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DYNAMIC MODELLING AND CORRELATION ANALYSIS OF EMISSION FROM MOTOR VEHICLES IN NIGERIA: A CASE STUDY OF ABEOKUTA OGUN STATE

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ABSTRACT

High traffic volume and traffic congestion on Nigerian roads have led to increase in the concentration of pollutants in the air and this has posed health risks for human population. In this study, we build appropriate time series models using some vehicular emission data obtained from Abeokuta, in Nigeria. Four pollutants namely, carbon monoxide (CO), carbon dioxide (CO_2), oxygen (O_2) and hydrocarbon (HC) were investigated. Correlation analysis was carried out on each pollutant to see if these pollutants were significant as time progresses. Trend models particularly linear and quadratic were fitted for each pollutants. Time series models were built for these pollutants following model building procedures. The CO, CO_2, O_2 and HC were significant as time progresses with an increasing trend. The fitted linear time series model for these pollutants was Autoregressive Integrated Moving Average (ARIMA) of different order and the non-linear counterpart was ARIMA bilinear(ARIMABL) of order one. ARIMABL performed better than ARIMA with a smaller residual variance and mean square error for forecast. With these models, appropriate measures should be taken by the relevant authorities to curb the danger the emission could cause to humans not only in Abeokuta but in Nigeria.

Keywords: *Motor vehicle emission, Trend models, Time series models, Correlation, Nigeria*

INTRODUCTION

High traffic volume and traffic congestion on Nigerian roads have led to increase in the concentration of pollutants in the air and this has posed health risks for human population. Traffic emission has continued to be a very significant urban health concern, contributing greatly to the overall impact of outdoor air pollution. Concentration of pollutants varies both spatially (by location) and temporally (by time) (Olayinka*et al.*, 2015). (As cited by Olayinka*et al.,* 2015, road vehicles are one of the principal emitters of gaseous and particulate air pollutants and are major contributors to urban air pollution (Chen, et al., 2009; Li, 2011). Air pollutants are increasing rapidly in many urban areas of the developing world such as Nigeria where environmental regulations are relatively lax or non-existent (WHO, 2005). Despite that the trends and sources of transport air pollution vary between cities, the impact on the society are the same and such impact includes health problems mostly for children, aged and the poorest, reduction in productivity, poorer quality of life, and degradation of the environment (Babajide*et al.*, 2015). (As cited by Babajide *et al.,* 2015, transport is a main sector which causes the environmental pollution and climate change. Emissions from transport, and especially motor vehicles, add considerably to the levels of greenhouse gases in the atmosphere, (OECD 2002). Owing to the rapid increase of motor vehicles and very limited use of emission control technologies, transport emerges as the largest source of urban air pollution, which is an important public health problem in most cities of the developing world. Air pollution in developing countries accounts for tens of thousands of excess deaths and billions of dollars in medical costs and loses productivity every year (Faiz*et al.*, 1996;Sivaloganathan, 1998). The World Health Organization estimated that around 2.4 million people die every year due to air pollution (WHO 2007). Poor economic condition of developing countries like Nigeria coupled with poor vehicle maintenance culture and importation of used vehicles have in many ways greatly contributed to the rise in the figure of emission concentration (Ibrahim, 2009). In addition, traffic-related pollution has also increased due to low quality fuel, poor traffic regulation and lack of air quality implementation (Okunola, *et al.*, 2012). Emission of gaseous and particulate air pollutants close to people's breathing zone pose a great risk on human health (WHO, 2005). Abeokuta the study area is experiencing increase growth in both human population and vehicular traffic, which has led to increasing cases of air pollution. This study develops statistical models particularly trend and time series models (because of their limitless in literature) for predicting vehicular emission. With these models, future values would be known and appropriate measures would be taken by the relevant authorities based on the predicted values.

METHODOLOGY

Data sources and Description

The study was carried out in Ogun State, a state in the Federal Republic of Nigeria. It is located in the south-western zone of the country. It occupies a total land area of 16409.26sq.km. The estimated population of the state by 1991 census was put at 3,214,161. It has twenty (20)Local Government Area of the state. Ogun state is bounded in the North by Oyo and Osun, in the south by Lagos and in the east by Republic of Benin. The state capital, Abeokuta, is 100km North of

Lagos, the commercial nerve centre of the country. The state is on latitude 7^0 9′ and $7^0$40′N of the equator and longitude $3^0$26′ and $3^0$40′East of the Greenwich meridian (Olayinka*et al.* 2015).The samples were taken from four local governments namely Abeokuta, Sagamu, Ijebu-Ode and Sango-ota. Each of these areas has sample points of which CO, CO_2, $O_2$and HC were monitored. The four areas have sample points selected for collection in the priority of high population and traffic congestion. Five personnel were employed and trained for the purpose of collecting data from moving vehicles which include both commercial and private. The data was collected for 7 days in a week and this went on for the study period of 14 months.

Correlation Analysis

In the population that you care about there is a particular relationship between two variables x and y. If you characterized this relationship as linear, you could calculate an exact correlation coefficient that accurately represents the relationship for this population. That would be called rho (ρ) (a Greek letter because this is a population parameter). Unfortunately, you cannot access ρ directly, because you cannot measure every member of the population. Instead you draw a sample from the population and calculate r, a sample statistic that you hope represents ρ. Based on the size of the r that you obtain, how likely is it that the underlying population can be characterized by a non-zero correlation coefficient? Null Hypothesis: $\rho = 0$ Alternate Hypothesis: $\rho \neq 0$ $\alpha = .05$. The formula for the test statistic is$t = r\sqrt{n-2}/\sqrt{1-r^2}$ (Wilson, 2015).

Time Plot

The first exploration of a time series data is the plot of the series over time and then a sample descriptive measure of the main properties of the series could be obtained. In this, we intend to look at outliers, troughs, presence of turning points that may be pronounced on the time plot (Shangodoyin and Ojo, 2002).

Trend Models

Trend refers to the general direction in which the graph of a set of observation made successfully in time (usually at equal intervals) tends to be going over a period of time. The time period to be made use of, however, depends on the objectives of the study. Again, the nature of the study will dictate whether to observe the sets of observations daily, weekly, monthly or annually. For the purpose of this study, weekly values were used because anyone that inhale air pollutants steadily within a week will visit hospital. Most of the trend curves in all human endeavours have the tendency to either grow increasingly or decreasingly in absolute terms or fluctuate over the period of time so considered. Such trend series can be described using appropriate mathematical models called trend models. Linear curve is used to estimate the trend curve of a set of observations measured over time, when the trend exhibits a straight line pattern. The simple linear curve is given as $X_t = a + bt + e_t$, when t is the time period, the least squares method enables us to estimate the parameters a and b. The fitted trend is $T_t = X_t = \hat{a} + \hat{b}t$ (2.1).To obtain T_t, substitute for t = 1, 2, …, n in equation (2.1).The quadratic trend curve is used to estimate the trend curve of a set of observations measured over time, when the trend fails to exhibit a straight line pattern. It is represented by $T_t = b_0 + b_1t + b_2t^2$ where, T_t = trend value, t = time index/ period, t^2 = the square of the i^{th}

time /period. The parameters of the above are estimated using the method of least squares (Ojo, 2010)

Time Series Model Building

Model Specification

In Shangodoyin and Ojo 2002 as well as Ojo and Olubiyi, 2019, autoregressive, moving average and autoregressive moving average models were studied. Also, Ojo and Olatayo, 2009 studied autoregressive integrated moving average models while autoregressive integrated moving average one-dimensional bilinear time series model was studied by Ojo in 2012

Model Selection and Estimation: Autocorrelation or serial coefficient provides an important guide to the properties of a time series. These quantities measure the correlation between observations at different distances apart. The set of values of ρ_k are known as the autocorrelation function (ACF), all the autocorrelation coefficients must be in the range (-1, +1). For preliminary model identification, the autocorrelation (ACF) and partial autocorrelation (PACF) functions are useful tools. We estimated the models in (2.4.1) using Yule Walker, Malquardt Algorithm and Newton-Raphson Iterative (Shangodoyin and Ojo, 2002;Ojo, 2012).Having selected a particular model from AR, MA and ARMA, there are different models that will be fitted from the selected model. The model determination methods used in this study were AIC and BIC (Shangodoyin and Ojo, 2002). Having selected and estimated the optimal models, the final stage is to forecast using the estimated model since this is a powerful useful instrument in planning and making a wise decision about future (Shangodoyin and Ojo, 2002). There are a number of measures of accuracy in the modelling and forecasting literature and each has advantages and limitations. For this work, we employed residual variance (RV) and root mean square error for forecast (RMSE) (Ojo and Rufai, 2016).

RESULTS AND DISCUSSION

Carbon Monoxide (CO)

Correlation between CO and Time (Correlation coefficient = 0.27, P-value = 0.022<0.05, N=56.)

Trend Models(Linear $\hat{T}_t = 1.496 + 0.06t$ **, Quadratic** $\hat{T}_t = 2.565 - 0.052t + 0.002t^2$ **)**

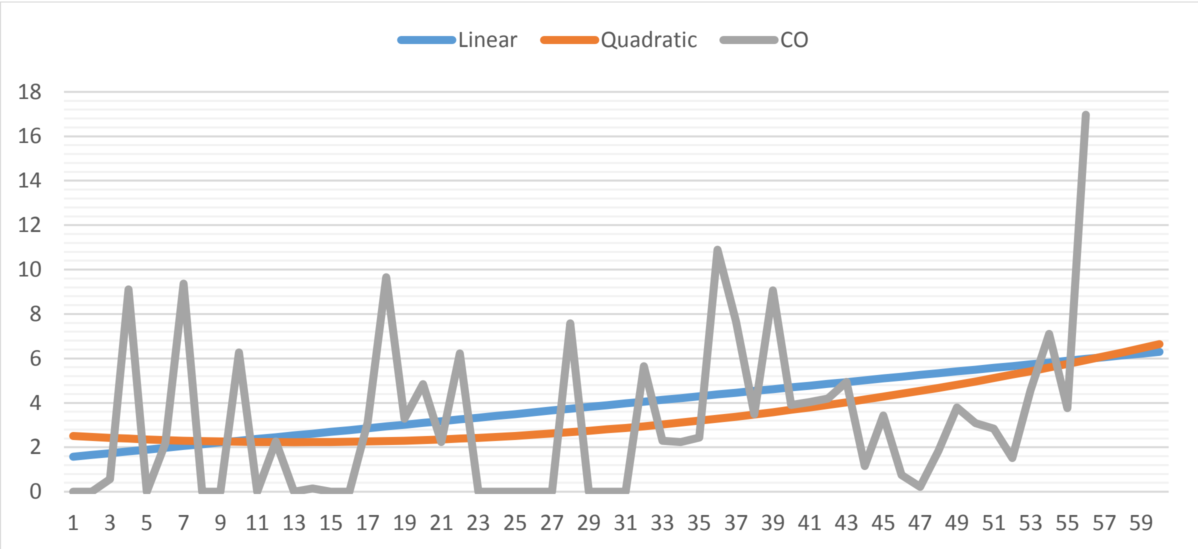
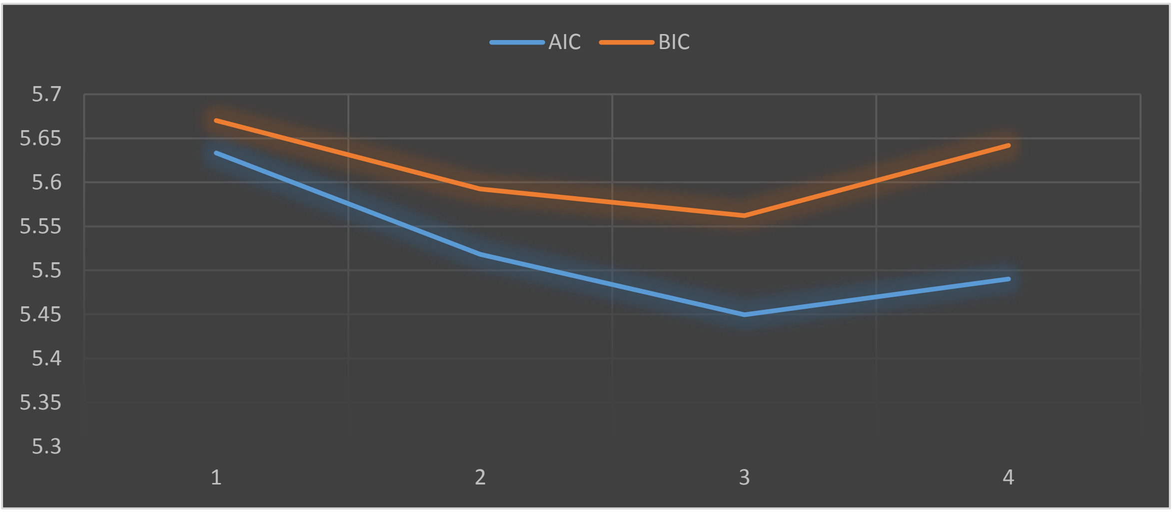


Figure 1: Time Plot, Linear and Quadratic Trends for Carbon Monoxide



Time Series Model Building for CO

Figure2: Plot of Akaike and Bayesian Information Criteria for Carbon Monoxide

Model Estimation

ARIMA (3, 1, 0) $\hat{X}_t = -0.773346X_{t-1} - 0.506491X_{t-2} - 0.099830X_{t-3}$ (AIC=5.449580, BIC=5.562152)

ARIMABL (3, 1, 0, 1, 1)

$$\hat{X}_t = -0.773346X_{t-1} - 0.506491X_{t-2} - 0.099830X_{t-3} - 0.008524X_{t-1}e_{t-1}$$

(AIC=5.4147, BIC=5.5622)

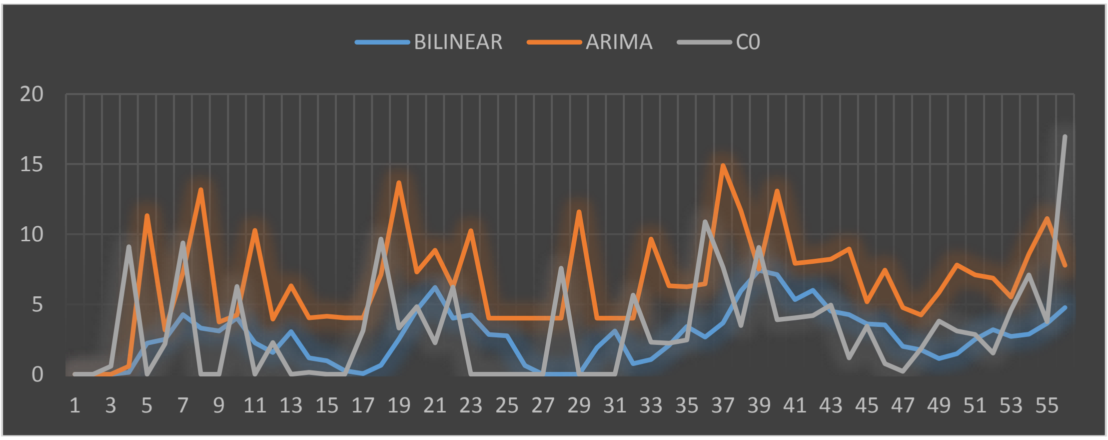


Figure3: Plot of Forecast and Carbon Monoxide

Carbon dioxide (CO_2)

Correlations between Carbon Dioxide and Time(Correlation coefficient = 0.45, P-value = 0.00<0.05, N=56.**)**

Trend Models (Linear $\hat{T}_t = 3.366 + 0.322t$ **, Quadratic** $\hat{T}_t = 5.682 + 0.082t + 0.004t^2$ **)**

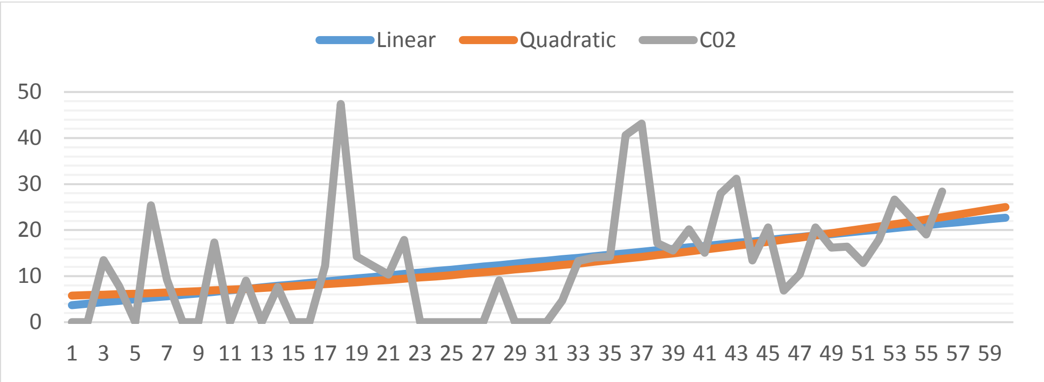


Figure 4: Time Plot, Linear and Quadratic Trends for Carbon Dioxide

Time Series Model Building for CO_2

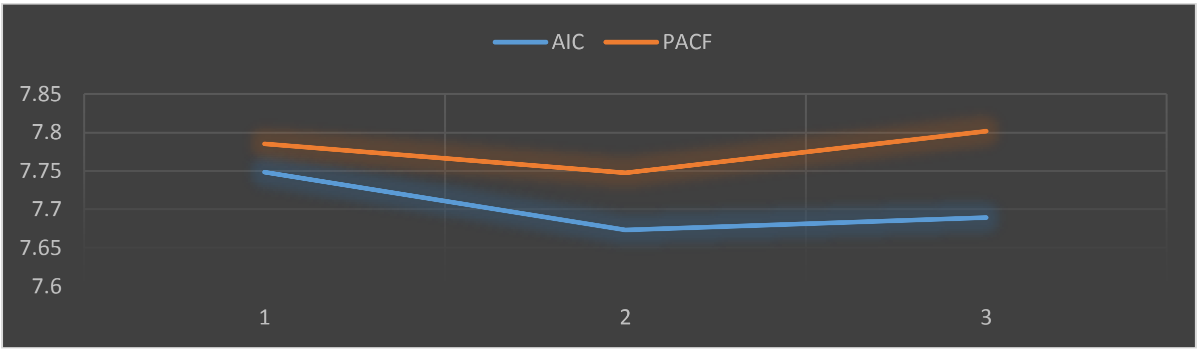


Figure 5: Plot of Akaike and Bayesian Information Criteria for Carbon Dioxide

Model Estimation for CO_2

ARIMA (2, 1, 0) $\hat{X}_t = -0.405074 X_{t-1} - 0.315049 X_{t-2}$ (AIC = 7.673143, BIC = 7.747494)

ARIMABL (2, 1, 0, 1, 1) $\hat{X}_t = -0.405074 X_{t-1} - 0.315049 X_{t-2} - 0.006022 X_{t-1} e_{t-1}$ (AIC = 7.586714, BIC = 7.622881)

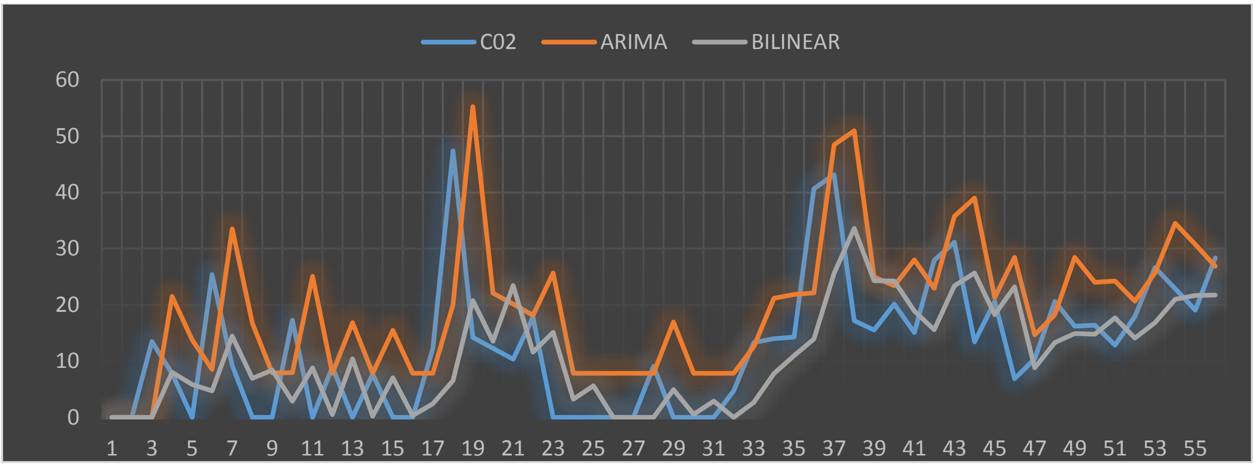


Figure 6: Plot of Forecast and Carbon Dioxide

Oxygen (O_2)

Correlation between Oxygen and Time (Correlation coefficient = 0.35, P-value = 0.00<0.05, N=56.)

Trend Models (**Linear** $\hat{T}_t = 1.491 + 0.27t$, **Quadratic** $\hat{T}_t = 7.871 - 0.386t + 0.012t^2$)

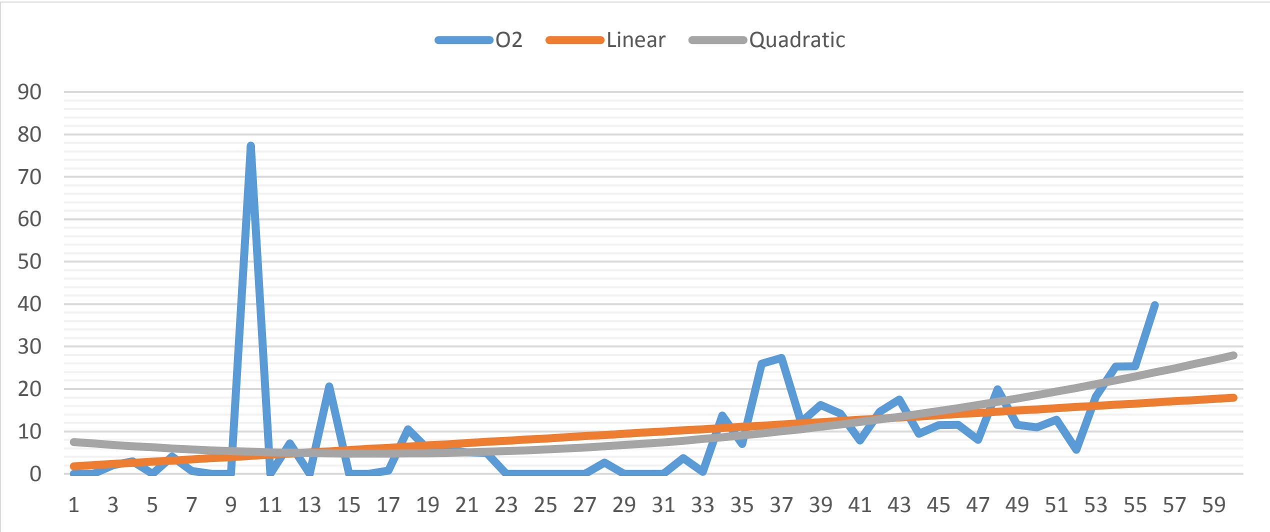


Figure 7: Time Plot, Linear and Quadratic Trends for Oxygen

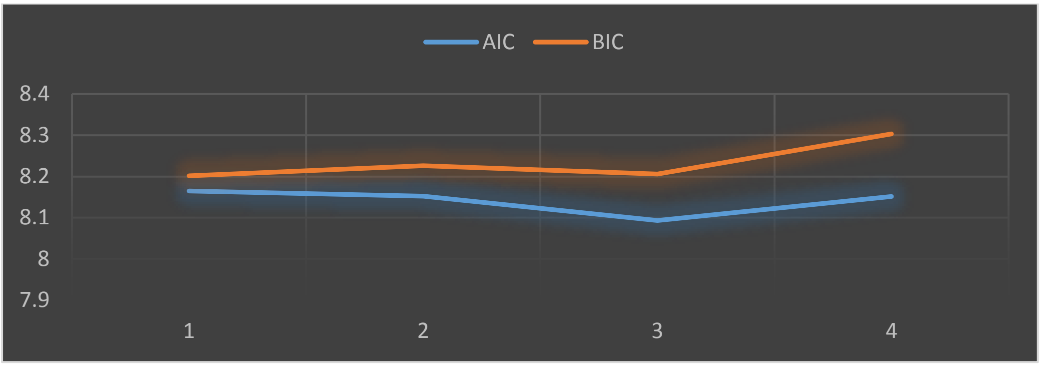


Figure 8: Plot of Akaike and Bayesian Information Criteria for Oxygen

Model Estimation for O_2

ARIMA (3, 1, 0) $\hat{X}_t = -0.762056 X_{t-1} - 0.490053 X_{t-2} - 0.337707 X_{t-3}$ (AIC = 8.093180, BIC = 8.205752)

ARIMABL (3, 1, 0, 1, 1) $\hat{X}_t = -0.762056 X_{t-1} - 0.490053 X_{t-2} - 0.337707 X_{t-3} - 0.003260 X_{t-1} e_{t-1}$ (AIC = 7.895589, BIC = 7.931756)

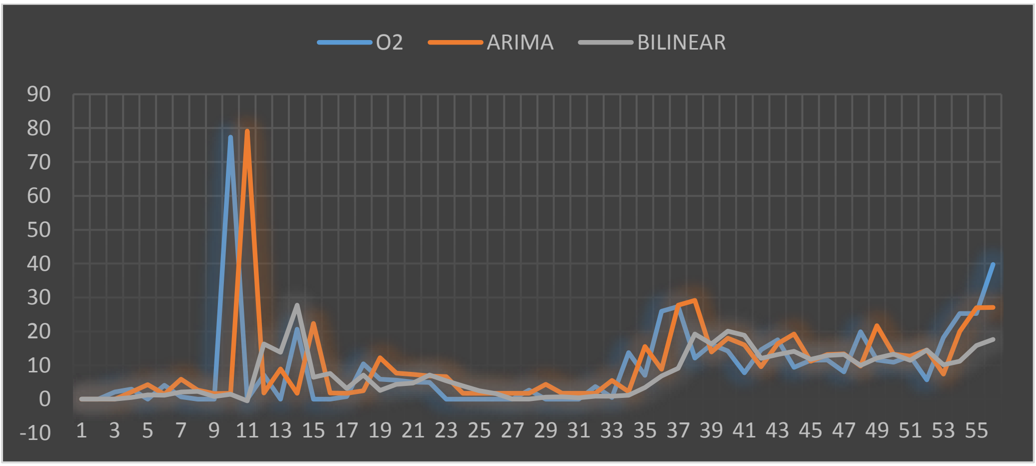


Figure 9: Plot of Forecast and Oxygen

Hydrocarbon

Correlations between Hydrocarbon and Time (Correlation coefficient = 0.47, P-value = 0.00<0.05, N=56.)

Trend Models (Linear $\hat{T}_t = 34.520 + 14.038t$, **Quadratic** $\hat{T}_t = 113.25 + 5.895t + 0.143t^2$)

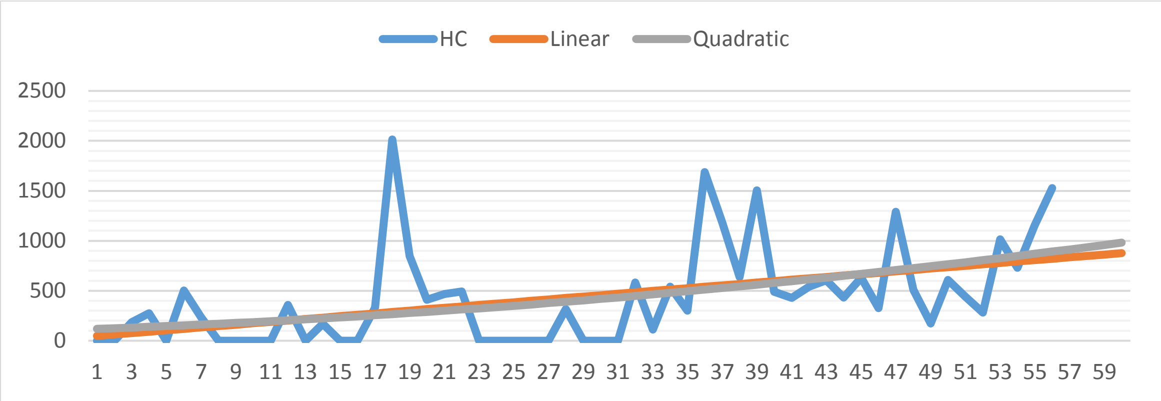


Figure 10: Time Plot, Linear and Quadratic Trends for Hydrocarbon

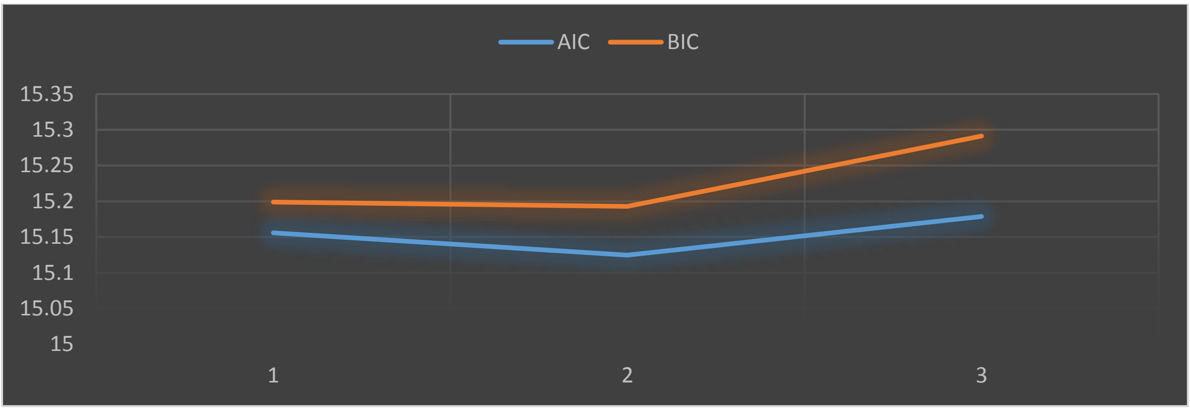


Figure 11: Plot of Akaike and Bayesian Information Criteria for Hydrocarbon

Model Estimation for Hydrocarbon

ARIMA (2, 1, 0) $\hat{X}_t = -0.519154\,X_{t-1} - 0.291608\,X_{t-2}$ (AIC = 15.12463, BIC 15.19898)

ARIMABL (2, 1, 0, 1, 1)

$\hat{X}_t = -0.519154\,X_{t-1} - 0.291608\,X_{t-2} - 0.7.49E - 05\,X_{t-1}e_{t-1}$

(AIC = 15.02484, BIC = 15.06100)

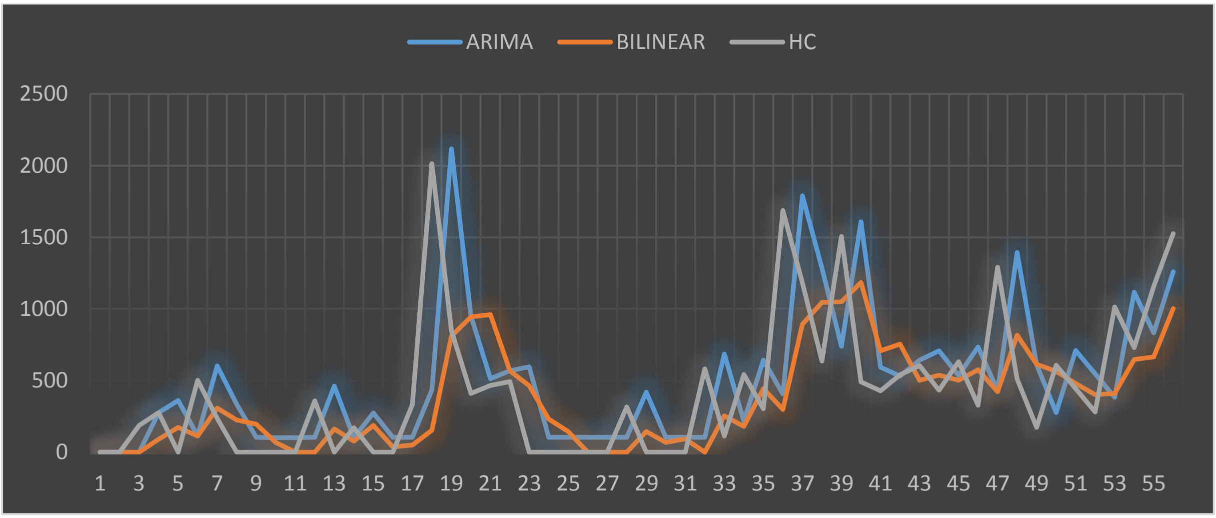


Figure 12: Plot of Forecast and Hydrocarbon

Table 1: Measures of Performance between ARIMA and ARIMABL

	Residual Variance		Mean Square Error for Forecast	
	ARIMA	ARIMABL	ARIMA	ARIMABL
CO	5.15	4.33	3.56	3.52
CO_2	118.59	111.30	12.67	10.55
O_2	172.13	150.80	15.43	12.32
HC	20,3229.66	18,9607.99	598.57	435.12

From the correlation analysis, carbon monoxide, carbon dioxide, oxygen and hydrocarbon were significant as time progresses. The trend models fitted in figure 1, 4, 7 and 10 showed an upward movement and the implication was that these pollutants were increasing with time. It will get to a period that human life will be seriously endangered if actions were not taken against the increase.The model selection suggested an ARMA model but when ARMA was fitted, the AR component was non-stationary and as a result ARIMA model was fitted. Figure 2, 5, 8 and 11 showed the order of the ARIMA models at which AIC and BIC were minimum. Figure3, 6, 9 and 12 showed the forecast using the ARIMA and ARIMABL models. Table 1 showed the performance of ARIMABL over ARIMA with a small residual variance and mean square error for forecast for all the pollutants.

CONCLUSION

This paper describes statistical modelling of motor vehicle emission particularly trend models and time series models. With these models, appropriate measures should be taken by the relevant authorities so as to curb the danger the emission could cause to humans not only in Abeokuta and Nigeria but in any part of the world where they are experiencing increased emission.

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