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A PREDICTIVE MODEL FOR ELECTRICITY CONSUMPTION IN MODIBBO ADAMA UNIVERSITY OF TECHNOLOGY, YOLA, USING ARTIFICIAL NEURAL NETWORKS (ANN)

BY

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Abstract:
A predictive model for monthly electricity energy consumption with good accuracy is still a great challenge in the University. Considering the fact that the University consumes huge amount of electricity for numerous operations (academics, research, social, economic etc.). Energy availability, consumption and costs can present a great challenge of either reduction or increase in energy consumption if not properly conserved and utilized. This research proposed an Artificial Neural Networks model that is used to predict efficiently and effectively the monthly electricity consumption in the University using previous consumption data. Three years (2016-2018) datasets from Works department and Students affairs division of Modibbo Adama University of Technology (MAUTech) Yola was collected. Regression Analysis and ANN was used to project electricity consumption. The model was developed and tested in Matlab (R2016b) with feedforward neural network architectures which was optimized with two algorithms (Levenberg-Marquardt and resilient back-propagation). Sigmoid and Linear activation functions were used in the hidden and outer layers respectively. The model has two input neurons and three output neurons. The number of hidden layer was obtained via an experiment with 10 neurons at the hidden layer. This reveals that the regression which is 0.9337 is the highest out of the thirty experiments carried out. The study shows that ANN can sufficiently predict future electricity consumption which in a long run will assist the University community in effective planning and utilization towards power consumption. The study recommended the use of different predicting tools which can also be used and compared for further studies.

Keywords: *Electricity consumption; artificial neural network; regression analysis.*

1. Introduction

Energy efficiency is indispensable in the pursuit to achieve sustainable development in the 21st century. Energy Consumption (Electrical, heat, etc.) in industrialized nations has become a major factor in global discussions towards ensuring sustainable development. In Nigeria, electricity is one of the oldest forms of energy available for daily activities. Its supply is inadequate to meet the need of an ever-increasing population. This is largely due to inadequate planning (Kofoworola, 2015). Energy consumption prediction is important to improve the energy performance of buildings, leading to energy conservation and reduction of environmental impact. The most frequently considered types of buildings are offices, residential, and institutions (Ouf & Issa, 2017).

Arimah (2015) revealed that the Nigerian electricity industry is beset with several technical, managerial, personnel, financial and logistical problems. Following the current energy consumption pattern, the world energy consumption may increase by more than 50% before 2030 (Suganthi & Samuel, 2016). According to Salahat and Awad (2017), Organizations need to have an idea of the future information of electricity consumption, this will help in making necessary arrangements to have consistency in the delivery and distribution of electricity. Energy consumption is influenced by many factors. These includes weather conditions, (especially the dry bulb temperature), building construction and thermal property of the physical materials used, occupancy behaviour, geographical location, operation of appliance, sublevel components, which include lighting systems, Heating, Ventilating, and Air Conditioning (HVAC) (Zhao and Magouls 2012; Ahmad *et al.*, 2014; Feng, Yan and Hong 2015).

Oyedepo *et al.*, (2015) opined that environmental degradation caused by the vast amount of energy consumption by Universities is becoming a major concern. Since Universities involve a large number of facilities and building users such as Students, academic and administrative Staff, Researchers, and others who work in the Universities. Huge amount of energy will be needed for operations, including teaching and research, provision of support services, and in residential and hostel areas. This amount of energy consumed has a huge financial implication on the side of the Universities. Jovanović, Sretenović, and Živković (2014) opined that scientists and engineers are moving from calculating energy demand towards analysing the real energy consumption of buildings. One of the reasons is that non-calibrated models used in determining energy demand cannot predict well energy consumed, so it is necessary to know the actual energy been consumed in buildings by using measured and analysed data.

Deb, Eang, Yang, and Santamouris (2015) asserted that forecasting in energy consumption is done to enhance effective energy management in institutional buildings. An accurate energy predicting model is essential because it provides an initial check for facility managers and building automation systems to mark any discrepancy between expected and actual energy use. More so, it provides a set of limits and targets within which the building's energy consumption should ideally fall. A good energy forecasting model can be merged with other building simulation models to generate useful operating variables.

Kaytez, Taplamacioglu, Camb, and Hardalac (2015) stated that electricity forecasting models are developed based on the nation or organizational need and condition. In order to effectively design a model for electricity consumption, it is important to put into consideration the parameters affecting electricity consumption and to choose a method suitable for the consumption model. Previous data collected and independent indicators like time of the day, weather, etc. are some of the factors affecting electricity consumption. Different approaches such as time series, econometric models, regression as well as soft computing techniques such as artificial intelligence, fuzzy logic, and genetic algorithms, nonparametric and functional methods, online machine learning methods, etc. are widely used for electricity consumption forecasting (Gaillard, Pierre, and YannigGoude, 2015). Therefore, it would be better to model electricity energy consumption with good accuracy in order to avoid uncertainties. Also, it is better to use models that can handle nonlinearities among variables as the expected nature of the energy consumption data is nonlinear.

Jovanović *et al.,* (2014) opined that Artificial Neural Network (ANN) are useful for forecasting and modeling. The advantage of ANN with respect to other models is the ability of ANN to model both linear and nonlinear relationship to an arbitrary degree of accuracy by adjusting the network parameters without the need to make any assumptions as are implicit in most traditional statistical approaches. ANNs are able to learn precisely the key information patterns within several dimensions and information domain.

The University as a research institution consumes a lot of electricity. In MAUTech Yola, the demand for electricity is constantly changing and the supply is not always certain due to scarce resources within the University (A.A Useni, Personal Communication, October 7, 2019). A model for monthly electricity energy consumption with good accuracy is still a great challenge in the University. Owing to the fact that the University consumes huge amount of electricity, a good predictive model for electricity consumption gives decision makers an opportunity to make sound decision, which has a profitable outcome and crucial for the well-being of the organization. Kaytez *et al.,* (2015) opined that underestimation of the electricity consumption would lead to potential outages that are devastating to life and economy, whereas overestimation would lead to unnecessary idle capacity that means wasted financial resources. In a similar development, Manjunatha *et al*. (2015) revealed that since Universities consume huge amount of energy for its numerous operations (academics, research, social, economic, etc.), energy availability, consumption and costs can present a great challenge of either reduction or increase in energy consumption if not properly conserved and utilized. To overcome these challenges, this calls for the need to develop an Artificial Neural Network model for the prediction of electricity consumption in MAUTech.

The study predicts accurately the monthly electricity consumption in the University, thereby improving the energy performance and conservation strategies of the University. The adoption of the system would improve efficiency in electricity demand and consumption. More so, this study will help electricity companies to take right decisions and optimize strategies for supply to its consumers. Furthermore, this research will contribute to inter-relationship among different disciplines, this is because the proper understanding of artificial neural network strengthen the understanding of other cognate disciplines explored in this study, such as electrical/electronics, automated systems, and machine learning.

Remaining of this paper is organized as follows. In the second section, literature review about energy consumption of Nigeria, other countries, and also some institutional building were presented. In the third section regression analysis used for determining which variables should be used in ANN modeling is demonstrated. In section 4 ANN approach used in this study is explained. In section 5 results of the ANN modeling and forecasting are presented. In section 6, the conclusion about this study is discussed.

2. Literature review

Energy demands and supply plays a key role in a nation's economy since it is a necessity for industrial activities, as a result, in the literature researchers intensively investigated the relationship between energy and other factors. In the literature, future energy need is a very attractive area of interest. In this study, the main focus is developing a predictive model for monthly energy consumption in MAUTech using ANN and/or MLR.

Yuana, Farnham, Azuma, and Emura (2018) developed a predictive ANN models to forecast the hourly electricity consumption of faculty buildings on three areas of the Osaka City University Sugimoto Campus. The Feed-forward ANN and back-propagation algorithm was employed to model the seasonal hourly electricity consumption under a MATLAB environment. The input variables include day of week, an hour of day, hourly dry-bulb temperature, hourly relative humidity, hourly global irradiance, and recorded hourly electricity consumption at the same hour and day of week in the previous weeks. These six variables were used to predict the future seasonal hourly electricity consumption for three areas in the Campus. The performance of proposed ANN models was evaluated using the RMSE metric and correlation coefficient (R^2). The correlation coefficient between actual measurement and ANN model prediction ranges between 0.96 and 0.99 at training stage and ranges between 0.95 and 0.99 at the testing stage. Results showed that both RMSE and its difference between training and testing samples in the Science and Technology area of the campus is the largest, followed by the Humanities College area. The Old Liberia Arts area has the smallest RMSE and its difference between training and testing samples. The researchers recommended more input variables could be used to improve the accuracy of ANN model. The ANN approach could be extended to the whole campus. More so, other ANN methods trained with other algorithms should be given consideration and compared in future work.

Deb *et.al.,* (2016) developed a model to forecast diurnal cooling load energy consumption in three institutional buildings at a university campus in Singapore over a period of two years and the variation then analyzed. The model was developed using machine learning tool, ANN. A feedforward ANN with 'Bayesian regularization' training algorithm was deployed. The study demonstrated that it is possible to predict many days in succession without alteration in the model parameters. Such output is important to develop day-to-day energy management strategies and can provide various energy consumption values which are recommended in building's energy use for the next coming days. The results show that the ANN model is able to train and predict the next day energy use based on five previous days' data with good accuracy, this implies the ANN could predict the energy in the three buildings with a good level of accuracy. The study recommended that in future to develop this model, it could be generalizing for a wider selection of institutional buildings.

Kaytez *et al.*,(2015) Conducted a research on forecasting Turkey electricity consumption. Three models of regression analysis, neural networks, and least squares support vector machines (LS-SVM) were compared in predicting Turkey electricity consumption. The training and test sets were treated in the same way in order to compare objectively the performances of MLR, ANN, and LS-SVM models. The forecast performances of the designed models are measured by their closeness to actual electricity consumption. The sensitivity and specificity levels of the analysis results were compared using a ROC analysis method based on statistics. The validity of the proposed model was checked by dependable indicators such as R2, adjusted R2, MSE, and F-test. The result shows that LS-SVM model has resulted in absolute training and testing errors of 0.876% and 1.004% respectively, which is more successful than the other two models. Also, the success of the ANN model in the training and testing processes is close to that of the LS-SVM model. the LS-SVM model achieved more successful results than the MLR and ANN models by 1.70% and 0.88% respectively. The analysed results indicate that the LS-SVM model can be used effectively for Turkey's long-term net electricity consumption forecast. In addition, a successfully trained ANN model is a powerful forecasting tool as well. Considering accurate and successful estimation of electricity consumption in Turkey, the Researchers recommended LS-SVM model as an alternative and also for policymakers and energy planners.

Jovanović *et al.,* (2014) developed a neural network model for heating energy consumption of one University campus in Norwegian University of Science and Technology - NTNU University campus Gløshaugen. The ANN model used is a three-layer feedforward neural network which composed of one input layer, one output layer, and one hidden layer. Levenberg–Marquardt (LM) learning algorithm, which is a variant of feedforward backpropagation, was used. The results showed that accuracy in predicting indices of the properly designed and trained multilayer ANN model with backpropagation algorithm can effectively model and predict heating consumption with great accuracy (error is less than 10%). The researchers opined that trends of calculated values and predicted values are very close to each other and future values are predicted with a high degree of accuracy. The study recommended analyses of the impact of different meteorological parameters in future research, in order to identify influencing factors and decrease number of input parameters.

Salahat and Awad (2017) proposed a model using the artificial neural network for short-term forecasting of the electrical power consumption in Palestine. Also, to find out the pattern of electrical power consumption with the dataset from Nablus city at the north of Palestine. The study deployed Multilayer Feed-Forward with Backpropagation Neural Networks (MFFNNBP) as a tool to predict the future electricity. The proposed model was able to predict the electricity consumption with an accuracy of more than 95%, which appears in the small mean square error. The result suggests that MLPNNBP model can be used as an important tool to perform a good prediction with least mean square error as short load forecasting model. The study recommended incorporation of MLPNN with optimization algorithms like genetic algorithms. Filtering data algorithms could be used to solve the problems of irregular points due to measurement of demand in many data in the electricity consumption time series.

Houimli, Zmami, and Ben-Salha (2019) used artificial neural networks to model and forecast the half-hourly electric load demand in Tunisia over the period 2000–2008. The model used is based on a Multilayer Perceptron artificial neural network to forecast short-term load curve by using past electric load data, climatic and calendar variables as inputs. The pattern search optimization algorithm that decides the optimal structure of the neural network model was used. Two additional algorithms the MLP with conjugate gradient and MLP with resilient back-propagation was employed. The experimental results when compared, suggest that the Levenberg–Marquardt training algorithm performs better and is the most efficient tool in forecasting the half-hourly electricity demand. The analysis also shows the superiority of the Levenberg–Marquardt algorithm compared to the resilient backpropagation algorithm and the conjugate gradient algorithm. The Researchers recommended the implementation of hybrid models combining neural networks with econometric models when focusing on electricity demand forecasting for future research.

Kankal, Akpınar, Kömürcü, and Özsahin (2011) applied Artificial Neural networks and regression analyses to forecast energy consumption in Turkey for the years 2008-2014. Socioeconomic and demographic variables (Gross Domestic Product-GDP, population, import and export amounts, and employment) were used as inputs. The researchers tested four different models with multilinear regression, power regression analysis, and ANN. The result of the analyses proposed Model 2 as a suitable ANN model (having four independent variables being GDP, population, import, and export) to efficiently estimate the energy consumption for Turkey. The proposed model predicted the energy consumption better than the regression models and the other three ANN models. In a similar development, Uzlu, Kankal, Akpınar, and Dede (2014) applied the artificial neural network model with the TLBO (Teaching Learning-Based Optimization) algorithm to estimate energy consumption in Turkey. The independent variables were Gross domestic product, population, import, and export data. The study compared performances of the proposed model with the classical back propagation-trained ANN (ANN-BP) by using various error criteria to evaluate the model efficiency and accuracy. Errors of the training and testing datasets showed that the ANN-TLBO model predicted the energy consumption better when compared to the ANN-BP model. Both Kankal *et al.,* (2011) and Uzlu *et al.,* (2014) revealed lower forecasts of energy consumption than the official projections. ANN training and use of the TLBO algorithm in energy modeling were respectively encouraged and recommended for future studies.

Birim and Tümtürk (2016) Conducted a research in which multiple linear regression (MLR) and artificial neural Networks were used to delineate the future projections of electricity demand in Turkey. The independent variables (GDP, population, import, export, employment, and natural gas proposed) were identified as the predictors of electricity consumption. Feedforward multilayer perceptron neural network was employed. The variables were used in stepwise regression to know which variables best predict the dependent variable. MLR was deployed to decide which independent variables will be chosen to predict future electricity consumption with ANN. Four different models (1-4) were proposed due to the regression analysis, these includes different combinations of four selected variables (population, import, natural gas, and employment). Results shows that the four proposed models follow similar trends and patterns and the forecasted values is lower when compared to the official estimated values with the exception to model 2. The researchers recommended that different possible outlines for the models should be considered for further study and the results should be evaluated. More so, the future electricity consumption can be extended beyond 2023.ANN is a suitable method for making predictions about electricity consumption forecasts.

Salami, Ajavon, Dotche, and Bedja (2018) presented a short-term prediction of electricity consumption model in Benin electricity community using two Artificial Neural Networks approaches (Multilayer Perceptron (MLP) and Radial Basic Function (RBF)). The learning stages and models were implemented in the Matlab environment, the nftool toolbox. Ten learning tags were considered in the simulation under the assumed hidden neurons. The MAPE errors for the models were computed. The MAPE for the MLP's model gave a lower MAPE error around 0.61% than that of the RBF's model (1.9%). The obtained results were compared to that of the linear multiple regression method. The results proved that the predicted data were very close to the real data while using these algorithms.

Kialashaki and Reisel (2013) developed multiple linear regression and artificial neural network models by applying various independent variables to predict future electricity consumption in residential sector of the United States. Stepwise regression method was used to choose the best independent variables for models. A feed-forward multilayer perceptron neural network was used coupled with a back-propagation technique for training. The proposed models were evaluated using the multiple linear regression method applying 7 independent variables (resident population, Gross domestic product (GDP), household size, median household income, cost of residential electricity, cost of residential natural gas, and cost of residential heating oil) and the dependent variable, which tested all possible combinations meaning 2^7 equations. Results obtained indicated that the models show robust outcomes when their R^2p is considered. In terms of predicting, the models show two different trends while their performances are at a similar level of accuracy during the test period. Three models were selected as the best and were used in ANN for future energy demand estimation. Due to the uncertainty in any extrapolation techniques, the researchers recommended that more research should be done to closely observe the accuracy of the ANN and MLR models developed in the study for predicting the energy demand.

Ghani *et al.,* (2019) developed and analysed prediction models to forecast load consumption for the city of Karachi Pakistan using two different models i.e. multi-layer feed-forward neural network (MFNN) and regression analysis (RA). Input parameters includes temperature, relative humidity, wind speed, dew point, and air pressure. Back-propagation algorithm was used for the forecasting in RA and MFNN. The models were developed and tested using data of eleven years for the month of October from 2008 to 2018. Simulation results were compared with actual data to measure the performance and level of accuracy of the predicting models. The Results show that the performance of MFNN surpasses that of the regression model in terms of prediction accuracy and provided best results with an accuracy level of up to 96% to 88%. More so, MFNN values was found to be closest to actual load values in terms of estimation accuracy. The use of more advance neural network models for better results was recommended for further research.

Wani and Shiraz (n.d) analysed electricity demand forecast of all-India demand data using multiple regression techniques. The technique was used in forecasting electricity demand by selecting different combinations of independent variables. Net State Domestic Product (NSDP), Sector-wise Domestic Savings Household sector, Consumers, Connected Load, etc. were independent variables and the energy consumption in domestic sector as dependent variable. The Forecasted results was compared with partial end-use technique. The results showed that domestic sector acts in a predominant capacity in the overall forecast of energy as seen in its effectiveness in determining the future electricity demand forecast of energy.

Electricity consumption simply means the total amount of electricity consumed by the economic agents of an economy at a specific time (Akinlo, 2019). According to USAID (2019), the degree of electricity accessibility is about 45% in Nigeria, out of which the supplies and consumption of electricity are dominated largely by the urban area of the country. The 80% of the total electricity demand in Nigeria is made up of electricity consumption from residential and commercial sectors of the economy, while electricity consumption from special tariff sectors, industrial and street lighting covered the remaining 20% of the total electricity demand in Nigeria (PHCN, 2009). The electricity generated and distributed in Nigeria is inadequate regardless of the attempt put in place to avoid shortcomings. As stated by World Bank (2017), the Nigeria economy is going to reach electricity supply crisis, which will definitely deprive the socio-economic development and the industrial growth to meet up with the economy's potential.

Oseni (2011) opined that energy cannot be replaced in key areas of the economy such as our educational institutions, agriculture, industries, transportation, and other key sectors in Nigeria. Its inaccessibility could pose adverse effects that could be unfavorable to the society at large. The future of energy production is critical owing to the increase in world population, swift industrialization, and world standard of living. Insufficient supply of energy limits socioeconomic activities, impacts economic development, and undesirably affects the quality of life. Oyedepo (2012) revealed that electricity today is the most common, useful, and desirable form of energy. Another very important factor worthy of note is that an increase in the electricity demands of a country occurs as a result of an increase in its population.

Ogundipe and Akinyemi (2014) carried out a study on the relationship that exists between electricity consumption and economic development by means of an extended neoclassical model for the period 1970–2011. The study adopted the Wald Block Endogeneity causality test to precisely find out the direction of causal relationship between electricity consumption and economic development. The researchers incorporated the distinct nature of Nigeria economy by controlling the role of institutions, technology, emissions, and economic structure in the electricity consumption-development argument. The results revealed that electricity consumption has substantial inverse relation on economic growth. This might not be independent of the exceedingly unreliable nature of power in Nigeria, which has led to the displacement of industries to neighbouring countries because of the high cost of producing electricity privately. The researchers recommended the need to re-strategize investment into the power sector and strengthen institutions/agencies that are responsible for electricity production and distribution.

Usman, Folorunso, and Alaba (2016) developed a model for predicting future electricity consumption in Nigeria of such system will result into efficiency in service delivery in the power sector. The model was built based on Radial Basis Function neural network RBF-ANN using data retrieved from the Central bank of Nigeria (CBN) annual bulletins. The study compared the performance of RBF network with backpropagation (BP) networks which is familiar with ANN models for time-series prediction. Computations of sum of square error (SSE), mean square error (MSE), and the correlation coefficients (R) of network models used was recorded. Results showed that Radial Basis Function (RBF) networks performs better with its ability to forecast the electricity consumption with a high level of accuracy and precision than Backpropagation (BP) networks. Also, provides the best platform for developing a forecast system. The study recommended that further research can be geared towards comparing the forecasted results of electricity consumption using the proposed model with equivalent artificial intelligence approaches such as self-organizing map, liquid state machine, etc., and using statistical tools to verify if there exists a significant difference between the outcomes.

3. Multiple Linear Regression Analysis

Regression analysis is a time series technique adopted in this study to show the relationship between input variables. MLR method is used to determine which variables will be selected to predict electricity consumption in the future. Benoit (2011) opined that the purpose of MLR is to ascertain which independent variables will be selected to forecast future electricity consumption with ANN. MLR is deployed after logarithmically transforming both independent variables and the dependent variable. By using logarithmic transformation in the MLR, relationship between the independent variables and the dependent variable remains nonlinear while linear model is still preserved. In this study, to predict the value of the dependent variable, independent variables whose values are known are used in MLR method. The Independent variable is the population of the school while the monthly electricity consumed is identified as the dependent variable.

Pre-processing data help networks to have better performance and faster learning. The input variables are pre-processed before being used to train the network. Data presentation is one of the important step for every neural network and the data collected was prepared before training and testing. The challenge of missing data was solved by the average of neighboring values during the year for that month. It is best practice to carry out the data normalization procedure before presenting the input data to the network model because mixing of variables with large and small magnitudes could confuse the learning algorithm on the importance of each variable, which could eventually lead to rejection of the variables with the smaller magnitude (Tymvios, Michaelides and Skouteli, 2008). Hence the minimum and maximum values are being normalized strictly within the range of [-1,1] (Beale, Hagan, and Demuth, 2017). In order to train the network, the data set would have to be normalized. Normalization implies that all the values from the data set should take values within the range of 0 to 1. Due to the nonlinearity of the input data, sigmoid function was used in the ANN model and for the avoidance of the network getting trapped in local minima, the historical data obtained from MAUTech was normalized onto the range [0.05, 0.95] before presenting them to the model for training and prediction. The normalization formula proposed by Smith (1993) and adopted by Talaee (2012) was applied for data normalization. Therefore, the data set to be used in this research would be done using the following formula: Equation (1) shows the computation of Min-Max normalization technique.

$$Q_n = \mathbf{0.05 + 0.95}\ \frac{Q_r - Q_{mi}}{Q_{max} - Q_{min}} \qquad (1)$$

Where,

$\mathbf{Q_n}$ = Normalized value
$\mathbf{Q_r}$ = Value that should be normalized
$\mathbf{Q_{min}}$ = Minimum value of q
$\mathbf{Q_{max}}$ = Maximum value of q
Data normalization was done using Matlab as a pre-processing step where Qmax for the entire data set was 312.5m3/s and Qmin was 1.7m3/s respectively. The output from the model was rescaled for ease of interpretation by reorganizing formula (1) to obtain formula;

Qpredicted = (Y-0.05)*327.1579+1.7
(1b)

Another method that is been used to normalize data is the data value averaging method. Data set can be enhanced by taking the average of the data, to smoothing the data we replace each point with the average of the neighboring points as in equation 8.

$$Y_2(i + k - 1) = (Y_1(i) + Y_1(i + 1) + Y_1(i + 2) + \cdots + Y_1(i + k - 1))/k \qquad (1c)$$

Where Y_2 is the new data, Y_1 is the original data, k is the number of neighboring points, and i from 1 to N where in number of input data.

4. Artificial Neural Network Approach

Neural Network is a system that is made up of interconnected neurons which are organised in layers. Artificial neural networks are input-output models whose pattern is schematically inspired from the functioning of biological neurons. Within the framework of these models, the channel of transfer of information in the network is characterised by the nature of the connections that could either be direct or recurrent (Houimli *et al.,* 2019). Neural networks are highly interconnected simple processing units composed in a way to model how the human brain carry out a particular task. Each of those units, also called neurons, forms a weighted sum of its inputs, to which a constant term called bias is added. This sum is then passed through a transfer function: linear, sigmoid or hyperbolic tangent (Pandey *et al*., 2016).

Birim & Tümtürk (2016) asserted that ANN is an information processing model that functions in a similar way like the working principles of human brain and contains artificial neurons which look like that of natural neurons in the brain. Artificial neural networks are computational metaphor which was inspired by the studies of brain and nervous systems in biological organisms. It is a branch of artificial intelligence developed in the 1950s aiming at imitating the biological brain architecture which solves problems through a series of repeated observations between neurons and synapses within the brain (Tan, Shi, and Tan, 2010).

According to Haykin (2008), artificial neural network is a machine that is designed to model the way in which brain performs a specific task or function of interest. It is usually carried out using electronic components or is simulated in software on a digital computer. The software tools work as a system of nodes and connectors which find relationships between given sets of inputs and outputs. The nodes represent the neurons which are the processing elements within the neural network with the natural propensity for storing experiential knowledge and making it available for use. Artificial neural network is, therefore, a network of layered nodes connected with directed arcs each with a numerical weight specifying the strength of connection which are automatically adjusted during training of the network. Neural Networks are information processing structure that consists of a number of input and output units composed in a systematic fashion. Between the input and output, there may be one or more hidden layers, each consisting of a number of processing units called neurons (Platon, Dehkordi, and Martel, 2015). According to (Nkoana, 2011), the weights of connections encode the information embedded in the network and the "intelligence" of a neural network emerges from the collective behaviour of neurons, each of which performs only very limited operation with each individual neuron finding a solution by working in parallel.

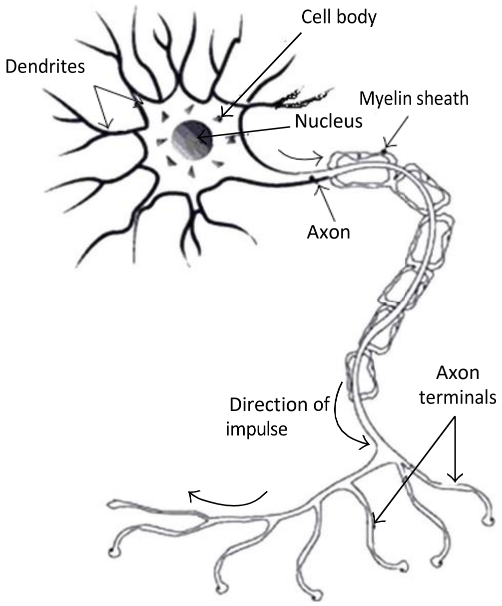

Figure 1: Structure of biological neuron (Koo, Liew, Mohamad, and Salleh, 2013)

According to Xiaofeng and Chunshan (2014), artificial neural network can be grouped into two major categories based on the connection pattern (architecture) as (i) feedforward networks in which no loop exists in the graph. The weighted connections feed activations only in the forward direction from the input layer to the output layer and (ii) feedback (or recurrent) networks in which loops exist because of feedback connections. Additional weighted connections are used to feed previous activations back into the network. The most common family of feedforward networks is a multilayer feedforward network in which neurons are organized into layers with connections strictly in one direction from one layer to another. It is important to point out that there are numerous variants of each of these networks.

4.41 ANN Modeling

In this research, procedures and libraries from Matlab Neural Network Toolbox were used to develop the neural network models. The research adopted a multilayer feed-forward neural network with one hidden layer. The architecture of the model and other parameters remained constant during the simulation period while learning algorithms and activation functions in both hidden and output layers were varied to obtain an optimum model. Different numbers of neurons between 2 to15 were tested to find the best structure. By comparing the performance of developed ANN models, the optimum number of neurons in the hidden layer was obtained as 10 for the models. Sigmoid and linear activation functions were the only functions used in the study in order to train the neural network, the secondary data obtained is used to adjust the weights, and feed forward and backpropagation is also adopted in an iterative procedure. It has three stages:

The feed-forward Pass: The first step is the initialization of the weights normally random then, we can calculate with the output function of the neural network which is represented as follows:

$$Y_i = f\left(\sum^{k} (W_{ij}X_{ij}) + b_j\right) \qquad (2)$$

Where,

Yi = value of the output signal

f = Activation function used in the network

k = Number of Neuron used

W_i = Weights at connection from i-th input variable

X = Input vector value(data) from i-th input variable

b_j = bias attach to the connections from j-th input variable

To determine the error (E) each NN output (Yi) will be compared with an observed value (Y_{ob}) using following equation:

$$E = Y_i - Y_{ob} \qquad (3)$$

This equation is used as criteria to stop the NN in a good performance as possible as, in this study, the mean square error (MSE) was used as criteria condition which equation is:

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(Yi - Yob)^2 \qquad (4)$$

Backward Pass: The Backwards Pass start from the goal with backpropagation is to update each of the weights in the neural network so that they cause the actual output to be closer the goal output, by minimizing the error for each output neuron and the network as a whole. This is used to calculate the error at the output layer back towards the input layer vector this process calculated as in the following expression:

$$\Delta w_{i+1} = \alpha \,.\, MSE.\, X_i \qquad (5)$$

Weight adjustment: The training process will continue until the MSE reach condition criteria value, and update the weights in each iteration using MSE by equation 6.

$$W_{new} = W_{old} + \alpha * \text{MSE} * X_i \qquad (6)$$

Where α is learning rate between 0 and 1. In each iteration, we checked the stop condition if it occurred or not.

Neural Network Training

The study applied supervised learning algorithm and the network was trained using the extensions of the most popularly used back-propagation training algorithm known as Levenberg– Marquardt (LM) and resilient back-propagation with both linear and sigmoid activation functions. In the back-propagation algorithm, interconnection weights are adjusted according to the error convergence technique to obtain the required output for the given inputs. The default values of initial weights and biases were used in network training.

Modelling Design Process

The study used supervised learning method and the multi-layer perceptron as the architecture with fully connected feed-forward network with one hidden layer, two input layers, and output layers. The values of future electricity consumption require the knowledge of the previous electricity consumption, these values are used as input to the model:

An efficient method of predicting with the use of neural networks is the Multilayer Feed- Forward Neural Networks Back Propagation (MFFNNBP). It is an MLPNN that passes the inputs and the weights from one layer to the next one through the feed-forward process and then it performs the weights update to be back-propagated to the previous layers in order to recalculate the weights (Qasrawi and Awad, 2015). The number of neurons in input layer, and output layer is determined by the input variables, and output variables respectively. But the neurons in hidden layer are determined by the complexity of the problem we solved. In this work, we are using neural network fitting tool in Matlab to determined our result. The neural network fitting tool (nftool) leads us to solve data fitting problems with the two-layer neural network, this network is feed-forward network type using Leven berg Marquardt algorithm in training (Gavin, 2009).

In MLPNN, the output of a layer will be an input for the next layer passing from the input layer to the output layer; the equations used for this procedure are illustrated as follows:

$$Output = f^2\left(\sum_{j=1}^{n} out_1 . w_{jk}\right) \quad (7)$$

Where the output of the first hidden layer out1, which is calculated using the following expression:

$$Out_1 = f^1\left(\sum_{j=1}^{n} in_i . w_{ij}\right) \quad (8)$$

Where f^1 and f^2 are the activation functions for output layer and hidden layer, which is calculated as in the following expressions:

$$f^1 = \frac{1}{1 + e^{-x}} \quad (9)$$

$$f^2 = x \quad (10)$$

5. Results and Forecasting.

5.2 The Artificial Neural Network Model Architecture

Kumar *et al.*, (2007) observed that one hidden layer with a sufficient number of hidden neurons is capable of approximating any continuous function. In this study, one hidden layer was adopted and in order to determine the optimum number of hidden nodes in the hidden layer, several approaches were considered including a rough estimate proposed by Masters (1993), which states that for a three-layer network with n input and m output neurons the hidden layer would have sqrt (n*m) neurons. Zhang *et al., (*1998) suggested an approach that the network with the number of hidden nodes being equal to the number of input nodes have better forecasting results.

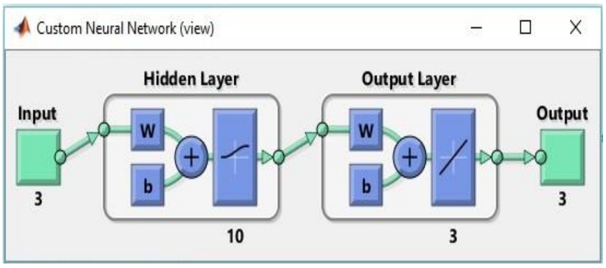

Figure 2.0: Developed ANNA with sigmoid function at the hidden layer and linear function at the output layer

5.3 Model Results

Figure *3* illustrates the determination of the best result obtained during training which is dictated by r value for test data set. According to Sivapragasam *et al.*, (2014), in Matlab, a high value of correlation coefficients (r) in test set demonstrates good prediction. Regression (r) value ranges from 0 to 1 and describes the amount of observed variance explained by the model. If r is equal to 1, it implies that the prediction replicates observation 100% of the time (Besaw *et al.*, 2010). The model for figure *6*, therefore, gave 93.37% prediction accuracy based on the r value for the test data set.

The best values of the parameters obtained during the training stage of the models were used to evaluate the competence of the network. Performance evaluation was determined by high value of correlation coefficient (r) in test data and smaller mean square error (MSE). According to Hung *et al.*, (2012), the network architecture which is a combination of weights, biases, number of hidden neurons, and training algorithm including activation function which gives the smallest validation set error is chosen and the network`s performance is evaluated by using the (r) value of test data set.

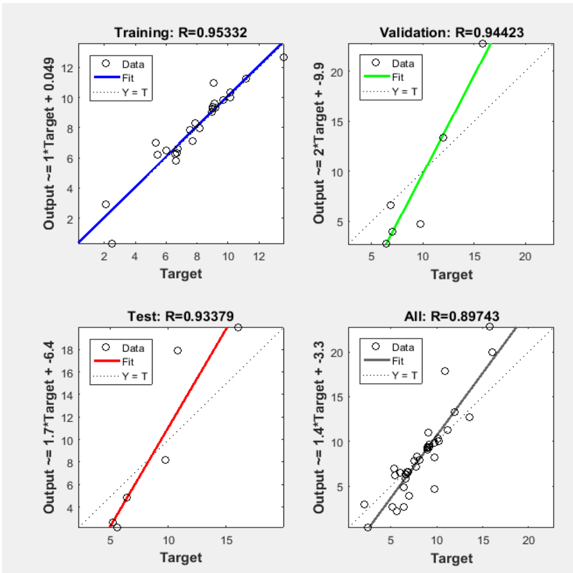

Figure 3: Schematics of ANN Training showing best correlation value on test data.

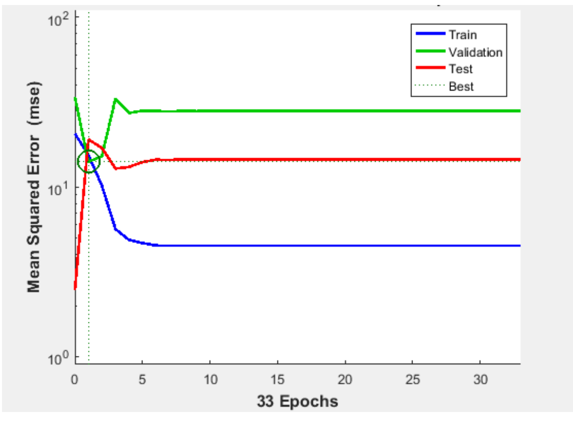

Figure 4 Display of an Artificial Neural Network training result

The results obtained for designing a model for electricity consumption for MAUTECH from 2016 to 2018 are shown in the figure 12.0 for the adopted model. The blue line represents the training, the green line the validation, and the red line the testing. In Figure 3.0, the dotted path shows the best path. At this point, the best validation performance is experienced in which the dotted horizontal line and the dotted vertical line intersects was achieved after thirty-three iterations. The performance stopped increasing at this point, and the training was stopped.

Training result of the network shown in Figure 3 illustrates that when the number of epochs increases, the errors of all three sets decline. At the beginning of training, the decrease in squared error is very sharp and then decreases gradually. According to Beale *et al.* (2017), training is stopped when error for validation set starts increasing if the model is constructed successfully, the test set and validation set error should show similar characteristics. In this case, training is stopped after 1 epoch. Figure 3 shows that they both follow the same pattern which proves that the model is reliable. It does appear that a little over-fitting has occurred because testing error increased before iteration 1. The performance of the model is measured with the mean squared error which reduces to 8947kwh after 1 epoch. The optimal validation performance was observed at epoch 1 without further increase, so the training was optimized at epoch 33.

The built model was used for the prediction of the monthly electricity consumption, which is obviously the aim of this project as earlier discussed. In the Prediction, three years was forecasted to know the actual electricity that was consumed in kilowatts.

Table 1.0: Results of Prediction of the Model

Neuron number	2016-2017: TRAINING					2018: TEST				
	RMSE [kWh]	CV [-]	MAPE [-]	R^2 [-]	Epochs	RMSE [kWh]	CV [-]	MAPE [-]	R^2 [-]	Epochs
6	7765	0.0878	12.09	0.9322	30	11675	0.1018	10.81	0.9389	32
7	7701	0.0872	11.98	0.9312	29	11782	0.1081	11.49	0.9376	34
8	7172	0.0805	10.42	0.9324	31	12783	0.1158	10.35	0.9385	33
9	8057	0.0901	12.23	0.9301	35	12991	0.1162	11.31	0.9351	37
10	**7075**	**0.0730**	**12.31**	**0.9337**	**33**	**8947**	**0.0724**	**10.32**	**0.9458**	**35**
11	7481	0.0789	10.81	0.9311	35	12379	0.0759	9.64	0.9304	38
12	7489	0.0829	10.64	0.9331	34	11059	0.1009	10.51	0.9359	37
13	7358	0.0817	11.81	0.9302	36	13979	0.1288	10.72	0.9363	39
14	7187	0.0809	11.93	0.9303	37	10285	0.0939	10.39	0.9368	42
15	7585	0.0837	11.91	0.9332	35	11341	0.1033	10.28	0.9391	44
16	7165	0.0815	10.64	0.9333	34	10483	0.0927	10.19	0.9380	45
17	7580	0.0839	12.41	0.9310	35	10872	0.1002	11.58	0.9376	49
18	6824	0.0878	10.32	0.9323	37	10376	0.0945	9.74	0.9354	49
19	7759	0.0856	10.96	0.9325	40	11431	0.1031	11.19	0.9398	48
20	7532	0.0822	10.42	0.9327	42	10428	0.0913	10.28	0.9365	50
25	7709	0.0875	12.38	0.9328	48	11431	0.1024	11.10	0.9383	51
30	7998	0.0899	12.93	0.9329	54	11671	0.1046	12.91	0.9302	56

The ANN development process started with 6 neurons in the hidden layer and the process was repeated increasing the number of neurons up to 30. As it can be seen from Table 1, the optimal prediction is obtained by the ANN model with 10 neurons. From obtained results, it can be concluded that trends of calculated values and predicted values are very close to each other, and future values are predicted with a high degree of accuracy.

5.5. Discussion

In this research, procedures and libraries from Matlab Neural Network Toolbox were used to develop the neural network models. The ANN design was set up using a simple binary class which is a subset of the supervised machine learning. The model design had input layers with (2) parameters, one hidden layer with (10) neurons, and 3 neurons at the output layer. Different numbers of neurons between 2 to 30 were tested to find the best structure. By comparing the performance of developed ANN models, the optimum number of neurons in the hidden layer was obtained as 10 for the models and the output layer is 3. The experimental simulations of the ANN model showed an optimal performance at 10 neurons in the middle layer with the predictive accuracy of 93.37%. The ANN model was trained with 33 epochs in order for the model to learn from the input parameters and the target values. The establishing and demonstrating the performance of the sigmoid and linear functions at hidden and output layers for a prediction application in the study adds to the view that linear activation function in ANN is most suitable for an output layer in prediction applications. The findings of the study shows that ANN trained with the Levenberg-Marquardt training algorithm and sigmoid activation function at the hidden layer and linear activation function at the output layer give accurate predictions to electricity consumption.

Forecasting in energy consumption is done to enhance effective energy management in institutional buildings. An accurate energy predicting model is essential because it provides an initial check for facility managers and building automation systems to mark any discrepancy between expected and actual energy use. More so, it provides a set of limits and targets within which the building's energy consumption should ideally fall. A good energy forecasting model can be merged with other building simulation models to generate useful operating variables. There is need for improvement on the performance of such prediction models, especially to areas where such models have never been applied like in MAUTech, therefore, this research is of more interest now as demand on water systems grow.

6. Summary, Conclusion

The research work developed an artificial neural network model for monthly electricity consumption prediction in a university campus using the five campuses of MAUTECH as a case study. A total of 59 data sets for 2016 to 2018 was collected from Students Affairs division and the Works department as secondary data. Sigmoid and Linear activation functions were used at the input and output layers respectively. Procedures and libraries from Matlab Neural Network Toolbox were used to develop the neural network models. Multilayer feed-forward neural network with one hidden layer, 10 neurons, and one output node was developed from Matlab. The model was therefore built with an MSE of 8947kwh and R of 0.93379 respectively. The model was built using 10 neurons after 33 iterations. After developing and running the models, verification and validation was done by comparing the results obtained from the model. This formed the basis of determining the models' prediction accuracy hence the objective was met.

The study recorded about 93.37%accuracy which was achieved at the 33epoch. This reveals that the model started learning at the 1 epoch with good prediction. One of the limitation for the research is in part of data collection phase. The study used two variables only (one independent variable and one dependent variable), and data of three years (2016-2018). More variables can be used and the number of years can be extended. More so, in application phase, only regression analysis and ANN methods for predicting were deployed. The study recommended that different predicting tools can also be used and compared.

6.1. Conclusion

The application of ANN for Electricity consumption is timely due to the constant increase in the population and the energy consumed. Under similar training data set, an artificial neural network trained with both Levenberg- Marquardt and resilient back-propagation algorithms with sigmoid activation function at hidden layer and linear activation function at the output layer are all capable of producing good results. The study achieved its goal of developing a tool that could be used by stakeholders to conveniently predict average monthly electricity consumption from previous electricity data and parameters like population data. It was shown that ANN technique can be used to predict future electricity consumption. During the process, it was discovered that ANN predict up to 93.37%accuracy which shows that the ANN can sufficiently assist the University community in forecasting future power consumption for effective utilization and planning.

6.2. Recommendations/Acknowledgement

The study, therefore, recommends the use of neural network model from Levenberg-Marquardt with sigmoid activation function at hidden layer and linear activation function at the output layer due to better results and faster convergence. The model can be improved further and customized to campuses for electricity consumption forecasting. A similar study should be carried out but with a different combination of input variables which affect electricity consumption in order to verify the results.

It is recommended that the university installs smart meters in the buildings and also the generator to understand the yearly, monthly, weekly, daily, and hourly consumption of electricity which could possibly cut down the consumption rate within the university community. More historical data could be gathered, say for ten to fifteen years in MAUTech or elsewhere in Nigeria at large, to design improved models that will better predict electricity consumption at a high level of accuracy. The accuracy of this work may be better improved by considering more input parameters such as climate, humidity, temperature, etc. that influence electricity consumption to build improved neural network models. The study, therefore, recommends the use of neural network model from Levenberg-Marquardt with sigmoid activation function at hidden layer and linear activation function at the output layer due to better results and faster convergence.

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