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STUDY AND DEVELOPMENT OF A SHORT-TERM LOAD FORECASTING USING STOCHASTIC TIME SERIES ANALYSIS: A CASE STUDY OF MAKURDI, NIGERIA.

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Abstract—Load forecasting has been an important process in Electrical Engineering since the early 20th century. For the purpose of Economic load dispatch and Power system planning, Short-term load forecasting is essential. In addition, participation in the electricity market requires the utilities to forecast their loads accurately. The present work involves development of Short Term Load Forecasting Model Using Time series Analysis for Makurdi load demand. Having 3 months load data October-December, 2014 work is carried out for model development using October-November load. An Autoregressive Integrated Moving Average (ARIMA) model is developed using the October-November,2014 load data and tested using the December,2014 data. The model adequacy was tested using Jarque-Bera Test of Normality of Residuals, Serial Correlation Lagrange Multiplier (LM) Test and Heteroskedasticity Test of ARCH Effect in the residuals. The accuracy of the forecasts is checked using the Maximum absolute percentage error (MAPE) of the forecasts. Weather variables are not considered.

Keywords—ElectricityDemand, Short-termForecasting, ARIMA, Stochastic time series analysis

I. INTRODUCTION

There are four types of load forecasts: very short-term, short-term, medium-term and long-term [1]. In today's deregulated electricity market forecast is key information [2]. It is important to forecast electrical energy consumption and maximum loads in a grid so that companies could make economic based decisions of installing or replacing electrical equipment in a grid to make it capable to generate, transmit and distribute forecasted energy and provide an acceptable level of power quality and reliability of power supply [3, 4, 5].

Electric power system operators make use of these forecasts for the daily operation of a system, structural planning for the system (e.g., construction of new power plants), or to meet long term trends of demand requirements[3].

Short-term load forecasting has long been a major issue of interest for the electricity industry. Traditionally, hourly forecasts with a lead time of one hour to seven days are required for the scheduling and control of power systems [6, 7, 8].

Subsequently, load forecasting can be categorized by three different horizons [1]:

1) Long-Term Load Forecasts: Longer than a year.
2) Medium-Term Load Forecasts: 1 week to a year.
3) Short-Term Load Forecasts: 1 hour to 1 week.
4) Very Short-Term Load Forecasts: less than an hour.

II. RESEARCH METHOD

To forecast the Short-Term (for 1st December-31st December, 2014) electricity demand in Makurdi, Benue State, Nigeria, Time Series Stochastic Method was used based on data from October-

November 2014. Time series forecasting method was formulated based on time series data. The following are detailsof the procedures used.

Firstly, ARIMA model (p, d, q) was identified with the following steps [9]:

A. The first step of ARIMA analysis was to make a time series plot and analyze whether it had stationary mean and variance or not. If the data is not stationary in the variance or mean, transformation or differencing will be done respectively.

B. Plot Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) of the data that has been stationary in mean and variance.

Secondly, to test the feasibility of the ARIMA obtained, the following was done

a) Parameter Estimation

Conducting parameter estimation based on the model obtained through SPSS and EViews7 software, and testing the significance of parameters to get a significant parameter model.

b) Diagnostic Checking

Conducting diagnostic checking through SPSS and EViews7 software and an examination of the residuals of the model significantly through:

i) Residual white noise Test

ii) Residual normally distributed Test

Lastly, subsequently load forecasting and evaluation of forecasting accuracy for the December, 2014.

III. RESULTS AND DISCUSSION

3.1 Data Collection/Presentation

The data used in this study covered the daily electric load consumption in Makurdi area of Benue State, Nigeria from 1st October, 2014 to 31st December, 2014. They were collected from Transmission Company, Apir - Makurdi, Benue State. The daily electricity demand (MW) data is shown in Table 1.

Table 1: Makurdi Daily Electricity Demand (MW) from 1st October, 2014-31st December, 2014

Date	Demand (MW)	Date	Demand (MW)	Date	Demand (MW)
1/10/2014	603.4	3/11/2014	367.2	6/12/2014	203.3
2/10/2014	378.8	4/11/2014	242	7/12/2014	323.9
3/10/2014	290.1	5/11/2014	353	8/12/2014	273.1
4/10/2014	425.5	6/11/2014	441.2	9/12/2014	179.5
5/10/2014	434.7	7/11/2014	337.9	10/12/2014	189.4
6/10/2014	389.4	8/11/2014	451.7	11/12/2014	231.6
7/10/2014	421	9/11/2014	495.7	12/12/2014	192.7
8/10/2014	401.1	10/11/2014	209.8	13/12/2014	332
9/10/2014	408.9	11/11/2014	65.9	14/12/2014	222.1
10/10/2014	282.1	12/11/2014	461.7	15/12/2014	272
11/10/2014	389.4	13/11/2014	367.7	16/12/2014	340.9
12/10/2014	458	14/11/2014	418	17/12/2014	244.4
13/10/2014	316.2	15/11/2014	487.6	18/12/2014	269.5
14/10/2014	282.6	16/11/2014	452	19/12/2014	340.5
15/10/2014	339.6	17/11/2014	363.8	20/12/2014	393
16/10/2014	211.1	18/11/2014	411.3	21/12/2014	486.9
16/10/2014	261.1	19/11/2014	330.3	22/12/2014	346
17/10/2014	254.2	20/11/2014	367.9	23/12/2014	447.9
18/10/2014	332.4	21/11/2014	284.8	24/12/2014	404.1

19/10/2014	268.1	22/11/2014	390.4	25/12/2014	439
20/10/2014	300.2	23/11/2014	428.3	26/12/2014	386.3
21/10/2014	352.1	24/11/2014	313.7	27/12/2014	431.6
22/10/2014	406.9	25/11/2014	241	28/12/2014	415.4
23/10/2014	438.7	26/11/2014	287.3	29/12/2014	432.9
24/10/2014	418.9	27/11/2014	165.6	30/12/2014	353.9
25/10/2014	383.4	28/11/2014	160.2	31/12/2014	362.2
26/10/2014	428	29/11/2014	104		
27/10/2014	445.2	30/11/2014	162.7		
28/10/2014	405.7	1/12/2014	147		
29/10/2014	460.6	2/12/2014	278		
30/10/2014	479.2	3/12/2014	76.4		
1/11/2014	484.1	4/12/2014	162.8		
2/11/2014	415.8	5/12/2014	409.7		

Source: Distribution Company of Nigeria, Apir - Makurdi, Benue State, Nigeria

3.2 Graphical properties of the time series

The plot of the time series (Makurdi Daily Electricity Demand (MW) for October – December, 2014) against time is presented in Figure 1.

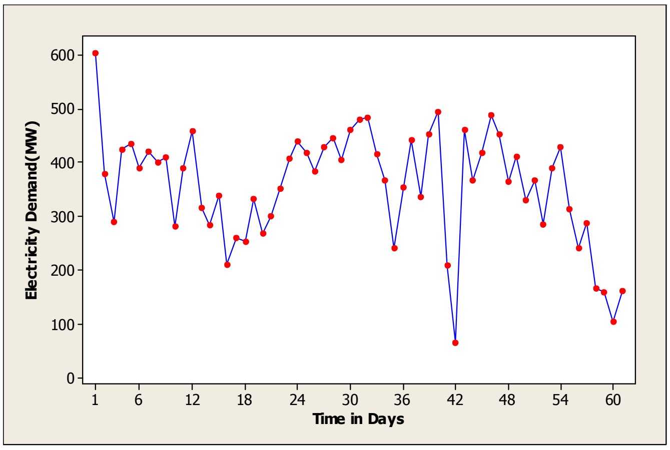

Fig. 1: Time Plot of Electricity Demand (MW) in Makurdi (Level)

3.3 Plots of Autocorrelograms of the series

The ACF and PACF of the series is examined. The result is presented in Fig.2 and Fig.3.

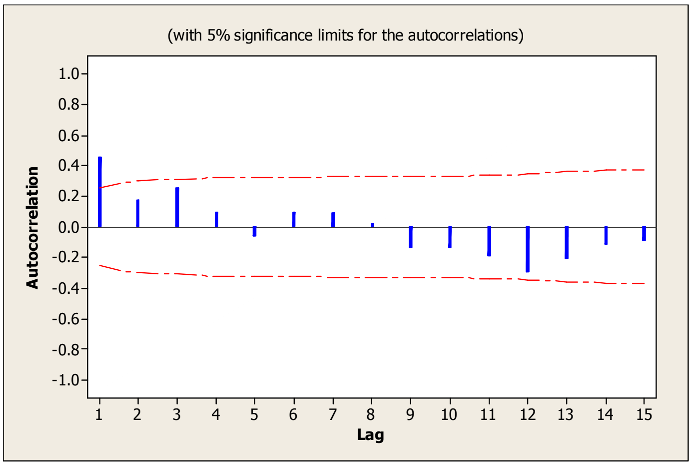

Fig. 2: Autocorrelation function for Makurdi daily consumption (MW)

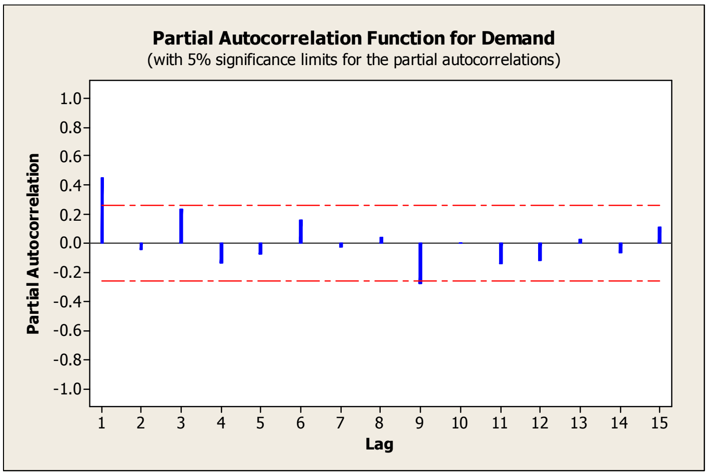

Fig. 3: Partial autocorrelation function for Makurdi daily consumption (MW)

It is observed from Figure 1 that the trend in the series is somewhat smooth, which suggest that the series has a stable mean and variance. The variability in the series appears to be uniform, which raises the possibility that the variance is homoskedastic (i.e. not changing with time). These observations suggest that the series is weakly or covariance stationary. Also, the series exhibits some gradual rise and fall, which detects the presence of some degree of autocorrelation in the series.
The ACF and PACF of the series are also examined thus;
The ACF and PACF are in the approximate two standard error bounds (the upper confidence limit and the lower confidence limit) computed as$\pm 2/\sqrt{N}$ [10],where N is the number of observations. If the autocorrelation and partial autocorrelation are within these bounds, it is not significantly different from zero at (approximately) 5% significance level. This means that, if all the values of the data or most of the values fall within these confidence limits, then, the data are independent of time and dependent, if otherwise.
There is also an evidence of weakly or covariance stationarity of the series in level as the autocorrelograms die out rapidly from its initial value of unity to zero at lag 5 in ACF and at lag 2 in PACF over time. This suggests that the residuals are purely random process and the series is stationary in level.

3.4 Unit Root and Stationary Tests of Daily Electricity Demand in Makurdi

As a pre-condition for estimation of a model describing daily electricity demand in Makurdi and because the order of integration of the series is of great importance for the analysis, the Augmented

Dickey-Fuller (ADF) unit root test due to Dickey and Fuller and KPSS stationarity test due to Kwiatkowski, Phillips, Schmidt and Shin was performed to determine the order of integration of the series. The result of the tests is reported in table 2.

Table 2: Unit Root and Stationarity Test of Daily Electricity Demand in Makurdi

Augmented Dickey-Fuller Unit Root Test					
Option	ADF Test Statistic	P-value	Critical Value		
			1%	5%	10%
Constant only	-4.613787***	0.0004	-3.544063	-2.910860	-2.593090
Constant & Trend	-4.753977***	0.0016	-4.118444	-3.486509	-3.171541
KPSS Stationarity Test					
Option	KPSS Test Statistic		1%	5%	10%
Constant only	0.287009***		0.739000	0.463000	0.347000
Constant & Trend	0.143057**		0.216000	0.146000	0.119000

Note: *** implies the significance of the test statistic at 1%, 5% and 10% while
** denotes the significance of the test statistic at 1% and 5% only.

The ADF unit root test was conducted in level with both constant (intercept) only and with constant and linear time trend. The result of the test shows that the data generating process of daily electricity demand in Makurdi is stationary in level at all conventional test sizes. This is because the ADF test statistics are -4.613787 with constant only and -4.753977 with constant and linear time trend, which are less than the critical values of the test at 1%, 5% and 10% significance levels. This result indicates that the series does not contain a unit root[11].

KPSS stationarity test was also conducted as a useful confirmatory analysis for ADF unit root test. This is because ADF unit root test has low power and suffers from size distortions especially when the sample size is very small. The KPSS Lagrange Multiplier test evaluates the following hypothesis using equations below [12]

H_0: $\rho < 1$ (i.e. the series is stationary) against

H_1: $\rho = 1$ (i.e. the series has a unit root).

The summary of the results of ADF and KPSS stationarity tests are presented in Table 2.

As shown in Table 2, the KPSS test statistics (0.287009) with constant only fails to reject the null hypothesis of level stationarity at 1%, 5% and 10% levels of significance. With constant and linear trend, the variable (demand) still fails to reject the null hypothesis of level stationarity at 1% and 5% significance levels, since the KPSS test statistic (0.143057) is less than the critical values at these significance levels. This confirms the result of ADF unit root test that the series under investigation is weakly or covariance stationary in levels and hence need no differencing or de-trending of any kind. Combining the results of the ADF Unit Root test and KPSS stationarity test, we conclude that the series (daily electricity demand in Makurdi) is stationary in level implying that it is integrated of order zero i.e. I (0).

3.5 Model order selection

Having identified an ARMA process for the series, the information criteria [13, 14] is used to determine the optimal values for the ARIMA (p, d, q). From the previous results of Augmented Dickey-Fuller unit root test and KPSS stationarity tests in Table 2 it was observed that $d = 0$. Using Akaike information criterion,(Akaike, 1974), Schwarz information criterion, (Schwarz, 1978) and Hannan-Quinn criterion, (Hannan, 1980), R-squared, R-squared (adjusted) p-value and Durbin Watson statistic, using parsimony, the model with the least information criteria and highest R-squared is chosen. This is reported in Table 5.

3.6 Model Estimation

Following the results of Table 5, ARIMA (4, 0, 1) seems to provide statistically adequate representation of the data generating process, but it fails to satisfy the invertibility condition of the MA component. (i.e. the MA component is non-invertible as it falls outside a unit circle). ARIMA (1, 0, 4), which is next to it is selected. After the best model has been chosen, estimate of the parameters of the model are obtained. The result of the parameter estimates of the optimal model using OLS (Ordinary least squares) [15] is presented in Table 3. .

From the result of the parameter estimates of Table 3, the data fits an ARIMA (1,0,4) model, which is presented below:

$$y_t = 343.87 - 0.5889 y_{t-1} + \varepsilon_t + 1.2581\varepsilon_{t-1} + 0.6302\varepsilon_{t-2} + 0.5414\varepsilon_{t-3} + 0.5326\varepsilon_{t-4} \; \dots (1)$$

Where;

y_t = Demand response (dependent) variable at time t

y_{t-1} = Demand response variable (MW) at time $t - 1$

ε_t = Error term at time t

$\varepsilon_{t-1}, \varepsilon_{t-2}, \varepsilon_{t-3}, \varepsilon_{t-4}$ are the error terms in the previous time periods that are incorporated in the response y_t.

Table 3: OLS Parameter Estimation of ARIMA (1, 0, 4) in Level

Dependent variable: Demand				
Variable	Coefficient	Std. Error	t-statistic	P-value
Constant	343.8717	25.69118	13.38481	0.0000
AR(1)	-0.588913	0.135404	-4.349302	0.0001
MA(1)	1.258140	0.124250	10.12590	0.0000
MA(2)	0.630233	0.190258	3.312510	0.0017
MA(3)	0.541403	0.192018	2.819542	0.0067
MA(4)	0.532573	0.119817	4.444877	0.0000
R-squared				0.4113
Adjusted R-squared				0.3568
DW statistic				1.9553
F-statistic		7.544457	Probability	0.00002

3.7 ARIMA (1, 0, 4) Model Diagnostic Checking

After fitting the model, it is checked for adequacy. Here the goodness of fit is examined by means of plotting the ACF and PACF of residuals of the fitted model. If most of the sample autocorrelation coefficients of the residuals are within the limits $\pm 1.96/\sqrt{N}$,where N is the number of observations, upon which the model is based, then the residuals are white noise indicating that the model is a good fit. The ACF and PACF plots of residuals are reported in Figure 4.The model has passed this test.Jarque-Bera normality [16], LM serial correlation and heteroskedastic tests were conducted on the residuals of the fitted ARIMA (1, 0, 4) model. The results of the tests are reported in Table 4.

Table 4: Normality, Serial Correlation and Heteroskedasticity Tests of Residuals

Test Statistic	Value	P-value
Jarque-Bera Test of Normality of Residuals		
Jarque-Bera	1.721483	0.4228
Serial Correlation Lagrange Multiplier (LM) Test		
F-statistic	0.111509	0.8947
nR^2	0.255234	0.8802
Heteroskedasticity Test of ARCH Effect in the Residuals		
F-statistic	0.874701	0.1860
nR^2	0.512668	0.1893

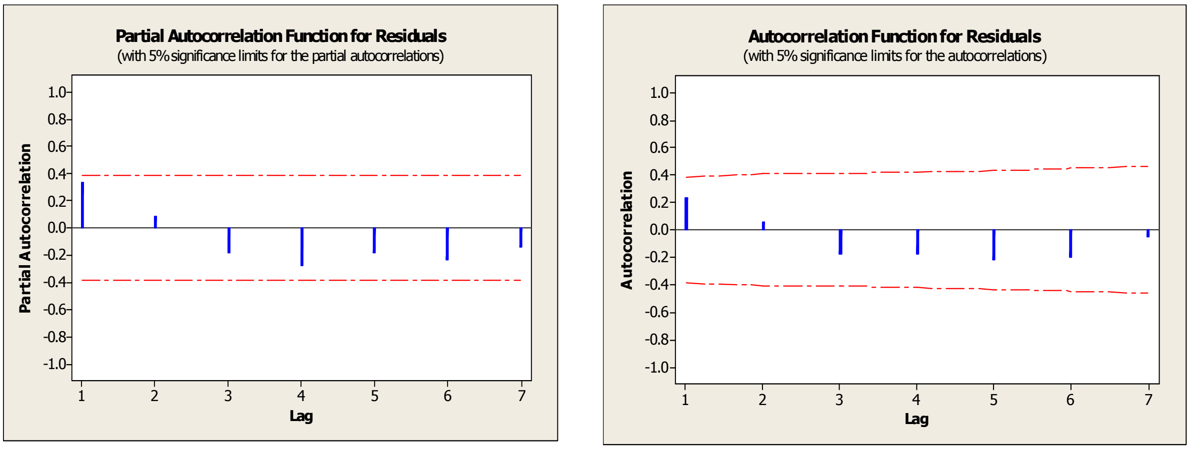

Figure 4: ACF and PACF Plots of Residuals

The results of the tests in Table 4 reveal that the residuals of the estimated model have satisfied the Jarque-Bera test for normality of residuals, because the p-value= *0.4228 > 0.05.*

The residuals have also passed the Bruesch-Godfrey serial correlation Lagrange Multiplier test, because the p-value of the nR^2 test statistic is *0.8802 > 0.05*.The null hypothesis of no ARCH effects remaining in the residuals of the estimated model is also accepted because the p-value of the nR^2heteroskedastic test statistic is *0.1893*, which is greater than 0.05. This implies that the residuals are homoskedastic. It is therefore concluded that the model is adequate, valid and good.

Table 5: Model Order Selection Using Information Criteria

S/n	Model	Information Criterion			R^2 (%)	$\bar{R}^2$ (%)	DW	P-value
		AIC	SIC	HQIC				
1	ARIMA (1,0,0)*	11.8092	11.8790	11.8365	24.35	23.04	1.86	0.0000
2	ARIMA (2,0,0)	11.8386	11.9442	11.8798	25.93	23.28	1.99	0.0003
3	ARIMA (3,0,0)	11.7934	11.9355	11.8488	32.43	28.68	1.93	0.0000
4	ARIMA (4,0,0)	11.8336	12.0128	11.9032	32.80	27.63	2.02	0.0003
5	ARIMA (0,0,1)*	11.8635	11.9327	11.8906	26.52	25.28	1.92	0.0000
6	ARIMA (0,0,2)	11.8807	11.9845	11.9213	27.66	25.16	2.10	0.0000
7	ARIMA (0,0,3)	11.9133	12.0517	11.9676	27.67	23.86	2.09	0.0003
8	ARIMA (0,0,4)*	11.7859	11.9589	11.8537	38.38	33.98	2.27	0.0000
9	ARIMA (1,0,1)	11.8196	11.9243	11.8606	26.06	23.47	2.00	0.0001
10	ARIMA (1,0,2)	11.8516	11.9912	11.9062	26.16	22.21	1.99	0.0006
11	ARIMA(1,0,3)	11.8400	12.9082	11.9082	29.41	24.27	1.91	0.0006
12	ARIMA(1,0,4)*	11.6918	11.9012	11.7737	41.13	35.67	1.96	0.0000
13	ARIMA(1,0,5)	11.7178	11.9622	11.8134	41.55	34.94	2.01	0.0000
14	ARIMA (2,0,1)	11.8608	12.0016	11.9156	26.79	22.80	2.03	0.0006
15	ARIMA (2,0,2)	11.8735	12.0496	11.9422	28.30	23.02	2.04	0.0011
16	ARIMA (2,0,3)	11.8441	12.0554	11.9266	32.73	26.38	1.98	0.0006
17	ARIMA(2,0,4)	11.7162	11.9627	11.8124	42.78	36.17	1.97	0.0000
18	ARIMA (2,0,5)	11.7571	12.0388	11.8671	42.37	34.46	1.99	0.0001
19	ARIMA (3,0,1)	11.8212	11.9988	11.8904	32.88	27.82	1.96	0.0006
20	ARIMA (3,0,2)	11.8033	12.0164	11.8863	36.31	30.19	1.92	0.0002
21	ARIMA(3,0,3)	11.8279	12.0765	11.9247	36.94	29.52	1.99	0.0004
22	ARIMA(3,0,4)	11.7658	12.0500	11.8765	42.75	34.73	1.99	0.0001

23	ARIMA(3,0,5)	11.7951	12.1142	11.9196	43.04	33.74	1.98	0.0003
24	ARIMA(4,0,1)*	11.5383	11.7533	11.6219	51.71	46.97	2.19	0.0000
25	ARIMA(4,0,2)	11.8468	12.0977	11.9443	36.62	28.90	1.99	0.0006
26	ARIMA(4,0,3)	11.8657	12.1525	11.9772	37.53	28.61	1.95	0.0010
27	ARIMA(4,0,4)	11.8109	12.1335	11.9363	42.91	33.39	2.00	0.0004
28	ARIMA(4,0,5)	11.8403	12.1989	11.9796	43.23	32.36	2.00	0.0007
29	ARIMA(5,0,5)	11.9099	12.3077	12.0641	41.96	29.06	1.93	0.0031

* implies that all the coefficients are significant, $\bar{R}^2$ means R-squared adjusted, DW means Durbin-Watson Statistic.

ARIMA (1, 0, 4) Forecast Evaluation

After obtaining a good ARIMA model, it is used for forecasting. The Maximum Absolute Percentage Error (MAPE) is then evaluated as demonstrated in Table 6. The Actual and Forecasted load are shown in Fig.5.

Table 6: Tabular Evaluation of Forecast Accuracy

S/n	Date	Actual (P_A)	Out of sample Forecast (P_F)	$\lvert P_A - P_F \rvert$	$\frac{\lvert P_A - P_F \rvert}{P_A} \times 100$
1	1/12/2014	147	NA	NA	NA
2	2/12/2014	278	193.4067	84.593	30.4292
3	3/12/2014	76.4	42.10546	34.295	44.8881
4	4/12/2014	162.8	127.7389	35.061	21.5363
5	5/12/2014	409.7	242.2474	167.453	40.8720
6	6/12/2014	203.3	251.8887	48.589	23.9000
7	7/12/2014	323.9	261.0085	62.891	19.4169
8	8/12/2014	273.1	269.6351	3.465	1.2687
9	9/12/2014	179.5	277.7951	98.295	54.7605
10	10/12/2014	189.4	285.5138	96.114	50.7465
11	11/12/2014	231.6	292.8151	61.215	26.4314
12	12/12/2014	192.7	299.7214	107.021	55.5378
13	13/12/2014	332	306.2543	25.746	7.7547
14	14/12/2014	222.1	312.4338	90.334	40.6726
15	15/12/2014	272	318.2792	46.279	17.0144
16	16/12/2014	340.9	323.8083	17.092	5.0137
17	17/12/2014	244.4	329.0385	84.638	34.6311
18	18/12/2014	269.5	333.9858	64.486	23.9279
19	19/12/2014	340.5	338.6655	1.834	0.5388
20	20/12/2014	393	343.0921	49.908	12.6992
21	21/12/2014	486.9	347.2793	139.621	28.6754
22	22/12/2014	346	351.2401	5.240	1.5145
23	23/12/2014	447.9	354.9866	92.913	20.7442
24	24/12/2014	404.1	358.5305	45.570	11.2768
25	25/12/2014	439	361.8828	77.117	17.5666
26	26/12/2014	386.3	365.0537	21.246	5.4999
27	27/12/2014	431.6	368.0532	63.547	14.7235
28	28/12/2014	415.4	370.8904	44.510	10.7149
29	29/12/2014	432.9	373.5742	59.326	13.7043
30	30/12/2014	353.9	376.1128	22.213	6.2766
31	31/12/2014	362.2	378.5142	16.314	4.5042

$$MAPE = \frac{1}{n}\sum_{i=1}^{i}\left[\frac{|P_F - P_A|}{P_A}\right]\times 100 = \frac{647.241}{30} = 21.574\%$$

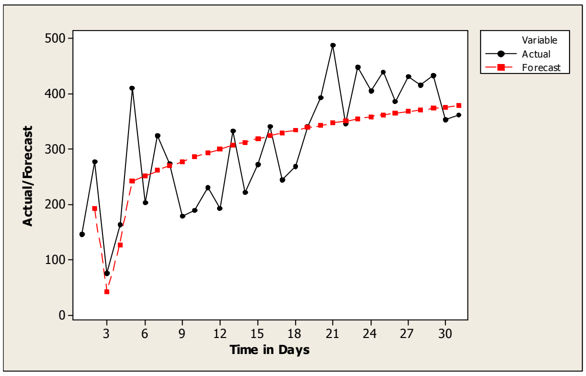

Figure 5: Time Plot of Actual and Forecasted Load

IV. CONCLUSION AND RECOMMENDATIONS

An attempt has been made for short term load forecasting using stochastic time series approach by studying and knowing how to develop an ARIMA model. The methodology identifies the model orders, accurate selection of input variables and involves estimation of model parameters. Then the model was used to forecast the future daily load for a period of one month (December, 2014) after it had passed JarqueBera Test of Normality of Residuals, Serial Correlation Lagrange Multiplier Test and Heteroskedasticity Test of ARCH effect in the residuals

At the end of the forecasting process, a maximum absolute percentage error of 21.5747% was found.

The MAPE result of the forecast shows that the variation between the actual electricity demand for Makurdi and the forecasted values falls within an error limit of 21.57% for the period 1st to 31st December, 2014.

For greater efficiency, one year data should be used with the first six months and last six months data as training and testing respectively.

Government and all the operators in the power sector should fix the electricity network infrastructure and all related infrastructure so that electricity needs can be met in Makurdi and its environs.

Makurdi community should reduce unnecessary power usage. People can use energy efficient technologies to improve national energy security. Energy saving at every household is also beneficial to reduce the cost of electricity bills.

The high value in MAPE can be attributed to instability in power supplied to Makurdi for the period of the study, which resulted to a high difference between the forecasted and actual power demand. It can, however, be marginally reduced if other sophisticated approaches like artificial intelligence, etc. are used.

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