ASSESSMENT OF ROAD TRAFFIC CRASHES ALONG ABEOKUTA - SAGAMU HIGHWAY IN OGUN STATE, SOUTH-WEST NIGERIA USING ARTIFICIAL NEURAL NETWORK

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Abstract

The severity of injuries in motor vehicle crashes is of considerable interest to policy makers and safety specialists. Traffic safety has been recognized as an important issue due to the large economic and social impacts of road crashes. The contribution of this study lies in the development of Artificial Neural Network (ANN) model to analyze traffic accident data and to predict the death and injury severity of traffic accidents based on a 5-year traffic accident records along Abeokuta – Sagamu interchange axis obtained from the Federal Road Safety Corps (FRSC) Ogun State sector command. The output of the data processing revealed that72 people were killed while 609 were injured over the 5 years period of this study. Analysis of traffic accident data was performed using ARIMA (Autoregressive Integrated Moving Average) data-mining software to develop and validate the ANN model. ARIMA is implemented in four stages; Identification, Estimation, Diagnostics checking and Forecasting. There was a total of 242 Road Traffic Crashes (RTC) along the interchange for the entire duration of the study.

Keywords: Road Traffic Crashes, Artificial Neural Network, ARIMA Model

Introduction

The phenomenon and aftermath of traffic crashes have long been recognized as convoluted events involving interactions between numerous factors related to the driver, traffic characteristics, roadway characteristics, and the environment. Traffic accidents are one of the leading causes of auto accident-related deaths and injuries globally, resulting in an estimated 1.3 million fatalities and 50 million injuries per year, according to World Health Organization 2018 data (Zhang, 2019). Furthermore, they are among kids and teenagers aged 5 to 14 and 15 to 29 worldwide, it ranks second in terms of mortality. In the United States, fatality and injury rates for road traffic crashes have become a crucial subject. According to Insurance Institute for Highway Safety (IIHS), there was 34,439 fatal motor vehicle crashes in the United States in 2016, resulting in 37,461 fatalities out of which 1,450 occurred in North Carolina. 24% of these fatal crashes were alcohol-impaired driving crashes. A number of factors can potentially affect injury severity in a crash and alcohol consumption is one of them. Safety has always been a big concern for transportation engineers, transportation planners, safety agencies, Federal agencies, and State agencies. Given the importance of the safety concern, the study of motor vehicle crashes and factors affecting injury severity related to alcohol consumption is critical. Prior studies on alcohol-related motor vehicle crash and injuries focused mainly on alcohol consumption and injury severity while examining only a few variables such as gender, age, seat belt usage, etc. Numerous studies have focused on driver's injuries and factors influencing the severity of the injury. A number of statistical techniques and models have been used by researchers to analyse driver injury severity. The most commonly used models are multivariate logistic regression (Li, 2018; Yang, Y., *et al*, 2022), mixed logit (Fu and Sayed, 2021) and Probit models (Asare and Mensah 2020), used an ordered probit model to investigate the factors affecting driver injury severity at signalized intersections, toll booths and roadway sections in Central Florida. All models demonstrated the noteworthiness of variables like driver's age, seat belt usage, gender, vehicle speed and type of vehicle. Alcohol consumption, roadway lighting conditions, and roadway curves had a more significant influence on the severity of the crash. Ordered probit models were also used by Johnston *et al*. (2019) to examine the risk of different injury levels sustained in single-vehicle crashes, two-vehicle crashes, and all other crash types. The results suggests that pickups and Sport Utility Vehicles (SUV) are less safe than passenger cars in the event of a single-vehicle crash. However, pickups and SUV's are associated with less severe injuries for drivers and more severe injuries for occupants of the colliding vehicle, in the event of two-vehicle crashes. Similarly, Kockelman and Kweon (2002) applied an ordered probit model to investigate factors that can potentially contribute to older driver crash injury severity. Their results showed that older drivers were more likely to sustain severe injuries while driving intoxicated and the injuries would be severe while driving a farm vehicle as compared to other vehicle types. In terms of age (Li, 2018) used a multivariate unconditional logistic regression model to examine factors influencing the severity of motor vehicle traffic crashes involving elderly 3 drivers in Ontario. Their results revealed that medical and physical conditions of elderly drivers in the age group of 65–74, do not appear to be correlated to the risk of a fatality. Li and Kim (2000) found that older drivers are more prone to sustain severe injuries regarding health effects on crash rates. Lourens, *et al*. (1999) found that gender and level of education have no correlation to crash occurrence. They discovered that teenage drivers have the most involvement in crash rate per mile-driven and conclude that drivers with prior traffic violations will positively affect crash rates. Morgan and Mannering (2011) showed the impact of factors which influence single-vehicle crashes on injury severity. They used a mixed log it model approach to assess the impact of age, gender and other factors on crash severity in the event of a single vehicle crash that occurred on wet, dry and snow-covered roadway surfaces. The research also showed that drivers of varying ages and gender react differently to pavement-surface conditions which have significant safety implications. Multinomial logit models or ordered probit models were commonly used by researchers in most of the prior studies where the dependent variable carried high discrete values. Moghaddam, Afandizadeh, and Ziyad (2010) apply a series of artificial neural networks to estimate crash severity as well as determine the significant factors impacting crashes on urban highways. Their results showed that the width of the highway, head-on-collision, following distance, avoiding lateral clearance, failure to control the vehicle, speeding, and deviation to the left by drivers are significant factors which increase crash severity on urban highways. Another relevant study was done by Abdelwahab and Abdel-Aty (2001) where they used a multi-layer perceptron (MLP) neural network to model two-vehicle crashes that occurred at signalized intersections. Their results demonstrate that, with respect to injury severity, rural roads are more dangerous than urban roads. Their results suggested that female drivers are more susceptible to injuries than male drivers. They also found that seat belt usage decreases the rate of injury severity and drivers in passenger cars are more likely to incur severe injuries as compared to other vehicle types. Abdelwahab and Abdel-Aty (2001) also use a multi-layer perceptron and a radial basis function neural network and compared it with calibrated logit models to evaluate the impact of Electronic Toll Collection (ETC) systems on highway safety and the traffic safety of toll plazas. The analysis investigates the locations in respect of the toll plaza structure and driver's injury severity. The comparison of both the models reveals that heavy-duty trucks, as well as vehicles which have ETC devices, are at a greater risk of crashes. Drivers who are ETC users also have higher likelihood of being injured in a crash. The results also differ in age and gender. Older and female drivers are more susceptible to severe injuries than younger and male drivers. A series of artificial neural networks were used by Delen, et al. (2006) to identify potential non-linear relationships between crash-related factors and injury severity levels. A sensitivity analysis was performed to identify the percentage of important crash-related factors. The results mainly state the change in the importance of crash factors with rising injury severity levels.

There are very few studies that have used artificial neural networks to model crash severity. The objective of this study lies in the development of Artificial Neural Network (ANN) model to analyze traffic accident data and to predict the death and injury severity of traffic accidents based on a 5-year traffic accident records along Abeokuta – Sagamu interchange axis

Materials and Methods

Study Area Map

The study area lies between latitudes 7.1475^0 N & 6.8322^0 N and longitude 3.3619^0 E & 3.6319^0 E as shown in Figure 1.

Figure 1: Map of the study Area

Data Collection

The road accident data were collected from Ogun State sector command which is one of the state command under Federal Road Safety Corps (FRSC). FRSC is the leading agency in Nigeria in charge of National road safety effort. The data collected showed the number of people killed and the number of people that sustained injuries, the number of road traffic crashes, the probably causes of the Road Traffic Crash (RTC) and the location of the RTC for a 5 years duration starting from January 2015 to December 2019.

Method of Analysis

The method used in analysing road traffic crashes involves plotting the RTC against time and using moving average to observe the general trend of the number of death due to road accident over the years. Mann-Kendall was used to investigate if there is a trend in the RTC Abeokuta-Sagamu while Sen Slope was used to check the magnitude of the trend. Autoregressive Integrated Moving Average (ARIMA) model was used to model the RTC.

ARIMA Model Development

The time series model building process using ARIMA model adopts the Box-Jenkins (Fattah, *et* al, 2018) approach. Figure 2, shows the methodology used in developing ARIMA models for time series data. ARIMA is implemented in four stages; Identification, Estimation, Diagnostics checking and Forecasting. The first step requires identification of the type of ARIMA model to be used. This involves checking if the time series data need transformation in other to stabilize the variance, after which stationarity of the model is checked. Stationarity is checked by simply looking at the trend of the time series data or the plot of the Autocorrelation Function (ACF) or performing Augmented Dick Fuller test. Stationarity of the model is checked in other to known the degree of differencing to apply to the time series data. A stationary model should have a constant mean and variance overtime in the time series plot, while a non-stationary model shows that the mean is not constant.

The ACF plots are shown in Figure 3, for both a stationarity and a non-stationary time series models. The ACF plot is the traditional tool used for determining stationarity of a time series. If the ACF die quickly as shown in the left figure in Figure 3, then the time series is station, otherwise non-stationarity can be confirmed as shown in the right figure in Figure 3. The Augmented Dick Fuller test is a statistical test that verify the stationarity of a time series data. The hypothesis of the Augmented Dick Fuller test are:

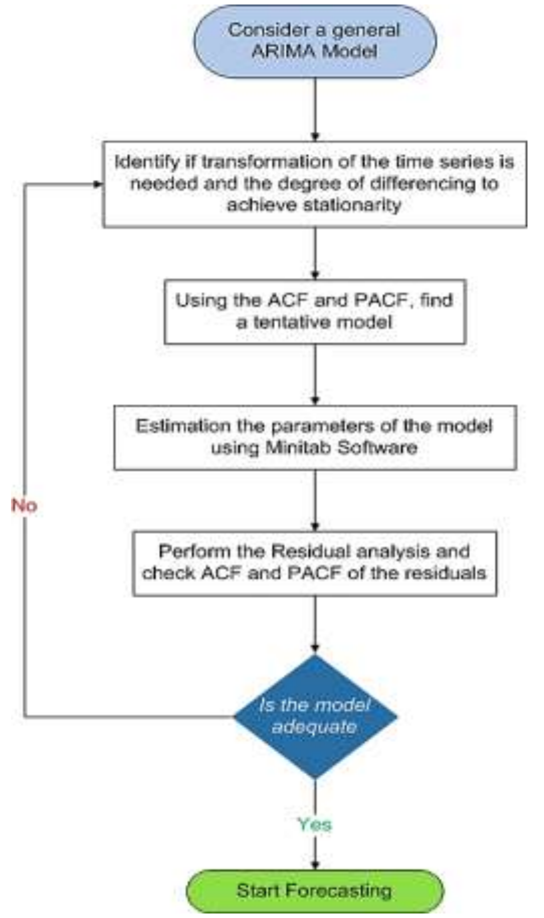

Figure 2: Stages of the time series model building process using ARIMA (Adapted from BJR, P18)

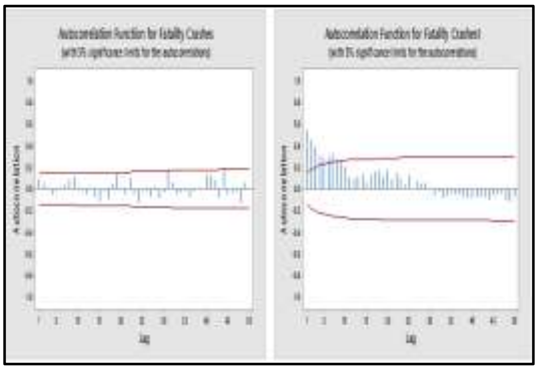

Figure 3: Autocorrelation plot of the original time series data

Null Hypothesis H_o : A unit root is present in the time series data.
Alternative H_1: No unit root is present in the time series data or the time series data is stationary.
If the p-value is less than the level of significance, then there is sufficient evidence to reject the null hypothesis and state that the time series is stationarity. If the p-value is greater than the level of significance, then one cannot reject the null hypothesis stating that the time series is non-stationary.
When non-stationary is confirmed in the time series, the time series are made stationary by differencing. Differencing is computed by subtracting the first time series data from the second time series data $(y_t - y_{t-1})$, after which the ACF is computed on the differenced data to check if stationarity has been achieved. If stationarity has not be achieved, we proceed to differencing the already differenced data and check if stationarity has been achieved. For most practical work, stationarity is achieved after the second difference. Once stationary has be achieved, then we proceed to identifying the best ARIMA model that would fit the time series data. Table 1, guide one in choosing a tentative model based on the ACF and Partial Autocorrelation Function (PACF) obtained after differencing.
With reference to Table 1, if the ACF plot look like a damped sine wave or decaying exponential function, then an Autoregressive (AR) model can be selected but if the PACF plot look like a decaying exponential function then a Moving Average (MA) model can be selected. The order of the moved for AR and MA are obtained by looking at the PACF and ACF plot respectively. If the PACF plot cuts off after certain lags, then the number of lags at which the PACF cut off will become the order, similarity with ACF when dealing with MA models. If the ACF and PACF plot have both components of AR and MA model then a full ARIMA model can be used as the tentative model.

Table 1: Summary of Properties of Autoregressive (AR), Moving Average (MA) and Mixed Autoregressive Moving Average (ARMA) process

	AR(p)	MA(q)	ARMA(p,q)
Model	$w_t = \phi_1 w_{t-1} + \ldots + \phi_p w_{t-p} + a_t$	$w_t = a_t - \theta_1 a_{t-1} - \ldots - \theta_q a_{t-q}$	$w_t = \phi_1 w_{t-1} + \cdots + \phi_p w_{t-p} - \theta_1 a_{t-1} + \ldots - \theta_q a_{t-q} + a_t$
Autocorrelation function (ACF)	Infinite; damped exponentials and/or damped sine waves; Tails off	Finite; cuts off after q lags	Infinite; damped exponentials and/or damped sine waves; Tails off
Partial autocorrelation function (PACF)	Finite; cuts off after p lags	Infinite; damped exponentials and/or damped sine waves; Tails off	Infinite; damped exponentials and/or damped sine waves; Tails off

Source: Adapted from BJR.

The second step after identifying the tentative model is to estimate the parameters of the model. The parameters of the model were estimated with statistical software known as Minitab Software. Figure 5 showed the interface of Minitab software. The input parameter needed for computation of the ARIMA model parameters are the time series data (number of road traffic crashes along Abeokuta-Sagamu Expressway), which will be inputted in the cells in the Minitab software. A dialog box of the ARIMA model which will be used for the estimation of the model parameter and can be prompted by clicking on Stat on the menu bar then clicking on Time Series before clicking on ARIMA on the drop down menu items. Further input parameters needed are the order of the AR, the order of MA and the differencing to be applied.

An important thing to note when developing ARIMA model using Minitab or any statistical package, is to uncheck the constant term in the model. stated that adding a non-zero intercept term to the model implies that there is an underlying deterministic first (linear) or second order polynomial trend in the data. A first or second order deterministic trend would require the process mean to evolve for future values according to a first or second order polynomial. In other words, the mean would never turn direction but continues to either increase or decrease. If the time series graph does not indicate a deterministic trend, then it is better to model the time series as a purely stochastic process. Therefore we can assume that the mean of the difference data and the "intercept" term is zero.

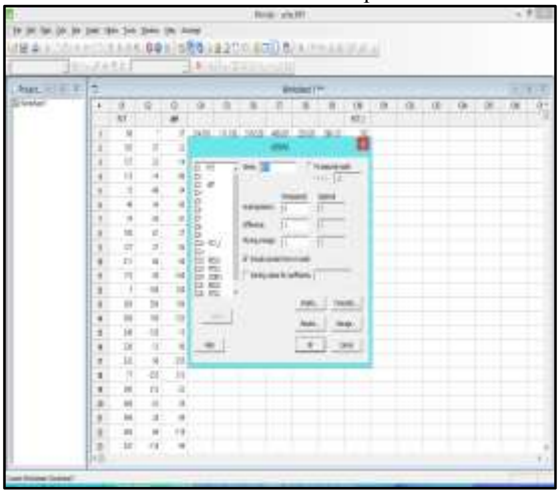

Figure 4: Interface of the Minitab Statistical software package

From this study, the model was developed as a purely stochastic process, due to the random occurrence of the number of road traffic crashes from year to year, therefore the include constant term was unchecked when developing the ARIMA model. The outputs obtained from Minitab software were the model coefficient, the Sum of Squared coefficient, T-statistic of the model coefficient, the p-value indicating if the model coefficient is required in the model. Other outputs obtained were the Modified Box-Pierce Chi-Square Statistic.

The third step involved performing residual analysis and checking the ACF and PACF plot of the residuals. The residual plot to be checked is the residual against the predicted/fitted values and the observation points. If the model is adequate, we expect that the residual plot against the predicted values should behave like a white noise. In other words, the residuals should not exhibit any patterns and they should be uncorrected with constant variance. The residual plot against the observation point should indicate randomness of the time series plot of the residual around the zero mean. Another important check is to see if the residuals violated the normality assumptions. It is expected that when the residuals are plotted on a QQ plot, that they should lie close to the upward sloping straight line. If this is the case, then normality is satisfied. The last check on the residual will be to compute the ACF and PACF on the residuals. The ACF and PACF plot should show that the ACF and PACF should not be larger than the 5% significant limits.

The fourth step involves using the model developed for prediction if all the check on the residual were satisfied. The study prediction will be done for year 2017 - 2020 to estimate the number of road traffic deaths that is expected from those years.

Results and Discussion

Trend Analysis for RTC along Abeokuta-Sagamu Expressway

Figure 5 shows the road traffic crashes along Abeokuta-Sagamu Expressway. It can be observed that the road traffic crashes fluctuated from months to month for the period under study. Ten RTC was recorded on May 2019, which was the highest recorded number of road traffic crashes for the period under study. The time series plot of the number of RTC showed a slight upward trend, indicating that the number of RTC might be on the rise. Mann Kendall statistic showed that the trend observed in the time series plot was statistically significant (p <0.0001) at level of significant of 5% (Table 2). The Sen Slope (0.0833) which indicates the magnitude of the trend confirmed that the trend of the road traffic crashes along Abeokuta-Sagamu Expressway is a positive trend.

Figure 6 show the distribution of road traffic crashes along Abeokuta-Sagamu Expressway. Figure 6 showed that the number of RTC per month have been on the rise since 2015. The year 2015 recorded the least mean RTC per month with just approximately 2 crashes happening per month in that year. An unusual high number of crashes were recorded on the month of June in 2015, which is shown on Figure 6 and indicated as an outlier in Figure 6. The highest number of crashes per month occurred in 2019 with a mean RTC value of 7. The RTC along Abeokuta-Sagamu Expressway from the duration of January 2016 to December 2019 has increased by over 250%. The result showed that little effort has been done in trying to reduce the number of road traffic crashes along Abeokuta-Sagamu Road.

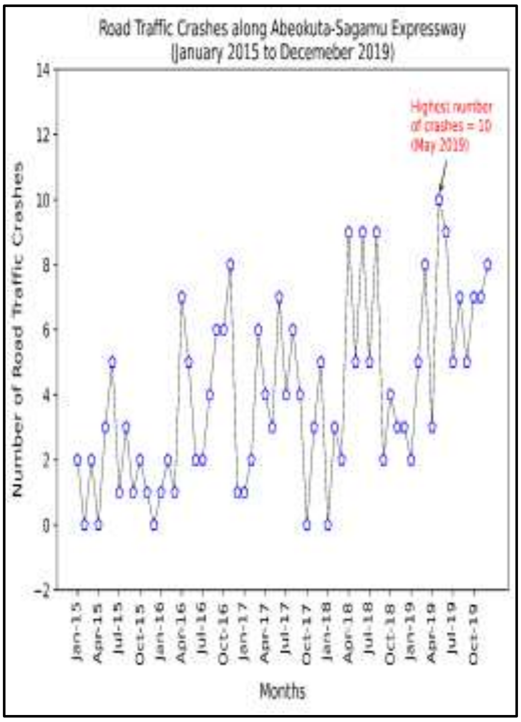

Figure 5: Road Traffic Crashes along Abeokuta-Sagamu Expressway

Table 2: Mann-Kendall and Sen Slope for RTC along Abeokuta-Sagamu Expressway

Kendall's tau	0.3960
S	667.0000
Var(S)	24212.3333
p-value (Two-tailed)	< 0.0001
Alpha	0.05

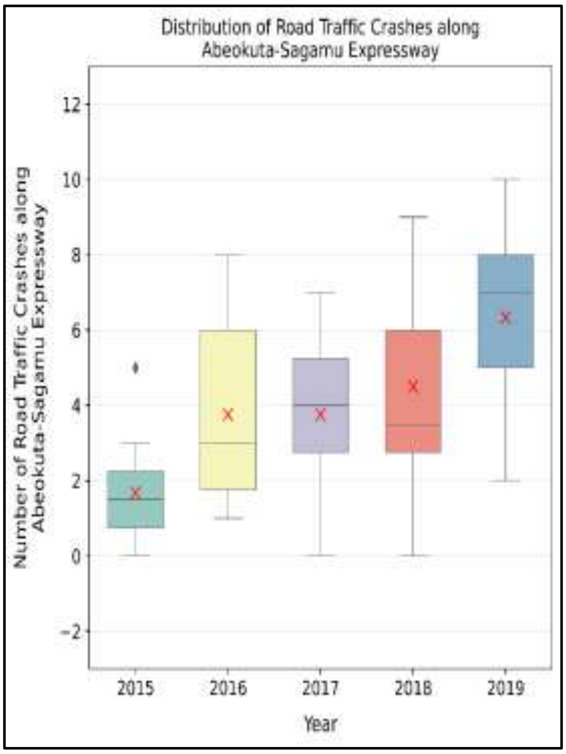

Figure 6: Distribution of Road Traffic Crashes

Geospatial Analysis of RTC along Abeokuta-Sagamu Expressway

Figure 7 shows the geo-spatial distribution of road traffic crashes along Abeokuta-Sagamu Expressway. It was observed that most of the road traffic crashes occurred at Kobape which is an area under Obafemi - Owode local government Area. A total of twenty four road traffic crashes occurred at Kobape and Buhari estate which are both located at Obafemi-Owode LGA, while a total of sixteen road traffic crashes occurred at Day Waterman and Siun LGA in the year 2019. The distribution of the road traffic crashes is shown in Table 3. The highest record of RTCs 42 (17.4%) was seen at Kobape followed by that observed at Buhari Estate zone 31 (12.8%), Day waterman area was 26 (10.7%), Siun was 25 (10.3%) while all the other twenty-nine locations were 118 (48.8%). The highest record of yearly RTCs was in 2019 which was recorded to be 77 throughout the year. Drivers causing accidents without stopping has been found to have major causes on the RTCs 58 (11.2%).

Very little RTA was recorded at Abeokuta, this may be attributed to the fact that since Abeokuta is located in a very densely populated area, the traffic build up in the city tend to make drivers reduce their speed. Also drivers tend to be more cautious when driving within Abeokuta due to the presence of more Police officers and traffic Police.

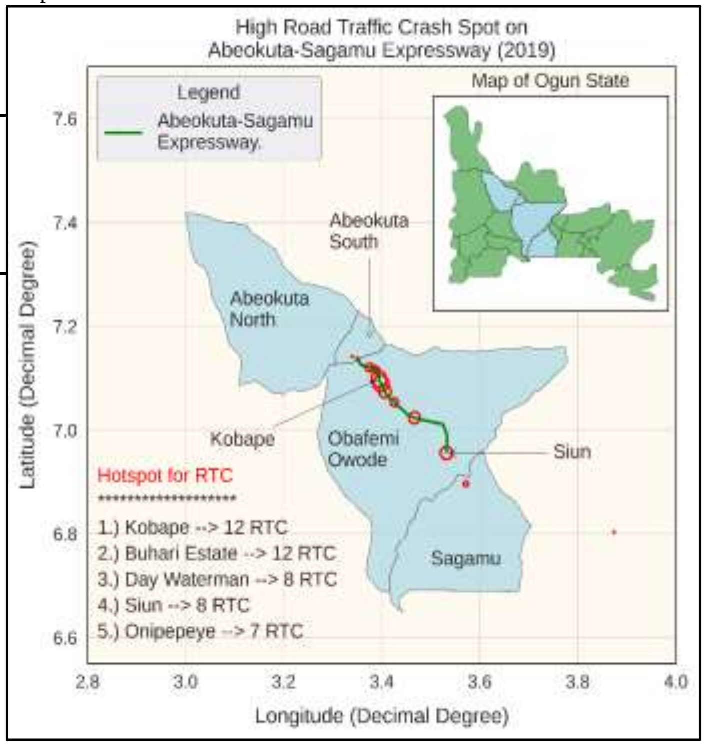

Figure 7 Geo-Spatial Analysis of Road Traffic Crashes along Abeokuta-Sagamu Expressway

Table 3: Distribution of Road Traffic Crashes along Abeokuta-Sagamu Expressway.

Latitude	Longitude	Location	RTC	LGA
7.098336	3.394336	Kobape	42	Obafemi-Owode
7.074252	3.406444	Day Waterman	26	Obafemi-Owode
6.955625	3.531764	Siun	25	Obafemi-Owode
7.089517	3.398574	Buhari Estate	31	Abeokuta South
-	-	Other 29 areas	118	Abeokuta South/Obafemi-Owode

Result from the ARMA Model

The result from the autocorrelation function and augmented Dick Fuller test are presented in Figure 8 and Table 4, respectively. Figure 7 showed that the autocorrelation for the RTC die after a few lag indicating that the RTC is stationary. (Onwunari, *et al*, 2019) stated that if a time series is non-stationary the ACF will not die quickly. The Augmented Dick Fuller test confirmed finding from the ACF graphs. Since the p-value (0.0137) was less than the level of significance of 5%, then there is sufficiency evidence to reject the null hypothesis which states that the RTC has a unit root, in other word that the RTC is non-stationary.

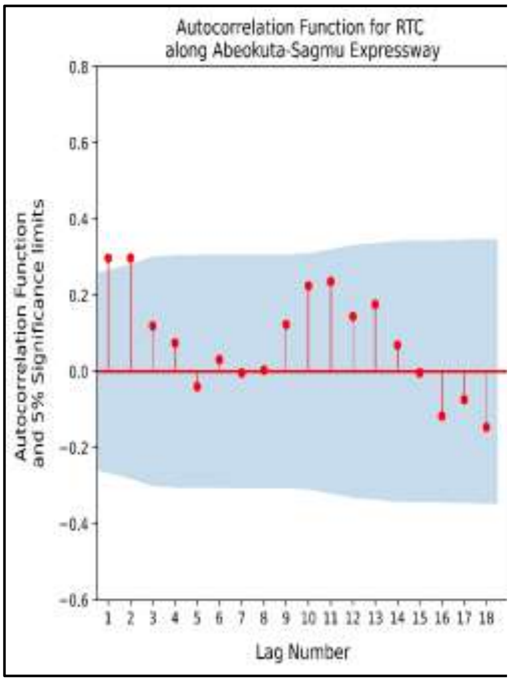

Figure 8: ACF for RTC along Abeokuta-Sagamu Expressway

Table 4: Augmented Dick Fuller Test for RTC along Abeokuta-Sagamu Expresway

Parameter	Values
Tau (Observed value)	-3.9814
Tau (Critical value)	-0.7343
p-value (one-tailed)	0.0137
Alpha	0.05

Since the RTC along Abeokuta-Sagamu is stationary, no differencing is required. In other to determine the type to time series model to fit on the data, the partial autocorrelation function was determined and the result is shown in Figure 9. The result from the ACF and PACF showed that it will not be easy to identify the particular ARMA model will fit the time series data. Due to the trend identified by Mann-Kendal, differencing of 1 was applied to the road traffic crashes to de-trend the data. Therefore various ARIMA (p, d, q) models was fitted and the best model was selected back on the lowest Bayesian information criterion (BIC). Table 5 shows the summary of the estimated model parameters.

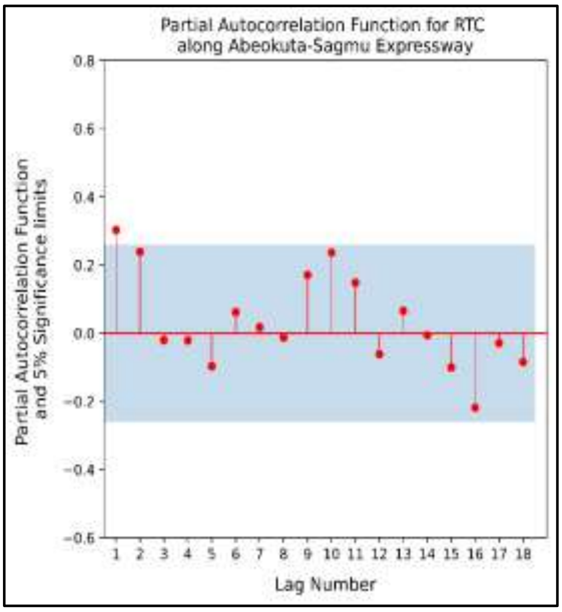

Figure 9: PACF for RTC along Abeokuta-Sagamu Expressway

The result of the various ARIMA (p,d,q) models developed is presented in Table 5 and the forecast RTC along Abeokuta-Sagamu Expressway is shown in Figure 10. Four ARIMA models were developed and the model parameters for the four models are shown in Table 5. From Figure 10, it was observed that ARIMA (0,1,1) and ARIMA (1,1,1) did not provide a good fit to the road traffic crashes. ARIMA (1,1,0) and ARIMA (2,1,0) showed relatively good fit to the time series data. From Table 5, it can be observed that for ARIMA (2,1,0) the p-value for the ar2 parameter (p-value=0.205) was not significant indicating that the ar2 component did not contribute to the prediction of the road traffic crashes and just the ar1 components contributed to the prediction of RTC. Looking at the AIC and BIC for ARIMA (1,1,0) and ARIMA (2,1,0) it can be observed that the AIC and BIC for ARIMA (1,1,0) was lower than the values for ARIMA (2,1,0). This showed that ARIMA (1,1,0) provided a good fit to the road traffic crashes time series data.

Table 5: Summary of Estimated Parameter coefficient for ARIMA model

Model	Parameters	Estimate	Standard error	t-value	P-value	AIC	BIC
ARIMA(1,1,0)	AR1	-0.5145	0.113	-4.540	0.000	277.42	283.49
	constant	0.0788	0.242	0.326	0.746		
ARIMA(2,1,0)	AR1	-0.6014	0.131	-4.598	0.000	277.80	285.90
	AR2	-0.1674	0.130	-1.284	0.205		
	constant	0.0794	0.205	0.388	0.700		
ARIMA(0,1,1)	MA1	-1.0	0.051	-19.775	0.000	264.50	270.58
	constant	0.0804	0.019	4.257	0.000		
ARIMA(1,1,1)	AR1	0.0936	0.134	0.699	0.487	266.01	274.12
	MA1	-1.000	0.049	-20.405	0.000		
	constant	0.0801	0.021	3.876			

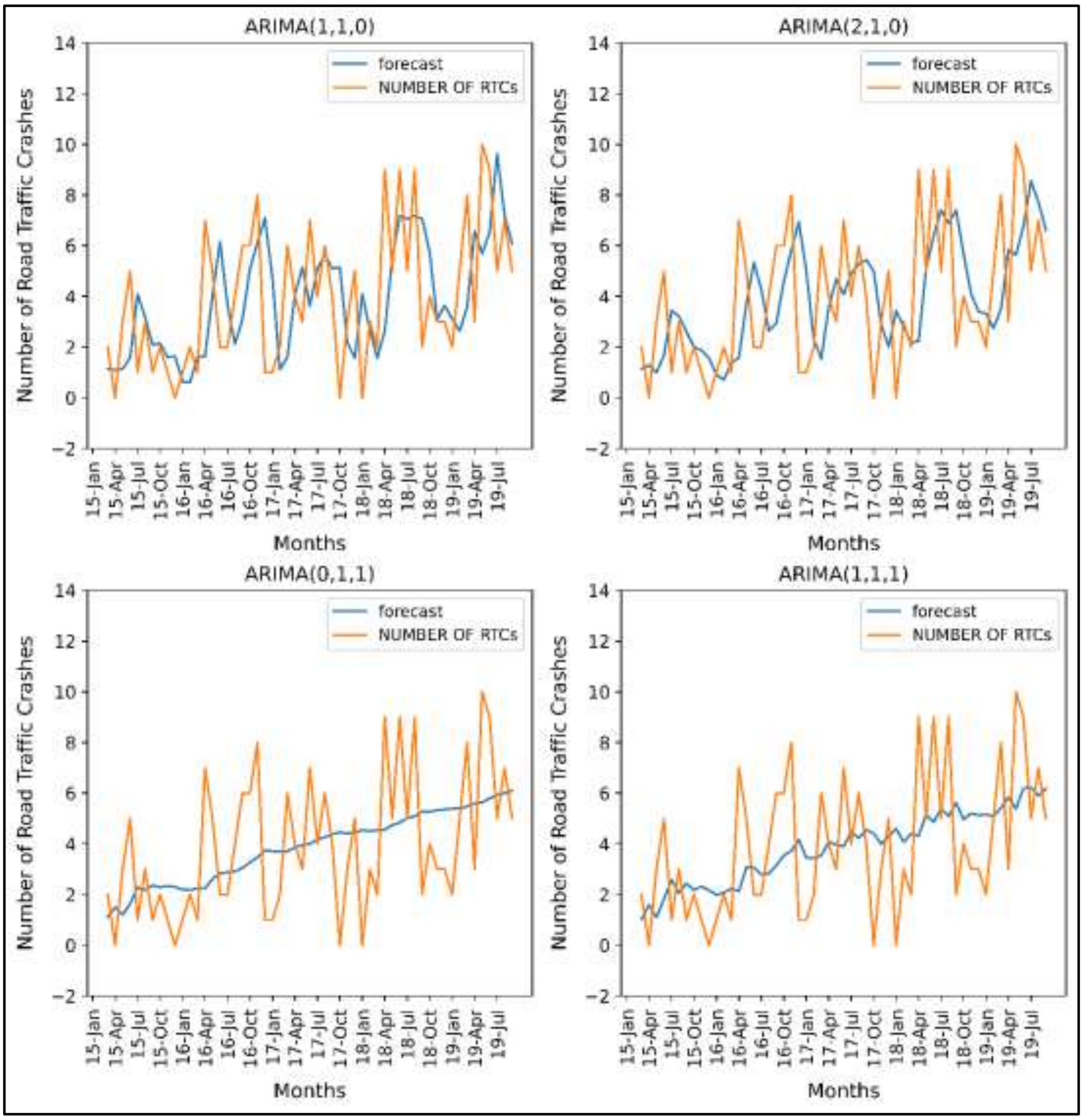

Figure 10:Actual against forecasted RTC along Abeokuta-Sagamu Expressway

The diagnostic plot for the road traffic crashes is shown in Figure 11. The residual plot showed that there was no systematic pattern and the residual were evenly distributed around zero and the autocorrelation plot showed that there was no autocorrelation at any lag that was significant since the autocorrelation value did not exceed the blue shaded area. This diagnostic plots confirms that ARIMA(1,1,0) is a reliable model that fit the time series data.

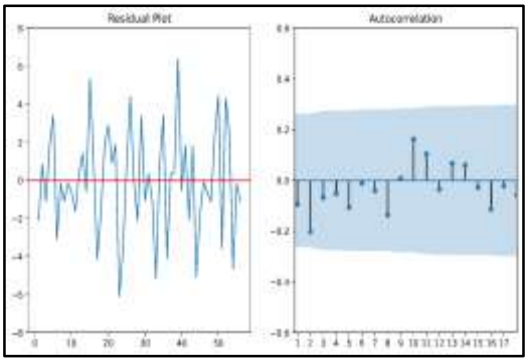

Figure 11: Diagnostic Plot of the Road Traffic Crashes

Conclusion

The processed data revealed that 72 and 609 people were killed and injured respectively within the 5 years period of the study. The following conclusions were drawn based on the results of the data analysis and evaluation conducted:

- There was a total of 242 RTCs along the interchange for the entire duration of the study.
- The highest record of RTCs 42(17.4%) was seen at Kobape followed by that observed at Buhari Estate zone 31(12.8%), Day waterman area was 26 (10.7%), Siun was 25 (10.3%) while all the other twenty-nine locations were 118 (48.8%).
- The highest record of yearly RTCs was in 2019 which was recorded to be 77 throughout the year.
- Drivers that causes accident without stopping has been found to have a major causes on the RTCs 58(11.2%).
- The RTC along Abeokuta-Sagamu Expressway from the duration of January 2016 to December 2019 has increased by over 250%.
- The autocorrelation for the RTC die after a few lag indicating that it is stationary.

• It was observed that ARIMA (0,1,1) and ARIMA (1,1,1) did not provide a good fit for the road traffic crashes. ARIMA (1,1,0) and ARIMA (2,1,0) showed relatively good fit to the time series.

Conflict Of Interest

The authors declare that there is no conflict of interest.

References

Abdelwahab, H., & Abdel-Aty, M. (2001). Development of Artificial Neural Network Models to Predict Driver Injury Severity in Traffic Accidents at Signalized Intersections. Transportation Research Record: Journal of the Transportation Research Board, 1746, 6–13. doi:10.3141/1746-02

Alkheder, S., Taamneh, M., & Taamneh, S. (2016). Severity Prediction of Traffic Accident Using an Artificial Neural Network. Journal of Forecasting, 36(1), 100–108. doi:10.1002/for.2425.

Asare, I. O. and Mensah, A. C. (2020): "Crash severity modelling using ordinal logistic regression approach," International Journal of Injury Control and Safety Promotion, vol. 27, no. 4, pp. 412–419.

Darci Akin (2011). Analysis of highway crsh data by negative binomial and poisson regression models. International Symposium on Computing in Science and Engineering. Kasadasi, Izmir, Turkey, Vol. 1.

Delen, D., Sharada, R. and Bessonov, M. (2006) Identifying Significant Predictors of Injury Severity in Traffic Accidents Using a Series of Artificial Neural Networks. Accident Analysis and Prevention, 38, 434-444.

Fu, C. and Sayed, T. (2021), "Random parameters Bayesian hierarchical modeling of traffic conflict extremes for crash estimation", Accident Analysis & Prevention, Vol. 157, Article no.106159.

Fattah, J., Ezzine, L., Aman, Z., El Moussami, H., & Lachhab, A. (2018). Forecasting of demand using ARIMA model. International Journal of Engineering Business Management, 10, 184797901880867. doi:10.1177/1847979018808673

Famoye, F. (2010). On the bivariate negative binomial regression model. Journal of Applied Statistics, 37(6), 969–981. doi:10.1080/02664760902984618.

Johnston, C., McDonald, J., & Quist, K. (2019). A generalized ordered Probit model. Communications in Statistics - Theory and Methods, 49(7), 1712–1729. doi:10.1080/03610926.2019.1565780.

Ki Kim.J, U. S. (2008). Age and pedestrian injury severity in motor-vehicle crashes: A heteroskedastic logit analysis.Accident Analysis and Prevention. 40(5):1695.

Kockelman, K. M., & Kweon, Y.-J. (2002). Driver injury severity: an application of ordered probit models. Accident Analysis & Prevention, 34(3), 313–321. doi:10.1016/s0001-4575(01)00028-8

Li, G. Highway Traffic Accident Severity Prediction Based on Ordered Logit and Multinomial Logit Model. Master's Thesis, Chang'an University, Shaanxi, China, 2018.

Li, L., & Kim, K. (2000). Estimating driver crash risks based on the extended Bradley-Terry model: an induced exposure method. Journal of the Royal Statistical Society: Series A (Statistics in Society), 163(2), 227–240. doi:10.1111/1467-985x.00167

Lourens, P. F., Vissers, J. A. M. ., & Jessurun, M. (1999). Annual mileage, driving violations, and accident involvement in relation to drivers' sex, age, and level of education. Accident Analysis & Prevention, 31(5), 593–597. doi:10.1016/s0001-4575(99)00015-9.

Morgan, A., & Mannering, F. L. (2011). The effects of road-surface conditions, age, and gender on driver-injury severities. Accident; analysis and prevention, 43(5), 1852–1863. https://doi.org/10.1016/j.aap.2011.04.024

Milton, J. C., Shankar, V. N., & Mannering, F. L. (2008). Highway accident severities and the mixed logit model: an exploratory empirical analysis. Accident; analysis and prevention, 40(1), 260–266. https://doi.org/10.1016/j.aap.2007.06.006.

Moghaddam.F.R., A. A. (2010). Prediction of accident severity using artificial neural networks. International Journal of Civil Engineering. 9(1), pg. 41-49.

Owunari S., Davies Ette H. and Etuk E. Amos (2019): Time series analysis of road traffic accident in Rivers State, Nigeria Ianna Journal of Interdisciplinary Studies, Volume 1, Issue 1. Pp. 120 – 134.

Saad, M., Abdel-Aty, M., & Lee, J. (2018). Analysis of driving behavior at expressway toll plazas. Transportation Research Part F: Traffic Psychology and Behaviour. doi:10.1016/j.trf.2017.12.008

Zhang, Y. The world health organization released the "2018 Global Road Safety Status Report". Chin. J. Disaster Med. 2019, 2, 100.