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DEVELOPMENT OF AN ARIMA MODEL FOR ELECTRICAL LOAD DEMAND OF TAKIE 11KV DISTRIBUTION SYSTEM

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ABSTRACT

Electrical load demand is very important in the economic development of any locality. The Takie 11kV distribution system has been facing severe imbalance between electrical load demand and electrical load supply thereby causing electrical load demand crisis and this has pulled back the economic growth of the town. In this research paper, Autoregressive Integrated Moving Average (ARIMA) model was used to formulate a prediction model for the load demand pattern in the distribution system to give opportunity to have a hint about the future load demand and planning in the distribution system. This paper aims at an optimal Autoregressive Integrated Moving Average (ARIMA) model for the monthly peak load demand patterns in the distribution system. The monthly peak load demand data from January2012 to December 2016 was collected from the load dispatch unit of the power sector for analysis. The ARIMA (0,1,1) model determined in this work revealed that the load demand is rapidly increasing with time and this indicated that the main behavior of the distribution system has been captured thereby helping the power sector in decision making process which will form the basis for planning and development in the distribution system. The accuracy testing was carried out using mean error (ME) mean absolute percentage error (MAPE) and root mean square Error (RMSE).

KEYWORDS: ARIMA, Load demand Prediction, Distribution System, Root Mean Square Error (RMSE), Mean Percentage Error (MPE) and Mean Error (ME).

INTRODUCTION

Electrical load demand planning is considered the backbone for an economic development and progress thus; it plays a crucial role in socio-economic development. It is a tool that has the capability of making useful contribution to planning and future policy formulation of the power sector. Time series prediction is an important issue of prediction in which past values of the same variables are given and analyzed to simulate a system model describing the specific relationship. The model is then used to predict time series into the future. (Peter 2013). Several methods of statistical prediction such as regression analysis, classical decomposition method, Box and Jenkins and exponential smoothing techniques have been used in the past. These techniques provide predictive models of different accuracy. The accuracy of the prediction is based on the minimum error of prediction. The appropriate prediction methods are considered from several perspectives such as prediction interval, prediction period, characteristics of time series, and size of time series (Bianco and Nardini, 2013). In this research paper, time series Autoregressive Integrated Moving Average (ARIMA) modeling procedure was used to determine an optimal Autoregressive Integrated Moving Average (ARIMA) model for the distribution systems and to make prediction. Monthly peak load demand data for Takie 11kV distribution system data from January 2012 to December 2016 was collected from the load dispatch unit logbook of the power sector in Ogbomoso. The model building process involves: tentative model identification from ARIMA class, estimation of parameters in the identified model, diagnostic check and model comparison including prediction of load demand pattern.

The time plot of the data was carried out to test for stationarity in data before model identification of the ARIMA (p, d, q) parameters from the plot of Autocorrelation coefficients (ACF) and Partial autocorrelation coefficient (PACF). Estimation of parameters in the identified model and diagnostic check is used to determine if an estimated model is statistically adequate before prediction of the load demand is determined. The data of January 2012 to December 2015 was used as the model sample and the optimal ARIMA (0,1,1) was considered while validation of the performances of the ARIMA model is performed by using January 2016 to December 2016 and the accuracy measures such as mean square (ME), mean square error (MSE), and root mean square error (RMSE) was used to determine reliability. R language software was used for the load demand data analysis.

Related Works

The modeling of load demand data through the application of Autoregressive Integrated Moving Average (ARIMA) has become a major tool by researchers to predict the future values of electrical load demands. Peter (2013) studied the predictive method for monthly electrical load consumption in Lebanon. They used two different univariate modeling methods namely, ARIMA and AR (1) with high pass filter. The best predicting method for this particular energy data was AR (1) high pass filter model. Zhu and Feng (2012) studied the issue of household energy consumption in China from 1980 to 2009 with construction VAR model. There were two predicting methods used and they are ARIMA and BVAR. The results showed that both of them can predict the sustained growth of household energy consumption (HEC) trends. Ediger and Akar (2007) applied SARIMA (Seasonal ARIMA) methods to estimate the future primary fuel energy demand in Turkey from the years 2005 to 2020. Pappas *et al.* (2018) introduced the utilization of traditional methodology, *i.e.*, an ARIMA model, to predict the electrical load demand. Different ARIMA models were selected and the criteria (Akaike Information Criterion: AIC and Bayesian Information Criterion: BIC) were utilized to justify the most appropriate one. Since there are no empirical or exact rules to derive the best predicting model, the most appropriate one was selected by choosing the model with the lowest error. Mostly, the error margins of the candidate predicting methods were slightly different. The ARIMA method was also deployed by Abdel-Aal and Al-Garni (2017) to predict monthly domestic electric energy consumption in the eastern province of Saudi Arabia and the optimum model in this case was the first ordered ARIMA With a multiplicative combination of seasonal and non-seasonal autoregressive parts. Cho and Chen (2015) compared the results of the univariate ARIMA and the traditional regression models to predict the short-term load by considering weather-load relationships.

MATERIALS AND METHOD

The procedural steps involved in this research paper are as follows:

Data collection: The monthly peak electrical load demand data for Takie 11kV distribution system was obtained from the power sector from January 2012 to December 2016.

Checking the data: The monthly peak load demand data was checked weather it is stationary or not using time plot in R language, if not then seasonality and trend is analyzed.

Differencing: The non seasonal differencing is applied in this work until the resulting data is stationary in mean and variance.

Tentative model identification: This step is to analyze the two graphical device which are the estimated autocorrelation function (ACF) and partial autocorrelation correlation function (PACF) to get an idea of the values of the appropriate model from the Autoregressive Integrated Moving Average (p,d,q) process.

Estimation of parameters in the identified model: the exact estimate of the coefficients of the model chosen from the identification stage is obtained.

Diagnostic checking of the model. This check is determined if an estimated model is statistically adequate. At this point the residual of the data are observed. The residual is the difference between the original data and fitted data. The generalized Box Jenkins ARIMA model with p,d,q, process has the following equation:

$Y_t = \mu + \alpha_1 Y_{t-1} + \alpha_p \varepsilon_{t-1}$ ------ $\theta_1 \varepsilon_{t-1}$ ------$\theta_q \varepsilon_{t-q}$

Where Y_t is the differenced time series data, α and θ are the unknown parameters and ε are independent error terms with zero mean. The lagged autoregressive (AR) process are symbolized by p and that of a moving average (MA) process are symbolized as q.

Development of ARIMA Model

The first step in this ARIMA model development was to plot the original data obtained against time using the time series function in R language software. Plots from these data are called time plot and they show up important features of the series such as trend, seasonality, outliers and discontinuities. The input data are adjusted to form a stationary series, one whose values vary more or less uniformly about a fixed level over time. Trends can now be adjusted by "regular differencing", a process of computing the difference between every two successive values, computing a differenced series which has overall trend behavior removed. If a single differencing does not achieve stationarity, it may be repeated although rare to have more than two regular differencing. Where irregularities in the differenced series continue to be displayed, log or inverse functions can be specified to stabilize the series such that the remaining residual plot displays values approaching zero and without any pattern. This is the error term, equivalent to pure, white noise.

RESULTS AND DISCUSSION

The graph shows that there is a sharp drop in the monthly load demand in 2012, and it was maintained till 2013 when it suddenly picked up till 2016. This may be due to the high demand for electrical loads or a general increase in population.

Figure 1 suggests a non stationary process with constant mean and variance. Figure 2 displays the plots of the original data, seasonal behavioral patterns of the data, trend in the data and the remainder which really explains the behaviour of the load demand in the distribution system.

Two graphical devices which are the autocorrelation function (ACF) and partial autocorrelation function (PACF) are used as guides for choosing one or more Autoregressive Integrated Moving Average (ARIMA) models that are appropriate. Figure 3 describes the features of the data that is the autocorrelation plot and the partial autocorrelation plot. The ACF and PACF show that the ACF decays exponentially and the PACF has a single spike at lag 1 indicating that the series is generated by an ARIMA (0, 1, 1) process,

The ACF plot of the residuals from the ARIMA (0, 1, 0) model shows all correlation within the threshold limits indicating that the residuals are behaving like white noise as illustrated in Figure 4.

Figure 5 shows that the Prediction values keep increasing throughout. This is due to the model parameters, structure and history of the data. There is no tendency of the series to have any downward trend over the years. The ACF, PACF, Q statistic, residual plots, Box-Ljung test, and accuracy measures proved thatARIMA (0, 1, 1) model provides the best predicting model for values of electrical load of Takie 11kV distribution system.

A Box-Ljung test returns a large p-value (0.4301), also suggesting the residuals are white noise and that the model is adequate.

The ACF and PACF show that the series is stationary. In addition, p-value of 0.01 in Augmented Dickey Fuller test indicates rejection of the null hypothesis and accepting the alternative that the series is stationary as shown in Table 1.

From Table 2, ARIMA (0,1,1) model has the lowest AIC and BIC and therefore the best out of the models tested.

From Table 3, the lowest values of the measures of accuracy indicate the optimal ARIMA model for reliable predction.

Table 4 shows the best model and parameter estimate of the selected model for Takie 11kV distribution system. Table 5 shows the residual errors from the fitted model.

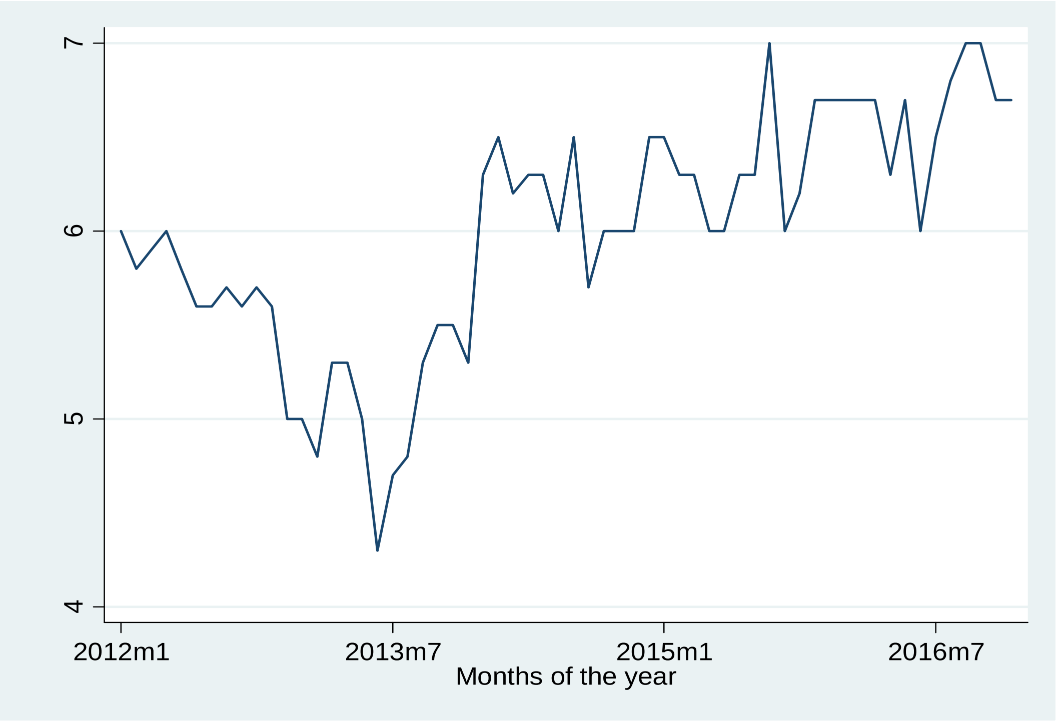

Figure 1: Time plot for Takie 11kV distribution system.

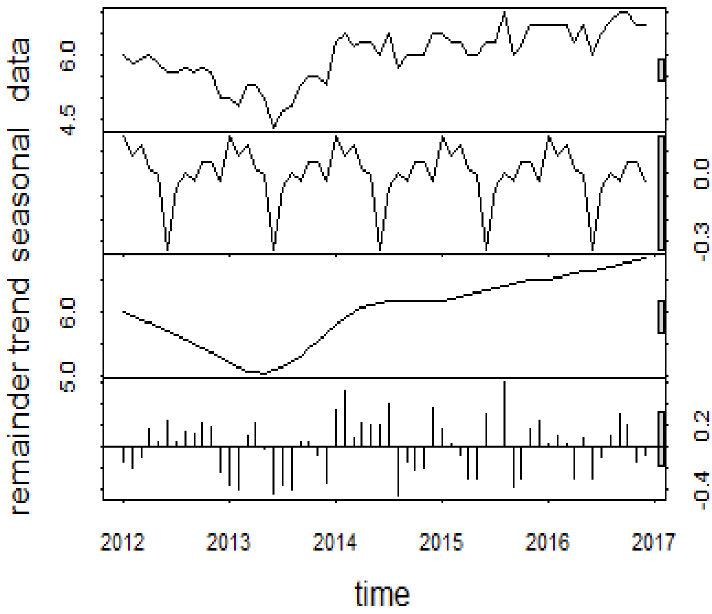

Figure 2: Trend, seasonal, and random plot.

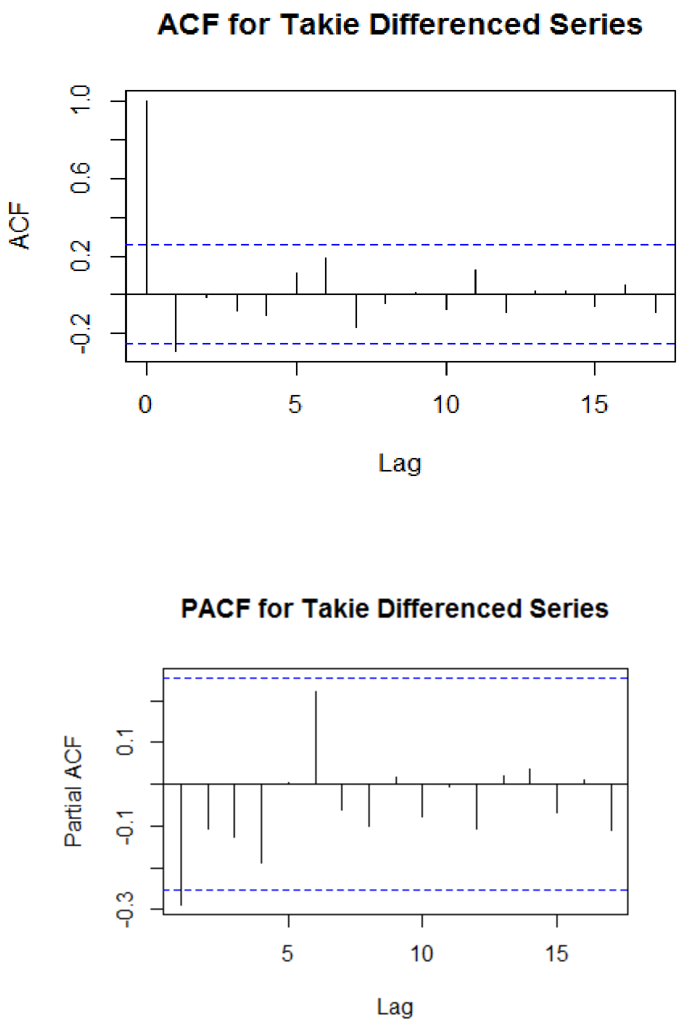

Figure 3: Differenced autocorrelation (ACF) and Partial autocorrelation (PACF) plots.

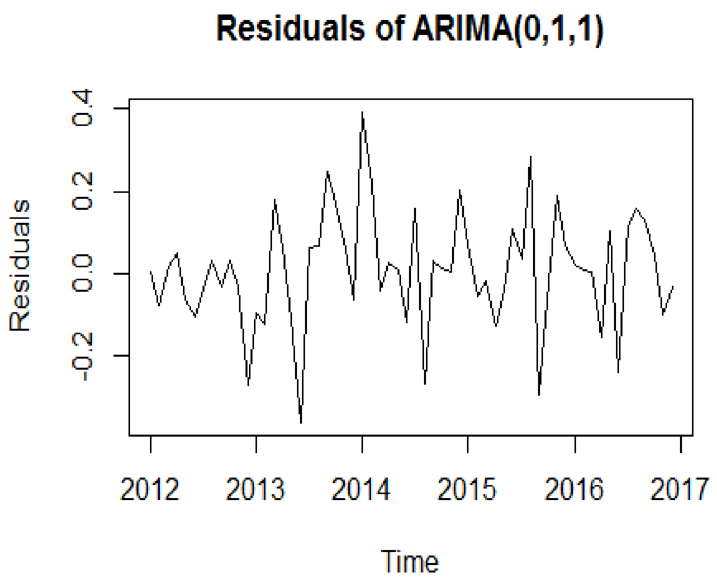

Figure 4: Residual plot of Takie 11kV distribution system.

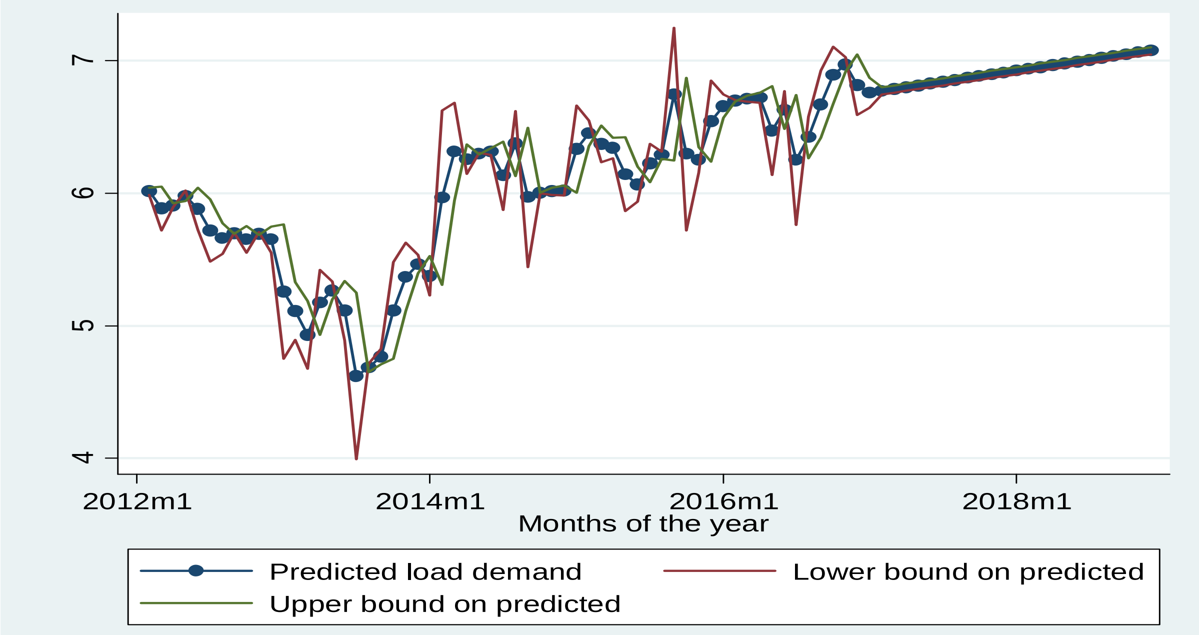

Figure 5: Monthly Load demand of Takie 11kV distribution system and 24 month Prediction.

Table 1: The ACF, PACF and Q Statistics Test values *ACF, PACF and Q statistics Tests.*

-1	0	1	-1	0 1
LAG	**AC**	**PAC**	**Q**	**Prob>Q [Autocorrelation] [Partial Autoco]**
1	-0.2893	-0.2893	5.1937	0.0227
2	-0.0135	-0.1078	5.2053	0.0741
3	-0.0801	-0.1293	5.6179	0.1318
4	-0.1024	-0.1935	6.3039	0.1776
5	0.1111	0.0010	7.1258	0.2114
6	0.1864	0.2500	9.4852	0.1481
7	-0.1692	-0.0600	11.466	0.1195
8	-0.0392	-0.1148	11.575	0.1712
9	0.0074	0.0104	11.579	0.2381
10	-0.0765	-0.1035	12.008	0.2845
11	0.1267	-0.0259	13.212	0.2797
12	-0.0905	-0.1407	13.84	0.3111

Table 2: ARIMA Model Identification and selection.

Model	Log-Likelihood	AIC	BIC
ARIMA (0,1,0)	-23.45	48.91	50.99
ARIMA (0,1,1)	-20.31	**44.61**	**48.77**
ARIMA (1,1,1)	-20.06	46.11	52.35
ARIMA (1,1,3)	-19.89	49.78	60.16
ARIMA (1,1,0)	-20.94	45.87	50.03
ARIMA (2,1,1)	-20.03	48.07	56.38
ARIMA (1,1,2)	-20.05	48.09	56.40
ARIMA (2,1,0)	-20.63	47.26	53.49

Table 3: Summary measures of the Prediction Accuracy.

Model	ME	RMSE	M APE
ARIMA (0,1,0)	0.0152	0.3419	0.0278
ARIMA (0,1,1)	0.0174	**0.3400**	**0.0501**
ARIMA (1,1,1)	0.0198	0.3381	0.0793
ARIMA (1,1,3)	0.0231	0.3364	0.1180
ARIMA (1,1,0)	0.0023	0.3365	0.1171
ARIMA (2,1,1)	0.0116	0.3571	-0.0016
ARIMA (1,1,2)	0.0228	0.3366	0.1157
ARIMA (2,1,0)	**0.0228**	0.3366	0.1157

Table 4: The best model and parameter estimates.

OPG						
D.takie	**Coef.**	**Std.**	**Err.**	**z**	**P>|z|**	**[95% Conf. Interval]**
Takie	|					
_cons |	.0137789	.0283703	0.49	0.627	-.041826	.0693837
ARMA	| ma |					
L1. | -.	3767079	.1255989	-3.00	0.003	-.6228772	-.1305386
/sigma	.3402425	.0284551	11.96	0.000	.2844714	.3960135

The developed ARIMA (0,1,1) model is

$$0.0138+\varepsilon_{t-1} - 0.3767\varepsilon_{-1} \qquad (2)$$

Table 5: Errors (residuals) from the fitted model.

2012	2013	2014	2015	2016
0.0029	-0.0943	0.3929	0.0699	0.0229
-0.0778	-0.1231	0.2155	-0.0548	0.0079
0.0157	0.1798	-0.0442	-0.0190	0.0028
0.0464	0.0624	0.0246	-0.1276	-0.1560
-0.0662	-0.1105	0.0086	-0.0443	0.1028
-0.1068	-0.3632	-0.1180	0.1056	-0.2422
-0.0371	0.0625	0.1591	0.0367	0.1159
0.0292	0.0676	-0.2688	0.2843	0.1566
-0.0319	0.2460	0.0307	-0.2938	0.1305
0.0310	0.1715	0.0107	-0.0210	0.0453
-0.0313	0.0596	0.0037	0.1896	-0.0989
-0.2716	-0.0654	0.2013	0.0658	-0.0343

CONCLUSION

In this paper, Autoregressive Integrated Moving Average (ARIMA) model has been analyzed and applied to Takie 11kV distribution system. A unit root test (Augmented Dickey Fuller) was applied to the data obtained and this concludes that the data was not stationary and after the first difference on the data it becomes stationary. R language software is used for fitting the coefficient of the model using graphs, statistics, ACFs and PACFs of residuals and after several iterations, the model determined is ARIMA(0,1,1). The use of Mean error (ME), root mean square error(RMSE) and mean absolute percentage error (MAPE) was used for measuring the performance accuracy. The model determined has given an insight into the electrical load demand pattern of Takie 11kV distribution system thereby helping the power sector in policy formulation and assist in addressing the imbalance being experienced in the distribution system.

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