Time series analysis of road traffic accident in Rivers State, Nigeria

[*1]Owunari S. Davies Ette H. Etuk[1] E. Amos[1]
[1]Department of Mathematics
Rivers State University, Port Harcourt
***Correspondence to Owunari D. Email: owunaridave@gmail.com**

Abstract

Background: Transport plays a significant role in the activities of man. Increase usage of road transport raises the likelihood of the occurrence of road traffic accident (RTA). Road accidents are considered major causes of death in the world today and thus are major health challenges all over the world. Accidents on our roads are serious problems that need attention. Road traffic accidents would increase in number if tangible efforts are not made to tackle the problem.

Objectives: The aim of the study is to fit a statistical model that would describe the accident data of Rivers State, Nigeria.

Methodology: Monthly road accident data for eight years beginning from January 2010 to December 2017 collected from the Federal Road Safety Corps, Rivers State Served as the data for the analysis. Box-Jenkins methods were employed in the analysis and the statistical software used was Eviews.

Results: The study revealed that there was no seasonality in the data. This is contrary to the belief that accidents in this part of the world are seasonal with higher occurrences in the months of September, October, November and December. The implication is that road accident within the study area occurs any time in the year and not only during specific seasons.

Conclusion: The data can be modeled using Box-Jenkins methods. The ARIMA (2,1,0) model is adequate to describe the RTA data of Rivers State, Nigeria.

Unique contribution: An ARIMA model for the RTA data of Rivers State was developed. The study revealed that the RTA data of Rivers State is non-seasonal contrary to the general belief that accidents are seasonal.

Key recommendation: Further studies should be examined to determine while road accident still occur despite government efforts.

Keywords: Road traffic accident; ARIMA model; autoregression; autocorrelation; moving average; transport.

Introduction

Transport plays a significant role in the daily activities of man. There are four main forms or means of transport namely; road transport, air transport, rail transport and water transport. Of these forms of transport, the most popular is road transport. As a country develops, it becomes more motorized, as a result more persons are expected to use road transport. This increase in the usage of road transport raises the likelihood of road traffic accident occurrence. Road traffic accidents are serious problems facing mankind today. Among all types of accidents, those caused by motor vehicle claim the largest number of lives and are likely to be the most serious (Norman, 1962). Road traffic accidents are major causes of injury and death around the world and a major public health problem (Peden *et al*., 2004). The number of road traffic deaths continues to rise steadily, reaching 1.35 million in 2016 (WHO, 2018). These numbers could rise in the future if nothing is done to check the trend. The World Health Organization (WHO) forecasts that persons killed in road traffic accidents would rise to about 2 million by 2020 if tangible efforts are not made to tackle the problem (WHO, 2015). Road traffic accidents are the concern of all governments of the world as they have enormous physical, emotional and economic implications. They can result to human and economic loss. The situation in Nigeria is not better.

Objectives

The aim of this paper was to use statistical methods to model the frequency of occurrence of road traffic accidents in Rivers State. The specific objectives are:

i. To identify patterns of the accident data over the period 2010-2017
ii. To develop a suitable time series forecasting model to fit the accident data in Rivers State over the period 2010-2017.

Justification for the study

There are safety strategies being put in place by the Nigerian Government to check the menace of road traffic accidents through its agencies. For these strategies to be effective continuous researches on the Road Traffic Accident (RTA) cases as well as on the implementation of the strategies need to be carried out. Therefore, considering the importance of the road and the increased level of road traffic accidents in recent years, there is the need for this study which aimed at obtaining a model which would show the pattern of road traffic accidents. This would provide an parameter for assessing the effectiveness of current strategies for reducing accidents on our roads and for the development of new strategies where necessary by those responsible for maintaining safety on our roads.

Literature review

Iwok (2016) modeled monthly road traffic accidents data in Port Harcourt, Nigeria, and found that seasonal-ARIMA model fitted the data. Emenike and Kanu (2017) examined how road traffic accidents can be caused by drivers distraction in Port Harcourt. The study revealed that the use of mobile phones and gadgets in vehicles were responsible for most accidents involving commercial drivers. Afere *et al*., (2015) used smoothing models to forecast monthly occurrence of fatal road accidents in Ondo State, Nigeria. Two cases were considered, the total cases reported and the number of deaths from accidents. A steady increase as a result of long term effects on road accident were observed for the two cases. A simple exponential smoothing model was observed to fit both cases. Balogun *et al*., (2015) employed time series approach to study the road accident data in Nigeria between 2004 and 2011. ARIMA (3,1,1) and MA (0,1,2) gave the best models that fit the accident cases in Nigeria. Atubi and Gbadamosi (2015) conducted a study to examine the universal positioning and the effects of road traffic accident in Nigeria. They concluded that applying the safety measures applied by countries that have had success in the reduction in the number of crashes and casualties can produce similar results as road accidents are predictable as well as preventable. Abdulkabir *et al*., (2015) studied the pattern of incidence of accident in Ibadan, Nigeria. Their analysis showed that the trend was upward. Sanusi *et al.*, (2016) used time series approach to produce suitable time series model that best described the road accident data for Nigeria for the period 1960 to 2013. The data were divided into four groups. Oyenuga *et al*., (2016) analyzed the pattern of monthly road accidents data along Oyo-Ibadan express road between 2004 to 2014. They employed moving average method to decompose the time series using additive model approach. From the result they observed that accidents and deaths were higher at festive periods. Oreko and Okiy (2017) employed intervention theoretical model technique to examine the performance of the government of Nigeria on the reduction of road accidents. Intervention measures can reduce the accident casualties in Nigeria, the study showed. Aluko (2018) studied the characteristics of victims of road accident data in Ado-Ekiti, Nigeria. A greater number of persons involved in road accidents were in the productive age, the study revealed. Al-Zyood (2017) conducted a study to seek the best ARIMA model for the forecast of car accident in Sandi Arabia. ARIMA (1,0,0) was found to be an appropriate model for the data. The model predicted an increasing trend for death and injuries from accidents in the future. Ahmed *et al.* (2017) carried out a comparative study of the road traffic accident situation of Algeria on the one hand and those of the Arab countries and the developed world on the other hand. The study revealed that the incidence of road traffic accidents in Algeria is on the increase and exceeded those recorded in some developed countries and other Arab countries. Human factor was observed to be mainly responsible for these accidents. Agyemang (2018) carried out a survey on seat belt usage in Accra. Safety and compliance with traffic regulation was established as the reason for high number of persons using seat belt. While the non-use of seat belt was attributed to discomfort and forgetfulness. Alsaeed *et al.* (2018) carried out a study on drivers' ability to be of assistance in case of road accidents in Al-Ahsa, Saudi Arabia between March and May, 2017. The findings revealed that there was insufficient experience among the participants to render assistance when they meet a scene of road accident.

Theoretical background

A succession of observations or measurements recorded a they occur in time is called a time series. When the observation or measurements are taken on the same variable, we have a univariate time series. While a multivariate time series involves measurements or observations on more than one variable. The measurements or observations are usually made at regular intervals of time. The observations must be listed in accordance with the time of occurrence as any change in this order would result to a different data because of the dependency in the data.

Time series analysis is used to obtain a model that describes adequately the important features of the series being analyzed. The model can be used to forecast future values of the series and as well as serve as a control standard. In time series analysis, some aspects of the past pattern are expected to continue to the future.

There are four basic components of time series namely trend (T), seasonal variations (S), cyclical variations (C) and irregular variations (I).

Let $X_1, X_2, X_3, .., X_t,$ be a time series. The lag operator L is given by

$$LX_t, = X_{t-1} \tag{1}$$

The back shift operator B is expressed as $BX_t = X_{t-1}$

The first order ordinary difference is given as

$$\nabla X_t = X_t - X_{t-1} = (1-L)X_t = (1-B)X_t \quad (2)$$

The dth order ordinary difference is given by

$$\nabla^d X_t = (1-L)^d X_t = (1-B)^d X_t \quad (3)$$

The autocorrelation function (ACF) which defines the correlations between the series and lagged values of the series is given as

$$ACF\ (h) = \frac{covariance\ (X_t,\ X_{t-h})}{Std.dev.(X_t)Std.dev.(X_{t-h})} \quad (4)$$

The ACF is useful in the identification of the structure of the series data. The partial autocorrelation function (PACF) is a correlation between two variables conditioned under the assumption that other related variables are taken into account. The PACF is also useful in the identification of the structure of the time series data.

Models of time series may have many forms depending on the stochastic processes involved. In modeling variations in the level of a process one of the following broad classes may be used, that is, the autoregressive (AR) models, the moving average (MA) models, and the integrated (1) models. In these models, observations have a linear dependence on previous observations. When these broad classes are combined, the results are the autoregressive moving average (ARMA) and autoregressive integrated moving average (ARIMA) models. The ARIMA model building process usually follows the Box-Jenkins method, which is mainly employed in this paper. The Box-Jenkins method consists of three steps iterative cycle which are model identification, model estimation, a diagnostic check for model adequacy followed by forecasting with the best model obtained. In some cases we may have more than one adequate model. The best out of these competing models is selected using any of the following: the mean square error (MSE), the Akaike information criteria (AIC), the corrected Akaike information criteria (BIC), and the number of model parameters. Lower values of MSE, AIC, AIC, and BIC are favourable. The principle of parsimony favours models with fewest parameters.

A stationary time series $\{x_t\}$ is said to follow an autoregressive moving average of orders p and q written as ARMA (P, q) if it satisfies the following equation

$$X_t - \propto_1 X_{t-1} - \propto_2 X_{t-2} - \cdots \propto_p X_{t-p} = \varepsilon_t - \gamma_1 \varepsilon_{t-1} - \gamma_2 \varepsilon_{t-2} - \cdots \gamma_q \varepsilon_{t-q} \quad (5)$$

Where $\{\varepsilon_t\}$ is called white noise and is a sequence of random variables with zero mean and constant variance.

A process X_t is said to be ARIMA (p,d,q) if

$$\nabla^d X_t = \text{ARMA (p,q)} \quad (6)$$

Where
$\nabla = 1 - B$ and $BX_t = X_{t-1}$

Materials and methods

A secondary data which comprises eight years of monthly RTA cases for the period 2010 to 2017 were collected from the Federal Road Safety Corps, Rivers State, Nigeria. There are 96 data points. In analyzing the data, Eviews was used. The model building process followed the Box-Jenkins method.

A time plot of the data is observed for stationarity, trend and seasonality. The autocorrelation function (ACF) of the data is observed for stationarity. Augmented Dicky Fuller (ADF) test, Phillips and Perron (PP) test, and Kwiatkowsky, Phillips, Schmidt and Shin (KPSS) test can be carried out to determine if the series is stationary. A stationary series is one whose ACF decrease quickly to zero while a non- stationary series has an ACF that does not decrease fairly quickly to zero or decays slowly. A non-stationary series needs to be transformed to a stationary one before it is analyzed. Transformation may involve ordinary differencing, seasonal differencing, taking the logarithm or square root of the original series, including taking the growth rates.

Transformation to a stationary series from a non-stationary series in the Box-Jenkins method is done by differencing. The number of times a series needs to be differenced to achieve stationarity gives the value of d. for a series that needs to be differenced once, d equals 1. It is 2 if the series needs to be difference twice, and so on.

Determination of the Orders d, p and q: Time plot of the original series data would indicate if the series is stationary. A non-stationary series is subjected to differencing process to remove non stationarity. To avoid unnecessary model complexity the order of differencing is limited to 2. On obtaining the stationary series, the ACF and PACF plot are then observed to obtain the parameters q and p respectively of the model.

Model Estimation: A nonlinear iterative process in the estimation of the model parameters is required in an ARIMA model when white noise terms are present. Eviews software is used in the estimation process. Eviews employs the least squares approach involving nonlinear iterative techniques for the estimation process.

Diagnostic Checking: The fitted model is tested for goodness of fit. A model will be accepted if the residuals of the fitted model have autocorrelations that are not significant at all lags. The Ljung Box-Pierce statistics must have all p-values above 0.05.

Results and discussion

Results

Figure 1 shows the time plot of the original series RTA before it was differenced. The plot shows an overall decreasing trend. This is an indication of a non-stationary data. Table 1 shows the correlogram of the accident data before differencing. The plot of autocorrelation function and partial autocorrelation function against time lag is given in the figure. The autocorrelation function decreases rather slowly to zero. Table 2 gives the ADF test result of the original series. The test is used to determine the presence of unit root in a time series.

Figure 2 gives the time plot of the series obtained after taking a first difference of the original data series. This is a plot of the first difference against time. Table 3 shows the result of the ADF test of the first difference series. While Table 4 gives the ACF and PACF plot of the first difference series at various time lags. The table gives the Q-statistics of the series as well. Table

5 gives the AIC values of the suggested models. These values are used to select the best model amongst the suggested models. Table 6 shows the parameter estimates of ARIMA (2,1,3) model. The unknown model parameters are obtained from this table. Table 7 shows the residual correlogram of the ARIMA (2,1,3) model. The ACF, PACF and Q-statistics of the residuals of the ARIMA (2,1,3) model are given in this table.

Discussion

The time plot of the original series RTA before it was differenced is shown in Figure 1. The figure shows an overall decreasing trend. There was an initial increasing trend up to the end of the year 2013 and thereafter a decreasing trend followed. The time plot indicates that the series is not stationary. There was an increasing trend initially up to the end of 2013 and thereafter the series began to show a decreasing or downward trend. This may be as a result of intervention measures applied by government agencies to the RTA problem. Table 1 shows the correlogram of the original series RTA before differencing. The initial autocorrelations are persistently large and decreases to zero rather slowly, which is the behavior of a non stationary series. The ACF further indicated that the series is non seasonal as there are no significant values of autocorrelations at lag 12 and multiples of lag 12. The result of the augmented dickey-fuller (ADF) test given in Table 2 further confirms that the series is not stationary. Results in the table reveal that the test statistic is -1.686598 and is less in absolute value than the absolute critical value at 1%, 5% and 10%. Also the p-value which is 0.4847 is greater than $\propto = 0.05$. Thus the series RTA is confirmed not stationary. Figure 2 shows the time plot of the first difference of the original series RTA. From the figure it is seen that the observations move irregularly but revert to its mean value and variability is also approximately constant. The time plot of the first difference series DRTA suggest a stationary series. The result of the ADF test given in Table 3 confirms that the series DRTA is stationary. The value of the ADF test is – 13.76301 which is greater than absolute critical value at 1%, 5% and 10% and the p-value is 0.0001 much lower than all critical value. Thus the series DRTA is stationary. The ACF of the series DRTA further confirms that stationarity has been achieved.

Since we have to take the first difference to make the original series RTA stationary our value for d is 1. The values of q and p in the ARIMA model are obtained from the ACF and PACF plots respectively of the stationary series DRTA. This is shown in Table 4. From the table, the only significant autocorrelations in the ACF plot are at lags 1,3 and 8 indicating MA (1) MA (3) and MA (8) behaviors. Also a look at the PACF plot indicates that the only significant partial autocorrelations are at lags 1 and 2 suggesting AR (1) and AR (2) behaviors. By applying the principle of parsimony AR(2) and MA(3) were selected. We then suggested different models and the best out of these suggested model was selected using the AIC criterion. The suggested models are ARIMA (2,1,3), ARIMA (2,1,2) ARIMA (2,1,1) and ARIMA (2,1,0).

The AIC values are given in Table 5. The ARIMA (2,1,3) model had the least AIC values and is chosen as the best model. The parameters estimate of the selected model is given in Table 6 and the diagnostic check of the model is given in Table 7. The residuals show no significant autocorrelations at all lags. Furthermore, the Q statistic show that there is no dependency among the residuals. Thus, the model is acceptable and can be used to make forecast.

ARIMA (2,1,3) model is the best model for forecasting road accidents in Rivers State. This is a non-seasonal autoregressive integrated moving average series with two AR terms and three MA terms. The model in terms of the differenced series DRTA (X_t) is given as

$$X_t = \propto_1 X_{t-1} + \propto_2 X_{t-2} + \varepsilon_t - \gamma_1 \varepsilon_{t-1} - \gamma_2 \varepsilon_{t-2} - \gamma_3 \varepsilon_{t-3} \quad (7)$$

The point estimate of each parameter of ARIMA (2,1,3) from table 4 are

$\widehat{\propto}_1$ = - 0.97 2501, $\widehat{\propto}_2$ = - 0.974786, $\hat{\gamma}_1$ = 0.420601

$\hat{\gamma}_2$ = 0.297310 and $\hat{\gamma}_3$ = - 0.653915

Only the estimates $\widehat{\propto}_1$ and $\widehat{\propto}_2$ are significant and so are retained while all others are dropped. Thus, the fitted ARIMA model for the road traffic accidents in Rivers State from 2010 to 2017 is ARIMA (2,1,0) model given by

$$X_t = -0.972501\, X_{t-1} - 0.974786 X_{t-2} + \varepsilon_t \quad (8)$$

And in terms of the observed series it becomes

$$y_t - y_{t-1} = 0.972501\,(y_{t-1} - y_{t-2}) - 0.974786\,(y_{t-2} - y_{t-3}) + \varepsilon_t \quad (9)$$

$$y_t = 0.027499\, y_{t-1} - 0.002285\, y_{t-2} + 0.974756\, y_{t-3} + \varepsilon_t \quad (10)$$

Equation 10 shows that the number of accidents at the present time is predicted using the values at the past first three periods and the value of the present error.

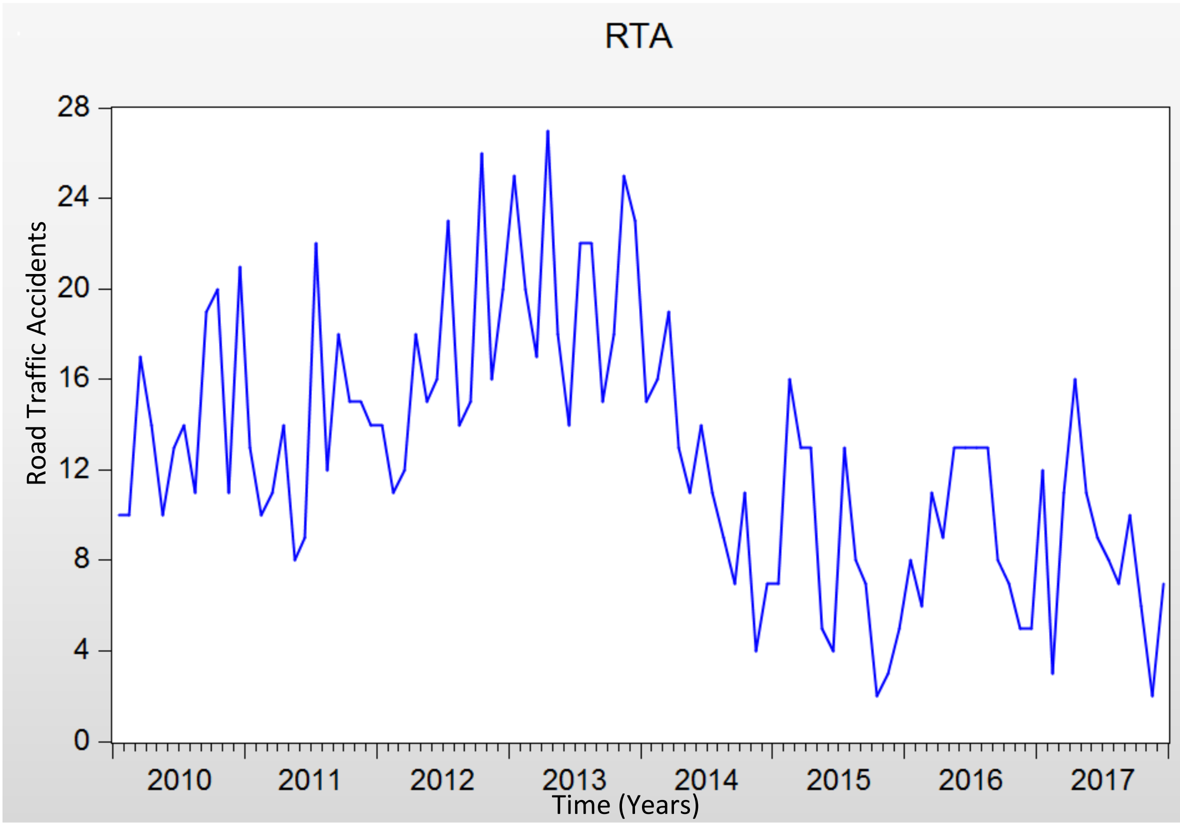

Figure 1: Time plot of road traffic accident in Rivers State from 2010 to 2017

Table 1: ACF and PACF of road traffic accident data in Rivers State.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.580	0.580	33.278	0.000
		2	0.483	0.222	56.667	0.000
		3	0.603	0.406	93.480	0.000
		4	0.466	-0.012	115.64	0.000
		5	0.341	-0.085	127.65	0.000
		6	0.427	0.112	146.70	0.000
		7	0.374	0.015	161.47	0.000
		8	0.276	-0.012	169.59	0.000
		9	0.424	0.242	189.04	0.000
		10	0.394	0.031	206.02	0.000
		11	0.322	0.047	217.52	0.000
		12	0.360	-0.030	232.02	0.000
		13	0.311	-0.110	242.95	0.000
		14	0.198	-0.110	247.45	0.000
		15	0.236	0.015	253.94	0.000
		16	0.175	-0.096	257.52	0.000
		17	0.082	-0.027	258.32	0.000
		18	0.083	-0.093	259.16	0.000
		19	0.029	-0.142	259.26	0.000
		20	-0.011	-0.034	259.27	0.000
		21	0.035	0.033	259.43	0.000
		22	-0.030	-0.100	259.54	0.000
		23	-0.097	-0.047	260.75	0.000
		24	0.042	0.182	260.98	0.000
		25	0.025	0.084	261.06	0.000
		26	-0.066	0.012	261.64	0.000
		27	-0.022	-0.032	261.71	0.000
		28	-0.038	-0.042	261.91	0.000
		29	-0.126	0.008	264.12	0.000
		30	-0.106	-0.010	265.72	0.000
		31	-0.091	0.031	266.92	0.000
		32	-0.183	-0.005	271.83	0.000
		33	-0.163	-0.042	275.82	0.000

Table 2: ADF Test for the Original Accident Data, RTA

Null Hypothesis: RTA has a unit root
Exogenous: Constant
Lag Length: 2 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.686598	0.4347
Test critical values:	1% level	-3.502238	
	5% level	-2.892879	
	10% level	-2.583553	

*MacKinnon (1996) one-sided p-values.

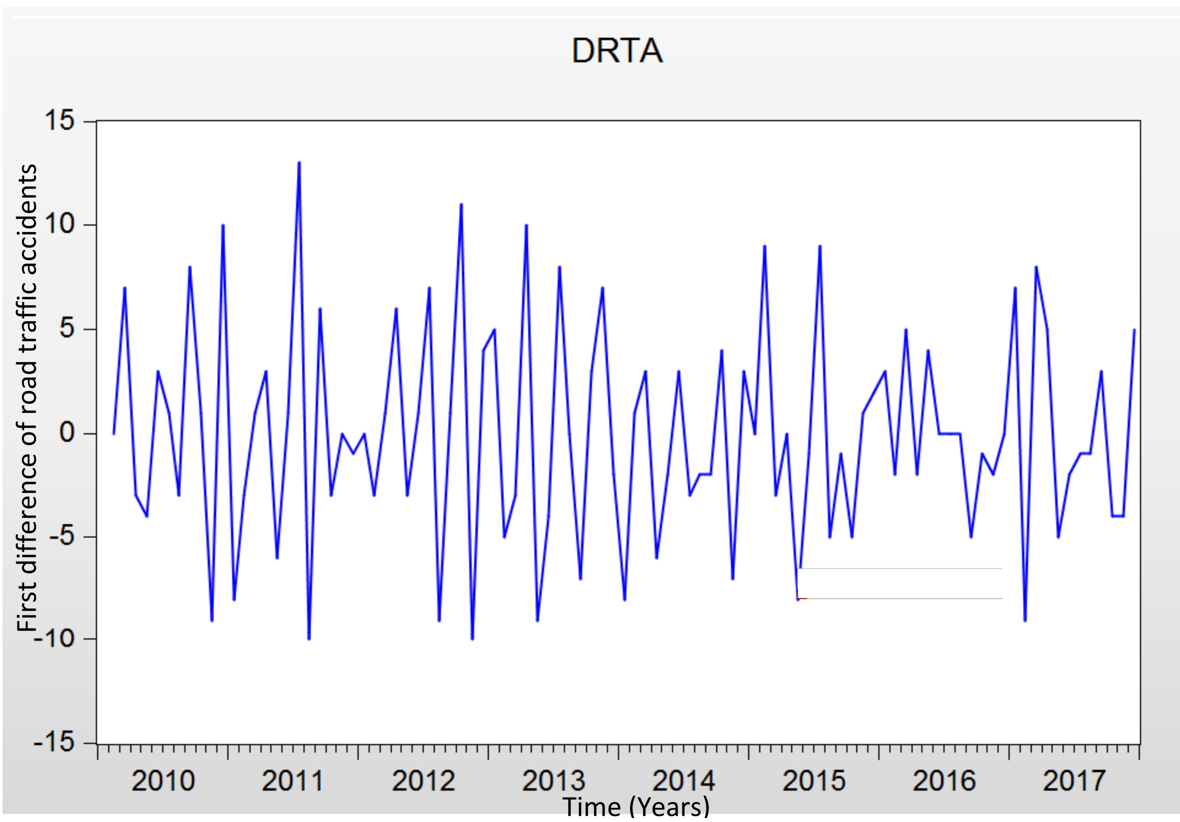

Figure 2: Time plot of the first difference series.

Table 3: ADF Test for the First Difference Series DRTA.

Null Hypothesis: DRTA has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-13.76301	0.0001
Test critical values:	1% level	-3.502238	
	5% level	-2.892879	
	10% level	-2.583553	

*MacKinnon (1996) one-sided p-values.

Table 4: ACF and PACF of the differenced series

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.403	-0.403	15.924	0.000
		2	-0.245	-0.486	21.858	0.000
		3	0.317	-0.040	31.924	0.000
		4	-0.027	0.044	31.997	0.000
		5	-0.249	-0.152	38.365	0.000
		6	0.172	-0.063	41.416	0.000
		7	0.056	-0.016	41.739	0.000
		8	-0.278	-0.235	49.932	0.000
		9	0.205	-0.036	54.456	0.000
		10	0.022	-0.079	54.510	0.000
		11	-0.101	0.023	55.628	0.000
		12	0.080	0.061	56.343	0.000
		13	0.073	0.084	56.945	0.000
		14	-0.177	-0.064	60.489	0.000
		15	0.126	0.058	62.317	0.000
		16	0.043	0.024	62.529	0.000
		17	-0.113	0.075	64.027	0.000
		18	0.081	0.120	64.804	0.000
		19	-0.028	0.001	64.897	0.000
		20	-0.106	-0.097	66.279	0.000
		21	0.134	0.046	68.523	0.000
		22	-0.008	-0.011	68.532	0.000
		23	-0.246	-0.230	76.269	0.000
		24	0.183	-0.153	80.598	0.000
		25	0.080	-0.066	81.437	0.000
		26	-0.163	-0.027	84.994	0.000
		27	0.090	0.001	86.083	0.000
		28	0.086	-0.045	87.095	0.000
		29	-0.117	0.006	89.020	0.000
		30	-0.008	-0.050	89.028	0.000
		31	0.122	-0.023	91.171	0.000
		32	-0.115	0.005	93.120	0.000
		33	0.010	0.076	93.135	0.000
		34	0.039	0.028	93.365	0.000
		35	-0.007	0.141	93.373	0.000
		36	-0.066	0.019	94.045	0.000

Table 5: The Values of Accuracy Measure for Different ARIMA Models

ARIMA MODEL	AIC
ARIMA (2,1,3)	5.708732
ARIMA (2,1,2)	5.775603
ARIMA (2,1,1)	5.756180
ARIMA (2,1,0)	5.736362

Table 6: The parameter estimates of ARIMA (2,1,3) model

Dependent Variable: DRTA
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 12/24/19 Time: 22:07
Sample: 2010M02 2017M12
Included observations: 95
Convergence achieved after 71 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	-0.972501	0.031930	-30.45681	0.0000
AR(2)	-0.974786	0.027162	-35.88732	0.0000
MA(1)	0.420601	78.78002	0.005339	0.9958
MA(2)	0.297310	100.2505	0.002966	0.9976
MA(3)	-0.653915	181.6328	-0.003600	0.9971
SIGMASQ	14.69358	1472.595	0.009978	0.9921

R-squared	0.450200	Mean dependent var	-0.031579
Adjusted R-squared	0.419312	S.D. dependent var	5.197079
S.E. of regression	3.960323	Akaike info criterion	5.708723
Sum squared resid	1395.890	Schwarz criterion	5.870020
Log likelihood	-265.1643	Hannan-Quinn criter.	5.773899
Durbin-Watson stat	2.013873		

Inverted AR Roots	-.49-.86i	-.49+.86i	
Inverted MA Roots	.65	-.54+.84i	-.54-.84i

Table 7: ARIMA (2,1,3) residual correlogram

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.009	-0.009	0.0082	
		2	0.008	0.008	0.0143	
		3	0.090	0.090	0.8314	
		4	-0.033	-0.031	0.9394	
		5	-0.093	-0.096	1.8340	
		6	-0.120	-0.132	3.3303	0.068
		7	-0.030	-0.027	3.4252	0.180
		8	-0.092	-0.076	4.3280	0.228
		9	0.026	0.042	4.3985	0.355
		10	0.067	0.061	4.8798	0.431
		11	0.139	0.140	7.0093	0.320
		12	0.008	-0.018	7.0166	0.427
		13	0.081	0.049	7.7526	0.458
		14	0.021	-0.019	7.8029	0.554
		15	0.024	0.048	7.8703	0.642
		16	0.037	0.060	8.0271	0.711
		17	0.016	0.070	8.0570	0.781
		18	-0.104	-0.088	9.3413	0.747
		19	-0.122	-0.110	11.159	0.674
		20	-0.046	-0.076	11.423	0.722
		21	-0.088	-0.068	12.378	0.718
		22	-0.140	-0.146	14.838	0.607
		23	-0.175	-0.210	18.744	0.408
		24	0.050	-0.019	19.071	0.452
		25	0.079	0.068	19.899	0.464
		26	0.017	-0.010	19.939	0.525
		27	0.050	-0.036	20.278	0.566
		28	0.084	0.014	21.243	0.566
		29	-0.005	-0.003	21.247	0.624
		30	-0.061	-0.033	21.776	0.649
		31	0.062	0.103	22.333	0.670
		32	-0.068	0.036	23.005	0.685
		33	-0.046	0.075	23.322	0.717
		34	-0.004	0.077	23.324	0.762
		35	-0.010	0.028	23.339	0.801
		36	-0.114	-0.132	25.379	0.751

Conclusion

Road traffic accident is considered one of the leading cause of death in our world today and is thus a major health challenge. Therefore, every effort aimed at reducing ot preventing road accidents would be a welcome relief. This study is aimed at identifying the patterns of RTA in Rivers State and hence develop an ARIMA model that fits the data. The accident data displayed an initial upward trend up to the end of the year 2013. Thereafter, the data began to show a downward trend. The change in the direction of the trend may be as a result of intervention measures by government agencies. ARIMA modeling was done and ARIMA (2,1,0) best fitted the road traffic accident of Rivers State. The model is adequate to describe the RTA data.

Recommendations

Forecasting with ARIMA (2,1,0) model is recommend for the RTA cases in Rivers State. The study did not consider the fatalities, type of vehicle involved and causes of these accidents. These can be investigated in future studies.

The government should carry out continuous re-evaluation of the measures aimed at reducing road traffic accidents so as to make them more effective. Officials should be trained that would help government enforce relevant laws to prevent road accidents.

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