Artificial Neural Network Model for Short-Term Electric Load Demand Forecasting: A Case of Nairobi Region

Evans Kiptum

***Abstract*— Power engineers and energy planners require accurate electric load demand forecasts for efficient load dispatch, good generation mix and generation planning. Load forecasting using traditional statistical methods is often difficult because a number of non-linear factors interplay to produce the final result. Artificial Neural Networks (ANNs) may be a good candidate to perform load forecasting, with proper training using appropriate learning data and algorithms, since they tolerate non-linear inputs. In this paper, we propose to use load demand data in megawatts (MW) from Kenya Power Company's connected customers in Nairobi region measured half-hourly over a period of one year (January to December 2014) to appropriately develop ANN models, train them and validate the data for the purpose of predicting the next day's load demand for seven consecutive days. Other variables used are day type and the month of the year. Three ANN models were used in this research namely: Multilayer Perceptron, Linear Network and Pattern Recognition Network. The best model is one that will give the least Root Mean Square Errors (RMSEs). The results of the predictions have given an indication of how ANN models may be used to forecast electric load demand in a given area under constraints of several intervening factors. Accurate predictions may save important operating costs for Kenya Power Company. The result of this study may be useful to the Ministry of Energy (for planning purposes) and Kenya Generating Company for economic load dispatch decisions.**

***Index Terms*— Load Forecasting, Artificial Neural Networks**

I. INTRODUCTION

Electric utilities find it important to know the electrical load demand predictions for their customers. Many statistical methods have been used to achieve the objective of load forecasting. Lately, because of the improvements in digital computing and Soft Computing (which allows but discourages imprecision and uncertainty), ANN models have become popular with researchers and system designers.

ANN is ''a data processing system consisting of a large number of simple, highly interconnected processing elements (artificial neurons) in an architecture inspired by the structure of the cerebral cortex of the brain''[1]. ANN is also described "to consist of a number of very simple and highly interconnected processors, called neurons, which are analogous to the biological neurons in the brain. The neurons are connected by weighted links from the inputs passing from one neuron to [2].

ANNs represent a technology that is rooted in many disciplines such as neurosciences, mathematics, statistics, physics, computer science, and engineering. ANNs have found applications in various processes which originally required much human intelligence, hence the term, artificial intelligence. According to [3], ANN resembles the human brain in two respects:

Knowledge is acquired by the network from its environment through a learning process, and
Interneuron connection strengths (synaptic weights) are used to store the acquired knowledge.

Reference [3] further asserts that neural networks find applications in such diverse fields as modelling, time series analysis, pattern recognition, signal processing, and control by virtue of their ability to learn from input data with or without a teacher. ANNs also offer other merits namely: better performance; no need for system modelling; tolerance of bizarre patterns (noisy inputs); and adaptive capability.

ANNs have been successfully used to design a variety of systems, entailing both linear (following a piecewise continuous pattern) and non-linear processes. Researchers from many scientific disciplines are today designing ANNs to solve a variety of problems in pattern recognition [5] prediction [6] & optimization [5] associative memory [4][5] and control [4].

ANNs may be used to perform electric load demand forecasting using data from previous history of load, temperature, humidity, luminosity, and wind speed among other factors. However, accurate models of load forecasting that use many of these factors increase the modelling complexity and computational requirements of the systems used to achieve this objective [6]. This project seeks to formulate an Artificial Neural Network model for load forecasting for Nairobi region.

Goal and Objectives of the Paper

The main goal of this paper is to formulate an Artificial Neural Network Model for Short Term Electric Load Demand Forecasting for Nairobi region (Nairobi County and its environs i.e., Kiambu and Ngong). This goal will be achieved by addressing the following specific objectives:

I. To assess how electric load forecasting may be achieved using Artificial Neural Network models.
II. To formulate an ANN model for use in forecasting electric load demand.
III. To evaluate the best ANN model for forecasting electric load demand based on the relative errors.

II. RELATED LITERATURE

Reference [5] describes how roots of all work on neural networks arose from neurobiological studies that date back to more than a century ago in a bid to speculate on exactly how the nervous system works. Another front for research came

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from psychologists who strove to understand exactly how learning, forgetting, recognition, and other such tasks are accomplished by animals. These research works have greatly assisted to enhance the understanding of the structure and architecture of artificial neural networks.

Structure of ANNs

Artificial neural networks refer to computing systems whose central theme is borrowed from the analogy of biological neural networks. The structure of ANN depicts some interconnection of nodes or networks through neurons, which are the basic building blocks of biological information processing systems [7]. A biological neuron is shown in Figure 1.

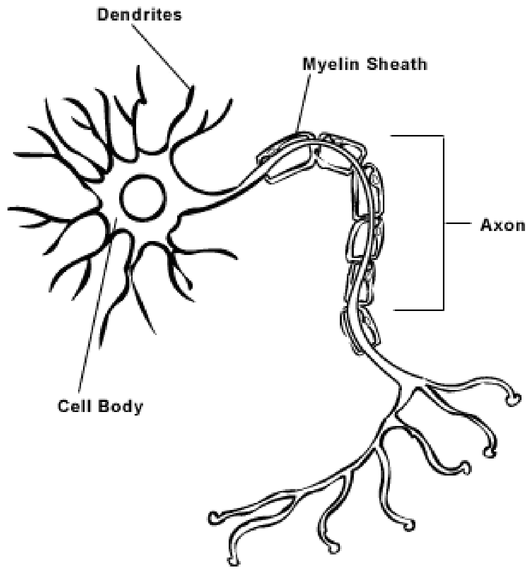

Figure 1: Single Biological Neuron

The neuron has three morphologically defined portions, which contribute to information processing signals by the neuron [7]. These are:

A cell body (soma) – which contains the cell nucleus.

The axon – this is the main conduction mechanism of the neuron.

Dendrites – branch out in tree-like fashion and are connected to the axons of other neurons via synaptic connections or synapses.

Architecture of ANNs

The neural architecture consists of three or more layers i.e., input, output and hidden layers [5][6].

Input Layer – a layer of neurons that receives information from external sources, and passes this information to the network for processing.

Hidden Layer – a layer of neurons that receives information from the input layer and processes them in a hidden way to other layers within the system.

Output Layer – a layer of neurons that receives processed information and sends output signals out of the system.

Bias – Acts on a neuron to provide a threshold for its activation.

Generally, there are three ANN architectures based on topology, node characteristics, learning or training algorithms. These are:

Single-layer feedforward networks – connections are between outputs of each layer and inputs of the next layer.

Multi-layer feedforward networks – have one or more hidden layers with computation neurons in between the input and output layers.

Recurrent networks – have no hidden layer but have at least one feedback loop feeding its output signal into the inputs of all the other neurons.

Forecasting Using ANNs

Past research of ANN-based load forecasting involved the daily peak load or total load with the factors of temperature, seasons, or day-types. The selection of training input variables is important in the accuracy of prediction. A typical ANN architecture for electric load forecasting is shown in Figure 2.

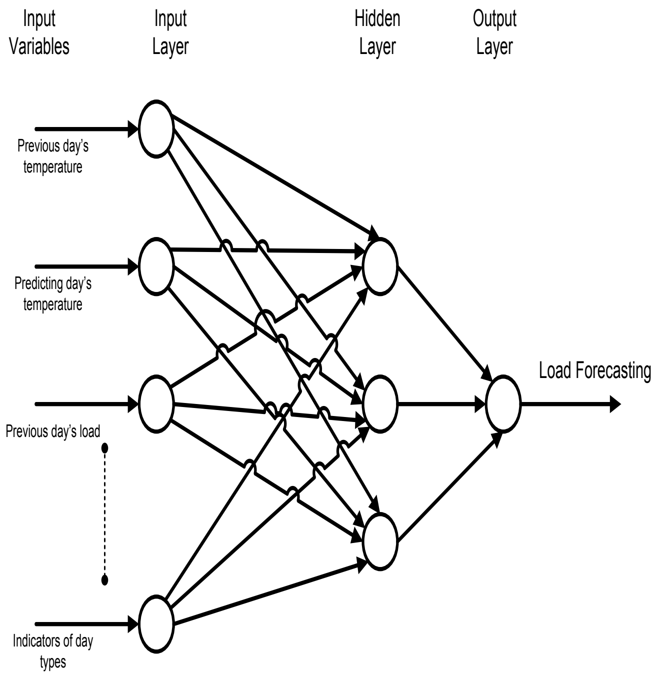

Figure 2: ANN Architecture for Load Forecasting

In Singapore, a three-layer-architecture back-propagation network model (BPN) was used to predict the daily peak load [8]. This study concluded that using a lower learning rate for the layers gives accurate prediction and that there is no firm criterion for selecting training inputs. Reference [9] used ANN model for flood forecasting in Greece.

Reference [10] used autoregressive integrated moving average (ARIMA), ANN and multiple linear regression (MLR) to forecast electricity demand in Thailand. This study concluded that there are no empirical or exact rules to derive the best forecasting model, but the most appropriate one is selected by choosing the model with the lowest error, which was the ANN model.

RESULTS AND DISCUSSION

Overview of Methodology

Data measured half-hourly between January and December was used (that is 365 days). Data sets for 365 days total (48x365) = 17,520. This set of data was then used to predict load demand for the next seven consecutive days, that is beginning from 25th – 31st December, 2014. The training data was selected from the 1st to the 364th day, that is, (364/365)*100 = 99.7% of the total data. The type of day had Monday through Sunday assigned the numbers 1 through 7 respectively. The number of day (that is 1st January was assigned day 1, progressing that way up to the 365th day being assigned the number 365. The simulation was achieved in MATLAB program using the Neural Network (NN) Toolbox [11]. The data sets were first arranged in an appropriate format in MS Excel, and then, later exported to MATLAB as matrices for ease of manipulation.

Data Graph for 365 Days

To generally appreciate the trend for the 17,520 annual data sets, a graph was produced as shown below.

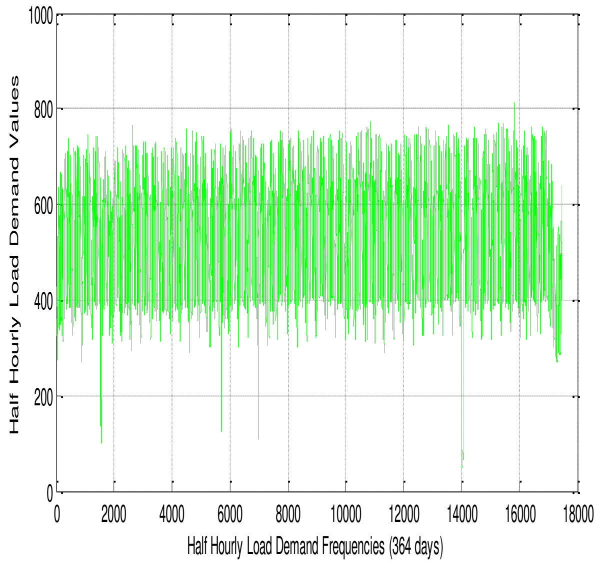

Figure 3: Data Trend for 365 Days

It can be seen from *Figure 3* that there is a normal pattern for the half-hourly load demand over the entire period, save for a few data valleys, which could have occurred due to loss of generation at those particular times. Neural networks learn by example and thus only the dominant pattern of the data is used for load forecasting in the subsequent sections.

Multilayer Perceptron Network Model

This network model is usually chosen because it has a number of hidden layers, which is better for extracting higher order statistics for large data sets. This network model experimented with different numbers of neurons in the hidden layer, epochs and transfer functions. As an example of showing the RMSE calculation that is used in load forecasting methods, the calculation yielded a value of **0.28** for 31st December, 2014. The predicted and actual load shapes for example days of: 25/12/2014; 26/12/2014 and 31/12/2014 are respectively shown in the figures below.

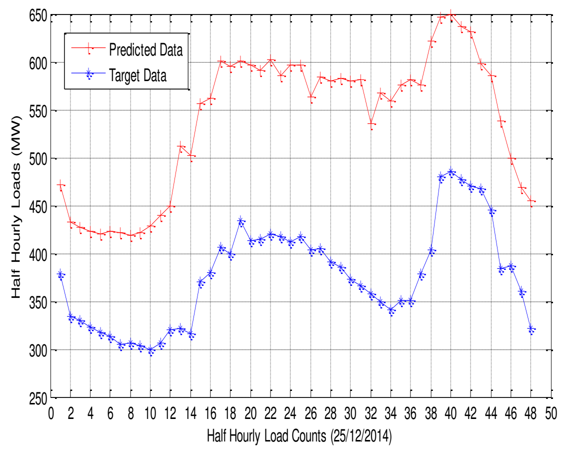

Figure 4: Load Forecasting Using MLP Network for 25/12/2014 (Thursday)

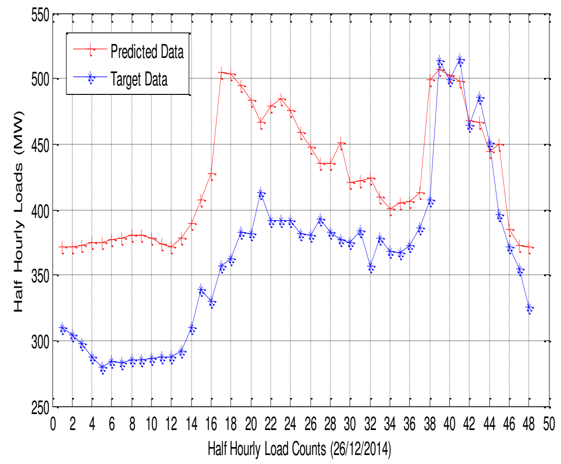

Figure 5: Load Forecasting Using MLP Network for 26/12/2014 (Friday)

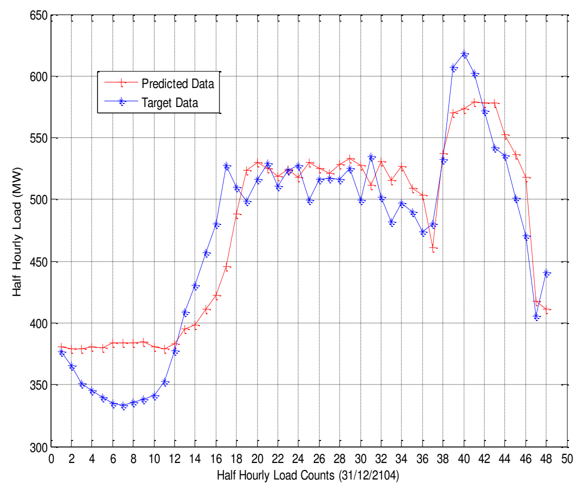

Figure 6: Load Forecasting Using MLP Network for 31/12/2014 (Wednesday)

Snapshots of the NN and Regression at the end of training are shown in *Figure 7* and *Figure 8*.

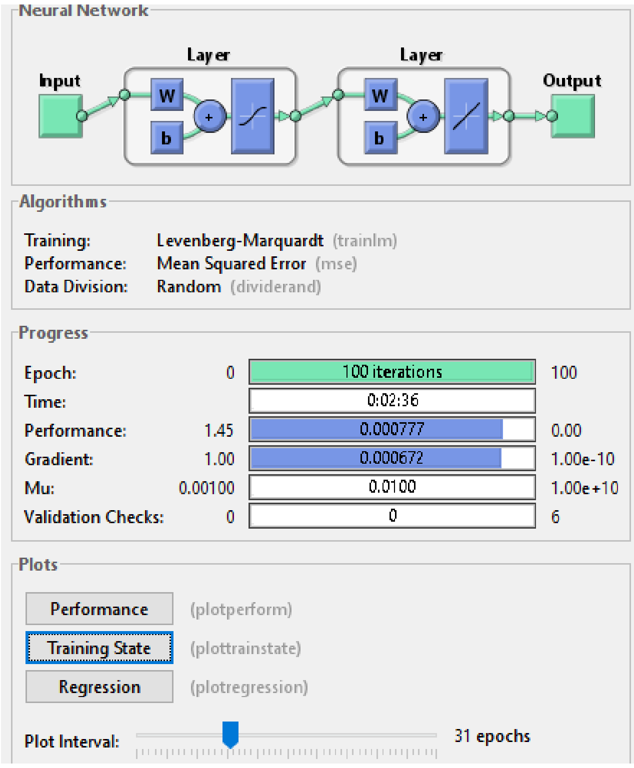

Figure 7: Snapshot of MATLAB NN Tool Modelling

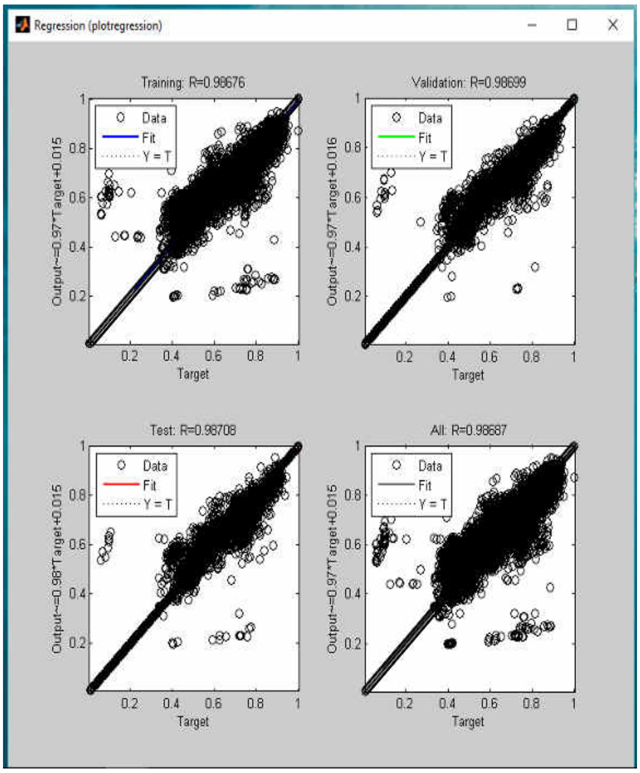

Figure 8: Snapshot of Regression in MLP Network

Linear Network Model

The Forecasted vs Actual Load Demand for example days of: 25/12/2014; 26/12/2014 and 31/12/2014 are shown in the figures that follow. The RMSE was computed for 31st December, 2014 and it yielded the value **0.13**.

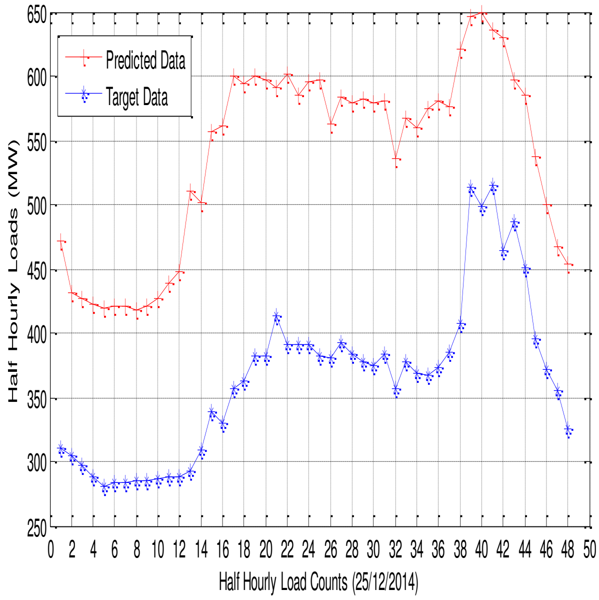

Figure 9: Load Forecasting Using Linear Network for 25/12/2014 (Thursday)

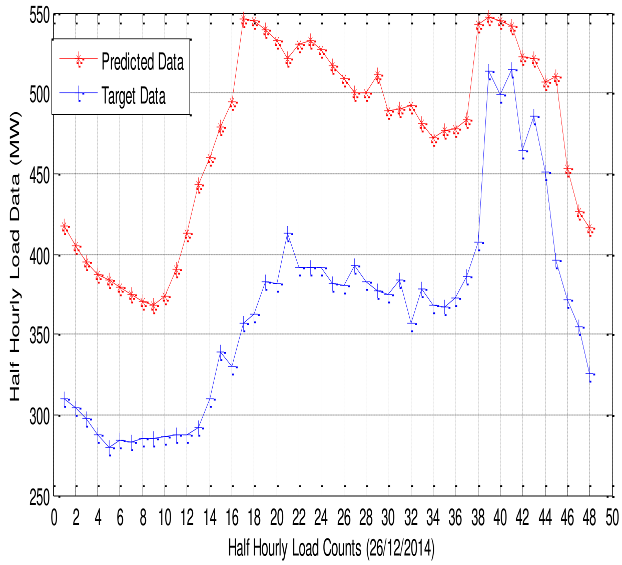

Figure 10: Load Forecasting Using Linear Network for 26/12/2014 (Friday)

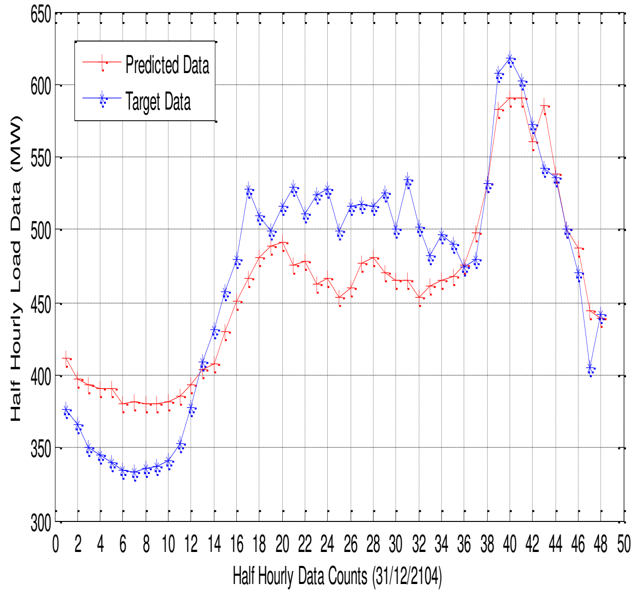

Figure 11: Forecasting Using Linear Network Model for 31/12/2014 (Wednesday)

Pattern Recognition

Pattern recognition classifies input data into objects or classes based on key features using either supervised or unsupervised classification. In this research, the Forecasted and Actual Load Demand data for the example days of: 25/12/2014; 26/12/2014 and 31/12/2014 were plotted in graphs as shown below. The RMSE was also computed in this network model and it produced the least value at **0.09** for 31st December, 2014, thus making this network model the best one to use for load forecasting exercise.

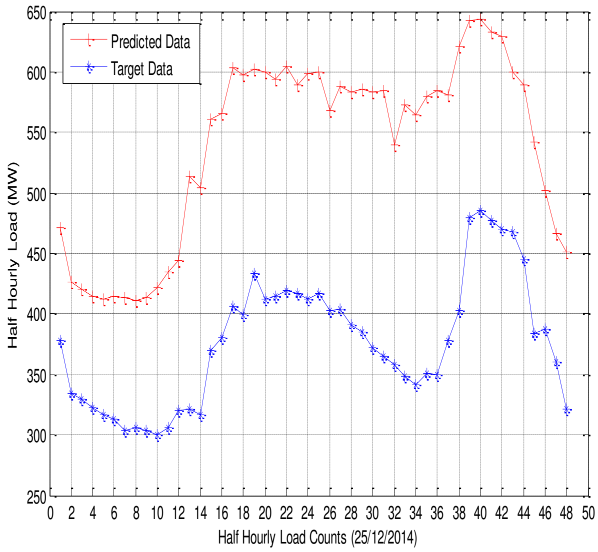

Figure 12: Load Forecasting Using Pattern Recognition Network for 25/12/2014 (Thursday)

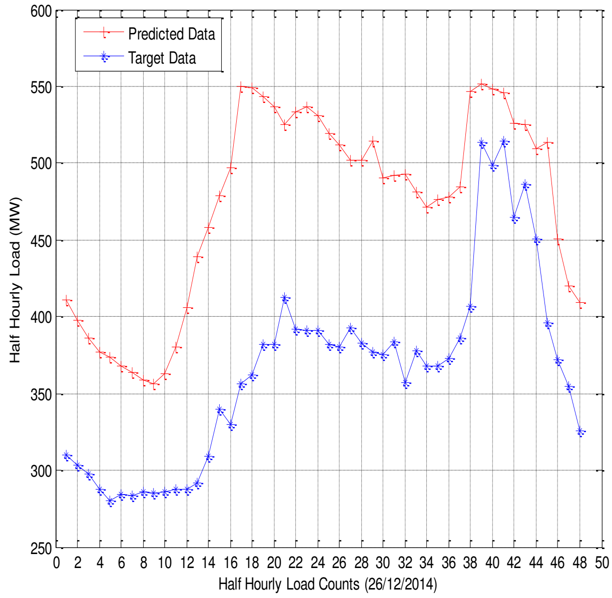

Figure 13: Load Forecasting Using Pattern Recognition Network for 26/12/2014 (Thursday)

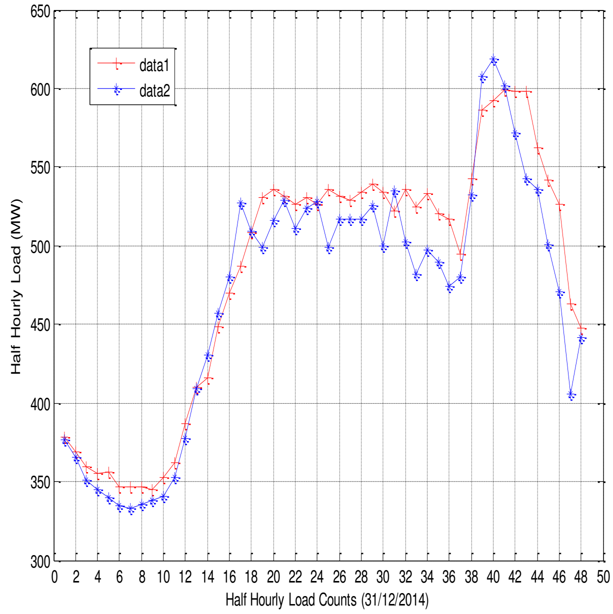

Figure 14: Forecasting Using Pattern Recognition Network for 31/12/2014 (Wednesday)

CONCLUSION

This research project was conducted with the view of strengthening the understanding of the many complex internal processes that take place in conventional intelligent systems for load forecasting that are used by utility firms. Three Artificial Neural Network models were used to simulate the load forecasting process with their levels of successes being measured from the relative values of the Root Mean Square Errors (RMSEs). The RMSE value was least in Pattern Recognition Network (**0.09**), followed by Linear Network (**0.13**) and Multilayer Perceptron network (**0.28**). However, the experimentation with Multilayer Perceptron network model was most interesting because such parameters as: the number of neurons in the hidden layer; the training algorithm;

and the number of epochs could be altered to arrive at optimal results. This research project will go a long way in helping future researchers understand the intricacy of load forecasting influenced by many intervening factors.

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