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Seasonal Time Series Modelling and Forecasting of Particulate Matter ($PM_{2.5}$) Datasets

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ABSTRACT

The results of man-made and natural releases of hazardous pollutants like particulate matter ($PM_{2.5}$) have serious effects on humanity. The prolonged proximity of such particles causes numerous critical and long-term ailments. Therefore, this study is used to model and forecast Nigerian yearly mean particulate matter to have an insight into future values. The methods used are descriptive statistics and Seasonal Autoregressive Integrated Moving Average (SARIMA) models. The results from the descriptive statistics of Nigerian yearly mean particulate matter ($PM_{2.5}$) signified the mean is 63.77ug/m^3 and the standard deviation is 7.84ug/m^3. The time plot showed that the series exhibited secular and seasonal variations. The series is stationary at the initial difference, as demonstrated by applying the technique of the Augmented Dickey-Fuller test. The tentative SARIMA model was determined using autocorrelation and partial autocorrelation function plots. The values of the Schwarz and Akaike information criteria (AIC) were used to select the optimal model after estimation with the ordinary least squares technique. The adequacy of the SARIMA$(1,1,1)x(1,1,1)_{12}$ model was determined based on residual autocorrelation, partial autocorrelation function plots and Modified Box-Pierce (Ljung-Box) Chi-Square Statistic. The SARIMA$(1,1,1)x(1,1,1)_{12}$ model forecast for Nigerian yearly mean particulate matter for 19 years signified a seasonal fluctuating movement from 2020 to 2039 andan estimated fluctuation within the interval 27.735 – 81.659ug/m^3 respectively for the next 19 years. Conclusively, the Nigerian yearly mean particulate matter from 1990 to 2019 and the forecast from 2020 to 2039 are above the World Health Organisation (WHO) standard of 10 ug/m^3 annual mean. Therefore, the high level of yearly mean particulate matter is alarming and this is expected to negatively affect the health of in Nigerian over the years.

Keywords: Particulate matter, SARIMA model, Time series model building, WHO standard, Nigeria.

INTRODUCTION

Global growth of human population is rapidlyincreasing, and major cities are becoming dense and overpopulated, and this has had a great deal of negative impact on the ecosystem.Numerous socioeconomic and financial variables are negatively affecting the ecosystem (Sadigov, 2022). The outcomes of this influence have given room for theemission of dangerous pollutants like nitrogen dioxide(NO_2),sulphur dioxide(SO_2),particulate matter ($PM_{2.5}$), and ground-level ozone (O_3)into the atmosphere (Manisalidis et al., 2020). Prolonged exposure to these particles has been linked to some severe and persistent medical conditions. Approximately 93 percent of young people worldwide face health hazards each day because of air pollution, and this has causes 6.7 million premature deaths annually (World Health Organization, 2024; Bălă et al., 2021). The WHO (2023)characterised air pollution as the existence of a variety of impurities including pollen, gases, haze, smell, combustion, or moisture, within the outdoor surroundings in amounts, forms, or duration that are hazardous or possibly dangerous to people, plants, animals, or belongings, and that unnecessarily disrupt safe satisfaction of people and their possessions. An aspect of the Universal Commons that numerous nations are making efforts to tackle is the issue of air pollution and its detrimental impact on the natural world (Li et al., 2020;Ukaogo, 2020).

Globally, particularly among advanced nations, big cities and urban centres have struggled with air pollution (Marlier et al., 2016; Krishna et al., 2019). Due to the persistent inability of national and local environmental programmes toeffectively tackle the dire pattern of air pollution, especially in the world's expanding megalopolis, the challenge appears to bemonumental. Understanding various kinds of land utilisation is crucial for studying the origins and features of air pollution because it affects multiple procedures which impact the cleanliness of the air, the most significant of which is the spread of pollutants (Bemsodi, 2018; Mbaoma et al., 2022; Thakrar et al., 2024).

In Nigeria's context and according to Sulaymon et al. (2023), the WHO ranked Nigeria as 39th out of the globe's most polluted countries, a sign of declining air quality, particularly in the biggest cities of the country, which has a negative impact on people's health. Owing to the vast number of diverse polluting factors, excessive $PM_{2.5}$ readings, and various forms of pollution which exist in Nigeria, an assortment of medical issues have arisen (Tao et al., (2019, Abulude et al., 2021; Fagorite et al., 2021). Importantly, particulate matter termed $PM_{2.5}$ which have a diameter of 2.5 micrometres or less. It can also occasionally have a diameter of 0.001 microns or less. The extremely tiny specification is a catalyst to health hazards when ingested and can lead to serious medical conditions that are temporary, such as more frequent coughing and chest infections, as well as making preexisting illnesses like asthma worse. Therefore $PM_{2.5}$ is seen as a significant factor that can be used to determine a nation's overall Air Quality Index (AQI) (Garcia et al., 2023; Tariq et al., 2023). In addition, there are various permanent and persistent diseases like ischemic heart disease, that is characterised by a reduction in the supply of oxygen to the heart, causing collateral harm to the heart tissue and an increased risk of cardiac arrest, chest pain, and ventricular fibrillation. Because $PM_{2.5}$ is so tiny, it may reach the circulatory system through the tiny air alveoli after penetrating deeply into the lung tissue. When within the circulatory system, it can do a great deal of harm, including halting reproduction, liver, and kidney mechanisms as well as harming arteries and entering additional organs (Gautam and Bolia, 2020).

Having discussed this, it isimportant to model and forecast Nigerian yearly mean $PM_{2.5}$ time series data to have a proper insight.Thereare many forecasting models used for pollution level forecasting, but these models do not account for periodic and seasonal trends usually present (Wang et al., 2009; Nath et al., 2021; Oshin and Okuo, 2024). This informs the development of theSeasonal Autoregressive Integrated Moving Average (SARIMA) model for modelling and forecasting Nigerian yearly mean particulate matter time series data since this model can account for periodic and seasonal trends usually present. As a way of determining the performance of this model, the step-ahead forecast and its accuracy metricswas determined for Nigerian yearly mean particulate matter.

METHODOLOGY

Time Plot

A time plot is agraph whichshowsinformation points gathered over aperiod of time. The time is representedon the vertical axis, while the parameter under investigation is represented by the horizontal axis. This is used to show how data changes over time and to identify variations and patterns in the data.

Augmented Dickey-Fuller Unit Root Test

By utilising, the Augmented Dickey-Fuller test, stationaritywasattained for the non-stationary series under consideration. This involved the utilization of associated standard errors that will be compared with the calculated value using the Dickey-Fuller table appropriate values.

Autoregressive Integrated Moving Average (ARIMA) Model

Autoregressive and moving average models with an order of integration (d), make up the ARIMA model. The standard notations for $AR(p)$ and $MA(q)$are expressed as

$$x_t = \emptyset_1 x_{t-1} + \emptyset_2 x_{t-2} + \cdots + \emptyset_p x_{t-p} + e_t \tag{1}$$

and

$$x_t = \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{t-q} \tag{2}$$

The combination of Eq (1) and Eq (2) gives the ARMA (p, q)model stated in Eq (3) as

$$x_t = \emptyset_1 x_{t-1} + \emptyset_2 x_{t-2} + \cdots + \emptyset_p x_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{t-q} \tag{3}$$

Utilising backward shift operator, Eq (3) becomes

$$(B)\nabla^d x_t = \theta(B) w_t \tag{4}$$

Seasonal Autoregressive Integrated Moving Average (SARIMA) model

The addition of seasonal terms to the ARIMA model gives a Seasonal model proposed by Box et al. (2008) which is an extension of the work of Box and Jenkins (1970). The

model is utilised to reflect and obtain seasonal variation characteristics within a dataset.
Given a time series $\{X_t\}$, a seasonal ARIMA model is of the form:

$$\emptyset_p(B)\Phi_P(B^S)^d(1-B^S)X_t = \theta_q(B)\Theta_q(B^S)\varepsilon_t \quad (5)$$

in Eq (5), B is a lag operator defined as $B^k X_t = X_{t-k}$, then

$$\emptyset_p(B) = 1 - \emptyset_1 B - \emptyset_2 B^2 - \cdots - \emptyset_p B^P \quad (6)$$

$$\Phi_p(B^S) = 1 - \Phi_s B^s - \Phi_2 B^{2s} - \cdots - \Phi_P B^{Ps} \quad (7)$$

$$\Theta_q(B) = 1 - \Theta_1 B - \Theta_2 B^2 - \cdots - \Theta_q B^P \quad (8)$$

and

$$\Theta_q(B^S) = 1 - \Theta_s B^s - \Theta_2 B^{2s} - \cdots - \Theta_q B^{Qs} \quad (9)$$

wherein $\phi(B)$and $\theta(B)$ polynomials for AR and MA, $\Phi_p(B^S)$ and $\Theta_q(B)$ are polynomial degrees for P and Q, d and D are levels of regular and seasonal differences, p, q, P, Q are order of seasonal and non-seasonal AR and MA, and the season duration is S.

Model building

The fundamental stages via the construction of the time series approach are identification, estimation, diagnosis as well as forecasting.

Model Identification

ACF and PACF are two components of a correlogram, where ACF is utilised for measuring lineal dependence within time series observations and the order of the model is identified using PACF. Eq (10) is utilised to define ACF as

$$\rho_k = \frac{E[(x_t-\bar{x})(x_{t-k}-\bar{x})]}{E[x_t-\bar{x}]^2} \quad (10)$$

and PACF as

$$x_t = \rho_0 + \sum_{k=1}^{K} \rho_{kk} x_{t-k} \quad (11)$$

in which $k = 1,2,\dots,K, \rho_{kk}$ is the $k^{th}k^{th}$ coefficient of autoregressive. The least principles of the Schwartz Bayesian (SBIC) and Akaike (AIC) Information Criterion are going to be utilised for selecting the optimal approach.

Parameter Estimation

Ordinary least squares estimationwasutilised to determine the approach parameters based on

$$\hat{\emptyset} = \sum_{t=2}^{n}(x_{t-1})(x_t) \Big/ \sum_{t=2}^{n} x_{t-1}^2 \quad (12)$$

After the estimation step, the most appropriate model for the series under considerationwas obtained utilising AIC and SBIC values.

Diagnostic Checking

The Modified Box-Pierce (Ljung-Box) Chi-Square Statistic stated in Eq (13)was utilised for diagnosing the validity of the estimated model.

$$Q(m) = n(n+2)\sum_{j=1}^{m}\frac{r_j^2}{n-j} \quad (13)$$

where n stands for operation differencing number.

Forecasting

Forecasting falls into two categories: in and post period where the latter is utilised to produce accurate forecasts and the former for building certainty about the model.

Performance Evaluation Metrics

The performance evaluation metrics whichwas utilised in this are Mean Absolute (MA), Root Mean Square (RMS) and Mean Absolute Percentage (MAP) errors given in Eq (14) to Eq (16).

$$MAE = \frac{1}{h+1}\sum_{t=s}^{h+s}(\hat{y}_t - y_t)^2 \quad (14)$$

$$RMSE = \sqrt{\frac{1}{h+1}\sum_{t=s}^{h+s}(\hat{y}_t - y_t)^2} \quad (15)$$

$$MAPE = \frac{100}{h+s}\sum_{t=s}^{h+s}\left|\frac{\hat{y}_t - y_t}{\hat{y}_t}\right| \quad (16)$$

where $t = s, 1+s, \dots, h+s$.For equivalent t principles, the quantities $\hat{y}_t$ *and* $y_t$represent the real and projected principles.

RESULTS AND DISCUSSION

Data Exploration

Nigerian yearly mean particulate matter ($PM_{2.5}$) time series data measured in micrograms per cubic meter ($(ug/m^3$)which was obtained from Nigeria Air Pollution Information and Air Quality Index (AQI) (2020) which spanned between 1990 and 2019 was analysed. The results in Table1 are the descriptive statistics of Nigerian yearly mean particulate matter ($PM_{2.5}$) and based on Table 1, the mean is 63.77ug/m^3 and standard deviation is 7.84 ug/m^3. The minimum yearly mean particulate matter

($PM_{2.5}$) was 48.63ug/m^3 in 2013 and the maximum was 75.04ug/m^3 in 2015 respectively. A sharp increase was noticed from 2015 to 2016 and this can be attributed to man-made and natural factors.

Table 1: Descriptive Statistics of Nigerian yearly mean particulate mat

Variable	Mean	St Dev.	Minimum	Maximum
Particulate matter	63.77	7.84	48.63	75.40

SARIMA Model Building

Nigerian yearly mean particulate matter ($PM_{2.5}$) displayed in Figure 1 signified the series is not stationary. This series exhibits secular and seasonal variations. Therefore, since the series exhibited this kind of variations, this informed the utilisation of SARIMA models. Stationarity of the series was attained based on the ADF test results presented with Table 1 which indicates stationary at the initial difference that is I(1) which is significant at 1%, 5% and 10% correspondingly.

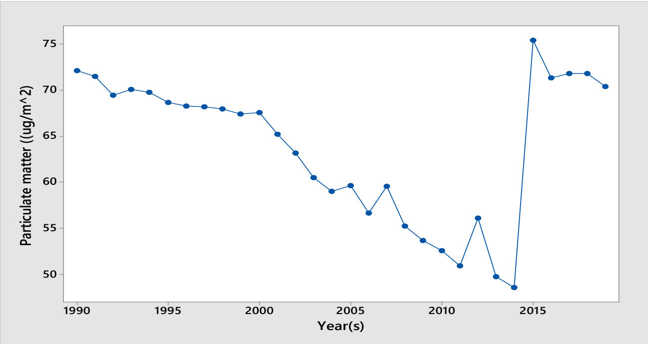

Figure 1: *Time plot of Nigerian yearly mean particulate matter in* (ug/m^2) *from 1990 to 2019*

Table 2: Augmented Dickey-Fuller test results

	Level of Significance	t-Statistic	Prob.*
Augmented Dickey -Fuller test statistics		-6.228730	0.0000
Test critical values:	1% level	-3.689194	
	5% level	-2.971853	
	10% level	-2.625121	

The Nigerian yearly mean particulate matter is stationary at $d = 1$ according to ADF test outcomes given in Table 2. The SARIMA approach estimated was identified utilising (ACF) and PACF plots. The PACF plot threshold occurred upon lag 2 and the ACF graph in Figure 2 tails out in lag 2, therefore, p = 1, 2 and q = 2 or p = 2 and q = 1, 2 were picked. The tentative ARIMA models are

$$ARIMA(1,1,1), ARIMA(1,1,2), ARIMA(2,1,1) \text{ and } ARIMA(2,1,2)$$

For the seasonal aspect of the model, the ACF cut out and the PACF tails out in the seasonal lags as seen in Tables 2 and 3, and these were utilised to recommend P = 1 or 2 and Q = 1, 2. The tentatively identified models for SARIMA are

$$SARIMA(1,1,1) \times (1,1,1)_{12}, SARIMA(1,1,2) \times (1,1,2)_{12},$$

$$SARIMA(2,1,1) \times (2,1,1)_{12} \text{ and } SARIMA(2,1,2) \times (2,1,2)_{12}$$

The four identified models for SARIMA approaches were fitted utilising the ordinary least square method. The better possible model in light of Nigerian yearly mean particulate matter was chosen concerning the least AIC and SIC values as seen in Table 3. The optimal model for Nigerian yearly mean particulate matter is $SARIMA(1,1,1) \times (1,1,1)_{12}$ model with regards to Table 3.

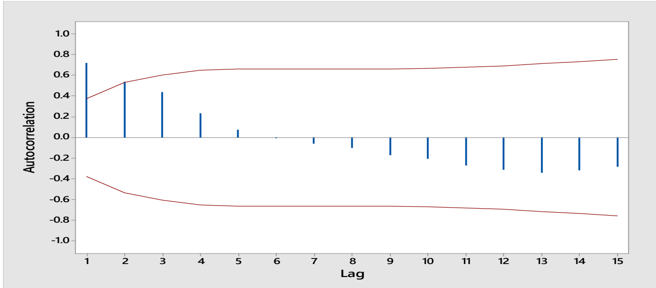

Figure 2: *ACF plot of Nigerian yearly mean particulate matter*

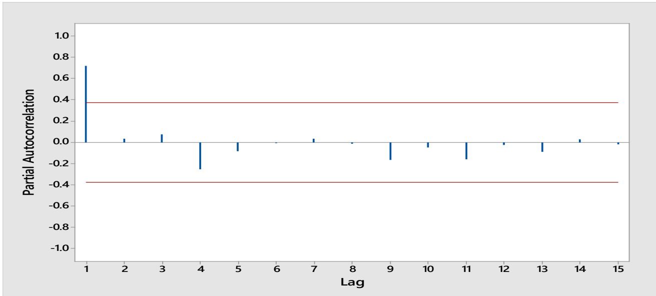

Figure 3: *PACF plot of Nigerian yearly mean particulate matter*

Table 3: Information criteria from the estimated SARIMA models

Inf. criteria	$SARIMA(1,1,1) \times (1,1,1)_{12}$	$SARIMA(1,1,2) \times (1,1,2)_{12}$	$SARIMA(2,1,1) \times (2,1,1)_{12}$	$SARIMA(2,1,2) \times (2,1,2)_{12}$
AIC	7.405851	7.588324	7.602908	7.778045
BIC	7.650914	7.931412	7.945996	8.219158

The SARIMA$(1,1,1)$x$(1,1,1)_{12}$ model adequacy for Nigerian yearly mean particulate matter forecasting was determined based on autocorrelation and partial autocorrelation plot of residual given in Figures 4 and 5. The Modified Box-Pierce (Ljung-Box) Chi-Square Statistic values in Table 4. further ascertained the suitability of the model. Therefore, SARIMA$(1,1,1)$x$(1,1,1)_{12}$ model is the most appropriate and sufficient model for estimating Nigerian yearly mean particulate matter.

Table 4: Modified Box-Pierce (Ljung-Box) Chi-Square Statistic

Lag(s)	Chi-square	Degree of freedom	P-value
12	11.20	2	0.004
24	39.60	14	0.00
36	60,80	26	0.00
48	70.00	38	0.001

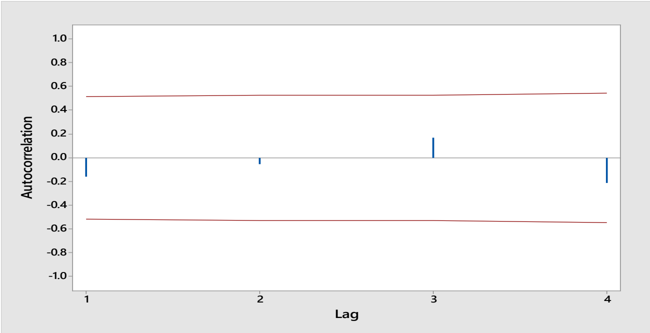

Figure 4: *ACF plot of residual*

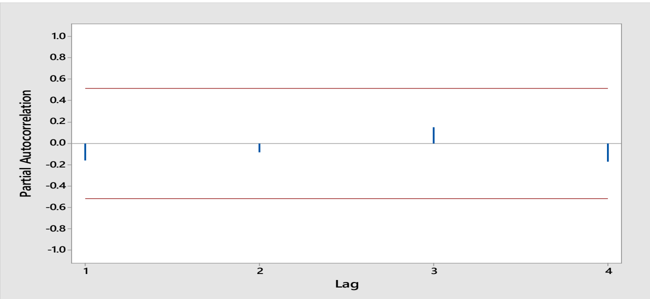

Figure 5: *PACF plot of residual*

The fitted SARIMA$(1,1,1)\mathrm{x}(1,1,1)_{12}$ model is used to obtain a forecast for Nigerian yearly mean particulate matter for the next 19 years. The forecast from the model is displayed in Figure 6 and Table 5 provided more clarification on the Nigerian yearly mean particulate matter forecast and, upper and lower bound values were displayed. In regard to Figure 6 and Table 5, Nigerian yearly mean particulate matter forecast signified a seasonal fluctuating movement for the next 19 years that is 2020 to 2039. Table 5 as well is used to present Nigerian mean yearly particulate matter lower and upper bounds, and forecast values which indicates Nigerian yearly mean particulate matter would continue to fluctuate and seasonal in movement over the forecasted period. This may rise within the interval 27.735 – 81.659ug/m^3 respectively in the next 19 years.

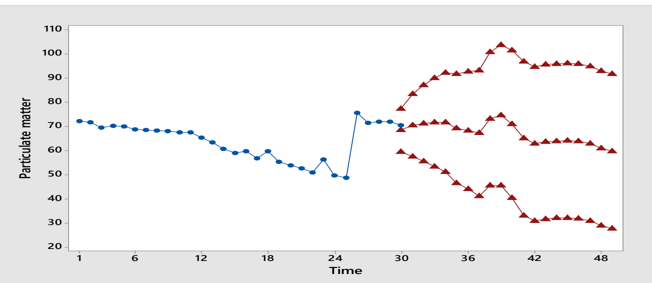

Figure 6: *Time plot of Nigerian yearly mean particulate matter forecast with SARIMA model from 2020 to 2039 with 95% confidence interval.*

Table 5: Forecast of Nigerian yearly mean particulate matter from 2020 to 2039 with 95% confidence interval

Year(s)	Forecast	Lower	Upper
2020	68.302	59.457	77.148
2021	70.337	57.472	83.201
2022	71.182	55.398	86.967
2023	71.633	53.352	89.915
2024	71.631	51.168	92.093
2025	69.050	46.613	91.487
2026	68.236	43.986	92.487
2027	67.126	41.188	93.063
2028	73.147	45.626	100.668
2029	74.486	45.468	103.505
2030	70.782	40.340	101.224
2031	64.973	33.171	96.776
2032	62.725	30.914	94.536
2033	63.517	31.679	95.355
2034	63.873	32.016	95.730
2035	64.032	32.154	95.911
2036	63.713	31.813	95.612
2037	62.719	30.798	94.639
2038	60.791	28.850	92.732
2039	59.697	27.735	91.659

The SARIMA$(1,1,1)\mathrm{x}(1,1,1)_{12}$ model performance evaluation metrics are given in Table 6 and this signified that MAE, RMSE and MAPE values indicated that SARIMA$(1,1,1)\mathrm{x}(1,1,1)_{12}$ is the better model since its performance assessment metrics are relatively low. Therefore, SARIMA$(1,1,1)\mathrm{x}(1,1,1)_{12}$ is the better model for forecasting Nigerian yearly mean particulate matter from 2020 to 2039. The Nigerian yearly mean particulate matter from 1990 to 2019 and the forecast from 2020 to 2039 are above the World Health Organization standard. The international standard is 10 ug/m^3 annual mean for normal yearly mean particulate matter. Therefore, the high level of yearly mean particulate matter in Nigeria is alarming.

Table 6: Forecast evaluation metrics for the models

Performance evaluation metrics	$SARIMA(2,1,5)\times(1,1,1)_{12}$
MAE	2.085470
RMSE	3.497472
MAPE	10.24077

CONCLUSION

This study is used to discuss and analyse Nigerian yearly mean particulate matter using yearly time series datasets from the period 1990 to 2019. The Seasonal Autoregressive Integrated Moving Average (SARIMA) model was utilised for modelling and forecasting Nigerian yearly mean particulate from 2020 to 2039. The result signified that Nigerian yearly meanparticulate matterwould continue to fluctuate and indicate a seasonal movement over the forecasted period and there may be fluctuation within the interval 27.735 – 81.659 ug/m^3 in the next 19 years. Conclusively, the Nigerian yearly mean particulate matter from 1990 to 2019 and the forecast from 2020 to 2039 are above the World Health Organization standard since the international standard is 10 ug/m^3 annual mean. Therefore, the high level of yearly mean particulate matter in Nigeria is alarming and this could potential affect the health of Nigerian over the years. The study recommends that adequate policiesbe put in place to combat the major sources of air pollution and especially, particulate matter that is detrimental to human health. The Nigeriangovernment at all levelsshould ensure the air quality level follows international standard and critical measures should be put in place to reduce exposure to particulate matter. This couldreduce morbidity and mortality attributed to particulate matter exposure.

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