
Short-term Electric Power Forecast Using Autoregressive Integrated Moving-Average (ARIMA)

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ABSTRACT

Demand planning for electricity consumption is a key development of any country. The aim of this project is the study of short-term electric power forecasting in Oleh, Delta State-Nigeria power sub-station however, this can only be achieved if the demand is forecasted accurately. In this research, autoregressive integrated moving average (ARIMA) was utilized to formulate prediction models of the electricity demand in Oleh. The objective was use the empirical data obtained for historical data regarding the electricity demand in Oleh from June to November 2016. The results showed that the ARIMA model reduced the mean absolute percentage error (MAPE) to 3.36%

Key words: Autoregressive integrated moving average (ARIMA), Moving Average (MA), Load Forecasting, Multiple Linear Regressions, Autocorrelation Function (ACF), DigDB Toolbox, Mean Absolute Percentage Error (MAPE)

INTRODUCTION

Forecasting is the process of making predictions of the future based on past and present data and most commonly by analysis of trends. Load Forecasting is a technique used by Power or Energy Providing Companies to predict the power/energy needed to meet the demand and supply equilibrium. The accuracy of forecasting is of great significance for the operational and managerial loading of utility company [1-3].

A power system must be well planned so as to ensure adequate and reliable power supply to meet the estimated load demand in both near and distant future. Basically, load forecast is no more than an intelligent projection of past and present demand patterns to determine future ones with sufficient reliability. The accuracy of load forecast has important effect on power system operations, as economy of operation and control of power system may be quite sensitive to forecasting errors. Thus, both positive and negative forecasting errors can result in increased operating costs [4, 5].

Load forecasting may be applied in the long, medium, short and very short term can be classified as load forecasting in terms of the planning horizon's duration up to 1 day for short term load forecasting (STLF), 1 day to 1 year for medium term load forecasting (MTLF) and 1 to 10 years for long term load forecasting (LTLF). Short term load forecasting (STLF) aims at predicting electric loads for a period of minutes, hours, days or weeks. STLF plays an important role in the real time control and the security functions of an energy management system. STLF applied to the system security assessment problem especially in the case of increase Renewable Energy Sources (RES) penetration in isolated power grids can provide in advance valuable information on the detection of vulnerable situations [6, 7].

FORMULATIONS OF FORECASTING MODELS

(i). The Autoregressive (AR) process: In the Autoregressive process, the current value of the time series $y_{(t)}$ is expressed linearly in terms of its ' p ' previous values [$y_{(t-1)}, y_{(t-2)}, \dots, y_{(t-p)}$] and a random

noiser $\Gamma_{(t)}$. For an autoregressive process of order ' p ' i.e. $AR_{(p)}$, the model can be written as [8 -10]:

$$y_{(t)} = \{_1 y_{(t-1)} + \dots + \{_p y_{(t-p)} + q_t \tag{1}$$

In order to write this in more convenient form, the following operators are introduced.

$$B y_{(t)} = y_{(t-1)}$$

$$B^m y_{(t)} = y_{(t-m)}$$

$$\text{And } (q) = 1 - \{_1 B^1 - \{_2 B^2 - \dots - \{_p B^p \tag{2}$$

So equation (2) and (3) can be written as,

$$A_{(q)} y_{(t)} = \Gamma_{(t)} \tag{3}$$

where,

- $y_{(t)}$ – Output or the load at time ' t '
- B – Backshift operator
- $A_{(q)}$ – Delay polynomial
- $\{_1 \dots \{_p$ – Coefficients of delay polynomial
- p – Order of the delay polynomial
- $\Gamma_{(t)}$ – Random noise

(ii). The Autoregressive Moving-Average (ARMA)

process, the current value of the time series $y_{(t)}$ is expressed linearly in terms of its previous ' p ' values

Process: In the autoregressive moving average

$|y_{(t)}, y_{(t-1)}, y_{(t-2)}, \dots y_{(t-p)}|$ and in terms of current and previous ' q ' values of a white noise

$|\Gamma_{(t)}, \Gamma_{(t-1)}, \dots \Gamma_{(t-q)}|$. For an autoregressive moving average process of order ' p ' and ' q ' i.e. $ARMA(p, q)$, the model is written as [11, 12]:

$$y_{(t)} = \{_1 y_{(t-1)} + \dots + \{_p y_{(t-p)} + \Gamma_{(t)} + \#_1 \Gamma_{(t-1)} + \dots + \#_q \Gamma_{(t-q)} \dots \tag{4}$$

By using the backshift operator defined earlier equation (4) can be written as,

$$A_{(q)} y_{(t)} = C_{(q)} \Gamma_{(t)} \tag{5}$$

Where,

$A_{(q)}$ and $C_{(q)}$ – delayed polynomials

while

p and q – orders of the delayed polynomials

(iii). The Autoregressive Integrated Moving-Average (ARIMA) Process: The time series defined

previously as an AR, MA or as an ARMA process is called a stationary process. This means that the

mean of the series of any of these processes and the covariances among its observations do not change with time. If the process is non-stationary, transformation of the series to a stationary process has to be performed first. This can be achieved, for

$$\nabla y_{(t)} = y_{(t)} - y_{(t-1)} = (1 - B)y_{(t)}$$

Using the definition of backshift operator, B . Consequently, an order ' d ' differenced time series is written as,

$$\nabla^d y_{(t)} = (1 - B)^d y_{(t)}$$

The differenced stationary series can be modeled as an AR, MA, or an ARMA to yield an ARIMA time series processes.

For a series that needs to be differenced ' d ' times and has the orders ' p ' and ' q ' for AR and MA components i.e. ARIMA (p, d, q) model is written as,

$$A_{(q)} \nabla^d y_{(t)} = C_q \Gamma_{(t)} \tag{6}$$

where $A_{(q)} \nabla^d$ and $C_{(q)}$ have been defined earlier

(iv). Autocorrelation Function (ACF):

Autocorrelation is a mathematical tool used for analyzing functions or series of values. Informally, it is the measure of how well a signal matches a time-shifted version of itself, as a function of the amount of

$$\dots_x = \{ \dots_{1 \dots 1} + \dots + \{ \dots_{p \dots k-1} \tag{7}$$

Where

$$\dots_k = X_x / X_0$$

$$X_x = E * [y_{(t)}, y_{(t+k)}] \tag{8}$$

If the function \dots is well defined its value must lie in the range [-1 1], with 1 indicating perfect correlation and -1 indicating perfect anti-correlation.

First, let us define the backward shift operator as

$$Bz_t = z_t - 1$$

$$B^n z_t = z_t \tag{9}$$

Using the backward shift operator, the difference operator can be written as

$$w_t = (1 - B)^d z_t \tag{10}$$

The residual (one-step prediction error) for an ARMA (p, q) process can be obtained from

$$\hat{e}_t = z_t - \left(\sum_{i=1}^p \phi_i * z_{(t-1)} - \sum_{i=1}^q \theta_i * \hat{e}_{(t-1)} \right) \tag{11}$$

If the specified model is adequate, and the appropriate orders p and q are identified, it should transform the observations to a white noise process.

the time series that are non-stationary in mean, by a differencing process. By introducing the ∇ operator, a differenced time series of order 1 can be written as [13]:

time shift. Autocorrelation is useful in finding repeating patterns in a signal. The autocorrelation function describes inherent correlation between observations of a time series which are separated in time by some lag ' k '. It is given by [14, 15]:

Thus, the adoption of MAPE as the measurement criteria for the accuracy of load forecasting, as following:

$$MAPE = \frac{1}{N} \sum_{i=1}^N \left| \frac{y_i - \hat{y}_i}{y_i} \right| \times 100\% \tag{12}$$

Where n is the number of cluster, y_i is the practical value of the partial system load from i^{th} cluster, and \hat{y}_i is the forecast value of partial system load from the i^{th} cluster.

Table 1: Descriptive statistics

Variable	Count	Mean	Std.	Minimum	Maximum
Time	168	4332.500	48.642	4249	4416
Load	168	135.089	17.053	99	189

Correlation Matrix

	Time	load
Time	1.0000	-0.1354
Load	-0.1354	1.0000

Table 2: Regression Coefficients Confidence Intervals

Independent variable	Regression coefficient b(i)	Standard error Sb(i)	Lower 95% conf. Limit of s (i)	Upper 95% conf. Limit of s (i)
Intercept	340.72446	116.812301	110.09519	571.35374
Time	-0.04746	0.026960	-0.10069	0.00577

Estimated equation

$$\text{Load} = 340.72446 - 0.04746 * \text{time}$$

Table 3: Predicted Values with Prediction Limits of Individuals

Actual Load (MM)	Predicted load (MM)	Standard Error of Predicted	95% Lower Pred. Limit of Individual	95% Upper Pred. Limit of Individual
156.000	139.052	139.052	105.201	172.904
156.000	139.005	17.142	105.160	172.850
144.000	138.958	17.139	105.120	172.795
142.000	138.910	17.135	105.079	172.741
140.000	138.863	17.132	105.038	172.687
138.000	138.815	17.128	104.997	172.633
136.000	138.768	17.125	104.957	172.579
134.000	138.720	17.122	104.916	172.525
133.600	138.673	17.119	104.874	172.471
133.200	138.625	17.115	104.833	172.417
132.800	138.578	17.112	104.792	172.364
132.400	138.530	17.109	104.751	172.310
132.000	138.483	17.106	104.709	172.257

Actual Load (MM)	Predicted load (MM)	Standard Error of Predicted	95% Lower Pred. Limit of Individual	95% Upper Pred. Limit of Individual
125.000	138.435	17.103	104.668	172.203
131.750	138.388	17.100	104.626	172.150
138.500	138.341	17.097	104.584	172.097
145.250	138.293	17.094	104.543	172.043
152.000	138.246	17.091	104.501	171.990
148.000	138.198	17.089	104.459	171.937
144.000	138.151	17.086	104.417	171.884

$$MAPE = \sum \left| \frac{Actual - Forecast}{Actual} \right| \times 100\% = 9.89\%$$

Plots Section

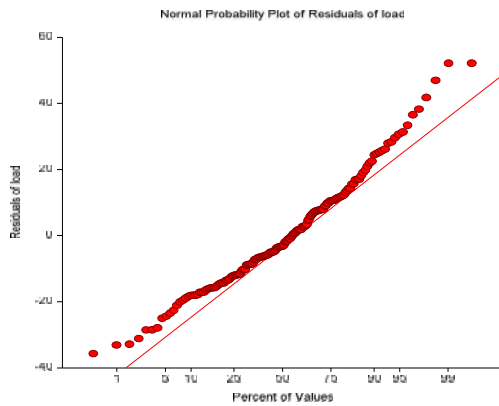


Fig 2: Graph of Normal Probability

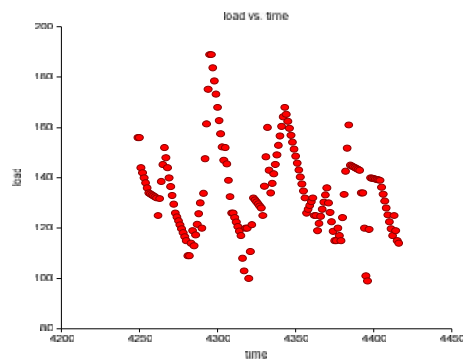


Fig 3: Graph of load vs. time

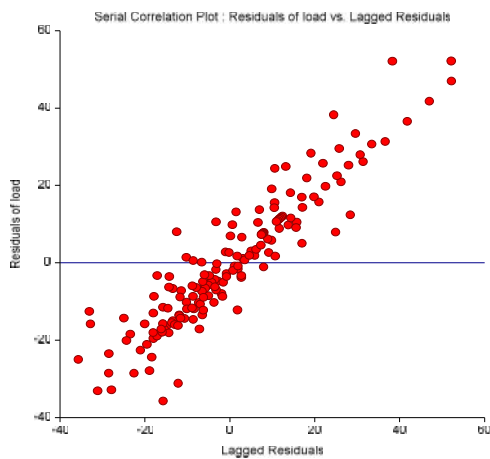


Fig 4: Graph of Correlation

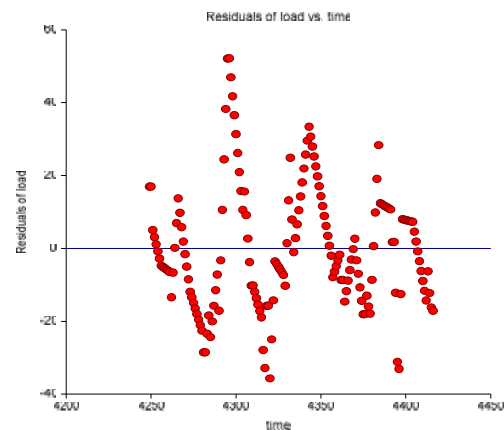


Fig 5: Graph of Residuals

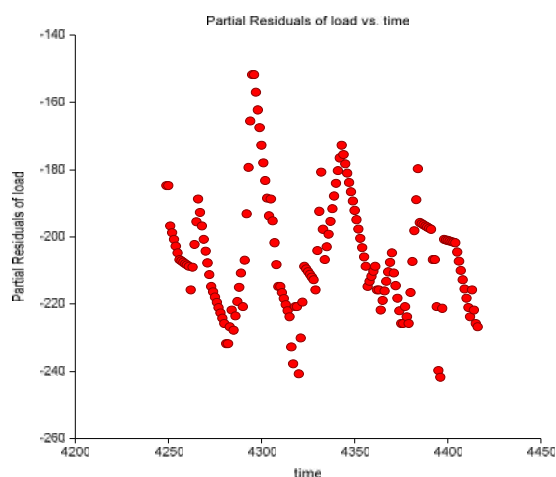


Fig 6: Graph of Partial Residual

AUTOREGRESSIVE INTEGRATED MOVING AVERAGE RESULT

Table: 4 (a) Minimization Phase Section

Item No	Error of Squares	AR (1)	AR (2)	MA (1)
0	1884790	0.1	0.1	0.1
1	467071.1	0.4540591	0.05961117	-0.3350204
2	274215.9	0.6570042	0.1813679	-0.4898499
3	269126.8	0.8015634	0.1036212	-0.3429795
4	267730.2	0.9551976	-0.04763107	-0.2056982
5	266968.7	1.101072	-0.1857113	-0.06944861
6	266785.2	1.182555	-0.2628157	0.01053412
7	266767.5	1.209987	-0.288647	0.03870403
8	266766.8	1.216208	-0.2944973	0.04529407

Model Description Section

Series Oleh_data-MEAN
 Model Regular (2, 0, 1) Seasonal (No seasonal parameters)
 Mean 145.1465
 Observations 4417
Adjacent Values method
 Iterations 8
 Residual Sum of Squares 266766.8
 Mean Square Error 60.43651
 Root Mean Square 7.774093

Table: 4 (b) Model Estimation Section

Parameter Name	Parameter Estimate	Standard Error	Prob. Level
AR (1)	1.216208	0.05846445	0.000000
AR (2)	-0.2944973	0.05479471	0.000000
MA (1)	0.04529407	0.06100319	0.457792

Table 4: (c) Asymptotic Correlation Matrix of Parameters

	AR (1)	AR (2)	MA (1)
AR (1)	1.000000	-0.995887	0.969147
AR (2)	-0.995887	1.000000	-0.964784
MA (1)	0.969147	-0.964784	1.000000

Table 5: Forecast Section of Oleh_data

Time (hrs)	Forecast (MW)	Lower 95% Limit	Upper 95% Limit
4418	116.3	92.8	139.7
4419	119.2	90.1	148.3
4420	122.1	89.0	155.1
4421	124.7	88.8	160.6
4422	127.1	89.1	165.1
4423	129.2	89.7	168.8
4424	131.1	90.4	171.8
4425	132.7	91.2	174.3
4426	134.2	91.9	176.5
4427	135.5	92.7	178.3
4428	136.6	93.4	179.8
4429	137.6	94.1	181.1
4430	138.5	94.8	182.3
4431	139.3	95.4	183.2
4432	140.0	95.9	184.0
4433	140.6	96.4	184.8
4434	141.1	96.8	185.4
4435	141.6	97.3	185.9
4436	142.0	97.6	186.4
4437	142.4	97.9	186.8

$$MAPE = \sum \left| \frac{Actual - Forecast}{Actual} \right| \times 100\% = 3.63$$

FORECAST AND DATA PLOT

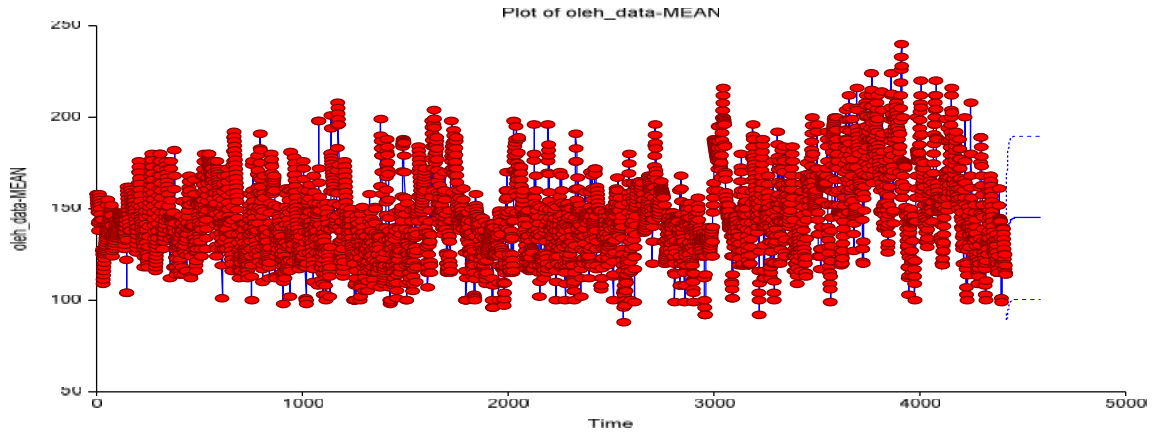


Fig 7: Graph of Forecast load

Table 6: Autocorrelations of Residuals of Oleh_data-MEAN

Lag	Correlation	Lag	Correlation	Lag	Correlation	Lag	Correlation
1	0.000203	13	0.025778	25	-0.008220	37	0.026244
2	-0.007370	14	0.007141	26	0.001945	38	0.017560
3	0.020944	15	0.010669	27	0.013669	39	0.016773
4	0.002657	16	0.002235	28	-0.002773	40	-0.011476
5	-0.005215	17	-0.001918	29	0.033952	41	-0.015243
6	-0.031730	18	-0.014708	30	0.029320	42	-0.000081
7	-0.062543	19	0.039367	31	0.004821	43	0.004144
8	0.028015	20	0.001124	32	0.007088	44	0.014394
9	-0.012855	21	0.017302	33	0.003509	45	0.011183
10	0.015065	22	0.016820	34	0.016837	46	-0.011470
11	0.037234	23	0.009019	35	0.003590	47	0.026569
12	-0.023052	24	0.048994	36	-0.016216	48	0.038441

AUTOCORRELATION PLOT SECTION

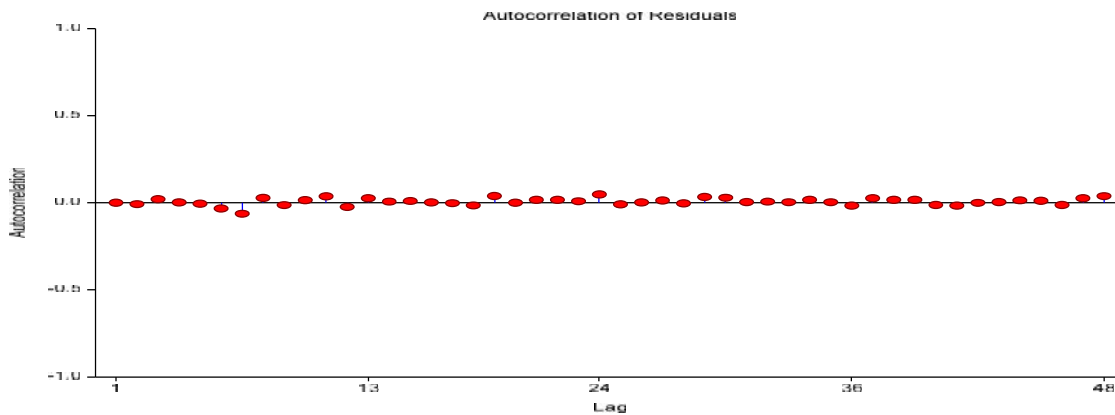


Fig 8: Graph of Autocorrelation of Residual

DISCUSSION

Although the ARIMA method has the best performance in this study considering its MAPE, for this reason, the bottom line is that this decision should not depend on only one criterion to judge which method is the appropriate one in each case. The critical issue in developing an ARIMA model is that its computation time is much higher than the MLR because of its sophisticated architecture. On the other hand, the great advantage of using the ARIMA model is that it only needs the information regarding only one variable to build a model. However it will take time to choose the optimal coefficient, especially if the statistical package used lacks the capability of searching for the right coefficient.

CONCLUSION

ARIMA short term load forecasting has been presented and applied to the practical power system. From the results it can be clearly seen that the ARIMA model approach is very effective. This method is suited because of very small errors are acceptable in a practical uses. Though the method gives satisfactory small errors but does not respond to the sudden change in load. From the results, we can also conclude that the error produced by the ARIMA. Due to the less error produced, the cost will automatically reduce for the system. It can be concluded that using forecasting techniques, it is possible to design good models that can do short term load forecasting that can help electricity generating plants to work efficiently and meet the load demands with less discrepancy between demand and supply.

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