SJIF Impact Factor: 7.001| ISI I.F.Value:1.241| Journal DOI: 10.36713/epra2016 ISSN: 2455-7838(Online)
EPRA International Journal of Research and Development (IJRD)
Volume: 5 | Issue: 7 | July 2020 - Peer Reviewed Journal

ANALYZING ROAD TRAFFIC ACCIDENT RELATED TRAUMA CASES AT KWEKWE GENERAL HOSPITAL IN ZIMBABWE: EMPIRICAL EVIDENCE FROM A BOX-JENKINS SARIMA MODEL

Dr. Smartson. P. NYONI
ZICHIRe Project, University of Zimbabwe, Harare

Mr. Thabani NYONI
Department of Economics, University of Zimbabwe, Harare

ABSTRACT

This study uses monthly time series data on Road Traffic Accident (RTA) related trauma cases at Kwekwe General Hospital (KGH) from Janaury 2010 to December 2019, to predict RTA related trauma cases over the period January 2020 to December 2021. As verified by unit root tests, the series under consideration is basically an I (1) variable. The study applied the Box-Jenkins approach to time series forecasting and presented the SARIMA (1, 1, 1)(1, 1, 1)$_{12}$ model. Residual analysis of this model proves that the model is stable and thus suitable for predicting RTA related trauma cases at KGH over the out-of-sample period. The results of the study reveal that RTA related trauma cases will generally rise at KGH over the out-of-sample period; characterized by seasonal repeats in December each year. The study offers a six-fold policy recommendation in order to help policy makers in improving road safety in Zimbabwe.

1.0 INTRODUCTION

Road Traffic Accident (RTA) is the leading cause of premature death (IFH, 2013) and has now become not only a major public health problem (Peden *et al.*, 2004) but also a serious economic burden (Danlami *et al.*, 2017) and yet the state of roads in Zimbabwe is appalling. The government is failing to cope with the much needed rehabilitation and repairs of roads. This is being fueled by harsh economic conditions prevailing in the country. Potholes are littered around all major roads causing accidents to motorists and pedestrians alike (Mutangi, 2015). Other causes of RTAs include reckless driving, violation of traffic laws (Muvuringi, 2012), human error, vehicle conditions, over-speeding (Aworeni *et al.*, 2010) as well as "*evil* spirits" haunting people (Mhandu & Kazembe, 2012) and many more. Studies, for example, Ursano *et al.* (1999), Mosaku *et al.* (2014) and Fekadu *et al.* (2019); have shown that RTAs are an important cause of trauma. This study seeks to analyze cases of all patients admitted to a Trauma Unit at Kwekwe General Hospital (KGH) following a road traffic accident.

The majority of RTA deaths in developing countries occur in pre-hospital settings (Mock *et al.*, 2003; Montazeri, 2004). In Zimbabwe, those injured face challenges in accessing healthcare (Muvuringi, 2012). It is an accepted strategy of trauma care that if basic life support, first aid and replacement fluids can be arranged within the first hour of the injury (the golden hour), lives of many of the RTA victims can be saved. The critical factor for this strategy is to provide initial stabilization to the injured within the golden hour. The time between injury and initial stabilization is the most critical period for the patient's survival. Thus disability and deaths following road accidents are

SJIF Impact Factor: 7.001| ISI I.F.Value:1.241| Journal DOI: 10.36713/epra2016 ISSN: 2455-7838(Online)
EPRA International Journal of Research and Development (IJRD)
Volume: 5 | Issue: 7 | July 2020 - Peer Reviewed Journal

preventable to some extent (Ministry of Health & Family Welfare, 2018). Prediction of trauma cases resulting from road accidents is an important component of road safety management because it can improve road safety for both travellers and road-safety administrators.

1.1 OBJECTIVES OF THE STUDY

i. To analyze RTA-related trauma cases at KGH over the period January 2010 to December 2019.
ii. To forecast RTA-related trauma at KGH over the period January 2020 to December 2021.
iii. To determine whether RTA-related trauma cases are increasing or decreasing at KGH over the out-of-sample period.

1.2 RELEVANCE OF THE STUDY

RTAs remain one of the issues that attract a lot of attention throughout the world (Danlami *et al.*, 2017) and have become one of the major causes of trauma in patients. About 50 million people experience RTAs and 1.2 million people in the world are killed annually due to RTAs. In fact, approximately 3000 people die from RTAs daily in the world (Peden *et al.*, 2004). RTAs are expected to increase until they become the seventh top cause of death worldwide by year 2030, if no rigorous action is taken to reduce their occurrence. Approximately 90% of RTA associated deaths and injuries occur in the developing countries (WHO, 2015) such as Zimbabwe. Developing countries in the Sub-Saharan Africa have the highest rates of accidents worldwide. Zimbabwe has been ranked number 126 on world rankings of deaths due to RTAs (WHO, 2014). Despite the increasing rates of RTA occurrences, very few studies have been done in the field of RTAs in Zimbabwe (Njodzi *et al.*, 2016). Furthermore, RTAs strongly contribute to mortality, morbidity and increased inequality among the productive age group and their dependents in Zimbabwe. Fatal road traffic accidents top all the risks and threats of life in the country (Andrews, 2011). At least 3669 people die annually due to RTAs in Zimbabwe (WHO, 2011). Interestingly, road traffic deaths and injuries are predictable and preventable (Ministry of Health & Family Welfare, 2018). This study will model and forecast RTA-related trauma cases at KGH in Zimbabwe. No RTA-related trauma cases have been analyzed and predicted in Zimbabwe so far. The government of Zimbabwe is committed to decreasing the trends of RTA-related trauma cases in the country. To achieve this noble goal, it is not unimportant to predict RTA-related trauma cases in order to suggest a reliable controlling model.

2.0 RELATED PREVIOUS STUDIES

In Iran, Monfared *et al.* (2013) used a monthly time series data set on RTAs covering the period March 2004 – March 2011. The authors applied the Box-Jenkins approach to time series forecasting and presented the ARIMA (0, 1, 2) model as the optimal model for prediction of RTAs. In Zimbabwe, Mutangi (2015) employed ARIMA models in order to analyze RTAs based on an annual data set covering the period 1997 – 2013 and found out that the ARIMA (0, 1, 0) model, that is, the random walk model, was the best model for Zimbabwe's annual traffic accident data. Jorgensen *et al.* (2016) used Exponential models, ARIMA models, negative binomial regression and scenario approaches to estimate possible trends and changes in casualties in two urban areas in Norway over the period 2008 – 2012. They concluded that without strengthened safety strategies, the authorities' 40% casualty reduction target most probably will not be achieved.

Danlami *et al.* (2017) used the Generalized Estimating Equation (GEE) to estimate road fatality based on selected exposure variables. GEE with negative binomial distribution was found to be suitable for use in short term road fatality prediction modeling. Ghedira *et al.* (2018) used ARIMA models to investigate RTAs in Tunisia based on a monthly data set covering the period January 2007 to December 2015 and basically found out that the ARIMA (0, 1, 2) model is the best model and the forecast of their best model shows that the number of RTAs would decrease in Tunisia.

In Saudi Arabia, Alrajhi & Kamel (2019) displays a tutorial for designing a prototype of an interactive analytical tool based on a multivariate LSTM model for time series data to predict future car accidents, fatalities and injuries. Their results indicate increased risk of RTAs in Saudi Arabia. Al-Hasani *et al.* (2019) employed the SARIMA models in order to study RTAs in Oman, based on 228 observations (January 2000 – December 2018), and found out that the SARIMA $(0, 1, 2)(1, 0, 1)_{12}$ model was the optimal model. In Australia, Hassouna & Pringle (2019) employed the ARIMA approach in order to analyze and predict crash fatalities based on a data set covering the period 1965 to 2018 and basically found out that, based on gender, the rate of male road fatalities in Australia was significantly higher than that of female road fatalities. The study also found out that the number of

SJIF Impact Factor: 7.001| ISI I.F.Value:1.241| Journal DOI: 10.36713/epra2016 ISSN: 2455-7838(Online)
EPRA International Journal of Research and Development (IJRD)
Volume: 5 | Issue: 7 | July 2020 - Peer Reviewed Journal

road fatalities for the next 5 years (2019 – 2023) was generally declining.

From the literature review above, clearly no study has been done to forecast RTA-related trauma cases in Zimbabwe or elsewhere. This paper is the first of its kind and is expected to go a long way in improving road safety and minimizing RTA-related trauma cases as well as preventing premature deaths in the country.

3.0 METHODOLOGY

In situations where data is collected and framed over a time period, the prediction can best be made using time series techniques. The most popular time series model in accidentology is the Autoregressive Integrated Moving Average (ARIMA) (Brajesh & Shakhar, 2015; Mutangi, 2015; Jorgensen *et al.*, 2016; Danlami *et al.*, 2017; Al-Zyood, 2017; Al-Zyood, 2017; Makridakis *et al.*, 2018; Ghedira *et al.*, 2018; Al-Hasani *et al.*, 2019; Hassouna & Pringle, 2019), whether seasonal, that is; SARIMA (for example, Al-Hasani *et al.*, 2019) or general, that is; simply ARIMA (for example, Hassouna & Pringle, 2019). In this paper, the SARIMA technique is applied. The basic algebraic specification of the SARIMA model applied in this study is as given below:

$$\varphi(B^s)\emptyset(B)\Delta^d\Delta_s^D TC_t = \theta_0 + \gamma(B^s)\theta(B)\alpha_t \quad \ldots [1]$$

The non-seasonal factors are given as:

$$\left.\begin{aligned} AR&: \emptyset(B) = 1 - \emptyset_1 B - \cdots - \emptyset_p B^p \\ MA&: \theta(B) = 1 + \theta_1 B + \cdots + \theta_q B^q \end{aligned}\right\} \quad \ldots [2]$$

The seasonal factors are given as:

$$\left.\begin{aligned} Seasonal\ AR&: \varphi(B^s) = 1 - \varphi_1 B^s - \cdots - \varphi_P B^{Ps} \\ Seasonal\ MA&: \gamma(B^s) = 1 + \gamma_1 B^s + \cdots + \gamma_Q B^{Qs} \end{aligned}\right\} \quad \ldots [3]$$

Where TC_t is the data series (that is ND), α_t is the disturbance term, B is the backshift operator, $\emptyset$ is the coefficient of the non-seasonal AR, θ is the coefficient of the non-seasonal MA, φ is the coefficient of the seasonal AR, γ is the coefficient of the seasonal MA, Δ^d is the difference operator, with d order of differencing and Δ_s^D is the seasonal difference operator, with D seasonal order of differencing and s length of the seasonal period. In this paper, a SARIMA $(p,d,q)(P,D,Q)_{12}$ model was constructed using monthly Trauma cases data from January 2010 to December 2019.

3.1 DATA

This study is based on monthly observations of newly recorded and managed Trauma (TC) cases at Kwekwe General Hospital (KGH) in the city of Kwekwe in Zimbabwe, from January 2010 to December 2019. The out-of-sample forecast covers the period January 2020 to December 2021. All the data employed in this study was gathered from KGH.

SJIF Impact Factor: 7.001| ISI I.F.Value:1.241| Journal DOI: 10.36713/epra2016 ISSN: 2455-7838(Online)
EPRA International Journal of Research and Development (IJRD)
Volume: 5 | Issue: 7 | July 2020 - Peer Reviewed Journal

3.2 DIAGNOSTIC TESTS AND MODEL EVALUATION

Unit Root Tests: Graphical Analysis

Figure 1: Graphical Analysis

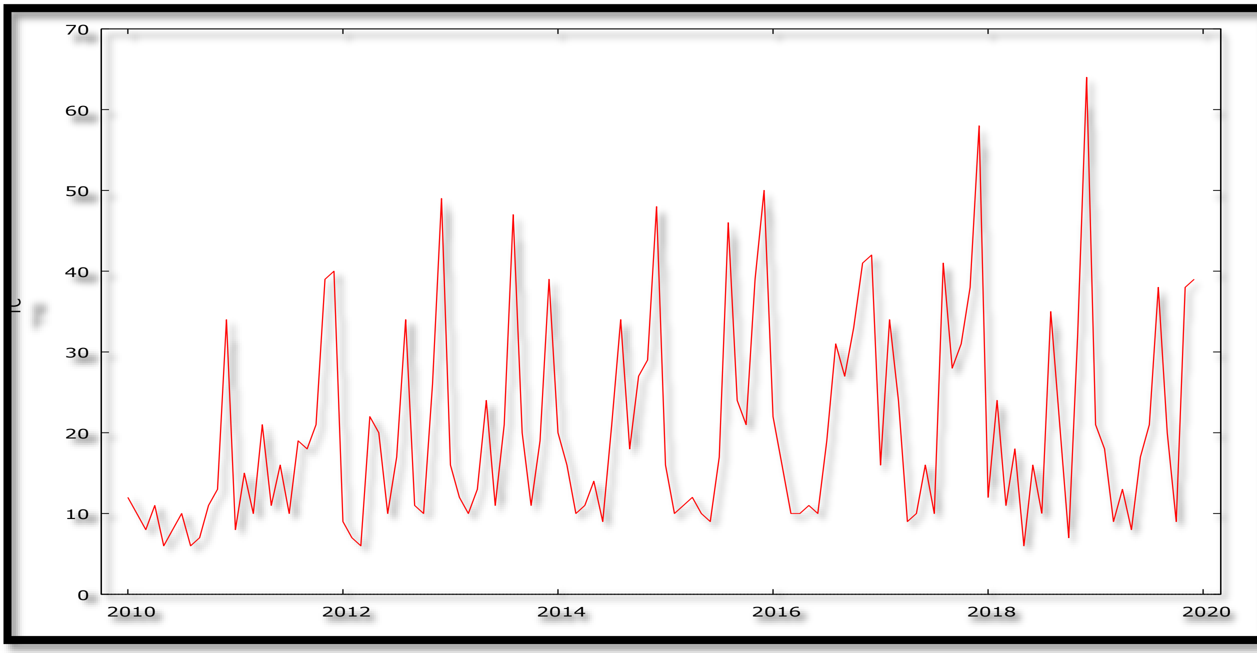


Figure 1 above shows that TC is generally trending upwards, although at a decreasing rate. The series is mostly likely non-stationary in levels. A formal unit root test will be carried out using the Augmented-Dickey-Fuller (ADF) test in order to confirm the level of stationarity. Striking to note, is the fact that there are peaks in almost every month of either August or December each year. This could be attributed to the fact that these are festive holidays and most people travel during these holidays. This also necessitates the need for a seasonal model to describe this data set; thus the paper applies the Box-Jenkins SARIMA model.

The ADF Test

Table 1: Levels-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
TC_t	-2.674360	0.0818	-3.491928	@1%	Stationary
			-2.888411	@5%	Not stationary
			-2.581176	@10%	Not stationary

Table 2: Levels-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
TC_t	-2.082639	0.5492	-4.045236	@1%	Not stationary
			-3.451959	@5%	Not stationary
			-3.151440	@10%	Not stationary

Table 3: without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
TC_t	0.652846	0.8557	-2.586550	@1%	Not stationary
			-1.943824	@5%	Not stationary
			-1.614767	@10%	Not stationary

SJIF Impact Factor: 7.001| ISI I.F.Value:1.241| Journal DOI: 10.36713/epra2016 ISSN: 2455-7838(Online)
EPRA International Journal of Research and Development (IJRD)
Volume: 5 | Issue: 7 | July 2020 - Peer Reviewed Journal

Table 4: 1st Difference-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
$D(TC_t)$	-14.05124	0.0000	-3.491928	@1%	Stationary
			-2.888411	@5%	Stationary
			-2.581176	@10%	Stationary

Table 5: 1st Difference-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
$D(TC_t)$	-14.27017	0.0000	-4.045236	@1%	Stationary
			-3.451959	@5%	Stationary
			-3.151440	@10%	Stationary

Table 6: 1st Difference-without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
$D(TC_t)$	-13.99980	0.0000	-2.586550	@1%	Stationary
			-1.943824	@5%	Stationary
			-1.614767	@10%	Stationary

Tables 1 – 6 indicate that TC is an I(1) variable.

Evaluation of the SARIMA Models (without a constant)

Model	AIC	U	ME	MAE	RSME	MAPE
SARIMA $(1,1,1)(1,1,1)_{12}$	**747.2870**	**0.52623**	-0.88451	6.0662	7.5874	39.426
SARIMA $(1,1,1)(0,1,0)_{12}$	764.3080	0.57911	-0.9107	6.4787	8.3499	38.201
SARIMA $(0,1,0)(1,1,1)_{12}$	786.4684	0.66835	-0.06364	7.4153	9.2744	43.034
SARIMA $(1,1,1)(1,1,0)_{12}$	757.4175	0.54356	-0.863	6.2311	8.0161	38.354
SARIMA $(1,1,0)(1,1,1)_{12}$	777.5487	0.60882	-0.039106	6.8752	8.8158	41.164
SARIMA $(0,1,1)(0,1,1)_{12}$	751.4687	0.5643	-0.84864	6.343	7.8812	41.518
SARIMA $(0,1,1)(1,1,1)_{12}$	749.8447	0.56284	-0.89933	6.3323	7.7561	41.517
SARIMA $(1,1,1)(0,1,1)_{12}$	748.7948	0.52860	-0.83316	6.1604	7.7149	39.902

A model with a lower AIC value is better than the one with a higher AIC value (Nyoni, 2018b). Furthermore, the Theil's U must lie between 0 and 1, of which the closer it is to 0, the better the forecast method (Nyoni, 2018a). Based on both the AIC and Theil's U, the study applies the SARIMA $(1,1,1)(1,1,1)_{12}$ model.

SJIF Impact Factor: 7.001| ISI I.F.Value:1.241| Journal DOI: 10.36713/epra2016 ISSN: 2455-7838(Online)
EPRA International Journal of Research and Development (IJRD)
Volume: 5 | Issue: 7 | July 2020 - Peer Reviewed Journal

Analysis of the Residuals of the SARIMA (1, 1, 1)(1, 1, 1)$_{12}$ Model

Residual Correlogram of the SARIMA (1, 1, 1)(1, 1, 1)$_{12}$ Model

Figure 2: Residual Correlogram

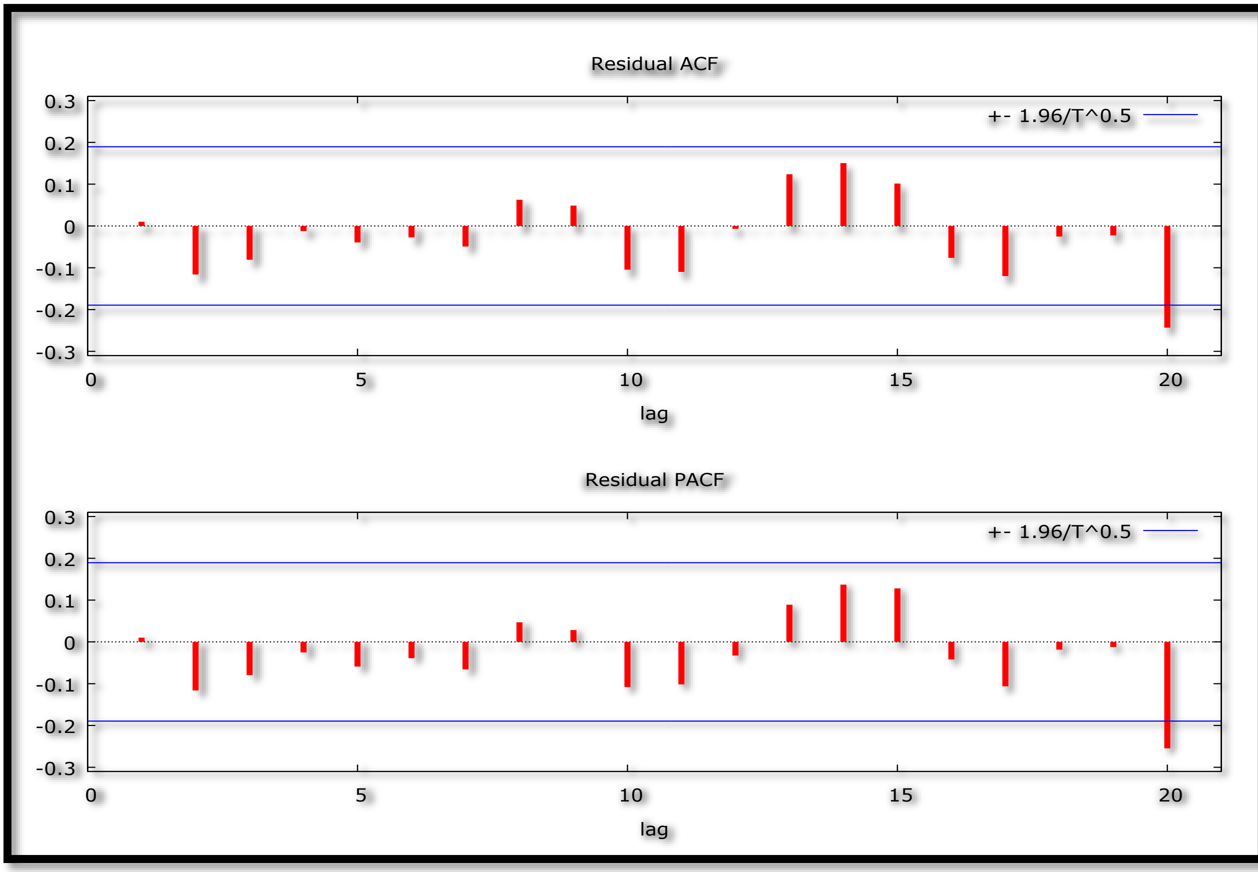
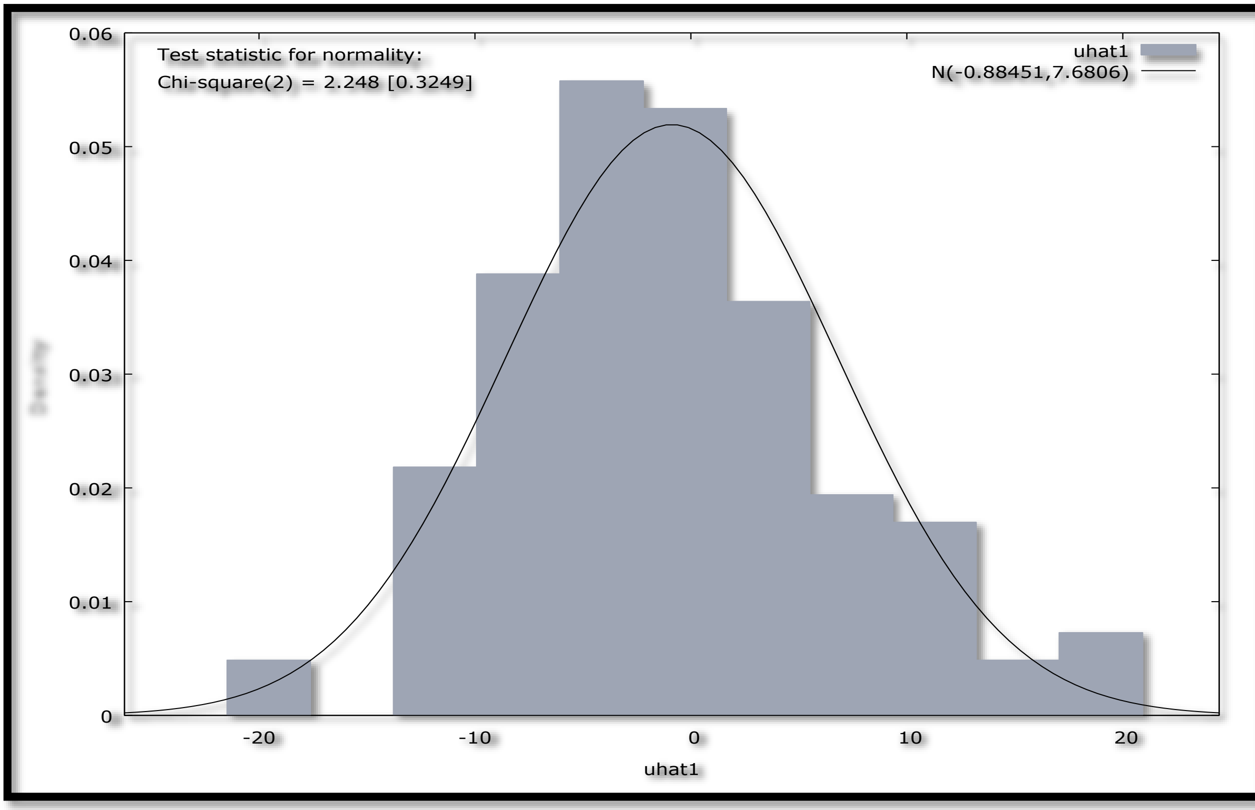


Figure 2 shows that the residuals of the applied model are stable and hence the model is adequate.

SJIF Impact Factor: 7.001| ISI I.F.Value:1.241| Journal DOI: 10.36713/epra2016 ISSN: 2455-7838(Online)
EPRA International Journal of Research and Development (IJRD)
Volume: 5 | Issue: 7 | July 2020 - Peer Reviewed Journal

Test for Normality of Residuals

Figure 3: Normality Test



Since the p-value, that is; [0.3249] is statistically insignificant, it implies that the residuals are normally distributed, hence the validity of the normality assumption.

4.0 RESULTS OF THE STUDY
4.1 DESCRIPTIVE STATISTICS

Table 7: Summary Statistics, using the observations 2010:01 - 2019:12, for the variable TC (120 valid observations)

Mean	Median	Minimum	Maximum
20.367	16.500	6.0000	64.000
Std. Dev.	C.V.	Skewness	Ex. kurtosis
12.649	0.62107	1.1482	0.68030

Table 7 shows that the average number of trauma cases over the period under study is 20 cases per month. The minimum number of trauma cases is 6 while the maximum is 64 and was recorded for December 2018.

SJIF Impact Factor: 7.001| ISI I.F.Value:1.241| Journal DOI: 10.36713/epra2016 ISSN: 2455-7838(Online)
EPRA International Journal of Research and Development (IJRD)
Volume: 5 | Issue: 7 | July 2020 - Peer Reviewed Journal

4.2 RESULTS PRESENTATION

Table 8: Main Results of the SARIMA (1, 1, 1)(1, 1, 1)$_{12}$ Model

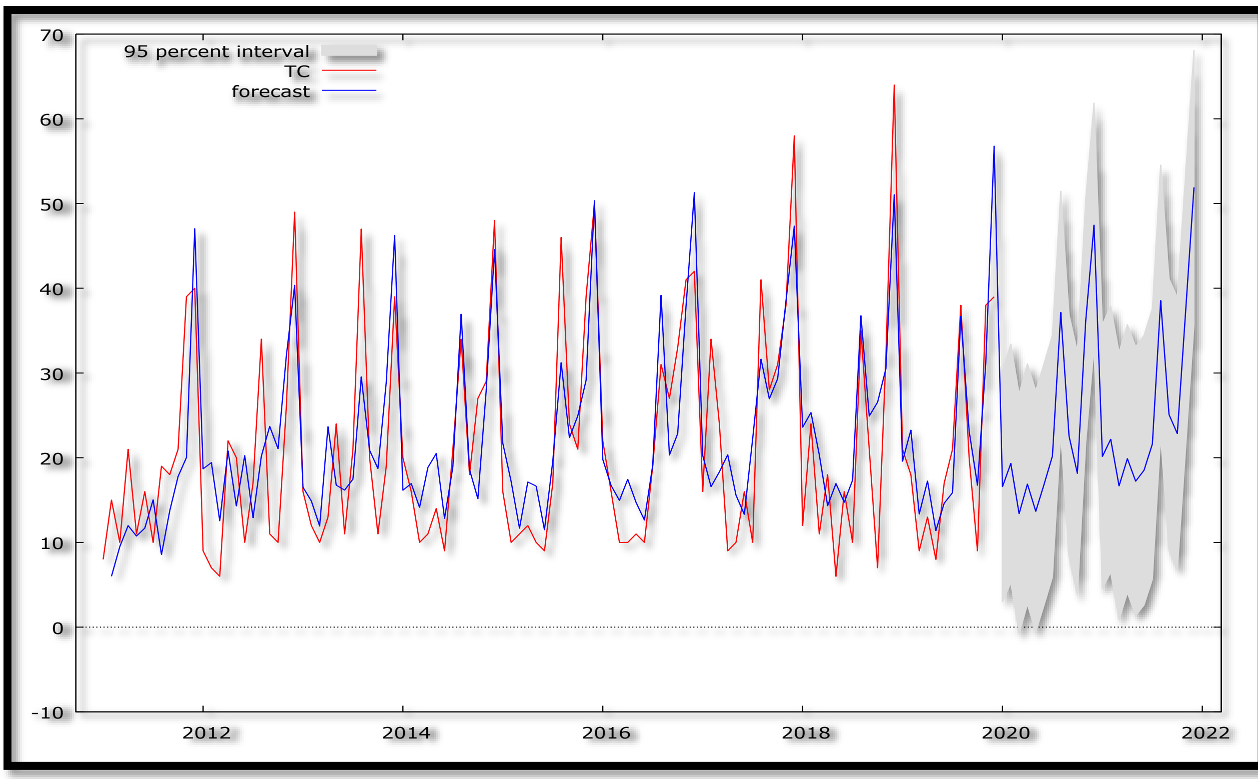
$$(1-0.328349B^{12})(1-0.221866B)\Delta\Delta_{12}TC_t = (1-0.956887B^{12})(1-0951559B)\alpha_t..[4]$$

Variable	Coefficient	Standard Error	z	p-value
$\emptyset_1$	0.221866	0.0990292	2.240	0.0251**
φ_1	0.328349	0.173536	1.892	0.0585*
θ_1	-0.951559	0.0611343	-15.57	0.0000***
γ_1	-0.956887	0.649773	-1.473	0.1408

NB: ***, ** and * imply statistical significance at 1%, 5% and 10% levels of significance

Forecast Graph

Figure 4: Forecast Graph



SJIF Impact Factor: 7.001| ISI I.F.Value:1.241| Journal DOI: 10.36713/epra2016 ISSN: 2455-7838(Online)
EPRA International Journal of Research and Development (IJRD)
Volume: 5 | Issue: 7 | July 2020 - Peer Reviewed Journal

Out of Sample Forecasts

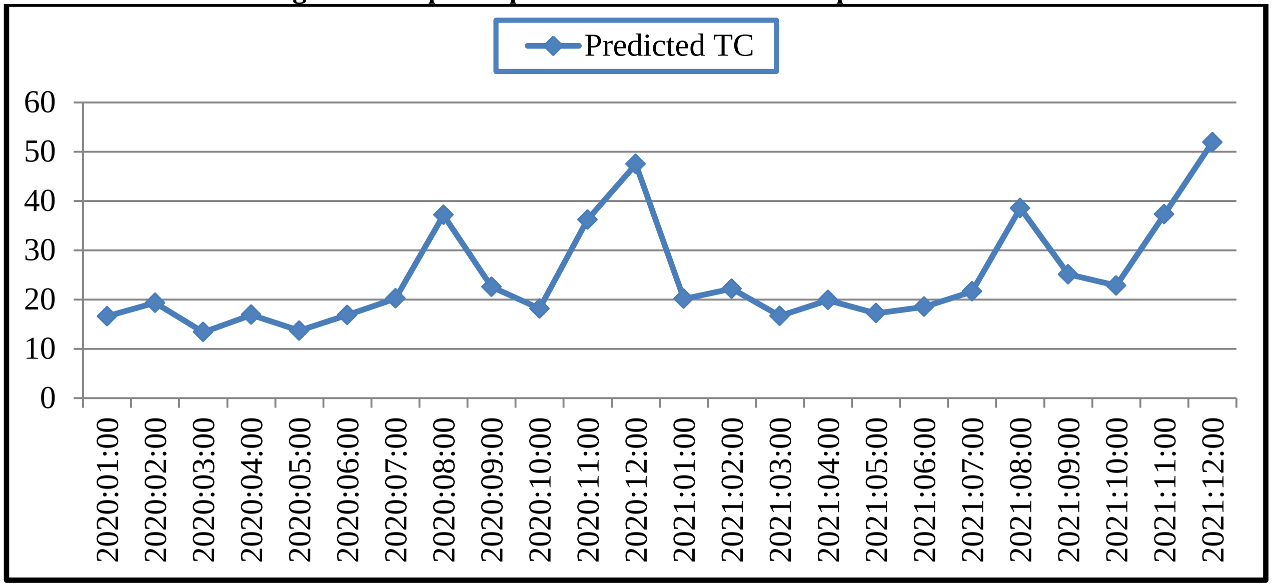
Table 9: Out-of-sample forecasts

Year: Month	Predicted TC	Standard Error	95% Confidence Interval
2020:01	16.5817	6.94029	(2.97896, 30.1844)
2020:02	19.3239	7.18937	(5.23303, 33.4148)
2020:03	13.3822	7.22864	(-0.785701, 27.5500)
2020:04	16.8876	7.24612	(2.68548, 31.0898)
2020:05	13.6704	7.25995	(-0.558872, 27.8996)
2020:06	16.8687	7.27300	(2.61386, 31.1235)
2020:07	20.1944	7.28587	(5.91440, 34.4745)
2020:08	37.1434	7.29868	(22.8383, 51.4486)
2020:09	22.5586	7.31146	(8.22840, 36.8888)
2020:10	18.1510	7.32421	(3.79584, 32.5062)
2020:11	36.1925	7.33695	(21.8124, 50.5727)
2020:12	47.4538	7.34966	(33.0488, 61.8589)
2021:01	20.1393	7.94218	(4.57290, 35.7057)
2021:02	22.1813	8.02201	(6.45849, 37.9042)
2021:03	16.6701	8.05351	(0.885483, 32.4546)
2021:04	19.8859	8.07725	(4.05473, 35.7170)
2021:05	17.2257	8.09939	(1.35121, 33.1002)
2021:06	18.5128	8.12113	(2.59568, 34.4299)
2021:07	21.6158	8.14274	(5.65630, 37.5753)
2021:08	38.5477	8.16428	(22.5460, 54.5494)
2021:09	25.0842	8.18575	(9.04040, 41.1280)
2021:10	22.8412	8.20717	(6.75546, 38.9270)
2021:11	37.2845	8.22853	(21.1569, 53.4121)
2021:12	51.9151	8.24984	(35.7457, 68.0845)

SJIF Impact Factor: 7.001| ISI I.F.Value:1.241| Journal DOI: 10.36713/epra2016 ISSN: 2455-7838(Online)
EPRA International Journal of Research and Development (IJRD)
Volume: 5 | Issue: 7 | July 2020 - Peer Reviewed Journal

Graphical Presentation of the Predicted Monthly TC Cases at KGH (Out-of-Sample)

Figure 5: Graphical presentation of out-of-sample forecasts



The main results of the SARIMA (1, 1, 1)(1, 1, 1)$_{12}$ model are show in table 8 above. Equation [4] is the mathematical expression of the model. Striking to highlight is the observation that most parameters of this model are statistically significant. Figures 4 and 5 as well as table 9 basically show out-of-sample forecasts of RTA-related trauma cases at KGH. The predicted RTA-related cases show a generally increasing trend, although the trend increases at a relatively decreasing rate. Striking to note is the fact that the out-of-sample forecasts show a repeat of seasonality in December of each year. This is quite reasonable because most people in Zimbabwe travel during the festive December holidays and during this time, as noted by Muvuringi (2012), most drivers practice reckless driving, probably due to over-excitement associated with the December holidays. The results of this study are a warning signal to policy makers in the country, especially in light of the need to improve road safety and avoid premature deaths and preventable injuries.

4.3 RECOMMENDATIONS

i. The government of Zimbabwe must capacitate and renovate KGH emergency medical facilities. In this regard, the emergency department should have all the required resuscitation equipment which is functional, including drugs and IV fluids all the time. It is also important for the hospital executive to consider extending the emergency department in order to handle large patient volumes in case of a serious bus accident.

ii. There is need for Basic Life Support ambulances at every 50km along highways such as the Harare – Bulawayo highway. In this regard, KGH should always have a standby rescue operation team. Furthermore, all clinical staff at KGH ought to have regular refresher trainings on emergency preparedness and management, Basic Life Support and Advanced Life Support as well as chest drain insertion for medical officers.

iii. There is need for specialized skill training to doctors, nurses and paramedics in order for KGH to be in a position to provide speedy and effective RTA-related trauma care.

iv. The government of Zimbabwe must continue spreading awareness regarding injury prevention and road safety. Furthermore, the government of Zimbabwe ought to encourage people to be blood donors in order to save lives of RTA victims and other patients who need blood and blood products urgently.

v. The government of Zimbabwe should also tighten the laws governing the driving of public motor vehicles.

vi. The government of Zimbabwe should improve the way roads are designed, constructed and managed.

SJIF Impact Factor: 7.001| ISI I.F.Value:1.241| Journal DOI: 10.36713/epra2016 ISSN: 2455-7838(Online)
EPRA International Journal of Research and Development (IJRD)
Volume: 5 | Issue: 7 | July 2020 - Peer Reviewed Journal

5.0 CONCLUSION

The costs of road safety to society are substantial and the suffering of the victims and their families huge (Aarts *et al*., 2016). Road safety remains one of the cardinal objectives of Zimbabwe's transport systems and yet RTA-related trauma cases are generally on the rise! In fact, in Zimbabwe, the prevailing level of RTAs and the consequent trauma cases is not acceptable. These RTA-related trauma cases often claim lives and cause a number of injuries out of which many victims are maimed for life. It has turned out that, especially in relation to RTA-related trauma cases in the country, there is still a significant knowledge gap on the area of modeling and forecasting. This study indicates that RTA-related trauma cases will generally increase at KGH over the out-of-sample period. The planning and implementation of relevant government policy actions should now be hinged on the forecasts of this study.

REFERENCES

1. *Aarts, L.T., Commandeur, R., Welsh, S., Niesen, M., Lerner, P., Thomas, N., & Bos, R. J. (2016). Study on Serious Road Traffic Injuries in the EU, European Commission, Brussels.*
2. *Al-Hasani, G., Khan, A. M., Al-Reesi, H., & Al-Maniri, A. (2019). Diagnostic Time Series Models for Road Traffic Accidents Data, International Journal of Applied Statistics and Econometrics, 2: 19 – 26.*
3. *Alrajhi, M., & Kamel, M. (2019). A Deep-Learning Model for Predicting and Visualizing the Risk of Road Traffic Accidents in Saudi Arabia: A Tutorial Approach, International Journal of Advanced Computer Science and Applications, 10 (11): 475 – 483.*
4. *Al-Zyood, M. (2017). Forecast Car Accident in Saudi Arabia With ARIMA Models, International Journal of Soft Computing and Engineering, 7 (3): 30 – 33.*
5. *Andrews, L. (2011). Zimbabwe Country Risk Assessment, ICS, Harare.*
6. *Aworeni, J. R., Azeez, A., & Olabode, S. O. (2010). Analytical Studies of the Causal Factors of Road Traffic Crashes in South Western Nigeria, International Research Journal of Education, 1 (4): 118 – 124.*
7. *Box, G. E. P., & Jenkins, G. M. (1970). Time Series Analysis: Forecasting and Control, Holden Day, San Francisco.*
8. *Brajesh, B., & Shekhar, C. (2015). Accidental Mortality in India: Statistical Models for Forecasting, International Journal of Humanities and Social Science Invention, 4 (4): 35 – 45.*
9. *Danlami, N., Napiah, M., Sadullah, A. F. M., & Bala, N. (2017). An Overview and Prediction of Malaysian Road Fatality: Approach Using Generalized Estimating Equations, International Journal of Civil Engineering and Technology, 8 (11): 452 – 465.*
10. *Fekadu, W., Mekonen, T., Belete, H., Belete, A., & Yohannes, K. (2019). Incidence of Post-Traumatic Stress Disorder After Road Traffic Accident, Frontiers in Psychiatry, 10 (519): 1 – 7.*
11. *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.*
12. *Hassouna, F. M. A., & Pringle, I. (2019). Analysis and Prediction of Crash Fatalities in Australia, The Open Transportation Journal, 13: 134 – 140.*
13. *IFH (2013). The Global Burden of Disease: Generating Evidence, IFH, Seattle.*
14. *Jorgensen, S. H., Jones, A. P., Rundmo, T., & Nordfjaern, T. (2016). Critical Approaches to Road Injury Trends, Forecasts and Scenarios: Two Urban Cases in Norway, NTNU, Trondheim.*
15. *Makridakis, S., Spiliotis, E., & Assimakopoulos, V. (2018). Statistical and Machine Learning Forecasting Methods: Concerns and Ways Forward, PLoS ONE, 13 (3): 1 – 26.*
16. *Mhandu, E., & Kazembe, T. (2012). Urban Myths Pertaining to Road Accidents in Zimbabwe: The Case of Chinhamo Service Centre Along Seke Road (Linking Harare and Chitungwiza), International Journal of Business and Social Science, 3 (17): 94 – 100.*
17. *Ministry of Health & Family Welfare (2018). Capacity Building for Developing Trauma Care Facilities on National Highways, Government of India, New Delhi.*
18. *Mock, C., Arreola-Risa, C., & Quansah, R. (2003). Strengthening Care for Injured Persons in Less Developing Countries: A Case Study of Ghana and Mexico, Injury Control & Safety Promotion, 10 (1): 45 – 51.*
19. *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 – 430.*

20. *Montazeri, A. (2004). Road-traffic-related Mortality in Iran: A Descriptive Study, Public Health, 118 (2): 110 – 113.*
21. *Mosaku, K., Akinyoola, A., Olasinde, A., & Orekha, O. (2014). Predictors of Post-traumatic Stress in Patients Admitted to a Trauma Unit Following Road Traffic Accident (RTA), Journal of Psychiatry, 17 (3): 1 – 6.*
22. *Mutangi, K. (2015). Time Series Analysis of Road Traffic Accidents in Zimbabwe, International Journal of Statistics and Applications, 5 (4): 141 – 149.*
23. *Muvuringi, M. P. (2012). Road Traffic Accidents in Zimbabwe, Influencing Factors Impact and Strategies, 48th International Course in Health Development, Royal Tropical Institute, Amsterdam.*
24. *Njodzi, M., Mugadza, G., Zvinavashe, M., Haruzivishe, C., Ndaimani, A., Mhlanga, M., Rukweza, J., & Kapfunde, A. (2016). Factors Associated With Road Traffic Accidents Among Survivors: A Pilot Study, Journal of Medical and Dental Science Research, 4 (7): 34 – 41.*
25. *Nyoni, T. (2018a). Modeling and Forecasting Naira/USD Exchange Rate In Nigeria: a Box-Jenkins ARIMA Approach, MPRA Paper No. 88622, University Library of Munich, Munich.*
26. *Nyoni, T. (2018b). Modeling and Forecasting Inflation in Kenya: Recent Insights From ARIMA and GARCH Analysis, Dimorian Review, 5 (6): 16 – 40.*
27. *Peden, M. M., Scurfield, R., & Sleet, D. (2004). Road Traffic Injury Prevention, WHO, Geneva.*
28. *Ursano, R. J., Fullerton, C. S., Epstein, R. S., Crowley, B., & Kao, T. (1999). Acute and Chronic Post-traumatic Stress Disorder in Motor Vehicle Accident Victims, American Journal of Psychiatry, 156: 589 – 595.*
29. *WHO (2011). Distribution of Road Traffic Deaths, WHO, Geneva.*
30. *WHO (2014). Road Traffic Injuries – World Report, WHO, Geneva.*
31. *WHO (2015). Road Traffic Injury Prevention – World Report, WHO, Geneva.*