A PREDICTIVE MODEL FOR ELECTRICITY CONSUMPTION IN UNIVERSITY CAMPUSES USING ARTIFICIAL NEURAL NETWORKS (A CASE STUDY)

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By

Mohammed Habib Itopa

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CERTIFICATION

This is to certify that the thesis titled “A PREDICTIVE MODEL FOR ELECTRICITY CONSUMPTION IN UNIVERSITY CAMPUSES USING ARTIFICIAL NEURAL NETWORKS (A CASE STUDY)” submitted to the school of postgraduate studies, African University of Science and Technology (AUST), Abuja, Nigeria for the award of the Master's degree is a record of original research *carried out by Mohammed Habib Itopa in the Department of Computer Science*.

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A THESIS APPROVED BY THE COMPUTER SCIENCE DEPARTMENT

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ABSTRACT

Energy efficiency is paramount in the quest to achieve sustainable development in the 21st century. Statistics in recent research have shown that in many sectors in any nation's economy, which include buildings, industries and transportation, energy consumption in buildings accounts for about 77%, a higher percentage than other sectors in Nigeria; the same is true worldwide. Energy consumption forecasting is a critical and necessary input to planning and monitoring energy usage, with particular reference to CO_2 and other greenhouse gas emissions. According to literature, very little research has been carried out in designing models for energy consumption in institutional buildings. In this research, the African University of Science and Technology (AUST) is considered as a case study, whereby the data collected is the monthly energy consumption for the period 2012–2014 and 2015–2017. The data was collected from the monthly electricity utility bills when the school was using a flat rate and when they were using a measured meter rating respectively. The two models were designed for the monthly prediction of electricity consumption of the buildings within the university using an artificial neural network. Results obtained from the two models were compared and showed that the model designed using the latter dataset could be adopted to forecast the electricity consumption of the school with respect to its population. This will further assist the university in monitoring the trends of energy consumption, classify factors and components that impact energy consumption within the university community and hence building policies on its usage and consumption. Moreover the possibility of using renewable energy in the university could also be integrated as a future work.

DEDICATION

I dedicate this thesis to Almighty Allah for his endless favour and grace upon me and my beloved parents Mallam Mohammed Othman Abdullahi and (Late) Mallama Sa'adat Oyamine Mohammed. May Almighty Allah in his infinite mercy reward you all with paradise. (Amin).

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LIST OF ABBREVIATIONS

ADB	African Development Bank
ANN	Artificial Neural Network
AUST	African University of Science and Technology
BPNN	Back Propagation Neural Network
FCT	Federal Capital Territory
GRNN	General Regression Neural Network
HVAC	Heating, Ventilating and Air Conditioning
IBM	International Business Machine
Ktoe	Kilo tone of Oil Equivalent
Kwh	Kilowatt Hour
MLP	Multilayer Perceptron
MSE	Mean Squared Error
NFTool	Network Fitting Tool
PHCN	Power Holding Company of Nigeria
R	Regression
RBFNN	Radial Basis Neural Network
SVM	Support Vector Machine

CHAPTER ONE INTRODUCTION

1.1 Background of Study

For any nation to be identified as being extremely industrialized, social, economic and industrial development must exist. 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 exceeds that of other sectors, including transportation and industries. For example, in the Nigeria, residential buildings consume as much as 77.8%, while transportation, industries and others account for the rest.

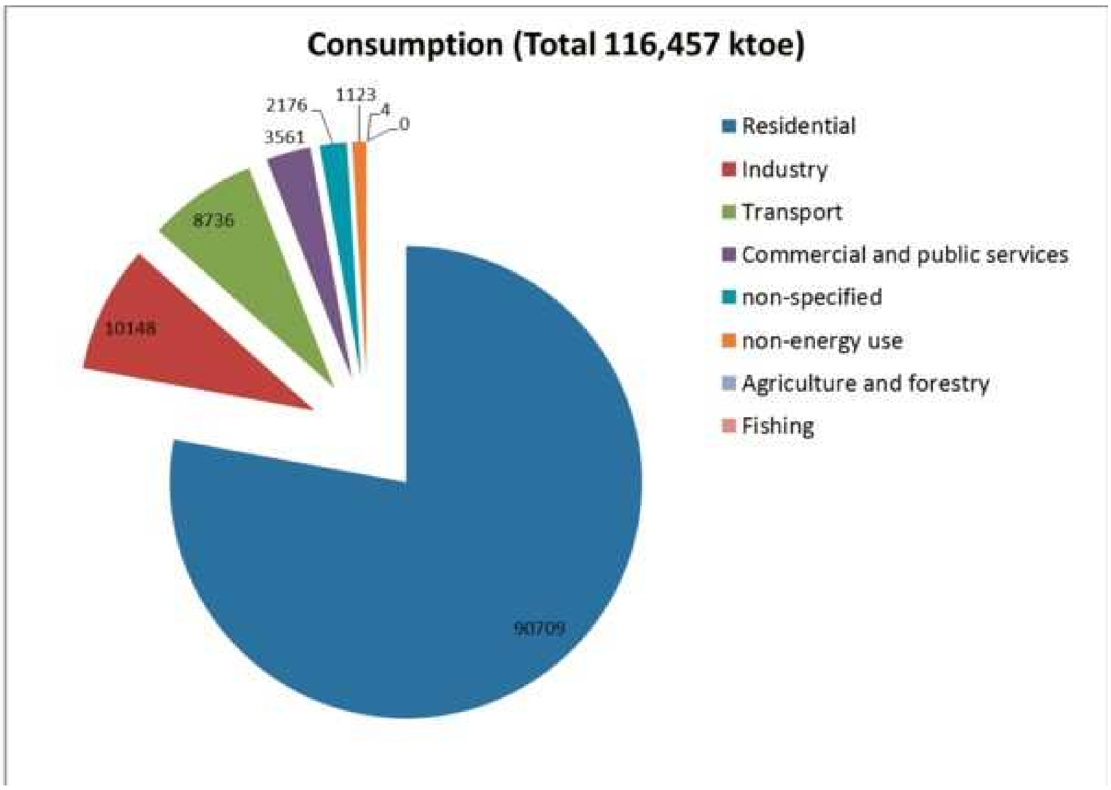

Figure1.1: Schematic Representation of Nigeria Energy Consumption by Sector

Source (Energypedia, 2012) 1 Ktoe (thousand tonnes of oil equivalent) = 11630000 kW/h

In Nigeria, electricity is one of the oldest forms of energy available for daily activities. It is also, unfortunately, in too short supply to meet the demand of an ever-increasing population. This is largely due to inadequate planning (Kofoworola, 2003).

Arimah (1993) gave an overview of the current situation of the Nigerian electricity industry where he mentioned that it is beset with several serious technical, managerial, personnel, financial and logistical 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 failures.

Studies have shown that by following the current energy consumption pattern, the world energy consumption may increase by more than 50% before 2030 (Suganthi & Samuel, 2012).

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, as 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 behaviour 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 behaviour, sublevel components, which include lighting systems, heating, ventilating and air conditioning (HVAC).

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

1.2 Statement of the Problem

In the 21st century, energy consumption in residential buildings is recognized as exceeding that of other sectors including transportation and industries, according to recent statistics.

In this research, it is important to develop a model that can perform an accurate prediction of energy requirement in educational institutions like university buildings.

The research also contributes to giving the university an insight into budget planning as well as conservation strategies.

1.3 Aim and Objectives

The aim of this research is to develop a model to forecast the monthly energy consumption required in institutional buildings using the African University of Science and Technology (AUST) as a case study.

Given the aim of this research, the objectives to be achieved are these:

1. To monitor the trend of electricity consumption on campuses and entrench an energy usage/consumption policy for University budgeting;
2. To understand and classify factors and components that affect electricity consumption within the university community; and
3. To compare the predictive performance of artificial neural network (ANN) models built with respect to their mean squared error (MSE) and their regression.

1.4 Expected Contributions

It is expected that an intelligent predictive model will assist in predicting the monthly electricity consumption required in university buildings, thereby improving the energy performance of buildings and conservation. This will help the universities to plan their budgets based on the population by giving an insight on the amount of electricity that is required.

1.5 Scope of the Work

The research involves developing an intelligent predictive model that will predict accurately the monthly electricity consumption required in university buildings. The African University of Science and Technology is being used as a case study for this research. A database was created for the monthly electricity consumption using the utility bills from 2012 to 2014 when the meter was not installed and a second database also containing readings from 2015 to 2017, the period the meter was installed.

ANNs are used for the purpose of this research and the results are compared to examine the built model with a better predictive accuracy.

1.6 Thesis Structure

The thesis is organized into five chapters as follows.

Chapter 1 covers the basic introductory part of the thesis.

Chapter 2 gives an insight into an overview of electricity consumption in Nigeria and institutional buildings, concepts related to machine learning prediction as well as a review of current and existing literatures.

Chapter 3 discusses the research methodology used as well as the system architecture and description, with a detailed discussion of the system implementation.

Chapter 4 provides a detailed discussion on the results and system implementation.

Chapter 5 rounds off the research by giving the summary, conclusions and suggestions for future work.

CHAPTER TWO LITERATURE REVIEW

2.1 Introduction

This chapter gives a brief overview of the literature on electricity consumption in Nigeria and institutional buildings (AUST campus) and their challenges.

Concepts that are used to define electricity consumption, that is short-term, midterm and long-term electricity consumption, using machine learning consisting of ANNs, will be analyzed.

Related and existing work on the subject using machine learning techniques like ANN is reviewed, thereby looking at what has been done, how it has been done, the results that have been obtained and the improvements that could perhaps be made to it.

2.2 Overview of Electricity Consumption in Nigeria

In the quest for sustainable development in the world, energy is progressively being viewed as a major driving force (Ogundipe, Akinyemi, & Ogundipe, 2016). Its inaccessibility could pose adverse effects that could be unfavourable to the society at large. Energy cannot be replaced in key areas of the economy such as our educational institutions, agriculture, industries, transportation and other key sectors. 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 (Oseni, 2011).

In 2009, a study conducted by the World Bank, results showed an indication that despite Sub-Saharan Africa having a greater population, the electricity consumption in the European Union was 11 times that of Sub-Saharan Africa (World Bank, 2011). Unavailability of electricity has been a serious problem in Nigeria, and it is generally known that most sub-Saharan Africa states are faced with a power crisis (Eberhard, Rosnes, Shkaratan, & Vennemo, 2011).

Today electricity is the most common and desirable form of energy. Another very important trend worthy of note is that an increase in the electricity demands of a country occurs as a result of an increase in its population (Oyedepo, 2012).

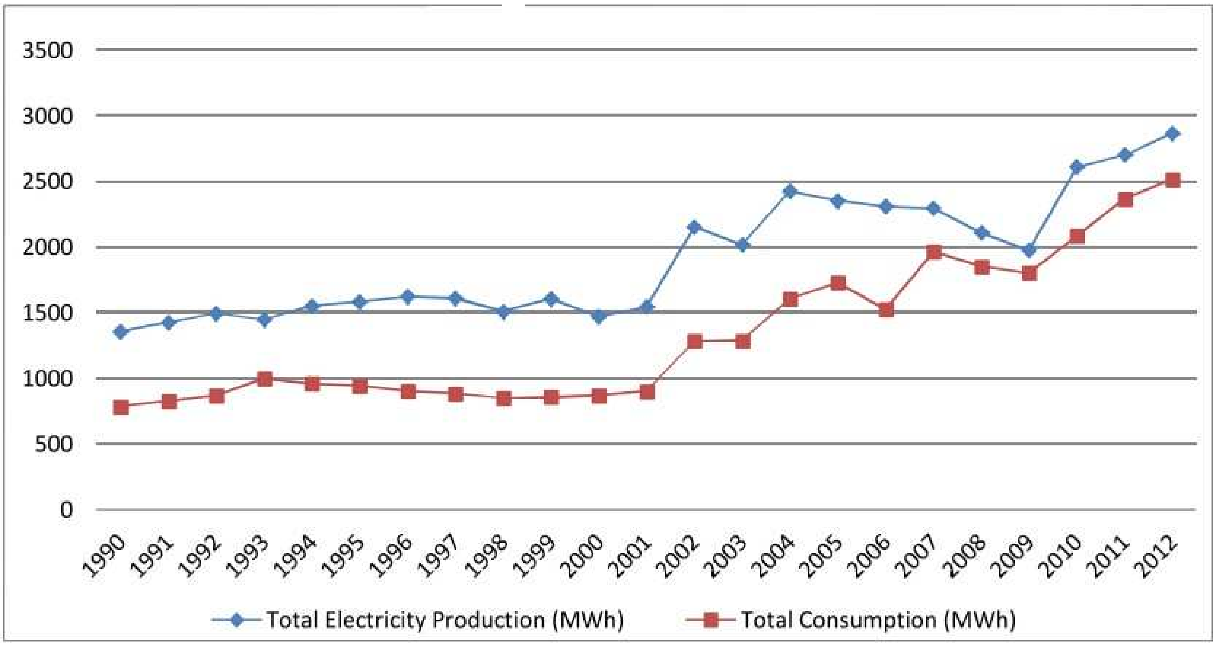

Figure 2.1: Electricity Production and Consumption in Nigeria

Source: Computed from World Development Indicators Database

In many developing countries, particularly in Africa, like Nigeria, and in some Southeast Asian countries, power supply is generally known for its unreliability and high disruption costs, which affect production efficiency and competitiveness. Africa is undeniably gifted with the widest range of energy resources for electricity generation, which include solar, hydro, geothermal, nuclear, coal, natural gas, petroleum, but the continent's power sector remains largely underdeveloped and electricity consumption in particular is relatively low (Economic Commission for Africa [2004] in Mayo, 2012).

At the country level, Nigeria, which is located in the West African region, is bounded by Niger to the north, the Atlantic Ocean to the south, Benin Republic to the west and Cameroon to the east. Nigeria is endowed with abundant resources but electricity generation is relatively low, with the current output less than 3000 kW/h (Bello-Iman, 2009).

According to the World Bank (2013), only 48% of Nigeria's population, or 174 million people, have access to electricity. Access to electricity is relatively low compared to other Africa countries.

Ogundipe et al. (2016) 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 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.

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

Figure 2.2: The Nigeria Electricity Grid Network Source (www.geni.org, n.d., 2011)

2.3 Electricity Consumption in Institutional Buildings

Electricity consumption in institutional buildings in Nigeria and worldwide is a concern. Forecasting this consumption has generated a lot of interest in building policies that will help institutions in building and conserving efficient energy systems.

(Tang, 2012) conducted an introductory audit framework around a Malaysian campus to obtain information such as the number and specifications of electrical appliances, built-up areas 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.

Deb, Eang, Yang, & Santamouris (2016) established a study of three institutional building in Singapore by developing a suitable model that could forecast the cooling load and energy consumption.

2.4 Machine Learning

The field of machine learning has existed since 1959 when, while was working at IBM, Arthur Samuel defined machine learning as a field of study that enabled computers to learn without being plainly programmed.

A more formal definition of machine learning was proposed by Tom Mitchell (1998), another renowned machine learning researcher, using a well-posed learning problem: stating that A is said to learn from experience E with respect to some task T and some performance measure P, if its performance on T, as measured by P, improves with experience E (Mitchell, 2006).

To further substantiate the application of this definition in the context of this research, we want to develop an energy prediction system. The task T of this system is to predict the power consumption required in university buildings as a function of the population. The performance measure P could refer to the predictive accuracy of the model. The system learns if we have more historical records of electricity consumption in buildings over time. Here the Experience refers to the set of already processed power consumption records. Hence, as more records of power consumption are added to the system, we achieve a predictive model with a high level of precision as regards its accuracy.

From the above definition, we can notice that performance is critical. This performance is achieved using some key metrics which include the population, occupancy behaviour etc., then we can tell whether the system learns from experience.

There are three types of machine learning algorithms. They are:

1. Supervised Learning;
2. Unsupervised Learning; and
3. Reinforcement Learning.

2.4.1 Supervised Learning

Supervised learning refers to the training of data sample from a data source and then using a test dataset also derived from the data sample to forecast or predict (Sathya & Abraham, 2013).

It is necessary for us to differentiate between two fundamental supervised learning models, classification models (classifiers) and regression models.

Regression models map an input space into a real-value domain while classifiers map an input space into pre-defined classes.

An example of a problem that fits into a regression problem is finding the demand for a certain product, like the electricity consumption required in university buildings. Similarly, an example of classification problem is a credit card fraud detection model that would take as input a set of recorded transactions. For each transaction, the training data would contain a flag that says if it is fraudulent or not. Other examples of supervised learning algorithms include K-Nearest-Neighbor, Support-Vector Machines, Neural Networks, Decision Trees, Random Forest, Naïve Bayes, and others.

2.4.2 Unsupervised Learning

Unlike the supervised learning algorithm, the data sets available for the unsupervised learning are usually not interpreted. The goal here is to find hidden structure in unlabelled data which includes finding which examples are similar to each other, and then grouping them in clusters.

The lack of direction for the learning algorithms in unsupervised learning can sometimes be gainful, since it enables the algorithm to look back for patterns that have not been earlier considered (Kohonen, Oja, Simula, Visa, & Kangas, 1996).

2.4.3 Reinforcement Learning

Reinforcement learning occurs when an agent learns through trial and error interactions with a dynamic environment (Giryes & Elad, 2011).

The goal of the machine is to learn to act in a way that maximizes the future rewards it receives (or minimizes the punishments) over its lifetime.

Reinforcement learning is closely related to the fields of decision theory (in statistics and management science), game theory, and control theory (in engineering).

2.5 Machine Learning Techniques in Electricity Consumption Prediction

Several machine learning techniques are leveraged to perform prediction in buildings energy requirements (Magoulès & Zhao, 2016). They include the following:

- Grey Models;
- Statistical Models; and
- Artificial Intelligence Models.

2.5.1 Grey Models and their Applications

When the data of a system is partly known, it is called a grey system. The grey model can be used to evaluate building energy behaviour when there is only incomplete or uncertain data (Zhao & Magoulès, 2012). (Jovi, Krmpoti, Jovi, & Juki, 2005) proposed an optimal grey prediction model for energy management in the ceramic industry. The results obtained was based on prediction error and data series characterization was observed to have high level of predictive accuracy.

2.5.2 Statistical Models and their Application

Statistical models have been widely considered for building energy estimates, including regression models, such as autoregressive model with extra inputs (ARX), autoregressive integrated moving average (ARIMA), autoregressive integrated moving average with extra inputs (ARIMAX) and conditional demand analysis (Magoulès & Zhao, 2016).

In some engineering models, regression models are used to correlate energy consumption together with climatic and weather variables to considerably improve forecasting accuracy.

(Aydinalp-Koksal & Ugursal, 2008) considered the use of a regression-based method called conditional demand analysis (CDA) to predict the energy consumption in buildings at the national level. After conducting the experiment and then making comparisons with both neural networks and engineering methods, results indicated that the CDA showed a better a predictive accuracy. Nevertheless, the downside of the CDA model was the lack of detail and flexibility, as it requires massive amount of historical data as input.

Lü, Lu, Kibert, & Viljanen (2015) proposed a method for forecasting based on a physical-statistical approach that will improve forecasting accuracy in heterogeneous buildings.

Statistical regression models essentially compare the energy consumption or index with the inducing variables. These empirical models are developed from historical performance data, which means that before training the models, we need to collect enough historical data. Much research on regression models has been carried out (Zhao & Magoulès, 2012).

2.5.3 Artificial Intelligence Models

2.5.3.1 Artificial Neural Network Models and their Applications

ANN models are the most widely used artificial intelligence models in the application of building energy prediction (Magoulès & Zhao, 2016). This type of model is good at solving nonlinear problems and is an effective approach to this complex application. Over the past 20 years, much research has been carried out using ANNs to evaluate various types of building energy consumption in diverse conditions such as electricity consumption, heating and cooling load, operation and optimization of sublevel components, and approximation of usage parameters.

In many building energy systems, ANN appears to be more applicable especially in computational models where attempts are being made to run a simulation of the powerful cognitive and sensory functions of the human brain and then using the capability to signify and employ the knowledge derived in the form of patterns.

Neural networks have the possibility of making improved, faster and more practical predictions than any of the traditional methods (Kalogirou, 2015).

Another advantage ANNs have over other models is their ability to model multivariable problems specified by the complex relationships among the variables (González & Zamarreño, 2005).

They also have the ability to extract hidden non-linear relationships between these variables by means of learning with training data. Several outstanding results in real applications have been realized with ANN in Short-Term Load Forecasting (STLF) using different types of ANN architectures.

A good example is the work of Khotanzad, Hwang, Abaye, and Maratukulam (1995), and Khotanzad et al. (1997).

2.5.3.2 Support Vector Machines and their Applications

Support Vector Machines (SVM) are increasingly being used in research and industry. They are considered to be extremely effective models in resolving nonlinear problems even with small amounts of historical sample data. Many studies of have used this model to conduct building energy analysis in recent years (Zhao & Magoulès, 2012).

Dong, Cao, and Lee (2005) first proposed the use of SVM to forecast electricity consumption of four buildings in the tropical region. A monthly bill of four years was used out of which a three years of data was used for training and the obtained model, and then applied to a one-year landlord utility in that year.

Li, Ren, and Meng (2010) established a predictive model for the annual electricity consumption in 59 residential buildings in China using SVM, traditional back propagation neural network (BPNN), radial basis function neural network (RBFNN) and general regression neural network (GRNN). It was found that the SVM and GRNN models achieved better predictive accuracy than the generalized BPNN and RBFNN models for prediction of annual building energy consumption.

2.6 Review of Related Works on Electricity Consumption Prediction

A remarkable amount of research has been conducted in the area of building models that assist in forecasting the required amount of energy in buildings.

González and Zamarreño (2005) designed a new approach for predicting short-term load prediction in buildings. They used a special type of ANN, which feeds back part of its output by means of a hybrid algorithm. The level of performance was excellent as regards the accuracy when evaluated with real data but the number of the neurons that composed the hidden layer and other parameters of the algorithm of the training were not analyzed in depth.

In a quest to understand the pattern of electricity consumption as well as the being able to predict its consumption levels in Hong Kong, Tso and Yau (2003) considered the use of decision tree and neural networks because of the use regression analysis reflected in the literature. Results showed that the neural network and decision tree had a better predictive accuracy when compared to the regression method that was used earlier.

Braun, Altan, and Beck (2014) illustrate future energy consumption demand of a supermarket in northern England by adopting multiple regression analysis based on gas and electricity data for 2012. The interest of this study is that previous literature had always focused on offices and homes and the impact of change in climate could affect the energy consumption in buildings.

The findings revealed that there will be an increase in electricity use by 2.1%, but gas consumption will drop by about 13%.

Usman and Alaba (2014) proposed a model for predicting future electricity consumption in Nigeria in order to boost the economy. The study used an ANN model that is often called Radial Basis Function (RBF) using data retrieved from the Central bank of Nigeria (CBN) annual bulletins. Results indicated that the RBF performed better when compared to its corresponding backpropagation network in terms of the level of predictive accuracy.

Ouf and Issa (2017) conducted a study to provide empirical evidence on the energy consumption in school buildings in Manitoba, Canada. They used multiple analysis of covariance (MANCOVA) to investigate the effect of the building on the annual consumption of electricity and gas combined.

Also, analysis of covariance (ANCOVA) was used to investigate the effect of the building age on the annual electricity, gas and separate total energy consumption.

Ten years of historical data of energy consumption in 30 selected school buildings was taken for the Canada study. It was the first study to be carried out. The outcome showed that the median total energy consumption of these schools was more than other Canadian benchmarks. That is the newer schools consumed less energy compared to the middle aged and older ones.

Deb et al. (2016) presented a study aimed at forecasting building energy 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 two machine learning tools, ANN and adaptive neuro fuzzy interface system (ANFIS). The division of the sample data obtained was shared in the ratio 60% and 40% for both the training and testing data respectively. The results obtained show that both ANN and ANFIS could forecast the energy in the three building with a good level of accuracy.

Kaytez, Taplamacioglu, Cam, and Hardalac (2015) conducted a study to design an accurate model for longterm electricity consumption forecasting, which is of paramount concern in any developing country for investors and companies. In order to achieve accurate forecasts, it is imperative to have a proper understanding of the electricity demand variation and timing.

From previous literature reviewed, the ANNs which are used to develop models lacked convergence to the actual value in some test data, thereby reducing the success rate. Similarly, test results not within acceptable limits in the traditional regression analysis had a higher error rate but the Least Square Support Vector Machines (LS-SVM) which are new techniques for energy consumption forecasting were adopted to develop this model. The study used historical data from 1970 to 2009 in Turkey. The results indicated that the proposed LS-SVM had more accurate and faster prediction method using diverse performance criteria even though a successful trained ANN model is a powerful forecasting tool as well.

Yu, Haghighat, Fung, and Yoshino (2010) designed a building energy predictive model based on a decision tree model in a Japanese residential building for classifying its Energy Usage Intensity (EUI).

Though this method is often used to classify and predict categorical variables, it has a competitive advantage over regression and ANN methods in being able to generate accurate and predictive models with an interpretable flow chart-like structure that enables users to extract very useful information. It also assists in ranking and identifying substantial factors of building EUI levels automatically.

The result also demonstrated that this method could assist building owners and designers significantly to reduce building energy consumption performance and the money spent on it.

2.7 Summary of Literature Review

According to the literature, we have understood that ANNs have gained a wider application in the field of building energy analysis when compared to other models with an optimal predictive accuracy like statistical models such as autoregressive model with extra input (ARX), autoregressive Input with moving average (ARIMA), Regression Analysis (linear and multilinear) Grey Models, SVM (Magoulès & Zhao, 2016). It is important to note that from the literature, that very little research has been carried out to model electricity consumption pattern in institutional buildings for energy efficiency.

CHAPTER THREE RESEARCH METHODOLOGY

3.1 Introduction

This chapter addresses the method of data collection and usage in modelling the ANN used to predict the monthly electricity consumption in institutional buildings, using AUST as a case study. It further explains the tool box, algorithms, learning approach and activation functions used to create the ANN model.

3.2 AUST Campus Information and Data

Before delving into the concept of machine learning and other models for building electricity consumption, specifically ANN, it is necessary to give a description of the African University of Science and Technology (AUST). AUST is a postgraduate school located at Abuja Nigeria. and has about 26 buildings spread over an area of one square mile with a varying population of approximately 150 enrolled students, 82 visiting faculty with an average of 15 present in a month and about 108 non-academic staff.

Figure 3.1 is a schematic of the AUST Building plan.

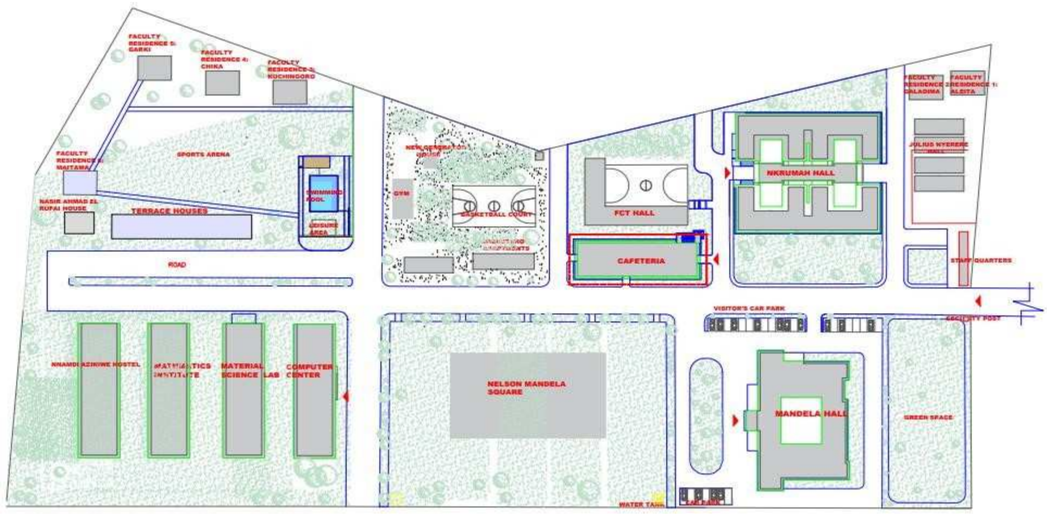

Figure 3.1: Schematic of AUST, FCT Abuja Building Plan

The Power Holding Company of Nigeria (PHCN) is responsible for electricity distribution in Nigeria by offering both prepaid and postpaid plans. AUST subscribes to the postpaid plan for its electricity supply plan.

The electricity consumption pattern for AUST can essentially be divided into diurnal and nocturnal periods, that is being active during the day and active at night. Obviously, energy consumption during the weekdays (working days) is higher when compared to weekends (non-working days). Fluctuations in the electricity consumption on the AUST Campus are varied by the population on campus, activities being held, as well as the type of electrical appliances, like launderette services, HVAC, energy saving bulbs, computers, laptops and accessories. AUST also has three generators for backup electricity, two 500 KVA and one 1,000 KVA respectively.

The peak hour of high power consumption, especially on weekdays, is 8 am to 5.30 pm daily while the offpeak hours with lower power consumption are between 6 pm to 7 am daily.

3.3 Weather Conditions at Abuja

Abuja is located at geographical coordinates 9º4’N, 7º29’E. It is the capital of the Federal Capital territory (FCT). It experiences three weather conditions, namely a warm, humid rainy season and an extremely hot dry season annually. In between these seasons, the harmattan occurs, accompanied by the north-east trade wind. The rainy season starts in April and ends in October, when daytime temperatures reach 28 ^{o}C–30 ^{o}C and night time lows range around 22 ^{o}C–23 ^{o}C. During the dry season, daytime temperatures can increase up to 40 ^{o}C and night-time temperatures can drop to 12 C, resulting in chilly evenings. The high altitudes and rolling terrain of the FCT act as a moderating influence on the its weather. The annual total rainfall is between 1100 mm and 1600 mm.

The monthly climatic data for Abuja Nigeria is given in Figure 3.2 below

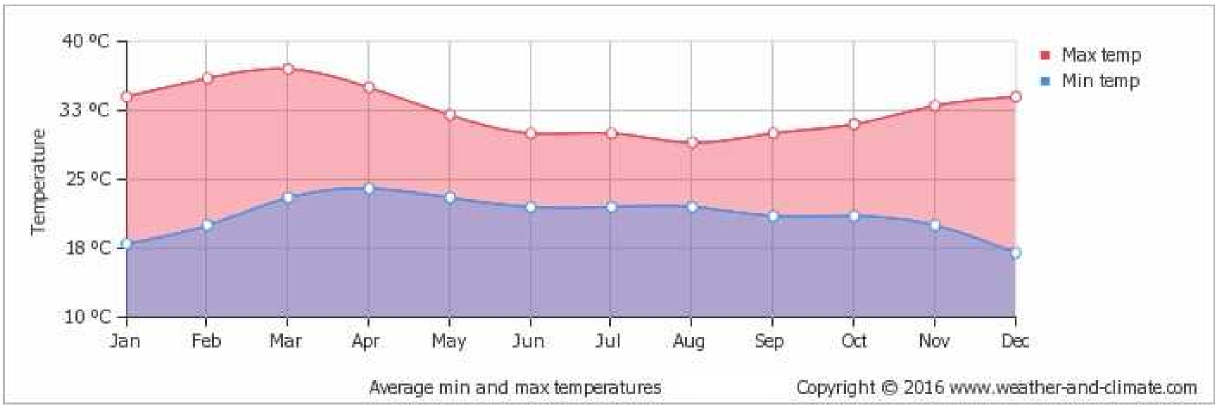

Figure 3.2: Average Monthly Climatic Data for FCT Abuja, Nigeria

Table 3.1: Tabular View of Average Monthly Temperature and Precipitation for FCT, Abuja

	Temperature			Precipitation
Months	**Normal**	**Warmest**	**Coldest**	**Normal**
January	27.6°C	34.7°C	20.4°C	0
February	29.3°C	36.8°C	22.8°C	0
March	30.2°C	37.1°C	24.5°C	1
April	28.9°C	35.7°C	24.8°C	4
May	27.3°C	32.8°C	23.7°C	9
June	26.0°C	30.7°C	22.3°C	12
July	25.1°C	29.1°C	22.1°C	14
August	25.2°C	28.8°C	21.8°C	16
September	24.9°C	30.0°C	21.6°C	16
October	26.3°C	32.0°C	21.5°C	8
November	26.9°C	34.4°C	19.4°C	0
December	26.7°C	34.7°C	19.3°C	0

3.4 Electricity Consumption Data for AUST

For the purpose of this research, the monthly electricity consumption utility bill of AUST was obtained. Two sets of data were collected spanning from January 2012 to Dec 2014 when the school was charged at a flat rate and January 2015 to the present, together with weather variables as well as the population of students, faculty, staff and the entire community collected for the same period on a scale of monthly average. The network was tested on the last 12 months of the dataset in 2016 obtained for this case study which was planned such that the nearer in time to the prediction, the more influential it was for the forecast.

The time series technique adopted allows for growth and variations in electricity consumption patterns. over the seven-year period being considered by this network. This will be further addressed in the next section.

3.5 Preliminary Data Analysis

Regression analysis is a time series technique adopted to show the relationship existing between the electricity consumption and population of AUST community.

In Figure 3.3, we can observe a straight line from the origin of the graph at 45 degrees. A distinctive relationship exists between the independent variable, which is the average monthly population, and the dependent variable, which is the monthly electricity consumption for the years 2015–2017 using a metering system.

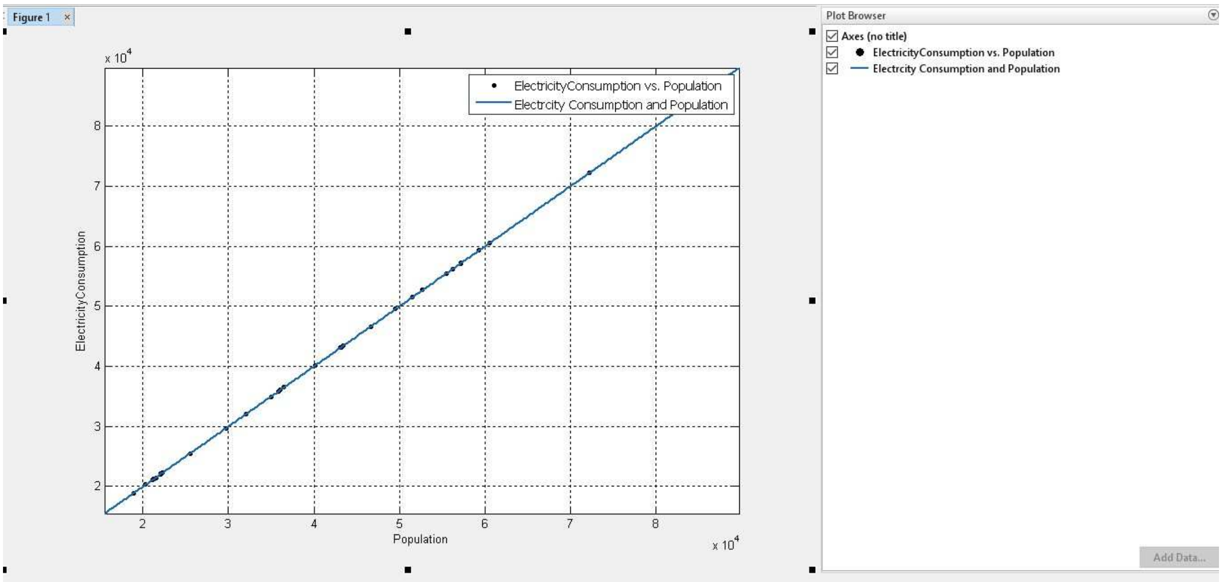

Figure 3.3: Schematic of AUST Electricity Consumption against Population (2015–2017)

Figure 3.4 below further shows us that a straight line at 180 degrees exists between the independent variable which is the average monthly population and the dependent variable which is also the monthly electricity consumption for the years 2012–2014 using a flat rate in the AUST community.

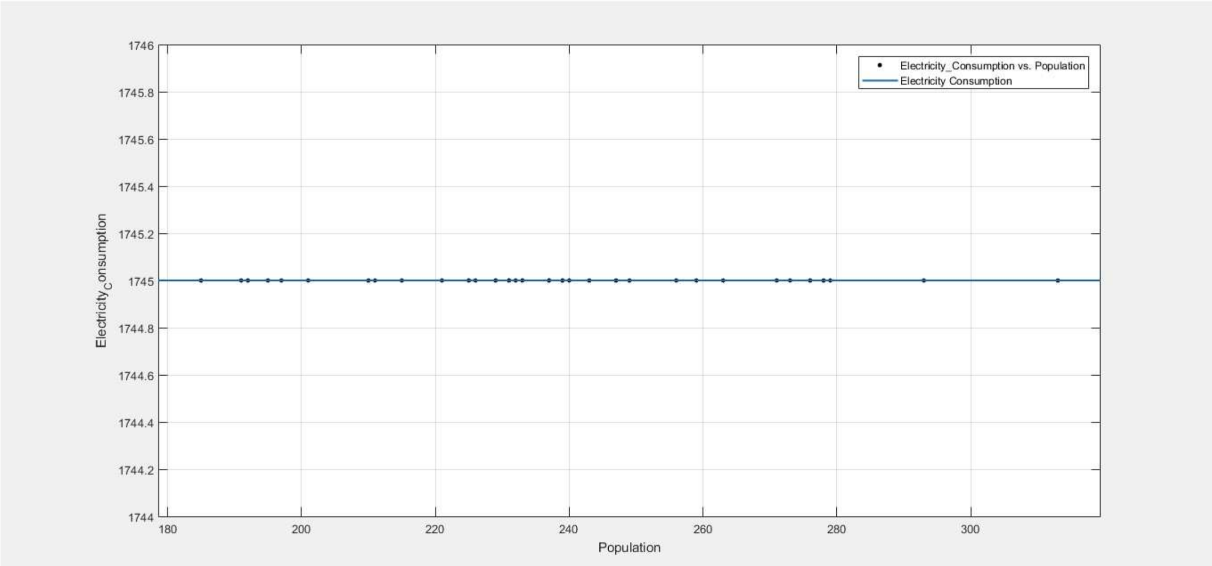

Figure 3.4: Schematic of AUST Electricity Consumption against Population (2012–2014)

3.6 Demystification of Artificial Neural Networks

ANNs can perform computations that can mimic how the human brain learns. They consist of a paralleldistributed structure of neurons that use the knowledge being learnt to match sets of inputs to outputs (Haykin, 2005).

The neuron, which is the fundamental unit of the ANN, is modelled just like the one in the brain, so that it possesses the ability to adapt to changes in the environment and thereby subsequently adapt it for forecasting by embedding memory of it in our model.

3.7 Forecasting with Artificial Neural Networks

One of the mostly popular ANN architectures being adopted for prediction algorithms is the multilayer perceptron (MLP). This is as a result of its plasticity in assuming a complex pattern (Samarasinghe, 2007).

MLPs comprise three layers, namely the input layer, the hidden layer and the output layer. Below is a schematic of the basic architecture of an MLP.

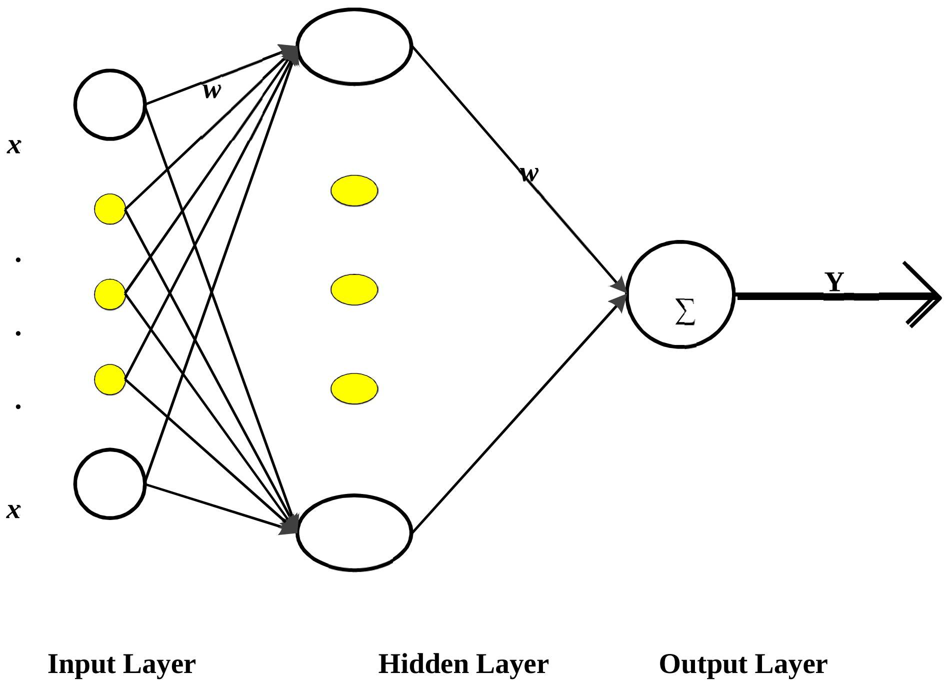

Figure 3.5: Schematic of the MLP Neural Network

From the figure above the input layer is indicated as $x_1 \ldots x_n$,. which normally sense the outside world. That is, the neurons on this layer include inputs like historical electricity consumptions, weather variables etc. The hidden layers are linked through weighted inputs represented by arrows labelled w_α. The role of the hidden layer is to first sum up the weighted inputs and then pass the values through a nonlinear transfer function denoted by **β.** The role of the transfer function is to shift the inputs from simple to complex linear and nonlinear domains. This further allows the ANN to perform a nonlinear mapping between the input and output. We notice that most frequently, we observe the number of hidden neurons to be one, though there is no decisive method to ascertain the number of neurons. Instead heuristics techniques are used that are specific to a particular domain (Hippert, Pedreira, & Souza, 2001).

Computation of the weighted values w_α is carried out at the hidden layer, which is connected to the output layer with the weighted inputs $w_{\beta,}$ which are computed at the output layer to arrive at a final value depending on the architecture of the neural network.

The MLP requires a historical dataset consisting of matching input and output for training to take place. During the learning phase, the network is presented with an input vector, which is then passed through the hidden layer and the output layer with a measurement on how well the predicted value matches with the expected value in the network model.

A comparison is performed between the absolute error to an acceptable threshold. If it is discovered that the error is large then an adjustment is made by back-propagating the information through the network.

w_{α} and w_{β}, which are the weights of the hidden and output layer respectively, are adjusted until an acceptable level of error is realized. Thus, in an MLP each of the neurons in the output layer evaluates two things: the output signal itself, which stands as a function of the weighted inputs to the neuron and the error linking the output signal and the desired output.

The calculation of this error can take many forms. Further highlights will be covered in section 3.11, which explains some of the essentials of the proposed model.

3.8 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 five years (2012 to October 2017). A total of 58 data sets was collected. Part of the data that was also collected was population of the university community used to develop this neural network model.

3.8.1 Input Variables

The input variable refers to the independent variable including the months influence the dependent variable which is the monthly electricity consumption. They include the following:

1. Population

2. Month.

Figure 3.6: Tabular View of the Input Variables and its Associated Units

S/N	INPUT SET	RANGE
1.	Month	1–12 (Jan–Dec)
2.	Population	185–313

From Figure 3.6 above, the input variables are the month which spans from January to December and the population of the university community which is in the range of 185 to 313.

3.8.2 Output Variables

The output data is the monthly electricity consumption deduced from the utility bills for each monthly and the previous.

Table 3.2: Tabular View of the Output Variables and Associated Units

S/N	OUTPUT SET	RANGE	UNITS
1	Electricity Consumption	18873 - 86350	Kilowatt Per Hour (Kwh)

Table 3.2 shows the range of the monthly electricity consumption in KW/h.

3.9 Data Preprocessing

After the complete dataset was collected, it was of high importance the data being collected was preprocessed to train the network efficiently. The procedure involved: (1) solving the problem of missing data; (2) data normalization; and (3) data randomization.

To solve the problem of missing data, the missing values are solved by the average of neighbouring 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, & Skouteli, 2008). Some type of normalization is standard procedure before applying the inputs to the network model. Hence the minimum and maximum values are being normalized strictly within the range of [-1,1], as shown in Beale, Hagan, and Demuth (2017).

A flowchart is shown in Figure 3.7 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.

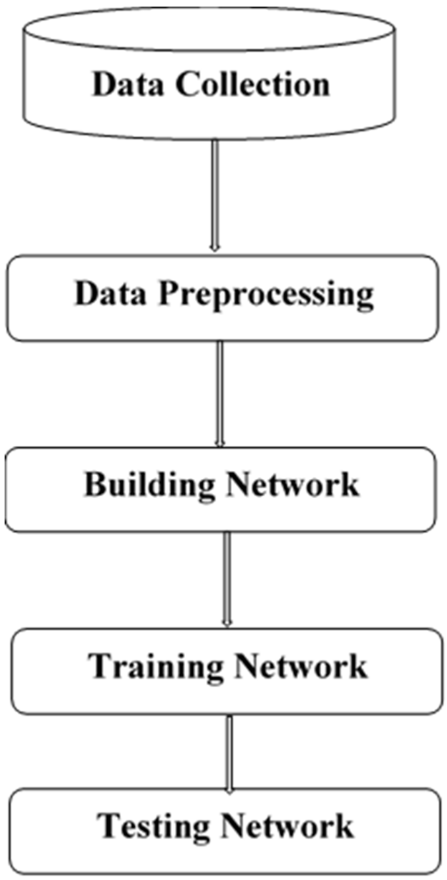

Figure 3.7: Dataflow Diagram for Designing the Network Model

3.10 Model Description of the Network Model for AUST

The model being developed assists in solving the problems of finding the patterns or trends in the dataset obtained from the monthly electricity consumption utility bills as shown in Figure 3.8. The model will be used to predict the monthly electricity consumption at AUST. The monthly electricity consumption is deduced from the utility bills.

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.

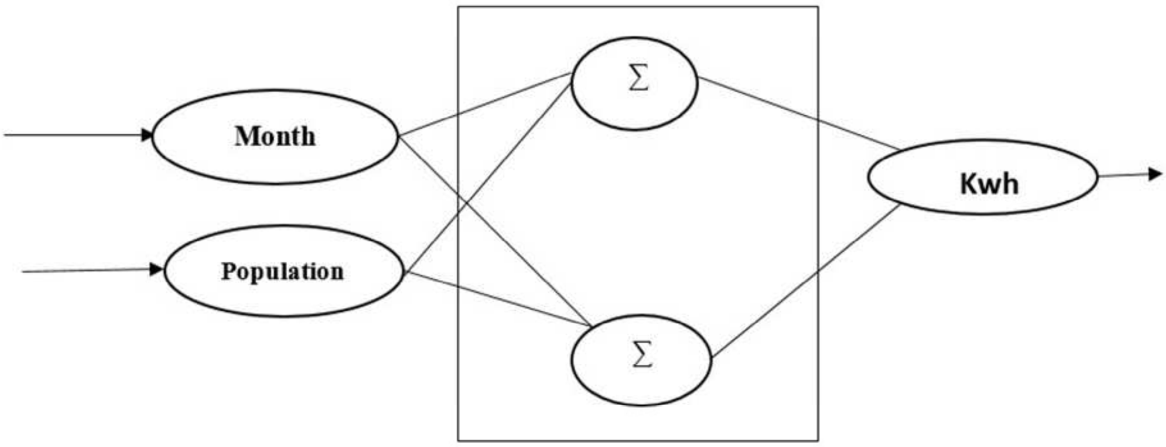

Figure 3.8: Architectural Framework of the ANN for AUST Electricity Consumption

Furthermore, considering the nature of the problem, the best neural network architecture to be employed is an MLP because the problem is not linearly separable, i.e. two months may have similar input weight but their electricity consumption may be different. Also, it is highly reliable in prediction and classification. Another reason for adoption of the MLP network is as a result of its flexibility, especially when there is a high level of complexity within the dataset (Samarasinghe, 2007).

Nonlinear neurons are contained in the hidden layer that accomplishes continuous conversion of the weighted inputs (Samarasinghe, 2007).

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

$f(x)\frac{1}{(1+e^{-x})}$ 3.1

3.11 Training the 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 (Samarasinghe, 2007) which combines the advantage of the GaussNewton 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 (Samarasinghe, 2007).

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).

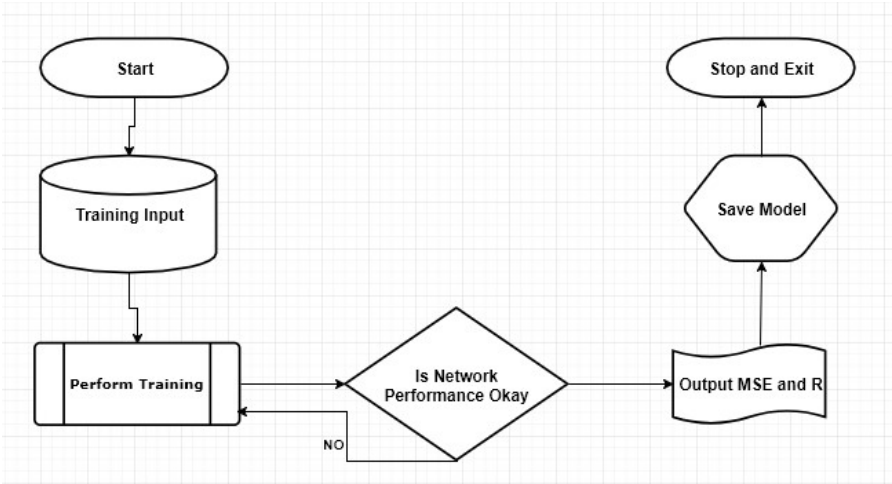

Figure 3.9: Training Flowchart for the ANN Model

3.12 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 for 2015 to the present, 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.

3.13 Performance Evaluation Analysis

In evaluating a model's performance, there are 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.:

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

Where t_i 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 x_i 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 (Deshpande, 2012). 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.

3.14 Implementation of ANN using MATLAB

The software used in this research is MATLAB, which is a multi-paradigm numerical computing environment. It has a network fitting tool referred to as NFTOOL used for solving data fitting problems. It maps a data set of numeric inputs and a set of numeric targets.

3.14.1 Neural Fitting Tool

MATLAB has a network fitting tool referred to as NFTOOL used for solving data fitting problems. It maps a data set of numeric inputs and a set of numeric targets. Essentially, it helps to select data, create and train a network and then evaluate its performance using the MSE and the regression analysis. It consists of a two-layer feed forward network with sigmoid hidden neurons and linear output neurons trained with the Levenberg-Marquardt algorithm (Sharma & Nijhawan, 2015). This algorithm typically takes less time, as training automatically stops when generalization stops improving, as indicated by an increase in the mean square error of the validation samples.

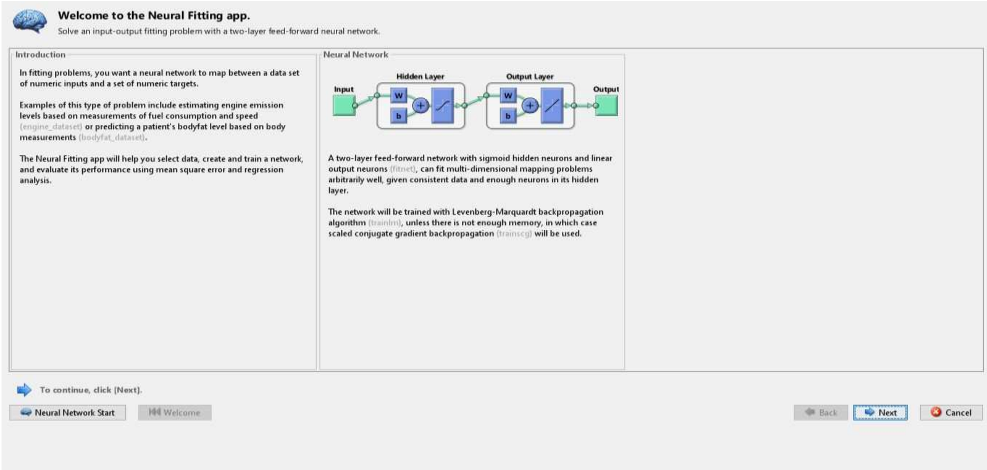

Figure 3.10: Schematic of the Neural Fitting Tool Start Pane

3.14.2 Data Selection from the Workspace Area

For data selection, we select the inputs and targets that define our fitting problem by importing them from our workspace accordingly.

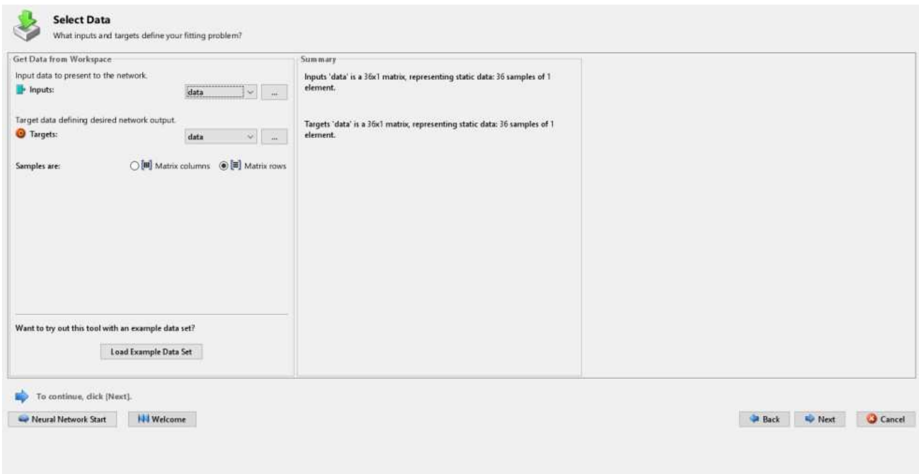

Figure 3.11: Schematic of the Data Selection in Neural Fitting Tool

3.14.3 Data Validation and Testing Pane

At this stage, the data samples are divided into three categories. They include the training set, testing set and validation set. In this project we had 36 samples divided in the ratios 70:15:15. During training, the network is adjusted according to its error. Validation measures the network generalization and halts network generalization when the network stops improving while the testing provides an independent measure of network performance during and after training.

Figure 3.12: Schematic of Data Validation and Testing in Neural Fitting Tool

3.14.4 Network Architecture Pane

On this pane are the number of neurons in the fitting network hidden layer. The number of neurons is changed if the network does not perform well after training.

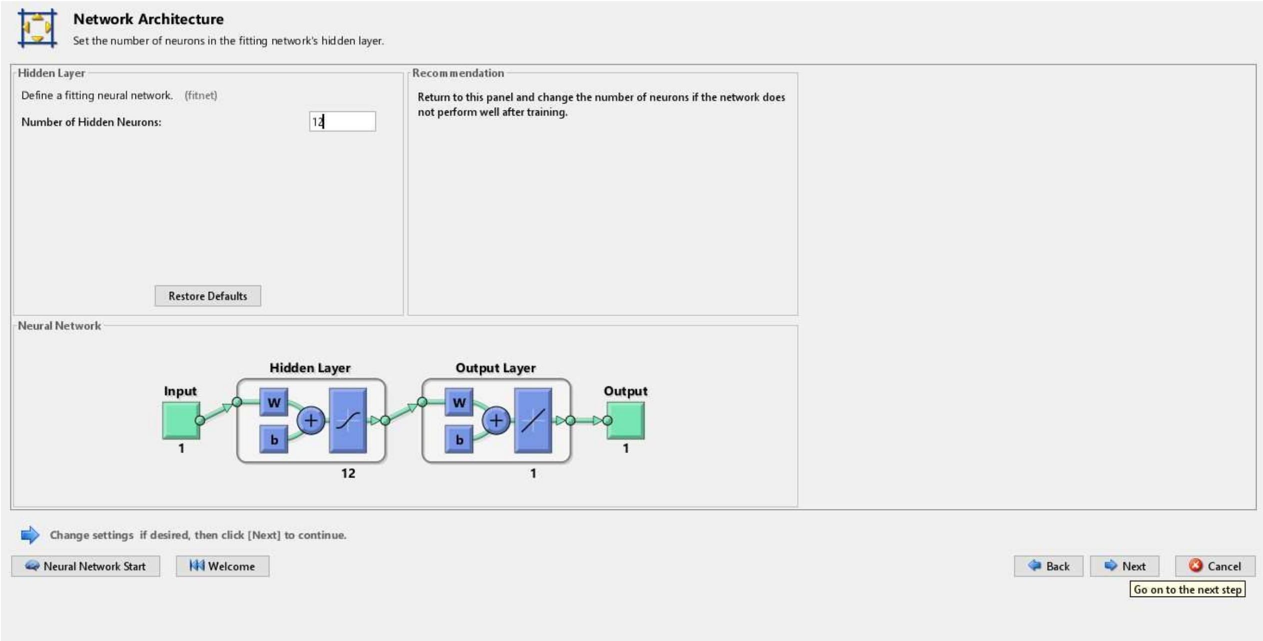

Figure 3.13: Schematic of Network Architecture in Neural Fitting Tool

3.14.5 Network Training Pane

On this pane, we specify the training algorithm to use to use, which includes Levenberg-Marquardt, Bayesian regularization and scaled conjugate gradient. Training automatically stops when generalization stops improving as indicated by an increase in the mean square error of the validation samples.

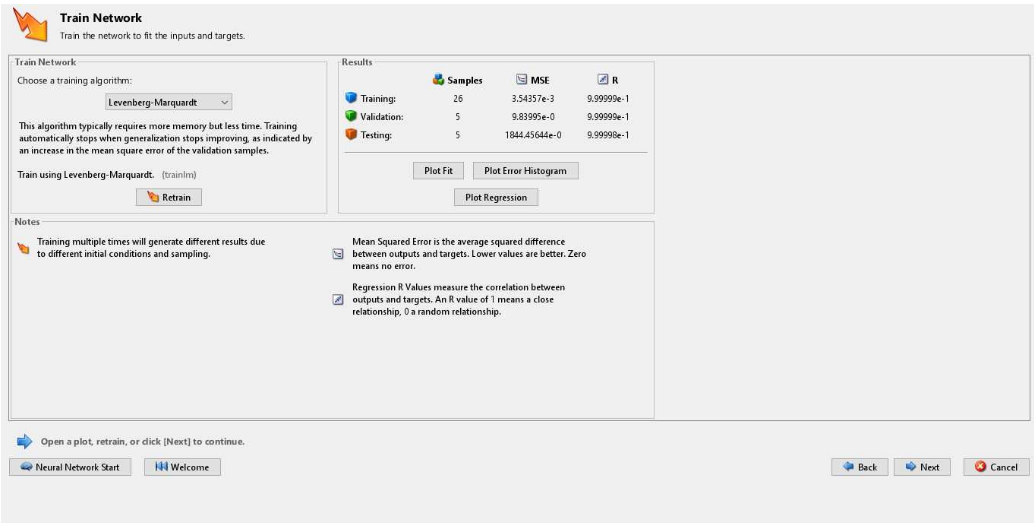

Figure 3.14: Schematic of the Training Pane in Neural Fitting Tool

3.14.6 Network Evaluation Pane

On this pane we test the network on more data and then decide if the network performance is good enough. Essentially, we retain the network, iterate by increasing the network size or using a larger data set for improved performance.

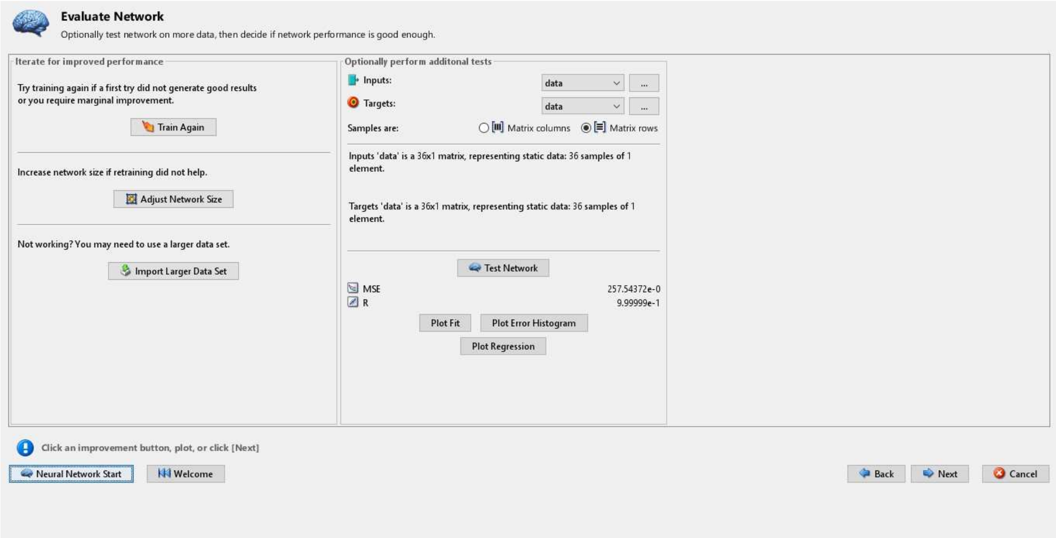

Figure 3.15: **Schematic of the Network Evaluation Pane in Neural Fitting Tool**

3.14.7 Application Deployment Pane

On this pane we can generate deployable versions of our trained network. This includes generating functions with matrix and cell array argument support, generating a Simulink diagram and a graphical diagram of the neural network.

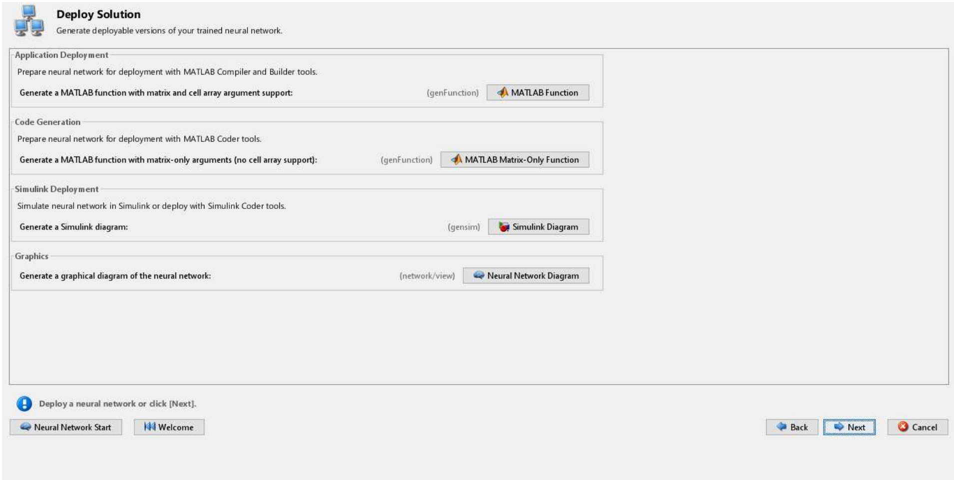

Figure 3.16: Schematic of the Application Deployment Pane in Neural Fitting Tool

3.14.8 Results Pane

We are able to generate scripts to solve similar problems, save results and then generate diagrams.

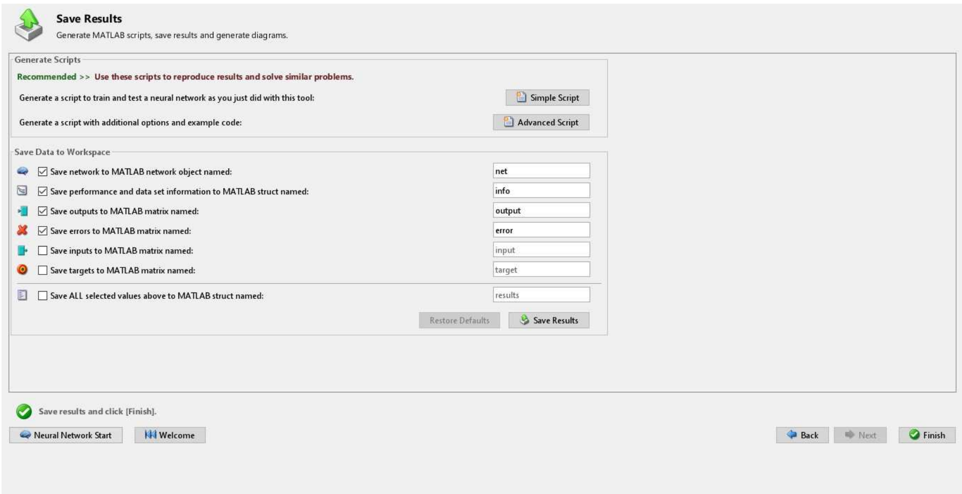

Figure 3.17: Schematic of the Result Pane in Neural Fitting Tool

CHAPTER FOUR RESULTS AND DISCUSSION

4.1 Introduction

In this chapter, the results obtained from developing the models for the monthly electricity consumption of AUST are discussed. This was achieved using the MLP neural network. The models were trained using two input variables (the month and population) and then 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 second model designed was for electricity consumption between 2012 to 2014 when AUST was charged at a flat rate, since not until 2015 did they have a metering system.

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.

4.2 Performance and Comparisons of the Models

The results obtained for designing a model for electricity consumption for AUST from 2015 to 2017 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.

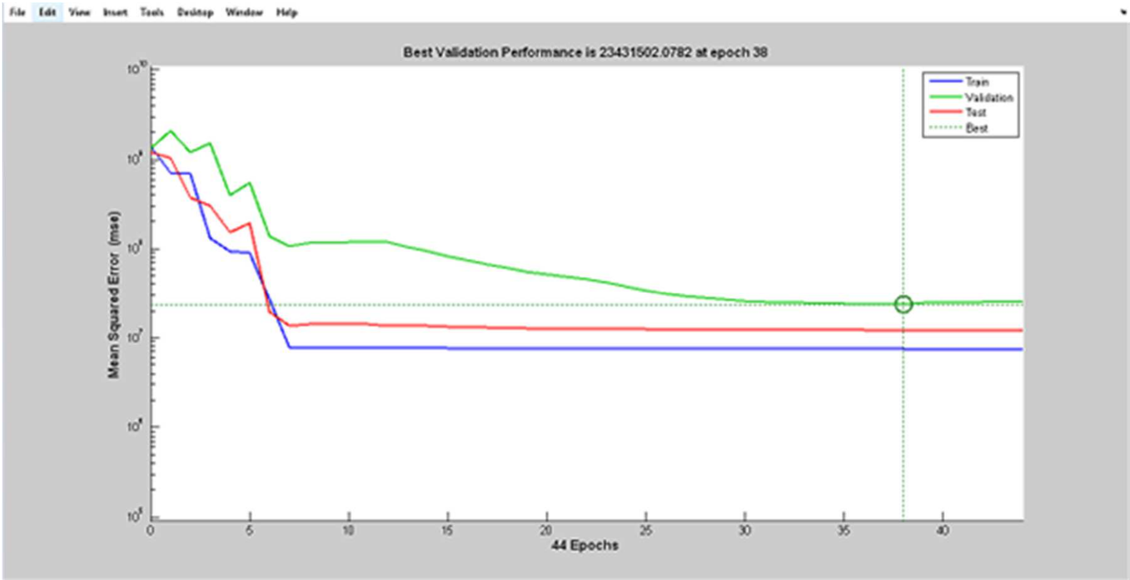

Figure 4.1: Schematic of Forecast Trend Made with 12 Neurons for 2015 to 2017

For the second model being built for 2012–2014 shown in Figure 4.2 below, we noticed that there were basically no visible lines (training, validation, test) in our model since the value of our MSE is zero.

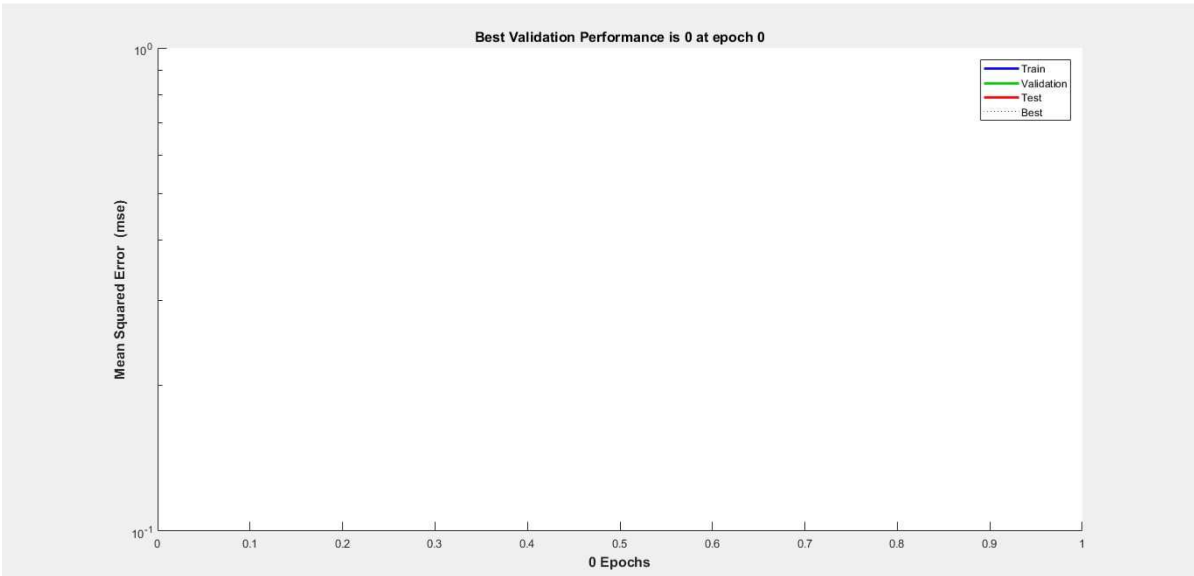

Figure 4.2: Schematic of Forecast Trend Made with 12 Neurons for 2012 to 2014.

4.3 Validation and Testing Results

Figure 4.3 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.

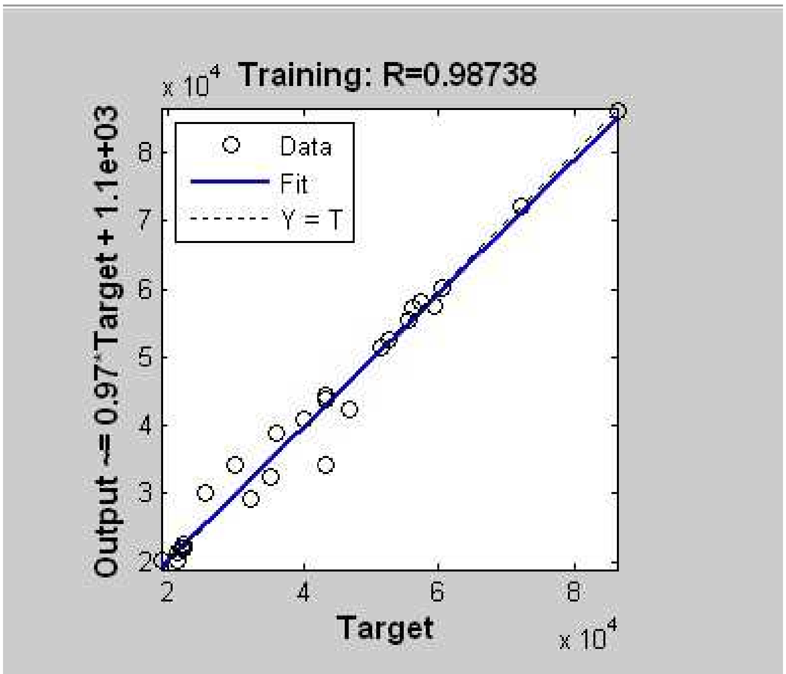

Figure 4.3: Schematic of Regression Training Graph for 2015 – 2017

Figure 4.4 represents the regression plot of the validation, which shows the relationship existing between the outputs of the network and the targets.

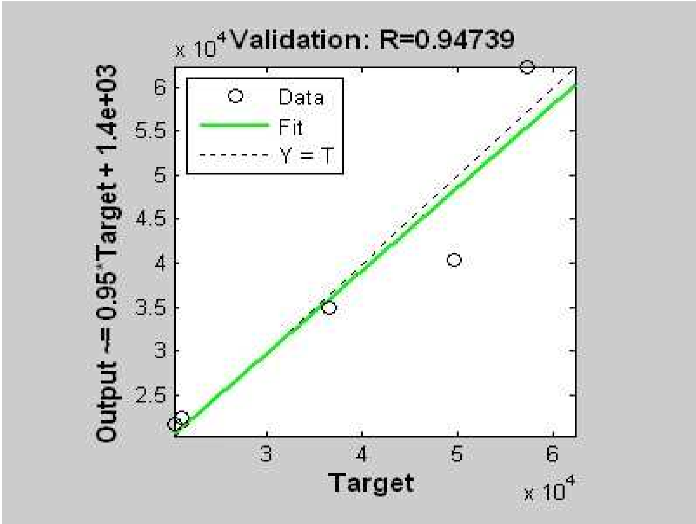

Figure 4.4: Schematic of Regression Validation Graph for 2015 – 2017

The results for this model derive from electricity consumption between 2012 and 2014, 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 2015–2017 data.

Table 4.1: Comparisons of the Built Models with Respect to MSE and R

Model	**Neurons Used in the Hidden Layer**	**MSE**	**R**
2012 to 2014	12	0	0
2015 to 2017	12	12106440.38	0.97

4.4 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 4.2 is deduced from the model built using the utility bills for the monthly electricity consumption from 2015 to 2017 using the metering system.

Table 4.3 is deduced from the model built using the utility bills for the monthly electricity consumption from 2012 to 2014 using the flat rate.

From Table 4.2 and Table 4.3 below, we observe that the model built using the metering system which is Table 4.2 has a better predictive accuracy when it comes to forecasting when compared to the former.

Table 4.2: Tabulation of Results Built Using the Dataset from 2015 to 2017

Months	Actual Consumption (Kwh)	Predicted Consumption (Kwh)
1	20320	19850
2	21340	21383
3	22102	22549
4	21230	21205
5	21140	21059
6	22325	22841
7	22019	22433
8	21494	21632
9	21320	21351
10	25514	24540
11	29708	27222
12	29708	27222

Table 4.3: Tabulation of Results Built Using the Dataset from 2012 to 2014

Months	Actual Consumption (Kwh)	Predicted Consumption (Kw/h)
1	1754	1754

2	1754	1754
3	1754	1754
4	1754	1754
5	1754	1754
6	1754	1754
7	1754	1754
8	1754	1754
9	1754	1754
10	1754	1754
11	1754	1754
12	1754	1754

CHAPTER FIVE CONCLUSION AND FUTURE WORK

5.1 Conclusion

The research work developed an artificial neural network model for monthly electricity consumption prediction in a university campus using AUST as a case study. This model was built using the MLP. Data was collected from 2015 to 2017, the period AUST started using a metering system that measured the monthly power consumption, and a model was therefore built with an MSE of 12106440.38 and R 0.97 respectively. Also, another model was built using the data collected from 2012 to 2014 when the school was charged at a flat rate by the PHCN realizing an MSE and R to be zero respectively. Hence, a regression graph could not be built using NFTOOL because the value of all our output, which is the dependent variable were all the same as indicated from the data we collected. But we could make an inference from Figure 3.4 which shows a straight-line graph of 180 degrees. This is not intelligent enough as it does not provide a good predictive model. The model was built using 12 neurons after 11 iterations

This research will enable the university to understand the trend of electricity consumption and then devise policies on energy management and savings. Also, it will assist the university on planning their budget by making adequate planning on the number of students to be admitted and the monthly electricity consumption required accordingly.

5.2 Future Work

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 from other institutional buildings in Abuja where AUST is located, 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 that influence electricity consumption to build improved neural network models.

Occupancy (students') behaviour such as how often the lightbulbs are being switched on, including the HVAC when they are not in use, could also be considered as a variable by using a questionnaire.

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APPENDIX

Some Scripts of MATLAB for the Built in Functions Used.

```
% Solve an Input-Output Fitting problem with a Neural Network
% Script generated by NFTOOL % Created
Mon Nov 14 02:10:09 WAT 2016
%
% This script assumes these variables are defined:
%
% data - input data.
% data - target data.
 inputs =
data'; targets
= data';

% Create a Fitting Network
hiddenLayerSize = 12; net =
fitnet(hiddenLayerSize);

% Choose Input and Output Pre/Post-Processing Functions % For a
list of all processing functions type: help nnprocess
net.inputs{1}.processFcns = {'removeconstantrows','mapminmax'};
net.outputs{2}.processFcns = {'removeconstantrows','mapminmax'};

% Setup Division of Data for Training, Validation, Testing %
For a list of all data division functions type: help nndivide
net.divideFcn = 'dividerand'; % Divide data randomly
net.divideMode = 'sample'; % Divide up every sample
net.divideParam.trainRatio = 70/100; net.divideParam.valRatio
= 15/100; net.divideParam.testRatio = 15/100;

% For help on training function 'trainlm' type: help trainlm %
For a list of all training functions type: help nntrain
net.trainFcn = 'trainlm'; % Levenberg-Marquardt

% Choose a Performance Function
% For a list of all performance functions type: help nnperformance net.performFcn
= 'mse'; % Mean squared error
```

```
% Choose Plot Functions
% For a list of all plot functions type: help nnplot
net.plotFcns = {'plotperform','plottrainstate','ploterrhist',...
 'plotregression', 'plotfit'};

% Train the Network
[net,tr] = train(net,inputs,targets);

% Test the Network outputs = net(inputs);
errors = gsubtract(targets,outputs);
performance = perform(net,targets,outputs)

% Recalculate Training, Validation and Test Performance
trainTargets = targets.* tr.trainMask{1}; valTargets =
targets.* tr.valMask{1}; testTargets = targets.*
tr.testMask{1}; trainPerformance =
perform(net,trainTargets,outputs) valPerformance =
perform(net,valTargets,outputs) testPerformance =
perform(net,testTargets,outputs)

% View the Network
view(net)
% Plots
% Uncomment these lines to enable various plots.
%figure, plotperform(tr)
%figure, plottrainstate(tr)
%figure, plotfit(net,inputs,targets)
%figure, plotregression(targets,outputs)
%figure, ploterrhist(errors)
```