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ANALYZING TRAUMA CASES AT GWERU PROVINCIAL HOSPITAL: WHAT DO ARIMA MODELS REVEAL

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ABSTRACT:

This study uses monthly time series data on trauma cases at Gweru Provincial Hospital (GPH) from Janaury 2010 to December 2018, to forecast trauma cases over the period January 2019 to December 2020. As shown 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 ARIMA (0, 1, 2) model. Residual analysis of this model apparently indicates that the model is stable and thus suitable for predicting trauma cases at GPH over the out-of-sample period. The results of the study reveal that trauma cases will be in stable equilibrium of approximately 15 cases per month over the out-of-sample period. The study offers a two-fold policy recommendation in order to help the GPH management team in improving survival of trauma patients.

INTRODUCTION:

Everyone is at risk of trauma (CSP, 2016). Trauma is the leading cause of death globally, especially in younger age groups and it causes many lost life years (WHO, 2012). Trauma can be defined as any serious injury to the body of a human being, often resulting from an accident or violence. In Zimbabwe, just like in any other developing country, trauma cases are usually as a result of natural disasters, road traffic accident, alcoholism, assault, sexual and domestic violence as well as occupational injury. Common symptoms of trauma include emotional numbing (for example, drinking too much alcohol), reduced (sometimes, hyper-awareness), awareness of surrounding, blame for others, loss of interest in former activities and change in sleeping habits. Due to a higher rate of injury and a lower level of care, developing countries have higher death rates than developed countries (Mock et al., 2004 & 5). Trauma patients are a significant group of patients for Emergency Medical Services (EMS) (Raatiniemi, 2016). Trauma places people at a higher risk for mental health issues such as depression and addiction. People who have experienced trauma are also at greater risk for suicide (CSP, 2016). Motivated by the need to improve survival and patient outcomes, this paper analyzes trauma cases recorded and managed at Gweru Provincial Hospital (GPH). This study is the first of its kind in Zimbabwe and is an eye-opener especially with regards to the need for effective emergency medical services in the country.

1 OBJECTIVES OF THE STUDY:

i. To analyze trauma cases at GPH over the period January 2010 to December 2018.
ii. To forecast trauma at GPH over the period January 2019 to December 2020.
iii. To determine whether trauma cases are increasing or decreasing at GPH over the out-of-sample period.

1.2 RELEVANCE OF THE STUDY:

Trauma is one of the world's most serious but neglected health problem (Mathur, 2008). This paper will model and forecast trauma cases at GPH in Zimbabwe. No trauma cases have been analyzed and predicted in Zimbabwe so far. The Ministry of Health & Child Care in Zimbabwe is committed to decreasing the trends of trauma cases in the country. To achieve this generous goal, it is instructive to predict trauma cases in order to suggest a reliable controlling model for use at GPH and for duplication in other similar hospitals in the country.

LITERATURE REVIEW:

Israel et al. (2012) employed descriptive statistics to study pediatric trauma due to motor vehicle accidents on a high traffic roadway in Brazil and finally concluded that children were at significantly higher odds of being treated for trauma while on a high way with heavy traffic flow. Monfared et al. (2013), in Iran, relied on a monthly time series data set on Road Traffic Accidents (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. Al-Thani et al. (2014) studied work-place related traumatic injuries in Qatar based on occupational injury surveillance for all work-related injury patients between 2010 and 2012 and found out that the incidence of work-related trauma is quite substantial in Qatar, although its mortality is relatively low in comparison to other countries of similar socioeconomic status. In Zimbabwe, Mutangi (2015) employed ARIMA models in order to analyze RTAs based on an annual data set covering the period 1997 – 2013 and revealed that the ARIMA (0, 1, 0) model was the best model for Zimbabwe's annual traffic accident data.

Jorgensen et al. (2016) made use of 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 and concluded that without strengthened safety strategies, the authorities' 40% casualty reduction target most probably will not be achieved. Danlami et al. (2017) employed the Generalized Estimating Equation (GEE) to estimate road fatality based on selected exposure variables. GEE with negative binomial distribution was shown to be suitable for use in short term road fatality prediction modeling. Ghedira et al. (2018) employed ARIMA models to investigate RTAs in Tunisia based on a monthly data set covering the period January 2007 to December 2015 and generally revealed found 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) presented 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 show an increased risk of RTAs in Saudi Arabia. Al-Hasani et al. (2019) used the SARIMA models in order to study RTAs in Oman, based on 228 observations (January 2000 – December 2018), and revealed that the SARIMA $(0, 1, 2)(1, 0, 1)_{12}$ model was the optimal model. Hassouna & Pringle (2019) employed the ARIMA approach in order to analyze and predict crash fatalities in Australia based on a data set covering the period 1965 to 2018 and 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 revealed that the number of 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 trauma cases in Zimbabwe or elsewhere. All the empirical papers reviewed, generally forecasted road traffic accident cases or fatalities. No study has attempted to analyze and forecast general trauma cases in the country or elsewhere and yet trauma is an important cause of death, especially in developing countries such as Zimbabwe. This study is the first of its kind and is anticipated to go a long way in improving GPH's preparedness in terms of handling and managing trauma cases.

MATERIALS & METHODS:

Guided by Box & Jenkins (1970), the general form of the ARIMA (p, d, q) can be represented by a backward shift operator as:

$$\emptyset(B)(1-B)^{d}TMC_{t} = \theta(B)\mu_{t} \quad \ldots\ldots [1]$$

Where the autoregressive (AR) and moving average (MA) characteristic operators are:

$$\emptyset(B) = (1-\emptyset_{1}B-\emptyset_{2}B^{2}-\cdots-\emptyset_{p}B^{p}) \quad \ldots\ldots [2]$$

$$\theta(B) = (1-\theta_{1}B-\theta_{2}B^{2}-\cdots-\theta_{q}B^{q}) \quad \ldots\ldots [3]$$

and

$$(1-B)^{d}TMC_{t} = \Delta^{d}TMC_{t} \quad \ldots\ldots [4]$$

Where $\emptyset$the parameter estimate of the autoregressive component is, θ is the parameter estimate of the moving average component, Δ is the difference operator, d is the difference, B is the backshift operator and μ_t is the disturbance term.

1 THE BOX-JENKINS METHODOLOGY:

The first step towards model selection is to difference the series in order to achieve stationarity. Once this process is over, the researcher will then examine the correlogram in order to decide on the appropriate orders of the AR and MA components. It is important to highlight the fact that this procedure (of choosing the AR and MA components) is biased towards the use of personal judgement because there are no clear – cut rules on how to decide on the appropriate AR and MA components. Therefore, experience plays a pivotal role in this regard. The next step is the estimation of the tentative model, after which diagnostic testing shall follow. Diagnostic checking is usually done by generating the set of residuals and testing whether they satisfy the characteristics of a white noise process. If not, there would be need for model re – specification and repetition of the same process; this time from the second stage. The process may go on and on until an appropriate model is identified (Nyoni, 2018c).

2 DATA COLLECTION:

This paper is based on 108 observations of monthly trauma cases (all age groups, all forms of trauma) at GPH. The data used in this paper was collected from GPH Health Information Department.

3 DIAGNOSTIC TESTS & MODEL EVALUATION:

Stationarity Tests: Graphical Analysis:

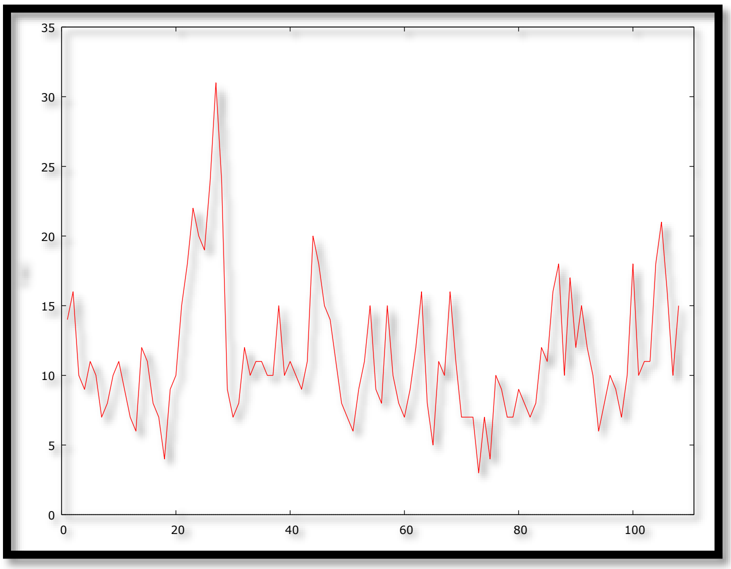

Figure 1

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The Correlogram in Levels:

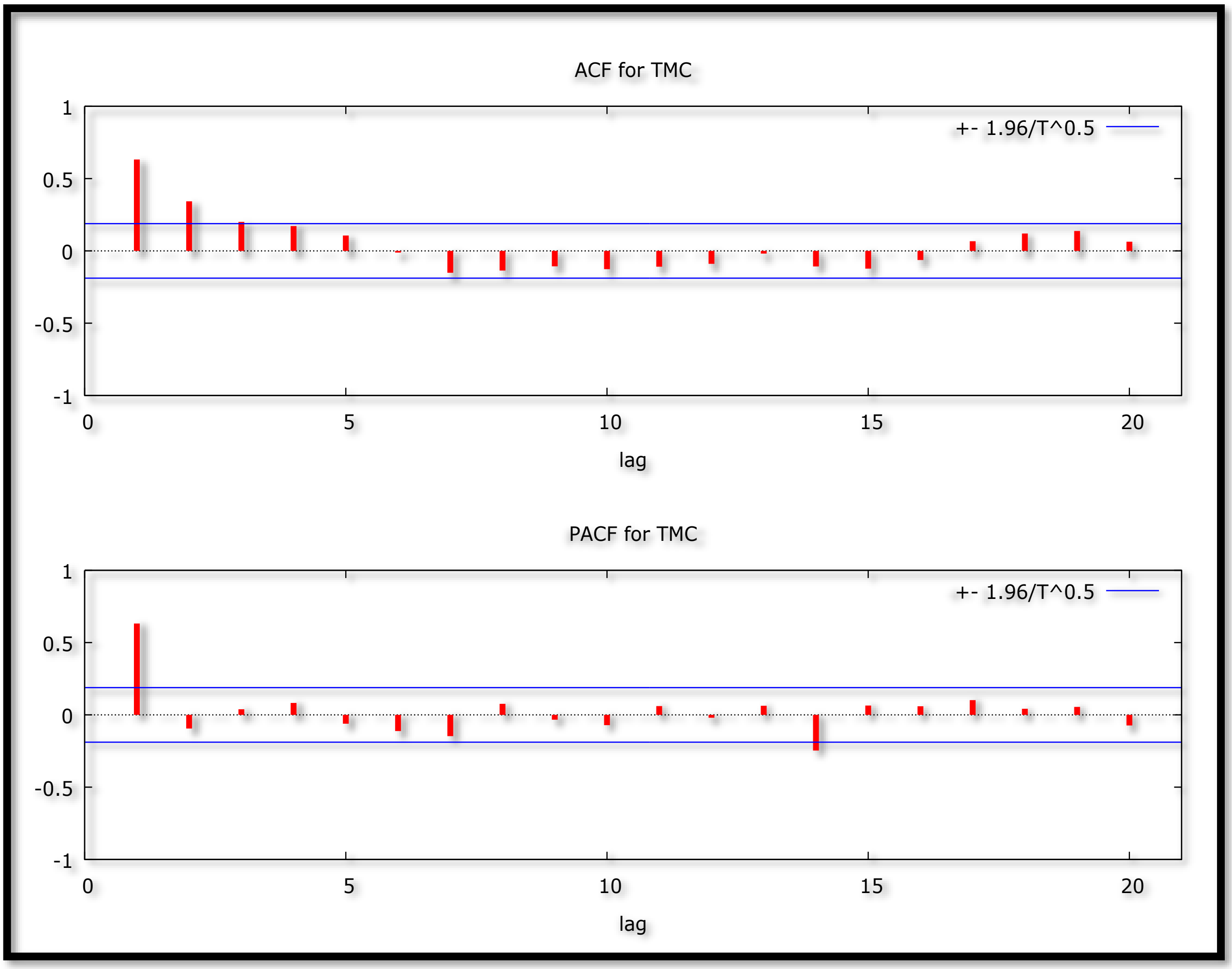


Figure 2

The ADF Test

Table 1: Levels-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
TMC	-4.823968	0.0001	-3.492523	@1%	Stationary
			-2.888669	@5%	Stationary
			-2.581313	@10%	Stationary

Table 2: Levels-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
TMC	-4.791815	0.0009	-4.046072	@1%	Stationary
			-3.452358	@5%	Stationary
			-3.151673	@10%	Stationary

Table 3: without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
TMC	-1.688434	0.0863	-2.586753	@1%	Not stationary
			-1.943853	@5%	Not stationary
			-1.614749	@10%	Stationary

The Correlogram (at 1st Differences):

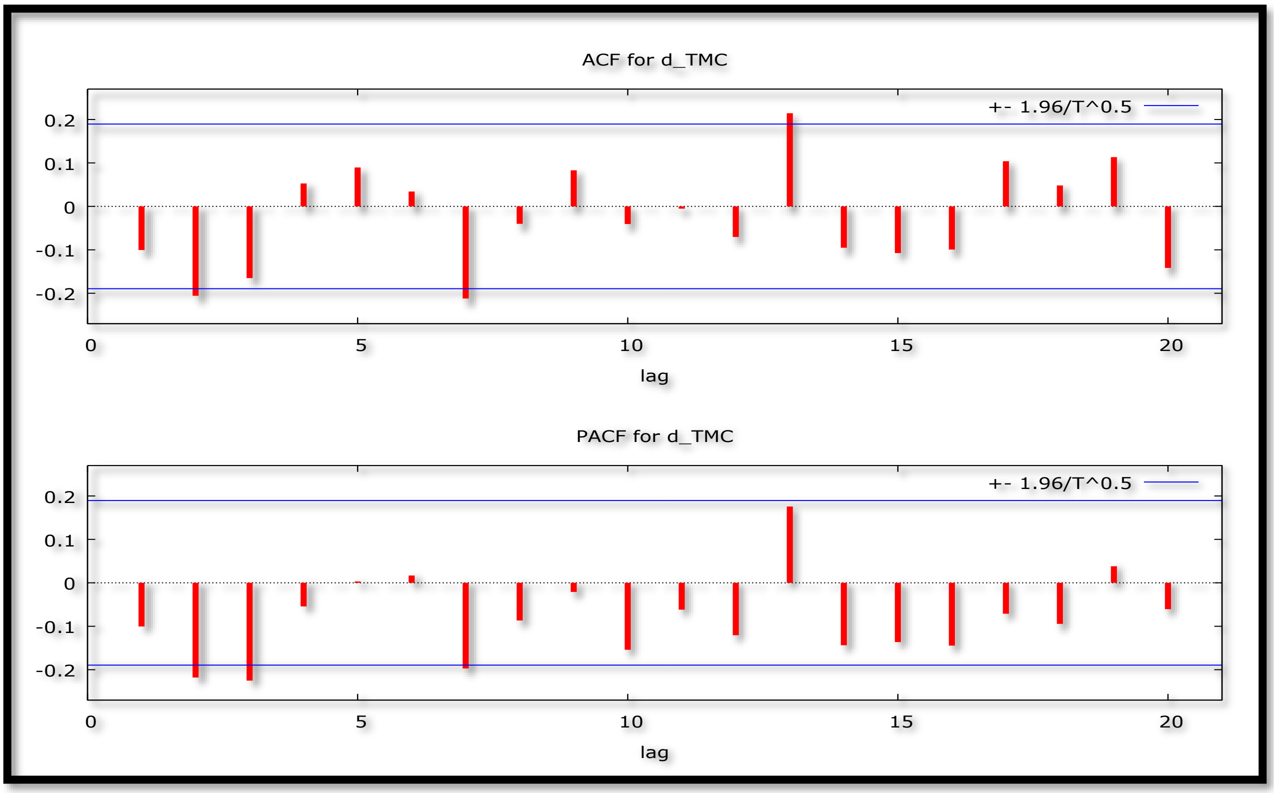


Figure 3

Table 4: 1st Difference-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
D(TMC)	-8.614838	0.0000	-3.494378	@1%	Stationary
			-2.889474	@5%	Stationary
			-2.581741	@10%	Stationary

Table 5: 1st Difference-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
D(TMC)	-8.557920	0.0000	-4.048682	@1%	Stationary
			-3.453601	@5%	Stationary
			-3.152400	@10%	Stationary

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

Variable	ADF Statistic	Probability	Critical Values		Conclusion
D(TMC)	-8.654481	0.0000	-2.587387	@1%	Stationary
			-1.943943	@5%	Stationary
			-1.614694	@10%	Stationary

Figure 1 shows that the series under consideration does not follow any particular trend and this makes it difficult to suspect existence of a unit root in the series. However, figure 2 shows that the series not stationary in levels. The ADF test (in tables 1 – 6) formally confirms that the series under consideration is in fact an I (1) variable.

Evaluation of ARIMA models (without a constant)

Table 7: Model evaluation

Model	AIC	ME	MAE	RMSE	MAPE
ARIMA (0,1,0)	-	0.0093458	3.1495	4.0105	30.132
ARIMA (0,1,1)	602.7342	0.0028479	3.094	3.9699	30.099
ARIMA (0,1,2)	**596.4720**	0.021668	2.9992	3.8195	29.487

A model with a lower AIC value is better than the one with a higher AIC value (Nyoni, 2018b) Similarly, the U statistic can be used to find a better model in the sense that it must lie between 0 and 1, of which the closer it is to 0, the better the forecast method (Nyoni, 2018a). In this paper, we only make use of the AIC in order to select the parsimonious model. Therefore, the ARIMA (0,1,2) model is chosen.

Residual & Stability Tests:

ADF Tests of the Residuals of the ARIMA (0, 1, 2) Model:

Table 8: Levels-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
ε_t	-9.683243	0.0000	-3.493129	@1%	Stationary
			-2.888932	@5%	Stationary
			-2.581453	@10%	Stationary

Table 9: Levels-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
ε_t	-9.674325	0.0000	-4.046925	@1%	Stationary
			-3.452764	@5%	Stationary
			-3.151911	@10%	Stationary

Table 10: without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
ε_t	-9.729713	0.0000	-2.586960	@1%	Stationary
			-1.943882	@5%	Stationary
			-1.614731	@10%	Stationary

Tables 8 – 10 show that the residuals of the ARIMA (0, 1, 2) model are stationary.

Stability Test of the ARIMA (0,1,2) Model:

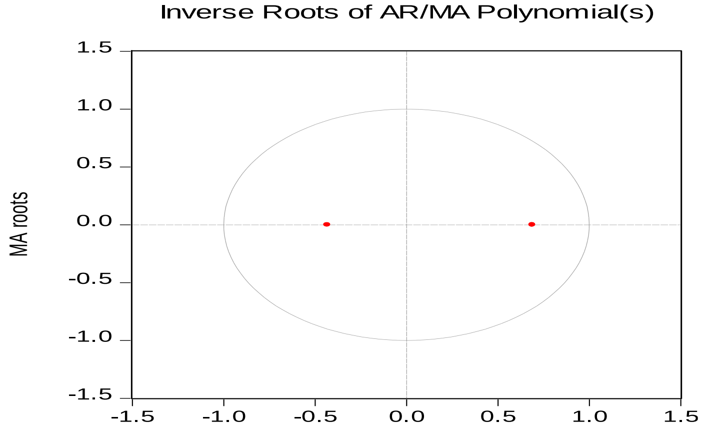
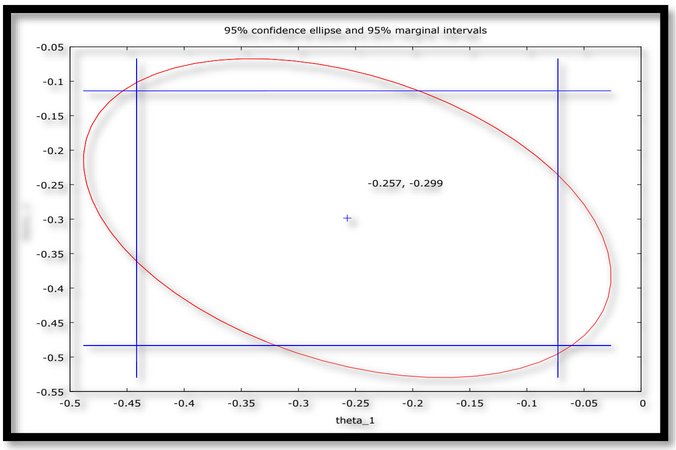


Figure 4: Inverse roots

Figure 4 above reveals that the ARIMA (0, 1, 2) model is very stable because the corresponding inverse roots of the characteristic polynomial lie in the unit circle.



95% Confidence Ellipse and 95% Marginal Intervals of the ARIMA (0, 1, 2) Model

Figure 5: Confidence ellipse

Figure 5 indicates that the accuracy of the selected optimal is satisfactory since the forecasts fall within the 95% confidence interval.

RESULTS:

1 DESCRIPTIVE STATISTICS:

Table 11: Descriptive Statistics

Description	Statistic
Mean	11.278
Median	10
Minimum	3
Maximum	31
Standard deviation	4.7040
Skewness	1.3281
Excess kurtosis	2.3283

The average number of trauma cases over the period under study is approximately 11 per month; the minimum number of trauma cases is 3 per month, while the maximum number of trauma cases per month is 31.

2 RESULTS RESENTATION

Table 12: Main Results of the Optimal Model

ARIMA (0, 1, 2) Model:

$$\Delta TMC_t = -0.257254\mu_{t-1} - 0.298571\mu_{t-2} \ldots\ldots\ldots\ldots\ldots\ldots [5]$$

P: (0.0057) (0.0014)

S. E: (0.0930161) (0.0931862)

Variable	Coefficient	Standard Error	z	p-value
MA (1)	-0.257254	0.0930161	-2.766	0.0057***
MA (2)	-0.298571	0.0931862	-3.204	0.0014***

FORECAST GRAPH:

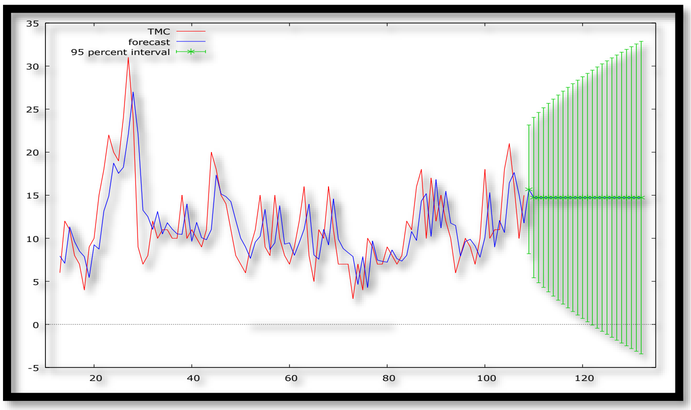


Figure 6: Forecast Graph

The main results of the estimated model are presented in table 12 above. Displayed in the same table, is equation [5], which is the mathematical expression of the model. As expected the coefficients of the MA components bear negative signs and are statistically significant. Figure 6 is the graphical presentation of both in-sample and out-of-sample forecasts. The optimal ARIMA (0, 1, 2) model predicted a constant number of approximately 15 trauma cases per month, implying that trauma cases in the GPH catchment area will relatively be in stable equilibrium for the out-of-sample period.

3 POLICY RECOMMENDATIONS:

In order to improve survival and patient outcomes, the study offers the following recommendations for consideration by GPH management team:

i. GPH should provide the socalled "trauma-informed intervention therapies", for example, psychological first aid, cognitive behavioral therapy (CBT), exposure therapy, narrative therapy as well as stress inoculation training (SIT).

ii. GPH management team should make sure that the hospital has enough resources, especially surgical equipments and pharmaceuticals for treatment of trauma patients.

CONCLUSION:

We are all at risk of trauma, in one way or the other, and yet trauma is a neglected health problem, especially in developing countries such as Zimbabwe. There is no doubt, trauma is costly to both society and government. Fortunately, trauma can be prevented and can also be treated successfully. In an attempt to enhance trauma patient survival and outcomes in Zimbabwe, this study focuses on GPH and consequently analyzes trauma cases using the Box-Jenkins ARIMA technique. The study finally presented the ARIMA (0, 1, 2) model which indicates that trauma cases at GPH will be in stable equilibrium over the period January 2019 to December 2020.

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