FUTOJNLS 2019 VOLUME- 5, ISSUE- 1. PP- 127 - 140

Futo Journal Series (FUTOJNLS)
e-ISSN : 2476-8456 p-ISSN : 2467-8325
Volume-5, Issue-1, pp- 127 - 140
www.futojnls.org

Research Paper July 2019

A Survey on Electric Load Forecasting in Nigerian Electrical Utility Networks

[1]Olabode, O. E., [2]* Okakwu, I. K., [3]Ade-Ikuesan, O. O. and [4]Amuda S. O

[1]Department of Electronic & Electrical Engineering, Ladoke Akintola University of Technology, Ogbomoso, Nigeria.
[2]Department of Electrical/Electronic Engineering, University of Benin, Benin City, Nigeria.*
[3]Department of Computer and Electrical Engineering, Olabisi Onabanjo University, Ago Iwoye, Nigeria.
[4]Technical Education Department, School of Vocational and Technical Education, Emmanuel Alayande College of Education, Oyo, Nigeria.
**Corresponding Author's Email: igokakwu@yahoo.com*

Abstract

The need for forecast of electrical load consumption in dwindling energy environment is central and integral process in energy management practices. Forecast keeps the stakeholders in power utility companies abreast of the surge in demand for power due to population growth as the year advances. This paper presents a comprehensive review of electric load forecasting in Nigerian electrical utility networks with a view to measure the level of work done on load forecasting as well as to measure the level of usage / popularity of artificial intelligence among Nigerian researchers. Based on available publications, appreciable work has been done on load forecasting using statistical approaches compared with application of artificial intelligence. Fewer papers examined/incorporated the effects of weather and climatic factors in the model(s) used for the forecast while off grid forecast has received less attention in Nigeria; these create a research gap for those who are still interested in solving load forecasting problems in Nigerian electrical utility networks. This publication will be of immense guide to other Nigerian scholars in power systems that are still willing to work in this regard.

Keywords: Artificial Intelligence, Load-forecasting, Long-term, Medium-term, Short-term, Statistical Techniques

1. Introduction

The Nigeria population is estimated by United Nations as equivalent to 2.57% of the total world population with numerical value of 197,727,366 and a population density of 215 per km^2 (Worldometers, 2018). These figures positioned Nigeria to be ranked as number seven in the list of countries in the world. The total land area was estimated to be 910,770 km^2 (351,650 sq. miles) with about 51.0 % (99,967,871 people in 2018) of the population living in urban centres (Worldometers, 2018). This is largely due to ample availability of job opportunities, better living standard and availability of cutting edge technologies / social amenities. Sadly, Nigeria is positioned to be the second country with the highest electricity deficit having about 82.4 million that lack access to electricity based on the research report released by the World Bank (Premium Newspaper, 2013; Oladeji & Sule, 2015). In 2015, it was also reported that about 75 percent of Nigerians do not have access to uninterrupted power supply (Alphonsus, 2016). Similarly, an estimate of 41% businesses in Nigeria generate their own electricity, while 56% had no access to electricity despite marginal improvement in power supply which stood at 4,884 MW in November 2015 and 5,074.7 MW in February 2016. The situation is indeed worrisome and more likely that Nigeria may not meet its target of 20,000 MW generation capacity by 2020 (Alphonsus, 2016).

Nigeria electric power utility is well established across six geo-political zones which are subdivided into thirty-six states and the Federal Capital Territory (FCT) (Okolobah & Ismail, 2013). Figure 1 shows the 36 states in Nigeria and FCT. Assessing the contemporary status of electricity generation in Nigeria with respect to her population showed a gross inadequacy in its supply. It is needless to re-emphasize that as population and per capital income of individual increases, demand for power will sky-rocket. Electric load forecasting has been a tool used by several Nigerian academia to keep the government and other concerned stakeholders in electricity industries abreast of Nigeria need of power as the population increases. The power system in Nigeria in recent times is known to everyone to be epileptic, grossly inadequate and unreliable (Anonymous, 2010). The performance stands to improve colossally if a precise electric load forecasting is designed and consequently implemented by the concerned parties, hence, the need to review researches in electric power demand forecast in Nigeria is thus, imperative.

Figure 1: Location of thirty-six states and FCT on the map of Nigeria (Oladeji & Sule, 2015)

2. Energy Management Practices; Electric Load Forecasting

One of the key energy management practices in power system engineering is load forecasting, which central and an integral process with far-reaching effects which span through contingency planning, load shedding and management strategies to commercialization strategies (Buitrago & Asfour, 2017). Load forecasting is an intelligent prediction of past and present load demand patterns with a view to ascertain with satisfactory reliability and accuracy the anticipated load growth (Okoye & Madueme, 2016).

Errors in load forecasting causes increased costs of operation. Projecting load lower than the actual load results in utilities not committing the necessary generation units and therefore, incurring higher costs due to the use of peak power plants while higher load projection escalates the operational costs due to unnecessary starting of baseline units that are not put to use (Buitrago & Asfour, 2017; Satish, Swarup, Srinivas & Rao, 2004).

Accurate forecast is non-negotiable as it equips the generation and transmission companies on the need to restructure their plans with a view to meeting up with the future load growth and market volatilities (Swasti, Jose, Mart & Vander, 2016). Based on the duration of forecast, three types of load forecasting can be identified; short term load forecasting (STLF), medium term load forecasting (MTLF) and long term load forecasting (LTLF). A forecast projected for duration of one hour to one week is referred to as STLF, MTLFs are usually from a week to a year while LTLF spans for duration longer than a year (Feinberg, Hajagos & Genethliou, 2003). STLF finds application in generation and transmission of electricity scheduling, MTLF is suitable for fuel purchases scheduling while LTLFs are employed in developing power supply and delivery system (generation units, transmission system, and distribution system) (Almeshaici & Soltan, 2011). Approaches for load forecasting can be broadly classified into statistical techniques and Artificial Intelligence (AI) approaches. All forms of autoregressive and parametric models are classed as statistical techniques while AI methods among others include artificial neural networks (ANN), fuzzy logic, expert systems and support vector machine (SVM) (Christian & Taylor, 2000).

3. Review of Literatures on Load Forecasting in Nigerian Electrical Utility Networks

Adepoju, Ogunjuyigbe & Alawode (2007) addressed short-term load forecasting with the aid of Artificial Neural Network (ANN) using Nigeria electric power system as case study. Historical load data for the month of August, 2003 were collected from Power Holding Company of Nigeria (PHCN). The pre-processing of the data sets, network training, and forecasting were the essential stages in their work. With the trained network tested on one week's data, 2.54% absolute mean error (AME) was achieved. The authors suggested that subsequent research should consider incorporating weather information in addition to customer class into the network.

Idoniboyeobu & Odubo (2010) presented both least square and exponential approaches to forecast electric load in Bayelsa State. The historical electrical load data that span from 1997 to 2006 were used to predict future load consumption from 2007 to 2020. The least square approach used failed to consider factors such as increase in load demand caused by industrialization in the state and deliberate government intervention on rural electrical, hence exponential approach was applied. The results of the analysis showed that the exponential techniques revealed a significant deviation from that obtained using the least square approach as the year increased. The authors concluded that electrical power demand for the state was comparatively low and steady due to absence of industrial development and that the initial installed capacity of 40 MW would be grossly inadequate by 2020, hence the need for upgrade.

Muhammad & Sanusi (2012) designed an ANN model for STLF using 132/33kV substation in Kano, Nigeria as case study. The Levernberg Marquardt BP algorithm was employed to determine the connection weights between the neurons. The network was trained using

2005 load data collected from power utility in Kano. The input data set as follow; 70% for as training set while 15% each was used for testing and validation of the network output results. Of all the values obtained for mean squared error (MSE), $5.84e^{-6}$ was the best after several networks architectures training and simulation. The accuracy of the forecasts was verified by comparing the simulated outputs from the network with the results obtained from the utility company. The authors concluded that the proposed technique is quite robust and suitable forecasting future load demands for the daily operational planning of power system distribution sub-stations in Nigeria.

Eneje, Fadare, Simolowo & Falana (2012) presented comparative analysis of three different models (compound-growth (CGM), linear regression model (LRM) and cubic regression model (CRM) to forecast electrical load demand of Ikorodu, Lagos state. Previous load data for the case study sourced from PHCN was used for the analysis. Pearson's correlation coefficient and mean absolute-percentage-error (MAPE) were the performance metrics used. Load forecast for the residential and non-residential load were done separately, LRM revealed that the annual growth for the year 2011 to 2015 decreased steadily while for the CGM, the annual growth was staggering, increasing up and decreasing without appreciable effect on the periodic load growth for each additional year. CGM has the best rank closest to unity and least value of MAPE; it was then employed to predict the future load. The authors concluded the study by soliciting for consolidation of the energy supply to the residential due to large gap in the load values.

Okolobah & Ismail (2013) proposed a novel electric peak load forecasting model that combines empirical mode decomposition (EMD) and ANN. The stages involved entailed collection and decomposition of historical load data (PHNC, Bida) into several intrinsic mode functions (IMFS) and a residue component using the EMD sifting process, separate building of neural network (NN) models for each of IMFS and residue component and lastly, combining the predictions from these models and making forecast. The results obtained with the proposed EMD-ANN model was compared with that obtained from a conventional NN model, it output forms the conventional BPNN model by 2.3% for the whole year model and by 1.8% for the weekday model, judging by the forecast accuracy of both models.

Amlabu, Agber, Onah, & Mohammed (2013) presented load demand forecasting with least squares technique using four different regional power supplies scenarios (Kaduna, Port-Harcourt, Osogbo and Shiroro) in Nigeria as case study. The trend of load pattern obtained with the least square technique for the four regions showed that the energy required increases as the year advances.

Musa & Mbaga (2014) investigated the application of ANN of smaller size to predict daily peak load for a period of one year, daily seasonal indices was calculated as the ratio of predicted load to actual load. Forecast results for three months selected from extremely different seasons showed that maximum forecast error drop from 11.32% for the ANN to 7.16% for the ANNSI. Correspondingly, AME drops from 3.58% for the ANN to 2.76% for the ANNSI. This shows the overall effectiveness of the ANNSI over the normal prediction using ANN.

Isaac, Felly-Njoku, Adewale, & Ayokunle (2014) presented MTLF of Covenant University (a typical private tertiary educational institution in Nigeria) as case study. Three different techniques (LRM, CGM and CRM) were used; load data between the period of January

2012 and January 2013 were collected from the institution. The results of load forecast obtained for each models were compared using MAPE and RMSE performance metrics. LRM produced the best error margin: 0.5792 and 41.34 for MAPE and RMSE, respectively.

Idoniboyeobu and Ekanem (2014) examined application of least square and regression exponential analysis to assess and to predict the electric load demand in three different major towns (Uyo, Ikot Ekpene and Eket) in Akwa Ibom State, Nigeria. Five years (2006-2010) monthly load allocation and utilization was sourced from PHCN for the analysis. The two approaches were independently investigated for the forecast, it was observed that the load growth was slow but steady and the projected power demand by the year 2020 was estimated to be 247.84 MW.

Ezennaya, Isaac, Okolie, & Ezeanyim (2014) presented application of time series analysis for LTLF of Nigeria electricity demand with a view to meet the vision of projected energy demand for 2025. The stochastic/probabilistic extrapolation method based on the time series analysis of past load demand curve using straight line graph/curve was employed. The energy consumption by industrial, residential and commercial for the years 2000-2012 obtained from National Bureau of Statistics and the Central Bank Statistical Bulletin was used for LTLF for period of 2013-2030. The authors idea was based on the results of the analysis that power generation or importation of about 20,000MW, totaling 300% of the present installed capacity will be required to adequately cater for the energy need of Nigerians by the year 2030.

Idoniboyeobu & Idumangi (2015) did a comprehensive comparative study on different numerical techniques (least square method, Lagrange interpolation method, second-order polynomial method, exponential functions, power function model and time series analysis) to forecast the load demand required in Bayelsa State, Nigeria for the year 2025. Electrical load data of allocation and utilization of power consumption of the state for past five (5) years (2006-2010) were collected from PHCN and Kolo Creek gas turbine power station, Nigeria. The strength and weakness of the each approach was comprehensively x-rayed and in all, second-order polynomial method gave the best fit as well as the least error of 0.66 and 272.25MW compared to other approaches. The work revealed that the daily peak load periods in Bayelsa State occurred between 6am – 9am and 7pm - 9pm respectively and that the load demand in the state may not likely go beyond 272.25MW given population growth rate of 2.9% and an expected population of 3.517million in 2025.

Osakwe, Akpan & Ekong (2015) investigated the efficiency auto-regressive moving average with exogenous input (ARMAX), Output-Error (OE) model and State-Space Innovations Form (SSIF) model for predicting power transmission and distribution using Akure in Nigeria and its environs as case study. A total of 51,350 data samples from PHCN were collected. The results obtained for these models and that from validation results showed that OE model predictor outperformed the other models with much smaller prediction errors, good prediction and tracking capabilities. The authors pointed out that moving average filter coupled with the nonlinear nature of the power transmission and distribution data account for poor performance of ARMAX and SSIF models. The authors concluded that OE model structure and its predictor structure is highly suitable for power transmission and distribution modeling and predictions in real scenarios. The work suggested that further studies should consider dynamic modeling and nonlinear model identification of the multivariable nonlinear systems using nonlinear neural network-based approaches.

Kalu, Isaac & Ozuomba (2015) proposed a MATLAB-based estimate and forecast of peak load demand using faculty of Engineering in Imo State University, Nigeria as case study. The collected data spanned for three years (2011 to 2013). The logarithmic technique was used to implement the peak load demand for years 2014 to 2020. Design, implementation, testing, integration and maintenance are the essential stages in the work. The MATLAB-based program developed has two modules; the peak load estimation module and peak load forecasting module, the proposed approach gave faster analysis. The work recommended that further studies should consider making the software to allow user to choose duration of load forecast such as weekly, monthly, quarterly and also, the software should also allow more peak load forecast methods to be available and selectable to users rather than making users to stick to the only option.

Oladeji & Sule (2015) presented electrical load survey and forecast for a typical off-grid rural decentralized hybrid power generating systems. Elebu, Kwara State, Nigeria was used as the case study; village head, school teachers, farmers among others were interviewed to ascertain their energy need; the anticipated peak load in first year of operation of the proposed hybrid power generating system was projected to be 40.18kW while the maximum projected demand at the end of tenth year was approximately equal to 57 kW. The survey conducted showed that the study area was a viable place for integration of small hydro, wind and solar energy. The authors argued that if stable and reliable operation was to be guaranteed, the installed capacity of the proposed hybrid power generating system should be more than 60kW otherwise, the system will be unstable and unreliable at the eleventh year.

Isaac, Tolulope, Ayokunle & Peter (2016) carried out a comparative study on MTLF using ANN and time series techniques (moving average, exponential smoothing). The real time load data of Covenant University was collected from the University power station. Based on the analysis using mean absolute deviation (MAD), mean squared error (MSE) and MAPE as performance metrics, ANN was found to outperform other methods their corresponding values are 0.225, 0.095 and 8.25 respectively.

Okelola & Adewuyi (2016) applied ANN to forecast monthly (July to December, 2017) load demand using Ogbomoso town in Nigeria as a case study. The historical load consumption data was collected from PHCN for analysis. The ANN used revealed that a non-linear relationship exited between the historical loads supplied to it during training phase. The authors concluded that the forecasted load related well with the actual load. However, the major setback of the work was that number of training epochs (iteration no) need to be constantly adjusted for the performance goal to be met where an assumed number is insufficient, hence an improvement is thus desired on this setback.

Esobinenwu (2016) developed ANN-based STLF model with improved accuracy using regional power control centre of Choba community in Nigeria which comprised of three campuses in the University of Port-Harcourt, Choba, Rivers State of Nigeria as case study. The historical electrical load data for the month of February, 2016 was used for the analysis. The proposed ANN was sufficiently trained with back propagation and tested with a view to achieve optimal topology, the optimal topology achieved was then used to predict load ahead at different time intervals. The performance metrics used are MSE and regression value (R). The result of analysis showed that ANN when sufficiently trained is suitable for predicting future electricity demand.

Bamigboye & Freidrick (2016) proposed a new method for STLF with particle swarm optimization (PSO) techniques using Osogbo 33-bus system in Nigeria as a case study. The essential steps employed in the work include pre-processing of the data sets, PSO algorithm, and forecasting. The training samples used were of the same data type as the learning samples in the forecasting process and selected by a fuzzy clustering technique according to the degree of similarity of the input samples considering the periodic characteristics of the load, thereafter, PSO was employed to optimize the model parameters cost of the electricity load demand. The inputs used for the PSO entailed one set of historical electricity demand data. Based on the results obtained, the authors concluded that the developed system have greater accuracy in prediction of electricity load demand, in addition it as well reduce forecasting errors significantly.

Olagoke, Ayeni & Hamba (2016) presented another approach for STLF with lead time of a day ahead (1-24 hours) using ANN. The major uniqueness of the work was that GA was used to generate the hidden layers in ANN as compared to other papers that employed try and error approach and ANN training was done using Levenberg Marquardt. The major merits of this approach include automation of network design which could have been done manually. Secondly, the design process was analogous to a biological process in which the NN blueprints are encoded in chromosome. Daily load data of 330/132/33kV substation in Ganmo, Kwara State, Nigeria for the month of May, 2014 was used. The input variables of interest were hour of the day, temperature (average temperature) and day of the week. The model was able to determine the non-linear relationship that exists between the historical load data and temperature. MAPE of 4.705 was obtained; hence the authors argued that the developed model is a viable tool to make a prediction of the next day (hourly) load.

Hambali, Akinyemi, Oladunjoye & Yusuf (2016) examined application of three decision tree classification models (classification and regression tree (CART), reduced error pruning tree (REPTree) and Decision Stump) to forecast electric power load for Yola/Jimeta power transmission station in Nigeria. Data for three months of previous load consumption (Date, Time (hourly record), Temperature for 24 hours daily, Input voltage and Output voltage) were obtained from Yola power transmission company office. The first two months data was used for the training while the last one month data was employed for validation and testing of the algorithms. The performance evaluations of three models were made using both 10-fold cross validation method based classification accuracy, error reports and execution time. The major merits of the proposed approach include provision of intuition information of data sets with minimal computational burden as well as it divulges the principles learnt by DTs for further interpretation. In all, REPTree decision tree technique produced a better result compared with the other two algorithms, hence, it is highly suitable to forecast electric load.

Okoye & Madueme (2016) explained in detail different methods ranging from statistical to artificial intelligence techniques that can be applied to electrical load forecasting, a detailed classification of these methods was made based on the type of load forecasting, STLF, MTLF and LTLF. A generalization was made based on the review that there is no suitable method that supersedes the other in getting the best result of the forecasting, hence, for a more accurate result in load forecasting there is therefore need to study the load carefully to get the optimal results.

Umoren, Okpura, & Markson (2017) developed a model based on the readily available data such as electric power consumption in KWh per capita, the population and land mass of a rural community to predict the rural electrification peak load demand. Orji town in Owerri North local government area in Imo state, Nigeria was used as the case study. Data were collected from United Nation and World Bank and based on the data collected a forecast of peak load consumption for 2025 stood at 261.79 kVA subject to expected population of 3971.791, with this 75% population was proposed to have access to electricity in the study area. The approach is only applicable to area where previous load data were not readily available.

Briggs & Ugorji (2017) proposed the application of regression exponential method (REM) and least square method (LSM) to assess and predict the future load requirement in Rivers State by the year 2025. Previous load consumption data for the state for a periods of five years ((2011 – 2015) were used to forecast the expected load consumption trend in the state from 2018 to 2025. The prediction for the year 2016 with REM and LSM yield 211.3 MW and 207.1 MW while the forecasted load for 2025 with REM and LSM are 2113 MW and 2071 MW respectively. The authors argued that positive relationship existed between the load demand and year that is as the year advances, the load demanded increases due to fast growth of development in the study area. The authors recommended REM since it captured the elastic demand of the consumers during peak and off-peak time with an appreciable growth rate of 21.6%. The major challenges encountered included non-availability of adequate data and functional metering system.

Isaac, Adetiba, Odigwe & Felly-Njoku (2017) compared performances comparison of regression analysis and ANN models on STLF using load demand data set obtained from Covenant University campus in Nigeria. MAPE and RMSE was used as performance metrics, the results from the comparative study showed that the ANN model was found to be superior due to its ability to handle the load data and it has lower MAPE and RMSE of 0.0285 and 1.124 respectively. Also, ANN forecasted the prospective load demands with a very minimal error when compared to the actual load demands.

Hambali, Saheed, Gbolagade, & Gaddafi (2017) addressed electric load forecasting using ANN. ANN was preferred due to its flexibility in data modeling. The historical electrical load data for a period of three months were collected from Yola power transmission company Adamawa State, Nigeria. The collected data were pre-processed after which, data mining algorithms were applied with a view to predict electric load. ANN algorithms using three different training approaches name multilayer-Perceptron model (MLP), radial basis function (RBF) and sequential minimal optimization (SMO) were employed and compared. The performance metrics used are sensitivity, specificity, accuracy and kappa statistics. Results obtained showed that MLP recorded an accuracy of 86% with MAE of 0.016, RBF had an accuracy of 76% with MAE of 0.030 while SMO produced an accuracy of 85% with MAE of 0.090 which indicated a promising level of electric load forecast. Conclusively, MLP has the highest classification accuracy and insignificant errors.

Uduak, Ini, Mfon, & Emmanuel (2018) applied interval Type-2 Fuzzy Logic (IT2FL) and Feed-Forward Neural Network with back-propagation tuning algorithm for STLF. Uyo city in Akwa-Ibom, Nigeria was used as the case study; the data used are temperature, humidity and past electric load. The effectiveness of IT2FL was improved by using interval type-2 fuzzy neural network (IT2FNN) which combines Type-2 Fuzzy Logic and neural network. IT2FNN was trained via back propagation learning algorithm, with this; cost function error-based was minimized. MAPE, MSE and RMSE were used as performance metrics. Simulation results showed that the IT2FNN approach outperforms IT2FL and T1FL methods. The performance of the proposed approaches largely depends on the appropriate selection of its set of inputs and its structure, which is the major limitation of the proposed approach.

Akpama, Vincent, & Iwueze (2018) applied ANN to LTLF for a period of 10 years (2018 to 2027)) energy consumption in Imo state, Nigeria. The data capturing the historical electric load demand, gross domestic product (GDP), population and industrial index of production (IIP) for 2007 through 2016 were sourced from Enugu Electricity Distribution Company (EEDC), Egbu, Owerri 132/33kV station. The data was divided into two sets input sets (year index, GDP, IIP and population) and target sets (annual peak load demand). The network training was done using feed-forward neural network with tap delay line, one special feature of this approach was that it combines conventional network topology (multi-layer perception) with good handling of time dependencies by means of a gamma memory. Based on the result of the analysis, the present installed capacity will not be able to adequately serve Owerri city in about ten years' time. The authors recommended an expansion in the generation capacity by about 7% annually.

Idoniboyeobu, Ogunsakin, & Wokoma (2018) proposed LTLF with the use of modified form of exponential regression model. The Nigeria power system was used as the case study, data for residential, commercial and industrial load demand in (MW) was collected between 2000 - 2012, from the Central Bank of Nigeria (CBN) and National Bureau of Statistics (NBS). The results obtained were compared to least-square and exponential model; a similar load pattern prediction was obtained. However, least-square showed linear behaviour while exponential and modified exponential exhibited non-linear behaviour. The performance of modified exponential model was found to be better with percentage error of 1.37% compared to existing model with 1.67, it was inferred that the generated energy from the respective generating station are grossly inadequate, hence a deviation between predicted energy demand (MW) and capacity allocated was reflected. The energy demand for future of 20 years was projected to be 395,870.2MW.

Aderemi, Misraa, & Ahujab (2018) applied demographic data approach to forecast the energy consumption of Canaan land where Covenant University was sited. The demographic data used include energy consumption in kWh per capita of the country, population and land mass area, the uniqueness of the approach as claimed by the authors entails simplicity and that it only makes use of readily available demographic user data rather than using previous energy consumption data. The results obtained were relatively lower compared to the actual energy consumption. This spelt the major limitation of the proposed approach as under-forecasting can result in huge capital lost, however, the proposed approach is only suitable for area where previous energy consumption data is not available.

Olabode, Okakwu, Ade-Ikuesan, & Fajuke (2018) proposed performance evaluation of regression exponential (REM) and least square techniques (LSA) on MTLF using Ogun State, Nigeria as case study. Based on the results of the analysis, LSA gave the least value of MAPE and RMSE when compared to REM. LSA was employed to predict load consumption for months of July-December, 2018. The study revealed a significant load growth for each month, the percentage load growth was estimated to be 34.06%, 33.54%, 36.10%, 31.10%, 32.23% and 30.15% for the months of July-December respectively. The authors argued that the low percentage load growth in the month of December was as a result of acute shortage in gas supply.

Ade-ikuesan, Osifeko, Okakwu, Folaranm, & Alao (2018) investigated probabilistic load forecast technique for predicting the load demand pattern in Ogun State, Nigeria. Energy consumption data for Ogun State for the years 2016 and 2017 was obtained from the regional headquarter of the Ibadan Electricity Distribution Company (IBEDC), Abeokuta. The results revealed that energy consumption had the probability tendency of rising above 98,469.40 MWh. It was also established that the probability of energy consumed to decrease below 46,494.68 MWh within the next few months was 5.98% and the probability that energy consumption for 2018 will fall between 98,469.40 MWh and 46,494.68 MWh was 91.84%. Based on the study, the percentage probabilities of 0.19% and 2.99% were estimated for the energy consumption not falling within 45,000 MWh to 50,000 MWh and 95,000 MWh to 99,500 MWh, respectively.

4. Discussion of Findings

The reviewed published research papers on load forecasting in Nigerian electrical utility networks from 2007 till date were meticulously analysed with a view to measure the level of work done on load forecasting as well as measure the level of usage / popularity of artificial intelligence among Nigerian researchers. The level of researcher papers reported on this concept is encouraging most especially from 2015 till date. However, most of these papers used statistical approaches. Few papers reported the use of AI in addressing load forecasting problems. Artificial neural network (ANN) was found to be the commonly used AI technique among the published papers on this concept and this may be due to its flexibility in data modeling as claimed by authors in (Hambali *et al.,* 2017). Other AI techniques found in the papers reviewed includes particle swarm optimization (Bamigboye & Freidrick, 2016), hybridized artificial neural network-genetic algorithm (ANN-GA) (Olagoke *et al.,* 2016) and ANN-Fuzzy logic approach (Idoniboyeobu *et al.,* 2018).

There is no account of usage of other powerful and recently discovered algorithm like cuckoo search algorithm (CSA), firefly algorithm (FA), fruitfly fly algorithm (FFA) for addressing forecasting problems on Nigerian grid etc. Again only fewer papers examined/incorporated the effects of weather and climatic factors in their model(s) for forecasting, while off grid forecast had received less attention in Nigeria; these create a research gap for those who are still interested in solving load forecasting problems in Nigerian electrical utility networks. This study agreed with the earlier statement of fact made by Kuster, Rezgui & Mourshed, (2017) that recurrent use of a model could imply its suitability for addressing a particular type of forecast, however, AI techniques had capacity to produce more accurate results than statistical approaches based on the common performance metrics (MAPE, RSME, AME and rank correlation coefficient among others) used for evaluating load forecasting models.

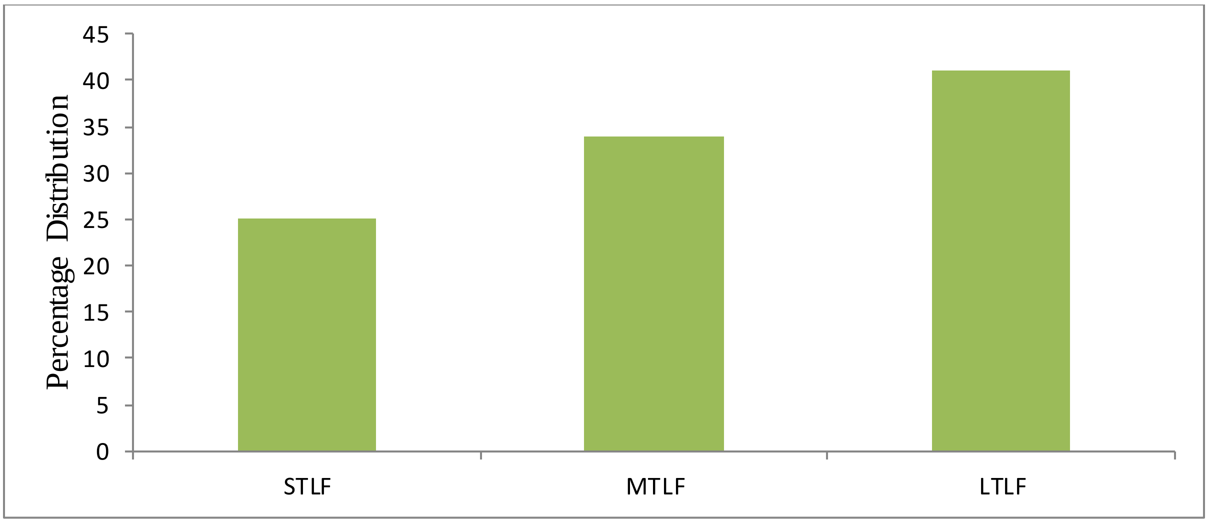

Figure 2: The percentage distribution of reviewed papers based on type of load forecasting problems

From Figure 2, 25% of the papers reviewed addressed STLF, 34% addressed MTLF while 41% solved LTLF. Figure 3 showed the distribution of reviewed papers on basis of states used as case study. Ogun State has the highest number of papers while Akwa-Ibom and Rivers State was ranked the second.

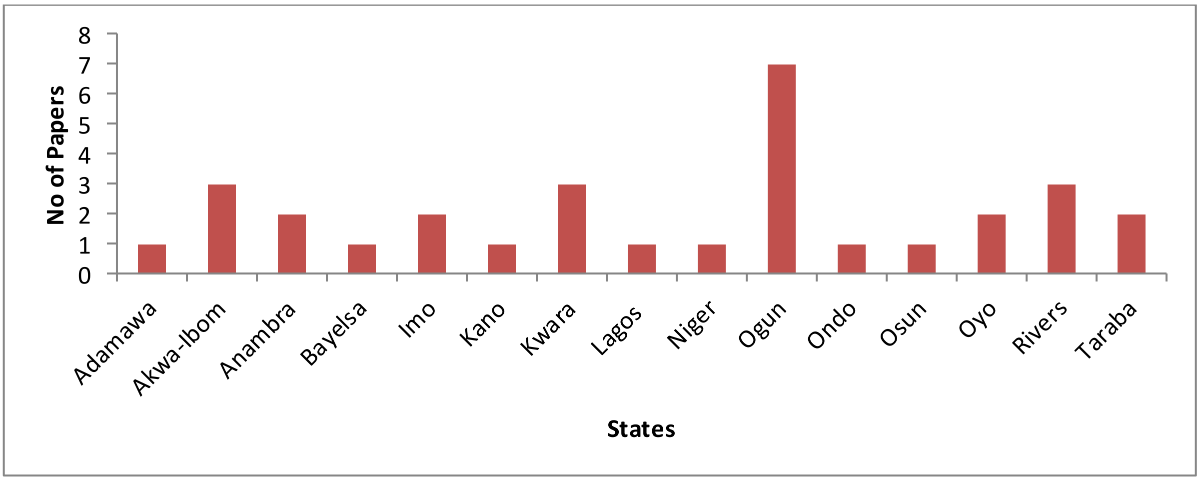

Figure 3: Distribution of papers reviewed on the basis of States used as case study

5. Conclusion

A comprehensive survey on electric load forecasting in Nigerian electrical utility networks with a view to measure the level of work done on load forecasting as well as to measure the level of usage / popularity of artificial intelligence among Nigerian researchers has been presented. Based on the available publications, appreciable work has been done on load forecasting using statistical approaches compared with application of artificial intelligence. It is recommended that the use of recently developed AI techniques should be encouraged among researchers in Nigerian. Also, to combat the problem of sourcing data from utility companies, relevant stakeholders should be sensitized on the need to keep up to date data which will assist researchers in carrying out researches in this regard. This, will in no small measure, boost the research output which will consequently be an eye-opener to stakeholders and power system planners on the need to take appropriate decisions regarding planning, execution and management of power need of the teeming Nigeria populace.

Reference

Ade-ikuesan, O.O., Osifeko, M.O., Okakwu, I.K, Folaranm, K.S & Alao, P.O (2018). Prediction of electricity consumption demand pattern for 2018 in Ogun State, Nigeria. Journal of *Applied Science and Environment Management*. 22 (6), 883 –886.

Adepoju, G.A., Ogunjuyigbe, S. O. A. & Alawode, K. O. (2007). Application of neural network to load forecasting in Nigerian electrical power system. *Pacific Journal of Science and Technology,* 8(1), 68-72.

Aderemi, O., Misraa, S. & Ahujab, R (2018). Energy consumption forecast using Demographic data approach with Canaan land as case study. *International Journal on Soft Computing,* 9(1), 1-29.

Akpama V. & Iwueze, (2018). Artificial neural network for energy demand forecast. *International Journal of Electrical and Electronic Science,* 5(1), 8-13.

Almeshaici, E. & Soltan, H (2011). A methodology for electric power load forecasting. *International Journal of Scientific and Research Publications,* 6(6), 554- 560.

Alphonsus, O. N (2016). An examination of the challenges of power supply in Nigeria in post-privatization era, 2013-2016. *Asian Journal of Basic and Applied Sciences,* 3(1), 34- 44.

Amlabu, C.A., Agber, J.U., Onah, C.O. & Mohammed, S.Y. (2013). Electric load forecasting: a case study of the Nigerian power sector. *International Journal of Engineering and Innovative Technology,* 2(10), 23-27.

Anonymous (2010). The menace of electric power crisis in Nigeria. Daily Sun, Monday January 10, 2010. 45

Bamigboye O. O & Freidrick, E (2016). Electricity load forecasting using particle swamp optimization techniques for optimization of Osogbo 33bus system in Nigeria. *International Research Journal of Engineering and Technology*, 3 (7), 783- 794.

Briggs, T.A. & Ugorji, K (2017). Assessment of electricity demand and prediction model for the future: Rivers State**.** *European Journal of Mechanical Engineering Research*, 4(1), 1-23.

Buitrago, J & Asfour, S. (2017). Short-term forecasting of electric loads using nonlinear autoregressive artificial neural networks with exogenous vector inputs. *Energies,* 10, 40.

Christian, N. & Taylor, J. S. (2000). An introduction to support vector machines and other kernel-based learning methods, Cambridge: Cambridge University Press.

Eneje, I. S., Fadare D. A., Simolowo O.E. & Falana, A. (2012). Modelling and forecasting periodic electric load for a metropolitan city in Nigeria. *An International Multi-disciplinary Journal, Ethiopia,* 6(1),101-115.

Esobinenwu, C.S (2016). Short term load forecasting using artificial neural network technique: case study of Choba community in Rivers State, Nigeria. *International Journal of Trend in Research and Development,* 3 (6), 810- 818.

Ezennaya O. S., Isaac O. E., Okolie U. O. & Ezeanyim O. I. C (2014). Analysis of Nigeria's national electricity demand forecast (2013-2030). *International Journal of Scientific & Technology Research*, 3(3), 333- 340.

Feinberg, E. A., Hajagos, J. T. & Genethliou, D. (2003). Statistical load modelling. Proceedings of the 7th IASTED. *International Conference: Power and Energy Systems, Palm Springs,* 88-99.

Hambali, M. A., Saheed, Y. K, Gbolagade, M. D. & Gaddafi M (2017). Artificial neural network approach for electric load forecasting in power Distribution Company. *E-Academia Journal*, 6(2), 80-90.

Hambali, M., Akinyemi, A., Oladunjoye, J. & Yusuf, N. (2016). Electric power load forecast using decision tree algorithms. *Computing, Information Systems, Development Informatics & Allied Research Journal*. 7(4), 29-42. http: //dx.doi.org/ 10.1016/ j.scs.2017. 08.009 Available at: http://www.worldometers.info/world-population/nigeria-population/ Retrieved on Tuesday 20th, November, 2018

Idoniboyeobu D.C & Ekanem, M.C. (2014). Assessment of electric load demand and prediction of future load demand; a case study of Akwa Ibom State of Nigeria*. Asian Journal of Scientific Research*, 7(4), 525-535.

Idoniboyeobu, D. C. & Idumangi, R. J. (2015). Comparative analysis for prediction of electrical power demand of Bayelsa State (Nigeria) by year 2025. *British Journal of Applied Science & Technology,* 5(3), 308-320.

Idoniboyeobu, D.C & Odubo, G.F. (2010). Electrical load forecasting in Bayelsa state of Nigeria by the year 2020. *NIJISS,* 9(1), 22-27.

Idoniboyeobu, D.C., Ogunsakin, A.J., & Wokoma, B. A. (2018). Forecasting of electrical energy demand in Nigeria using modified form of exponential model. *American Journal of Engineering Research,* 7(1),122-135.

Isaac A.S, Felly-Njoku C. F., Adewale, A. A. & Ayokunle A. A (2014). Medium- term load forecasting of Covenant University using the regression analysis methods. *Journal of Energy Technologies and Policy,* 4(4), 10-16.

Isaac A.S., Adetiba, E., Odigwe, I.A. & Felly-Njoku, F. C. (2017). A comparative study of regression analysis and artificial neural network methods for medium-term load forecasting. *Indian Journal of Science and Technology,* 10(10), 1-7

Isaac, S., Tolulope, O., Ayokunle A. & Peter, A (2016). Short-term load forecasting using the time series and artificial neural network methods. *IOSR Journal of Electrical and Electronics Engineering,* 11(1), 72-81.

Kalu, C., Isaac, E. & Ozuomba, S (2015). Development of MATLAB-based software for peak load estimation and forecasting: a case study of faculty of engineering, Imo State University Owerri, Imo State, Nigeria. *European Journal of Engineering and Technology,* 3(8), 20-29.

Kuster, C., Rezgui, Y. & Mourshed, M. (2017). Electrical load forecasting models: A critical systematic review. *Sustainable Cities and Society,* 11(1), 72-81.

Muhammad, B. & Sanusi, S.A (2012). Short-term load forecasting using artificial neural network. *Proceedings of the International Multi-conference of Engineers and Computer Scientists,* 1, 1- 6.

Musa, S. Y. & Mbaga, E. V. (2014). Daily Nigerian peak load forecasting using network seasonal indices. *Nigerian Journal of Technology,* 33(1), 114-118.

Okelola M. O. & Adewuyi, P. A. (2016). localized power load forecasting: a case study of Ogbomoso in Nigeria. *International Journal on Power Engineering and Energy,* 7(1), 601- 606.

Okolobah, V. & Ismail, Z. (2013). An empirical mode decomposition approach to peak load demand forecasting. *Indian Journal of Science and Technology,* 6(9), 5201-5207.

Okolobah, V. & Ismail, Z. (2013). An empirical mode decomposition approach to peak load demand forecasting. *Indian Journal of Science and Technology,* 6(9), 5201-5207.

Okoye, A.E., & Madueme, T.C. (2016). A theoretical framework for enhanced forecasting of electrical loads. *International Journal of Scientific and Research Publications,* 6(6), 554- 560.

Olabode, O. E., Okakwu, I. K., Ade-Ikuesan, O. O. & Fajuke, I. D. (2018). Performance evaluation of medium-term load forecasting approaches: A case study of Ogun State, Nigeria. *Journal of Advances in Science and Engineering,* 1(2), 9-16.

Oladeji, A.A. S. & Sule, B. F. (2015). Electrical load survey and forecast for a decentralized hybrid power system at Elebu, Kwara state, Nigeria. *Nigerian Journal of Technology,* 34(3), 591 – 598.

Olagoke, M. D., Ayeni, A.A. & Hamba, M.A. (2016). Short term electric load forecasting using Neural Network and Genetic Algorithm. *International Journal of Applied Information Systems,* 10 (4), 22-28.

Osakwe, R. O. A., Akpan, V.A. & Ekong, S.A. (2015). ARMAX, OE and SSIF model predictors for power transmission and distribution predictions in Akure and its environs in NIGERIA. *Nigeria Journal of Pure & Applied Physics,* 6(1), 6 – 25.

Premium Newspaper June 4th 2013, http://pmnewsnigeria.com/2013/06/04

Satish, B., Swarup, K.S., Srinivas, S. & Rao, A.H. (2004). Effect of temperature on short term load forecasting using an integrated ANN. *Electric Power Systems Research*, 72, 95-101.

Swasti R. K, Jose, L. R, Mart, A.M.M. & Vander, M. (2016). Long-term load forecasting considering volatility using multiplicative error model, 1-24.

Uduak, U., Ini U., Mfon, N. & Emmanuel, B. (2018). Interval type-2 fuzzy neural networks for short-term electric load forecasting: A comparative study. *International Journal on Soft Computing,* 9(1),1-29.

Umoren, A.M., Okpura, N. I. & Markson, I. (2017). Rural electrification peak load demand forecast model based on end user demographic data. *Mathematical and Software Engineering*, 3(1), 87-98.

Vadhera, S.S. (2004). Power system analysis and stability, Khana Publishers, NaiSarak, Delhi.