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RESEARCH ARTICLE OPEN ACCESS

ASSESSMENT OF THE ADEQUACY OF ELECTRICAL ENERGY DEMAND FORECAST MODEL FOR THE NIGERIA POWER DISTRIBUTION SYSTEM VIA STATIONARITY TEST

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ABSTRACT

Electric energy demand forecasting model is an essential tool in the course of planning in electricity industry. Though, there has been increasing concern to fix models for various domains. The adequacy and accuracy of these models for forecasting reasonable energy generation capacity, scheduling and system management planning are paramount. Inaccurate model will give forecasting that are either underrated that will incapacitate socio-economic growth by not supply enough electrical energy for development, or overestimated leading to excess electrical energy generation without commensurate returns on investment, another form of economic jeopardy. In this paper, Assessment of the adequacy of Electrical Energy Demand Forecasting Model for the Nigeria Power Distribution System via Stationarity test was performed as crucial stage in development of time series technique of energy demand forecast model. In the stationarity investigation of data set under the null hypothesis as a test tool for the confirmation of stationarity and non-stationarity of energy demand data for processing and further analyses of energy demand in power distribution system in Nigeria. Data were collected from five 33kV feeders each with sixty-point of monthly peak Load demand for five years (2015-2019) from Ibadan Electricity distribution Company (IBEDC). R- Software was used as optimization tool for the analyses. The end result was interpreted by Critical values for Augmented Dickey-Fuller method. Findings shows that data from three of the feeders were non-stationary they will go through data differencing to make the data suitable for further investigations as a mixture of an autoregressive integrated moving average ARIMA while two are stationary and can be authenticated for further analyses. The application of this test to further difference the datapoints that are non-stationary will lead to stationary dataset, hence, give viable model for accurate energy demand forecasting model development.

I. INTRODUCTION

Nigeria a nation producing electrical energy in anticipated large quantity for more than a decade, the rate at which electrical energy supply support structure and expansion in the country is poor, hence, power supply remains insufficient to meet the people demand [1]. Nigeria been the most populous country in Africa with over two hundred million population, meeting the electrical energy demand of the inhabitants in this era is a big task, a high volume of production activities and more demand for electrical energy is expected, for these reasons the government privatized Power sector in 2013, in anticipation to bridge demand-supply gap. However, the result was far from expectation, rather the heights of the tasks was changed, the gap is wider with population and socio-economy growth [1],[2].

Currently, over forty percent of the total inhabitants of Nigerians are off national grid [3]. The remaining 59.3% though connected, reliable power supply poses serious challenges nearly ninety-percent of the energy demanded is not met. In the Nigerian

Energy sector study, it was estimated that electricity demand will rise to the tune of 213,122 MW by 2040**.** Although the results of these studies be at variance extensively, the fact remains that there is wide gap in electrical energy demand and supply profile. In the coming years, industrial, commercial and domestic electricity demand is expected to rise considerably. Domestic demand with lion share will have rapid growth as a result of expansion at a reasonable rate yearly and growth in population that is estimated at 2.7% per annum. [4],[5]

Reliable power supply is an inevitable infrastructure for the economic growth of any nation. Yet, insufficient energy supply, in the presence of ever-increasing energy demand characterized by the unreliability, forced power outage, and unplanned load-shedding is rampant in Nigeria a supposed developing nation. Energy management and planning is one of the major ways of obtaining a reliable power supply and forecasting of energy demand is an optimization tool in power system planning and management. To obtain adequate and reliable forecasting algorithm is an immense challenge. The decision, therefore, to eliminate or minimize the risk of either inadequate or over-estimated power demand with the aid of careful planning and application of useful tools such as forecasting that is accurate is a necessity [6].

In the light of above-mentioned facts, there is a need for adequate planning using the appropriate forecasting model as a tool for accurate energy demand for the teeming population. However, time series model is one of the most effective models for energy demand because it gives room for trends and variations, this is of course the choice for this study, however, to achieve this the historical data for the time series analysis must be stationary [6]. Identification of stationary data phases in time series is an essential step in data mining and analysis. By statistical rule, data with constant mean, variance and covariance are stationary [7],[8]. Stationarity indicates that the mathematical features of a time series or the data mining that produced the series does not vary for some period of time [7]. Time series data may either stationary or not. Stationarity sequences are values that are unchanging and near to an average value of the data mining and other value of statistical central tendency [9]. A stationary time series will tend to return to its mean called mean reversion and fluctuate around this mean. Stationarity is diverse in nature, it could be wide, weak, strict or second order if it has a constant average and variance value [10].

Strictly stationary serial data has constant auto-covariance configuration in addition to mean and variance. When a series holds this covariance stationarity, the covariance configuration is steady over time [9]. Explicitly, the auto-covariance maintain constant measure of central tendency and dispersion irrespective of the point of sequential reference. Periodic systems are easy to predict, in the sense that their gesture has an iterating pattern. Interestingly, stationarity procedures circumvent the challenges of unauthentic regression [11]. Stationary is essential in data mining since its absence can muddled the appropriateness of developed model hence rubbish the forecasting result at intervals. The result of which will not give the desire model for accurate planning. Moreover, typical authentication tests to confirm adequacy of developed model such as Chi-squared, Q and Durbin-Watson statistic T, F, etc. are effective when variables are stationary otherwise, these tests cannot be bank upon.

Stationarity can be ascertained in several ways: graphical representation, autocorrelation and partial autocorrelation valuations, autocorrelation coefficients and quantified examinations. Several methods is applicable in stationarity specified tests such as: Unit root test, Dickey-Fuller and Augmented Dickey-Fuller, Kwiatkowski Phillips-Schmidt-Shin (KPSS), Zivot and Andrews, Variance Ratio Test (VRT). However, when the data point is average in real life time series, which is the case of this study, sixty datapoints per feeder, Augmented Dickey-Fuller (ADF) technique is preferable because of its robust result [12]. The application of Augmented Dickey-Fuller examination is comfortable through consecutive correlation. The ease of ADF test in complex series modeling is grandeur than others in its class. The method has more advantages of being more potent, specific and straight forward [12]. Results from ADF analysis are: p-value, value of the test statistic, number of lags, the critical value cutoffs. The interpretation of these and the significance will confirm stationarity and non-stationarity of the series [13]. Consequently, stationarity investigation should take the lead in sound data analysis for time series modeling. Principally, the exploration is highly crucial especially when dealing with systems for which the data acquisition procedure does not guarantee stationarity: if only short and unique time series is accessible and if the experimental circumstances is not amendable or the amenability is restricted. However, this scenario is a common occurrence in many fields of endeavor especially, electrical energy operation and management [13],[14].

R-software application for statistical analyses was used for the studies. There are now thousands of Packages for R specifically designed for specialized data manipulation or data analysis which enhance data visualization that produce publication-ready quality charts [15]. These graphs for pictorial valuation of the sequence revolved around the analyses of autocorrelation and partial autocorrelation plots. Relationship between a time series with trends in the autocorrelation explain the connection of the series and its features [14],[16]. To compute autocorrelation, the correlation are computed, and the lagged series is noted which is preliminary successions copy, this proceed a once or a multiple of times in the. A lagged sequence with single lag is the original series proceeding once; whereas, lag-2 is the initial series moved forward two time periods, on between the series and a lagged version of the series. Interpretation of the autocorrelation function (ACF) and partial autocorrelation function PACF plot will faction out stationarity and non-stationarity functions in collaboration with the p-value and lag order [17].

Peak load forecast is ideal for preparation of power system operation at the time of highest demand from the consumers, hence ideal for this analysis. [18],[19]. Peak load contribution, also referred to as peak power, peak demand, critical demand, or maximum demand is usually caused by spikes in usage which may result from a variety of factors. Peak demand, although the period is transient, all the same very crucial, when electricity is in high demand because the sharp the evidence of peak load curve is a necessity for adequacy in forecasting processes. However, the electricity companies must generate the maximum capacity and have the transmission and distribution infrastructure to handle the peak demand for economic reasons non-conventional methods of generation can serve as standby for such periods [20]. In Nigeria, stakeholders were focusing much attention on electric power generation plants and transmission systems with little responsiveness on distribution. With extraordinary increase in energy demand by all classes of consumers and population expansion, the complication of power distribution system became more elaborate. This led to daily challenges in Nigeria power distribution system that draw thoughtfulness and careful planning [21]. Therefore, the interest of this study was to assess the adequacy of the energy demand data via stationarity test for accurate model development in Nigeria power distribution system for effective planning to mitigate these myriad challenges in power sector.

II. METHODOLOGY

II.1 TIME SERIES MODELLING

A time series is a succession of data or action that follows a particular order or trend in an interval of time. Time series forecasting uses a procedure to calculate future ideals founded on previously observed and present occurrence. Its values are in progressive order hence makes the analysis diverse from cross-sectional studies, without natural ordering of the observations, action or information [22]. Time series analysis may be in frequency or time domain [23]. The time domain includes an algorithm that estimate the strength and wavelet while frequency domain takes account of autocorrelation and cross relationship analysis [24]. The flawless examination of time series data by inspection is graphical illustrations. However, other approaches are entails; autocorrelation analysis to examine serial dependence, spectral analysis to study recurrent performance which may not be seasonal, separation into components representing trend, seasonality, variation of diverse mode, and cyclical anomaly splitting a time-series into a sequence of sections. Models for time series data can be in various form and characterize diverse stochastic procedures. In model building there are variations in the level of a process, three classes, the autoregressive (AR) models, the integrated (I) models, and the moving average (MA) models. These classes depend linearly on previous data points. Combinations of these ideas produce autoregressive moving average (ARMA) and autoregressive integrated moving average (ARIMA) models [24].

II.2 AUGMENTED DICKEY-FULLER (ADF) MODELLING EQUATIONS

The mathematical models of Augmented Dickey-Fuller (ADF) test are expressed by equation (1) to (3). In a series with the sequence of $Y_1, Y_2, \dots\dots\dots\dots\dots..Y_N$

The noble scholars Dickey and Fuller considered sets differential-form autoregressive equations [25].

$$\Delta Y_t = \gamma Y_{t-1} + \sum_{j=1}^{p} (\delta_j \Delta Y_{t-j}) + e_t \quad (1)$$

$$\Delta Y_t = \alpha + \gamma Y_{t-1} + \sum_{j=1}^{p} (\delta_j \Delta Y_{t-j}) + e_t \quad (2)$$

$$\Delta Y_t = \alpha + \beta t + \gamma Y_{t-1} + \sum_{j=1}^{p} (\delta_j \Delta Y_{t-j}) + e_t \quad (3)$$

Where:

t is the time of operation,

α is the intercept constant called a drift,

β is the coefficient on a time drift,

γ is the coefficient awarding process root, i.e., the focus of testing,

p is the lag order of the first-differences autoregressive procedure,

e_t is the left-over term for similar distribution.

The dissimilarity in the three equations in the presence of the deterministic elements α (a drift term) and βt (a linear time trend). The effort of testing is neither the coefficient γ equals to zero, what means that the original $Y_1, Y_2, \dots\dots\dots\dots\dots..Y_N$, process has a unit root; hence, the null hypothesis of γ = 0 (random walk process) is tested in contrast to the alternative hypothesis γ < 0 of stationarity. More comprehensive, the null and alternative hypotheses corresponding to the models above are as follows in expression (4) to (9) [25],[26].

$$H_0 : Y_t \text{ is random walk OR } \gamma = 0 \quad (4)$$

$$H_1 : Y_t \text{ is random walk OR } \gamma < 0 \quad (5)$$

$$H_0 : Y_t \text{ is random walk around a drift OR } \{= 0, \alpha \neq 0\} \quad (6)$$

$$H_1 : Y_t \text{ is level stationary process OR } \{< 0, \alpha \neq 0\} \quad (7)$$

$$H_0 : Y_t \text{ is random walk around a trend OR } \{= 0, \beta \neq 0\} \quad (8)$$

$$H_1 : Y_t \text{ is level stationary process OR } \{< 0, \beta \neq 0\} \quad (9)$$

II.3 DESCRIPTION OF SITE LOCATION

In this study the feeders used are located in Ogun State, Nigeria. Ogun is one of the western states of Nigeria. The state is prominent in a high concentration of citadel of learning and localization of industries in Nigeria. The state has the most industrialised local Government area in Nigeria with Agbara and Ota Industrial estates. Ogun is blessed with higher schools of learning and the famous in Nigeria both private and public. It has a large arable landmass with good fertility for agricultural practice for plant and animal production. The settlement in the state comprises of urban, sub-urban and rural which account for the energy demand pattern of the state. The State energy demand pattern can serve as a good subset for Nigeria because of its growth rate and characteristics [27]. The electrical energy structure of the state is of six district sections with the headquarters at the state capital Abeokuta. The transmission stations include Sagamu with 132/33/11/0.415kV step down power transformers and five others. These six stations feed twenty-seven injection substations managed by Ibadan Electricity Distribution Company (IBEDC) that supplies forty-seven feeders out of which five are chosen for this study.

II.3.1 SYSTEM CONFIGURATION

In electric power distribution, Feeders are voltage power line conveying power from a supply substation to the distribution transformers. They convey power from a transformer or switch gear to the consumer via a distribution panel. The 11kV lines are used in residential and commercial areas feeding the distribution power transformers that distributes power to the structures in the area. Whereas, 33kV lines serves higher voltages rating that distribute power from one sub-station to another and unit point load in industries with high voltage consumption.

The data was acquired from the Ibadan Distribution Company (IBEDC), the monthly peak load for five years (2015 to 2019) in five different 33kV feeders in Ogun state for the study. These are presented in Table 1 to 5 the feeder are: Sagamu, Ikene, NNPC/OGIJO, Owode Egba, and Phoenix (Real).

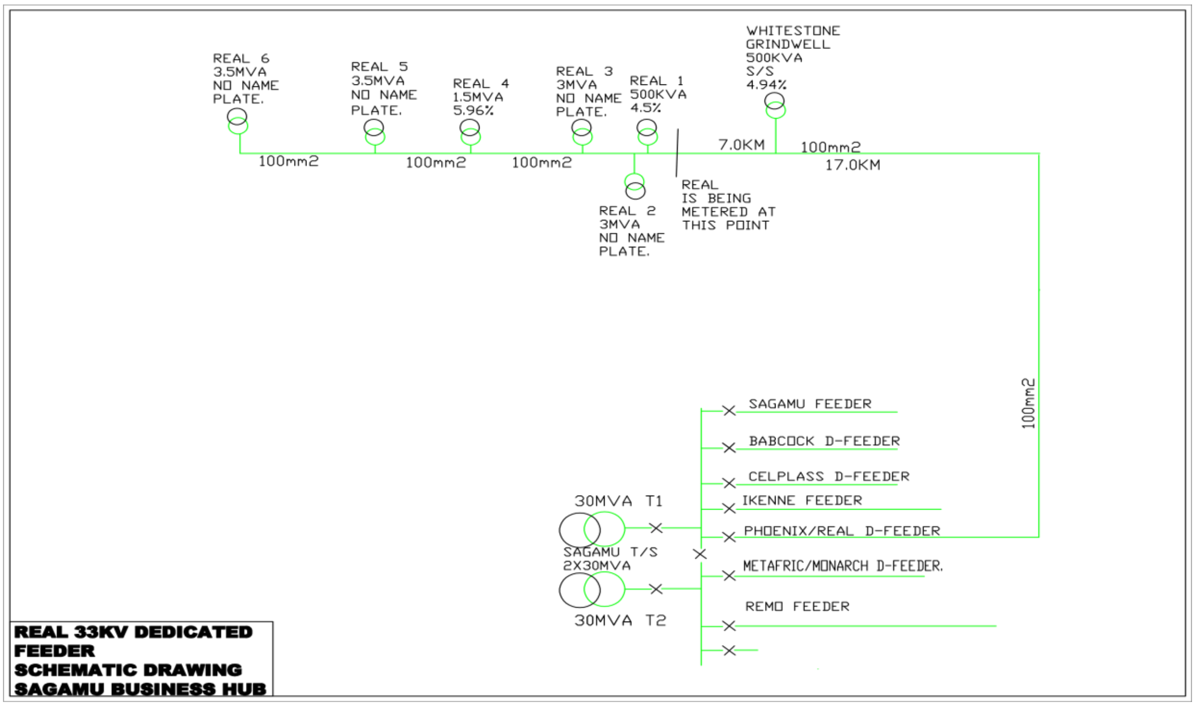

Figure 1: Line Diagram 33kV Feeders.
Source: Authors, (2024).

Table 1: Sagamu 33kv Feeder Monthly Peak Load 2015-2019 (MW/hr).

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2015	14.4	14.3	13.8	17.9	14.8	18.1	16.8	15.9	21.5	21.2	17.0	21.2
2016	18.2	18.0	17.5	22.1	18.6	22.4	20.9	19.9	26.0	25.7	21.1	25.7
2017	22.5	22.1	21.7	26.8	22.9	27.0	25.5	24.4	31.1	30.8	25.7	31.0
2018	27.2	25.6	26.4	32.0	27.2	32.3	30.6	29.3	36.7	36.3	30.8	36.5
2019	32.3	30.7	31.5	37.7	32.5	38.0	36.1	34.7	42.7	42.3	36.3	42.0

Source: Authors, (2024).

Table 2: Ikene 33kv Feeder Monthly Peak Load 2015 2019(MW/hr).

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2015	10.0	8.4	7.6	8.8	18.6	13.4	15.4	16.2	15.5	16.7	14.5	17.3
2016	13.1	11.3	10.3	11.8	23.0	17.1	19.3	20.2	19.4	20.7	18.3	21.5
2017	16.7	14.7	13.5	15.2	27.8	21.2	23.7	24.7	23.8	25.2	22.6	26.1
2018	20.8	18.5	17.2	19.1	33.1	25.8	28.6	29.7	28.7	30.2	27.4	31.2
2019	25.4	22.8	21.4	23.5	38.9	31.9	34.0	35.1	34.1	36.7	32.6	36.8

Source: Authors, (2024).

Table 3: NNPC/Ogijo 33kv Feeder Monthly Peak Load 2015-2019 (MW/hr).

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2015	14.4	17.6	22.2	19.9	19.2	16.6	20.1	18.8	19.6	17.1	17.7	20.2
2016	19.8	21.8	26.9	24.4	23.6	20.7	24.6	23.1	24.0	21.2	21.9	24.7
2017	24.2	26.5	32.0	29.3	28.5	25.2	29.6	27.9	28.9	25.8	26.6	29.7
2018	29.1	31.6	37.7	34.7	33.9	30.2	35.0	33.2	34.3	30.8	31.8	35.1
2019	34.5	37.2	43.8	40.6	39.7	35.7	40.9	38.9	40.1	36.5	37.4	41.0

Source: Authors, (2024).

Table 4: Owode/Egba 33kv Feeder Monthly Peak Load 2015-2019 (MW/hr).

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2015	17.5	14.7	19.0	21.5	17.0	12.5	10.4	16.0	13.8	17.1	10.8	11.5
2016	21.8	18.5	23.4	26.2	21.1	16.0	13.6	20.0	17.8	21.2	14.1	14.9
2017	26.5	22.8	28.2	31.3	25.7	20.0	17.3	24.5	22.0	25.6	17.9	18.8
2018	31.6	27.6	33.5	36.9	30.8	24.5	21.5	29.4	26.7	30.8	22.1	23.1
2019	37.2	32.9	39.3	43.0	36.3	29.4	26.1	34.8	31.9	36.4	26.8	27.9

Source: Authors, (2024).

Table 5: Phoenix Real 33kv Feeder Monthly Peak Load 2015-2019 (MW/hr.).

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2015	19.4	18.9	13.2	14.0	11.8	11.8	11.4	12.0	8.8	12.1	11.3	13.3
2016	23.8	23.2	16.8	17.8	15.2	15.3	14.8	15.5	11.8	15.6	14.7	16.9
2017	28.7	28.0	20.9	22.0	19.1	19.2	18.7	19.4	15.2	19.5	18.5	21.0
2018	34.1	33.3	25.5	26.7	23.5	23.6	23.0	23.8	19.1	23.4	22.8	25.6
2019	39.9	39.1	30.5	31.9	28.3	28.4	27.8	28.7	23.5	28.8	27.5	30.6

Source: Authors, (2024).

II.4 DATA ANALYSIS

The Augmented Dickey-Fuller (ADF) testing technique Modelling Equations (1) to (3) and expression (4) to (9) were used for the coding. The test were carried out with R-Software codes in Rstudio that give the Autoregressive Functions (ACF) and Partial Autoregressive Functions (PACF) plot for interpretation of stationarity and nonstationarity. The data was processed to confirm its stationarity status as indicated in Table 6. (Decision Rule: Reject Ho-hypothesis if the p-value is less than or equals to α(0.05), otherwise, do not reject.). Statistics tests value, lag order and p-value were computed by the R software for proper analyses, inferences and confirmations. Rstudio is an integrated development environment (IDE) for R. It comprises a console, syntax-highlighting editor that backings direct encryption implementation, as well as apparatuses for maneuvering, the past, mending and workspace management [28]. The package is for mathematical design that supports the development of applications in R environment. Rstudio requires R version 3.0. 1 or higher. Since R versions can be installed juxtaposed on a system. Code for the analysis is as follows:

```
```{r,echo=FALSE,comment= "",warning=FALSE,eval=T}

library ("tseries")

```
```

Reading data in

```
```{r,echo=FALSE,comment= "",warning=FALSE}

dat <- read.csv("mamaData.csv",header = T)

a = ts(dat$SAGAMU, frequency = 12,start = c(2015,1))

b = ts(dat$IKENE, frequency = 12,start = c(2015,1))

c = ts(dat$NNPC.OGIJO, frequency = 12,start = c(2015,1))

d = ts(dat$OWODE.EGBA, frequency = 12,start = c(2015,1))

e = ts(dat$PHOENIX.REAL, frequency = 12,start = c(2015,1))

```Autocorrelation and partial autocorrelation plot of Data

```{r,echo=FALSE,comment= "",warning=FALSE}

acf2(a, main = "SAGAMU ")

acf2(b, main = "IKENE ")

acf2(c, main = "NNPC OGIJO ")

acf2(d, main = "OWODE EGBA ")

acf2(e, main = "PHOENIX REAL ")

```
```

Augmented Dickey F. Test

```
```{r,echo=FALSE,comment= "",warning=FALSE}

adfSAGAMU <- adf.test(a)

adfIKENE <- adf.test(b)

adfNNPC <- adf.test(3c)

adfOWODE <- adf.test(d)

adfPHOENIX <- adf.test(e)

adfSAGAMU

adfIKENE

adfNNPC

adfOWODE

adfPHOENIX

```
```

III. RESULT AND DISCUSSION

III.1 CRITICAL VALUES FOR AUGMENTED DICKRY-FULLEY

The augmented Dickey–Fuller (ADF) value, is a negative number. The higher the negative value the more effective the refusal of the hypothesis that there is a unit root at some level of confidence. However, in the work of Fuller the standard in the Table 6 was established as the yardstick for interpretation of ADF test.

Table 6: Thresholds values for (ADF).

	DATA WITHOUT DRIFT	DATA WITH DRIFT		DATA WITHOUT DRIFT
No of data in the set	1%	5%	No of data in the set	1%
T = 25	-3.75	-3.00	T = 25	-3.75
T = 35	-3.64	-2.96	T = 35	-3.64
T = 50	-3.58	-2.93	T = 50	-3.58
T = 75	-3.54	-2.91	T = 75	-3.54
T = 100	-3.51	- 2.90	T = 100	-3.51
T = 150	-3.48	-2.89	T = 150	-3.48
T = 250	-3.46	-2.88	T = 250	-3.46
T = 500	-3.44	-2.87	T = 500	-3.44
T = ∞	-3.43	-2.86	T = ∞	-3.43

Source: [20].

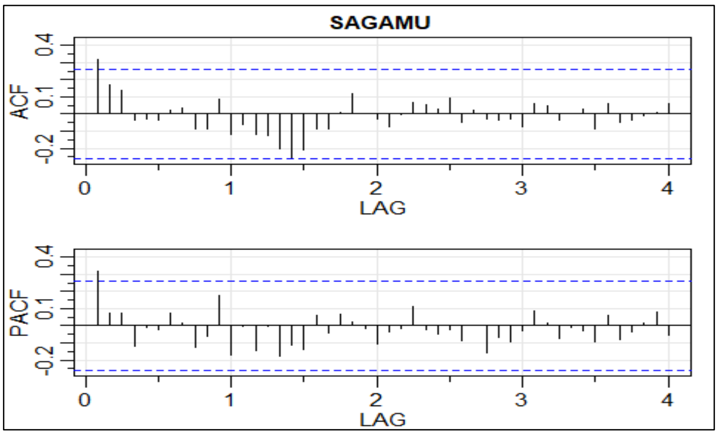

Figure 2: Sagamu feeder 33kV Autoregression and Partial Autoregression plot.
Source: Authors, (2024).

Hypothesis Result of Sagamu 33KVA feeder Augmented (ADF Dickey-Fuller)
Dickey-Fuller = -4.9325,
Lag order=3,
p-value=0.01
alternative hypothesis: stationary

The ACF and PACF graphs in Figure 2 show that the part of data that falls within the range of dotted lines are high in fact only one line is in the significant range which implies that this data are not significant and high possibility that a result or relationship is caused by something other than chance, in addition the ACF scatter along the horizontal axis with more negative parts which make the stationarity status a bit confusing. PACF plot show scatter functions that is neither decaying nor sine waves. As regards the test- statistics -4.9325 is quite low for a data point is sixty between fifty and hundred with threshold of -3.50 to -3.45, this show element of doubt in the validity of the test. However the lag order of 3 for real life data of this form may lead to complex analyses hence will require further analysis on transformation and authentication with adequacy test before field application, p-value of 0.01 (1%) this is sufficiently low, this validate the stationary of the series [29].

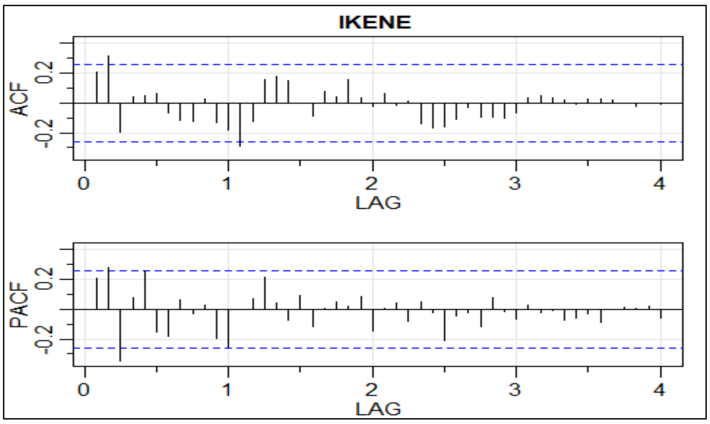

Figure 3: Ikene feeder 33kV Autoregression and Partial Autoregression plot.
Source: Authors, (2024).

Hypothesis Result of NNPC/OGIJO 33kVA feeder Augmented Dickey-Fuller (ADF)
Dickey-Fuller = -0.81603
Lag order = 3
p-value = 0.9551
alternative hypothesis: nonstationary

The ACF and PACF graphs in Figure 3 show that the proportion of data that are within the range of dotted lines are high which implies that this data are not significant and high possibility that a result or relationship is caused by something other than chance, in addition the ACF scatter along more in negative parts of the plot. As regards the test- statistics -0.81603 is tremendously high for the data point, with threshold of -3.50 to -3.45, this show component of ambiguity in the judiciousness of the test. However the lag order of 3 for real life data of this form may lead to multidimensional analyses hence will require further analysis (authentication with adequacy test) before field application, p-value of 0.9551 as against ≤ 0 .05 is too high, hence, the validation of nonstationary feature of the series [29].

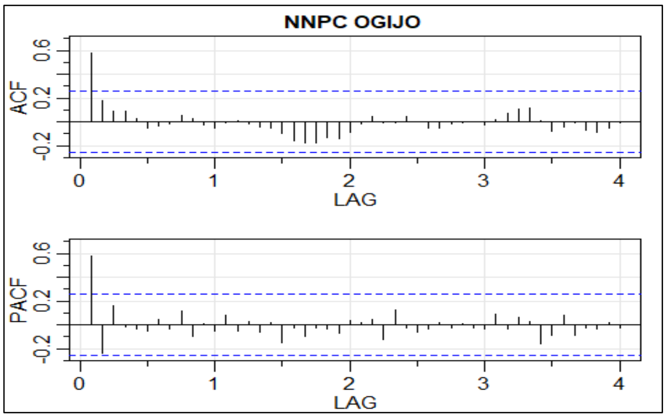

Figure 4: NNPC/OGIJO feeder 33kV Autoregression and Partial Autoregression plot.
Source: Authors, (2024).

Hypothesis Result of NNPC/OGIJO 33kVA feeder Augmented Dickey-Fuller (ADF)
Dickey-Fuller = -0.81603
Lag order = 3
p-value = 0.9551
alternative hypothesis: nonstationary

The ACF and PACF graphs in Figure 4. show that the proportion of data that are within the range of dotted lines are high which implies that this data are not significant and high possibility that a result or relationship is caused by something other than chance, in addition the ACF scatter along more in negative parts of the plot. As regards the test- statistics -0.81603 is tremendously high for the data point, with threshold of -3.50 to -3.45, this show component of ambiguity in the judiciousness of the test. However the lag order of 3 for real life data of this form may lead to multidimensional analyses hence will require further analysis (authentication with adequacy test) before field application, p-value of 0.9551 as against ≤ 0 .05 is too high, hence, the validation of nonstationary feature of the series[29].

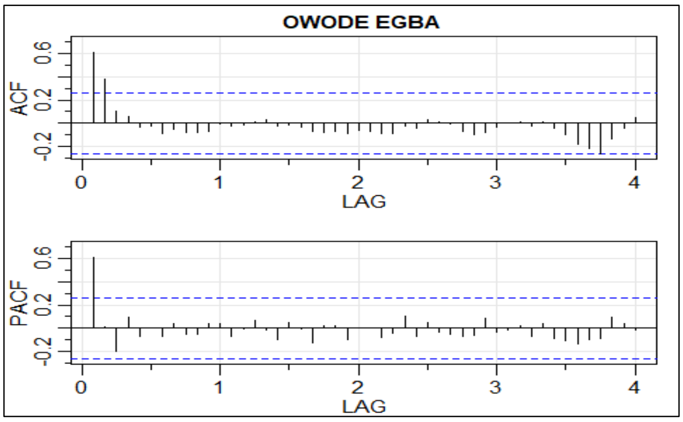

Figure 5: Owode Egba feeder 33kV Autoregression and Partial Autoregression plot.
Source: Authors, (2024).

The ACF and PACF graphs presented in Figure 5. above show that the ratio of data that falls within the range of Blue dotted lines are high which implies that this data are not significant and high possibility that a result or relationship is caused by something other than chance, in addition the ACF scatter along more in negative arts of the plot. As regards the test- statistics -1. 4093, is extremely high for the data point, with threshold of -3.50 to -3.45 this show component of uncertainty in the rationality of the test. However the lag order of 3 for real life data of this form may lead to multifaceted analyses hence will necessitate further investigation (authentication with adequacy test) before field application, p-value of 0.8135 in contradiction of ≤ 0 .05 is too high, hence, the validation of nonstationary feature of the series [29].

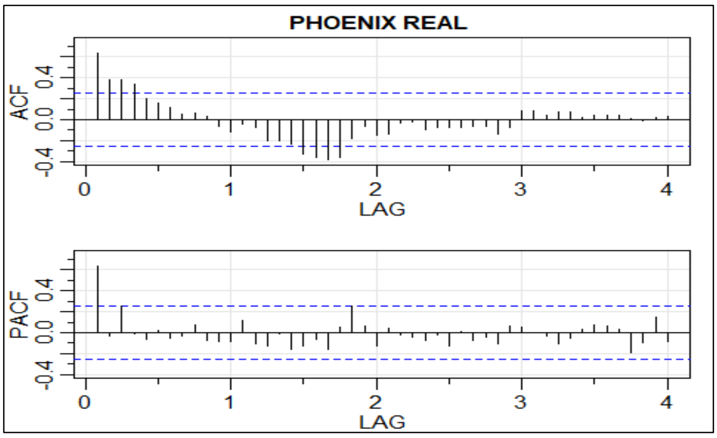

Figure 6: Phoenix 33kV feeder Autoregression and Partial Autoregression plot
Source: Authors, (2024).

Hypothesis Result of Phoenix 33kVA feeder Augmented Dickey-Fuller (ADF)
Dickey-Fuller = -2.0736
Lag order = 3,
p-value=0.545
alternative hypothesis: nonstationary

The ACF and PACF graphs in Figure 6 show that the proportion of data that falls within the range of Blue dotted lines are high which implies that this data are not significant and high likelihood that a result or relationship is caused by something other than chance, in addition the ACF scatter along more in negative parts of the plot. As regards the test- statistics -2.0736 is very high for the data point, (with threshold of -3.50 to -3.45), this show component of uncertainty in the rationality of the test. However the lag order of 3 for real life data of this form may lead to multifaceted analyses hence will necessitate further investigation for authentication with adequacy test before field application, p-value of 0.545 as against ≤ 0 .05 is too high, hence, the validation of nonstationary feature of the series.

III.2 SYSTEM CONFIGURATION

Ho = the series is non-stationary, Hi = the series is stationary: [26],[29].

Decision Rule: Reject Ho if the p-value is less than or equals to α (0.05); otherwise, do not reject. ADF Hypotheses rejecting the null hypothesis means that the given guess is not fit for application for lack of numerical significance; Acceptance of the null hypothesis is an indication that Ho is not rejected. The ADF test makes sure that the null hypothesis is accepted unless there is strong evidence against it to reject in favour of the alternate stationarity hypothesis [30-32].

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