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An Intelligent Predictive Model for Electricity Consumption in Institutional Buildings Using Artificial Neural Networks

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Abstract
Energy consumption in buildings account for a higher percentage of about 40% unlike the other sectors in Nigeria and the world at large. Energy efficiency is paramount to achieving this goal. Energy consumption forecasting is a critical and necessary input to planning and monitoring energy usage which further realizes to the world's utmost fraction of CO_2 alongside other greenhouse gas emissions. previous literature has shown that few researches have been carried out in designing models for energy consumption in institutional buildings. In this research, the African University of Science and Technology (AUST) was considered as a case study, whereby the data being collected is the monthly energy consumption for a period of (2007 - 2018). Two models, flat rates and metered rates were built using to forecast monthly electricity consumption of the buildings within the university using ANN. Results obtained from the two models were compared with respect to their mean squared error and regression to show the one with a better predictive accuracy. The possibility of using renewable energy (RE) in the university could also be integrated as a future work.

Keywords
Building Energy, Prediction Model, Artificial Neural Networks (ANN), Energy Consumption, Institutional Buildings.

I. Introduction

For any nation to be tagged as being remarkably industrialized, there must exist social, economic and industrial development. Energy consumption has become a prime focus in global discussions towards ensuring sustainable development.

Recent studies have shown that in many parts of the world, energy consumption of buildings exceed that of other sectors including transportation and Industries. For example, in Nigeria, residentials (buildings) consume as much as 77.8% while transportation, industries and others cover the rest. In Nigeria, electricity is one of the oldest forms of energy available for daily activities. It is also, unfortunate of its inadequacy to meet the demands of an ever-increasing population. This is largely due to inadequate planning [1].

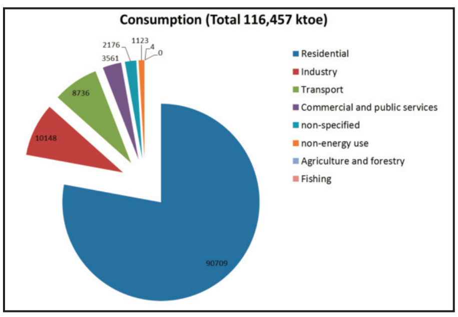

Fig. 1: Schematic Representation of Nigeria Energy Consumption by Sector

Source [2] 1 Ktoe (thousand tons of oil equivalent) 11630000kWh

[3] gave an overview of the current situation of the Nigerian electricity industry where he mentioned that the Nigeria electricity industry is plighted with several serious technical, managerial, personnel, financial and logistic problems. Moreover, the demand for electricity has continued to surpass capacity; the end result has been the delivery of poor and shoddy services which is evidenced by recurrent power failure.

Studies have shown that by following the current energy consumption pattern, the world energy consumption may increase more than 50% before 2030 [4],

Energy consumption forecasting is significant especially for improving the energy performance of buildings, leading to energy conservation and reducing its environmental impact.

However, the energy system in buildings is quite complex because the energy types and building types vary greatly. The most frequently considered building types are offices, residential and institutions.

Few studies have been carried out in this field especially in educational institutions in Nigeria.

The energy behavior of a building is influenced by many factors, such as weather conditions, especially the dry bulb temperature, building construction and thermal property of the physical materials used, occupancy behavior, sublevel components which include Heating, Ventilating and Air Conditioning (HVAC), and lighting systems.

Due to the complexity of the energy system, accurate consumption prediction is quite difficult.

In this research, we developed and compared two models that can perform an accurate monthly prediction of energy especially requirement in educational institutions like university buildings using the African University of Science and Technology (AUST) as a case study. A database was created for the monthly electricity consumption using the utility bills right from January 2007 – December 2018. The school used both flat rate between and measured metering system from January 2007 to December 2012 and January 2013 to December 2018 respectively.

This research would assist in monitoring the trend of electricity consumption on campuses using some metrics, build policies and budgeting, understanding, compare the predictive performance of both models built with respect to their Mean Squared Error (MSE) and Regression (R).

II. Related Works

A. Overview of Electricity Consumption

In the quest of sustainable development in the world, Energy is progressively being viewed as a major driving force [5].

Its inaccessibility could pose some adverse effect which could be unfavorable to the society at large. Energy cannot be replaced

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in key areas of the economy such as our educational institutions, agriculture sector, industries, transportation systems and other key sectors. The future of energy is expected to transcend owing to the increase in world population, swift industrialization and world standard of living of our population. Insufficient supply of energy limits socioeconomic activities, impacts economic development and undesirably affect the value of life [6].

In a study conducted by the World Bank revealed that despite the Sub-Saharan Africa having a greater population, the electricity consumption in the European Union was 11-fold of the consumption in the Sub-Saharan Africa (World Bank, 2011). Unattainability of electricity has been quite a serious problem in Nigeria, as it is generally known that most Sub-Saharan Africa states are in the core of power crisis [7].

In our present-day, electricity is the most commonly and desirable form of energy. Another very important trend worthy of note is that an increase in the electricity demand of a country occur as a result of an increase in its populace [8].

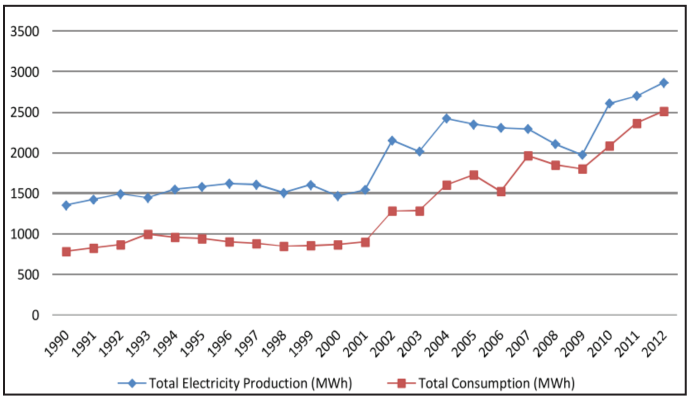

Fig. 2: Electricity Production and Consumption in Nigeria

Source (Computed from World Development Indicators Database)

In many developing countries, particularly in Africa like Nigeria and some Southeast Asia countries, power supply is generally known for its unreliability and high disruption costs which affects production efficiency and competitiveness. Africa is undeniably gifted with the widest range of energy resources for electricity generation which includes solar, hydro, geothermal, nuclear, coal, natural gas, petroleum, etc. but the continent's power sector remains harshly underdeveloped and the energy in particular electricity consumption in particular are relatively low [9].

At the country level, Nigeria which is located in the West African region is surrounded by Niger to the north, Atlantic Ocean to the south, Benin Republic to the west and Cameroon to the east. Nigeria is heavily endowed with an abundant resource but electricity generation is relatively low with the current output less than 3000 [6].

According to the World bank (2013), only 48% of Nigeria with over 174 million people have access to electricity. The access to electricity is relatively low compared to other Africa countries. [5] conducted 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. Electricity consumption influences a 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 neighboring countries as a result of the high cost of producing electricity privately.

It is imperative to re-organize investment and support towards the power sector and the institutional agencies respectively that are responsible for the production and distribution of electricity.

Fig. 3: The Nigeria Electricity Grid Network
Source (www.geni.org, n.d., 2011) [10]

B. Electricity Consumption in Institutional Buildings

Interestingly, Electricity consumption in our Institutional building in the world as well as Nigeria is quite considered a concern. Forecasting this energy has gained a lot of interest to help in building policies that will help this institution in building and conserving efficient energy systems.

[11] conducted an introductory audit framework around the Malaysian campus to obtain information such as the number and specifications of electrical appliances, built-up area and ambient temperature to understand the relationship between these factors and energy consumption. It was established that the number and types of electrical appliances, population and the activities impacted the energy consumption. Recommendations were made towards improving the energy efficiency of the campus. [12] established a study of three institutional building in Singapore by developing a suitable model that could forecast the cooling load and energy consumption.

III. Methodology

A. AUST Campus Information and Data

First, confirm that you have the correct template for your paper size. This template has been tailored for output on the A4 paper size. If you are using US letter-sized paper, please close this file and download the Microsoft Word, Letter file.

B. Preliminary Data Analysis

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C. Data Collection

The scope of the data for the research was obtained from the African University of Science and Technology, Abuja. This includes the monthly electricity utility bills for a period of six years (January 2007 to December 2018). A total of 132 was collected.

Part of the data that was collected was population of the university community used to develop this neural network model. The input variables include the relative humidity and population within the university community while the output variable is the monthly electricity consumption.

D. Data Preprocessing

The data collected was preprocessed to train the network efficiently. The procedure involved solving the problem of missing data. Data normalization and standardization are used in this regard to clean our dataset.

To solve the problem of missing data, the missing values are 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.

A flowchart is shown in fig. 4 that explains the sequence involved in the network design. In principle, data is collected via the utility bills into a database. It is then preprocessed to solve for the problem of missing values through data normalization and randomization. The network is then built, trained and tested.

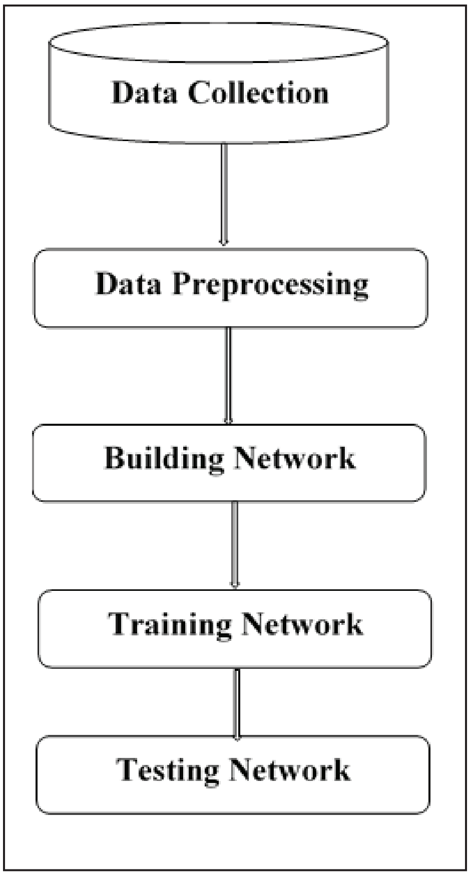

Fig. 4: Dataflow Diagram for Designing the Network Model

E. Architectural Framework of the Model

The major factors that actually affect this electricity consumption rate are the population of the community, which includes students, faculty, and staff, which represents the input parameter to the network. The corresponding output result, which is the monthly electricity consumption, is used as the output dataset (target). The choice of using a hidden layer is a result of combination of historical successes and the desire to maintain simplicity, which is in accordance to Occam's razor, with an acceptable level of prediction accuracy.

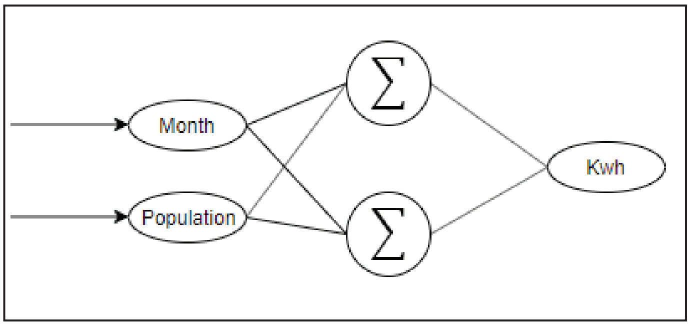

Fig. 5: Architectural Framework of the ANN for AUST Electricity Consumption

The activation function used for conversion here is the sigmoid logistic function, defined in equation 3.1.

$$f(x) = \frac{1}{1 + e^{-z}} \qquad \text{equation 3.1}$$

F. Training Network

During the training process, the weights in the input layer and the output layer are adjusted until the combination of their weights produces an acceptable output. The learning method adopted was the Levenberg-Marquardt algorithm, being one of the most common and efficient optimization methods in converging to the optimum weights [13] which combines the advantage of the Gauss Newton and steepest descent methods to minimize error. The entire training dataset or some portion of it is referred to as a batch and this process of training is often referred to as epoch-based learning [13].

During every few iterations, the ANN is passed some inputs from the validation set to understand how well it could predict the output. In a situation where there is a sign of being unable to generalize, or predict outputs outside the training within the acceptable error, this could trigger early stopping to occur, thus keeping the network from learning details of the network.

Another important aspect is choosing the number of neurons in the hidden layer for the architecture of the ANN. There is no standard procedure for this but it is instead a subjective factor which is illustrated in the extensive reviews (Hippert, Pedreira, & Souza, 2001).

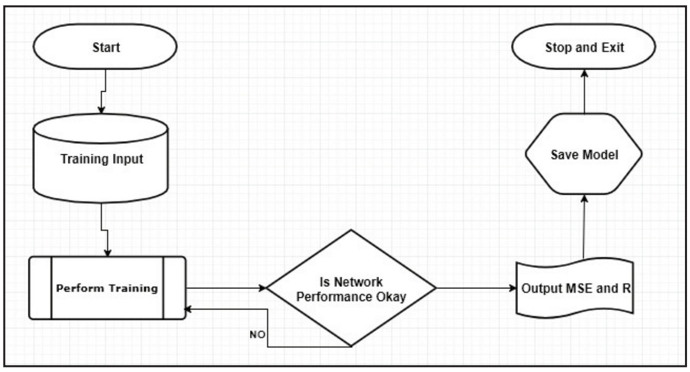

Fig. 6: Training Flowchart for the ANN Model

G. Network Model Parameter Investigation

The number of hidden neurons chosen was based on the MSE and regression (R). The model to be designed is for the power consumption between 2012 to 2014 when the school was charged at a flat rate of 1745 kW/h while the second model designed was

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for 2015 to 2018, after the meter was installed. Twelve neurons were chosen to design the two network models because of the number of months in a year. The results were compared (MSE and R) with respect to their performance.

H. Performance Evaluation Analysis

In evaluating a model's performance, there are a number of error measurements to be considered. According to literature, the MSE refers to the error that is to be minimized to realize an acceptable output from the ANN.

The MSE is shown as the function of the weights below in equation 3.2.:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}[t_i - f(w_m, x_i)]^2 \qquad \text{equation 3.2}$$

Where ti refers to the value of the target output of the i-th input and f is the output of the function and which is a function of w and xi input and finally N is the number of the training set.
When the MSE between two consecutive epochs is less than the minimum error that is specified, then the training stops. As mentioned earlier, training also stops when the validation resolves that overfitting is occurring.
The MSE also determines how well the network output fits the desired output, but it does not reflect whether two sets of the data move in same direction. The R value, which is also considered in this research, also measures correlation between outputs and targets. An R value close to 1 means a close relationship while the reverse indicates a random relationship. A comparison of the MSE and R values for all number of nodes was carried out. The lowest MSE value was selected as the optimum number of nodes in the hidden layer and also the R value, which is the highest.

IV. Results and Discussions

Detailed results of the built models for electricity consumption are presented in this section. Two models were built with different data set for both flat rate and metering system from January 2007 to December 2012 and January 2013 till December 2018 respectively. The models where trained using two input variables which includes relative humidity and population within the university with the monthly electricity consumption as our target variable.
After this the network with the best model was adopted for electricity consumption prediction for AUST using the historical data from 2015 to 2017.
The experiment was conducted using 12 neurons in the hidden layer and the results for the prediction for both when the meter was absent and present. During the experiment, 70% of the data was used for training, 15% of the data for validation and then the remaining 15% for testing.

A. Performance Comparisons of the Models

The results obtained for designing a model for electricity consumption for AUST from 2015 to 2018 are shown below for the adopted model. The blue line represents the training, the green line the validation and the red line the testing. In Figure 4.1 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 six iterations.

The performance stopped increasing at this point, and the training was stopped. For this model, the best validation performance was observed at epoch 1 without further increase, so the training was stopped at epoch 38.

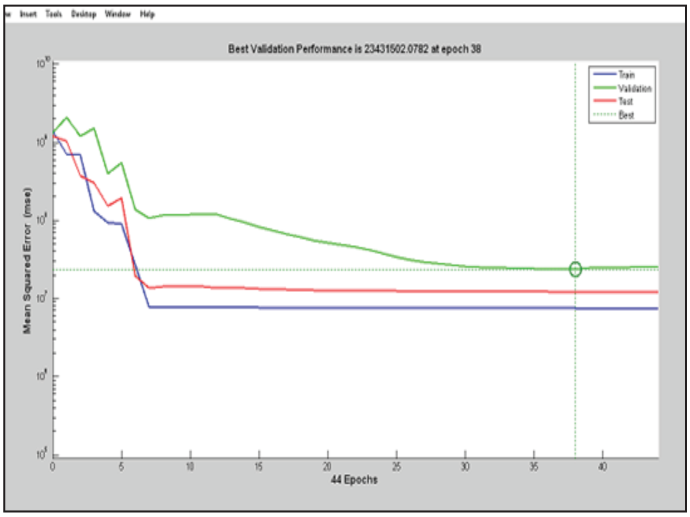

Fig. 7: Schematic of Forecast Trend Made with 12 Neurons for 2013 to 2018

For the second model being built using flat rate data from 2007–2012 as shown in fig. 6 below, we noticed that there were basically no visible lines (training, validation, test) in our model since the value of our MSE is zero.

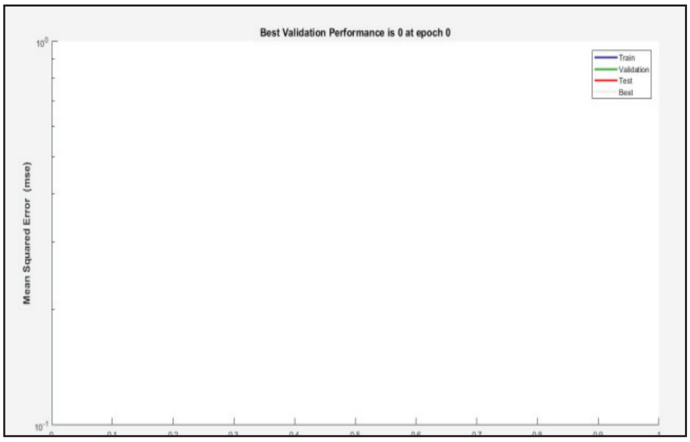

Fig. 8: Schematic of Forecast Trend Made with 12 Neurons for 2007 to 2012 using flat rate.

B. Validation and Testing Results

Fig. 7 represents the regression plot of the training, which shows the relationship existing between the outputs of the network and the targets. Essentially, the four plots represent the training, validation, testing and the general data for the model. The dashed line in each plot represents the targets = perfect result – outputs. The solid line represents the best fit linear regression line between the outputs and targets. The R value is just an indication of the relationship between the outputs and the targets. If R = 1 then we can deduce that there is no exact linear relationship between the outputs and the targets. Our training is a good fit if the value of R is equal to or greater than 0.93. In our case the training data has a value of R = 0.98, the validation has an R value of 0.94, the test result shows a value of R = 0.97 and the general overall results indicate an R value of 0.98. Therefore, we can say that this model has a very good result.

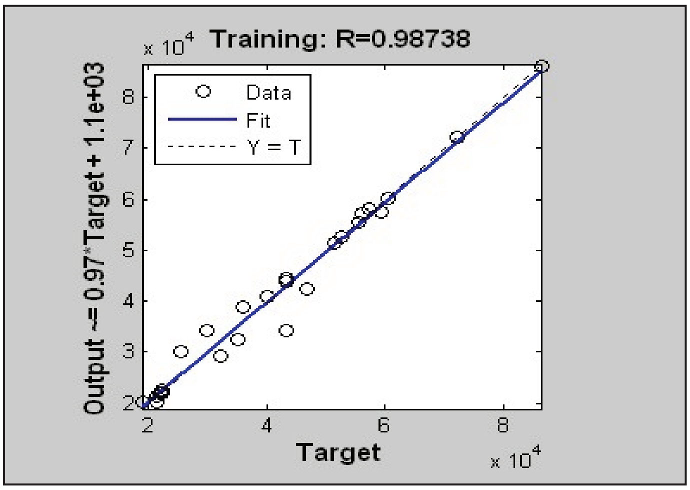

Fig. 9: Schematic of Regression Training Graph for January 2013 – December 2018

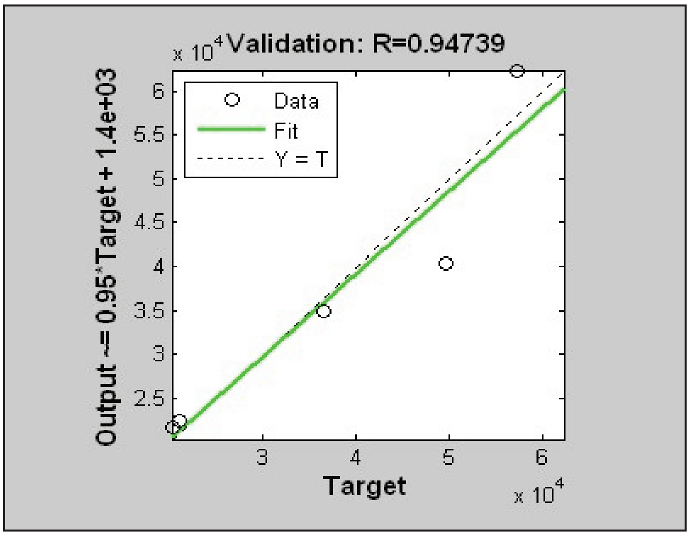

Fig. 10: Schematic of Regression Validation Graph for 2015 – 2017

In fig. 8, the shows the relationship between the outputs of the network and the targets.

The results for this model derive from electricity consumption between 2007 to 2013, that is the flat rate. The regression of the training, validation and testing results could not be displayed because our target outputs are all the same.
But we can refer to Figure 3.4, which shows a straight-line graph at about 180 degrees. Hence the MSE and R is observed to be zero since it is a straight-line graph unlike the former which was built using the 2013 – 2018 data.

Table 1: Comparisons of the Built Models with Respect to MSE and R.

Model (Jan. – Dec.)	Neurons Used In The Hidden Layer	MSE	R
2007 - 2014	12	0	0
2015 - 2018	12	12106440.38	0.97

C. Prediction of Electricity Consumption with the Built Models

The built models were used for the prediction of the monthly electricity consumption, which is obviously the aim of this project as earlier discussed.

Table 2 is deduced from the model built using the utility bills for the monthly electricity consumption from 2015 to 2018 using the metering system.
Table 3 is deduced from the model built using the utility bills for the monthly electricity consumption from 2007 to 2012 using the flat rate.
From Table 2 and Table 3 below, we observe that the model built using the metering system which is Table 2 has a better predictive accuracy when it comes to forecasting when compared to the former.

Table 3: Results of Model Built Using the Dataset from 2007-2012 Flat Rate

Months	Actual Consumption (Kwh)	Predicted Consumption (Kwh)
1	1740	1740
2	1740	1740
3	1740	1740
4	1740	1740
5	1740	1740
6	1740	1740
7	1740	1740
8	1740	1740
9	1740	1740
10	1740	1740
11	1740	1740
12	1740	1740

Table 2: Tabulation of Results Built Using the Dataset from 2015 to 2018 Metered Rate.

Months	Actual Consumption (Kwh)	Predicted Consumption (Kwh)
1	20320	19850
2	21340	21383
3	22102	22549
4	21230	21205
5	21140	21089
6	22325	22841
7	22019	22433
8	21494	21632
9	21320	21381
10	25514	24540
11	29708	27222
12	29708	27222

V. Conclusion

This paper presents two models to assist institutional buildings to make electricity consumption predictions using some metrics. One of the models was adopted to forecast monthly electricity consumption for AUST with a high level of precision with respect to their Mean Squared Error (MSE) and regression R. This will assist the university to understand the trend of electricity consumption, plan their budget and also understand some other factors that impact on electricity consumption within the university community.

As part of future work, smart meters may be installed in each building within the university including the generator to gather at both peak and off-peak periods. More input parameters as well as additional historical data may be considered to design models with better predictive accuracy.

VI. Acknowledgement

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