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MODELLING MEAN ANNUAL RAINFALL PATTERN IN PORT HARCOURT, NIGERIA

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ABSTRACT
The paper examines the modelling of mean annual rainfall pattern in Port Harcourt, Nigeria. The data on rainfall used covered the period of 1981 to 2016. The results of ACF and PACF indicated an autoregressive moving average model since the order of integration of the data is zero and, ACF and PACF neither dies off nor cut off at any lag. Sum of squares deviation forecast criteria (SSDFC) was adopted to select the best performing sub-classes of ARMA(p, q) that fits the data. Among ARMA(1, 1), ARMA(1, 2) ARMA(2, 1) and ARMA(2, 2) models estimated, SSDFC chose ARMA(1, 2) as the best performing model. The selected model were supported by AIC and BIC respectively. The forecast generated using ARMA(1, 2) indicates a mean annual rainfall forecast value of 191.537 mm for 2018. Hence, ARMA(1, 2) can be used to predict long term quality of water for agriculture and hydrological purpose and to create long term awareness against flood and control strategy for Port Harcourt.
KEYWORDS: *ARMA models, SSDFC, Rainfall Pattern*

1.0 INTRODUCTION

Water resources are essential renewable resources that are the basis for existence and development of a society. Proper utilization of these resources requires assessment and management of the quantity and quality of the water resources both partially and temporally. Water crises cause by shortages, floods and diminishing water quality, among other, are increasing in all parts of the world. Again, according to Vanguard Newspaper on July 24, 2017,"Floods sacks homes and churches in Rivers". In Rumuolumeni community, in Obio/Akpor Local Government area of the state, there was panic, following the flood that submerged over 100 homes and four churches in the area (Onoyume and Iheamnachor (2017)). Hence, it becomes imperative to carry out this project. The project focuses on the time series analysis of annual rainfall in River state. Rivers State is a predominantly low-lying pluvial state in southern Nigeria, located in the eastern part of the Niger Delta on the ocean-ward extension of the Benue Trough. The inland part of the state consists of tropical rainforest, and towards the coast, the typical Niger Delta environment features many mangrove swamps. Rivers State has a total area of 11,077 km² (4,277 mi²), making it the 26th largest state in Nigeria. Surrounding states are Imo, Abia and Anambra to the north, Akwa Ibom to the east and Bayelsa to the west. On the south, it is bounded by the Atlantic Ocean. Its topography ranges from flat plains, with a network of rivers to tributaries.

Rainfall is generally seasonal, variable, as well as heavy, and occurs between the months of March and October through November. The wet season peaks in July, lasting more than 290 days. The only dry months are January and February having little or no effect. Total annual rainfall decreases from about 4,700 mm (185 in) on the coast, to about 1,700 mm (67 in) in the extreme north. It is 4,698 mm (185 in) at Bonny along the coast and 1,862 mm (73 in) at Degema. For Port Harcourt, temperatures throughout the year are relatively constant with little variation throughout the course of the seasons. Average temperatures are typically between 25 °C−28 °C. Some parts of the state still receive up to 150 mm (6 in) of rainfall during the dry period. Relative humidity rarely dips below 60% and fluctuates between 90% and 100% for most of the year.

Rainfall is one of the most important natural factors that determine the agricultural production in across the globe, particularly in the

South Eastern part of Nigeria. The variability of rainfall and the pattern of extreme high or low precipitation are very important for agriculture as well as the economy of the state. The mean annual characterises the long-term quality of water available to a region or state for hydrological and agricultural purposes. Under non-irrigated condition, it provides an upper limit to a regions sustainable agricultural potential in regard to biomass production if other factors (e,g light, temperature, topography, soils) are not limiting. However, mean annual precipitation is not only important for general statistic but also probably climatic variability best known to hydrologist and farmers, and to which they can relate many other things.

The present study is different from few empirical studies on the subject matter as it examines modelling mean annual rainfall pattern in Port Harcourt, Rivers state, Nigeria. In its dimension, compares different sub-classes of autoregressive moving average model using sum of squares forecast deviation criterion to select the best performing ARMA(p,q) specification.

2.0 LITERATURE REVIEW

A lot of researchers have paid considerable attention towards modelling and forecasting the amount of rainfall pattern in various parts of Nigeria.For instance, Etuk *et al* (2013) modelled monthly rainfall in Port Harcourt, Nigeria, using seasonal ARIMA (5, 1, 0)x(0, 1, 1)12 model. The time-plot shows no noticeable trend. The known and expected seasonality is clear from the plot. Seasonal (i.e. 12-point) differencing of the data is done, then a nonseasonal differencing is done of the seasonal differences. The correlogam of the resultant series reveals the expected 12-monthly seasonality, and the involvement of a seasonal moving average component in the first place and a nonseasonal autoregressive component of order 5. Hence the model mentioned above. The adequacy of the modelled has been established. Adejuwon(2011) studied Power spectral analysis of annual rainfall for Edo and Delta States (formerly Mid-Western Region) in Nigeria using data for 1931 – 1997 in order to identify any regular periodicities which may be present. The Hanning filter was employed for the purpose of smoothing the power spectral. Irregular short-term periodicities were evident with significant cycles of between 3 and 6 years.

Osarumwense (2013) has modelled the quarterly rainfall data as a (0, 0, 0)x(2, 1, 0)4 seasonal ARIMA model. Olofintoye and Sule(2010) fitted the trend line y = 0.3903x – 587.5125 which is indicative of a positive trend for rainfall. A few other researchers who have published research results on Port Harcourt rainfall are Chiadikobi *et al.*(2011), Dike and Nwachukwu(2003) and Salako(2007). Etuk, et al.,(2013) identified and established the adequacy of a Seasonal ARIMA (5,1,0)(0,1,1)12 for modelling and forecasting the amount of monthly rainfall in Portharcourt, Nigeria; Edwin and Martins(2014) examined the stochastic characteristics of the Ilorin monthly rainfall in Nigeria using four different modelling techniques (Decomposition, Square root transformation-deseasonalisation, Composite and Periodic Autoregressive) where they compared the results from the various methods employed.

Again, Akpanta *et al*(2015) modelled the frequency of monthly rainfall in Umuahia, Aba state, Nigeria. They found that the plots of the ACF and PACF show spikes at seasonal lags respectively, suggesting SARIMA (0,0,0) (1,1,1)12. Though the diagnostic check on the model favoured the fitted model, the Auto Regressive parameter was found to be statistically insignificant and this led to a reduced SARIMA (0, 0, 0) (0, 1, 1)12 model that best fit the data and was used to make forecast. Alawaye and Alao (2017), examined the Time Series Analysis on Rainfall in Oshogbo Osun State, Nigeria, using monthly data of rainfall between 2004-2015. The time plot reveals that the rainfall data show high level of volatility characterized by seasonal and irregular variations. And the logistic model applied showed to be better and then used to forecast the rainfall for the next 2 years.

3.0 MATERIAL AND METHOD

This chapter highlights the different methods that were used in the study. It includes method and sources of data collection, method of variable measurement, and method of unit root test, model specification, and model identification, method of data analysis, model comparison techniques and diagnostic checks.

3.1 Method and Sources of Data Collection

There are two main sources of data such as the primary and secondary data. The primary data are those data that are collected first hand by the researcher with the aid of questionnaire, interviews etc while the secondary data are those that are collected by another researcher both are still used for the same purpose of research work. This study employed the secondary data as a result of the cost and time incurred in collecting primary data and due to the availability of secondary data. The source of data was from central bank of Nigeria (CBN) (2016) statistical bulletin.

The type of data that was used for this study was the time series data because it was a sequence of data that are recorded sequentially with time and are carried out at regular interval of time, as in the mean annual rainfall. And the univariate time series data collected covered the period of 1981-2016 (36 observations of mean annual rainfall data).

3.4 Method of Variable Measurement

Rainfall is usually measured in millimetre using rain gauge. This special kind of drum is then used to record the depth of the rainfall collected. Rain gauge is usually about 50cm tall and is place on the ground just high enough to avoid splashes.

3.7 Unit Root Test

The study will use the Augmented Dickey-Fuller (ADF) test since there is no level shift in the variable and the sample size is relatively large. Investigating whether a sequence contains a unit root, consider the [4] and [5] tests as follows

$$\Delta y_t = \alpha_0 + \alpha_1 t + \phi y_{t-1} + \sum_{j=1}^{p-1} \beta_j \Delta y_{t-j} + \mu_t \tag{7}$$

$$\Delta y_t = \alpha_0 + \phi y_{t-1} + \sum_{j=1}^{p-1} \beta_j \Delta y_{t-j} + \mu_t \tag{8}$$

$$\Delta y_t = \phi y_{t-1} + \sum_{j=1}^{p-1} \beta_j \Delta y_{t-j} + \mu_t \tag{9}$$

In (7) there is both the drift term and the deterministic trend. The drift term is excluded in (8) and (9) excludes both the intercept term and the deterministic trend. The null hypothesis H_0: ϕ =0 versus the alternative H_1: ϕ <0. If the ADF test statistic is greater than 1%, 5% and 10% critical values, the ADF test null hypothesis of a unit root is accepted.

3.8 Model Specification: ARMA(p, q) Model

These mixed processes are denoted as ARMA(p,q) processes. They enable us to describe processes in which neither the autocorrelation nor the partial autocorrelation function breaks off after a finite number of lags. The general *autoregressive moving average process* with AR order p and MA order q can be written as

$$y_t = \delta + \alpha_1 y_{t-1} + \cdots + \alpha_p y_{t-p} + u_t - \beta_1 u_{t-1} - \cdots - \beta_q u_{t-q} \tag{10}$$

with u_t being a pure random process and $\alpha_p = 0$ and $\beta_q = 0$ having to hold.

Using the lag operator, we can write

$$\left(1 - \alpha_1 L - \cdots - \alpha_p L^p\right) y_t = \delta + \left(1 - \beta_1 L - \cdots - \beta_q L^q\right) u_t \tag{11}$$

Alternatively,

$$\alpha(L) y_t = \delta + \beta(L) u_t \tag{12}$$

where u_t is a sequence of random variables with zero mean and constant variance, called *a white noise process,* and the α_j's and β_j's constants. As factors that are common in both polynomials can be reduced, α(L) and β(L) cannot have identical roots. The process is stationary if – with stochastic initial conditions – the stability conditions of the AR term are fulfilled, i.e. if (L) only has roots that are larger than 1 in absolute value. If p = 0, the model above becomes a *moving average model of order q* (designated MA(q)). If, however, q = 0 it becomes an *autoregressive process of order* p (designated AR(p)). Besides stationarity, invertibility is another important necessity for a time series. It ensures the uniqueness of the model covariance structure and, therefore, allows for meaningful expression of current events in terms of the past history of the series.

3.9 Model Identification

The ACF of an MA(q) model cuts off after lag q whereas that of an AR(p) model is a combination of sinusoidals dying off slowly. On the other hand the PACF of an MA(q) model dies off slowly whereas that of an AR(p) model cuts off after lag p. AR and MA models are known to exhibit some duality relationships. Parametric parsimony consideration in model building entails the use of the mixed ARMA fit in preference to either the pure AR or the pure MA fit.

3.10 Model Comparison

There are several model selection criteria in literature such as; Bayesian information criterion(BIC),Aikaike information criterion(AIC), residual sum of squares and so on.

If n is the sample size and RSS is the residual sum of squares, then, BIC and AIC are given as follows;

$$BIC = \ln(RSS/n) + k(\ln n/n) \tag{13}$$

$$AIC = 2k + n\ln(RSS/n) \tag{14}$$

Where, n is the sample size, k is the number of estimated parameters (for the case of regression, k is the number of regressors) and RSS is the residual sum of squares based on the estimated model. However, it is good to note that both BIC and AIC are affected by the number of parameters included to be estimated in a model. For the case of BIC, it penalizes free parameters while AIC becomes smaller as the number of free parameters to be estimated increases. But for this study, sum of squares deviation forecast criterion introduced by Amaefula(2011) which is of the form;

$$SSDFC = \frac{1}{m}\sum_{i=1}^{m}\left(y_{t,\{l,i\}} - \hat{y}_{t,\{l,i\}}\right)^2 , \quad i = 1,2,\cdots,m \tag{15}$$

Where l is the lead time, m is the number of forecast values to be deviated from the actual values (m should be reasonably large), $y_{t,\{l,i\}}$ is the actual values of the time series corresponding to the i[th] position of the forecast values and $\hat{y}_{t,\{l,i\}}$ is the forecast values corresponding to the i[th] position of the actual values. In comparison, the model with the smallest value of SSDFC is the best fitted model that can describe to the closest precision the behaviour of the underlying fitted model.

3.10. Model Estimation

The coefficients are estimated using an iterative algorithm that calculates least squares estimates. At each iteration, the back forecasts are computed and sum of squares error (SSE) is calculated. For more details, see Box and Jenkins(1994).

4.0 DATA ANALYSIS AND RESULTS

This section presents the graphical plot of rainfall data, results of unit root test, trend analysis, plots of ACF and PACF and ARMA model and the forecast result.

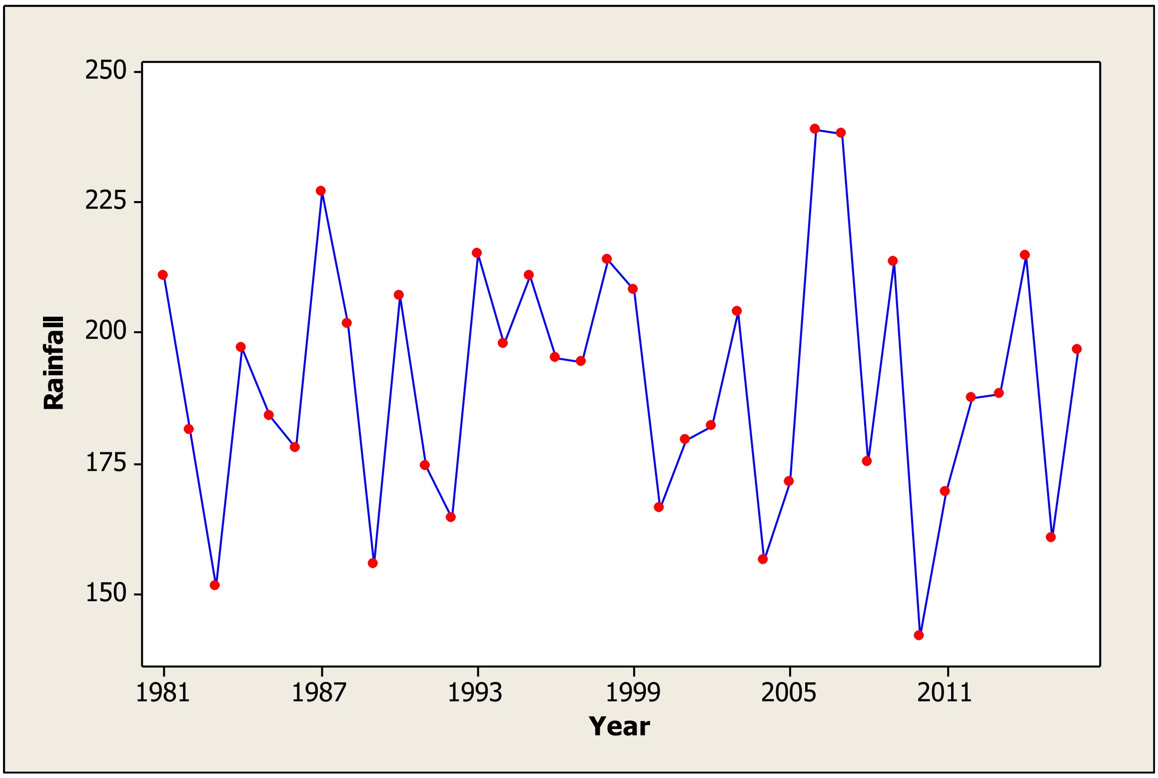

Figure1. Time series plot of rainfall data in Port Harcourt from 1981-2016

The plot in Figure1 indicates that yearly rainfall in Port Harcourt has the highest peak in 2006 and lowest in 2010.

Table 1. Analysis of ADF Unit Root Test

---------- Interpolated Dickey-Fuller ---------

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-6.085	-4.288	-3.560	-3.216

MacKinnon approximate p-value for Z(t) = 0.0000

The result in Table 1 above shows that rainfall data is integrated order zero I(0), hence the variable (rainfall) is stationary and it is significant at 1% level.

4.3 Plots of ACF and PACF

The plots of ACF and PACF are presented in Figure4 and Figure5 below;

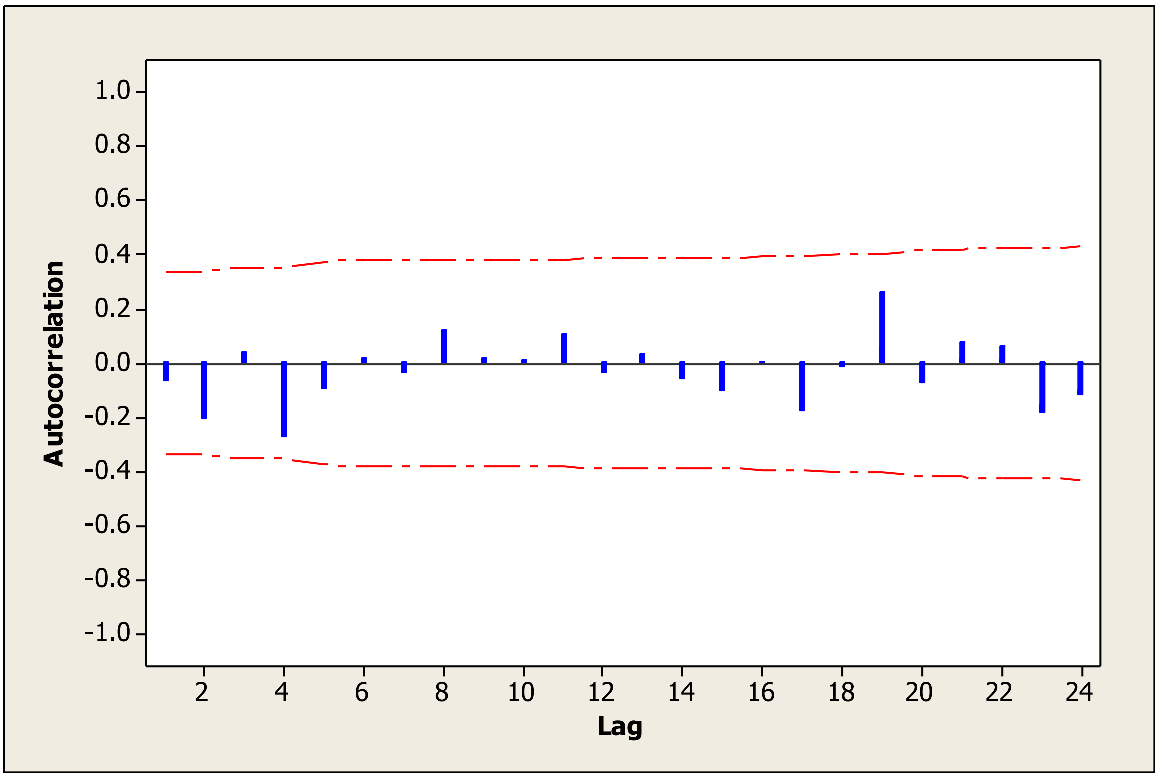

Figure4. Autocorrelation function for Rainfall data (with 5% significance limits for the autocorrelations)

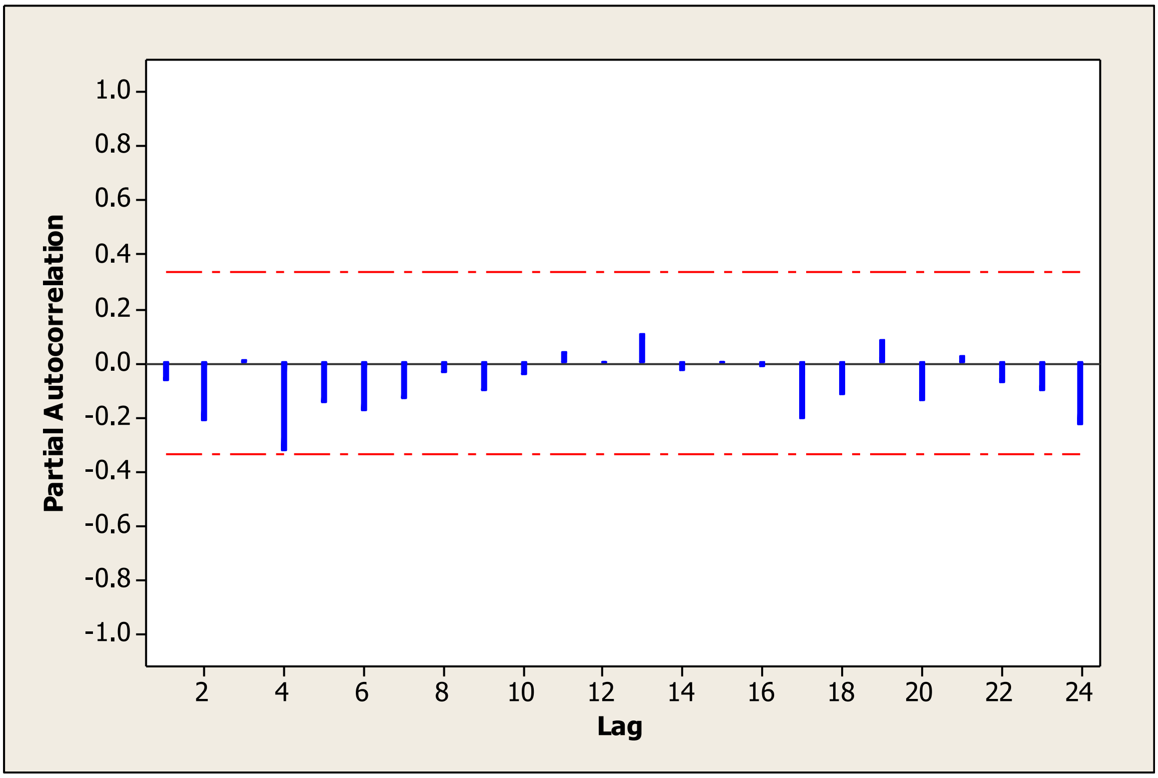

Figure5. Partial Autocorrelation function for Rainfall data (with 5% significance limits for the partial autocorrelations)

Since the ACF neither cuts off after lag q as in the case of MA(q) model nor dyes off slowly as in the case of AR(p) model, then ARMA(p,q) model is identified.

4.4 Estimate of ARMA(p,q) models

In this section, we will fix two sub-classes of ARMA(p,q) model; ARMA(1,1) and ARMA(2,2) models and compare the two models fixed using residuals sum of squares (RSS).

The parameter estimates of ARMA(1,1) is given in Table3 below;

Table3. Estimates of ARMA(1, 1)model Parameters

Type	Coef	SE Coef	T	P
AR 1	0.5895	0.1866	3.16	0.003
MA 1	0.9633	0.1327	7.26	0.000
Constant	78.4449	0.2965	264.59	0.000
Mean	191.088	0.722		

Number of observations: 36, Residuals: SS = 16721.7 MS = 506.7 DF = 33

Table4. Estimates of ARMA(1, 2) model Parameters

Type	Coef	SE Coef	T	P
AR 1	0.0861	0.2660	0.32	0.748
MA 1	0.4346	0.2384	1.82	0.078
MA 2	0.6955	0.2116	3.29	0.002
Constant	175.051	0.250	698.85	0.000
Mean	191.534	0.274		

Number of observations:36, Residuals: SS = 13892.7 , MS = 434.1 DF = 32

Table5. Estimates of ARMA(2, 1)model Parameters

Type	Coef	SE Coef	T	P
AR 1	-0.6753	0.3905	-1.73	0.093
AR 2	-0.2681	0.1871	-1.43	0.162
MA 1	-0.6428	0.3843	-1.67	0.104
Constant	369.757	6.633	55.74	0.000
Mean	190.269	3.413		

Number of observations: 36, Residuals: SS = 18763.7, MS = 586.4 DF = 32

The parameter estimates of ARMA(2,2) is given in Table4 below;

Table6. Estimates of ARMA(2, 2)model Parameters

Type	Coef	SE Coef	T	P
AR 1	-0.0654	0.3591	-0.18	0.857
AR 2	0.2052	0.2849	0.72	0.477
MA 1	0.3182	0.3064	1.04	0.307
MA 2	0.8378	0.2858	2.93	0.006
Constant	164.769	0.225	733.36	0.000
Mean	191.543	0.261		

Number of observations: 36, Residuals: SS = 13562.9 , MS = 437.5 DF = 31

Table7. Model comparison using SSDFC

Model	RSS	SSDFC	AIC	BIC
ARMA(1, 1)	16721.7	586.321	227.0740	6.4396
ARMA(1, 2)	13892.7	571.951	222.4016	6.3538
ARMA(2, 1)	18763.7	587.344	233.2218	6.6543
ARMA(2, 2)	13562.9	576.546	223.5367	6.4293

A comparison of the four sub-classes of ARMA models in Table7 above using SSDFC indicates that and ARMA(1, 2) has the smallest SSDFC value hence, it is the preferred model. The choice of ARMA(1,2) is also confirmed by BIC and AIC.

4.5 Diagnostic Test

This section will provide results of Ljung-Box statistic to check whether the residuals are correlated. And also test for normality of the error term using

Table8. Modified Box-Pierce (Ljung-Box) Chi-Square statistic

Lag	12	24
Chi-Square	7.0	19.0
DF	8	20
P-Value	0.540	0.521

The result of Table8 shows that the probability of Ljung-Box) Chi-Square statistic is greater than 5% significant level, this indicates that the residuals of the ARMA(1, 2) are not correlated. Hence the model is adequate.

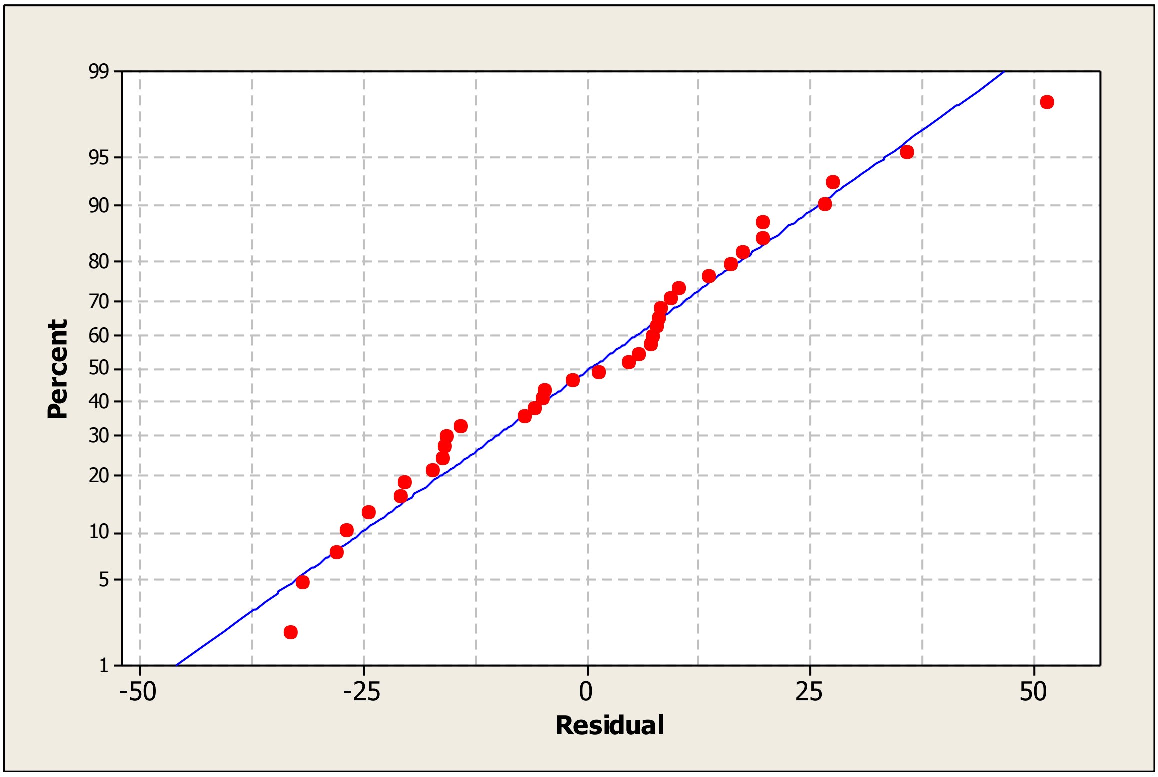

Figure6. Normal probability plot for residual

The result of Figure 6 indicates that the residual of the model is normally distributed.

Table9. Forecast generated using ARMA(1, 2)

Period	Forecast	95% Limits Lower	95% Limits Upper	Actual
34	204.187	163.339	245.034	214.625
35	195.758	152.501	239.015	160.558
36	191.898	139.463	244.333	196.792
37	191.565	139.068	244.062	
38	191.537	139.039	244.034	

The forecast generated in Table9 shows that mean annual rainfall for Port Harcourt for 2018 is 191.537mm (visible in period 38)

5.0 CONCLUSION AND RECOMMENDATION

The project work considered the time series analysis of mean annual rainfall pattern in Port Harcourt and fits the appropriate sub-class of ARIMA(p,q) model that best described annual rainfall pattern. The study compared four different estimated ARMA models; ARMA(1, 1), ARMA(1, 2), ARMA(2, 1) and ARMA(2, 2) models using SSDFC and the result showed that ARMA(1, 2) model is preferred. The choice model using SSDFC was supported by BIC and AIC. And the forecast value generated for 2018 using ARMA(1, 2) model is 191.537 mm for 2018.

The forecasted mean annual rainfall for 2018 might be useful information on the volume of rainfall that is expected this year, 2018. Hence, ARMA(1, 2) model can be use to study annual precipitation in Port Harcourt and for predicting average annual rainfall in the state.

5.3 Recommendations

The following recommendations are made from the findings of this project;

I. The government can use the ARMA(1, 2) to predict long term quality of water for agriculture and hydrological purpose.

II. The model can be use to create long term awareness against flood and control strategy

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