model, SARIMA $(1, 1,1)(1,1,2)_{12}$ emerged as the appropriate model after examining different competitive models. Moreover, the out of sample forecasted result indicates that, an increasing trend of road traffic accident in Addis Ababa.

In the nonlinear SETAR modelling, graphical method, Keenan test, Tsay test and likelihood ratio test were used check non linearity features of the data. A delayed parameter was selected as (d=5) with eight order of lower and upper regime using grid search method. Henceforth, SETAR (2,8,8) was identified amongst the tentative models and out of sample forecasts were made for 24 months. Finally, It was shown that, SETAR (2, 8, 8) model performs better than SARIMA $(1,1,1)(1,1,2)_{12}$ model in forecasting road traffic accident of Addis Ababa.

5.2. Recommendation

- Addis Ababa police traffic commission should modernize road traffic accidents data recording system in detailed and improved reporting template. It is more desirable, if the analyst acquires data published on a monthly basis.
- This study showed the increasing pattern of road traffic accident over the forecasted period and recommends policy maker to pay more attention on preventive measures for road traffic accidents.
- In this study, the researcher focused on the application of SARIMA and SETAR models in forecasting road traffic accident of Addis Ababa. Hence, further studies may employ Artificial Neural Network (ANN) and Multinomial Logit model to identify the impact of climate change on RTAs using different sets of rainfall data.

References

Abdel-Aty, M.A., Radwan AE.,(2000).Modeling traffic accident occurrence and involvement. *Accident Anal Prev. 32(5):633–42*.

Abdi, T. A., Hailu, B. H., Adal, T. A., van Gelder, P. H., Hagenzieker, M. P., & Carbon, C. C. (2017). Road crashes in Addis Ababa, ethiopia: empirical findings between the years 2010 and 2014. *African Research Review*, *11*(2), 1-13.

Abegaz, T., Berhane, Y., Worku, A., Assrat, A., & Assefa, A. (2014). Road traffic deaths and injuries are under-reported in Ethiopia: a capture-recapture method. *PLoS One, 9*(7).

Abegaz, T., & Gebremedhin, S. (2019). Magnitude of road traffic accident related injuries and fatalities in Ethiopia. *PloS one*, *14*(1).

Adebola, F. B., Sanusi, R. A., & Adegoke, N. A. (2015). Consequences of road traffic accident in Nigeria: time series approach. *Int J Comp Appl Technol and Res*, *4(4), 262-273*.

Adhikari, R., & Agrawal, R. K. (2013). An introductory study on time series modeling and forecasting. *arXiv preprint arXiv:1302.6613*.

Adu-Poku, K. A., Avuglah, R. K., & Harris, E. (2014). Modeling Road Traffic Fatality Cases in Ghana. *Mathematical Theory and Modelling*, *4*(13), 113-120.

Agbeboh, G. U., & Osarumwense, O. I. (2013). Empirical analysis of road traffic accidents: A case study of Kogi State, North-Central Nigeria. *International Journal of Physical Sciences*, *8*(40), 1923-1933.

Aidoo, E. (2010). Modelling and Forecasting inflation rates in Ghana: An application of SARIMA models.

Akeyede, I., Adeleke, B. L., and Yahya, W. B. (2015). On forecast strength of some linear and nonlinear time series models for stationary data structure. American Journal of Mathematics and Statistics, 5(4):163–177.

Amo, T., & Meirmanov, S. (2014). The Epidemiology of Road Traffic Accident (RTA) in Ghana, 2001-2011. *Life Science Journal*, *11*(9).

Avuglah, R. K., Adu-Poku, K. A., & Harris, E. (2014). Application of ARIMA models to road traffic accident cases in Ghana. *International journal of statistics and applications*, 4(5), 233-239

Badawi, M. O. H. A. M. M. E. D. (2016). Comparative analysis of sarima and setar models in predicting pneumonia cases in the northern region of Ghana (Doctoral dissertation).

Bahadori Monfared, A., Soori, H., Mehrabi, Y., Rahmati Roudsar, M., Esmaili, A., Salehi, M., & Delpisheh, A. (2013). A model for prediction of on the rate of mortality due to road traffic accidents in Iran. *Research in Medicine*, *36*(5), 7-11.

Balogun ,O.S. Awoeyo, O.O and Dawodu, O.O.(2014).Use of time series analysis of road data in Lagos state. International Journal of Advanced Research (2014), Volume 2, Issue 5:1045-1059.

Bekele, T. G., & Sima, T. H. ROAD TRAFFIC ACCIDENT CAUSE AND EFFECT ON SOCIO ECONOMY OF ADDIS ABABA CITY.

Berhanu, G. (2000). Effects of road and traffic factors on road safety in Ethiopia. *IST RAPPORT 2000: 11*.

Bijleveld, F. D. (1997). Effectiveness of daytime motorcycle headlights in the European Union.

Boero, G., & Marrocu, E. (2002). The performance of non-linear exchange rate models: a forecasting comparison. *Journal of Forecasting*, *21*(7), 513-542

Boero, G., & Marrocu, E. (2004). The performance of SETAR models: a regime conditional evaluation of point, interval and density forecasts. *International Journal of Forecasting*, *20*(2), 305-320.

Box, G. E., & Jenkins, G. M. (1970). Time series analysis: Forecasting and control Holden-Day. *San Francisco*, 498

Box, G. E., & Jenkins, G. M. (1976). Time series analysis: Forecasting and control San Francisco. *Calif: Holden-Day*.

Box, G. E., Jenkins, G. M., & Reinsel, G. C. (1994). Time series analysis: Forecasting and control. 3rd Prentice Hall. *Englewood Cliffs NJ*.

Brooks, C. (2019). *Introductory econometrics for finance*. Cambridge university press.

Caner, M., & Hansen, B. E. (2001). Threshold autoregression with a unit root. *Econometrica*, *69*(6), 1555-1596.

Chatfield, C. (2000). *Time-series forecasting*. Chapman and Hall/CRC.

Chen, S. (2011). *On order identification of time series models and its applications* (Doctoral dissertation, Rutgers University-Graduate School-New Brunswick).

Chong, M., A. A., et al. (2005). "Traffic Accident Analysis Using Machine learning Paradigms." Informatica 29(1).

Chortareas, G. E., Kapetanios, G., & Shin, Y. (2002). Nonlinear mean reversion in real exchange rates. *Economics Letters*, *77*(3), 411-417.

Clements, M. P., & Smith, J. (2001). Evaluating forecasts from SETAR models of exchange rates. *Journal of International Money and Finance*, *20*(1), 133-148.

Clements, M. P., Franses, P. H., & Swanson, N. R. (2004). Forecasting economic and financial time-series with non-linear models. *International Journal of Forecasting*, *20*(2), 169-183.

Cryer, J. D., & Kellet, N. (1991). *Time series analysis*. Royal Victorian Institute for the Blind. Tertiary Resource Service.

Daie, G. F., & Tebarek, L. M. (2013). Identifying major urban road traffic accident black-spots (RTABSs): A sub-city based analysis of evidences from the city of Addis Ababa, Ethiopia. *Journal of Sustainable Development in Africa*, *15*(2).

Desaling Germay, M. (2016). Modeling and Forecasting Unemployment Rate In Sweden using various Econometric Measures.

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American statistical association*, *74*(366a), 427-431.

Dijk, D. J. C. (2003). Brooks-Introductory Econometrics for Finance. *De Economist*.

Edward, N. (2011). Modelling and Forecasting Using Time Series Garch Models: An Application of Tanzania Inflation Rate Data. *University Of Dar Es Salaam*.

Eke, N., Etebu, E. N., & Nwosu, S. O. (2000). Road traffic accident mortalities in Port Harcourt, Nigeria. *Anil Aggrawal's Internet Journal of Forensic Medicine and Toxicology*, *1*(2).

Engle, R. F., & Bollerslev, T. (1986). Modelling the persistence of conditional variances. *Econometric reviews*, *5*(1), 1-50.

Eze, C. M., & Okonkwo, C. R. (2018). On the Modelling of Road Traffic Crashes: A case of SARIMA Models. *Journal of Advance Research in Mathematics And Statistics (ISSN: 2208-2409)*, *5*(8), 15-35.

Favour, O. I., Joshua, A. F., & Ismail, S. O. (2016). Statistical analysis of pattern on monthly reported road accidents in Nigeria. *Science Journal of Applied Mathematics and Statistics*, *4*(4), 119.

Fentahun, A. (2011). *Mining Road Traffic Accident Data for Predicting Accident Severity to Improve Public Health–Role of Driver and Road Factors in the Case of Addis Ababa* (Doctoral dissertation, Addis Ababa University).

Fori, T., Ackah, B., & Ephraim, L. (2012). Statistical models for forecasting road accident injuries in Ghana. *International Journal of Research in Environmental Science and Technology*, *2*(4), 143-149.

Foroutaghe, M. D., Moghaddam, A. M., & Fakoor, V. (2019). Time trends in gender-specific incidence rates of road traffic injuries in Iran. *PloS one*, *14*(5).

Franses, P. H., & Van Dijk, D. (2000). *Non-linear time series models in empirical finance*. Cambridge University Press.

Ghedira, A., Kammoun, K., & Saad, C. B. (2018). Temporal Analysis of Road Accidents by ARIMA Model: Case of Tunisia. *International Journal of Innovation and Applied Studies*, *24*(4), 1544-1553.

Gloria, R., & Gonzalo, J. (2002). Introduction to Time Series Analysis. *University of California, Carlos III de Madrid*.

Goswami, A., & Sonowal, R. (2009). A statistical analysis of road traffic accidents in Dibrugarh City, Assam, India. *Division of Epidemiology and Nutrition, Regional Medical Research Centre*.

Gourieroux, C., & Jasiak, J. (2001). *Financial econometrics: Problems, models, and methods*. Princeton University Press.

Gulay, E. (2019). Forecasting the total electricity production in South Africa: Comparative analysis to improve the predictive modelling accuracy. *AIMS Energy*, *7*(1), 88.

Hansen, Bruce E. "Inference when a nuisance parameter is not identified under the null hypothesis." *Econometrica: Journal of the econometric society* (1996): 413-430.

Hamilton, J. D. (1994). *Time series analysis* (Vol. 2, pp. 690-696). New Jersey: Princeton.

Hansen, P. R., & Timmermann, A. (2012). Choice of sample split in out-of-sample forecast evaluation.

Hasanzadeh, J., Moradinazar, M., Najafi, F., & Ahmadi-Jouybary, T. (2014). Trends of mortality of road traffic accidents in Fars Province, Southern Iran, 2004-2010. *Iranian journal of public health*, *43*(9), 1259.

Helen, A. (2018). *Road Traffic Crashes Severity Analysis in Nifas-Silk/Lafto Sub City, Addis Ababa, Ethiopia* (Doctoral dissertation, AAU).

Hermans, E., Wets, G., & Van den Bossche, F. (2006). Describing the evolution in the number of highway deaths by decomposition in exposure, accident risk, and fatality risk. *Transportation research record*, *1950*(1), 1-8.

Hesari, A., & Esmaeli, A. (2004). Estimates of deaths from traffic accidents on life expectancy at birth and the financial burden it (2002). *Health Inf Manag*, *1*(2), 27-35.

Heydari, S. T., Sarikhani, Y., Moafian, G., Aghabeigi, M. R., Mahmoodi, M., Ghaffarpasand, F., ... & Hoseinzadeh, A. (2013). Time analysis of fatal traffic accidents in Fars Province of Iran. *Chinese journal of traumatology*, *16*(2), 84-88.

Hordofa, G. G., Assegid, S., Girma, A., & Weldemarium, T. D. (2018). Prevalence of fatality and associated factors of road traffic accidents among victims reported to Burayu town police stations, between 2010 and 2015, Ethiopia. *Journal of Transport & Health*, *10*, 186-193.

Hsu, K. H., Li, J. F., Lin, Y. B., Hong, C. Y., & Huang, Y. C. (2010). A SETAR Model for Taiwan Stock Exchange Capitalization Weighted Stock Index: Non-linearities and Forecasting Comparisons, 13(1), 74-88.

Hyndman, R. J., & Koehler, A. B. (2005). Another look at measures of forecast accuracy", Monash University.

Karlsson, N., & Karlsson, S. (2016). Forecasting of the inflation rates in Uganda: A comparison of ARIMA. *SARIMA and VECM models*.

Kebede, A. (2015). *Road Traffic Accident Related Fatalities in Addis Ababa City, Ethiopia: An Analysis of Police Report 2013/14* (Doctoral dissertation, Addis Ababa University).

Keenan, D. M. (1985). A Tukey nonadditivity-type test for time series nonlinearity. *Biometrika*, *72*(1), 39-44.

Kwiatkowski, D., Phillips, P. C., Schmidt, P., & Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root. *Journal of econometrics*, *54*(1-3), 159-178.

Li, J. (2006). Threshold Autoregressive Modeling of Bond Series-Japanese Case. *Investment management and financial innovations*, (3, Iss. 4), 120-132.

Ling, S., & McAleer, M. (2002). Stationarity and the existence of moments of a family of GARCH processes. *Journal of Econometrics*, *106*(1), 109-117.

Ljung, G. M., & Box, G. E. (1978). On a measure of lack of fit in time series models. *Biometrika*, *65*(2), 297-303.

Makridakis, S., Wheelwright, S. C., & Hyndman, R. J. (2008). *Forecasting methods and applications*. John wiley & sons.

Manikandan, M., Prasad, V., Mishra, A. K., Konduru, R. K., & Newtonraj, A. (2018). Forecasting road traffic accident deaths in India using seasonal autoregressive integrated moving average model. *International Journal of Community Medicine and Public Health*, *5*(9), 3962.

Mansouri, F., Khanjani, N., & Pourmousa, R. (2013). Forecasting ambient air pollutants by time series models in Kerman, Iran. *Journal of School of Public Health and Institute of Public Health Research*, *11*(2), 75-86.

McLeod, A. I., & Vingilis, E. R. (2008). Power computations in time series analyses for traffic safety interventions. *Accident Analysis & Prevention*, *40*(3), 1244-1248.

McQuarrie, A. D., & Tsai, C. L. (1998). *Regression and time series model selection*. World Scientific.

Mebrahtu, B. (2002). *Taxi traffic accidents in Addis Ababa: causes, temporal and spatial variations, and consequences* (Doctoral dissertation, Addis Ababa University).

Mehmandar, M., Soori, H., & Mehrabi, Y. (2016). Predicting and analyzing the trend of traffic accidents deaths in Iran in 2014 and 2015. *International journal of critical illness and injury science*, *6*(2), 74.

Mekasha, F. (2015). *Road Traffic Accident: Causes and Control Mechanisms: in Addis Ababa City* (Doctoral dissertation, Addis Ababa University).

Mekonnen, F. H., & Teshager, S. (2014). Road traffic accident: the neglected health problem in Amhara National Regional State, Ethiopia. *Ethiopian Journal of Health Development*, *28*(1), 3-10.

Mekonnen, T. (2007). *Empirical Analysis on Traffic Accidents Involving Human Injuries (The Case of Addis Ababa* (Doctoral dissertation, Addis Abeba university).

Monfared, A. B., Soori, H., Mehrabi, Y., Hatami, H., & Delpisheh, A. (2013). Prediction of fatal road traffic crashes in iran using the box-jenkins time series model. *Journal of Asian Scientific Research*, *3*(4), 425.

Mossie, G. (2009). *Applying Data Mining to Identify Determinant Factors of Drivers and Vehicles in Support of Reducing and Controlling Road Traffic Accident: In the Case of Addis Ababa City* (Doctoral dissertation, Addis Ababa University).

Mutangi K., (2015), Time series analysis of road traffic accidents in Zimbabwe. Int J Stat and Appl 5 (4),141-149.

Nafisah (2018).Acomparative analysis of forecast performance between sarima and setar models using macroeconomic variables in Ghana

Naghawi, H. (2018). Negative Binomial Regression Model for Road Crash Severity Prediction. *Modern Applied Science*, *12*(4), 38-48.

Nanga, S. (2016). Time series analysis of road accidents in Ghana. *Dama International Journal of Researchers*, 68-75.

Nau, R. (2015). Statistical forecasting: notes on regression and time series analysis. *Notes and materials for an advanced elective course on statistical forecasting that is taught at the Fuqua School of Business, Duke University*.

Ossenbruggen, P. J., J. Pendharkar, et al. (2001). "Roadway safety in rural and small urbanized areas." Accidents Analysis and Prevention 33(4): 485-498

Petropoulos, F., & Kourentzes, N. (2014). Improving forecasting via multiple temporal aggregation. *Foresight: The International Journal of Applied Forecasting*, *34*, 12-17.

Phillips, P. C., & Perron, P. (1988). Testing for a unit root in time series regression. *Biometrika*, *75*(2), 335-346.

Potter, S. M. (1999). Nonlinear time series modelling: An introduction. Journal of Economic Survey, 13:505–528.

Quddus, M. A. (2008). Time series count data models: an empirical application to traffic accidents. *Accident Analysis & Prevention*, *40*(5), 1732-1741.

Ramsey, J. B. (1969). Tests for specification errors in classical linear least-squares regression analysis. *Journal of the Royal Statistical Society: Series B (Methodological)*, *31*(2), 350-371.

Samuel, J. C., Sankhulani, E., Qureshi, J. S., Baloyi, P., Thupi, C., Lee, C. N., ... & Charles, A. G. (2012). Under-reporting of road traffic mortality in developing countries: application of a capture-recapture statistical model to refine mortality estimates. *PloS one*, *7*(2).

Sanusi, R. A., Adebola, F. B., & Adegoke, N. A. (2016). Cases of road traffic accident in Nigeria: a time series approach. *Mediterranean journal of social sciences*, *7*(2 S1), 542-542.

Shumway, R. H., & Stoffer, D. S. (2017). *Time series analysis and its applications: with R examples*. Springer.

Sjoberg, J. (2010). Prediction of industrial production based on nonlinear time series models. *Mathematical Statistics Stockholm University, Examensarbete, paper*, *3*.

So, M. K., & Chen, C. W. (2003). Subset threshold autoregression. *Journal of Forecasting*, *22*(1), 49-66.

Talke, I. S. (2003). *Modelling volatility in time series data* (Doctoral dissertation, University of Natal).

Tesema, T. B., Abraham, A., & Grosan, C. (2005). Rule mining and classification of road traffic accidents using adaptive regression trees. *International Journal of Simulation*, *6*(10), 80-94.

Tibebe, B. (2005). Application Of Data Mining Technology To Support Road Traffic Accident Severity Analysis At Addis Ababa Traffic Office. *AAU, Faculty of Informatics, Department of Information Science*.

Tsay, R. S. (1986). Nonlinearity tests for time series. *Biometrika*, *73*(2), 461-466.

Tsay, R. S. (1989). Testing and modeling threshold autoregressive processes. *Journal of the American statistical association*, *84*(405), 231-240.

Tsay, R. S. (2005). *Analysis of financial time series* (Vol. 543). John wiley & sons.

Tong, H. (1978). On a threshold model.

Tong, H. (1990). *Non-linear time series: a dynamical system approach*. Oxford University Press.

Tong, H., & Lim, K. S. (2009). Threshold autoregression, limit cycles and cyclical data. In *Exploration Of A Nonlinear World: An Appreciation of Howell Tong's Contributions to Statistics* (pp. 9-56).

Tong, H. (2012). *Threshold models in non-linear time series analysis* (Vol. 21). Springer Science & Business Media.

Tulu, G. S., Washington, S., Haque, M. M., & King, M. J. (2017). Injury severity of pedestrians involved in road traffic crashes in Addis Ababa, Ethiopia. *Journal of Transportation Safety & Security*, *9*(sup1), 47-66.

WHO, (2018). *Global status report on road safety 2018: Summary* (No. WHO/NMH/NVI/18.20). World Health Organization.

Willmott, C. J., & Matsuura, K. (2005). Advantages of the mean absolute error (MAE) over the root mean square error (RMSE) in assessing average model performance. *Climate research*, *30*(1), 79-82.

Van den Bossche, F., Wets, G., & Brijs, T. (2004). A regression model with ARIMA errors to investigate the frequency and severity of road traffic accidents.

Yannis, G., Papadimitriou, E., & Folla, K. (2014). Effect of GDP changes on road traffic fatalities. *Safety science*, *63*, 42-49.

Yazdani Cherati, J., Ahmadi Baseri, E., & Ghadami, M. (2013). Mapping of mortality rate in suburban accidents, Mazandaran Province, 2007-2010. *Journal of Mazandaran University of Medical Sciences*, *22*(97), 50-58.

York, J. C., & Gernand, J. M. (2017). Evaluating the Performance and Accuracy of Incident Rate Forecasting Methods for Mining Operations. *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part B: Mechanical Engineering*, *3*(4).

Yousefzadeh-Chabok, S., Ranjbar-Taklimie, F., Malekpouri, R., & Razzaghi, A. (2016). A time series model for assessing the trend and forecasting the road traffic accident mortality. *Archives of trauma research*, *5*(3).

Zewude, B. T., & Ashine, K. M. (2016). Determinants of Traffic Fatalities and Injuries in Wolaita Zone, Ethiopia. *The International Institute for Science, Technology and Education*, *8*(10), 38-42.

Zhang, G. P. (2003). Time series forecasting using a hybrid ARIMA and neural network model. *Neurocomputing*, *50*, 159-175.

Zivot, E. and Wang, J., (2005).Modeling financial series with S-PLUS, Springer, 2nd edition, chapter 18: Nonlinear Time Series Model.651-676.

Appendix

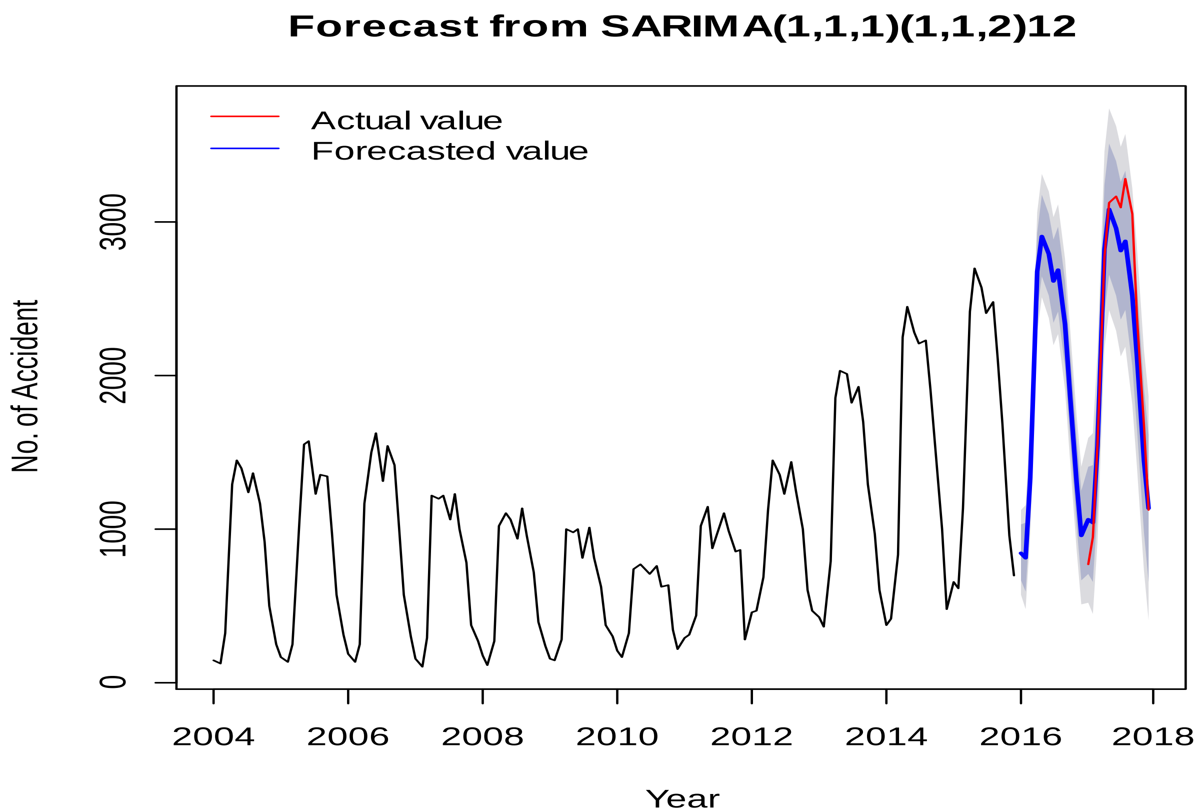


Figure A1: out-of-sample forecast graph of SARIMA (1, 1, 1)(1,1,2)12 model for the road traffic accident Addis Ababa.

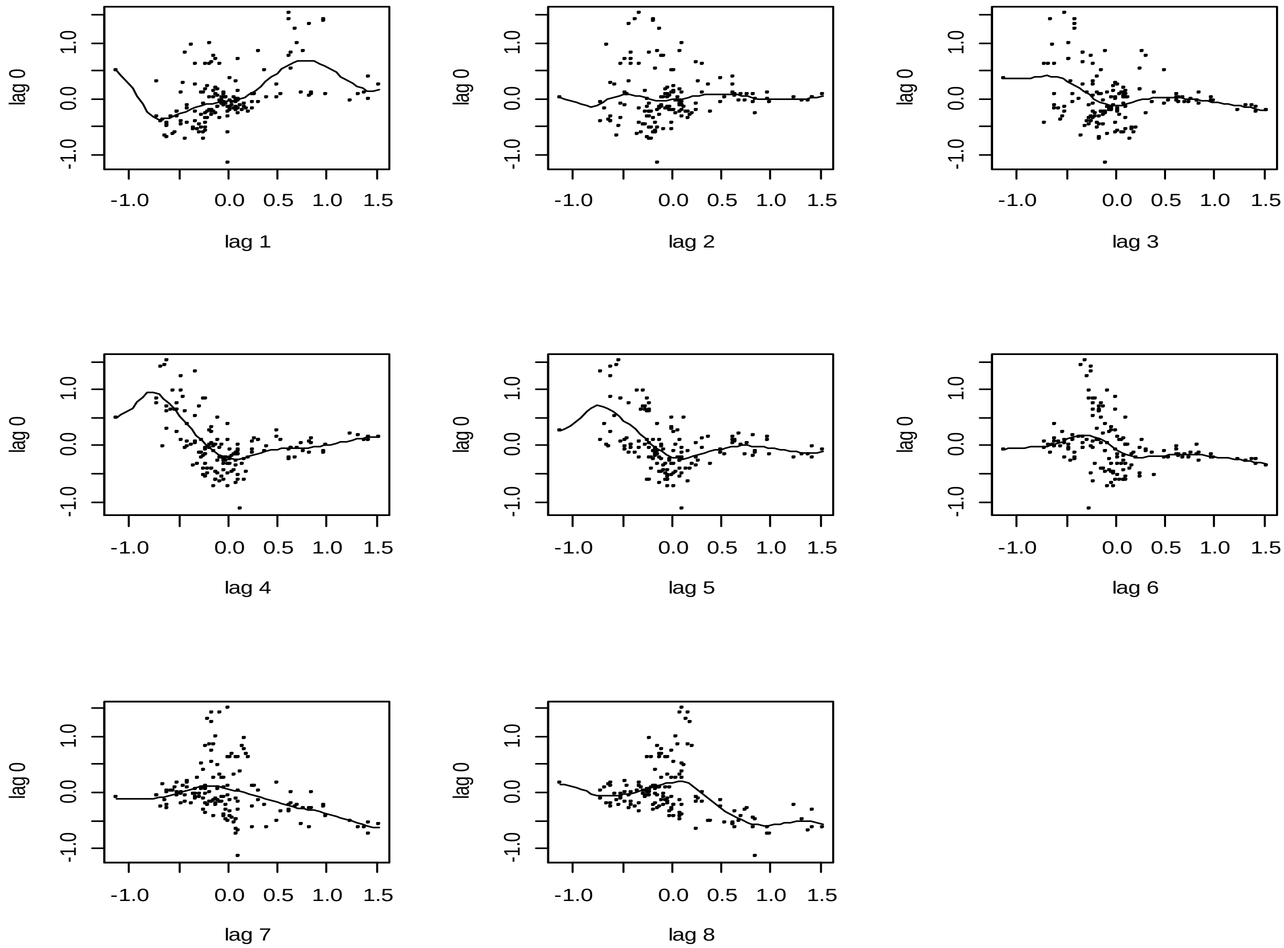


Figure A2: Lag plots of log of monthly road traffic accident of Addis Ababa

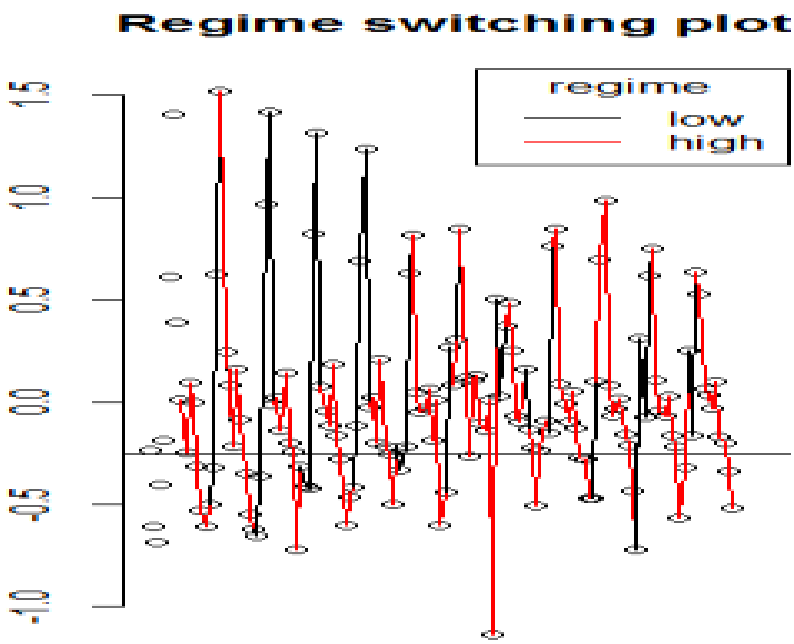


Figure A3: Data falls in the lower and upper regimes of a fitted SETAR (2,8,8) model

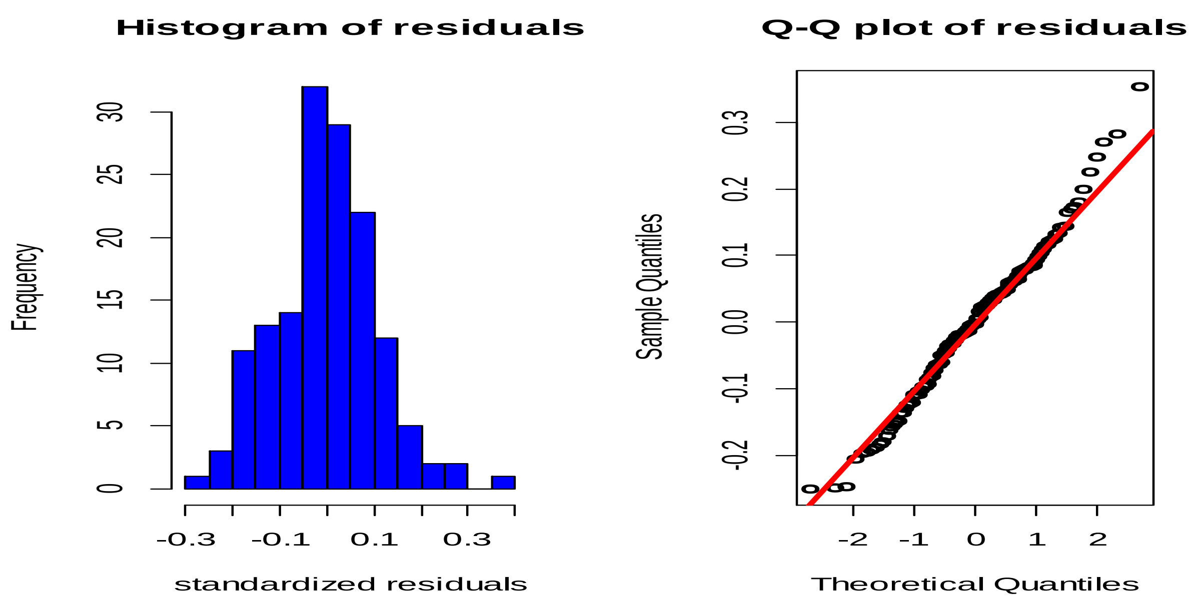


Figure A4: Histogram and Q-Q plot of standardized SETAR (2,8,8) residuals

Table A1: Comparison of SARIMA model

Model type	AIC	BIC	Correlation	Model type	AIC	BIC	correlation
SARIMA(0,1,1)(0,1,1)12	-73.65	-64.76	NO	SARIMA(2,1,1)(0,1,1)12	-80.10	-65.28	NO
SARIMA(0,1,1)(0,1,2)12	-75.64	-63.79	NO	SARIMA(2,1,1)(0,1,2)12	-81.86	-64.08	NO
SARIMA(0,1,1)(1,1,0)12	-70.71	-61.82	NO	SARIMA(2,1,1)(1,1,0)12	-74.27	-59.46	NO
SARIMA(0,1,1)(2,1,0)12	-75.36	-63.51	NO	SARIMA(2,1,1)(2,1,0)12	-80.51	-62.73	NO
SARIMA(0,1,1)(2,1,1)12	-73.54	-58.72	NO	SARIMA(2,1,1)(2,1,1)12	-83.32	-62.58	NO
SARIMA(0,1,1)(2,1,2)12	-73.48	-55.70	NO	SARIMA(2,1,1)(2,1,2)12	-78.18	-60.40	NO
SARIMA(0,1,1)(1,1,1)12	-74.25	-62.40	NO	SARIMA(2,1,1)(1,1,1)12	-79.86	-59.12	NO
SARIMA(0,1,1)(1,1,2)12	-75.41	-60.59	NO	SARIMA(2,1,1)(1,1,2)12	-73.22	-55.44	NO
SARIMA(0,1,2)(0,1,1)12	-80.88	-66.06	NO	SARIMA(2,1,2)(0,1,1)12	-80.16	-59.42	NO
SARIMA(0,1,2)(0,1,2)12	-81.90	-67.08	NO	SARIMA(2,1,2)(0,1,2)12	-78.53	-54.83	NO
SARIMA(0,1,2)(1,1,0)12	-75.82	-63.97	NO	SARIMA(2,1,2)(1,1,0)12	-79.37	-52.71	NO
SARIMA(0,1,2)(2,1,0)12	-82.18	-67.37	NO	SARIMA(2,1,2)(2,1,0)12	-78.55	-57.81	NO
SARIMA(0,1,2)(2,1,1)12	-80.54	-62.76	NO	SARIMA(2,1,2)(2,1,1)12	-81.32	-57.61	NO
SARIMA(0,1,2)(2,1,2)12	-80.73	-59.99	NO	SARIMA(2,1,2)(2,1,2)12	-76.27	-64.41	NO
SARIMA(0,1,2)(1,1,1)12	-80.00	-66.06	NO	SARIMA(2,1,2)(1,1,1)12	-82.43	-64.65	NO
SARIMA(0,1,2)(1,1,2)12	-82.72	-64.94	NO	SARIMA(2,1,2)(1,1,2)12	-76.27	-64.41	NO
SARIMA(1,1,0)(0,1,1)12	-63.60	-54.72	NO	SARIMA(1,1,1)(0,1,1)12	-82.43	-64.05	NO
SARIMA(1,1,0)(0,1,2)12	-66.31	-54.46	NO	SARIMA(1,1,1)(0,1,2)12	-82.43	-62.35	NO
SARIMA(1,1,0)(1,1,0)12	-55.42	-46.53	NO	SARIMA(1,1,1)(1,1,0)12	-83.31	-62.57	NO
SARIMA(1,1,0)(2,1,0)12	-67.02	-55.17	NO	SARIMA(1,1,1)(2,1,0)12	-82.43	-61.23	NO
SARIMA(1,1,0)(2,1,1)12	-65.09	-50.27	NO	SARIMA(1,1,1)(2,1,1)12	-81.23	-64.65	NO

SARIMA(1,1,0)(2,1,2)12	-66.39	-48.61	NO	SARIMA(1,1,1)(2,1,2)12	-80.45	60.89	NO
SARIMA(1,1,0)(1,1,1)12	-64.35	-52.50	NO	SARIMA(1,1,1)(1,1,1)12	-79.16	62.58	NO
SARIMA(1,1,0)(1,1,2)12	-68.39	-53.57	NO	SARIMA(1,1,1)(1,1,2)12	-85.29	-67.51	NO
SARIMA(2,1,0)(0,1,1)12	-71.26	-59.41	NO	SARIMA(1,1,2)(0,1,1)12	-80.12	-65.31	NO
SARIMA(2,1,0)(0,1,2)12	-73.04	-58.23	NO	SARIMA(1,1,2)(0,1,2)12	-81.86	-64.08	NO
SARIMA(2,1,0)(1,1,0)12	-66.23	-54.37	NO	SARIMA(1,1,2)(1,1,0)12	-74.28	-59.47	NO
SARIMA(2,1,0)(2,1,0)12	-73.52	-58.70	NO	SARIMA(1,1,2)(2,1,0)12	-82.19	-64.41	NO
SARIMA(2,1,0)(2,1,1)12	-71.57	-53.79	NO	SARIMA(1,1,2)(2,1,1)12	-80.48	-59.74	NO
SARIMA(2,1,0)(2,1,2)12	-72.01	-51.27	NO	SARIMA(1,1,2)(2,1,2)12	-81.34	-57.64	NO
SARIMA(2,1,0)(1,1,1)12	-71.56	-56.75	NO	SARIMA(1,1,2)(1,1,1)12	-80.51	-62.73	NO
SARIMA(2,1,0)(1,1,2)12	-74.01	-56.24	NO	SARIMA(1,1,2)(1,1,2)12	-83.32	-62.58	NO