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BAHÇEŞEHİR ÜNİVERSİTESİ

SHORT-TERM LOAD FORECASTING BY USING ARTIFICIAL NEURAL NETWORKS

Master's Thesis

USMAN NAJEEB KHAN

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THE REPUBLIC OF TURKEY

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NATURAL AND APPLIED SCIENCES

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ABSTRACT

SHORT-TERM LOAD FORECASTİNG

BY USİNG ARTİFİFİCAL NEURAL NETWORKS

Usman Najeeb Khan

Electrical and Electronics Engineering

Asst. Prof. Dr. Cavit Fatih Küçüktezcan

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Load forecasting is a vital component for power systems. For any electric power organization, it is their main role to provide electric energy in an economical and secured manner maintaining the quality. In power systems, electric load forecasting is a very essential issue and has been studied widely so that to attain more precise load forecasting results. Since in power systems the next day's power generation must be scheduled every day, day-ahead short-term load forecasting (STLF) is an important daily task for power companies. The short-term load forecast represents the electric load forecast for a time span of few hours to a several days.

This thesis uses the method of Artificial Neural Networks (ANN) to create a STLF model for Faisalabad Electric Supply Cooperation (FESCO). FESCO can be described as an institutional/industrial-type electric load. The ANN is a mathematical/computational tool that mimics the way human brain processes information. Several types of ANNs are revealed in this research, among them Feed-Forward (FF) neural networks have been used to create a STLF model.

Two different methods ReliefF and Correlation analysis are presented and used for the selection of important input variables which will be used as inputs of ANN. The inputs given to the ANN are historical electric load and average air temperature data.

Correlation method provides better results for the selection of input variables rather than the ReliefF method. The ANN uses the historical electric load and weather data as an input and provides a forecasted electric load at its output. Average air temperature data is used in this research in order to achieve better short-term load forecasting results.

Furthermost ANNs in the literature are used to forecast day ahead electric load for a transmission-level system with resulting load forecast errors ranging from nearly 0.1% to 2.3%. This research indicates that an ANN can be used to forecast the smaller, more disordered load profile of an institutional/industrial-type power system and results in a similar forecast error range. In addition, the in-service constraints of the FESCO electric load will be investigated along with the weather profiles for the site.

Through detailed performance evaluations, this research demonstrate that the presented forecasting method is capable of predicting the day ahead electric load accurately.

Keywords: Short-Term Load Forecast, Artificial Neural Network, Multi-Layer Perceptron, Feed-Forward Neural Network, Back-Propagation Algorithm

ÖZET

SHORT-TERM LOAD FORECASTİNG
BY USİNG ARTİFİFİCAL NEURAL NETWORKS

Usman Najeeb Khan

Elektrik ve Elektronik Mühendisliği

Asst. Prof. Dr. Cavit Fatih Küçüktezcan

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Yük tahmini, güç sistemleri için hayati bir bileşendir. Elektrik enerjisinin ekonomik ve güvenli bir şekilde tüketiciye sağlanması elektrik güç sistemi kurumlarının temel rolüdür. Güç sistemleri için önemli bir konu olan elektriksel yük tahminin daha yüksek başarımla yapılabilmesi amacıyla çalışılmaktadır. Güç sistemlerinde, ertesi güne ait güç üretiminin şimdiden planlanması gerektiğinden kısa dönem yüh tahmini, sistem operatörleri ve üretim şirketleri için oldukça önemlidir. Kısa dönem yük tahmini birkaç saat ile birkaç güç arasındaki zaman dilimini kapsamaktadır.

Bu çalışmada, yapay sinir ağları yöntemi kullanılarak Faisalabad Elektrik Tedarik Şirketi için kısa dönem yük tahmini gerçekleştirilmiştir. Yapay sinir ağları, insan beyninin bilgi işleme sürecini taklit eden bir hesaplama aracıdır. Bu çalışmada, çeşitli yapay sinir ağları tipleri arasından ileri doğru ilerleyen yapay sinir ağları seçilerek kısa dönem yük tahmini için kullanılmıştır.

Çalışmada kullanılan yapay sinir ağlarının giriş değişkenlerinin belirlenmesi için ReliefF ve korelasyon analizi yöntemleri kullanılmıştır. Sadece geçmiş elektriksel yük ve hava sıcaklığı verilerinden türetilmiş çok sayıdaki öznitelik içerisinden, yük tahmini için diğerlerine nazaran daha etkin olan öznitelikler bu yöntemlerle belirlenmiş ve farklı öznitelik seçim yöntemlerinin yapay sinir ağları performansına etkileri incelenmiştir. Bunun neticesinde, korelasyon analizi ile seçilen değişkenlerin kullanıldığı sinir ağları performansının daha yüksek tahmin başarısına sahip olduğu görülmüştür.

Literatürde önerilen yapay sinir ağları yöntemlerinin iletim seviyesindeki elektriksel yükün gün öncesi tahmininde kullanımında %2.3'e varan hata oranları görülmektedir. Bu çalışma, daha küçük ve düzensiz profildeki yüklerin tahmininde de yapay sinir ağlarının benzer bir hata oranına sahip olduğunu göstermiştir. Ayrıntılı performans değerlendirmelerine göre, bu araştırmada önerilen tahmin yönteminin gün öncesi elektriksel yükü kabul edilebilir bir oranda tahmin edebildiği görülmüştür.

Anahtar Kelimeler: Short-Term Load Forecast, Artificial Neural Network, Multi-Layer Perceptron, Feed-Forward Neural Network, Back-Propagation Algorithm.

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ABBREVIATIONS

ANN	:	Artificial Neural Network
AR	:	Auto Regressive
ARIMA	:	Auto Regressive Integrated Moving-Average
ARMA	:	Auto Regressive Moving-Average
BP	:	Back-Propagation
CNN	:	Convolution Neural Network
FESCO	:	Faisalabad Electric Supply Corporation
FF	:	Feed Forward
HVAC	:	Heating, Ventilation and Air Conditioning
KBES	:	Knowledge-Based Expert Systems
LM	:	Levenberg-Marquardt
LTLF	:	Long-Term Load Forecasting
MAPE	:	Mean Absolute Percentage Error
MLP	:	Multi-Layer Perceptron
MLR	:	Multiple Linear Regression
MTLF	:	Medium-Term Load Forecasting
NH	:	Nearest-Hit
NM	:	Nearest-Miss
NTDC	:	National Transmission and Dispatch Company
RMSE	:	Root Mean Square Error
RNN	:	Recursive Neural Network
STLF	:	Short-term Load Forecasting
STS	:	Stochastic Time Series
TF	:	Transfer Function
VSTLF	:	Very-Short-Term Load Forecasting

1. INTRODUCTION

Load forecasting is a vital component for power systems. For any electric power organization, it is their main role to provide electric energy in an economical and secured manner maintaining the quality. At present, there is no substantial energy storage in the electric transmission and distribution system. For the purpose of best operation and planning of electric power system, electric load of present and future must be evaluated. And for an optimal power system operation, electrical generation must follow electrical load demand. The generation, transmission and distribution utilities require some means to forecast the electric load so they can utilize their infrastructure efficiently, securely and economically. [1]

Since in power systems the next day's power generation must be scheduled every day, day-ahead short-term load forecasting (STLF) is an important daily task for power companies. Its accuracy affects the economic operation and reliability of the system greatly. While on the other hand, over prediction of short-term load forecasting will lead to an important large reserve capacity, also related to high operating cost. It is estimated that in British power system every one percent increase in the forecasting error is associated with an increase in operating cost of 10 million pounds per year [2].

The purpose of this research is to perform short-term load forecasting (STLF) for a specific organization. The organization to be studied is the Faisalabad Electric Supply Cooperation (FESCO). FESCO is served directly by National Transmission and Dispatch Company (NTDC) at 132 and 66 kV. The voltages are then stepped down to 11 kV at FESCO and distributed throughout the site. During fiscal years FY16 and FY17, FESCO's average power usage was approximately 1607MW with a peak summer demand of approximately 2596MW.

The advantage of short-term load forecasting for the specific organizations such as FESCO is that the organization can use the forecasted load and various energy demand management techniques to plan for peak electric load reduction by implementing various means such as electric load-shedding, on-site generation and via demand response agreements.

According to electric load prediction survey [3] published, it indicated that of the 22 research reports considered, 13 made use of air temperature only, 3 made use of temperature and humidity, 3 utilized additional weather parameters, and 3 used only load parameters for short-term load forecasting model. This reveals that the air temperature is an important factor which directly affects the short-term load forecasting model. In this research historical load demand data and daily average air temperature is utilized as an input to Artificial Neural Network (ANN).

1.1 OBJECTIVES

The main objective of this research is to propose a short-term load forecasting model with high accuracy based on the historical data of electric load demand and daily average air temperature by using Artificial Neural Networks (ANN) for FESCO.

Since accurate load forecasting is still a greater challenge, another objective of this research is to compare both Correlation and Relief methods for the selection of best attributes useful in forecasting day-ahead average load more efficiently. The research focuses on using Artificial Neural Networks (ANN) in creating a short-term load forecasting model.

1.2 OUTLINE OF THESIS

The thesis is organized orderly into 5 chapters which are defined as under:

Chapter 1 reveals the importance of proposing short-term load forecasting model with high forecasting accuracy based on the historical data of electric load demand and daily average air temperature using Artificial Neural Networks (ANN) for FESCO. It also displays the objective and outline of the thesis.

Chapter 2 explains the term load forecasting, time horizons of load forecasting and its types. The key factors which affect the load forecast are revealed. Various short-term load forecasting methods such as Multiple Linear Regression, Time Series, Knowledge-Based expert systems, Similar-day Approach and Neural Networks are also discussed. This chapter also presents some important ANNs.

Chapter 3 presents STLF using Artificial Neural Networks (ANN). There are 3 important steps involved in proposing a neural network model which are selection of input variables, network training, and forecasting. For the selection of a number of variables, two methods are used and also discussed in this chapter.

Chapter 4 presents the results of two different methods used for the selection of input variables which are used as an input of ANN. Scatter plots of time-lagged load and time-lagged weather data are also shown in this chapter. At the end, the chapter presents the results of day-ahead load forecast model using Artificial Neural Networks (ANN). The simulations obtained from the research has been also shown in this chapter.

Chapter 5 summarizes the research and results presented in this thesis. This chapter also proposes a future work in electrical STLF.

2. LITERATURE REVIEW

Electric load forecasting is utilized by an electric energy organization to predict the amount of electric power required to supply in order to meet up the demand. In power systems, electric load forecasting is a very important issue and has been studied widely so that to attain more precise load forecasting results [4].

Load forecasting is beneficial to an electric energy organization in making necessary decisions which include generating and purchasing electric energy, development of infrastructure and load shedding.

Load forecasting can be further classified into 4 main types as a very-short-term load forecast, short-term load forecast, medium-term load forecast and long-term long forecast.

2.1 TIME HORIZONS OF LOAD FORECASTING

2.1.1 Very-Short-Term Load Forecast (VSTLF)

The economic dispatch and load frequency control in power systems require load forecasts with shorter time leads, from one minute to several dozen minutes. Very-Short-term Load Forecast (VSTLF) is a type of forecast which usually predicts the load from one minute to half an hour ahead [5]. VSTLF is further classified into classical approaches and techniques based on artificial intelligence.

2.1.2 Short-Term Load Forecast (STLF)

This type of load forecast predicts load from one hour to one month [6]. STLF help electric energy organizations to anticipate load flows and make decisions that prevent overloading. Timely implementation of such decisions lead to the improvement of network reliability and reduce occurrences of load shedding and equipment failure. Later in sections, the key factors which affect the STLF and the main methods which are used to achieve STLF are briefly discussed.

2.1.3 Medium-Term Load Forecast (MTLF)

Medium-Term Load Forecast (MTLF) is a type of forecasting which predicts load usually from month to a year [6]. MTLF is useful in unit maintenance and to determine the amount of fuel required for power plants.

2.1.4 Long-Term Load Forecast (LTLF)

Long-Term Load Forecast (LTLF) is a type of forecasting which predicts load longer than a year [6]. LTLF is used to supply electric energy organization management with the prediction of future needs for expansion, purchasing equipment, and inter-tie tariff setting.

2.2 FACTORS AFFECTING THE PERFORMANCE OF LOAD FORECAST

Load forecasting using different time horizons are very useful to an electric power organization under different operations. The nature of these forecasts differs as well. For example, for a certain area, it is possible to predict the next day load with an accuracy of approximately 1-3%. However, it is impossible to predict the next year peak load with the similar accuracy since accurate long-term weather forecasts are not available.

Figure 2.1: FESCO daily average demand load 1/1/2016 to 6/30/2017 [1]

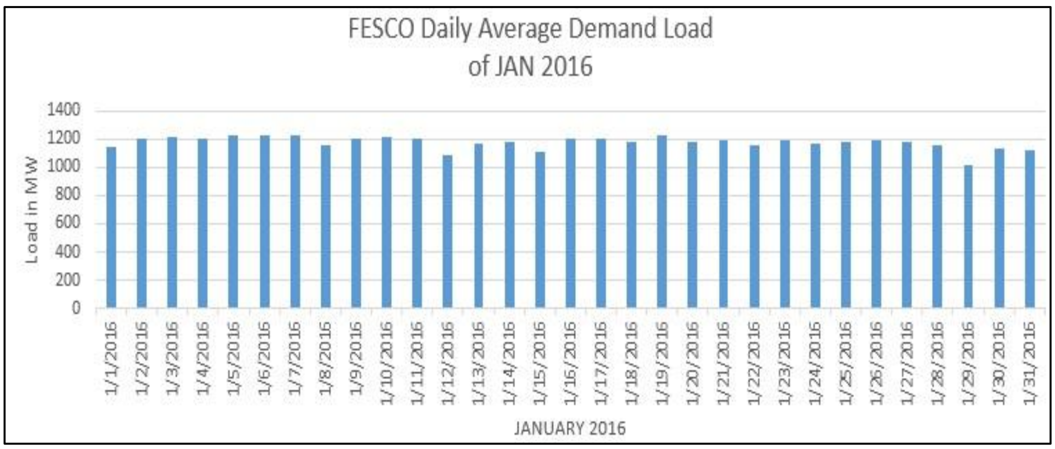
Source: Y. Al-Rashid and L.D. Paarmann, 1996 [1].

There are several factors which affect the load forecast and influence system load behavior includes economic, customer Class (industrial, residential, etc.), weather, time and random disturbances. Some of these important factors are detailed under:

2.2.1 Time Factor

The time factor includes the time of the year, the day of the week and hour of the day. There are significant differences in load between weekdays and weekends.

Figure 2.2: FESCO daily average demand load of January 2016 [2]



Source: H.S Hippert, C. E. Pedreira and R. C. Souza, 2005 [2].

Figure 2-2 shows a significant difference in a daily average demand load of FESCO for the month of January 2016. Since in Faisalabad city Friday is considered as a holiday by the majority of textiles, industries, and markets. A major difference can be seen in demand load for 1/1/2016, 1/8/2016 and vice versa because of Fridays. Table 2-1 represents the average demand load of FESCO for different days of the week in the year 2016.

Table 2.1: FESCO Average demand load for each day in 2016

Day	Number of the days in 2016	Average demand load (MW)
Friday	53	1587
Saturday	53	1633
Sunday	52	1648
Monday	52	1651
Tuesday	52	1667
Wednesday	52	1641
Thursday	52	1654

Source: H.S Hippert, C. E. Pedreira and R. C. Souza, 2005 [2].

2.2.2 Weather Factor

Weather factor has a significant effect on the short-term electric load forecasting of a power system. And according to electric load prediction survey [3] published, air temperature is the most important factor considered for short-term load forecasting model. Weather-sensitive loads, such as heating, ventilating, and air-conditioning (HVAC) equipment, strongly affects the power systems as these electrical loads tend to be the larger loads on the system. Switching on and off HVAC apparatus can produce electrical load profiles that appear to have random power swings. In figure 2-2 the electric load peak occurs at 2596MW in the last week of June when the average air temperature is close to its maximum. And also, the bottom average demand load occurs at 960MW during the second week of December when the average air temperature is close to its minimum.

Table 2-2. Shows the average demand load and air temperature of the last week of June 2016 and Table 2-3. Shows the average demand load and air temperature of the second week of December 2016.

Table 2.2: FESCO demand load of summer week in 2016 [3].

Date	Average demand load (MW)	Average air temperature (°C)
6/24/2016	2332	39
6/25/2016	2466	42
6/26/2016	2366	38
6/27/2016	2224	38
6/28/2016	2118	35
6/29/2016	2501	38
6/30/2016	2596	39

Source: Eugene A. Feinberg and Dora Genethliou, 2006 [3].

Table 2.3: FESCO demand load of winter week in 2016 [3].

Date	Average demand load (MW)	Average air temperature (°C)
12/8/2016	1174	20
12/9/2016	1044	18
12/10/2016	1110	21
12/11/2016	1030	20
12/12/2016	960	20
12/13/2016	1073	21
12/14/2016	1170	21

Source: Eugene A. Feinberg and Dora Genethliou, 2006 [3].

2.2.3 Random Factor

Random factors that affects the electrical load profile contains all the random interferences in the load pattern that cannot be expressed by weather and time factor. The random factor can consist of significant loads which occur randomly having no operating schedule which makes prediction difficult. Random factor includes planned or unplanned electric load shedding, festival or event, etc.

2.3 LOAD FORECAST METHODS

Since load forecasts can be divided into four types which are discussed in section 2.1 having different time spans, therefore this means that for each of the type, there will be the most appropriate methods to operate the forecast models. For MTLF and LTLF, the so-called end-use and econometric approach are broadly used. For VSTLF and STLF several methods are used and most of these methods are discussed in this research.

2.3.1 Multiple Linear Regression (MLR)

Multiple linear regression utilizes two or more explanatory variables and a response variable by fitting a linear equation to the observed data and seeks to represent the linear relationship between them. This method uses explanatory weather and non-weather variables to predict the electrical load at a specified time t. These variables tend to have a great impact on electrical load and are selected by correlation analysis with the load [7]. Regression coefficients are calculated by using least square estimation techniques. And these coefficients are multiplied by the variables [8]. Every value of the dependent variable y is associated with a value of the independent variable x.

The MLR electrical load model has the following form:

$$y(t) = a_0 + a_1(t) + \ldots + a_n x_n(t) + a(t) \qquad (2\text{-}1)$$

where,

$y(t)$ = electrical load

$x_1(t) \ldots x_n(t)$ = explanatory variables correlated with $y(t)$

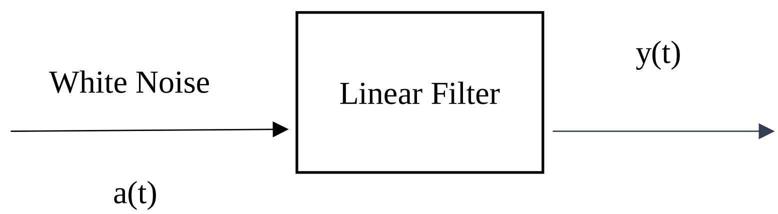
$a(t)$ = a random variable with zero mean and constant variance.

$a_0, a_1, \ldots, a_n$ = regression coefficients.

2.3.2 Time Series

Time series can be defined as a sequential set of data measured over time, such as the hourly, daily or weekly peak load. It uses historical load data to predict the future load [9]. The electric load y(t) is modeled as the output of a linear filter with a random series input a(t) also called white noise. This random input has a zero mean with fixed unknown variance σ_a^2 (t). Different models of STLF can be classified depending on the characteristic of the linear filter [10].

Figure 2.3: Load time series modeling [10].



Source: T.G. Manohar and V.C. Veera Reddy, 2008 [10].

The **Autoregressive (AR**) model defines the forecasted electric load y(t), in terms of the previous load values and a random noise signal a(t) [11].

$$y(t) = \phi_1 y\,(t-1) + \phi_2 y\,(t-2) + \ldots + \phi_p y\,(t-p) + a(t) \tag{2-2}$$

The **Moving-Average (MA)** model defines the forecasted electric load y(t), in terms of the current and previous values of series of random noise signals. This noise series is constructed from the forecast errors or residuals when load observations become available [11].

$$y(t) = a(t) - \Theta_1 a\,(t-1) - \Theta_2 a\,(t-2) - \ldots - \Theta_{q1} a\,(t-q) \tag{2-3}$$

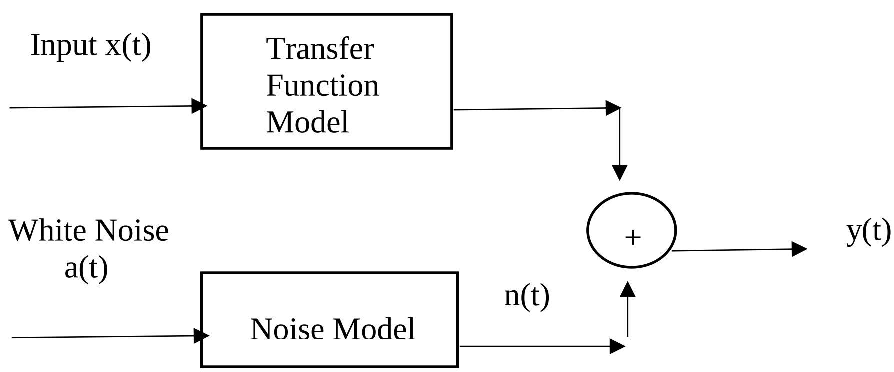
The **Autoregressive Moving-Average (ARMA)** model defines the forecasted electric load y(t), with the combination of **AR** and **MA** model.

$$y(t) = \phi_1 y\,(t-1) + \phi_2 y\,(t-2) + \ldots + \phi_p y\,(t-p) + (t) - \Theta_1 a\,(t-1) - \; 2a\,(t-2) - \ldots\ldots\ldots \Theta_{q1} a\,(t-q) \tag{2-4}$$

The **AR, MA and ARMA** processes are also called stationary process. If the process is non-stationary, a transformation is required which is achieved by differences in **ARMA** model. The transformed model is called **Autoregressive Integrated Moving Average (ARIMA)** model.

The **Transfer Function (TF)** model uses **AR, MA, ARMA or ARIMA** model to represent white noise and load data with one or more variables such as air temperature, wind speed, humidity, etc. which tends to have a strong effect on electric load profile [11]. Using a **TF** these other variables can be modeled as shown below in Figure 2-4.

Figure 2.4: Transfer function (TF) model [11].



Source: Z. H. Ashour, M. A. Abu El-Maged and M. A. El-Fattah Farahat, 1991[11].

2.3.3 Expert System

An expert system is a computer-based program comprising a large historical database and a set of rules which are used to search the historical database for the best solution to a particular problem. Expert systems are an emerging technology with many fields such as STLF [11]. The expert systems are followed by IF-THEN rules and mathematical expressions which are used to make forecasts. Some rules have to be updated continually while others do not change over time [12].

2.3.4 Similar-day Approach

The similar-day approach is widely used for STLF. This approach investigates historical database for same characteristics to the forecasted day. Same characteristics include dates, weather, the day of the week, etc. A load of same day matching the characteristics is considered as a forecast. Though many days can match the characteristics, various techniques have been developed and used to reduce the error and improve the efficiency of forecast [13].

2.3.5 Neural Networks

Neural Networks (NN) or Artificial Neural Network (ANN) method has been widely studied and used for load forecasting since 1990 [14]. Neural networks are essentially non-linear circuits that have the demonstrated capability to do non-linear curve fitting. A neural network is a machine that is designed to model the way in which the human brain performs a particular task. The brain is a highly complex, nonlinear and parallel information processing system. As there are billions of neurons in the human brain, ANN basic processing components are the neurons. These neurons are programmed to act similarly to the neurons in the brain by receiving an input, performing a particular task based on the input and produce an output. Chapter 3 discusses the Neural Networks in detail.

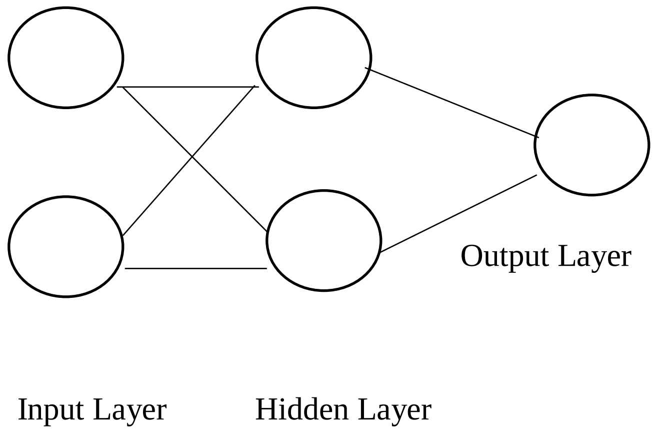
2.4 TYPES OF NEURAL NETWORKS

There are several types of Neural Networks each based on different architecture. Neural Networks can be further classified in to 4 general categories being preferred and used in machine learning. Given below are the types of Neural Networks:

2.4.1 Feed Forward Neural Network

Though it can be understandable by the term feed forward which means that the direction or information given flows in a forward one direction. This approach became practical in 1950’s [15]. In FF network, all the nodes are fully connected and the data flows from input layer to output layer without any back loops. Given below is the figure of FF network with one hidden layer.

Figure 2.5: Feed forward neural network [15]



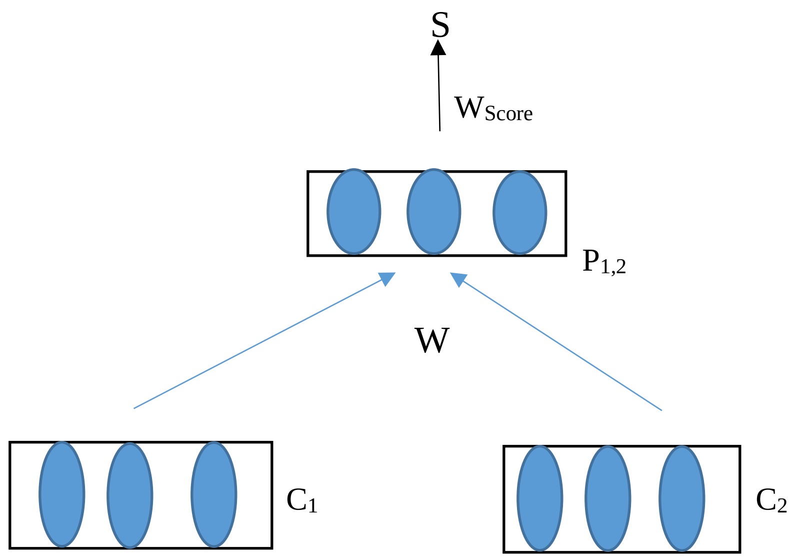
Source: Chen H, Canizares C.A and Singh A, (2001).

The hidden layers can be varied according to the requirements. In this research, a MLP method is used for STLF which is briefly discussed in chapter 3. The function of these three input, hidden and output layers are also briefly discussed.

2.4.2 Recursive Neural Network (RNN)

Recursive Neural Networks (RNN) are non-linear adaptive models having the ability of learning deep structured information. They were introduced in late 90's [17]. These computational models are suited for both regression and classification problems being capable of carrying non-supervised and supervised training tasks. The most popular algorithm used to train the RNN is the back-propagation method. Back-propagation method is also briefly discussed in the next chapter.

Figure 2.6: Simple recursive neural network architecture [17]



Source: Frasconi P, Gori M and Sperduti A, 1997 [17]

The network is made by applying the same set of weights recursively over a structure to make a structured forecast over variable-size input structures by traversing the provided structure in topological order. Recursive Neural Networks are very powerful in learning hierarchical, tree-shape structures. These models have not been broadly accepted, due to their inherent complexity. And also due to the fact of computationally expensive training phase. RNN has been found not to the best appropriate for structured processing due to the convergence problem [18]. In figure 2-6, if C_1 and C_2 are n-dimensional vector representing nodes, their parent p will also be an n-dimensional vector, calculated as:

$P_{1,2} = \tanh(W[c_1;c_2])$

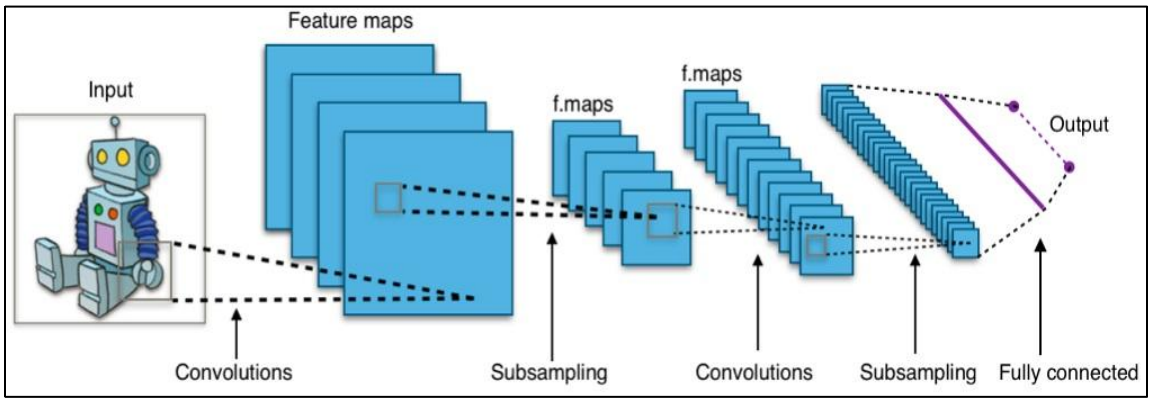
(2-5)

Where W is the trained n x 2n weight matrix.

2.4.3 Convolutional Neural Network (CNN)

Convolutional Neural Network consists of one or more than one convolutional layers partially or fully connected and utilizes a variation of Multilayer Perceptron (MLP) which are discussed in the next chapter.

Figure 2.7: Typical convolution neural network architecture [19]



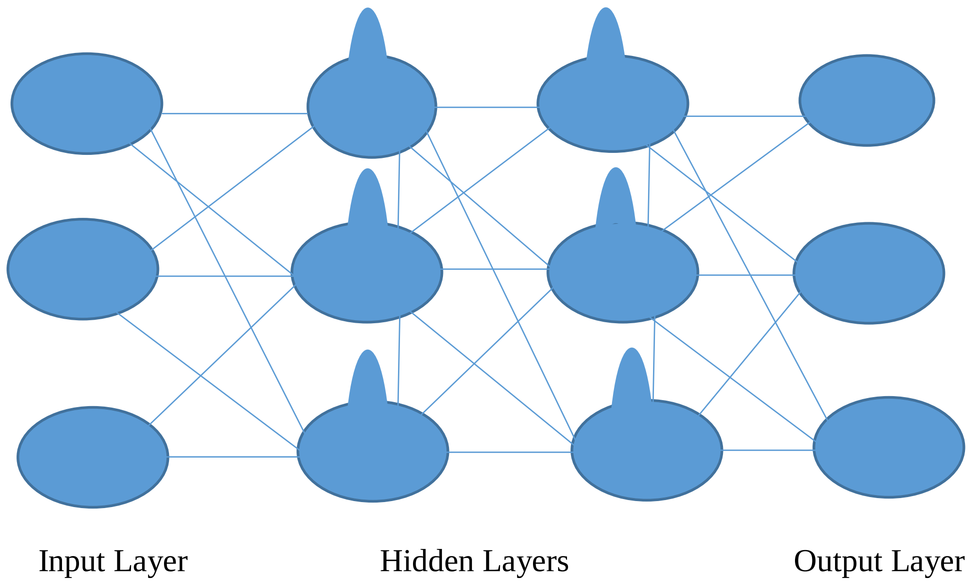
Source: Y. Bengio, R. Ducharme and P. Vincent, 2003 [19]

As it can be viewed from Figure 2-7 given above, CNN uses several convolution layers for carrying out the output. In these layers convolution operation is applied passing the results to the next layers. This method allow the network to be deeper with much fewer parameters. CNN shows tremendous results in image and speech applications [19].

2.4.4 Recurrent Neural Network

Recurrent Neural Networks are unlike a FF neural network, is an alternate of RNNs in which the connection between neurons makes a directed cycle. The first network of this type was called Jordan Network, when each of the hidden cell recieved its output with fixed delay. In this network, the output depends not only on the present inputs but also on the previous step's neuron state [20].

Figure 2.8: Recurrent neural network architecture [20]



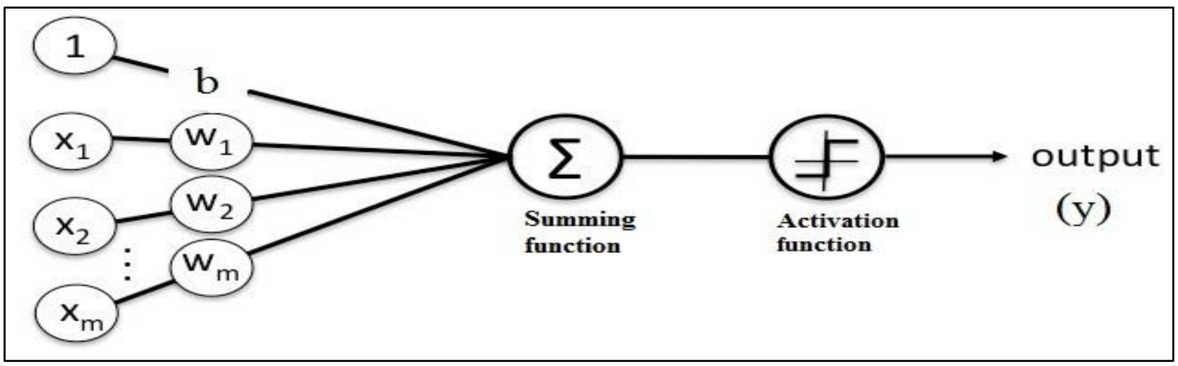
Source: Mesnil G, He X, Deng L and Bengio Y, (2013) [20]

Figure 2-8, represents the architecture of recurrent neural network. The memory lets the users to solve non linear problems like speech recognition and connected handwriting and text classifications. The most common examples of recurrent neural network are texts, a word can be analysed only in context of previous words or sentences.

3. SHORT-TERM LOAD FORECAST USING ANN

ANNs have received an extensive share of the research attention in STLF since the late 1980's. Artificial Neural Networks are mathematical tools or computer-based programs that mimic the way human brain processes information [14]. The basic processing element in neural networks is neurons. In ANNs a group of artificial neurons is interconnected and processes information using a connectionist approach to computation. The neuron is shown mathematically in Figure 3-1.

Figure 3.1: An artificial neuron model [14]



Source: Resource: Chen H, Canizares C.A and Singh A, (2001) [14]

As shown in above Figure 3-1, a neuron model consists of a combination of inputs represented by X_i each having unique weights W_i which are associated with those inputs. Additionally, there is another constant input 1 having its unique weight b also called the bias. The main function of bias is to provide every input node X_i with a trainable constant value. The output (y) of a neuron is computed as:

$$y= f\,(X_1W_1+X_2W_2+X_mW_m+b) \qquad (3\text{-}1)$$

The linear combination of all these inputs (X_iW_i+b) is given as an input to a function. This function is called the activation function as shown in Figure 3-1 above. The activation function is a non-linear function. The reason behind this is that the training of ANN requires the activation function to be differentiable and not decreasing [15]. It is important because of the fact, that most real-world data is nonlinear and we want neurons to learn these nonlinearities. There are several activation functions. Every activation function takes the single input and performs certain fixed mathematical operations [15]. Some of the activation functions are given below:

i. Sigmoid Function: This activation function receives the input and distributes it to range between 0 and 1. The mathematical expression of the sigmoid function is given below:

$$\sigma(x)=\frac{1}{1+e^{-x}} \tag{3-2}$$

ii. tanh Function: This activation function takes a real-valued input and divides it to the range [-1, 1]. The mathematical expression of this function is given below:

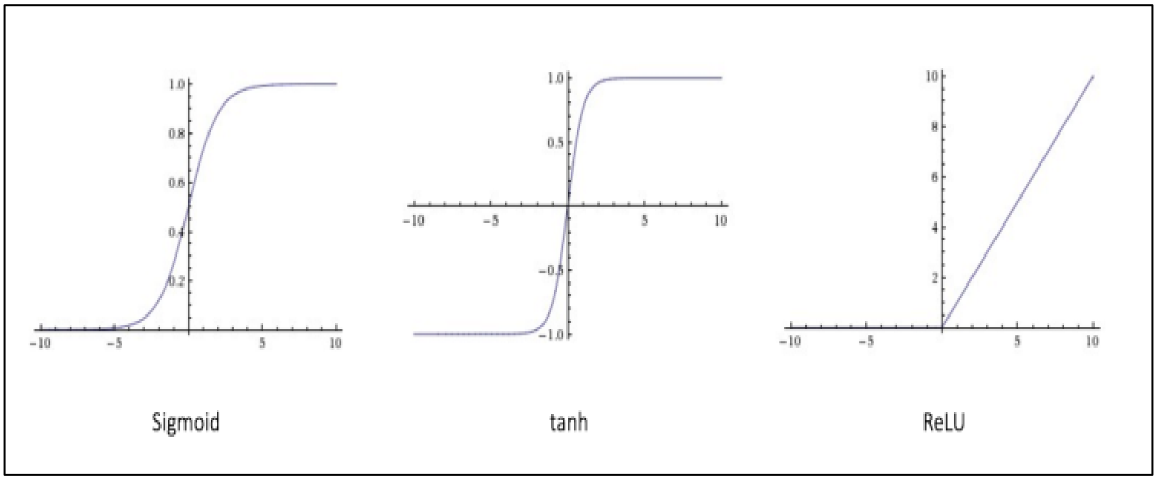
$$\tanh(x)=2\sigma(2x)-1 \tag{3-3}$$

iii. ReLU Function: ReLU stands for Rectified Linear Unit. This type of activation function receives a real-valued input and thresholds it at zero (replaces negative values with zero)

$$f(x)=\max(0,x) \tag{3-4}$$

Figure 3-2 shows each of these activation functions given below:

Figure 3.2: Different activation functions [15]



Source: H.S. Hippert, C.E. Perdreiraand R.C. Souza, 2001 [15]

The architecture of an ANN tells that how its several neurons are placed in relation to each other. These arrangements are structured essentially by directing the synaptic connections of the neurons. In general, the architecture of ANN can be divided into three parts, named layers, which are given below:

i. Input Layer: The process of the input layer is to receive the data or information provided and pass it to next layer which is called hidden layer. The data is normalized to limit values produced by the activation functions.

ii. Hidden Layer: The data or information received in the input layer is passed to the hidden layer. Hidden layer has no direct access to outside world. The process of hidden layer is to extract patterns associated with the task or system being analyzed. Most of the internal processing from a network is performed in hidden layers. A feedforward network will only have a single input layer and a single output layer, it can have zero or multiple Hidden Layers.

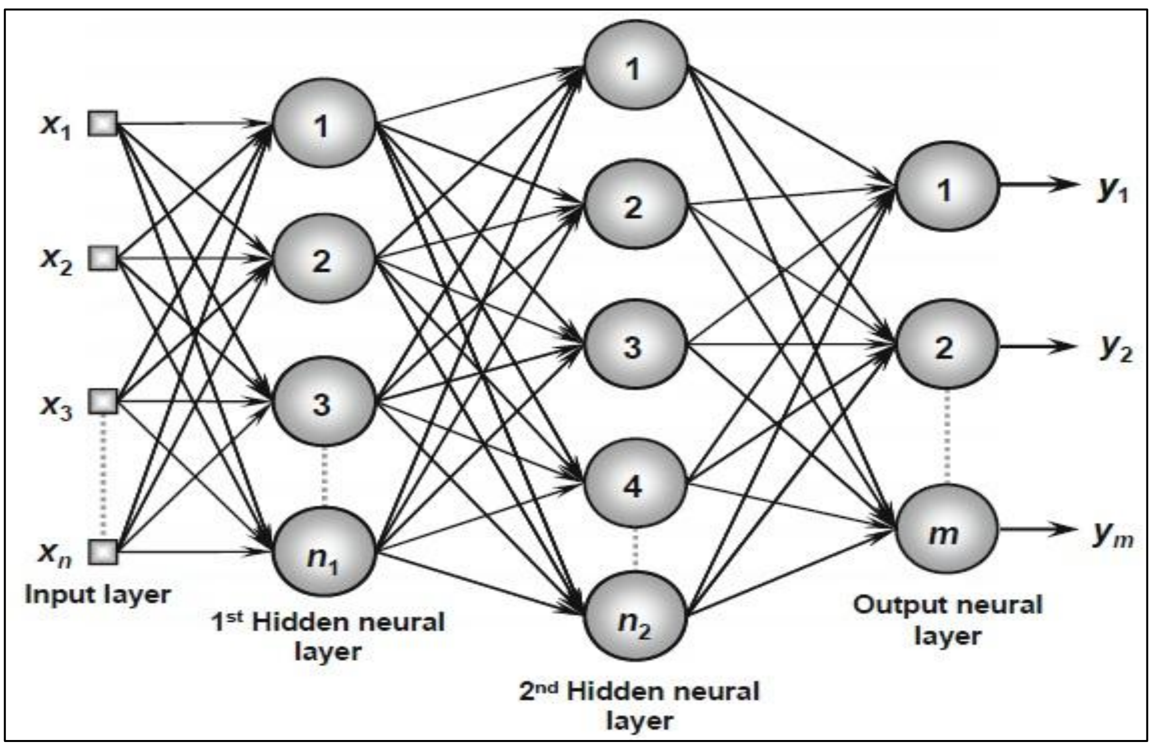
iii. Output Layer: The data or information passed from the hidden layer is finally processed in the output layer. This layer is responsible for computations and presenting an output to a network created.

The main architecture of ANN can be divided into single-layer feedforward, multilayer feedforward, recurrent and mesh networks [16]. In a feedforward network, data or information provided travels in only one direction. This research uses a multilayer feedforward network which is discussed in next section.

3.1 MULTILAYER PERCEPTRON

Multilayer Perceptron or Multi-layer feedforward neural network has an input layer, one or more hidden layers, and an output layer. While, when one hidden layer is enough to learn the linearity, multilayer perceptron is used to also learn the non-linearity in the given data or information [15]. Figure 3-3 given below shows the feed-forward network with multiple inputs.

Figure 3.3: Multi-layer feedforward network [15]



Source: H.S. Hippert, C.E. Perdreiraand R.C. Souza, 2001 [15]

X_1, X_2,..., X_n is the data or information given to the input layer of the network. The network has multiple hidden layers with n neurons. Finally, one output neural layer composed of m neurons representing the respective output values of the problem being analyzed.

3.2 NETWORK TRAINING

Artificial Neural Networks are produced by using some training algorithms. There are generally three classes for training ANNs:

1. Supervised Learning

In supervised learning, each training sample comprises of input data and their corresponding outputs. Supervised learning is further grouped into regression and classification problems. The training algorithms use mathematical operations to learn the relation between input and output. Backpropagation (BP) algorithm is mostly used for training ANNs under supervised class which is discussed later in this chapter [16].

2. Unsupervised Learning

In unsupervised learning, there is only an input data x and no corresponding output data. According to the inputs provided to the network, the weights are changed. ANN treats the set of data or information provided as a random variable. The network then provides a solution using those random variables [21]. Unsupervised learning technique is further grouped into clustering and association problems.

3. Semi-Supervised Learning

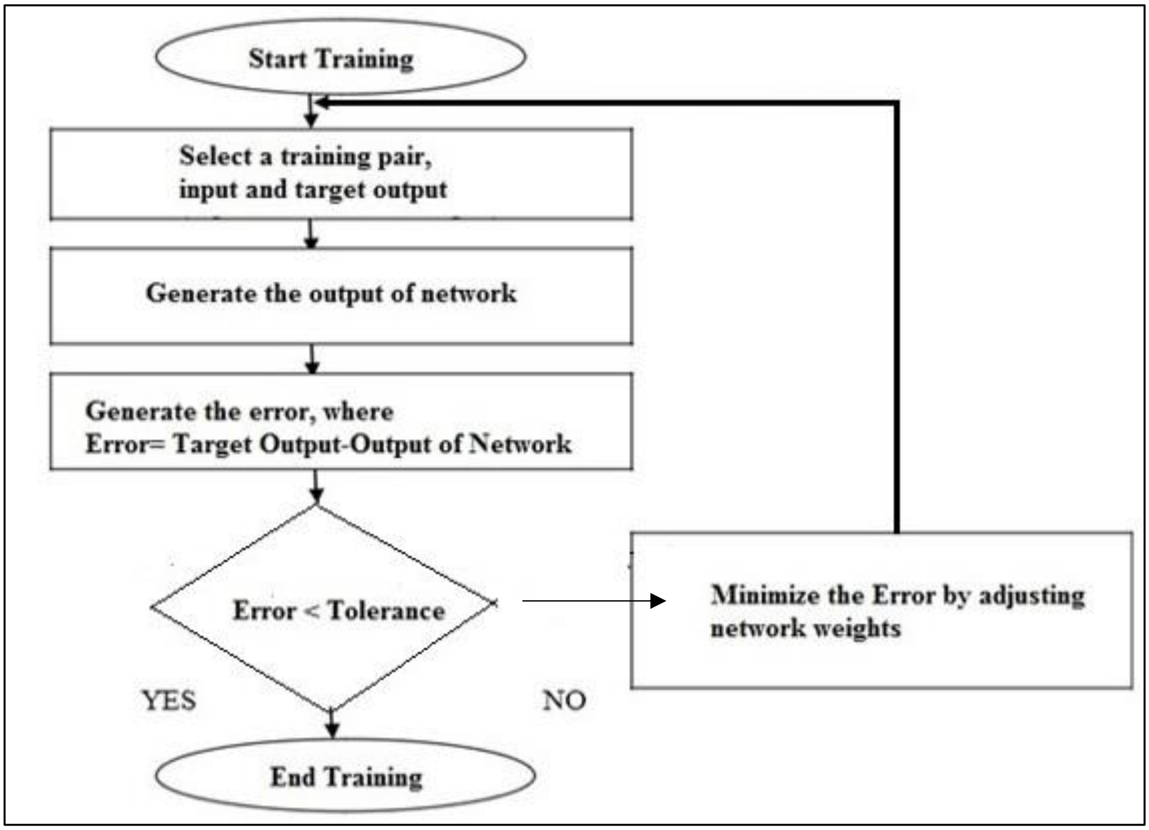
In semi-supervised learning, there is an input data x and only some of the output data is labeled y. A combination of supervised and unsupervised techniques can be used in semi-supervised learning.

3.3 BACKPROPOGATION ALGORITHM

Backpropagation (BP) algorithm is mostly used for training ANNs under supervised class [16]. ANNs consists of nodes in different layers, which includes input, hidden and output layers. As shown in Figure 3-1 and Figure 3-3, nodes of different adjacent layers have “weights” associated with them. For assigning correct weights training is required. And since ANNs can have multiple hidden layers, assigning correct weights to multiple hidden layers can be a complex task. This task is achieved by using Backpropagation (BP) algorithm.

BP algorithm is based on Widrow-Hoff delta learning rule. In this method, initially, all weights and bias for different hidden layers are randomly assigned. The data or information is provided to the network, the ANN is activated and an output is noted down. This output is then compared with the target output and an error is generated. The generated error is then propagated back to hidden layers and weights are adjusted accordingly. The process keeps on repeating until the minimum error is achieved. The training process flowchart using backpropagation algorithm is shown in Figure 3-4.

Figure 3.4: Backpropagation training flowchart [16]



Source: M. Ramezani, H. Falaghi, and M. Haghifam, 2005 [16]

The backpropagation training process is described in ten steps given below [16]:

i. Network weights are initialized.

ii. Add the weighted input and apply activation function to calculate the output of the hidden layer.

$$h_j = f\,[\Sigma_i\, X_i W_{ij}] \tag{3-5}$$

where,

h_j is the output of hidden neuron j for i inputs

x_i is the input data of input neuron i

W_{ij} are the synaptic weights between input neuron i and hidden neuron j

f is the activation function

iii. Add the weighted output of hidden layer and apply activation function to calculate the output of the output layer.

$$O_k = f\,[\,\Sigma_j\, h_j\, W_{jk}\,] \qquad (3\text{-}6)$$

where,

O_k is the output of output neuron k

W_{jk} is the synaptic weight between hidden neuron j and output neuron k

iv. Calculate back propagation error.

$$\delta_k = (t_k - O_k)\;f'(O_k) \qquad (3\text{-}7)$$

where,

f' is the derivative of the activation function

t_k is the target of output neuron k

v. Compute the weight correction term

$$\Delta W_{jk}(n) = \eta\delta_k h_j + \alpha\Delta W_{jk}(n-1) \qquad (3\text{-}8)$$

where,

η is the training ratio

α is the moment coefficient

vi. Add the delta input for each hidden neuron and generate an error

$$\delta_j = \Sigma_k\, \delta_k\, W_{jk}\, f'(\,\Sigma_i\, X_i\, W_{ij}\,) \qquad (3\text{-}9)$$

vii. Compute weight correction term

$$\Delta W_{ij}(n) = \eta\delta_j X_i + \alpha\Delta W_{ij}(n-1) \qquad (3\text{-}10)$$

viii. Update the weights

$$W_{jk}(n+1) = W_{jk}(n) + \Delta W_{jk}(n) \qquad (3\text{-}11)$$

$$W_{ij}(n+1) = W_{ij}(n) + \Delta W_{ij}(n) \qquad (3\text{-}12)$$

ix. Repeat step (ii) for the following number of errors:

$$MSE = \frac{1}{2p}[\Sigma_p\Sigma_k\,(d^p{}_k - O^p{}_k)^2] \qquad (3\text{-}13)$$

where,

p is the patterns in the training set and MSE is the mean square error

x. Training is ended.

Even though the backpropagation method is very efficient for training MLP or feedforward neural networks, but the training process takes a lot of time due to the nature of gradient descent [22]. There are many methods produced to refine the backpropagation algorithm, and one of them is the Levenberg-Marquardt (LM) algorithm. Levenberg Marquardt combines the speed of Gauss-Newton's method and the stability of error backpropagation algorithm during training steps. This research uses Levenberg-Marquardt algorithm for training and creating an ANN.

To reduce the overtraining and hence preventing the overfitting factor cross-validation process is adopted. Cross-validation process divides the training data set into a test set and validation set. Data or information set provided to ANN is trained using the test set and tested after every few iterations using the validation set. When the validation set performance starts to decrease training is completed [15].

An ANN for load forecasting can be trained on a training set of data that consists of time-lagged load data and other non-load parameters such as weather data, time of day, the day of the week, month, and actual load data [3] [24]. In this research, the time-lagged data of average demand load and the average air temperature was created as shown Table 3-1. The important data was selected through two different methods discussed in the next section of this chapter. In Table 3-1, Avg Load in MW represents the target data and the Avg Temp to Prev2 Temp in °C represents the input time-lagged data.

Table 3.1: Time-lagged load and air temperature data [1]

Date	Avg. Load (MW)	Avg. Temp (°C)	Prev1 Load (MW)	Prev2 Load (MW)	Prev3 Load (MW)	Prev4 Load (MW)	Prev5 Load (MW)	Prev1 Temp (°C)	Prev2 Temp (°C)
1.06.2016	1227	18	42374	42373	1214	1200	1146	22	19
1.07.2016	1229	20	42375	42374	1208	1214	1200	18	22
1.08.2016	1159	20	42376	42375	1221	1208	1214	20	18
1.09.2016	1200	22	42377	42376	1227	1221	1208	20	20
1.10.2016	1216	22	42378	42377	1229	1227	1221	22	20
1.11.2016	1205	18	42379	42378	1159	1229	1227	22	22
1.12.2016	1086	15	42380	42379	1199	1159	1229	18	22
1/13/2016	1170	18	42381	42380	1216	1199	1159	15	18
1/14/2016	1176	18	42382	42381	1205	1216	1199	18	15
1/15/2016	1105	18	42383	42382	1085	1205	1216	18	18

Source: Y. Al-Rashid and L.D. Paarmann, 1996 [1].

The predictor variables are the time-lagged load and weather data which is the average air temperature, given as an input of ANN. Forecast error is calculated by comparing the forecasted load generated by ANN with the actual load. Forecast error is often presented in terms of the Root Mean Square Error (RMSE) with units of kW [2] [15] as shown in (3-14), but more commonly in terms of the Mean Absolute Percent Error (MAPE) with units of percent [2] [15] [24] as shown in (3-15)

$$\text{RMSE} = \sqrt{\frac{1}{N}\ x\ \sum_{t=1}^{N}(y_t - \bar{y}_t)^2} \qquad (3\text{-}14)$$

$$\text{MAPE} = \frac{1}{N}\ x\ \sum_{t=1}^{N}\left(\frac{|y_t - \bar{y}_t|}{y_t}\ x\ 100\right) \qquad (3\text{-}15)$$

in which,

N is the number of samples,

y_t = target load at time t

$\bar{y}_t$ = forecasted load at time t

An ANN created with particular input load and weather data will be system dependent. The network created with one system, will more likely not give satisfactory results on another system due to different properties. However, the same ANN architecture may be reused on the new system, but retraining will be required [15].

3.4 DATA-PREPROCESSING

All ANNs have random mapping capacities theoretically, but before the training process, it is appropriate to normalize the data for certain scaling differences between the variables [25]. Since there are many highly correlated variables but many of them do not provide a relevant information extracted from the data. These uncorrelated variables decrease the learning performance of the neural network. To overcome these uncorrelated variables several methods have been used so far. Neural network training can be made more efficient if certain preprocessing steps are performed on the network inputs and targets [22].

Since providing an appropriate set of inputs will reduce the overfitting factor and increase the efficiency of ANN. And to achieve this two methods Correlation and Relief was used in this research.

3.4.1 Correlation Analysis

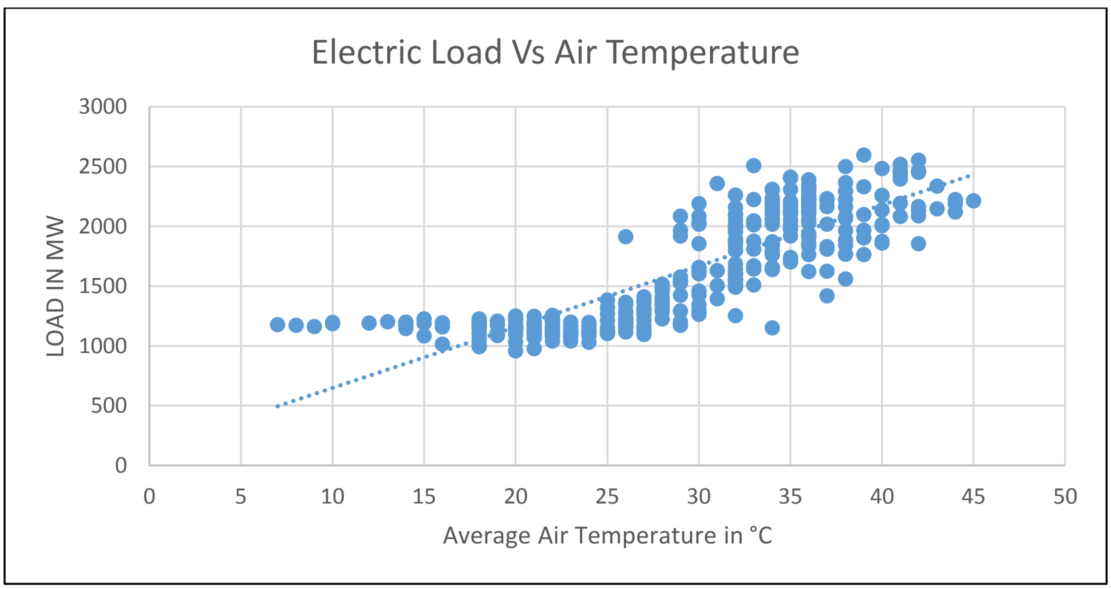
Correlation is a statistical tool that is used to determine the relationship between two variables. The statistic is called a correlation coefficient [26]. A correlation coefficient describes the direction (positive or negative) and degree (strength) of the relationship between two variables. A correlation coefficient can vary from -1.00 to +1.00. Correlation coefficient closer to 0 represents less relationship. The correlation coefficient is achieved by calculating the covariance between input variable x and target variable y and standard deviation of each variable. Equation (3-16) shows how to calculate the correlation between two variables x and y

$$r_{(x,y)} = \frac{COV(x,y)}{SxSy} \tag{3-15}$$

$r_{(x,y)}$ represents the correlation of the variables x and y, whereas $COV_{(x,y)}$ is the covariance of the variables x and y. S_x and S_y are the standard deviations of random variables x and y respectively.

Figure 3-5 shown represents the one-year correlation between FESCO electric demand load and average air temperature.

Figure 3.5: One-year correlation between electric demand load and average air temperature [10]



Source: Z. H. Ashour, M. A. Abu El-Maged and M. A. El-Fattah Farahat, 1991 [10]

3.4.2 Relief Method

Relief algorithm is considered among the most successful one for the selection of features due to its simplicity and effectiveness. The basic function of Relief algorithm is to iteratively estimate feature weights according to their ability to distinguish instances located near each other [27]. For distinctive instances, the algorithm iteratively selects a random instance and after that searches for its two nearest neighbors - the nearest hit (NH) from the same class and the nearest miss (NM) from the different class. The difference between the current instance and its NH and NM along the corresponding attribute axis will result in the estimation of weight for each feature. Relief algorithms perform better than other filter methods because of the feedback performance of a nonlinear classifier when searching for important attributes [28]. Relief method is used for classification problem, whereas the ReliefF is the upgraded Relief used for the regression problems since the target values are continuous variables in regression tasks [27].

The pseudo code for the Relief algorithm is given below:

1: set W[A] = 0;   set all feature Weights(W[A]) to zero
2: **for** i := 1 to m **do**
  3: select an instance R_i randomly
  4: find nearest hit NH and nearest miss NM;   (instances)
    5: **for** A := 1 to a **do**
      6: W[A] := W[A] - diff(R_i[A],NH[A]) + diff(R_i[A],NM[A]);
      7: **end for**
8: **end for**

a is the number of attribute(features)

n is the total number of instances

m is the random training instance selected from n

ReliefF method is used in the research for the selection of important features on regression problems. There are two major drawbacks to Relief method that they are computationally expensive and they may fail to remove the unimportant variables, which results in poor forecast while used as an input [28].

In this research both of the methods, Correlation analysis and Relief method are used to extract an important set of useful data in forecasting day-ahead demand load. And this task is achieved by a commercial machine learning software named “WEKA”. In WEKA, all the data is imported first by means of file conversion. And after that by choosing both methods individually, results are driven rankly. Chapter 4 shows the results for both methods and as well as the results of day-ahead load forecast for FESCO.

4. RESULTS AND DISCUSSIONS

This chapter presents the scatter plots created to visualize the relationship and drift between electric load and the predictor inputs. This chapter also shows the results of the time-lagged load and historical air temperature data used to extract important attributes set by means of two methods, Correlation analysis and Relief method. The best attributes set is later used to forecast day-ahead load using ANN. The results of day-ahead load forecast are also shown in this chapter. And at the end discussions are made using the achieved results.

4.1 SELECTION OF INPUT VARIABLES

In order to achieve an adequate fit for the network, the dataset is first refined using two different techniques Correlation and Relief method. And this task was achieved with the aid of Commercial Software "WEKA". The results are given below for both methods:

4.1.1 Relief Method

The created time-lagged load data comprising a load of previous five days along with their averages and derivative differences, same with the historical weather data, all were given as an input test set to WEKA®. The target dataset y was selected. And by using different values of nearest neighbors k, results are displayed by means of the Ranker method. Ranker method is only capable of producing a ranked list of attributes for attribute evaluators. Given below are the results of attribute evaluator using Relief Method for different values of nearest neighbors k.

Table 4.1: Top-ranked variables by ReliefF attribute evaluator k=10 [27]

VARIABLES	RANK
Prev1 Load	0.036469
1st Dev Load Prev1	0.035651
Avg Prev 1-2 Load	0.025734
1st Dev Load Prev2	0.021467
1st Dev Load Prev3	0.021379
Prev2 Load	0.021000
Prev5 Load	0.020613
Avg Prev 1-3 Load	0.020574
Precipitation in mm	0.018991
Avg Prev 1-5 Load	0.018762

Source: Kira K and Rendell L, 1992 [27]

Table 4.2: Top-ranked variables by ReliefF attribute evaluator k=20 [27]

VARIABLES	RANK
Prev1 Load	0.039570
1st Dev Load Prev1	0.034740
Avg Prev 1-2 Load	0.029290
Avg Prev 1-3 Load	0.023900
Prev2 Load	0.022930
Prev5 Load	0.022020
Avg Prev 1-5 Load	0.021670
Avg Prev 1-4 Load	0.021440
1st Dev Load Prev2	0.020970
1st Dev Load Prev3	0.020680

Source: Kira K and Rendell L, 1992 [27]

Table 4.3: Top-ranked variables by ReliefF attribute evaluator k=30 [27]

VARIABLES	RANK
Prev1 Load	0.042096
1st Dev Load Prev1	0.034114
Avg Prev 1-2 Load	0.031304
Avg Prev 1-3 Load	0.256520
Prev2 Load	0.024452
Avg Prev 1-5 Load	0.022996
Avg Prev 1-4 Load	0.022925
Prev5 Load	0.022440
1st Dev Load Prev2	0.020785
1st Dev Load Prev3	0.020235

Source: Kira K and Rendell L, 1992 [27]

Table 4.4: Top-ranked variables by ReliefF attribute evaluator k=40 [27]

VARIABLES	RANK
Prev1 Load	0.043610
1st Dev Load Prev1	0.033918
Avg Prev 1-2 Load	0.032766
Avg Prev 1-3 Load	0.270070
Prev2 Load	0.025349
Avg Prev 1-5 Load	0.024561
Avg Prev 1-4 Load	0.024415
Prev5 Load	0.023014
1st Dev Load Prev2	0.021420
Prev3 Load	0.020718

Source: Kira K and Rendell L, 1992 [27]

As shown from Table 4-1 to Table 4-4, depending on the nearest neighbors k different variables are displayed rankly showing a connection with output variable y.

For each value of k (10, 20, 30, 40, 50), test sets were made from the results shown in Table 4-1 to Table 4-4. In the beginning, total 5 test sets were selected comprising 10 to 14 variables respectively and were utilized as an input to ANN. Matlab® aided the work with ANNs. The hidden layers were varied from 15 to 25 in order to minimize the training error. Later in this chapter, selection of hidden layers are also discussed. The network was trained using LM algorithm. The results of attributes set depending on the nearest neighbor k are shown in the Table 4-5 given below:

Table 4.5: MAPE for different variables set for different values of k [27]

nearest neighbors (k)	MAPE % 10 Variables	MAPE % 11 Variables	MAPE% 12 Variables	MAPE % 13 Variables	MAPE % 14 Variables
k=10	3.999	3.96	3.88	4.2541	3.471
k=20	4.1712	3.91	3.88	3.7456	3.7289
k=30	4.2657	4.15	3.76	3.2056	3.871
k=40	4.3225	3.98	4.22	3.7581	3.7439
k=50	4.2038	4.17	4.2	3.9686	3.662

Source: Kira K and Rendell L, 1992 [27]

From Table 4-1, it can be seen that the minimum MAPE is achieved for the nearest neighbors k=30. The minimum MAPE is 3.2% for a 13 variable test set. This information was recorded and the test set was saved for the later operations.

4.1.2 Correlation Analysis

Pearson correlation coefficient was used to calculate the magnitude of the linear correlation between electric demand load and weather data, electric demand load and time-lagged load and weather data. This method was also performed with the aid of commercial software "WEKA". Results of this method are shown below in Table 4-6:

Table 4.6: Correlation analysis between electric load and time -lagged load and weather data [26]

VARIABLES	RANK
Prev1 Load	0.96720
Avg Prev 1-2 Load	0.95676
Avg Prev 1-3 Load	0.95016
Avg Prev 1-4 Load	0.94440
Avg Prev 1-5 Load	0.94057
Prev2 Load	0.93618
Prev3 Load	0.91368
Prev4 Load	0.89580
Prev5 Load	0.88734
Avg Temp	0.87117

Source: H. Almuallim and T. G. Dietterich, 1992 [26]

As shown in Table 4-5, the load of the previous day is highly correlated with the target load y. The value for previous day load is 0.9672. And this correlation tends to decrease as the time span increases. The average air temperature is also highly correlated with the value of 0.87117 as shown in Figure above.

Utilizing the results achieved with correlation analysis shown in Figure 4-5, 12 test sets were created comprising 3 to 14 variables respectively. Each test set was given as an input to ANN.

These samples were further divided into training, validation and testing set. The number of samples were 547 which were further divided 80% for training and 20% for testing. After training the network, results were gathered in terms of MAPE% shown in Table 4-7 below.

Table 4.7: MAPE for different input variables test sets

Number of Variables (n)	n=3	n=4	n=5	n=6	n=7	n=8	n=9	n=10	n=11	n=12	n=13	n=14
MAPE (%)	6.03	6.81	5.93	6.36	6.33	6.45	6.28	5.19	5.78	5.06	5.38	5.35

Source: H.S Hippert, C. E. Pedreira and R. C. Souza, 2005 [2]

In Table 4-7, less data was given as an input to ANN as compared to the data provided to ANN, the results are shown in Table 4-8.

In table 4-8, the training set contains 383 samples, while validation and testing both sets contain 82 samples. The hidden layers were varied from 15 to 25 in order to acquire better results by reducing the MSE.

After training the network results were gathered in terms of MAPE shown in Table 4-6 below. The minimum MAPE 3.07% was achieved for the test set with 12 variables.

Table 4.8: MAPE for different input variables sets

Number of Variables (n)	n=3	n=4	n=5	n=6	n=7	n=8	n=9	n=10	n=11	n=12	n=13	n=14
MAPE (%)	4.45	4.33	4.36	4.17	4.22	4.21	4.35	3.86	3.63	3.07	3.38	3.44

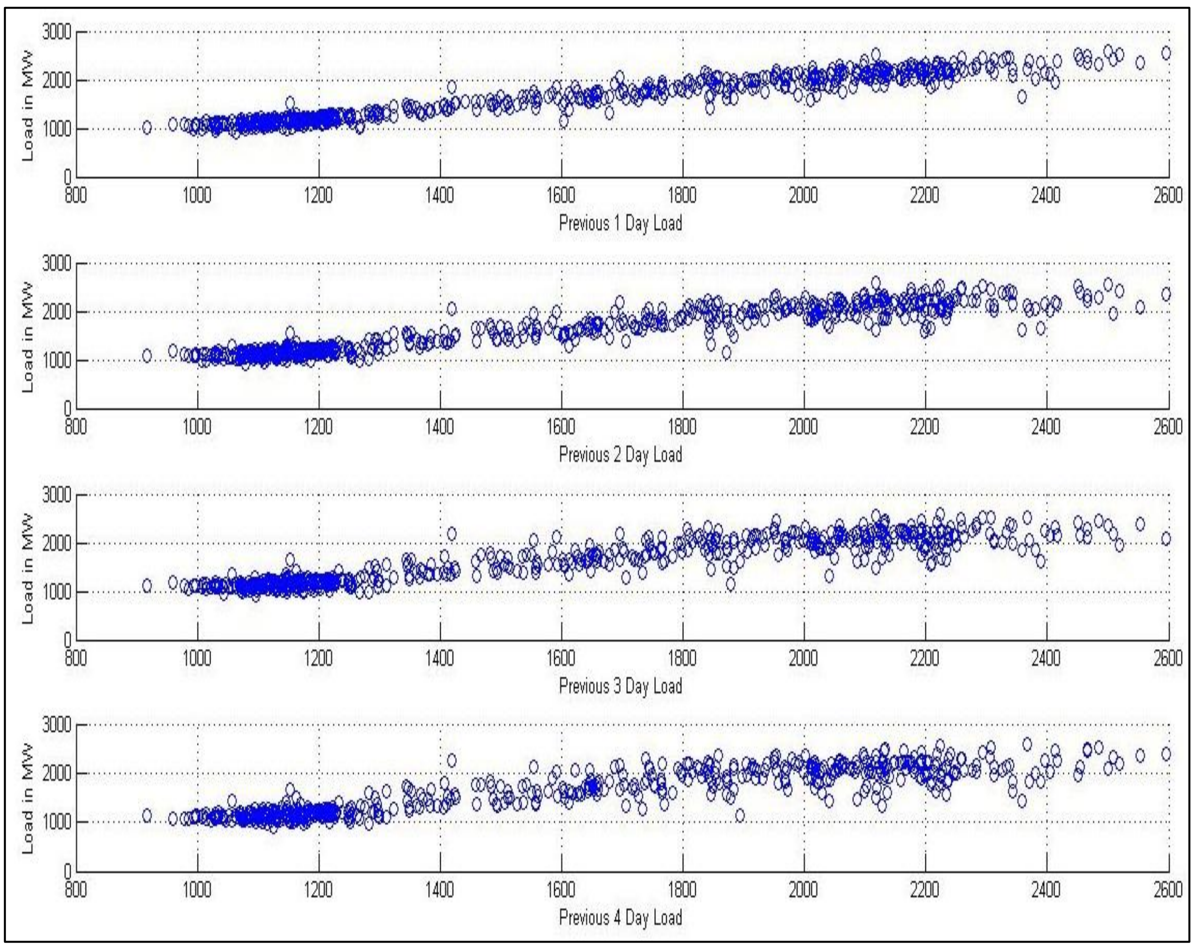
Source: H.S Hippert, C. E. Pedreira and R. C. Souza, 2005 [2]

Even though the Relief method is considered among the best methods [28] for providing an attribute set highly related to the target set. But for our custom (FESCO) data, Correlation method provides the best of all with a MAPE of 3.07%, which comes in the acceptable range as discussed in Section 2.2 [1].

4.2 PREDICTOR SCATTER PLOTS

Scatter plots helps in visualizing and understanding a linear relationship between target variable y and input variables x. Given below are the scatter plots for the electric demand load and time-lagged load and weather data.

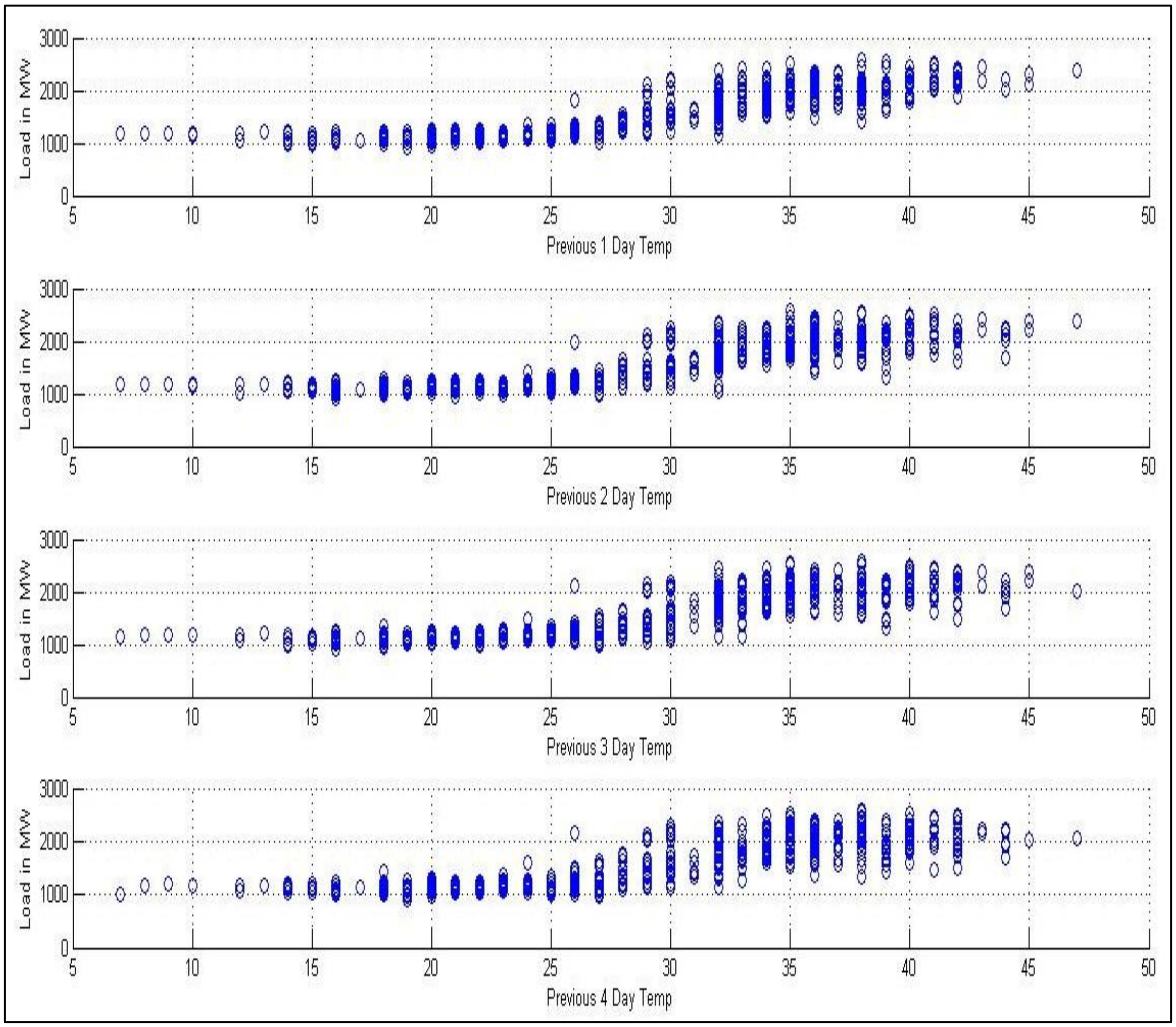
Figure 4.1: Scatter plot between electric load and previous 4 days load [10]



Source: Z. H. Ashour, M. A. Abu El-Maged and M. A. El-Fattah Farahat, 1991 [10]

From Figure 4-1, it can be seen that the previous day load is highly correlated with the electric load. While on the other hand, this correlation tends to decrease with the increase in the time span. Previous 4th Day Load shows a less relationship than the previous day load.

Figure 4.2: Scatter plots between electric load and previous 4 days average air temperature [10]

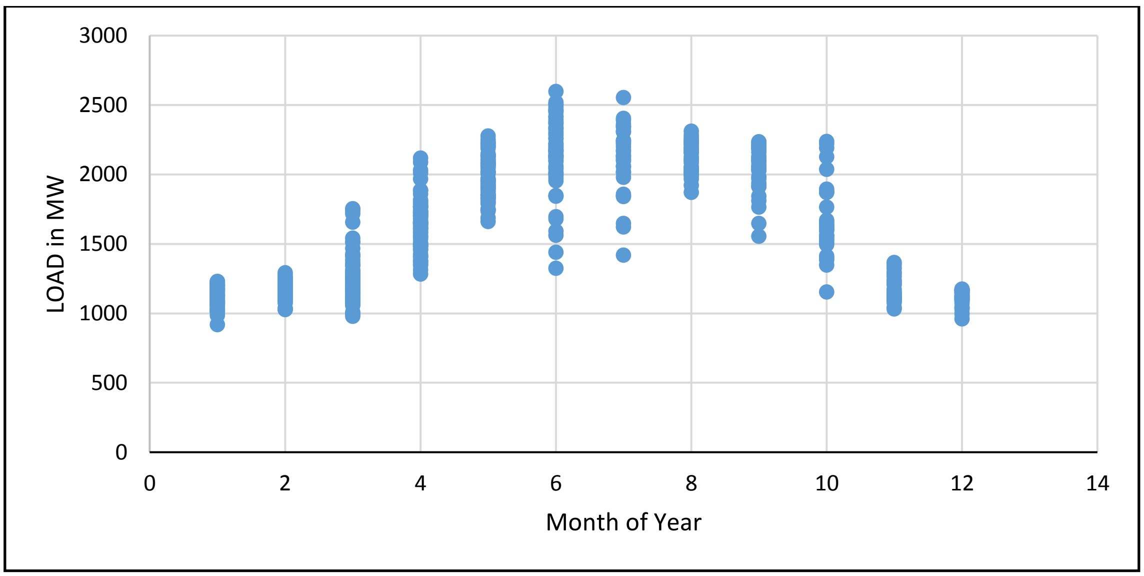


Source: Z. H. Ashour, M. A. Abu El-Maged and M. A. El-Fattah Farahat, 1991 [10]

From Figure 4-2, the relationship between electric load and previous 4 days can be seen. The previous day daily average air temperature is more correlated than the previous 4th-day air temperature.

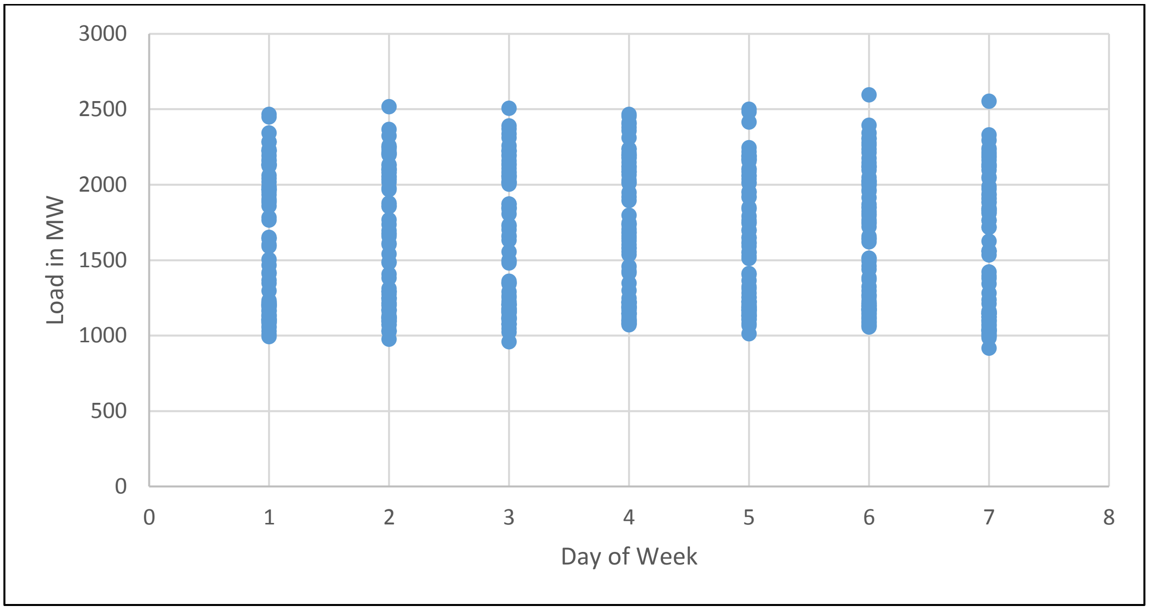
Figure 4-3 and Figure 4-4 show the scatter plots between electric load and each month of the year and electric load and each day of the week.

Figure 4.3: Electric load and month of year scatter plot



Source: Z. H. Ashour, M. A. Abu El-Maged and M. A. El-Fattah Farahat, 1991 [10]

Figure 4.4: Electric load and day of week scatter plot [10]



Source: Z. H. Ashour, M. A. Abu El-Maged and M. A. El-Fattah Farahat, 1991 [10]

From Figure 4-3, it can be that maximum demand load occurs in the mid of the year. While on the other hand, electric load demand for the month of December is minimum. Figure 4-4, shows that the peak demand load occurred for the 6th day of the week which is Thursday. As mentioned earlier in chapter 2, Friday is considered as a holiday for FESCO.

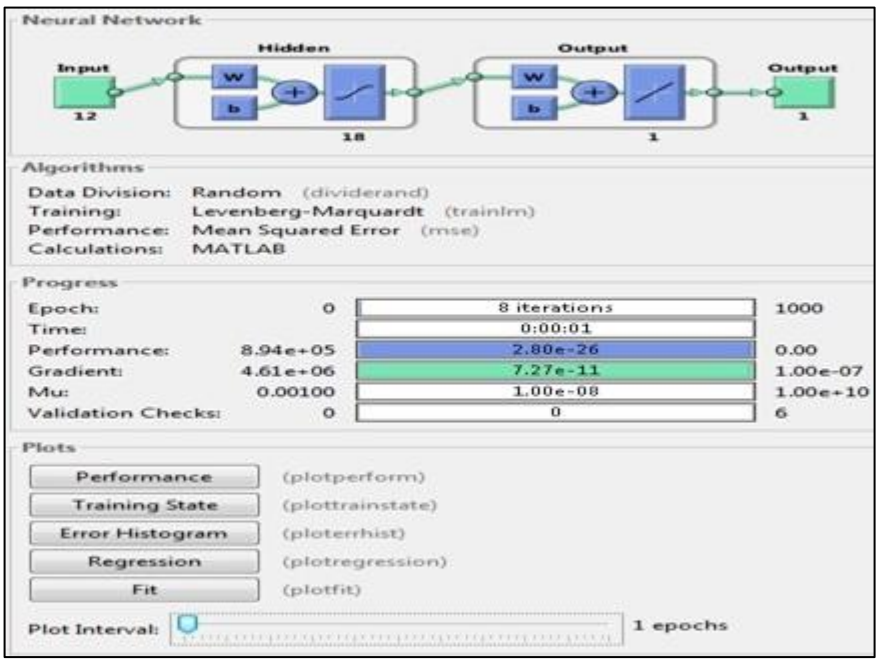
4.3 SHORT-TERM LOAD FORECAST RESULTS AND DISCUSSIONS

The results gathered by the Correlation analysis were further used to create an ANN comprising 547 samples. The results are shown in Table 4-2. Using this information, first of all, the test set comprising 547 samples representing all days were divided into each day of the week.

Each ANN representing each day of week contains 78 samples which were further divided into 70 percent for the training set, 15 percent for validation set and 15 percent for testing set. Figure 4-6, shows MATLAB® Neural Network tool plot. The input of Neural Network contains 12 inputs, hidden layers were fixed to 18 and 1 output layer representing day-ahead load forecast for each individual day.

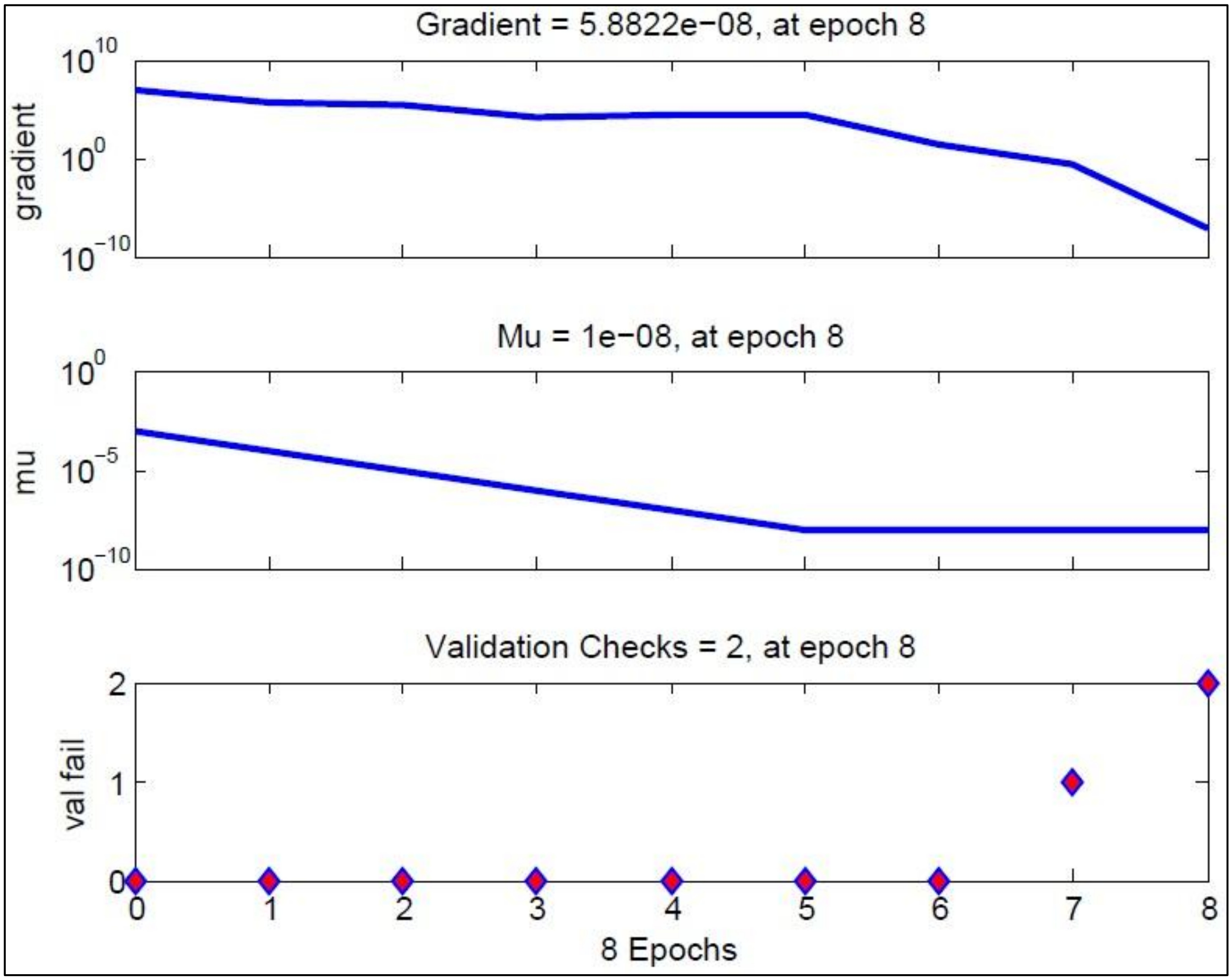
Each training cycle is called an Epoch. In general, the error reduces after more training epochs but might increase on the validation set. By default, the training stops after six consecutive increases in a validation error. The training of Neural Network stops if the number of an epoch is completed or the performance on the validation set reaches its minimum.

Figure 4.5: MATLAB® neural network tool plot [22]



Source: Demith H and Beale M, (1998) [22]

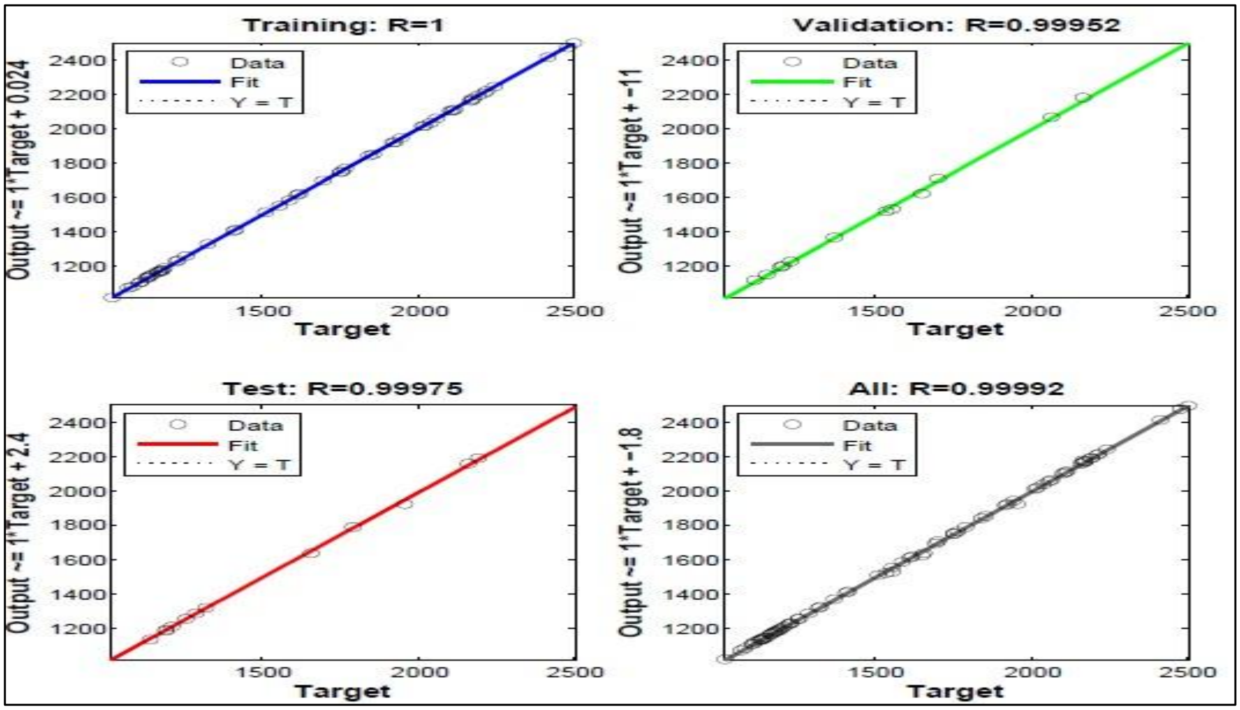
Figure 4.6: MATLAB® training state plot [22]



Source: Demith H and Beale M, (1998) [22]

Figure 4-6, given above represents three different graphs. The top graph shows the drift in gradient values for each number of the epoch. After 6 epochs the graph for gradient values decreases gradually. The middle plot shows the learning rate (mu) for each epoch number. The graph decreases gradually until 5 number of epochs and becomes constant after that. The last plot shows the plot of validation checks against each number of the epoch. A sudden change in gradient plot is observed at validation plot.

Figure 4.7: MATLAB® regression plot [22]



Source: Demith H and Beale M, (1998) [22]

Figure 4.7 shows the regression plot of Thursday data for day-ahead load forecast. The regression plot contains a plot of training, validation, and testing states. A solid line represents the best fit between output and target data. The dotted line represents the targets which are results-output. Each circle represents data. R values tell the relationship between output and the target value. If R is close to 1, it reveals the perfect linear relationship between outputs and targets. From the regression plot R=1 for training, R=0.99 for validation, R=0.99 for testing and R=0.99 for all. The R-value almost 1 for all sets represents satisfactory results for forecasting.

The data samples were further divided into training, validation and testing set. The number of samples were 78 which were further divided 80 percent for training and 20 percent for testing. After training the network, results were gathered in terms of MAPE% shown in Table 4-9 below.

Table 4.9: Day-ahead load forecast for each day of the week for different variables test set [2]

Day	Day of Week	MAPE % 10 variables	MAPE % 11 variables	MAPE % 12 variables	MAPE % 13 variables	MAPE % 14 variables
Friday	6	9.38	10.42	11.40	11.80	12.40
Saturday	7	9.01	8.39	8.80	8.30	6.00
Sunday	1	10.32	9.80	8.10	9.62	10.70
Monday	2	10.64	10.02	5.21	6.14	9.03
Tuesday	3	9.38	10.83	10.19	10.82	10.43
Wednesday	4	8.87	7.56	7.70	7.90	9.00
Thursday	5	0.28	0.85	0.233	0.50	0.22

Source: H.S Hippert, C. E. Pedreira and R. C. Souza, 2005 [2]

ANN with 12 input variables was found best of all variables set. The minimum MAPE achieved is 0.14% for 12 variables set of Thursday and maximum MAPE achieved is 2.34% for 12 variables set of Monday. Table 4-10, represents the results of day-ahead load forecast for each day of week for different variables set.

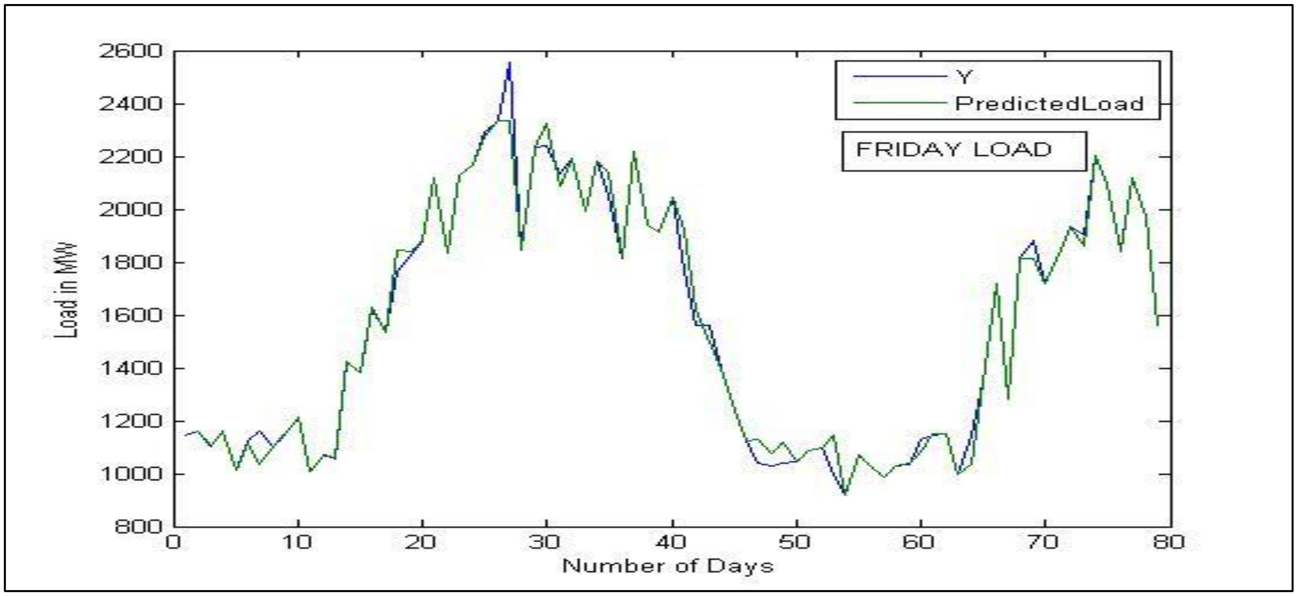
Table 4.10: Day-ahead load forecast for each day of the week for different variables set [2]

Day	Day of Week	MAPE % 10 variables	MAPE % 11 variables	MAPE % 12 variables	MAPE % 13 variables	MAPE % 14 variables
Friday	6	2.47	2.41	1.43	2.21	2.44
Saturday	7	2.32	2.29	1.96	2.36	2.49
Sunday	1	3.21	3.27	2.11	2.81	2.22
Monday	2	3.00	2.81	2.34	2.81	3.24
Tuesday	3	2.53	2.49	2.44	3.10	3.20
Wednesday	4	2.94	2.03	1.80	2.14	2.55
Thursday	5	0.06	0.05	0.14	0.37	0.24

Source: H.S Hippert, C. E. Pedreira and R. C. Souza, 2005 [2]

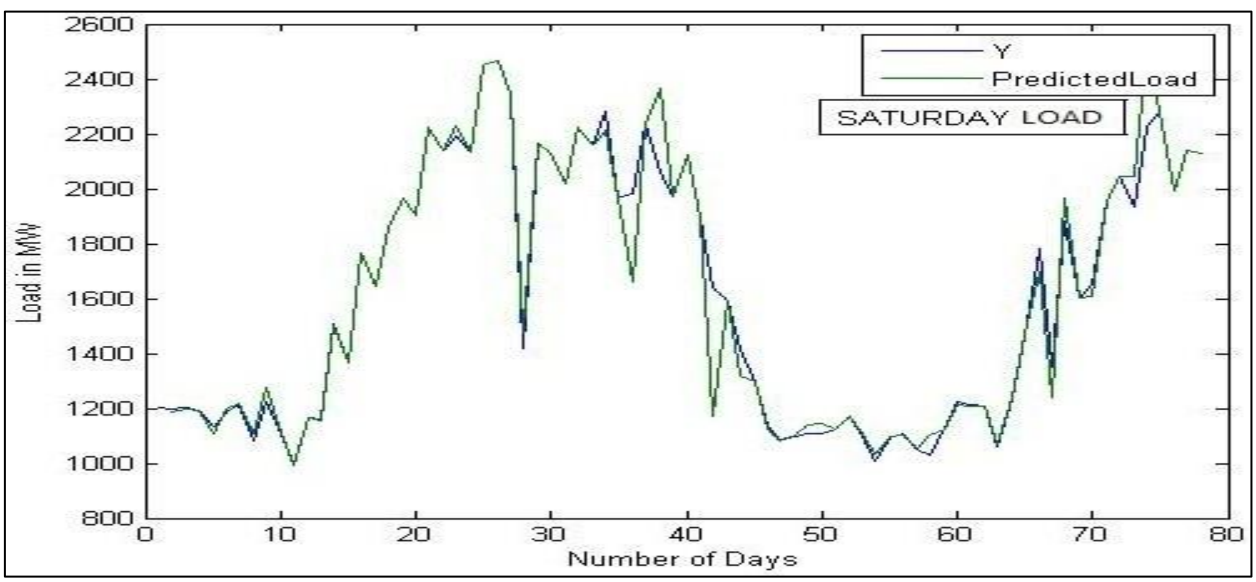
Figure 4-8 to Figure 4-14 shows a comparison of forecasted and actual load for each day of the week.

Figure 4.8: Comparison between actual and forecasted load for Friday



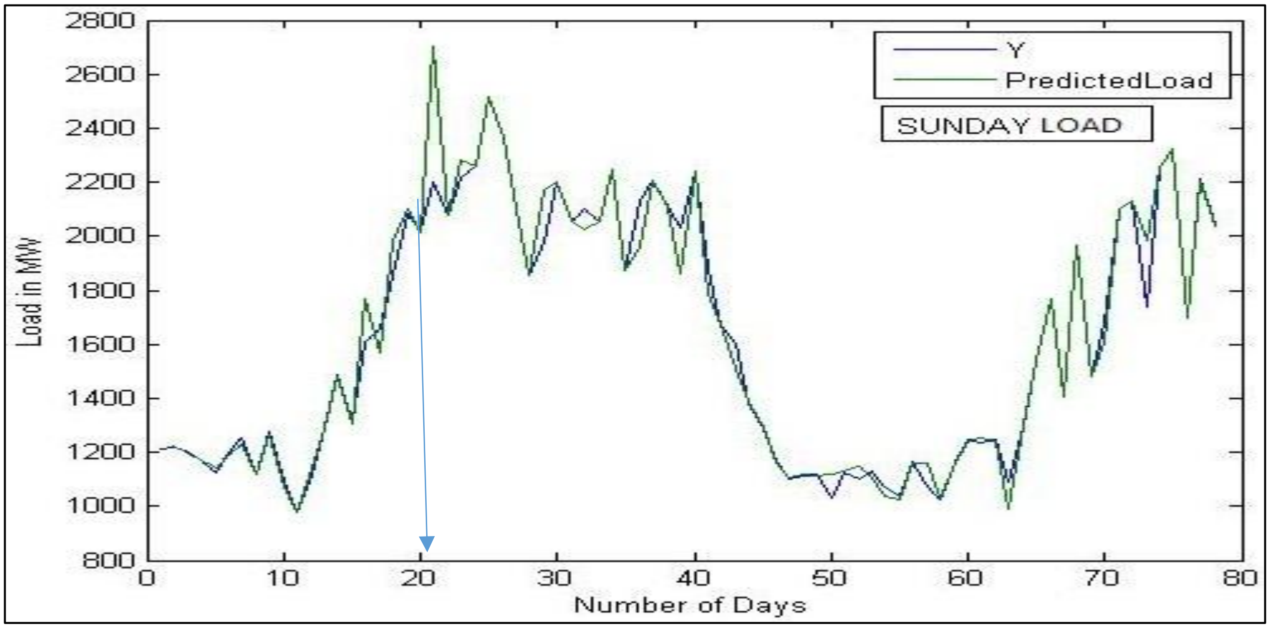
Source: Demith H and Beale M, (1998) [22]

Figure 4.9: Comparison between actual and forecasted load for Saturday



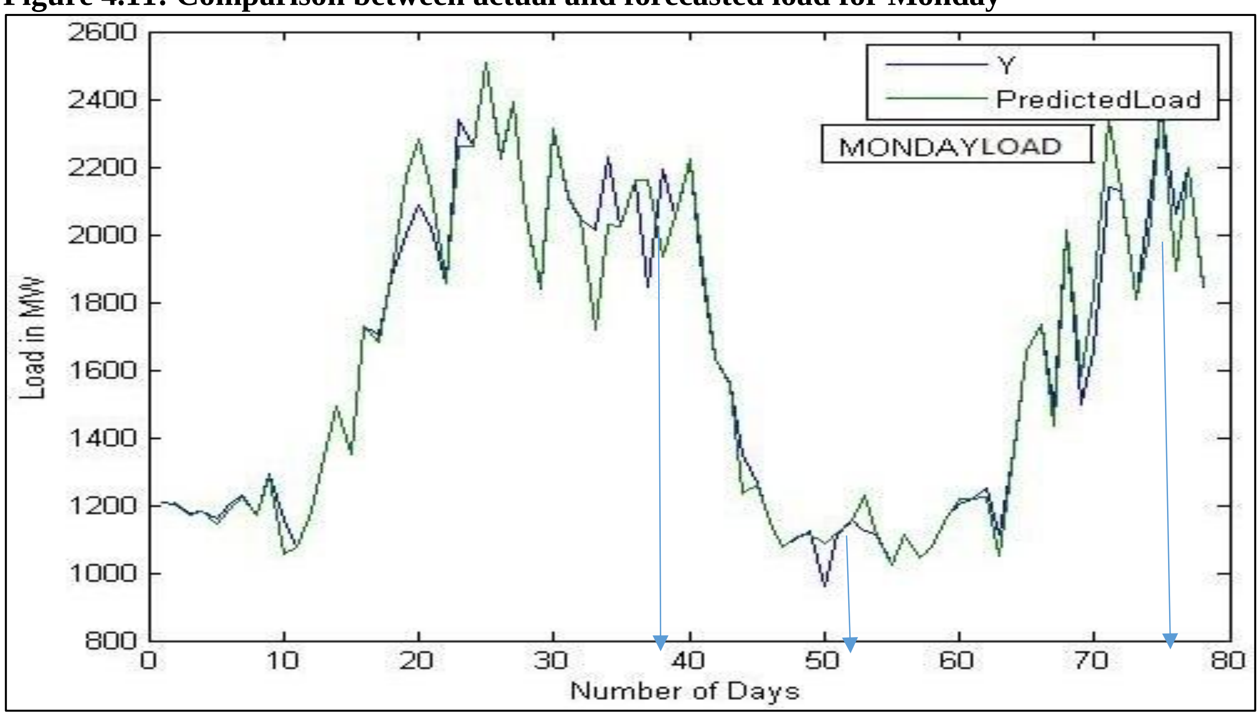
Source: Demith H and Beale M, (1998) [22]

Figure 4.10: Comparison between actual and forecasted load for Sunday



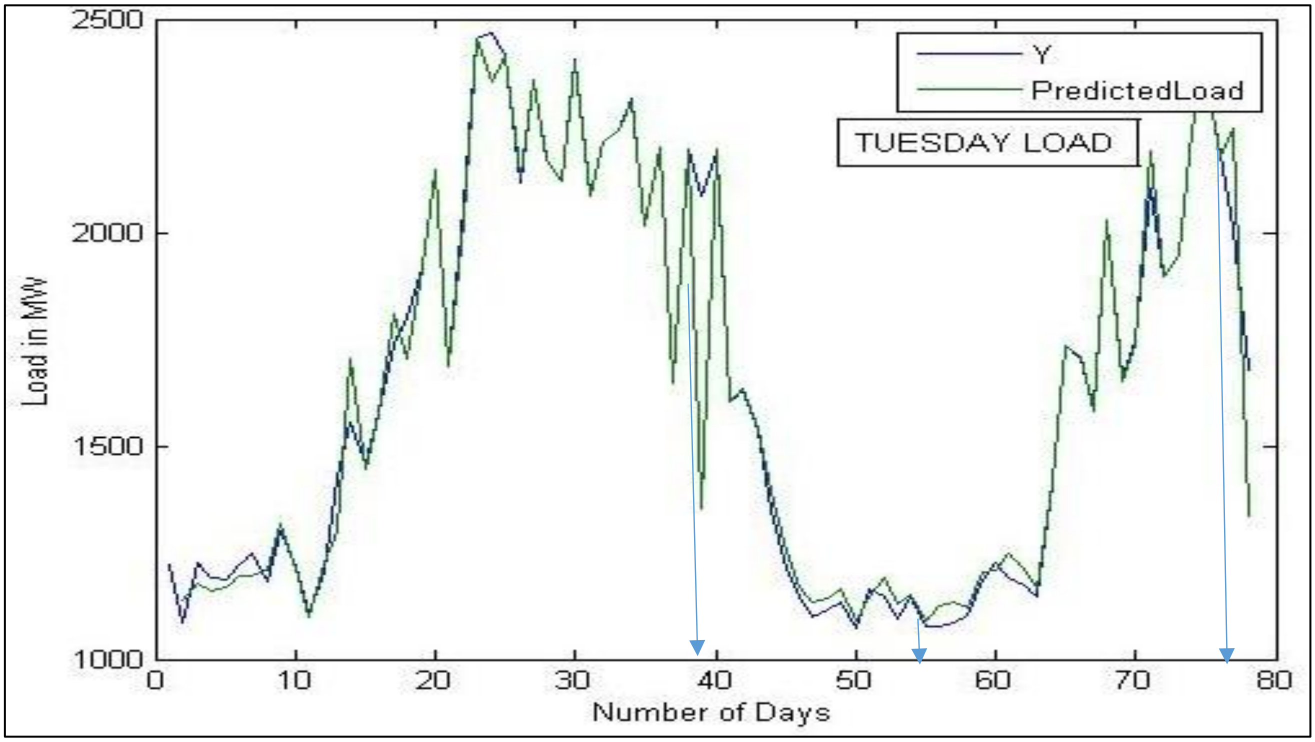
Source: Demith H and Beale M, (1998) [22]

Figure 4.11: Comparison between actual and forecasted load for Monday



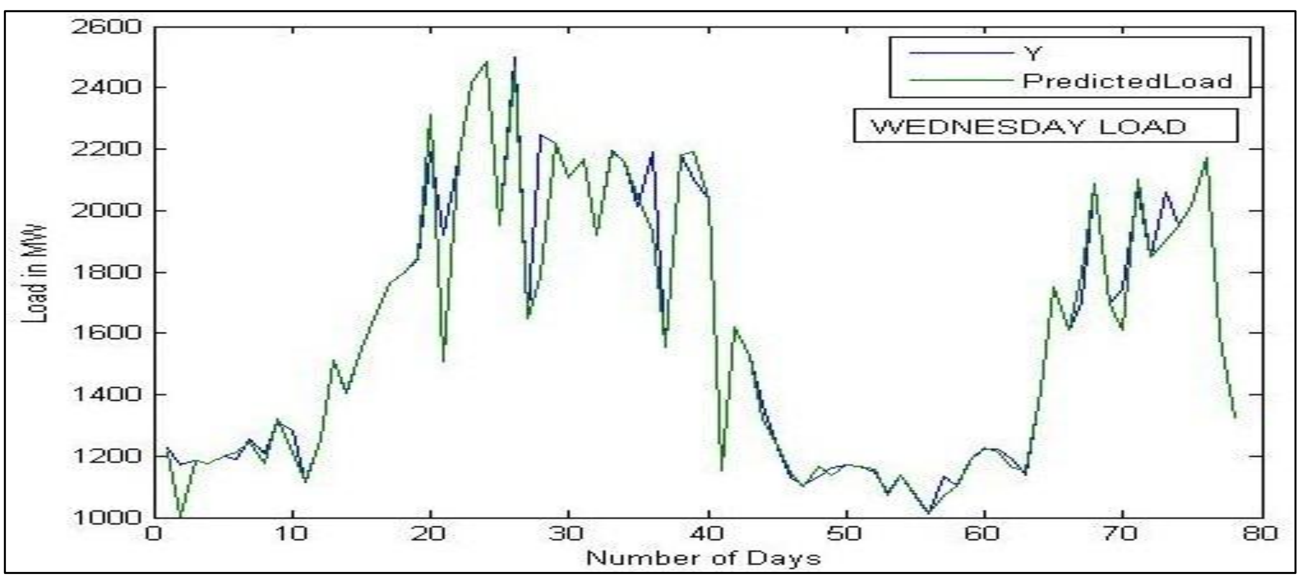
Source: Demith H and Beale M, (1998) [22]

Figure 4.12: Comparison between actual and forecasted load for Tuesday



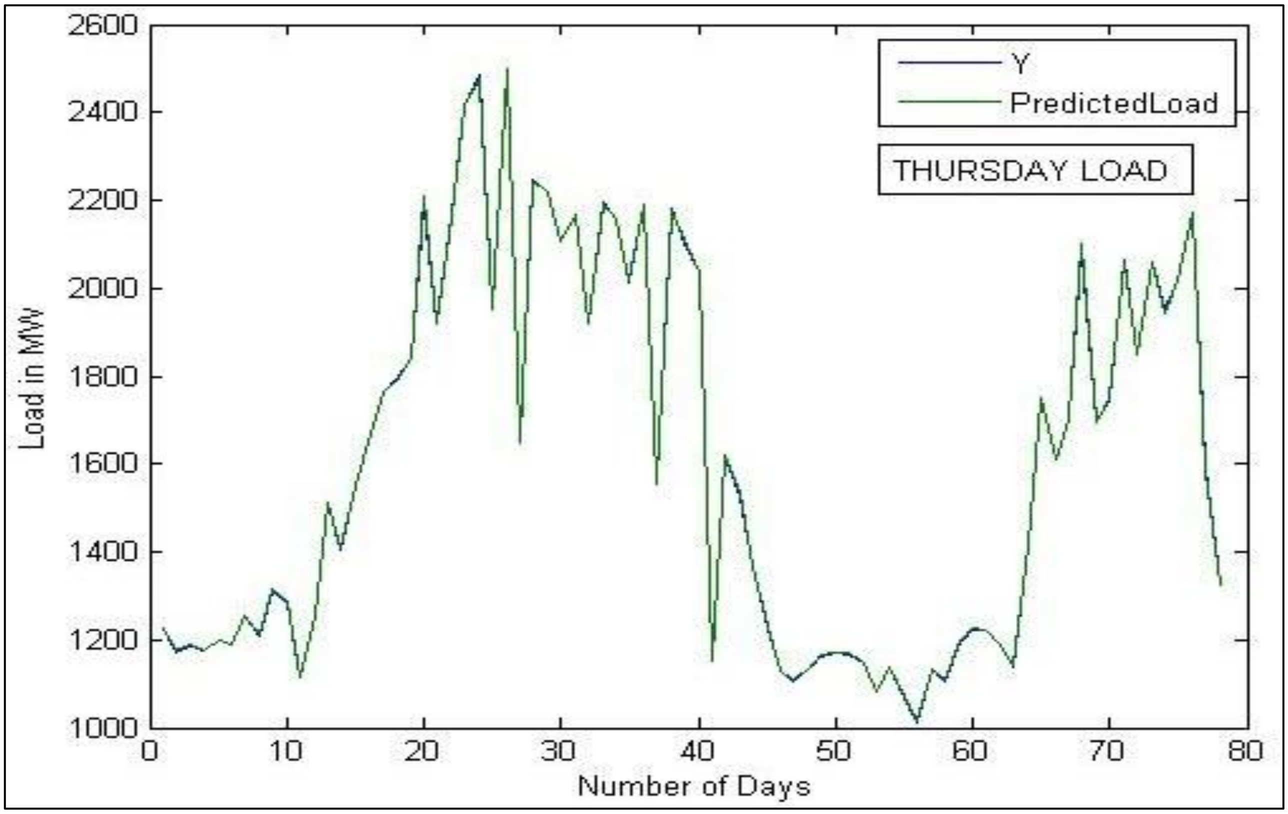
Source: Demith H and Beale M, (1998) [22]

Figure 4.13: Comparison between actual and forecasted load for Wednesday



Source: Demith H and Beale M, (1998) [22]

Figure 4.14: Comparison between actual and forecasted load for Thursday



Source: Demith H and Beale M, (1998) [22]

From Table 4-3, it can be that the MAPE for 12 variables set, which was used to construct the comparison plots of days, three days have MAPE higher than 2%, which are Sunday, Monday, and Tuesday. From Figure 4-11, it can be that the difference in actual and forecasted load on 21st Sunday is very much. This can be due to some planned or unplanned load shedding. Whereas, the marked days for Monday and Tuesday plots, shown in Figure 4-12 and 4-13, the high difference in actual and forecasted load is due to a cultural holiday in Pakistan. Appendix A shows the list of holidays for FESCO.

5. CONCLUSIONS AND FUTURE WORK

It is a key role of any electric organization for providing electricity in an economical and secured manner maintaining the quality. In order to achieve this goal, the behavior of the power system must be learned. By examining the system's operational bounds, responding to customer needs and reaction to weather events will provide an understanding on system loading. Short-term load forecasting can provide that insight for day ahead to aid in making power system operational decisions.

5.1 CONCLUSIONS

The process where electrical energy usage for an organization is planned and linked with some other system's load is referred to energy demand management. In an energy demand management, electrical peak reduction is a vital component. And in order to meet up the energy demand management, electric load forecasting is used to assist the planning for the peak load demand reduction. Peak demand load reduction varies for each particular day due to load forecast and organizational operations. By knowing the system peak demand load and forecasted electric load, it becomes easier for an organization to schedule the peak demand load days orderly to reduce the demand load. For example, in Figure 2-1 and Table 2-1, daily FESCO peak demand load of summer occured in the last week of JUNE, also in Figure 2-1 and Table 2-2, FESCO peak demand load of winter occured in the second week of DECEMBER, where it is necessary high electricity demand load should be scheduled for operations for the mentioned weeks.

Several tradional STLF methods which includes multiple linear regression, time series, expert system, similar-day approach were discussed in Chapter 2. Many of these methods had been used previously in many forms by the utilities to aid in planning short-term operations. Stochastic time series are much better than the other methods discussed in the research. This is due to the fact that electrical load is a non linear process, and these models are intended to model linear process.

Chapter 2 also discusses Neural Networks and its types. Neural Networks or Artificial Neural Networks (ANN) became useful for STLF in late 1980's. ANN is a mathematical model that mimics the way human brain processes information. Many famous ANN models which includes feed-forward neural network, recursive neural network, convolutional neural network and recurrent neural network were revealed in Chapter 2.

Recursive Neural Networks (RNN) are computational models which uses the feed forward network phenomenon, designed for learning deep structured information. And are suitable for both regression and classification problems. The most popular algorithm used to train RNN is the back-propagation (BP) algorithm. This algorithm has been found to give more accurate results with feed forward neural networks. The fact that RNNs are not being preferred for STLF is due to their inherent complexity and convergence problem.

Convolutional Neural Networks (CNN) are type of feed forward neural computational models designed to solve deep structured information with much fewer parameters. The information is carried out to final layer using several convolution layers in which convolution operations are performed. CNNs have been found outstanding models for image processing and speech recognition.

Recurrent neural networks are unlike feed forward networks, the connections between neurons which is the basic element in processing information, makes a directed cycle. Each of the hidden cells received its own output with one or more iterations or fix delays, a part from that they are like common feed forward neural networks. Recurrent neural networks were found promising for connected handwriting and text classifications.

Feed forward neural networks are based on simple topology, the information provided flows only in one direction, from input layer to output layer passing through a hidden layer. If more than one layer is used for the desired operation, the process leads to MLP.

Multilayer Perceptron (MLP) uses more than one hidden layer for processing given information or data and carry out the results at the output layer. These hidden layers have different weights associated with them. For assigning correct weights training is required. Back-Propagation (BP) algorithm is mostly used for training ANNs under supervised class. BP algorithms gives much stability during training process but they lack in learning speed and this is due to the nature of gradient descent. Levenberg-Marquardt algorithm is used in this research for training MLPs because LM algorithm combines the speed of Gauss-Newton's method and the stability of error backpropagation algorithm during training steps. Training a neuron in an ANN helps to understand the trends in a load with the given specific inputs.

The size and structure of ANN should not be more complex when a forecasting is performed with an out-of-sample input data. The network created for one power system with particular input and targets will give low errors when used on another system but for this training maybe required. Complex ANNs can over fit their training data with generating low error on in-sample input data but high errors on out-of-sample input data.

Two different methods ReliefF and Correlation analysis were used in this research to extract those important variables helpful in load forecasting and hence minimizing the overfitting factor. ReliefF method was applied and the minimum MAPE 3.2% was achieved for a 13variables test set. While, the minimum MAPE 3.0% was achieved for 12 variables test set using the Correlation analysis method. Mean Absolute Percentage Error (MAPE) was used for the load forecasting in this research instead of Mean Square error (MSE) and this is because the MAPE allows comparison among different series which are not possible with MSE.

Correlation analysis method provided variables set with a MAPE of 3.0% which comes in an acceptable range as discussed in the STLF literature. These variables set was later used for day ahead load forecasting. The minimum MAPE achieved is 0.14% for Thursday and maximum MAPE (%) achieved is 2.34% for Monday.

Correlation Analysis provided very important variables which gives good load forecasting results rather than the ReliefF method. The correlation tends to decrease with an increase in forecasting time horizon. The correlation coefficients for the time-lagged load and weather data variables are influenced by the change in season.

Since most of the existing STLF literature prefer load forecasting for a transmission level power system, the resulting error generated for FESCO were presented in this research, which should be viewed as very good. The transmission-level forecasts benefit from load aggregation across the larger transmission network. Even a small change in the load of FESCO power system will create overall a big effect in systems load, possibly generating higher errors forecast.

ANNs used for load forecasting tends to give poor load forecast results if there is an unexpected power outage or certain event, because a sudden change in system load will affect the overall system. These outages are unpredictable and may have resulted in some forecast errors. The average air temperature used for load forecasting is 100% accurate, however in any event there are slight chances in the increase of MAPE of load forecasting due to the human error in noticing down the air temperature precisely and timely.

Matlab® neural network fitting tool aided the work for carrying out load forecasting results. This fitting tool have both self-directed learning and self-adaptive capabilities. For a certain group of input output dataset, we can directly identify their mutual relationship and meanwhile obtain associated parameters without learning the specific mapping relation.

It is expected that this valuable data set will help the research community to develop novel forecasting techniques for demand response applications.

5.2 FUTURE RESEARCH

Since ANNs are considered as black-box models. Unplanned outages and certain events are unpredictable and causes higher errors in forecasting. If these outages are known and given as an input of the ANN, the trained ANN will provide more accurate forecast results and hence reducing the MAPE. Providing the outages as an input to ANN, will help in understanding the phenomenon during the training process and created network should be capable of predicting these outages. Power outages and some certain events were not included in the literature. Future research should attempt to include power system operational information as inputs to the ANN.

In this research average air temperature were used as a predictor input of ANN along with the demand load data, for future research some other important weather parameters in load forecasting, like humidity and air speed can be used for acquiring more accurate load forecasting figures.

There are many deficiencies in this research due to limited time and resources. This research still has some future works to do, which is also a problem faced in the STLF area, including: the learning and training procedures and processes of neural network are still relatively complex, uncertain parameters will directly lead to the change in the output results. A hybrid network can also be made as a future work for better load forecasting results.

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APPENDICES

Appendix A.1 FESCO HOLIDAYS SCHEDULE

DATES	EVENT
2/5/2016	Kashmir Day
3/23/2016	Pakistan Day
5/1/2016	International Labor Day
7/1/2016	Bank Holiday
7/5/2016	Eid-ul-Fitr Holiday
7/6/2016	Eid-ul-Fitr
7/7/2016	Eid-ul-Fitr Holiday Day 2
7/8/2016	Eid-ul-Fitr Holiday Day 3
8/14/2016	Pakistan Independence Day
9/12/2016	Eid-ul-Azha Holiday Day 1
9/13/2016	Eid-ul-Azha Holiday Day 2
9/14/2016	Eid-ul-Azha Holiday Day 3
10/11/2016	Ashoora Day 1
10/12/2016	Ashoora Day 2
11/9/2016	Allama Iqbal Day
12/12/2016	Eid Milad-un-Nabi
12/25/2016	Muhammad Ali Jinnah Day
1/2/2017	Bank Holiday
2/5/2017	Kashmir Day
3/23/2017	Pakistan Day
6/26/2017	Eid-ul-Fitr Holiday Day 1
6/27/2017	Eid-ul-Fitr Holiday Day 2
6/28/2017	Eid-ul-Fitr Holiday Day 3