Short-Term Electrical Load Prediction Model For A Distribution Company In Nigeria

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Abstract— Load prediction is an important factor in power system safety and economy for power system operation. This research developed and compared a model for short and middle-term load demand prediction in Benin electricity company (BEDC) of Nigeria using historical data. Hourly load demand data (Day ahead load) from 2018 to 2020 was obtained from Nigeria Electricity Regulating Commission (NERC). The preprocessing and standardization of the data were done, and the data set was randomly split into training (Jan 2018 to Dec 2019) and testing (January 2020 to June 2020) data using Autorgression moving integrated average (ARIMA) for the predictive model. The model was used to predict three scenarios (One week, Two weeks, and One Month). The performance of the model was measured using mean absolute error (MAE), mean absolute percentage error (MAPE), and root mean square error (RMSE). Also, the error of the model was computed for the three scenarios. The results of the performance metrics and the computed errors of the model show that the model is more accurate for the Short term Prediction with MAPE errors of 9%, 11%, and 12% for the three scenarios, respectively. This suggests that the model is more favorable for the first scenario (Seven Days) when predicting the immediate future. This research recommends that ARIMA is best used for Short term prediction for better accuracy of the model. Also, further study should be carried out to improve this model by using exogenous data such as temperature and humidity.

Keywords—component; formatting; style; styling; insert (key words)

I. Introduction

Energy is an integral part of the economic development of any country. In most developing countries, the energy to the consumer was transformed from one stage to another, for example, the generator to the transmission and the distribution before getting to the end-users [1]. Nigeria's electricity is divided majorly into three which are generation companies, transmission companies and the distribution companies [2, 3]. The distribution companies interface with the end-users and determine the amount of supply to the end-user. However, there has been a lot of argument in the electricity sector of Nigeria due to the unavailability of supply to the end-users. Also, the technical problem of grid collapse and fault in the system has been one of the reasons for the unavailability of supply. Distribution companies need to maintain their network in order to ensure good and quality supply to the end-users and reduce the power loss in the network. Also, if there is a mismatch below or above the permissible range between the load and the power generated, it will lead to the loss of some generators which can suddenly cause a system collapse in the network. It is therefore necessary to predict the load consumed by the discos in order to generate accurate power in the network. However, there are a lot of factors that affect the consumption of the end-users which includes weather condition, working days and holidays, and seasonal variation this parameter can be used in forecasting the electrical load which can be in term of Short term load prediction (STLP) (load prediction for 1 day to 1 week) and Medium-term load prediction (MTLP) (load prediction) from several weeks to one or several years). However, because of the rapid changes in energy resource outputs, which frequently result in voltage violations (either less than 0.95 pu or larger than 1.05 pu) [4,5], distribution voltage regulation has become increasingly difficult. Traditional voltage control strategies perform poorly in settings with such rapid generation variability. In a contemporary electric power grid, preventing voltage breaches necessitates active supervision by distribution system operators to effectively monitored system parameters. Using historical data and load/DER projections, they would be able to predict the grid's near-future behaviours, allowing them to plan preventative control actions ahead of time to prioritize and better coordinate efforts against voltage breaches [6]. The uncertainty in this voltage prediction process is caused by a variety of factors, including load size, generation output, step-voltage regulator tap settings, switching capacitor banks, and network topology change. The recent use of large-scale deployment of smart meters in distribution networks opens up new potential for voltage prediction and regulation. As a result, this research describes a data-driven method for predicting hourly load profiles in distribution networks. Nigeria has eleven distribution stations which supply electricity to all consumers and are classified based on the tariff's band. The discos shared the states which they covered and the hours of supply to the consumers depend on the tariff band to which the consumer is connected. Also, the daily load demand by all DISCOS will be sent to the transmission company. This research focuses on the hourly load prediction for Benin Electricity Distribution Company (BEDC) in Nigeria for accurate load management based on historical load demand. Time series algorithm was used for Short term load prediction and Medium term Load Prediction. The model developed for the scenarios was compared to one another and the most accurate was regarded as the best.

A. *Time Series Prediction Techniques Selecting*

***Autoregression**: The regression model is used to forecast the variable of interest using a linear combination of predictors. While auto regression model, is used to forecast the variable of interest using a linear combination of past values of the variable [7]. The term auto regression implies that it is a regression of the variable against itself. The algorithm for autoregression for order p is presented in (1).*

$$y_t = c + ay_{t-1} + by_{t-2} + \cdots dy_{t-p} \dots + \varepsilon \quad (1)$$

where ε_t is white noise and a, b, c and d are the co-efficient of the past variables while y_{t-1}, y_{t-2} and y_{t-p} are the values of the past data.

Autoregression Moving Average (ARMA): ARMA is different from AR, predicted error in the model. The algorithm is represented by (2).

$$y_t = c + ay_{t-1} + by_{t-2} + \cdots dy_{t-q} \dots + \varepsilon_t \quad (2)$$

where ε_t is white noise. ε_t, is the error in the predicted variables.

Autoregression Integrated Moving Average (ARIMA): By combining differencing with autoregression and a moving average model, we obtain a non-seasonal ARIMA model. ARIMA is an acronym for Autoregressive Integrated Moving Average (in this context, "integration" is the reverse of differencing). The full model can be written as presented in (3).

$$y_t = c + \emptyset_1 y_{t-1} + \emptyset_2 y_{t-2} + \cdots \emptyset_p y_{t-p} + \emptyset_1 \varepsilon_{t-1} + \emptyset_2 \varepsilon_{t-2} + \cdots \emptyset_q \varepsilon_{t-q} + \varepsilon_t$$
(3)

Where c is constant, is the moving average parameter, yt-1, yt-2 and yt-p are the values of the past data. In this research, autoregression integrated moving average will be used to predict the hourly load consumption of BEDC.

II. Methodology

This study analyzes Benin Electricity Distribution Company (BEDC). The variables of interest are hourly active load consumption and the time of consumption. The input data set contains over 20,000 distinct scenarios created in excel file from January 2018 to 2020. Data analysis is implemented in Python, including preprocessing steps such as features standardization. The daily load demand (Day ahead of BEDC was obtained which makes over 20,000 data. Three scenarios (One Week, Two weeks and One month) for short term and middle term prediction was created using ARIMA to determine the most accurate for the model. These methods are particularly attractive, as they have the ability to handle the linear relationships between load and the factors affecting it directly from historical data. The input data set is randomly split into training and testing. The training data is (Jan 2018 to June 2020) and the testing Data is (July 2020 to December 2020). These subsets are fixed throughout this study to ensure a fair comparison among the three scenarios. The absolute error between the predicted and actual value was computed using (1) and various performance metrics are analyzed for each prediction technique; they are based on prediction residuals. The metric performance index shown in (4 - 7) represent mean absolute error (MAE), mean absolute percentage error (MAPE) and root mean square error (RMSE) In these metrics, the importance assigned to each residual depends on only its own magnitude so that the cost of predictions is uniform across the domain of the target variable.

$$error = |k_t - l_t| \quad (4)$$

$$MAE = \frac{1}{n}\sum_{t=1}^{n} |k_t - l_t| \quad (5)$$

$$MAPE = \frac{1}{n}\sum_{t=1}^{n} \left|\frac{k_t - l_t}{k_t}\right| \quad (6)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(k_t - l_t)^2} \quad (7)$$

where k is the predicted load t is the time and l is the actual load while n is the data samples.

III. RESULTS

The load consumption between the years 2018 to 2020 is shown in Fig. 1, the results indicate that there is a seasonal variation in the load consumption from one year to another.

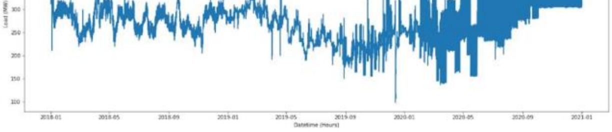

Fig. 1: BEDC Load Consumption between 2018 to 2020.

A. Comparison of predicted and actual load

The predicted and actual load for the first seven days, 14 days and 31 days in the Month of July 2020 is predicted in Fig. 2 to Fig. 4. These periods were not included in the training data set and the results show that the model performs better for the first seven days compared to 14 days and 31 days. The results indicate that the ARIMA model in this work is capable of looking to the immediate future. However, the model is less accurate when predicting to future greater than seven days as shown in Fig. 2 (14 Days) and 3 (one Month) respectively.

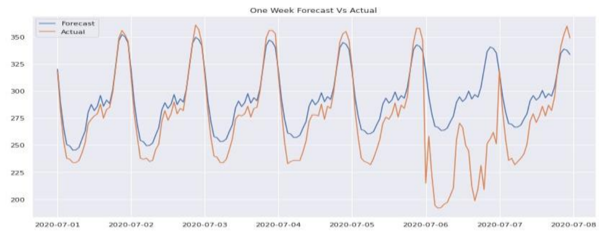

Fig. 2: Predicted and Actual Loads for Seven Days

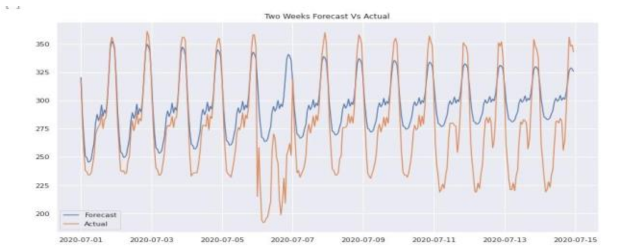

Fig. 3: Predicted and Actual Loads for 14 Days

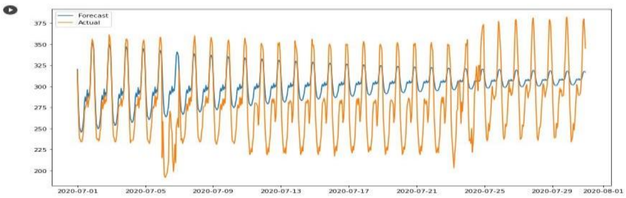

Fig. 3: Predicted and Actual Loads for One Month

B. Model ERROR and Performance Metric for the Three Scenarios

The error in the model for the three scenarios is presented in Fig. 4 to Fig. 7. The results in Fig. 1 shows that the error in the model when predicting for (7days) ranges from 0 to 100, in Fig. 2, the model error varies from 3 to 150 and in Fig. 3, the model varies from 4 to 5. This indicates that ARIMA model tends to perform better when predicting the immediate future (short term One to Seven Days). Also, the results of the performance metrics (MAE, MAPE and RSME) in Table 1, validate that the model tends to perform better when predicting immediate future short-term prediction (one week) are lower compared to that of medium prediction (two weeks and one Month).

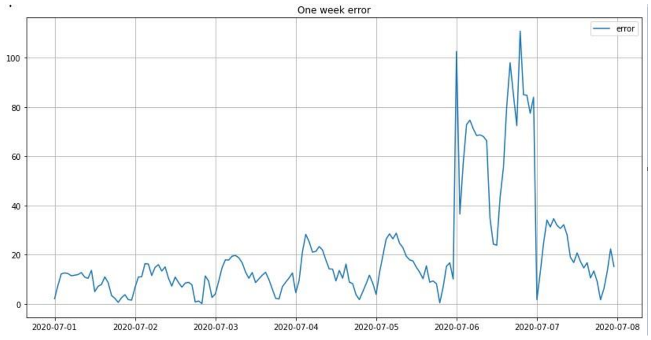

Fig. 4: Model Error in the Predicted Values for Seven Days

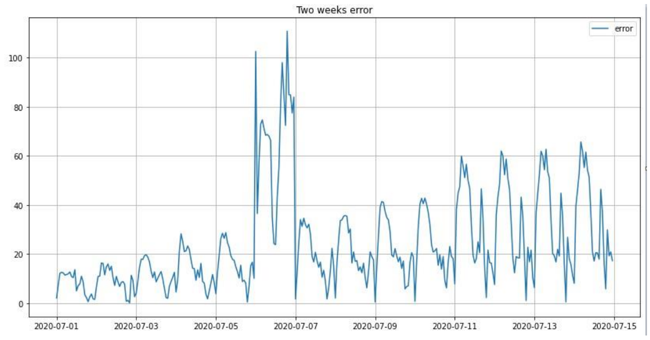

Fig. 5: Model Error in the Predicted Values for Two Weeks

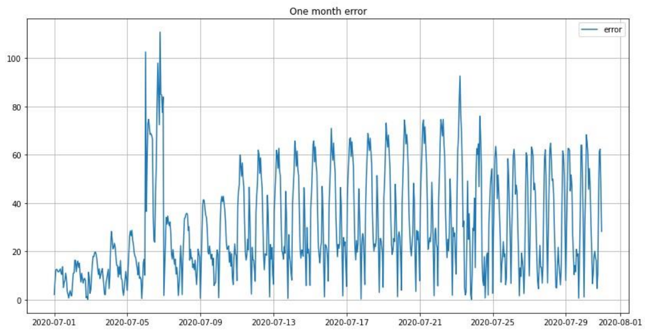

Fig. 6: Model Error in the Predicted Values for a Month

Table 1: Model Performance Index

Time	Performance Metrics		
	MAE	**MAPE**	**RMSE**
One week (7 Days)	20.83	0.09 (9%)	30.63
Two Weeks (14 days)	24.44	0.1 (10%)	31.52
One Month (31 days)	30.28	0.12 (12%)	36.96

IV. Conclusion

Electricity demand prediction has an important significance in security and the cost of energy. With the use of machine learning techniques, which serve as one of the promising approaches for the planning of electricity generation, market regulations, and planning of the distribution network, accurate prediction models are needed for secure and reliable energy system operation. This research developed forecasting models based on the time series algorithm that analyzed on BEDC electricity day-ahead load demand. The model shows a favorable accuracy when predicting the immediate (STLP) future and less accuracy when predicting the medium-term load (two weeks and one Month). This research recommends that ARIMA should be used for STLP for better accuracy and ARIMA model accuracy can be improved using environmental variables.

V. Reference

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