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Probabilistic Long-Term Energy Consumption Forecast in Nigeria: Ado-Ekiti as a Case Study

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ABSTRACT

Load forecast is very important in the energy industry. Deterministic energy consumption forecast has a lot of limitations since it does not take care of randomness and uncertainties. This study employs probabilistic energy consumption forecast in Ekiti State using standard normal distribution as a tool. It focuses on the energy consumption in Ekiti State using the available data from Benin Electricity Distribution Company (BEDC), Ado-Ekiti office. The study shows energy consumption in the state has a tendency of rising above 8601.5MWh (the maximum for year 2017) by 4.65% in 2018. It was established that the probability of the energy consumption falling below 4970MWh is 8.38%. The consumption of energy in year 2018 in the state may fall between 4970MWh and 8601.5MWh monthly at a probability of 86.97%. Energy consumption in year 2018 will mostly fall between 5500MWh and 8000MWh particularly. It is unlikely it falls between 3500MWh and 4000MWh (0.98%) and 9000MWh and 9500MWh. The result of this work can be used by stakeholders in the power industry for planning activities.

1. INTRODUCTION

Energy forecasting is a broad term that describes all form of forecast done in the energy industry which include supply, demand, price of electricity, gas, water, and renewable energy forecast (Hong *et al.*, 2016). From these listed forms of energy forecast, demand/load forecasting is used by power companies to predict active load at various load buses ahead of actual load occurrence (Ali et al., 2016). It is also useful for resource planning and attracting investments in the energy sector (Anand and Suganthi, 2017).

Demand forecasting plays an important role in power system planning, operation, control and management (Quan *et al.*, 2014). According to different forecast horizons, load forecast can be carried out on a long-term, mid-term, short-term and very short-term basis (Dang-Ha *et al.*, 2017). Short and medium-terms forecast refers to a forecast done over half an hour to few hours and a few days to few weeks respectively while long-term forecast is done over a period of 1 week to 1 year or more ahead (Sepasi *et al.*, 2017; Verma *et al.*, 2017).

Nigeria, a country with the largest economy in Africa is presently facing a myriad of challenges in its power sector. Several attempts have been made by successive administrations to solve these problems with nothing significant to show for it (Ogunleye, 2017). Emodi and Yusuf (2015) identified efficiency, performance, planning as some of the obstacles to improved electricity access in the country. Also, energy demand forecasts, if done accurately, can address these obstacles because it helps the decision makers know the volume and trend of future energy consumption to better schedule and plan the operations of the supply system (Ghalehkhondabi *et al.*, 2017). Due to this reason, this paper aims at carrying out an energy consumption forecast in Nigeria using Ado-Ekiti as a case study.

Several forecast techniques have been developed and discussed in the literature (Li, 2011). These include: linear regression, non-linear regression, probabilistic time series, and neural network methods. Melodi *et al.* (2016) proposed a probabilistic long-term load forecast and algorithm for application on Nigerian transmission system. The study applied a developed system specific algorithm comprising Monte Carlo, and artificial neural network techniques that considers location's predominant driving factors as population and GDP growth of the Nigerian system. An initial analysis on obtainable historic data for these factors and load was carried out to obtain possible variability characteristics. The algorithm was then implemented in MATLAB-Excel workspaces. Normal mode impact of obtained regional forecasts on test system was obtained by long term power flow computation with NEPLAN software. Adedokun (2016) employed autoregressive integrated moving average (ARIMA) model to forecast electricity consumption in Nigeria. Results from the study revealed that, Nigeria will only attain the 2011 level of electricity consumption in Italy in the year 2671 if the current trend of electricity generation and consumption is maintained. The study further showed that with a consistent annual increase of 10% or 20%, taking 2012 as the base year, Nigeria can achieve Italy's level in 2050 or 2032, respectively. In another study, Tripathi and Singh (2008) used two types of neural networks, generalized regression neural network (GRNN) and probabilistic neural network (PNN) to forecast load demand in Australia. The results show that the forecasted load is very close to the actual load. The maximum error in load forecasting was found to be 7.62 percent and 6.45 percent in the GRNN and PNN models, respectively, whereas the maximum value of Mean Average Percentage Error (MAPE) is 4.0 percent in the case of GRNN and 9.51 percent in the case of PNN during different days of the week. In Panklib *et al.* (2015), an artificial neural network (ANN) and a regression model were applied to forecast long term electricity consumption in Thailand. The inputs of both nonlinear models are gross domestic product, population. Maximum ambient temperature and electricity power demand were then used as inputs in the neural network to predict electricity consumption. The results showed that the ANN model can give more accurate estimations than regression model as indicated by the performance measures, namely coefficient of determination, mean absolute percentage error and root mean square error.

The reviewed literature revealed a paucity of study on long-term load forecast in Nigeria especially with the recently decentralized electricity distribution network in the country, hence the need for this study. This study solves the problem of long-term load forecasting in the decentralized electricity distribution network of Nigeria using probabilistic load forecasting.

2. METHODOLOGY

2.1. Research Data

The data that was used in this study was obtained from Benin Electricity Distribution Company, Ekiti State Office, Ado-Ekiti. It represents the monthly energy consumption (MWh) in Ekiti State from January 2017 to December 2017. It should be noted that 10 years forecast was proposed for this study but owing to dearth of reliable data that could date back as far back as 2006, monthly study covering January 2017 to December 2017 was selected. The reasons for the shortcomings include change in ownership of Nigeria power system i.e from National Electric Power Authority (NEPA) to Power Holding Company of Nigeria (PHCN) in which BEDC is a shareholder. Investigation revealed that:

i. manual mode of record keeping was adopted before the new company took over. Consequently, most of the data for energy consumption in the state could not be traced or found. The ones found had a lot of lost values
ii. data collected by private sector especially in a developing nation like Nigeria is more reliable than the ones from the public sector (government).

Table 1: Monthly energy consumption from Jan 2017 to Dec 2017 in Ekiti State

S/N	Month	Energy consumption (MWh)
1	January	8601.5
2	February	8231
3	March	6645
4	April	7092
5	May	6377
6	June	5125
7	July	5937
8	August	5017
9	September	4970
10	October	6224
11	November	7136
12	December	7935
Total		79,290.5

2.2. Modelling

With reference to Table 1, the research data was modelled as standard normal distribution data (curve). The equation of standard normal curve is given in Equation 1 (Stroud and Booth, 2013)

$$y = \phi(Z) = \frac{e^{-\frac{Z^2}{2}}}{\sqrt{2\pi}} \tag{1}$$

$$Z = \frac{x-\mu}{\sigma} \tag{2}$$

Where
μ = mean of monthly energy consumption in 2017
σ = standard deviation of monthly energy consumption in 2017
$\phi(Z)$ = probability density function
Z = standard normal variable

3. RESULTS AND DISCUSSION

From standard normal distribution table, the probabilities that the monthly energy consumption will fall within some selected ranges of values are shown in Table 2.

Table 2: The probabilities that the energy consumption will fall within some selected range in 2018

S/N	Range of energy consumption (MWh)	Probabilities	% Probabilities
1	9000 - 9500	0.0147	1.47
2	8500 - 9000	0.0337	3.37
3	8000 - 8500	0.0651	6.51
4	7500 - 8000	0.1056	10.56
5	7000 - 7500	0.1441	14.41
6	6500 - 7000	0.1652	16.52
7	6000 - 6500	0.1591	15.91
8	5500 - 6000	0.1288	12.88
9	5000 - 5500	0.0877	8.77
10	4500 - 5000	0.0501	5.01
11	4000 - 4500	0.0241	2.41
12	3500 - 4000	0.0098	0.98

A probabilistic analysis was conducted on the monthly data of energy consumption in Ekiti State for year 2018. The results obtained are shown as follows:

The probability that the energy consumption will be greater than or equal to 8601.5MWh (the maximum monthly energy consumption in year 2017) in the next few months was calculated as follows:

The area from $Z = 0$ to $Z = \infty$ is 0.5000 (See appendix for standard normal curve)

The area $Z = 0$ to $Z = 1.68$ is 0.4535

$P(X \geq 8601.5) = P(Z \geq 1.68) = 0.5000 - 0.4535$

$= 0.0465$ or 4.65%

The probability that the energy consumption will be less than or equal to 4970MWh in the next few months was calculated as follows:

The area from $Z = 0$ to $Z = -\infty$ is 0.5000

The area $Z = 0$ to $Z = -1.38$ is 0.4162

$P(X \leq 4970) = P(Z \leq -1.38) = 0.5000 - 0.4162$

$= 0.0838$ or 8.38%

The probability that the energy consumption will fall between 4970MWh and 8601.5MWh was calculated as:

$P(4970 \leq X \leq 8601.5) = P(-1.38 \leq Z \leq 1.68)$

= 0.4535 + 0.4162

= 0.8697 or 86.97%

It can be further explained that there is a tendency that energy consumption in the state especially in 2018 can go below 4970MWh (8.38%) than rising above 8601.5MWh (4.65%). This implies that the probability of energy consumption in 2018 falling below the lowest energy consumption in 2017 is almost as twice as the probability of energy consumption rising above the peak consumption (8601.5MWh) in 2017. It can be formulated that

$$P\ (X \geq 8601.5) \approx 1.04\sqrt{3}\ P\ (X \geq 4970)$$

$$\textbf{P}\text{eak value} \approx \sqrt{3}\ x\ deep\ value$$

This scenario is not unconnected with the pipeline vandalism and theft that occurred in 2017. *Mutatis mutandis*, the energy consumption could take entirely a different shape as load consumption in Nigeria had been predicted to increase by 8000MW annually (Onah et al., 2015). Energy consumption in 2018 will mostly fall between 5500MWh and 8000MWh particularly between 6500MWh and 7000MWh (16.52%). It is unlikely that it falls between 3500MWh ~ 4000MWh and 9000MWh ~ 9500MWh. Furthermore, it is noteworthy that the peak monthly consumption of the study occurred in January 2017 as shown in Table 1 while the lowest energy consumption (4970MWh) took place in September 2017.

4. CONCLUSION

This work considered the probabilistic long-term energy consumption forecast in Nigeria using Ado-Ekiti as a case study. A probabilistic analysis was conducted on the monthly energy consumption data obtained for 2017. The results of this study showed that in 2018, energy consumption in Ekiti State might not go beyond 8601.5MWh which was the maximum for 2017. The probability of the consumption exceeding this stipulated point was estimated at 4.65%. However, there is a higher chance of the consumption going below 4970MWh than rising above 8601.5MWh at a probability of 8.38%.

5. CONFLICT OF INTEREST

There is no conflict of interest associated with this work.

REFERENCES

Adedokun, A. (2016). Nigeria electricity forecast and vision 20: 2020: Evidence from ARIMA model. *Energy Sources, Part B: Economics, Planning, and Policy*, 11(11), pp. 1027-1034.

Ali, A. T., Tayeb, E. B., and Shamseldin, Z. M. (2016). Short term Electrical Load Forecasting Using Fuzzy Logic. International Journal of Advancement in Engineering Technology, Management and Applied Science (IJAETMAS), 3(11).

Anand, A. and Suganthi, L. (2017). Forecasting of Electricity Demand by Hybrid ANN-PSO Models. *International Journal of Energy Optimization and Engineering (IJEOE),* 6(4), pp. 66-83.

Dang-Ha, T. H., Bianchi, F. M. and Olsson, R. (2017). Local Short-Term Electricity Load Forecasting: Automatic Approaches. arXiv preprint arXiv:1702.08025.

Emodi, N.V. and Yusuf, S.D. (2015). Improving electricity access in Nigeria: obstacles and the way forward. *International Journal of Energy Economics and Policy*, 5(1), pp. 335-351.

Ghalehkhondabi, I., Ardjmand, E., Weckman, G. R. and Young, W. A. (2017). An overview of energy demand forecasting methods published in 2005–2015. Energy Systems, 8(2), pp. 411-447.

Hong, T., Pinson, P., Fan, S., Zareipour, H., Troccoli, A. and Hyndman, R. J. (2016): Probabilistic energy forecasting: Global energy forecasting competition 2014 and beyond. *International Journal of Forecasting*, 32(3), pp. 896-913.

Li, W. (2011). *Probabilistic transmission system planning*. Vol. 65, John Wiley & Sons.

Melodi, A. O., Momoh, J. A. and Adeyanju, O. M. (2016). Probabilistic long-term load forecast for Nigerian bulk power transmission system expansion planning. In: Power Africa, 2016 IEEE PES, pp. 301-305.

Onah, J. N., Anyaka, B. O., Nweke, J. N. and Ani C. C. (2015). A mathematical Approach to Load Forecasting of an Unreliable Electric System Using Least Squares Approach. *International Journal of Advance Research, IJOAR*, 3(10), pp. 1-6.

Ogunleye, E. K. (2017). Political economy of Nigerian power sector reform. The Political Economy of Clean Energy Transitions, 391.

Panklib, K., Prakasvudhisarn, C. and Khummongkol, D. (2015). Electricity consumption forecasting in Thailand using an artificial neural network and multiple linear regression. *Energy Sources, Part B: Economics, Planning, and Policy*, 10(4), pp. 427-434.

Quan, H., Srinivasan, D. and Khosravi, A. (2014). Short-term load and wind power forecasting using neural network-based prediction intervals. *IEEE transactions on neural networks and learning systems*, 25(2), pp. 303-315.

Sepasi, S., Reihani, E., Howlader, A. M., Roose, L. R. and Matsuura, M. M. (2017). Very short-term load forecasting of a distribution system with high PV penetration. *Renewable Energy*, 106, pp. 142-148.

Stroud, K. A. and Booth, D. J. (2013). *Engineering mathematics*. Palgrave, Macmillan.

Tripathi, M. M., Upadhyay, K. G. and Singh, S. N. (2008). Short-term load forecasting using generalized regression and probabilistic neural networks in the electricity market. *The Electricity Journal*, 21(9), pp. 24-34.

Verma, A., Tripathi. M.M. and Upadhyay, G (2017). A Review Article on Green Energy Forecasting. *Renewable Energy*, 1(1), pp.1-8.