Short-term Load Forecasting using Neural Network for a Residential Building

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ABSTRACT

As energy consumption rises it becomes important for electric utilities to make adequate plan for this increase to avoid inefficiencies in generation, transmission and distribution of electrical energy. One of the ways of tackling this is to forecast the load for a period of time for proper energy management and utilization. Load forecasting has gained so much popularity over the years however having an accurate load forecast has become a great challenge for researchers as this is very important in power system management.

The aim of this study is to have an idea of energy performance in residential buildings, analyze the historical data to see the trend line of energy consumptions in residential buildings, identify factors that influence the increase in energy use and then employ a short term load forecast using Neural Network (NN) in order to encourage proper utility planning. Factors affecting load consumptions are studied, different short-term load forecasting models are reviewed and a neural network architecture is proposed.

A 1.233% mean absolute percentage error (MAPE) result is obtained by analysing the load data, classifying it into day types, selecting similar days and constructing the neural network architecture. From the results obtained it can be concluded that the tendency of the neural network to forecast load consumption is accurate.

Keywords: Energy consumption, short-term load forecasting, neural network

ÖZ

Enerji tüketimi arttıkça, elektrik kurumlarının bu artış için elektrik enerji üretimi, iletimi ve dağıtımında oluşabilecek yetersizliklerden kaçınmak için gerekli planlamayı yapması önemlidir. Bunu takip edebilmenin bir yolu, uygun enerji yönetimi ve kullanımı için belli bir süre boyunca yük tahmini yapmaktır. Yük tahmini yıllar geçtikçe çok yaygınlaşmıştır ancak güç sistemi yönetiminde önemli yeri olan yük tahminin doğru yapılabilmesi araştırmacılar için zorlu bir görevdir.

Bu çalışmanın amacı, konutlarda enerji performansı ile ilgili bilgi edinmek, konutlarda enerji tüketim trendini önceki verileri çözümleyerek incelemek, enerji artışındaki etmenleri belirlemek ve daha sonra uygun planlamaya teşvik amacıyla Yapay Sinir Ağı kullanarak kısa dönem yük tahmini gerçekleştirmektir. Yük tüketimini etkileyen etmenler araştırılmış, farklı kısa dönem yük tahmini modelleri incelenmiş ve yapay sinir ağı mimarisi sunulmuştur.

Yük verisi incelenerek gün tipleri sınıflandırılmış, benzer günler seçilmiş ve yapay sinir ağı mimarisi oluşturularak, % 1.233 ortalama mutlak yüzde hatalı sonuçlara ulaşılmıştır. Elde edilen sonuçlara göre, yapay sinir ağının yük tahmininde doğru sonuçlar verdiği söylenebilir.

Anahtar Kelimeler: Enerji tüketimi, kısa dönem yük tahmini, yapay sinir ağı

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With a grateful heart, I dedicate this thesis to my amazing and wonderful family, friends and loved ones for their support and encouragement (in words and in kind).

I love you all!

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LIST OF ABBREVIATIONS

ARIMA	Autoregressive integrated moving average
ARIMAX	Autoregressive integrated moving average with exogenous variables
ARMA	Autoregressive moving average
BP	Back-propagation
EP	Evolutionary programming
ES	Expert systems
KIBTEK	Cyprus Turkish Electrical Authority
MAPE	Mean absolute percentage error
MLP	Multilayer perceptron
NN	Neural Network
Tce	Ton of standard coal equivalent
TRNC	Turkish Republic of North Cyprus
TV	Television
STLF	Short term load forecasting
SVR	Support vector regression
VSTLF	Very short term load forecast

LIST OF SYMBOLS

Δc	Desired outputs
$\widehat{Day}$	Day type for the forecasted day
Day^p	Day type of the previous days searched
E	Energy function
$\varepsilon(t)$	White noise component
H_A	Actual load
H_F	Forecasted load
i	Index for hour
j	Smallest integer
$L(h)$	Load at hour h
$L_n^k(n = 1{\sim}24)$	24 hour load consumption curve on similar day
$L(t)$	Load at time t
$\max(x)$	Maximum value for variable x
$\min(x)$	Minimum value for variable x
N	Total number of hours
p	Training pattern
r_i	Estimated slowly varying coefficients
$s(t)$	Standard load
t	Time
$t(h)$	Temperature that corresponds to the load $L(h)$
$\hat{T}_{max}$	Maximum temperature on forecasted day
$\hat{T}_{min}$	Minimum temperature on forecasted day

T_{max}^{p}	Maximum temperature of the previous day
T_{min}^{p}	Minimum temperature of the previous day
$\widehat{w}_i (i = 0,1,2,3)$	Weights
x	Input neuron
$x^{'}$	Normalized x
x_i	Input signals
y	Output
$y_i(t)$	Independent factors such as weather

Chapter 1

INTRODUCTION

1.1 Problem Statement

The Energy consumption in buildings makes up 45% of the energy consumption in the world today. As a result of drastic economic development in countries, increase in standard of living and the income of the people, energy consumption in buildings has greatly increased.

In [1], it is stated that between 1996 and 2006, energy consumption in China alone increased from 0.243 billion tce (ton of standard coal equivalent) to 0.563 billion tce making it a 1.3 fold increase. In 2006 Residential buildings consumed 0.255 billion tce of energy approximately 40 percent of total energy consumption in buildings [1]. This implies that residential buildings consume a more of the total building energy consumption [1].

Domestic and international factors affect energy consumption in residential buildings which is associated with differences in time, locality and other features. [2]. Location and size of residential buildings equally play a major role in energy consumption. Small apartments require less energy as they need less air conditioning/heating, transfer area and less occupation. The amount and type of energy consumed in residential buildings is directly related to the weather condition, architectural design, energy systems and economic level of occupants [3].

As energy consumption rises it is important for electric utilities to make adequate plan for this increase to avoid inefficiencies in generation, transmission and distribution of electrical energy. One of the ways of tackling this is to forecast the load for a period of time for proper energy management and utilization.

1.2 Purpose

The aim of this study is to have an idea of energy performance in residential buildings, analyze the historical data to see the trend line of energy consumptions in residential buildings, identify factors that influence the increase in energy use and then employ a short term load forecast using Neural Network (NN) in order to encourage proper utility planning.

1.3 Organization of Thesis

This thesis is divided into 5 chapters. It is organized as follows.

Chapter 2 contains a literature review of load forecasting which includes introduction to load forecasting, different types of load forecasting, various short term forecasting methods. Chapter 3 covers the methodology which includes the analysis of the historical data and the application of neural network algorithm to get a forecast result. Chapter 4 presents the results and discussion on the result is made. The final chapter summarizes the research work and concludes the study. The following conventions are used:

- 24 hours' time duration.
- The data from KIBTEK (Cyprus Turkish Electrical Authority) is used for the case study.
- Mean Absolute Percentage Error (MAPE) is used as a measure of forecast accuracy.

Chapter 2

LITERATURE REVIEW

2.1 Factors Affecting Load Consumption

Load forecasting has gained so much popularity over the years but having an accurate load forecast has become a great challenge to researchers as this is very important in power system management [4].

Various factors bring about the variation in load consumption. This includes weather, time and rate of occupancy. The load of an electric company consists of different consumption units of which the larger part of it is consumed by activities that go on in industries. While residential buildings use electricity in form of heating, lighting, cooling, laundry etc. services such as street lighting, railway traffic etc. offered by the government also demands electricity. The factors that affect load consumption solely depend on the consumption unit. In residential buildings, the factors that influence load consumption are very difficult to ascertain as the differences in human behaviors and psychology affect the consumption decisions.

2.1.1 Weather

The weather is the most important factor that affects load consumption. Temperature, humidity and so on are examples of weather factors. Temperature has a significant effect on the load consumption of buildings. The change of weather affects the way in which electrical appliances like space heater, water heater and air conditioner are used. This brings about variations in load patterns. It is important to make use of the relevant and related weather factor as the inputs of short term load forecasting.

2.1.2 Time

Time factors affecting load consumption in residential buildings include the season, week day/weekend and its time and also the holiday factors. For example the typical load curve of a weekday in a residential building in Turkish Republic of North Cyprus (TRNC) is shown in Figure 2.1 with the time interval of 1 hour. This implies that there are a total of 24 sample points in one day. The load is low and stable from 0:00 to 4:00, having a little rise from 4:00 to 9:00 and then drops until around 12:00. A fluctuation occurs till around 17:00 where it increases until 19:00. The change in load consumption shows the life style of the occupants: working time, leisure time, lunch time, and sleeping time. Putting this factor into consideration can benefit the load forecasting result.

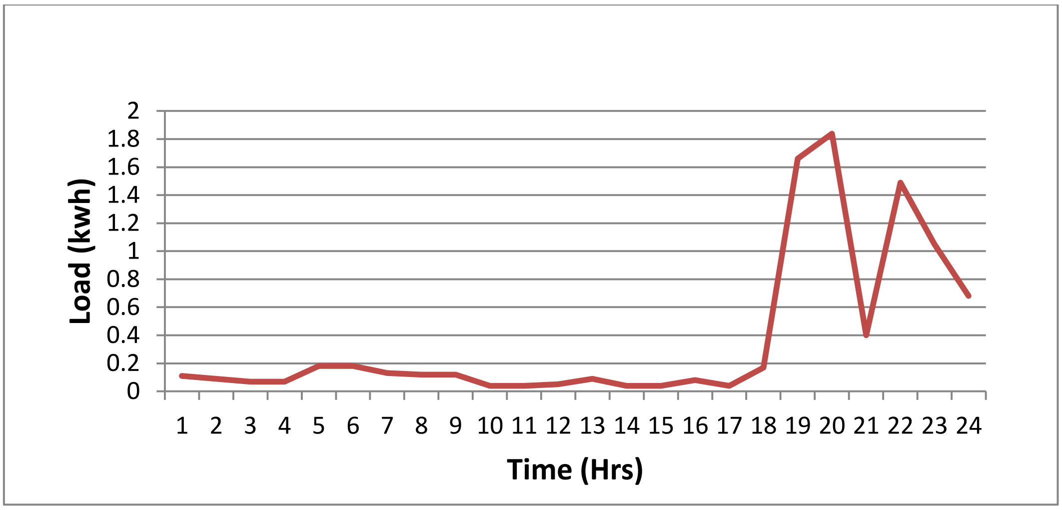

Figure 2.1: Typical load consumption pattern of a residential building in TRNC in a weekday.

2.1.3 Rate of occupancy

The level of occupancy in a residential building affects the load consumption levels, through the behavior and interactions with the environment and the schedule of occupants. For example, considering two separate residential buildings having a house wife/nursing mother and a working class mother respectively in each. There will be more energy usage in the building being occupied by the house wife as there will be a lot of consumption of load which will occur from the use of television sets, heating and cooling appliances to maintain an acceptable temperature for the baby, computers, microwaves to mention a few. On the other hand the reverse is the case for the working mother. That is why during holidays and weekends the load consumption tends to increase as occupants stay more at home.

Over time standard of living and population distribution factors play a major role in knowing how the demand of electricity evolves. This work is based on only one house therefore the economic and demographic factors is not significant and will not be discussed.

2.2 Classification of Load Forecasting

Load forecasting is majorly classified into three categories. Long-term forecasting, medium-term forecasting and short-term forecasting. [5].

Long-term forecasting: This is important for maintenance scheduling and demand side management. It is usually for a load of more than one year.

Medium-term forecasting: Very important for maintenance planning, fuel scheduling and hydro reservoir management. This is done for a load of one week to one year.

Short-term forecasting: Basically for day-to-day operations and system security analysis. It is needed for control and scheduling of power systems. It is usually used to forecast load of 24 to 168 hours. In this thesis short-term load forecasting is focused on.

2.3 Developed Short Term Load Forecasting Models

The literature review of short term forecasting is categorized into two.

1. **Statistical methods**: Here equations are obtained by using the relationship between load and factors that affect the historical data after training. This includes multiple linear regression [6], stochastic time series [7], general exponential smoothing [8], state space [9], support vector regression (SVR) [10-11]. Normal statistical methods can forecast only the load of normal days not considering that of holidays and weekends. This is as a result of the rigidity in its structure.
2. **Artificial intelligence methods**: These methods try to emulate the way humans think and reason using the knowledge of past data to forecast future load. This method includes expert system [12], neural network (NN) [13] and fuzzy inference system [14]. Expert system shows experienced operators into an “If...then” statements, but this is very challenging as it cannot be expressed easily. The artificial neural network establishes a input and output mapping. It deals with the relationship between load and its relative factors better in a nonlinear manner. Fuzzy inference system is similar to expert system but it makes use of a simplified fuzzy logic system and it reduces model errors and

the number of functions to hold nonlinear behavior of short term loads, regardless of this it requires the experience of an expert. Artificial intelligence models are best used in learning the relationship between historical load and its relative factors.

Some Short Term Load Forecasting (STLF) models includes:

2.3.1 Regression models

Regression is one of the commonly used statistical methods. It is among the oldest model proposed for load forecasting. In regression method, [15-17] pre-specified functional forms are assumed; this explains the relationship between load and factors that affect it. These factors includes but not limited to weekday index and weather. Regression analysis of historical data is estimated using functional coefficients [17].

In regression model, load is divided into standard load and a part that is linearly dependent on some factors. The model can be written as:

$$L(t) = s(t) + \sum_{i=1}^{n} r_i y_i(t) + \varepsilon(t) \tag{2.1}$$

where $L(t)$ represents load, $s(t)$ is the standard load at time t, r_i is the estimated slowly varying coefficients, $y_i(t)$ are the independent factors such as weather and $\varepsilon(t)$ is the white noise component.

According to the research made by Engle et al in [18], several regression models for the next day load forecasting have been presented. The models were influenced by holidays, average loads, and weather. The applications of regression models in load forecasting were defined by [19-21]. Although it is insensitive to disturbances which happen often during reading, it is easy to implement.

2.3.2 Time series models

Time series is a dynamic type of forecasting model. The working principle is based on the fact that the load time series is converted into a stationary time series by differentiation while the white noise is filtered from the other series. This method assumes that load patterns are time series signals with seasonal, weekly and daily forecasts. The knowledge of time series has been applied in fields like image processing, finance and in electrical load forecasting over the years.

The most commonly used time series methods is ARMA (autoregressive moving average), ARIMA (autoregressive integrated moving average) and ARIMAX (autoregressive integrated moving average with exogenous variables) [22-24].

ARMA model is used for processes that are fixed while ARIMA is dynamic in nature. They both use time and load only as input variables. ARIMAX is mostly used for load forecasting. The application of ARIMAX models for forecasting of load was extensively explained by Cho et al [25]. Gorawar et al developed different models for short term load forecasting using time series analysis [26]. Chao-Ming and Hong-Tzer developed an evolutionary programming (EP) algorithm to indicate auto-regression moving average (ARMA) model for one week hourly load forecasts. This method is used to simulate evolution process [27].

The challenge of this model is in the inability to handle abnormal load conditions. If the behavior of the load is inconsistent on a particular day, from the normal conditions this will reflect in the load forecast. Also since the load behavior can change rapidly some periods of the year, the model cannot adapt to the new conditions quickly.

2.3.3 Neural network models

Neural networks sometimes called artificial neural networks have been a widely researched load forecasting technique for over a decade now [28]. This model is inspired by the biological nervous system (the brain), it is made up of neurons that function in a parallel manner. The neurons are linked to synaptic weights which adapt through learning. They have parallel and distributed processing structures. There are different types of NNs which are known based on their topology and learning rules. NNs are arranged in small number of connected layers of elements between network inputs and outputs. The aim of this model is to classify days into different day types or to choose the most appropriate days in the history to be used as a benchmark for load forecasting. For short term load forecasting, the most commonly used network structure is the Multilayer Perceptron (MLP), which uses back-propagation learning algorithm. Back-propagation has supervised learning in which historical data is shown as the input in order to get the desired output - which is forecasted load.

Nahi Kandil et al [29] proposed a Neural network based short term load forecasting model for Quebec in which only temperature was used as input to prove that load can be forecasted without the use of load history as an input. Bakirtzis in [30] worked on an NN based short term load forecasting model for the Greek Public Power Corporation where they trained the network using a three-layer feed forward NN with a back-propagation algorithm using historical hourly load data, temperature and day of the week as inputs. Papalexopoulos et al. [31] also worked on a multilayer neural network for load forecasting but instead used season, weather and historical loads as inputs.

2.3.4 Expert Systems

Expert Systems (ES) are heuristic in nature. This technique is based on rules gotten from human experts. ES predicts load based on these rules, which are gotten from expert's knowledge and experience. In expert system new information and rules are added to the knowledge base. The system implements the rules into software which then automatically makes forecasts without any expertise. Rahman and Bhatnager first developed this technique [32] which used load and factors affecting it as a rule base. This is accompanied by a parameter database that learns from pervious data by solving an optimization problem which helps model the variations accurately. These variations are changes in season.

Ku-Long Ho et al in [33] developed an expert system to forecast the Taiwan power system load which was incorporated in a personal computer using a 5-year database to establish eleven day-types. Weather factors were put into consideration. Expert systems are affected by changing conditions. Since the opinion of the expert is not always stable and cannot be relied on, it is difficult to have a clear expert judgment. This might lead to unstable rules.

2.3.5 Fuzzy inference system models

Fuzzy model have been used in various areas. Bagis [34], Mastorocostas et al [35], Pandian et al [36], Ranaweera et al [37] applied fuzzy approach in the area of forecasting. Research studies have shown that there is a non-linear relationship between factors and electricity load demand. Factors such as weather, social activities, standard of living, affect the demand for electricity consumption. Using only historical load data it is very tough and demanding to establish an accurate load forecast. Since the relationship between load consumption and other variables that are independent is complex it is more suitable to use fuzzy logic method. Fuzzy logic deals with the nonlinearity of forecasted load curves and the change in weather variables [38]. Research carried out by Ranaweera and Pandian showed that fuzzy inference system is a better alternative to neural network and time series models. It converts input data to fuzzy values value of “True” or “False” and then compares patterns extracted during training. Similar values are chosen and mapped to the prediction input. It also most times combines with neural networks to form a fuzzy neuron hybrid system [39].

2.3.6 Wavelet models

STLF is very difficult to embark on as it has a very noisy data collection process and cumbersome load features. Che Guan et al [40] proposed a Very short term load Forecast (VSTLF) with a combination of wavelet neural network and data filtering. Since load features are complex and have different frequency components having different unique patterns traditional neural network is not sufficient. Wavelet model improves the traditional NN method.

Single-level wavelet decomposition was used on a data set from New England in United States [41] to forecast loads in 1 hour into the future in 5 min steps in a moving window manner. The wavelet model consists of a 3 layer network weights and summing nodes built based on an algorithm. The first layer, which is the summing node, joins the weight scales of signals into the output. The algorithm complies these variables into vectors.

In STLF, the most critical problem is in the selection of training set and this poses a big challenge. If training set having different factors (like weather, day type) from the forecasted day is selected the chances of having a large forecasting error is high. Also selecting a large training set unsystematically will increase the time of training which will either reduce the convergent speed or lead to no convergent. It is therefore very important to reduce the time of learning and NN structure. To tackle this challenge neural network model based on selection of similar day is proposed.

Chapter 3

METHODOLOGY

3.1 Introduction

This chapter presents the details of the methodology used in this study, discussing the analysis of the historical data obtained from KIBTEK, what is done with it using neural network for the development of the short-term load forecaster. The research work concludes and analyses the implementation of the following methodologies:

- Constructing neural network architecture that can be trained using historical load data.
- Training of the network using back propagation algorithm with different parameters such as learning rate, the momentum factor and number of neurons in the hidden unit under maximum acceptable error.
- Finding the optimum parameters for the test patterns.
- Finding the forecasted values using the optimum values for parameters.

3.2 Data Analysis

3.2.1 Initial Data

KIBTEK supplied data from their database for 2011 to 2013 for a residential building which is made up of 2 occupants both of them working. Load and weather measurements are hourly based and calendar events on daily bases. In this study, load trend to be forecasted is made up of hourly load readings. The hourly electric load consumption of KIBTEK is used in this study for testing.

The hourly temperature data gotten from Wunderground [42] is also available. As a result of the presence of missing data the data between April-May 2012 and April 2013 is used although load data for a longer period of time is preferable for an intensive testing. The presence of bad or missing data in the historical load consumption curve affects the accuracy of load forecasting result. Bad data occurs as a result of mistakes or carelessness in load consumption reading and transmission (which are normally far from the actual values), unexpected incidents like short-circuiting which can cause a change in the load curve suddenly [43]. Load consumption curve for a household with two occupants for April 2012 is shown in Figure 3.1 as an example.

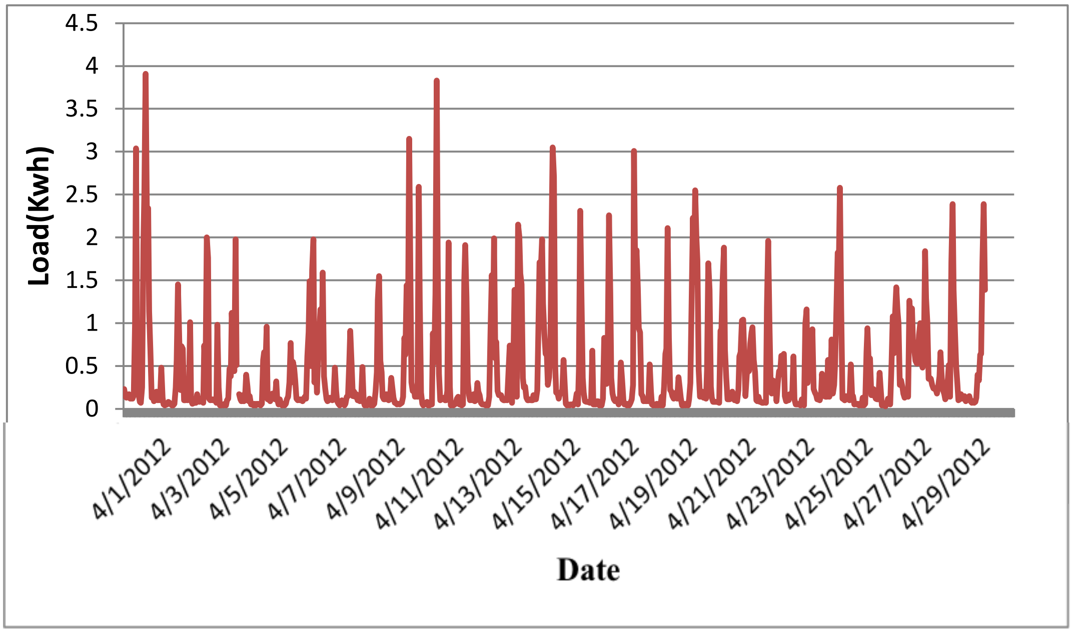

Figure 3.1: The load curve for April 2012.

The daily and weekly patterns are observed in the load curve. The weekly pattern starts from the working day. On weekdays (working days) social activities increases compared to weekends (Saturdays and Sundays) and holidays which implies that load consumption increases. In Figure 3.2 the load for one week in April 2012 is shown.

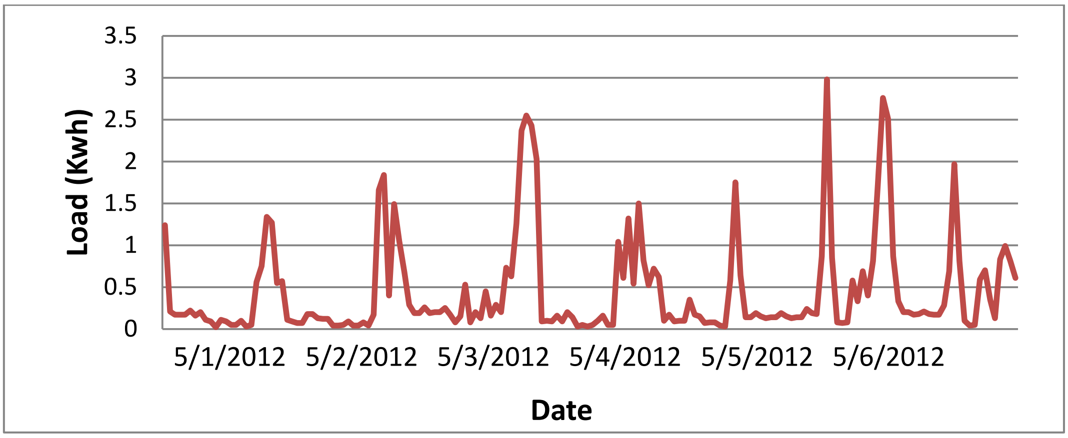

Figure 3.2: Load Consumption for one week for a household with two occupants for May 2012

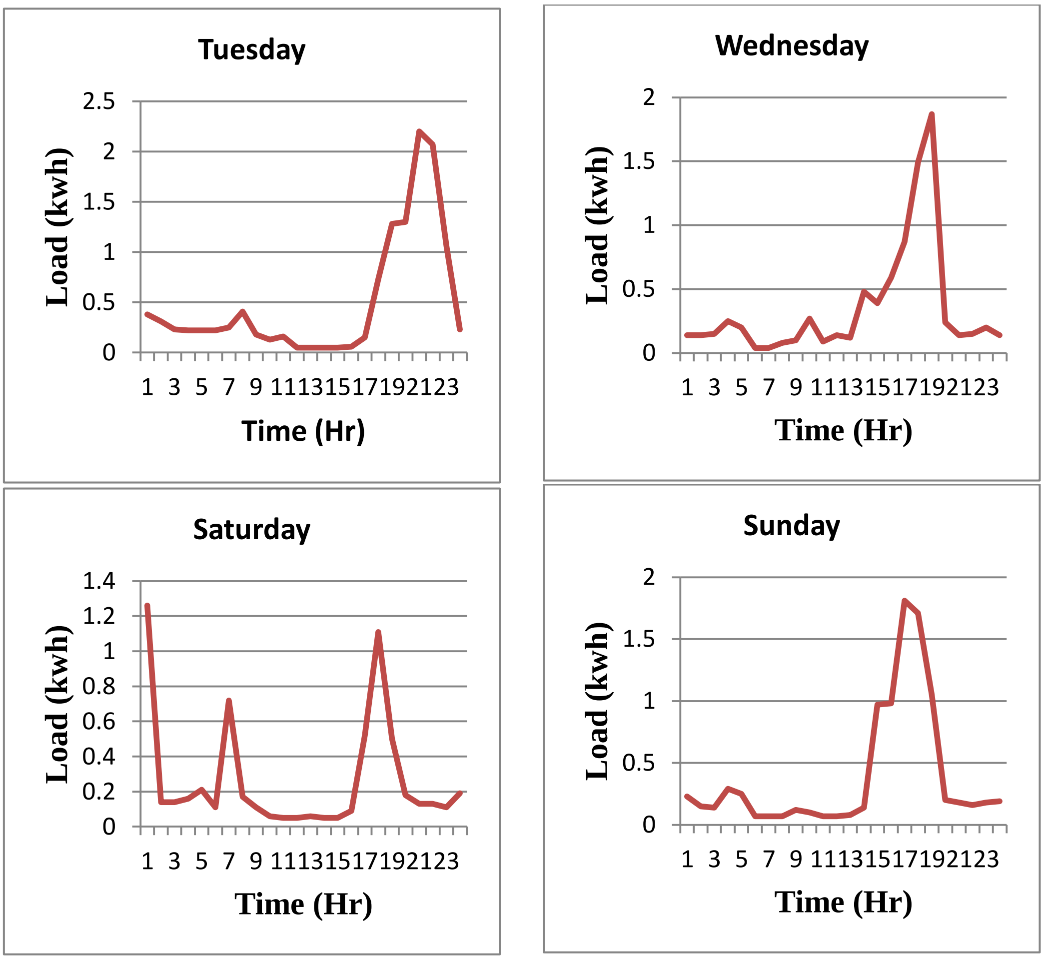

Figure 3.3: Selected daily load consumption trend

The daily pattern as seen in Figure 3.2 shows the behaviour of the occupants of the building during the day. Basically a lot of people rest at night, this decreases the electrical consumption at late night hours. Also in the day, activities like lunch time, relaxation etc. occurs. The daily load consumption pattern tends to change.

3.2.2 Day type classification

Figure 3.3 indicates the obvious differences between the days. This implies that during short-term load forecasting it is important to divide the days into several day types with each of them been known by its load pattern. It is obvious the load consumption pattern for Saturdays and Sundays is different compared to the week-days. The major question is how can special days like legal and religious holidays be classified? Most times the special days fall into the same class with Sundays [44]. However the load consumption trend for special days differs.

For day type classification, Hsu and Yang [45] made use of self-organizing feature maps, grouping the days with similar load patterns together. Since the category of the day to be forecasted has to be determined, self-organizing feature map is not appropriate. Classifications can be done similarly without the aid of neural network. In this study, the forecasting model will make use of the classified days which are: 1 – Sunday/special days, 2 – Mondays, 3 – Tuesdays to Fridays, 4 – Saturdays.

3.3 Selection of Similar Days

The basis of this selection lies in the fact that the searched previous days must have the similar features with the forecasted days in the training set. To improve the accuracy of short-term load forecasting it is essential to select the training set within similar days. This as well reduces the time of training.

The limits on the selection of similar days corresponding to the forecasted day are shown in Figure 3.4. The similar day is chosen from the set of the past thirty days from the day before the forecasted day in the present year and the past sixty-one days before and after the forecasting day in the previous year. If there is a change in the forecasting day similar days are selected in the same manner.

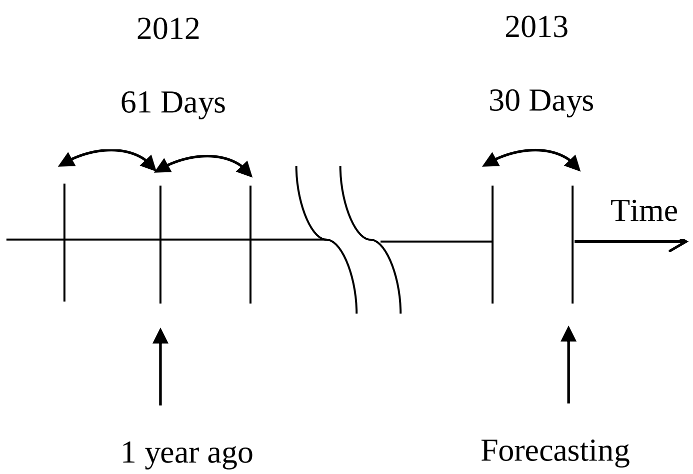

Figure 3.4: Limits selection of similar days

A total of ninety-one days is examined in order to select one similar day. For both the forecasting day and the days in the training set a similar day is selected. In this study, the similar days between searched previous days and forecasted day is found based on Euclidean norm with weight factors.

Generally the following equation is used as an Euclidean norm with weight factors:

$$D = \sqrt{\widehat{w}_1(\Delta T_{max})^2 + \widehat{w}_2(\Delta T_{min})^2 + \widehat{w}_3(\Delta Day)^2} \quad \textbf{(3.1)}$$

$$\Delta T_{max} = \hat{T}_{max} - T_{max}^{p} \quad \textbf{(3.2)}$$

$$\Delta T_{min} = \hat{T}_{max} - T_{min}^{p} \quad \textbf{(3.3)}$$

$$\Delta Day = \widehat{Day} - Day^{p} \quad \textbf{(3.4)}$$

Equation 3.1 gives the hourly calculation of Euclidean norm where $\hat{T}_{max}$ and $\hat{T}_{min}$ are the maximum and minimum temperatures on the forecasted day, T_{max}^{p} and T_{min}^{p} are the maximum and minimum temperatures of the previous days searched, $\widehat{Day}$ is the day type for the forecasted day, Day^{p} is the day type of the previous days searched, and $\widehat{w}_1, \widehat{w}_2\ and\ \widehat{w}_3$ are the weights which can be known using the least squares method based on the regression model constructed using historical data.

$$P_{max} = \widehat{w}_0 + \widehat{w}_1 T_{max} + \widehat{w}_2 T_{min} + \widehat{w}_3 Day \quad \textbf{(3.5)}$$

P_{max} represents the maximum power load and $\widehat{w}_0$ the bias. The weight factors are determined to show how a load factor affects the maximum power and hence determine the similar day by putting this into consideration in the Euclidean norm. (3.5) is expressed for ninety-one days that is been analysed. By solving these ninety-one equation based on the multi-regression model, the weights $\widehat{w}_i(i = 0,1,2,3)$ are calculated. Inserting these values into (3.5) gives the values of D for the analysed ninety-one days. The day with the smallest value is the similar day for the forecasted day. This implies that the smaller the Euclidean results the better the evaluation of similar days.

3.4 Construction of NN Architecture

3.4.1 Proposed NN architecture

Neural networks refer to a type of model motivated by the functionality of the biological nervous system. Neural networks store knowledge through the process of learning.

There are different types of neural network models categorized in many ways but the most common of them all is based on the learning principle. A neural network makes use of a supervised or unsupervised learning as it learns from examples. In supervised learning, the network is shown the input and desired output. In unsupervised learning, only the input signal is shown. The most common supervised model of neural network is the multi-layer perceptron network (MLP). Most researched short-term load forecasting models are based on it. It is made up of multiple layers of computational units called perceptrons which interconnected in a feed-forward manner. The output is gotten by taking a linear combination of the input signals and by transforming it using an activation function.

The output of the perceptron is written as:

$$y = \varphi(\sum_{i}^{n} w_i x_i - \theta) \qquad \textbf{(3.6)}$$

where y represents the output, x_i the input signals, w_i the neuron weights, θ is the bias term and φ is the activation function which can either be a linear function, step function, logistic function or a hyperbolic tangent function. The MLP network normally used is made up of three layers: an input layer, hidden layer and an output layer. This can be seen in Figure 3.5.

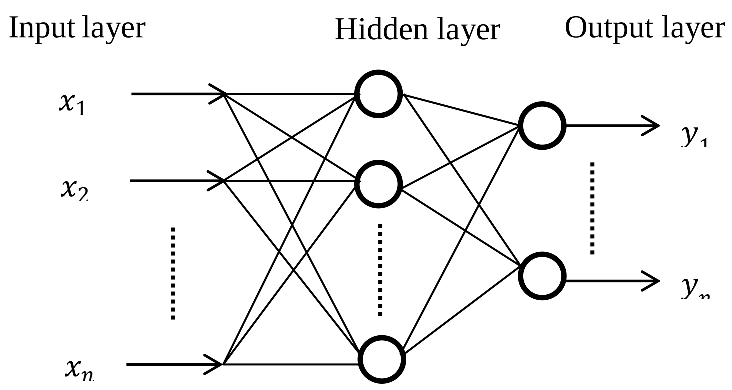

Figure 3.5: A three layer multilayer perceptron network

The activation function in the hidden layer is nonlinear and that of the output layer is either nonlinear or linear. In this work to achieve a high level of computational capabilities a multilayer perceptron network is used. For the learning process in a MLP network back propagation algorithm is used, this technique implements gradient descent method, where the gradient of the sum of squared errors with respect to the weight is approximated by propagating the error backwards in the network [48].

The following cost or energy function is used as criteria for stopping the learning process:

$$E = \frac{1}{2}\sum(\Delta y - \Delta c)^2 \quad \textbf{(3.7)}$$

where Δy and Δc represent the actual output and desired outputs respectively. The objective is to minimize E. If $E = 0$ the network has reached the minimized output.

Before a back propagation (BP) network can be trained some parameters must be determined. These parameters are:

I. Weights: The initial weights are to have small random values. Studies have shown that if the initial weights in the same layer are equal there will not be convergence in BP algorithm [49].

II. Learning rate: The success and convergence of the BP algorithm relies absolutely on the value of the learning rate. The optimum value of the learning rate depends on the system. However a small value of learning rate is recommended [50].

III. Momentum term: The momentum term is usually added into the BP update as it makes the algorithm work faster, it is also system dependent just like the learning rate.

IV. Hidden neurons.

The following is the summary of a back propagation algorithm for a three-layer neural network:

1. Initial weights and bias to small random values.
2. Choose a pattern.
3. Compute the net input and output of each unit in the hidden and output layers.
4. Compute error at the output units.
5. Update weights and biases to indicate the errors that were propagated.
6. Go back to step 2 and repeat for the next pattern unit E does not decrease any further.

3.4.2 Selection of input data

The selection of input data for a load forecasting network is very important as BP network realizes nonlinear mapping from the inputs to the outputs, this selection can be based on experience [51-53], statistical analysis and correlation analysis. If the load at hour h is denoted as $L(h)$, the input selection based on the experience of the expert will be $L(h-1)$, $L(h-24)$, $t(h-1)$, etc. where $t(h)$ is the temperature that corresponds to the load $L(h)$. For correlation analysis, peaks occur at multiples of 24 hour lags which show that there is a great correlation between loads at the same hours with each other. This indicates that it can be chosen as input variables.

The historical load consumption and temperature are most times used as input data although in some extreme cases wind-speed and sky cover is chosen.

Input data can be grouped into 8 classes [51-55]:

1. Historical loads
2. Historical and future temperature
3. Hour of day indicator
4. Day of the week
5. Wind speed
6. Sky cover
7. Rainfall
8. Wet or dry day

For this work the classes 1-4 of the data are enough to give accurate forecasting results. Although for extreme weather conditioned areas the last 4 classes are recommended due to the nonlinear relationship between the loads and the weather condition.

3.4.3 Choice of hidden neurons

Determining the optimum number of hidden neurons to be used is a very important decision to take as it can affect the accuracy of forecasting results. For example if the hidden neurons are too small there will be inaccurate forecasting results as a result of inadequate information. Similarly, if the hidden neurons are so numerous training will take a long time [51].

According to Gownri et al [56], the number of hidden neurons can be determined using the following rule of thumb:

a) $(x - 1)$ hidden neurons
b) $(x + 1)$ hidden neurons
c) For every 5 input neurons there are 8 hidden neurons. This can be seen in a network that has 5 inputs, 8 hidden neurons and 1 output.
d) $^{p}/_{x}$ neurons

where $'x'$ represents the input neuron and $'p'$ the number of training patterns.

3.4.4 Normalization

It is very important to normalize the output and input variables of the network before training the network in order to obtain a good result and to reduce the time of calculation. Normalization involves changing all values of attributes in the dataset to values in the interval (0, 1) or (-1, 1). There are two basic types of normalization techniques:

a. Range (Min-Max Normalization): This technique implements a linear transformation on the given data. It removes the minimum value of an attribute from each value of the attribute and further divides the difference by the range of the attribute.

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)} \quad \textbf{(3.8)}$$

where $\min(x)$ and $\max(x)$ is the minimum and maximum value for variable x respectively. If $\max(x)$ is equal to $\min(x)$ the normalized x' is set to 0.5.

b. Decimal scaling normalization: It normalizes when the decimal point of values of an attribute is moved. A modified vale $x^{'}$ corresponding to x is obtained using:

$$x^{'} = \frac{x}{10^{j}} \tag{3.9}$$

where j is the smallest integer such that $\max(| x^{'}|) < 1$

For this study the max-min normalization is used because of the presence of the sigmoid activation function. Also it preserves all the relationship associated with the data without the addition of any bias.

3.4.5 Input and output patterns

The proposed model consists of 28 input units and 24 output units of load. Input variables for the proposed 24-output neural network are 24 hour load consumption curve on similar day $L_n^k(n = 1 \sim 24)$, maximum temperature on forecasted day $\hat{T}_{max}$, minimum temperature on forecasted day $\hat{T}_{min}$, maximum temperature deviation between forecasted day and similar day ΔT_{max}^k and minimum temperature deviation between forecasted day and similar day ΔT_{min}^k. Since there are 28 input units and 24 output units the hidden neurons is varied between the ranges of 26 to 50 in order to determine the optimal value [57].

Chapter 4

RESULTS AND DISCUSSIONS

4.1 Learning System of the Proposed Neural Network

During the process of obtaining the forecast result, the way in which the network learned can be seen in summary below:

a) The data is read from an excel file using the ‘xlsread’ function.

b) The read and loaded data is then normalized to the range of 0-1.

c) The network is then constructed, having an input unit 28 and an output unit of 24 as mention in the methodology in Chapter 3. The transfer function used is the sigmoid function. The number of hidden layer is selected based on trial and error as it proved to be more efficient in the network. For this study, 50 neurons are used in the hidden layer.

d) The network is trained using previous data. In this study, the data used for the training is from April-June 2012 and April 2013.

e) After the training process is completed, the network is tested using the data from May 2013 (May is used for testing because the study began in this month).

f) The output of the network is de-normalized to get a comparison between the actual data and the results which are written down.

g) The final step is the evaluation of the performance of the network. The mean absolute percentage error (MAPE) is the measure of the performance of the network used.

The neural network is implemented using MATLAB, during the 24 hour load forecast the back propagation algorithm in respect to the explained methodology is run. In order to get knowledge of how stable the network is from the random values, different weights were initialized. The weights are set to random small values. While adjusting these values, it is noticed that the performance of the network varied. The weights either increased or decreased the performance of the network. These weights are adjusted from 0.05 to 0.1. Learning variables of the neural network can be seen in Table 4.1 which is obtained by trial and error.

Table 4.1: Varied parameters of the neural network

Learning rates	0.05-0.1
Momentum constant	0.1-0.6
Iterations	1000

Learning the neural network for iteration more than 2000 cannot bring about a better and more stable performance so 1000 iteration is sufficient. The network is trained using the data of 91 days. The training continues until the error comes to a constant value. The network is retrained as the forecast date changes.

4.2 Results and Discussion of Forecast

The short-term load forecast is trained using the 5 months data obtained from KIBTEK consisting of April to June 2012 and April to May 2013. The neural network is implemented using MATLAB R2012a while the month of May 2013 is used for forecasting. The load forecast performance is seen in the form of mean absolute percentage error (MAPE). This is one of the most common measures of error forecast criteria used in evaluating the performance of the network. It measures the absolute error as percentage and it is defined as:

$$MAPE(\%) = \frac{1}{N}\sum_{i=1}^{N}\frac{\left|H_A^i - H_F^i\right|}{H_A} \times 100 \qquad \textbf{(4.1)}$$

where H_A is the actual load, H_F is the forecasted load, N is the total number of hours, i is the index for hour. The learning rate of 0.05 to 0.1 was varied in the network but since the optimum value is needed the learning rate (0.1) which had the lowest MAPE was selected with momentum constant of 0.1. The MAPE corresponding to the 31 days for all the varied learning rates can be seen in Table 4.2 and Figure 4.1 while the selected MAPE having the 0.1 learning is seen in Figure 4.2 below.

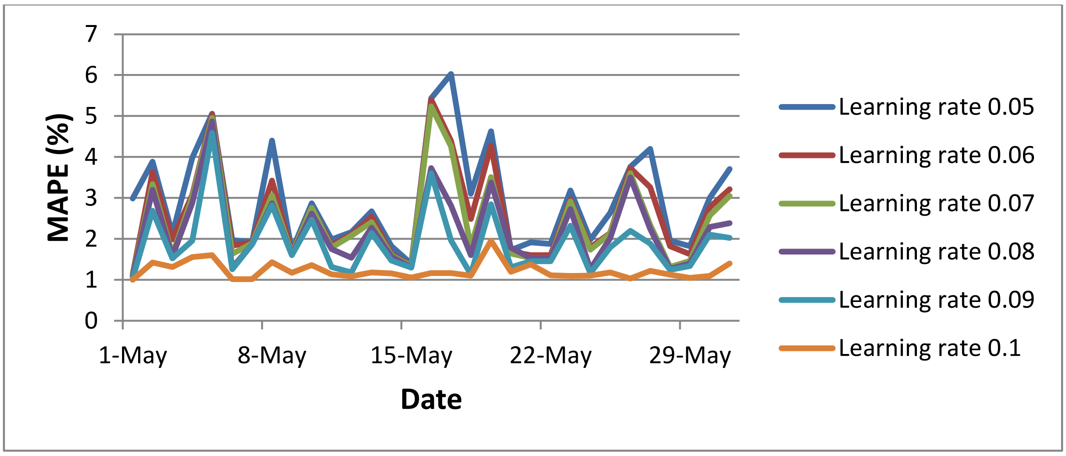

Figure 4.1: Mean absolute percentage error for the varied learning rates

Table 4.2: MAPE for varied learning rates

MAPE (%)						
Date	**Learning rate 0.05**	**Learning rate 0.06**	**Learning rate 0.07**	**Learning rate 0.08**	**Learning rate 0.09**	**Learning rate 0.1**
1-May	2.984	1.132	1.102	1.078	1.0321	1.001
2-May	3.886	3.625	3.335	3.197	2.690	1.424
3-May	2.118	1.990	1.613	1.573	1.529	1.318
4-May	3.981	3.071	3.016	2.879	1.957	1.557
5-May	5.058	5.031	4.959	4.869	4.591	1.605
6-May	1.975	1.836	1.633	1.302	1.261	1.018
7-May	1.921	1.913	1.891	1.871	1.866	1.017
8-May	4.405	3.422	3.066	2.867	2.826	1.429
9-May	1.707	1.666	1.635	1.610	1.607	1.177
10-May	2.869	2.760	2.758	2.616	2.475	1.363
11-May	1.988	1.844	1.794	1.755	1.313	1.132
12-May	2.168	2.115	2.084	1.539	1.183	1.092
13-May	2.673	2.539	2.406	2.274	2.142	1.180
14-May	1.822	1.630	1.598	1.567	1.470	1.157
15-May	1.395	1.347	1.337	1.306	1.297	1.055
16-May	5.432	5.401	5.241	3.733	3.601	1.167
17-May	6.028	4.390	4.259	2.819	1.966	1.169
18-May	3.101	2.483	1.804	1.606	1.134	1.101
19-May	4.625	4.278	3.509	3.378	2.845	1.953
20-May	1.731	1.688	1.644	1.786	1.305	1.195
21-May	1.914	1.605	1.537	1.532	1.459	1.378
22-May	1.876	1.605	1.537	1.532	1.459	1.110
23-May	3.185	2.963	2.913	2.727	2.323	1.093
24-May	1.977	1.794	1.740	1.259	1.164	1.103
25-May	2.634	2.143	2.127	2.018	1.794	1.182
26-May	3.760	3.729	3.601	3.501	2.195	1.036
27-May	4.194	3.264	2.338	2.247	1.889	1.221
28-May	1.957	1.820	1.316	1.270	1.243	1.131
29-May	1.821	1.626	1.464	1.404	1.339	1.047
30-May	3.001	2.774	2.574	2.293	2.105	1.100
31-May	3.704	3.214	3.047	2.382	2.025	1.399

From Table 4.2 it is observed that 0.1 learning rate had the smallest MAPE error for all the days in the month of May consecutively. This implies that this learning rate has the forecasting accuracy since it has a small MAPE. Therefore, it has to be chosen.

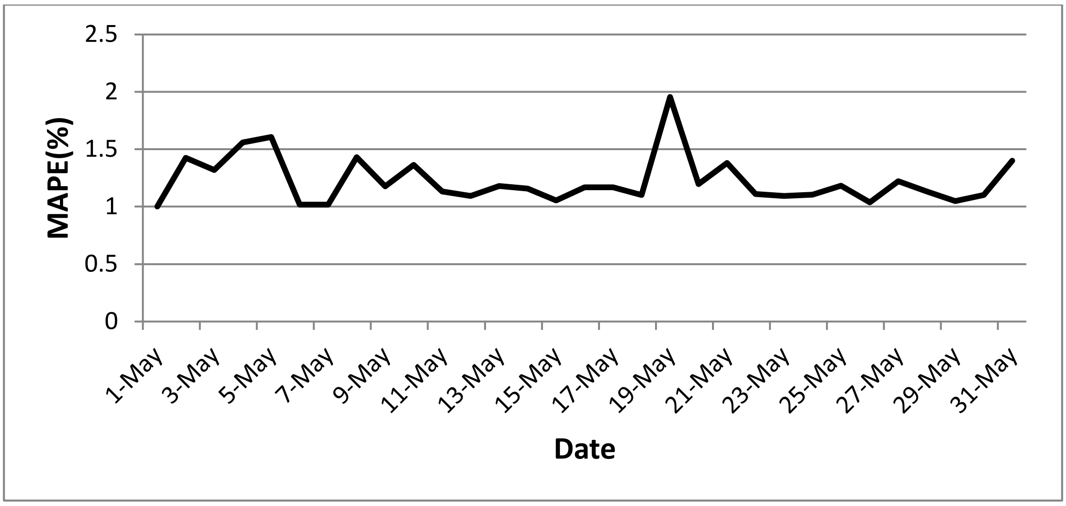

Figure 4.2: Mean absolute percentage error for the month of May

In order to get the mean absolute percentage errors, some optimum values for some variables are chosen. These optimum values are 0.1 for the learning rate, 0.1 for momentum constant, 1000 iteration and 50 hidden neurons. These optimum values are reached based on trial and error. With these parameters the results obtained can be seen in Figures 4.3 to 4.34.

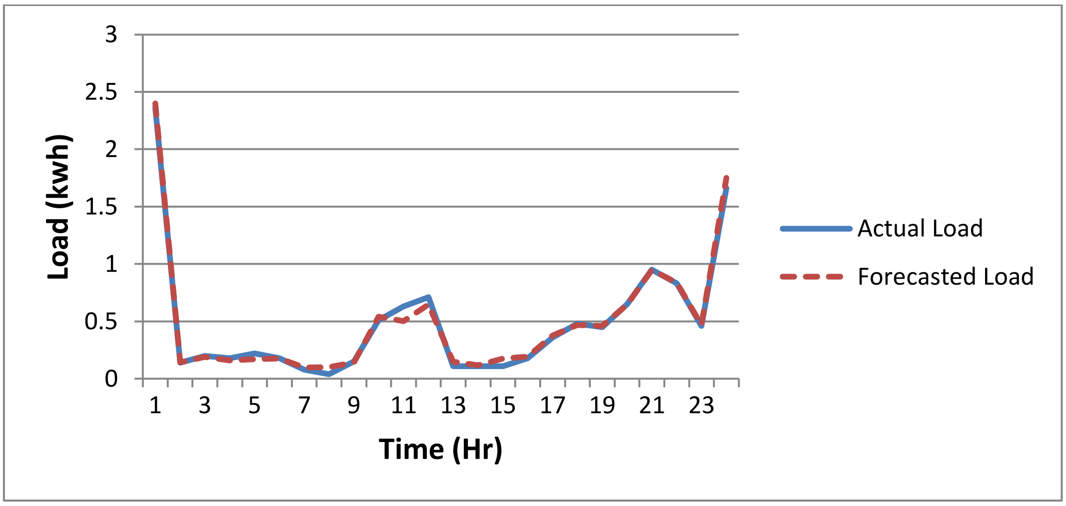

Figure 4.3: Actual and forecasted load curves for May 1.

The forecasted load curve for May 1 is gotten by selecting the load of April the same and the load of April and May the previous year. Similarly, in Figures 4.4 – 4.33 the same process is carried out to get the remaining load forecast curves for respective days.

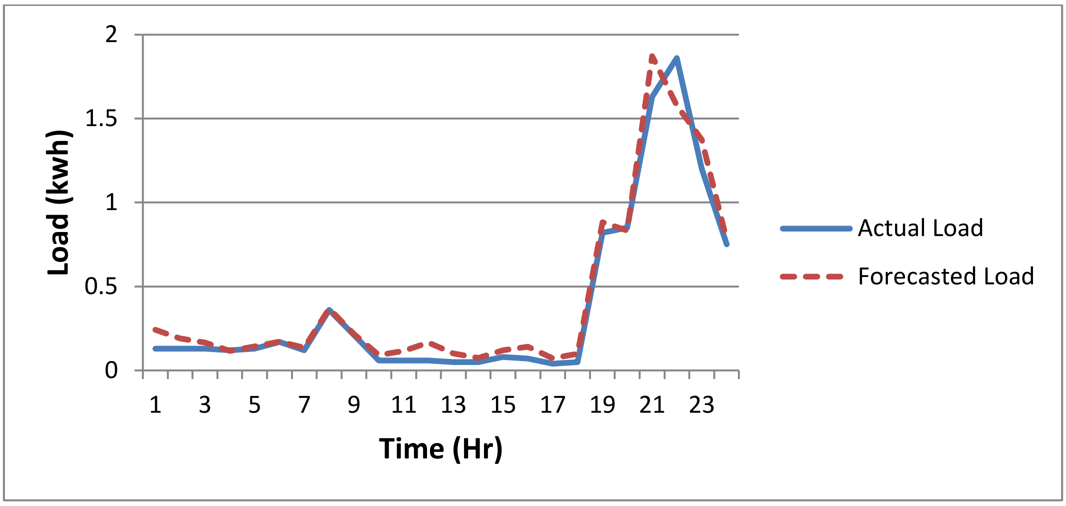

Figure 4.4: Actual and forecasted load curves for May 2.

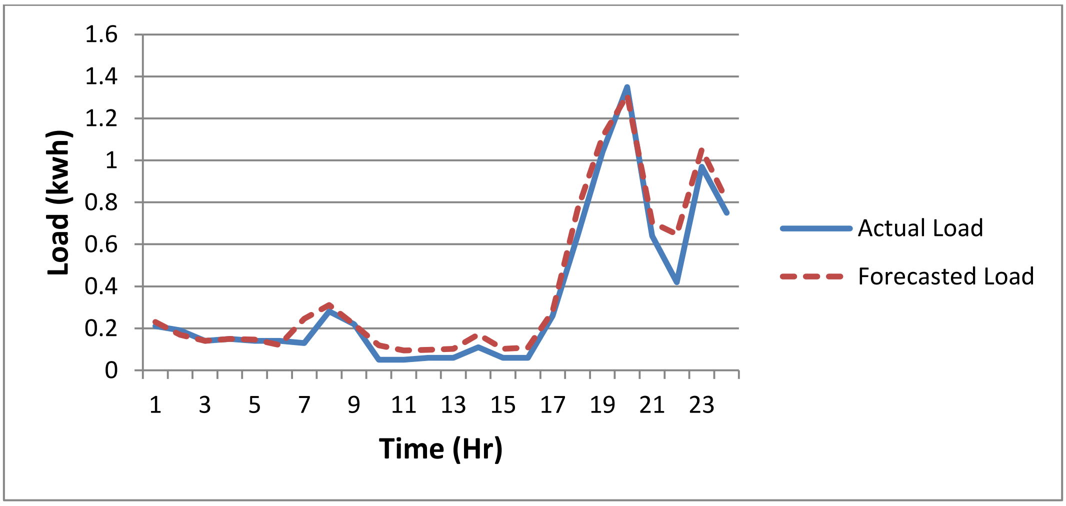

Figure 4.5: Load forecasting curve for May 3.

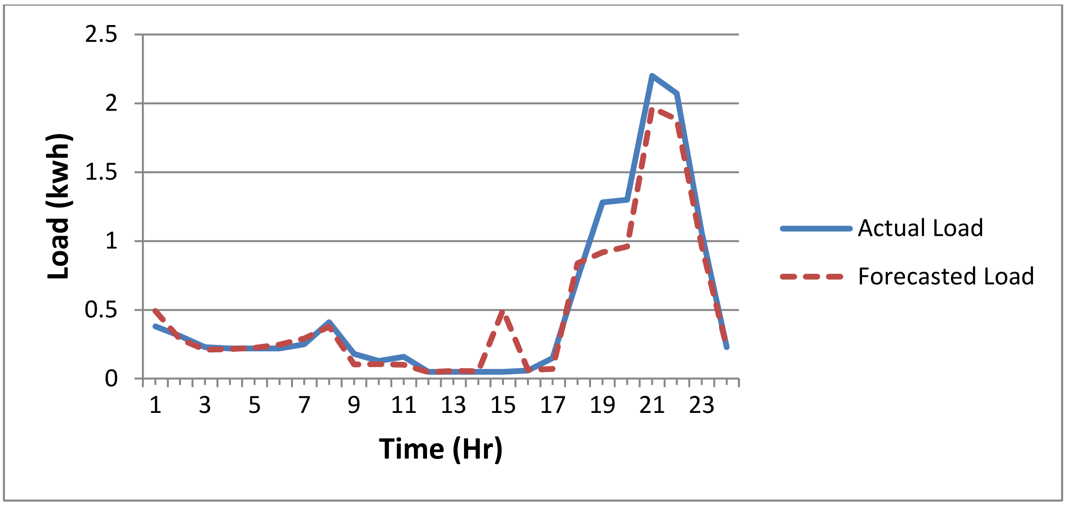

Figure 4.6: Load forecasting curve for May 4.

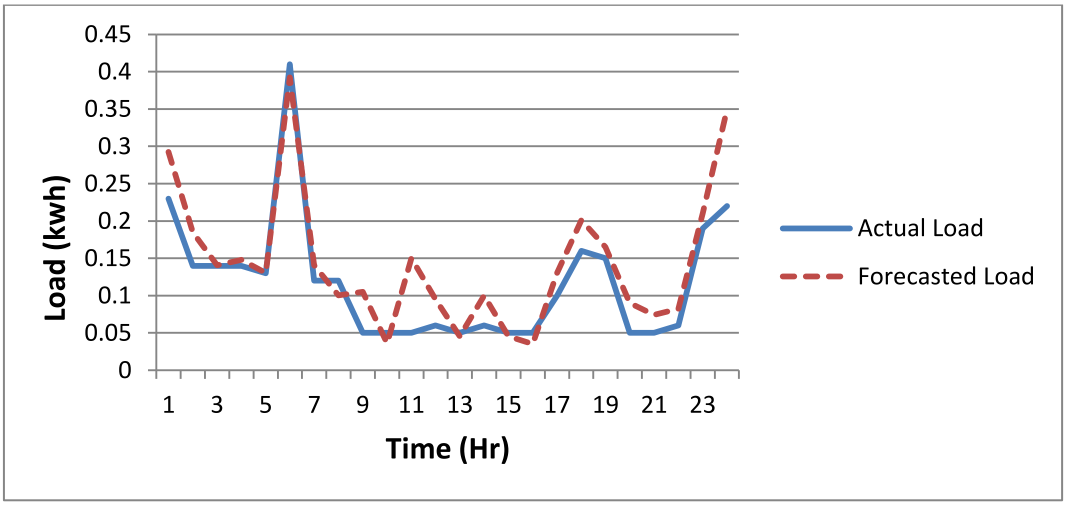

Figure 4.7: Load forecasting curve for May 5.

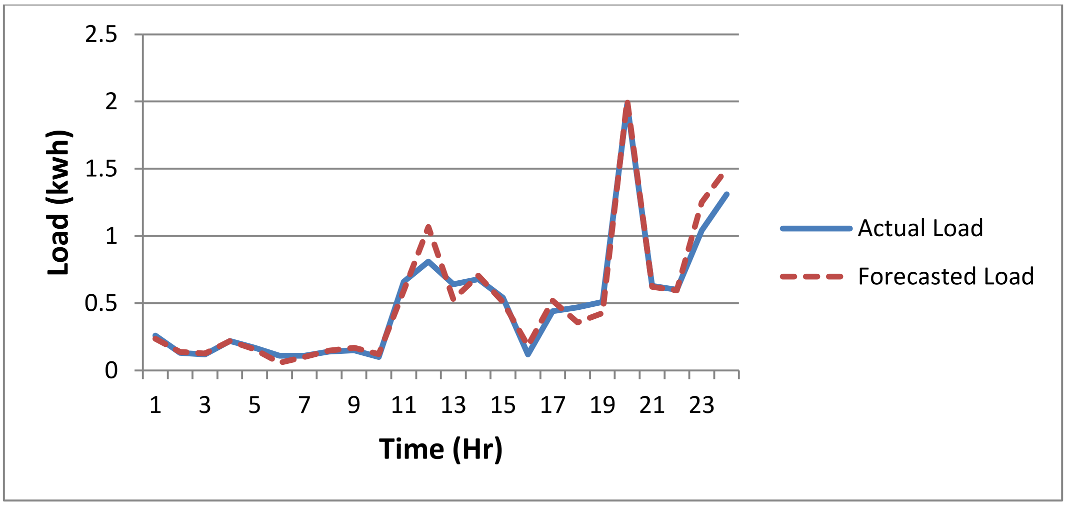

Figure 4.8: Forecasting result for May 6.

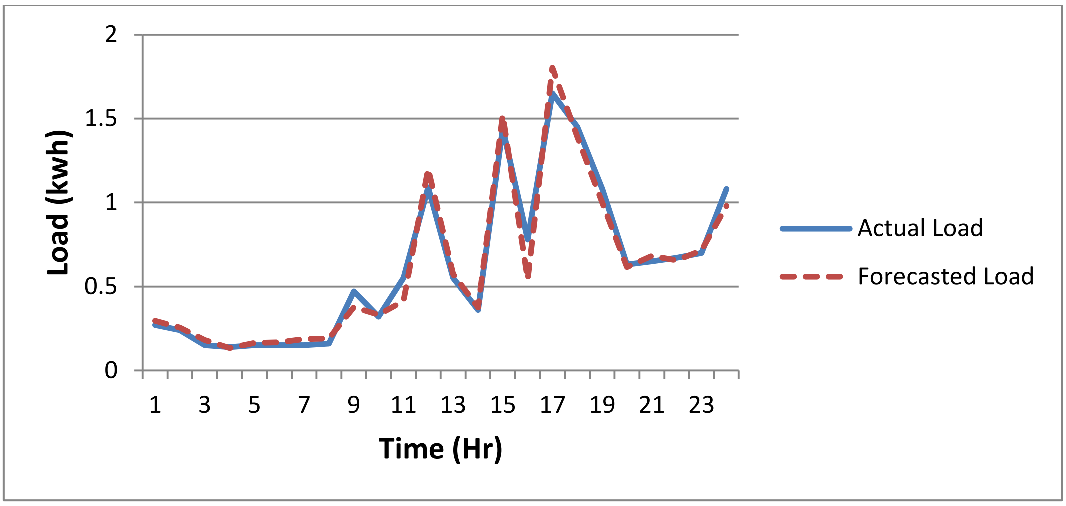

Figure 4.9: Forecasting result for May 7.

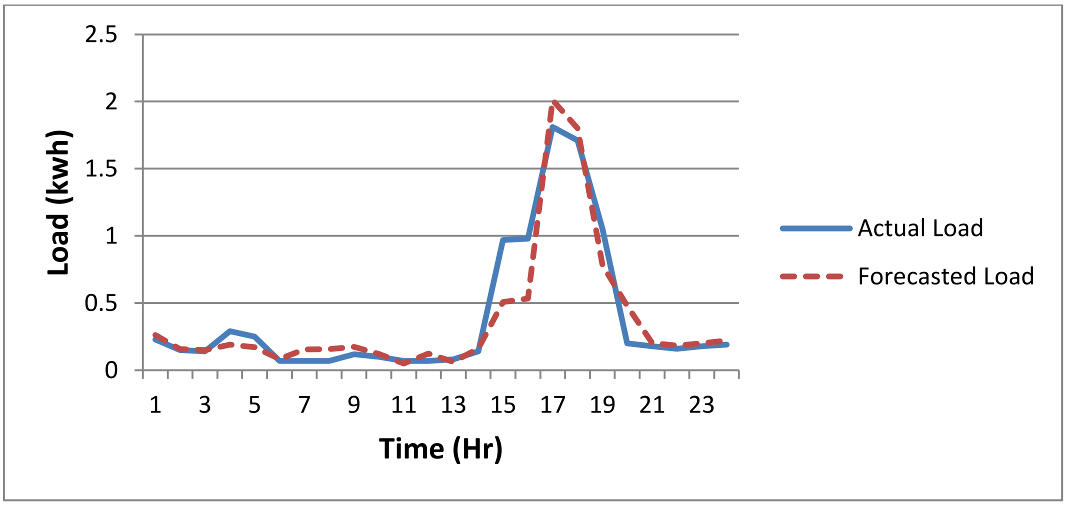

Figure 4.10: Forecasting result for May 8.

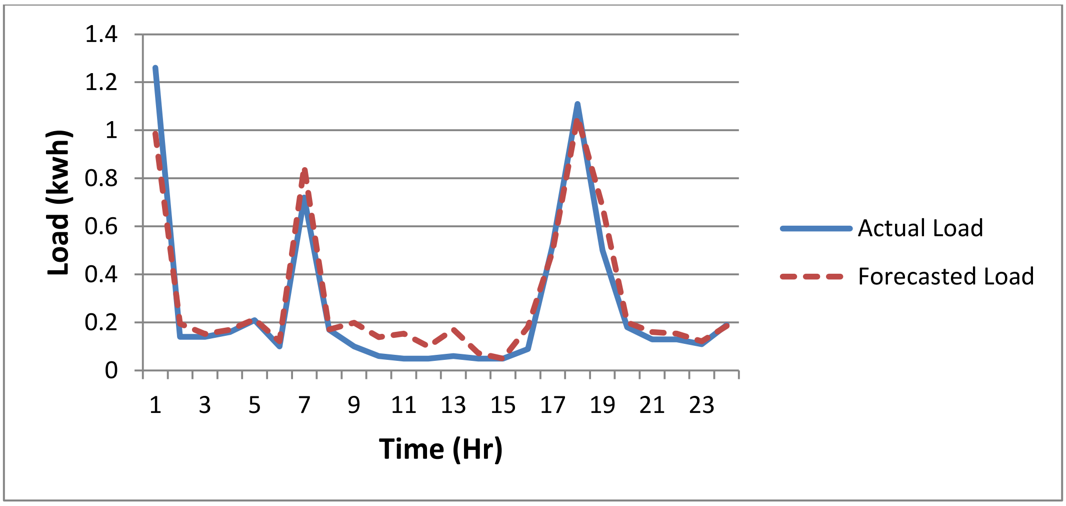

Figure 4.11: Combined actual and forecasted load curves for May 9.

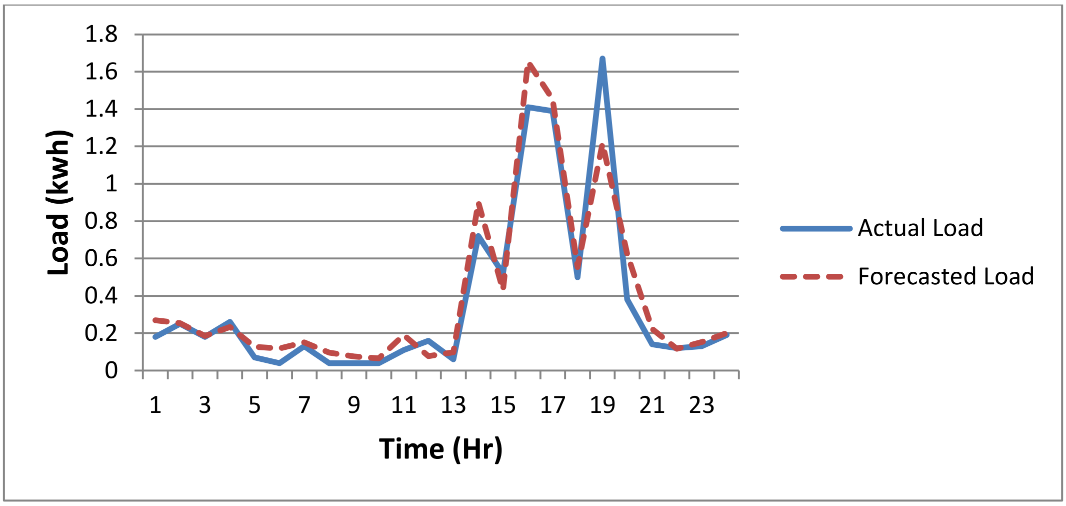

Figure 4.12: Combined actual and forecasted load curves for May 10.

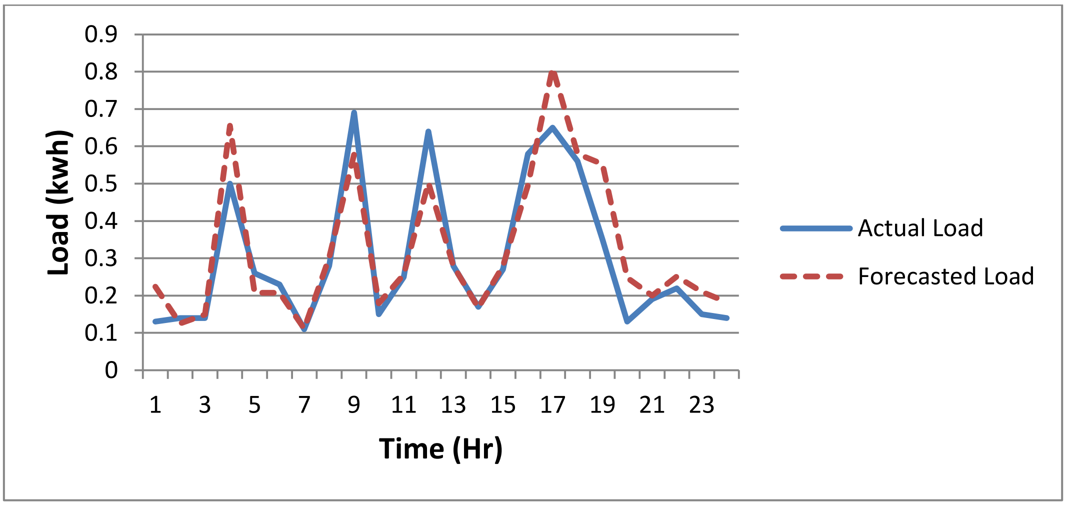

Figure 4.13: Combined actual and forecasted load curves for May 11.

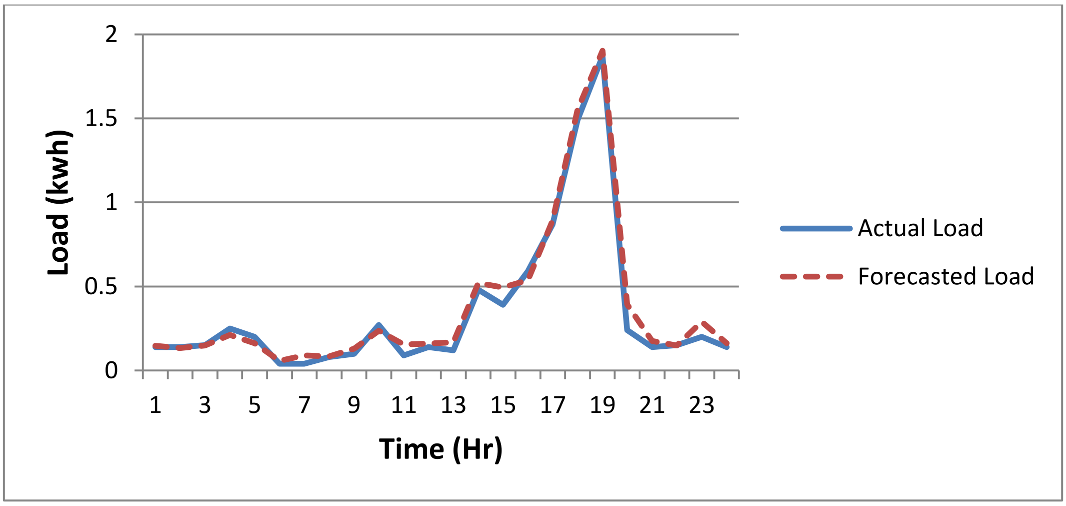

Figure 4.14: Forecast for May 12.

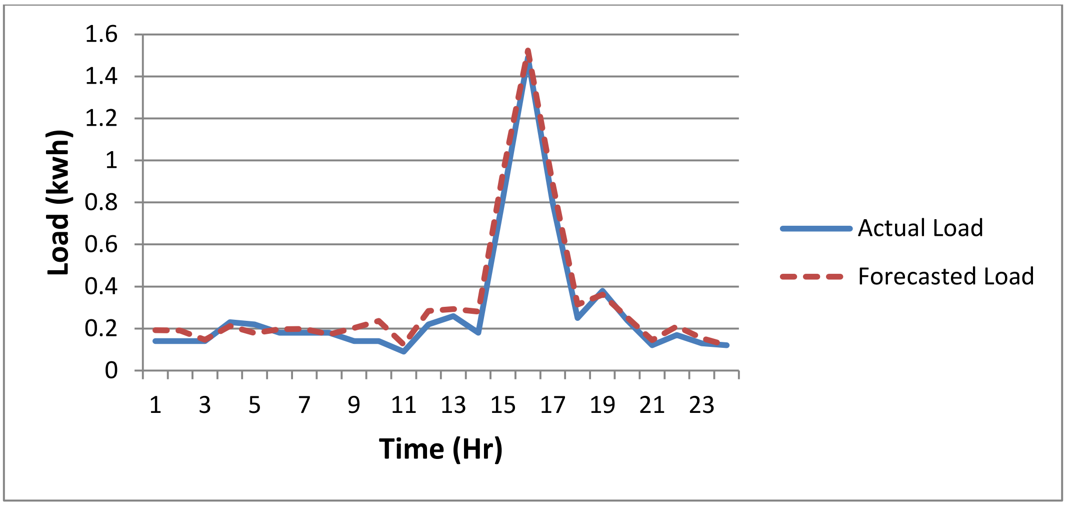

Figure 4.15: Forecast for May 13.

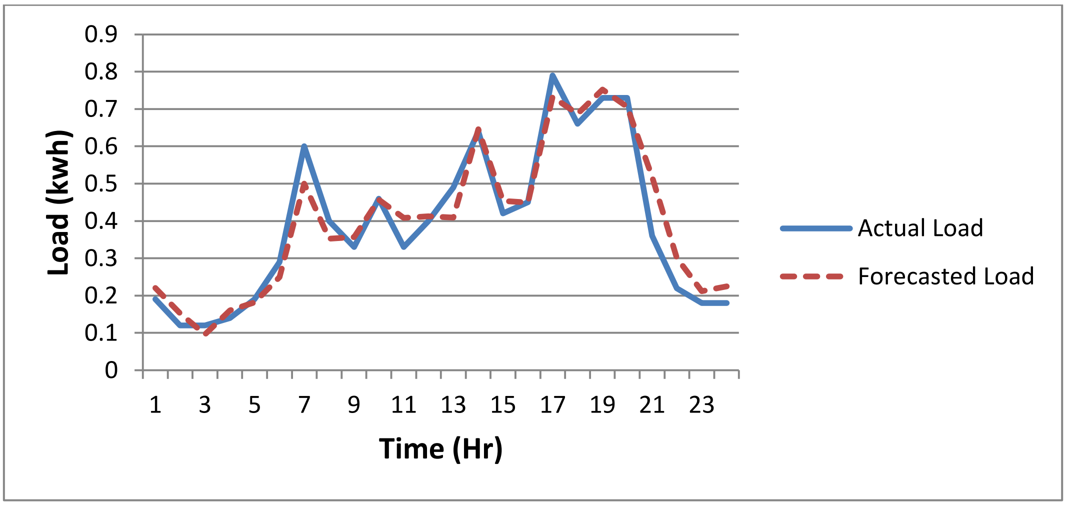

Figure 4.16: Forecast for May 14.

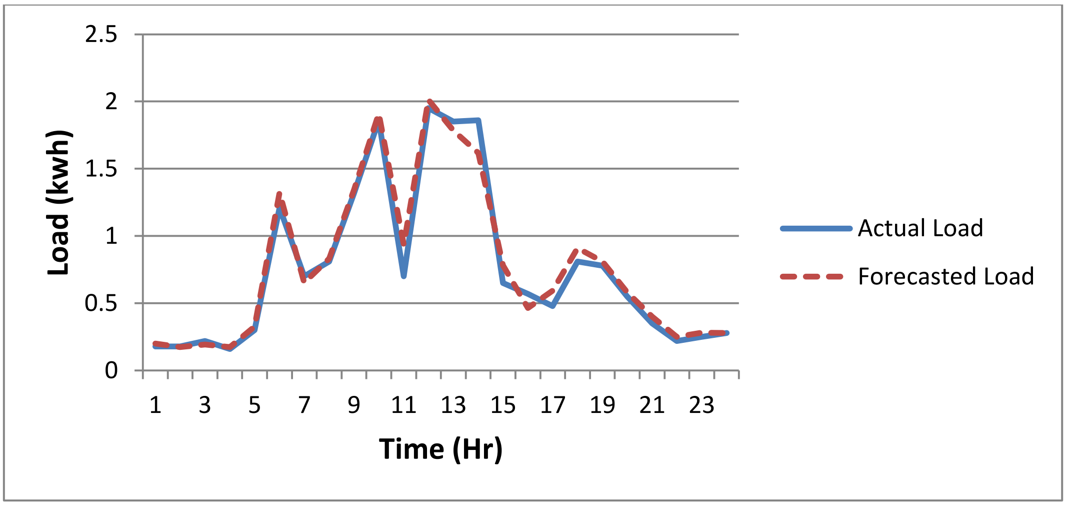

Figure 4.17: Actual and forecasted load curves for May 15.

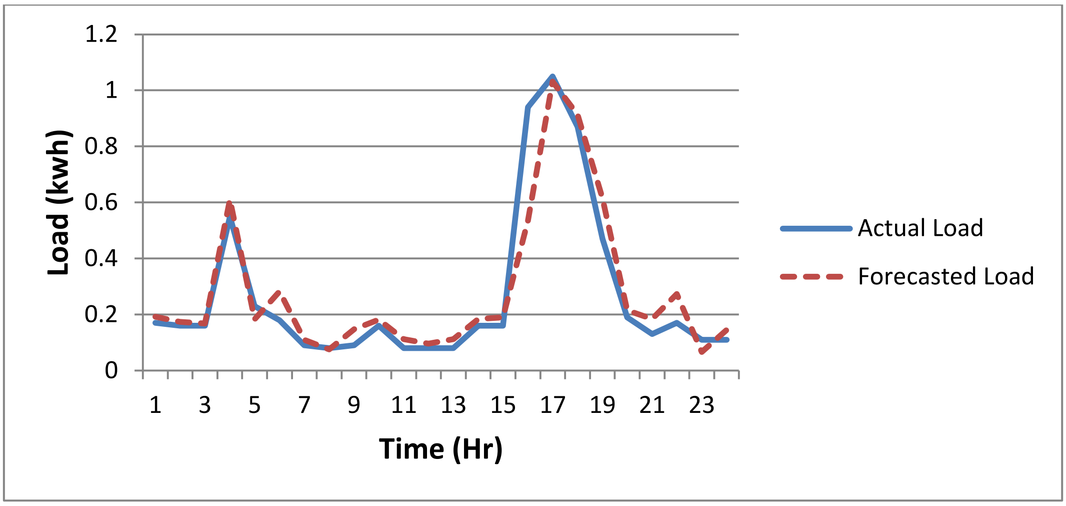

Figure 4.18: Actual and forecasted load curves for May 16.

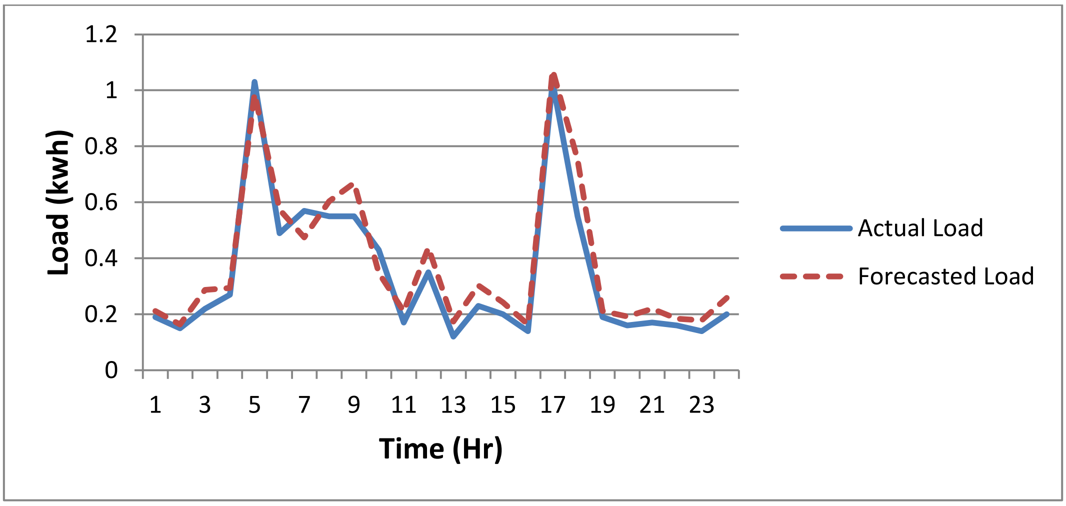

Figure 4.19: Actual and forecasted load curves for May 17.

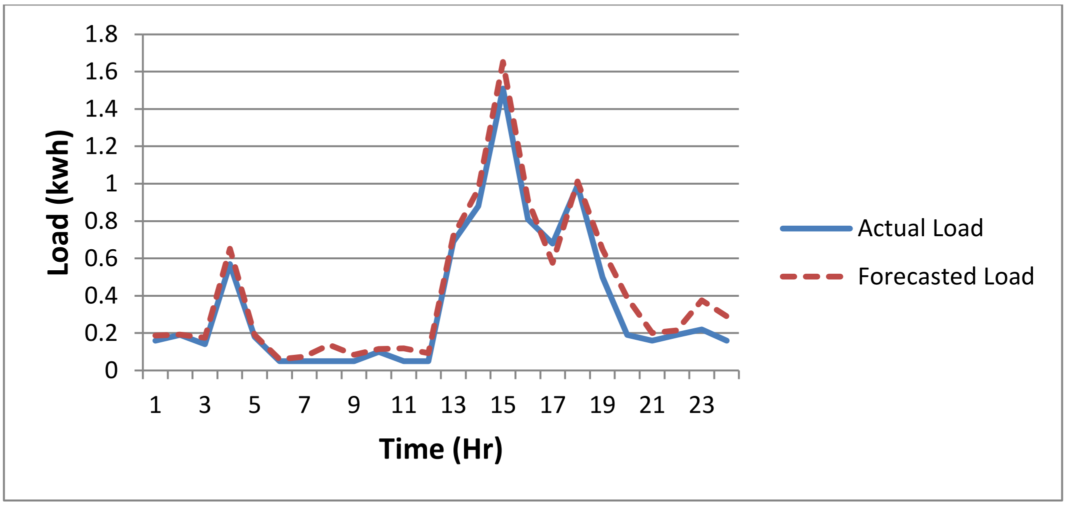

Figure 4.20: Actual and forecasted load curves for May 18.

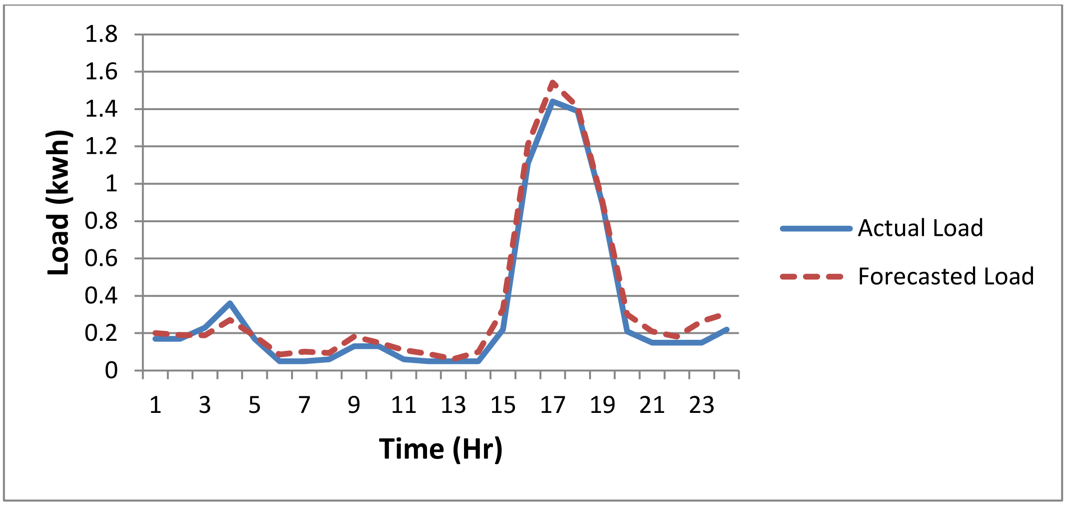

Figure 4.21: Actual and forecasted load curves for May 19.

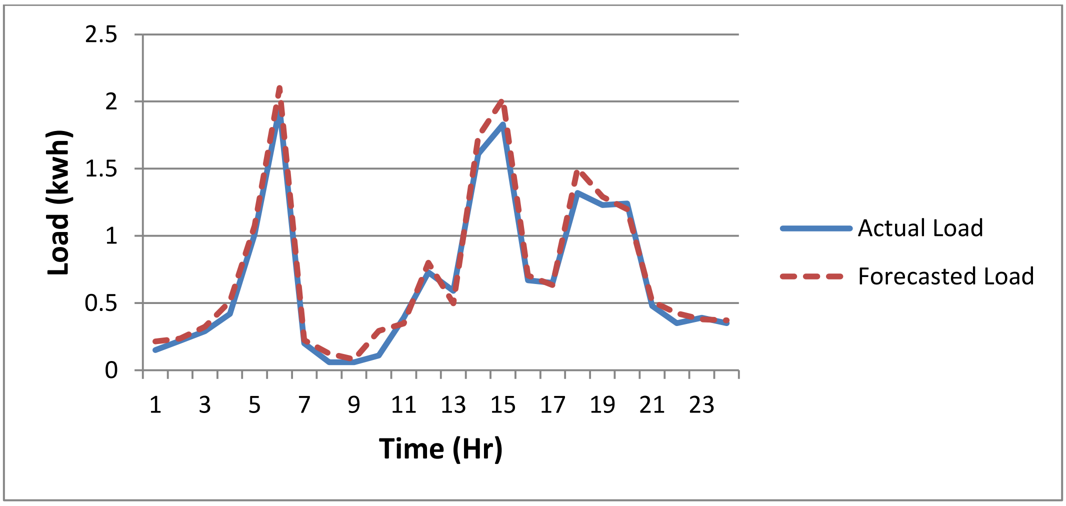

Figure 4.22: Actual and forecasted load curves for May 20.

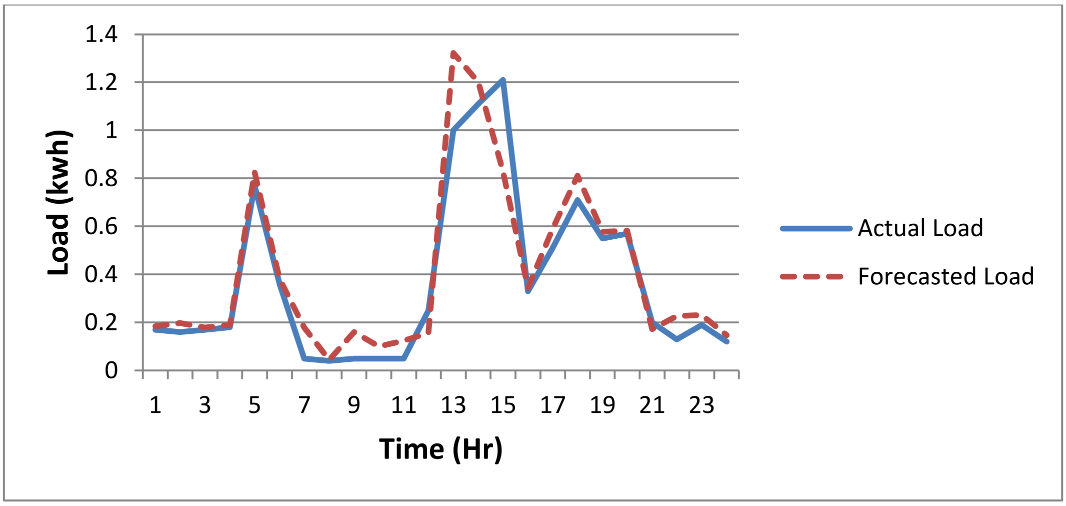

Figure 4.23: Actual and forecasted load curves for May 21.

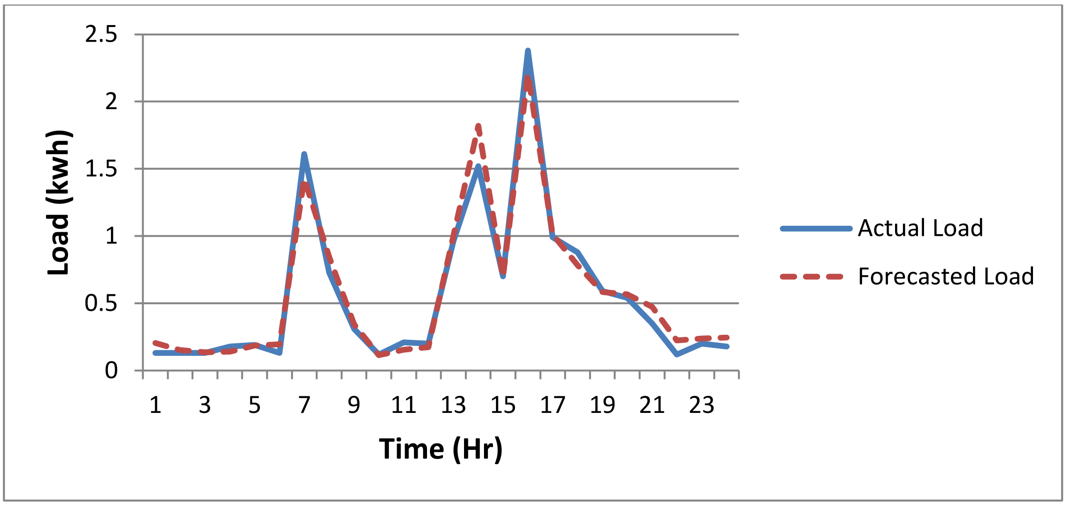

Figure 4.24: Actual and forecasted load curves for May 22.

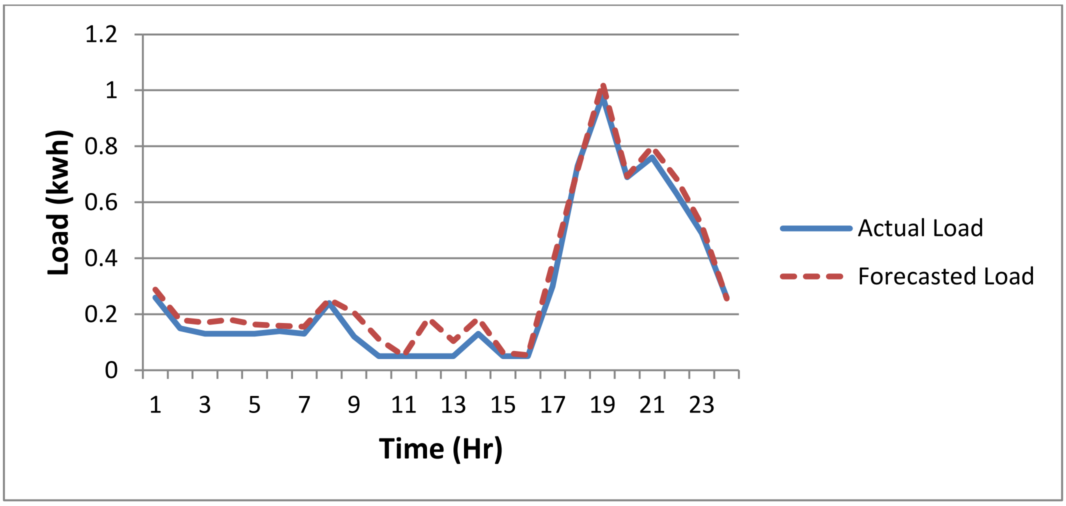

Figure 4.25: Actual and forecasted load curves for May 23.

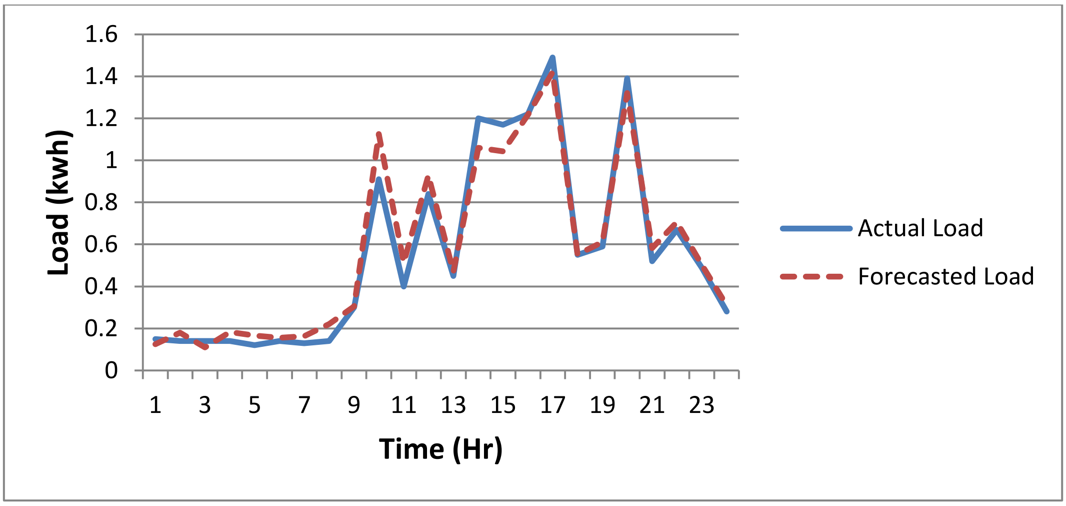

Figure 4.26: Actual and forecasted load curves for May 24.

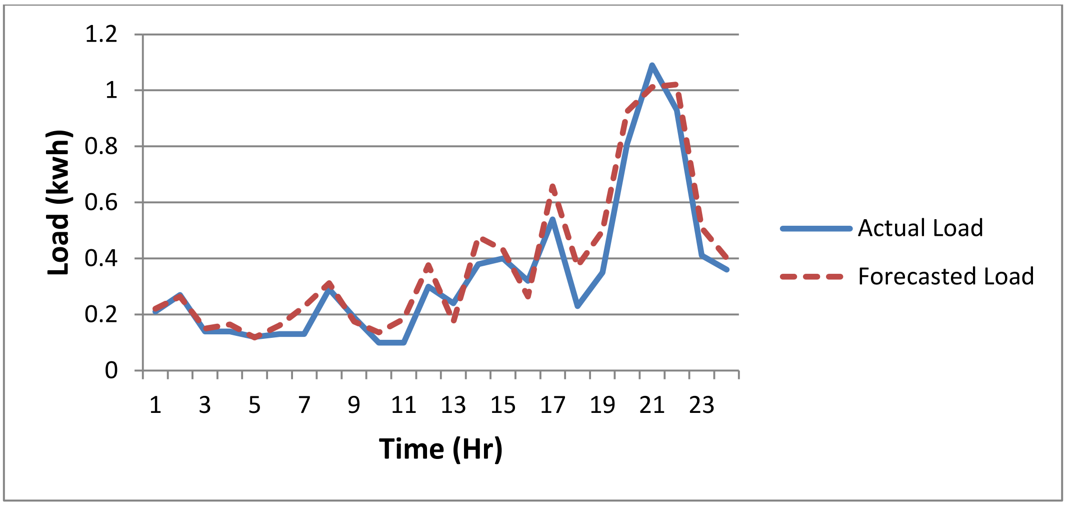

Figure 4.27: Actual and forecasted load curves for May 25.

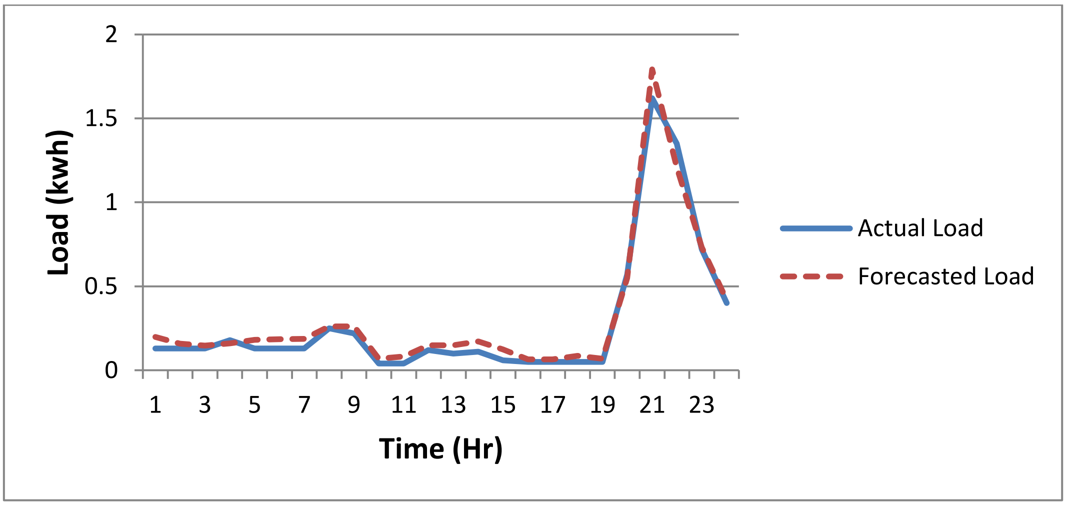

Figure 4.28: Actual and forecasted load curves for May 26.

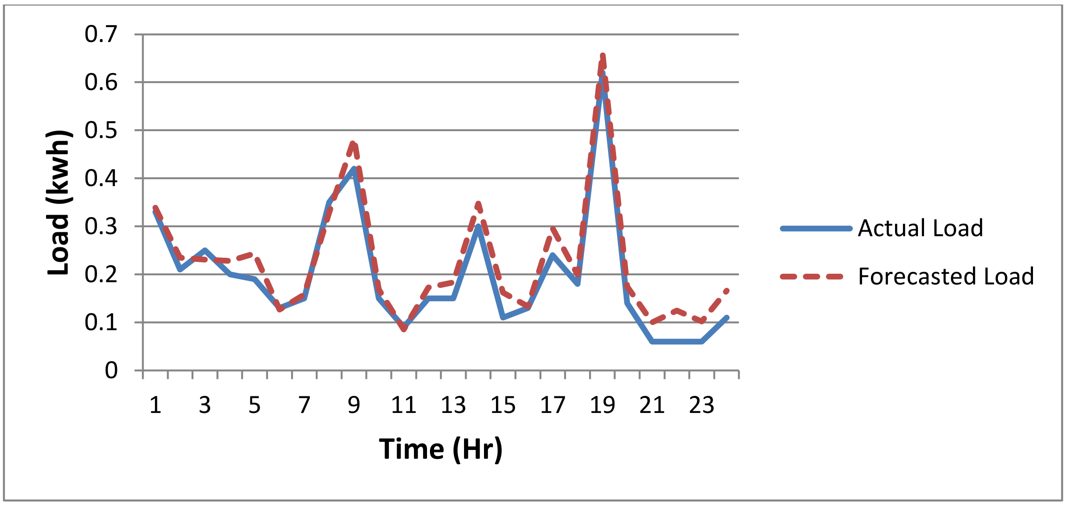

Figure 4.29: Actual and forecasted load curves for May 27.

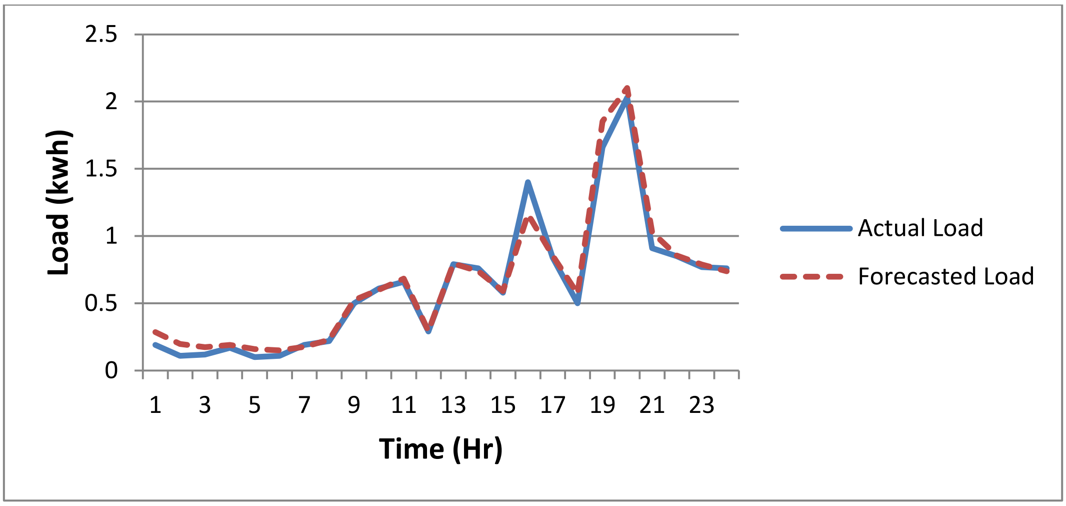

Figure 4.30: Actual and forecasted load curves for May 28.

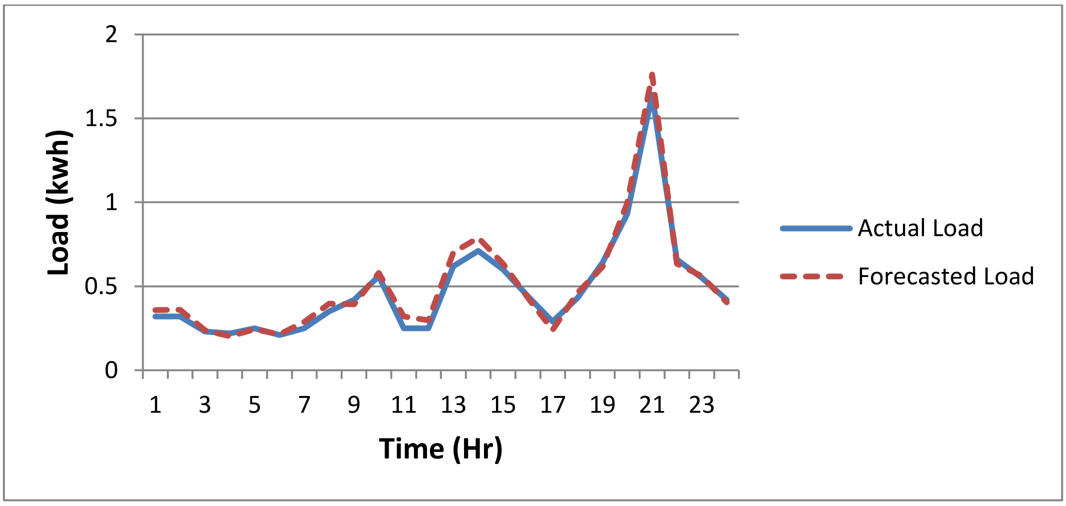

Figure 4.31: Actual and forecasted load curves for May 29.

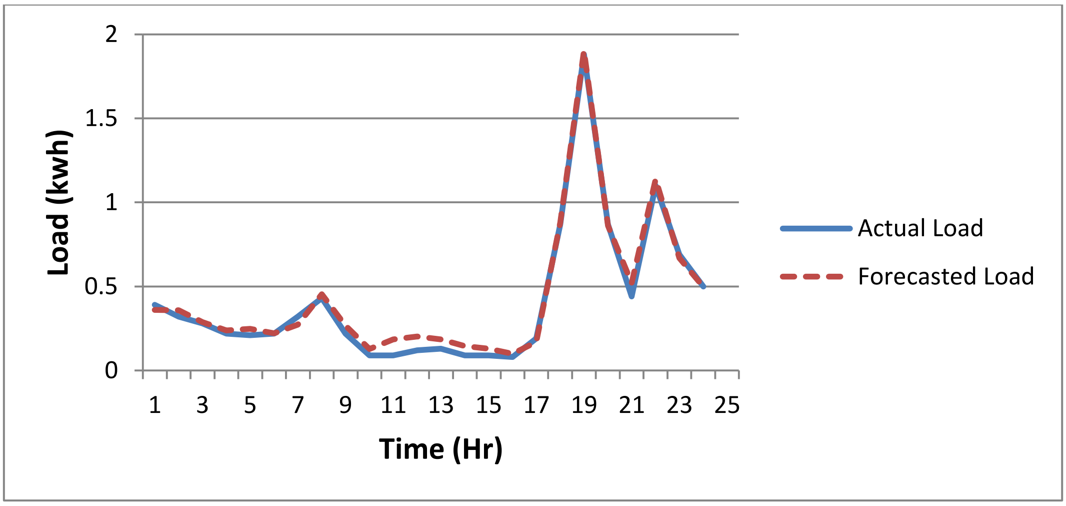

Figure 4.32: Actual and forecasted load curves for May 30.

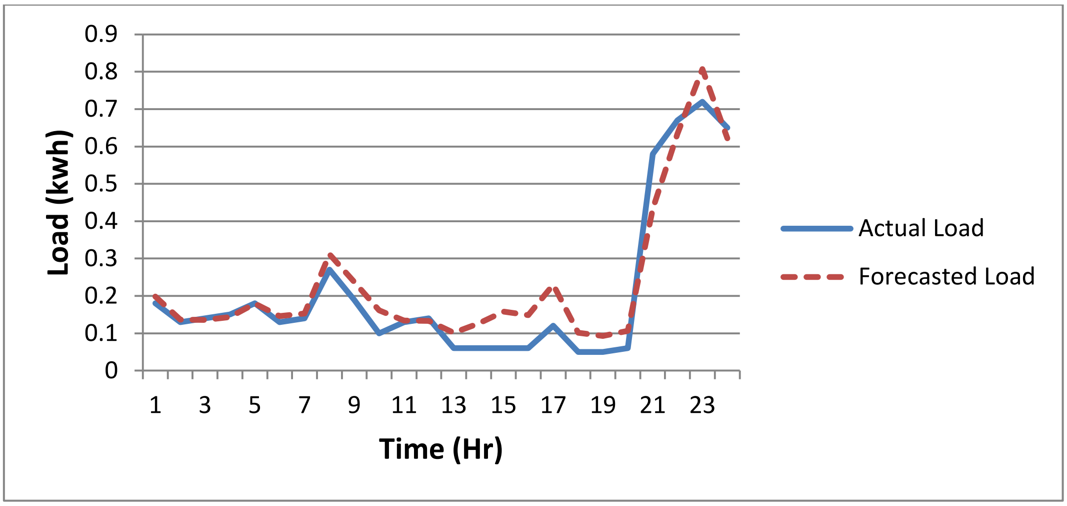

Figure 4.33: Actual and forecasted load curves for May 31.

The actual and forecasted weekly load is plotted in order to have an idea of what the curve looks like. Figure 4.34 shows the combined curve for the actual and forecasted load.

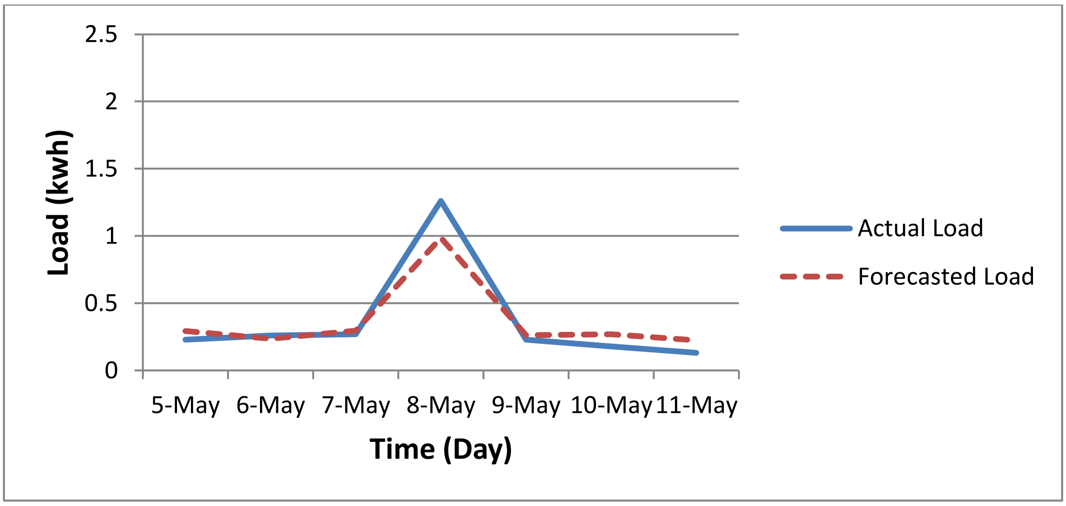

Figure 4.34: One week combined actual and forecasted load curves.

Generally forecasts are totally not always accurate as it always deviates from the actual values. From Figures 4.3 to 4.33 it is observed that the forecasted load curves almost corresponded with the actual load curves. This shows that the tendency of the network to forecast load consumption is accurate.

Chapter 5

CONCLUSION AND FUTURE WORK

5.1 Conclusion

For utilities, accurate short-term load forecast plays an important role as it helps in electrical energy systems planning and operations. This study is aimed at analyzing electrical load consumption for a residential building using neural network based short-term load forecast approach. The MAPE performance obtained using this approach is 1.233%. Bearing in mind that a MAPE between 1% and 5% is the reachable goal and it can be said that 1.233% is an acceptable limit compared to the literature. This shows that neural network is a vital tool in achieving optimum results for short term load forecasting.

The proposed approach has great benefit as it is experimentally easier, simple and cost effective. The knowledge and experience gotten from the use of neural network in short-term load forecasting for a single residential building can be applied to a region provided it is a short-term load forecast.

In this study a single house made up of two occupants was used as a case study. These occupants were both working so this did not make much difference in the trend of energy consumption. Similar studies can be done for an entire region with different households having different characteristics like some houses having home stay mothers, children etc. This will help utility companies have a proper planning since there will be a better generalization of the load forecast. Also the feasibility of installing individual residential solar systems for power generation can be checked by this forecasting method.

5.2 Future Work

It is possible to improve on the accuracy of the forecast. This can be done by using real-time load data. This work is posed with the challenge of inaccurate/missing data making the selection of data needed difficult. This is important as the more accurate the real-time data reading is the more accurate the forecast will be. Smart meter reading system makes it possible to get real-time electrical energy data whenever it is needed. Data based on smart meters can be used to obtain a more accurate load forecast. The use of smart meters in homes is highly encouraged.

In the future the use of different learning algorithm and other machine learning techniques is recommended.

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