CHAPTER 1

INTRODUCTION

Load forecasting anticipates the amount of power needed to supply the demand. It helps to meet the demand and manages growth better. Load forecasting is an important component for power system energy management. Precise load forecasting helps the electric utility to make important decisions on purchasing and generating electric power, unit commitment, to reduce spinning reserve capacity, schedule maintenance plan network planning and infrastructure development. Besides playing a key role in reducing the generation cost, it is also essential for the reliability of power system. The system operator uses the load forecasting results to get prepared for load shedding, power purchase, hydro scheduling, hydro thermal coordination and switching on/off peaking units. Load forecasts are important for energy suppliers, Independent System Operators, financial institutions, and other participants in electric energy generation, transmission, distribution, and energy markets.

1.1 OVERVIEW

Load forecasts reveal the occurrence of load growth. It is used by power companies to meet the demand. Forecasting with negative error could severely affect consumer production level. With accurate load forecasting, the operating cost gets reduced and daily operation of plants and units work smoothly. An increase of 0.5 % in accuracy saves several millions of Rupees in the operation of plants. The weather condition plays an important role which is taken into consideration to improve the forecast accuracy. The
intelligent techniques and combination of few techniques used recently has helped to achieve minimum error. Due to large historical data needed for forecasting the hourly load, the time taken for the network to converge increases. Hence achieving minimum error and less training time make the forecasting approach precise and applicable. Selection of better training methods helps forecasting to be more accurate.

The accuracy of forecast is a critical feature in power system load forecasting. Estimation of future load with historical data remained difficult up to now, especially for forecasting the load on holidays and days with extreme weather condition. Undoubtedly, both utility companies and consumers are challenged to predict their respective load accurately. This challenge has been in existence for decades. Due to its high complexity, thus a variety of load forecasting techniques ranging from classical to intelligent systems have been developed till date, and highlighted in a number of studies. The ultimate distinction of these methods can be drawn on the basis of forecast accuracy.

1.2 LOAD FORECAST HORIZONS

Load forecasts have three different horizons: short term forecasts which are carried out for an hour to a week, medium term forecasts are carried out for a week to a year, and long term forecasts are carried out for more than a year. Long term forecasts are intended for capacity expansion plans, capital investment and corporate budgeting. These types of forecasts are often complex in nature due to future uncertainties such as political factors, economic situation and per capita growth etc. Outage scheduling, maintenance of plants and networks come under medium term forecast. In power system the next day’s power generation must be scheduled every day which is executed with Short Term Load Forecasting (STLF). This work
discusses about STLF with developed models. Different forecast horizons are given in Figure 1.1.

![Forecast Horizon Diagram](image)

**Figure 1.1 Forecast Horizons**

STLF is a necessary daily task for load dispatch and its accuracy greatly affects the economic operation and reliability of the system. Overprediction of STLF leads to the unnecessarily large reserve capacity, which is also related to high operating cost while underprediction of STLF leads to insufficient reserve capacity preparation and, in turn, increases the operating cost by the use of peak units.

The most popular techniques used for load forecasting are time series based models, similar day approach and intelligent system based models. Some of the conventional forecasting methods have major drawback such as their inability to map the non linear characteristic of the load. Thus a substitute of classical methods with intelligent system based models to a great extent is essential. Most forecasting models use statistical techniques or artificial intelligence algorithms such as neural networks, fuzzy logic, and expert systems (Feinberg et al 2005).

Amongst all the other intelligent techniques, the use of Artificial Neural Networks (ANN) in STLF is very predominant. Most recent load forecasting works are based on ANN and a majority of these works have presented good estimates. ANNs are capable of generalization and learning
non-linear relationships between variables and these approaches are often favoured for STLF problems (Philippe et al 2008). The other important feature of ANNs is their capability to adjust the synoptic weights iteratively between layers. Conventional methods on the other hand require static complex mathematical equations but still perform poorly in comparison to intelligent based approaches.

With the recent development of new mathematical models like data mining and artificial intelligence tools, it is potentially possible to improve the forecasting result. With the recent trend of deregulation of electricity markets, STLF has gained more importance and greater challenges. Hence precise forecasting helps the electrical energy trade and spot price establishment for the system to gain minimum purchasing cost from the energy market.

This chapter presents in detail about load forecasting with its horizons and in specific STLF. A detailed literature survey is discussed with the researcher’s contribution to this area. The objective and scope of the thesis along with the thesis outline are also stated in this chapter.

1.3 FACTORS INFLUENCING SYSTEM LOAD

Generally, the load of an electric utility is composed of different classes of consumption. A large part of the electricity is consumed by industrial activities. Another part is used by commercial and domestic in the form of heating, lighting, cooking, laundry, etc. Also many services offered for society demand power, like street lighting, railways, etc.

The electricity supply and demand must be in balance. If the demand increases, the peaking plants start generation while Demand Side Management (DSM) works to reduce the energy supply consumption. Hence
DSM also influence on the other side of STLF. Various factors which are essential for accurate forecasting and influence system load behavior are given in Figure 1.2. They are:

- Weather influence
- Time and Day
- Random Disturbances
- Customer Category

![Diagram](image)

**Figure 1.2 Factors influencing STLF**

### 1.3.1 Weather Influence

Weather is the most important individual factor that influences STLF. Weather factors include temperature, humidity, precipitation, wind speed, cloud cover, light intensity and so on.
Figure 1.3 Load curve for a working day in winter and summer

Figure 1.4 Load curve for a week in summer - 08.06.2009 to 14.06.2009
The change of weather causes the change of consumers’ comfort and in turn increases the usage of some appliances such as room heater, water heater and air conditioner. The load curve for a working day in winter followed by summer is given in Figure 1.3. Weather sensitive load also includes appliances of agricultural need for cultivation due to offset of monsoon or delayed water release from dam. In the areas where summer and winter have great meteorological difference, the load patterns differ greatly.

Normally the intraday temperatures are important weather variables in terms of their effect on the load; hence they are often selected as the independent variables in STLF. Temperatures of the previous days also affect the load profile by heat buildup and in turn a new system peak. Humidity is also another important factor, which affects the human being’s comfort greatly. People feel hotter in the environment of 35 to 70% relative humidity than in the environment of 37 to 50% relative humidity. Due to these reasons the temperature humidity index is also employed as an affecting factor. Furthermore, wind chill index is another factor that measures the cold feeling. Hence selecting the weather variables as inputs of STLF holds good.

A general guideline on the effect of weather related conditions on the system load has been discussed in the work of Say, M.G (1976). Typically, the temperature had great impacts which are as follow:

- a change in 1°C temperature will produce a change of about 1% in load
- an overcast sky compared to a clear sky will increase 3-4% of the load
- a thick fog may increase the load by 10-12%
- an increase of 1% in load for every 4km/h wind velocity.
Figure 1.5 Weather model for summer (02.04.2009)

Figure 1.6 Weather model for winter (04.11.2009)
An STLF would be a complete forecast only by using weather related conditions such as temperature, humidity and wind speed (Satish et al 2004). The various parameters of weather for a sample day in summer are given in Figure 1.5 and for a sample day in winter are given in Figure 1.6.

1.3.2 Time and Day

Time and day factors influence the load for a particular time of the day. Actually the load variation with time reflects the arrangement of people’s daily life: working time, leisure time and sleeping time. The weekly load curve is given in Figure 1.4, during which the temperature of chennai city was at the maximum of 40.2°C and minimum of 38.9°C during that week. The STLF focuses for a week.

There are also other rules of load variation with time. The weekend or holiday load curve is lower than the weekday curve, due to the decrease in working load. From the load curves on different occasions in the same month given in Figure 1.7 it can be seen that there are certain rules of load variation. The days are split into national holiday, religious festivals, weekdays and weekend. Shifting to and from daylight savings time in certain countries and start of the school year also contribute to the significant change of the previous load profiles. Periodicity is another property of the load curve. There is very strong daily, weekly, seasonal and yearly periodicity in the load data. Taking good use of this property can benefit the load forecasting accuracy.

1.3.3 Random Disturbances

The modern power system is composed of numerous electricity users. Although it is not possible to predict how each individual user consumes the energy, the amount of total loads of all small users shows good statistical rules and in turn, leads to smooth load curves.
Figure 1.7 Load curve on different occasions during winter
The starting and shutting down of large loads like steel mill always lead to an obvious impulse to the load curve. This is a random disturbance, since for the dispatchers, the startup and shutdown time of these users is quite random. When the data from such a load curve are used in load forecasting training, the impulse component of the load adds to the difficulty of load forecasting. Special events, which are known in advance but whose effect on load is not quite certain, are another source of random disturbance.

A typical event like a world cup cricket match can cause increase usage of television. But the dispatchers cannot decide the exact amount of usage. Other typical events include employees strike and the government’s compulsory demand side management due to forecasted electricity shortage.

1.3.4 Customer Category

Factors affecting the load depend on the category of customers. The classes of customers are Residential, Commercial and Industrial which are given in Figure 1.8. The industrial load is mostly determined by the level of production. The load is often quite steady, and it is possible to estimate its dependency on different production levels.

![Figure 1.8 Load curve for different customer category](image-url)
However, from the point of view of the utility selling electricity, the industrial units usually add uncertainty in the forecasts. The problem is the possibility of unexpected events, like machine breakdowns or strikes, which can cause large unpredictable disturbances in the load level. The high tariff for the industrial units makes them shift to self generation. The commercial load is almost time dependent and same for most of the days except holidays. The Residential load depends on the expansion of the city or town due to increase in the growth of population. If the census data are taken periodically and available on time then the growth pattern for the residential load can be easily determined.

1.4 REQUIREMENTS OF LOAD FORECASTING

In most of Energy Management Systems (EMS) and load dispatch centers there is an STLF module. A good STLF system should fulfill the following requirements:

- Accuracy
- Speed
- Detection of bad data
- User friendly
- Automatic forecasting

1.4.1 Accuracy

The most important requirement of STLF process is its prediction accuracy. A good accuracy is the basis of economic dispatch, system reliability and trading in electricity markets. The main goal of most STLF literatures and also of this thesis is to make the forecasting result as accurate as possible.
1.4.2 Speed

Employment of the latest historical data and weather forecast data helps to increase the accuracy. The historical data and weather forecast data are employed by the STLF program to reduce the running time of computers and to obtain the forecasted result at the earliest. Therefore the speed of forecasting is a basic requirement of the forecasting program. Programs with too long training time should be abandoned and new techniques shortening the training time should be employed. While employing new techniques with shorter training time accuracy should not be compensated.

1.4.3 Detection of bad data

In the modern power systems, the measurement devices are located over the system and the measured data are transferred to the control centre by communication lines. Due to the sporadic failure of measurement or communication, sometimes the load data that arrive in the dispatch centre may be wrong, but they are still recorded in the historical database. In the early days, the STLF systems relied on the power system operators to identify and get rid of bad data manually. The new trend is to let the system itself do it instead of the operators, to decrease their work burden and to increase the detection rate.

1.4.4 User friendly

The interface of the load forecasting should be easy, convenient and practical. The users can easily define what they want to forecast and whether through graphics or tables. The output should also be with the graphical and numerical format, in order that the users can access it easily and record for later use.
1.4.5 Automatic forecasting

To reduce the risk of individual imprecise forecasting, several models are often included in one STLF system. In the past, such a system always needs the operator’s interference wherein the operator decides on weight for every model to get the combinative outcome. To be more convenient, the system should generate the final forecasting result according to the forecasting behavior of the historical days.

1.5 PROBLEMS IN STLF

There are few problems that exist during forecasting which are discussed in detail below

- Input-output relationship
- Expert’s experience
- Anomalous days
- Weather data
- Training problem
- Reliability

1.5.1 Input-Output relationship

Most of the STLF methods hypothesize a network structure in ANN to represent the relationship between the input and output variables. To hypothesize the network structure is a difficult task since it needs a detailed prior knowledge of the problem. If the network structure were not selected properly, the prediction result would be unsatisfactory. For example, when a problem itself is a quadratic, the prediction result will be very poor if a linear input-output relationship is supposed. Moreover, it is always difficult to select the input variables. Too many or too few input variables would decrease the
accuracy of prediction. Decision should be taken to find out the influential variables and the insignificant for a certain situation. Insignificant ones that do not affect the load behavior should be abandoned.

Since it is hard to represent the input-output relationship in one function, the mode recognition tool and clustering has been introduced in STLF (Erkmen et al 1997). This tool divides the sample data into several clusters and each cluster has a network structure to represent the input and output relationship. This method tends to have better forecasting results because it reveals the system property more precisely. But a priori knowledge is still required to do the clustering and determine the network structure for every cluster.

1.5.2 Expert’s experience

The experienced staffs in power grids and load dispatch centers are good at manual load forecasting. They forecast better than computer forecasting. So it is natural at power grids and dispatch centers to use expert systems and fuzzy inference for load forecasting. But transforming the experts experience to a rule database is a difficult task, since the experts forecasting is often intuitive.

1.5.3 Anomalous days

The unusual load is also not easy to get predicted precisely, due to dissimilar load behavior compared with those of ordinary days. These days include public holidays, consecutive holidays, days preceding and following the holidays, days with extreme weather or sudden weather change, TV shows and special events. Although the sample number can be greatly enhanced by including the days that are far away from the target day, the past 5 years historical data can be employed instead of one or two years. The load growth
through the years might lead to dissimilarity of two sample days. The experimental results indicate that days with sudden weather change are extremely hard to forecast. For these types of days the property of the previous neighboring days and the property of the previous similar days are taken for forecasting.

1.5.4 Weather data

Many models employed weather factor since it influences the forecasting result. Although the technique of weather forecasting, like the load forecasting, has been improved in the past several decades, the accuracy is still not enough. An inaccurate weather forecasting could cause large error. Another problem is, sometimes the detailed weather forecasted data cannot be provided. The normal one day ahead weather report information includes maximum temperature, minimum temperature, average humidity, precipitation and maximum wind speed.

1.5.5 Training problem

Load forecasting with ANN is basically training and predicting the problem, which is related to two data sets: training data and testing data. Historical training data are trained in the proposed model and a basic representation can be obtained which is in turn used to predict the testing data. For the out coming training module, if the training error for the training data is low but the error for the testing data is high, overfitting is said to have occurred. Overfitting is a problem that occurs during training of load forecasting which is a disadvantage of ANN. ANNs show perfect performance for training data prediction but much poor performance for the future data prediction. Proper training methods should be applied to avoid overfitting since the goal of STLF is to predict the future unknown data.
1.5.6 Reliability

Industrialization and economical development take place at a faster pace while there is a lag in power investment hence energy shortage has appeared in many countries and mostly in developing countries. To avoid reliability problem and assure the power supply of very important users, compulsory demand side management is often executed. This demand destroys the natural property of load curve. When this kind of load curve is included in training, it serves as noise and deteriorates the final results. Removal of noise becomes difficult to attain the natural load curve. So the load data should be a reliable to be used for forecasting with a proper load curve.

1.6 FORECASTING METHODS

Different categories of load forecasting serve for different purposes. In this thesis short term load forecasting which serves the next day(s) unit commitment and reliability analysis is focused. In most cases historical data are insufficient or not available at all, yet it is anticipated for planners to accurately forecast, thus qualitative forecasting methods are generally used. Among others, these methods include: Delphi method, curve fitting and technological comparisons. Other forecasting techniques such as decomposition methods, regression analysis, exponential smoothing, and the Box- Jenkins approach are quantitative methods. The following techniques used for load forecasting are:

- Regression models
- Time series
- Time of day model
- Similar day approach
Regression models

Regression model is one of the most widely used statistical techniques. Regression models normally assume that the load can be divided into a standard load component and a component linearly dependent on some explanatory variables (Engle et al 1992). The model can be written as in Equation (1.1).

\[ z(t) = b(t) + \sum_{i=1}^{n} a_i y_i(t) + e(t) \]  

(1.1)

where \( b(t) \) is the standard load, \( e(t) \) is a white noise component, and \( y_i(t) \) are the independent explanatory variables. The most typical explanatory variables are weather factors.

In a typical regression model different consumer categories are modeled by separate regression models. The load is divided into a rhythm component and a temperature dependent component (Haida et al 1994). The rhythm component corresponds to the load of a certain hour in the average temperature of the modeling period. Regression models are among the oldest methods suggested for load forecasting. They are quite insensitive to occasional disturbances in the measurements and it is easy implementation. The serial correlation, which is typical when regression models are used on time series, can cause problems.
1.6.2 Time series

Time series methods are based on the assumption that the data have an internal structure, such as autocorrelation, trend or seasonal variation. The methods detect and explore such a structure. Time series have been used for decades in fields such as economics, digital signal processing, as well as electric load forecasting. In particular, Auto Regressive Moving Average (ARMA), Auto Regressive Integrated Moving Average (ARIMA) and Auto Regressive Integrated Moving Average with Exogenous Variables (ARIMAX) are the most often used classical time series methods (Fan et al 1994), (Cho et al 1985). ARMA models are usually used for stationary processes while ARIMA is used for nonstationary processes and is the extension of ARMA. ARMA and ARIMA use the time and load as the only input parameters. Since load generally depends on the weather and time of the day, ARIMAX is the most natural tool for load forecasting among the classical time series models.

1.6.3 Similar day approach

Similar day approach is based on searching historical data for days within one, two or three years with similar characteristics to the forecast day. Similar characteristics include weather, day of the week and the date. The load of a similar day is considered as a forecast. Instead of a single similar day load, the forecast can be a linear combination or regression procedure that can include several similar days. The trend coefficients can be used for similar days in the previous years.
1.6.4 State space model

In the linear state space model, the load at time $t$ can be written as in Equations (1.2) and (1.3)

$$z(t) = c^T x(t)$$  \hspace{1cm} (1.2)

$$x(t+1) = Ax(t) + Bu(t) + w(t)$$  \hspace{1cm} (1.3)

The state vector at time $t$ is $x(t)$, and $u(t)$ is a weather variable based input vector. $w(t)$ is a vector of random white noise inputs. Matrices $A$, $B$ and the vector $c$ are assumed constants. In fact, the basic state space model can be converted into an ARIMA model and vice versa, so there is no fundamental difference between the properties of the two model types (Campa et al 1987). A potential advantage over ARIMA models is the possibility to use prior information in parameter estimation via Bayesian techniques. Yet, the advantages are not very clear and more experimental comparisons are needed.

1.6.5 Time of day model

This approach presents a simple form of load forecasting using the previous week’s actual load pattern to predict the present week’s load. Alternatively, a set of load patterns is stored for typical weeks with different weather conditions. These are then heuristically combined to create the forecast. The equation of the model can be written as in Equation (1.4).

$$\hat{L}(t) = \sum_{i} a_i f_i(t) + \varepsilon(t)$$  \hspace{1cm} (1.4)
where the load at time t, $L'(t)$ is considered to be the sum of explicit time functions, $f_i(t)$ usually sinusoids with a period of 24 hrs or 168 hrs depending on the forecast lead time, $a_i$ are slowly time varying coefficients, and $\varepsilon(t)$ represents the error term (Gross et al 1987).

1.6.6 Expert system

Expert systems are heuristic models that usually account both quantitative and qualitative factors. Many models of this type have been proposed since the mid 1980's. A typical approach is to try to imitate the reasoning of a human operator. The idea is then to reduce the analogical thinking behind the intuitive forecasting to formal steps of logic (Rahman et al 1988). A possible method for a human expert to create the forecast is to search in history database for a day that corresponds to the target day with regard to the day type, social factors and weather factors. Then the load values of this similar day are taken as the basis for the forecast.

On the other hand, the expert system consists of a rule base defining relationships between external factors and daily load shapes. A popular approach has been developed with rules on the basis of fuzzy logic (Kim et al 1995). The heuristic approach in arriving at solutions makes the expert systems attractive for system operators. Also the system can provide the user with the line of reasoning followed by the model.

1.6.7 Intelligent System Based Models

1.6.7.1 ANN

An ANN or Neural Network (NN) is a computational model inspired by a biological nervous system. The network consists of interconnected group of neurons and processes information using a
connective approach to computation. The distributed processing by neurons results in intelligent outcome. ANN based model learns to perform a desired task directly from examples using special training algorithms. ANN is discussed thoroughly in the forthcoming chapters, based on this further models are developed.

1.6.7.2 Fuzzy Logic

The term fuzzy logic emerged in the development of the theory of fuzzy set which Zadeh pioneered by the mid 1960s. A fuzzy logic model is a logical mathematical procedure based on an IF-THEN rule system that mimics the human way of thinking in computational form. Generally, a fuzzy rule system has four modules (Alvisi et al 2005):

a. Fuzzification of the input – process that transforms the crisp into a fuzzy input.

b. Fuzzy rules – IF-THEN logic statement that connects the input to the output variables.

c. Fuzzy inference – process that elaborates and combines rule outputs.

d. Defuzzification of the output – process that transforms the fuzzy output into a crisp output.

In specific load forecasting, fuzzy rules based on demand forecasts must be developed to provide domain specific information to enhance the non-linear models. The expert knowledge developed in the model can easily be incorporated using linguistic descriptions to high quality data for load forecasting.
1.6.7.3 Evolutionary Computing

Literature of most recent STLF works report that Genetic Algorithm (GA) is one of the suitable approaches especially for load forecasting network structure optimization (Naggar et al 2007). Most of the drawbacks associated with traditional intelligent systems are the dependence on initial parameters, more training time, network topology can easily be addressed by using this method (Srinivasan 1998). The standard back propagation training based rules can be used to solve a variety of simple optimization problems. However, when the complexity of the problem increases, their performance falls rapidly.

Other drawbacks include issues like, long training period, single point search, scaling, initial parameters dependence etc. However, GA is regarded as an alternative approach. The use of GA was initially discovered in the mid 1970s by John Holland. The main idea was to design artificial systems retaining the robustness and adoption properties of natural systems. Since the inception, these methodologies were then further improved by other researchers and are now widely used in various fields such as business, science, engineering etc. GA mimics the biological processes to perform a random search in a defined N-dimensional possible set of solutions. For an optimization problem, one needs to search and find the best solution in a given search space. The idea behind the GA’s principle is inspired by Darwin’s theory of evolution (survival of the fittest).

1.6.7.4 Data Mining

Data mining is the process that explores information data in a large database to discover rules, knowledge, etc (Hasti et al 2001, Han et al 2006) and a method was proposed for STLF using data mining. The method is based on a hybrid technique of optimal regression tree and an ANN. It classifies the
load range into several classes, and decides to which class the forecasted load belongs, according to the classification rules. Then Multi Layer Perceptron (MLP) is used to train the sample in every class. A clarification on the nonlinear relationship between input and output variables in a prediction model is used.

### 1.6.7.5 Wavelets

A STLF model of wavelet based networks was proposed by Li et al (2003) to model the highly nonlinear, dynamic behavior of the system loads and to improve the performance of traditional ANNs. The three layer network of the wavelet, the weighting, and the summing nodes are built by an evolutionary computing algorithm. Basically, the first layer of wavelet nodes decomposes the input signals into diverse scales of signals, to which different weighting values are given by the second layer of weighting nodes. Finally the third layer of summing nodes combines the weighted scales of signals into the output. In the evolutionary computing constructive algorithm, the parameters to be tuned in the networks are compiled into a population of vectors. The populations are evolved according to the stochastic procedure of the offspring creation, the competition of the individuals, and the mutation.

### 1.7 LITERATURE REVIEW

Abd (2009) proposed a model for electricity load forecasting based on Framelet Neural Network (FNN) technique for Baghdad city. FNN technique was implemented to the time series data, decomposing the data into number of framelet coefficient signals. The decomposed signals were fed into NN for training. To obtain the forecast, the output from the NN was recombined using the FNN technique. The implementation of FNN has reasonably enhanced the learning capability of the NNs in the model, thus
minimizing their training frequencies. The NN was able to determine the nonlinear relationship that exists between the historical load data supplied during the training phase and on that basis, made a prediction of what the load would be in the next day.

Abdul Hamid et al (2010) proposed an ANN trained by Artificial Immune System (AIS) learning algorithm for STLF. In this study, the AIS was implemented as an optimization technique to determine the optimal weight of the neurons in the ANN with an objective to minimize the output error. The proposed AIS learning algorithm was used to train the ANN and its prediction capability was tested using two different historical data sets. As comparison, ANN with Backpropagation (BP) learning algorithm was implemented to perform the same task. The performance of the proposed AIS learning algorithm was better compared to that of the BP learning algorithm.

Afkhami et al (2006) developed an ANN model for STLF that can forecast daily load profiles with a load time of one day to next 24 hours. Days of year was divided using the average temperature. Groups were made according to the linearity rate of curve. Ultimate forecast for each group was obtained by considering weekday, weekend, temperature and humidity. For forecasting load curve of holidays, first pick and valley was calculated and then the neural network forecast was reshaped with the new data. The network was trained using hourly historical load data and daily historical max/min temperature and humidity data of Yazd utility.

Alves da Silva et al (2000) described load forecasts through multilayer perceptron trained by the BP algorithm. Three techniques for the computation of confidence intervals for this NN based STLF were presented. Error Output, Resampling and Multilinear Regression were adapted to NN. A
comparison of the three techniques was performed through simulations of online forecasting.

Amjady et al (2011) proposed a new STLF strategy composed of a pre processor and a novel hybrid forecast engine. The pre processor performs tasks like normalization and feature selection. The hybrid forecast engine was a NN based predictor equipped with a new learning algorithm, Modified Harmony Search algorithm (MHS). The proposed MHS had both local and global search abilities and can optimally determine the weights of the NN to minimize its validation errors. MHS can widely search the solution space in various directions, thus avoiding being trapped in local minima. Based on the MHS, the proposed hybrid forecast engine efficiently learns the input-output mapping function of the forecast process, and predicts the future values of the forecast feature with high accuracy and robustness.

Ardalani-Farsa et al (2010) proposed a residual analysis using hybrid Elman NARX neural network along with embedding theorem to analyze and predict chaotic time series. Using embedding theorem, the embedding parameters are determined and the time series is reconstructed into proper phase space points. The embedded phase space points are fed into an Elman neural network and trained. The residual of predicted time series is analyzed, and it was observed that residuals demonstrate chaotic behavior. The residuals are considered as a new chaotic time series and reconstructed according to embedding theorem. A new Elman neural network was trained to predict the future value of the residual time series. The residual analysis was repeated several times. Finally, a NARX network was used to capture the relationship among the predicted value of original time series and residuals. The method was applied to Mackey–Glass and Lorenz equations which produce chaotic time series to a real life chaotic time series and Sunspot time series, to evaluate the validity of the proposed technique.
Brunelli et al (2008) studied air quality in buildings near industries based on models for short lead time forecasting (1–3 hrs). Pollutant concentrations reduction could be obtained using cleaner fuels and/or stopping the production of some industries. The Elman based forecaster was designed, tested and compared with stochastic model or a traditional MLP neural network based forecaster. The forecaster shows interesting results for one, two, and three hours ahead SO\textsubscript{2} concentration prevision.

Buhari et al (2012) developed an ANN based STLF model for the 132/33KV sub Station, Kano, Nigeria. The recorded daily load profile with a lead time of 1-24 hours for the year 2005 was obtained from the utility company. The Levenberg-Marquardt optimization technique for learning rates was used as a BP algorithm for the multilayer feed forward network using Matlab ANN Toolbox. The accuracy of the forecasts was high by this training. The forecasted next day 24 hourly peak loads was obtained based on the stationary output of the ANN with a performance mean squared error.

Charytoniuk et al (2000) presented a novel approach to STLF by the application of ANN to model load dynamics. The proposed algorithm was robust compared to the traditional approach when actual loads were forecasted and used as input variables which were implemented for online load forecasting in a power utility in United States. It provided more reliable forecasts, especially when the weather conditions were different from those represented in the training data. To assure robust performance and training times acceptable for online use, the forecasting system was implemented as a set of parsimoniously designed NN. Each network was assigned a task of forecasting bad for a particular time lead and for a certain period of day with a unique pattern in load dynamics.
Charytoniuk et al (2000) addressed an issue of the optimal design of a NN based STLF for developing a multilayer feed forward neural network for load forecasting. An algorithm was presented for performing two important steps of that process. Input variable selection was carried out by forming a set of variables significantly correlated with the forecasted load and then by removing redundant, mutually correlated variables using singular value decomposition techniques. Selection of the optimal number of hidden neurons was based on the observation that oversized networks display near collinearity in the outputs of their hidden neurons. Hence, the presence of redundant hidden neurons can be detected by examining column dependency in the matrix of the hidden neuron outputs computed from the training data.

Chen et al (2001) proposed an ANN based STLF technique that uses a three layer feed forward neural network and a BP training method. It considers electricity price as one of the main characteristics of the system load. The load price relationship is highly nonlinear and difficult to model directly; hence, by considering price as another input to a neural network, it was shown that it was possible to readily account for the impact of price on system load. The historical load data for the Ontario hydro system as well as the prices from the neighboring electricity market was used for testing, demonstrating that price does have an impact on the performance of a STLF technique.

Chen et al (2008) reported a similar day based wavelet neural network method to forecast the next day’s load. The key idea of this method was to use a similar day method to prepare good input data, and use the combination of wavelet and neural networks to approximately capture features of different frequency load components. Numerical testing results show that this method helps to improve forecasting quality. Using precipitation is important to get good prediction for the noisy high frequency
load component. This method was also applicable to other load forecasting problems such as next hours load forecasting or regional load forecasting.

Chow et al (1996) described a novel technique for electric load forecasting based on neural weather compensation. This method is a nonlinear generalization of Box and Jenkins approach for nonstationary time series prediction. The proposed weather compensation NN was built by considering the load consumption as a nonstationary time series and the whole dynamic range of ANN are fully utilized. Hence, the weather compensation NN produces accurate load predictions. Based on the offline simulations, the forecast error can be reduced by 0.7 when employing NARI model. If the constant updating scheme is applied, the NARI model is adaptive to the changing conditions and capable of providing more accurate load forecast with a further 0.2 reduction in forecast error.

Daneshdoost et al (1998) proposed a multi layered feed forward ANN combined with the fuzzy set based classification technique for STLF. The hourly data was classified into classes based on the fuzzy set representation of two weather variables: dry bulb temperature and relative humidity. The classification is based on the fact that the power system load is heavily influenced by the weather condition. The fuzzy set was used to assist the classification process in order to achieve the smooth transition between the classes of weather condition. The proposed technique was tested and its performance was evaluated by the Mean Absolute Percentage Error (MAPE) of three measures of hourly load, peak load, and total daily energy. The set of ANN'S was shown to forecast the system's load up to 120 hours ahead.

Dash et al (1997) discusses about the functional link network for STLF. The load and weather parameters are modeled as non linear ARMA process and parameters of the model are obtained using functional link network. The network uses to enhance the input using the auto enhanced
functional link net. This system was proposed to produce robustness and increases the accuracy of forecasting.

Dong xing Duan (2009) proposed an ant colony clustering model based on Elman neural network for representative training samples. The historical load data were pre processed by using ant colony clustering method. The clustered data were chosen as training samples for the network. Dynamic neurons Elman network was adopted and the dynamic characteristics mapping ability of this network was realized through the initial status of memory. Prediction results were deduced from simulation of one historical data by using Elman network model. The method combined the ability of solving non-linear problems of ant colony clustering and ANN The learning efficiency of precision of model was enhanced to a great degree.

Feng Zhao et al (2007) proposed a STLF model for dynamic nonlinear characteristics of power system load. The model was based on Wiener model and Elman recursive neural network to fit in with its nonlinear part. Kalman filter was used to remove the white noise of the system. To meet the dynamic nonlinear requirements of STLF, Elman dynamic recursive neural network was used. The proposed model was emphasized to increase learning efficiency, strong adaptability and high forecast precision.

Filho et al (2011) used two methodologies for short term multimodal load forecasting. The first individually forecasts the local loads and the second forecasts the global load and individually forecasts the load participation factors to estimate the local loads. A modified general regression NN and a procedure to automatically reduce the number of inputs of the ANN was proposed. To design the forecasters, the previous study of the local loads was not necessary, thus reducing the complexity of the multinodal load forecasting. The model was tested for New Zealand distribution subsystem.
Filik et al (2007) introduced a new approach to STLF using Auto Regressive (AR) and ANN models to the power system of Turkey. The load forecasting for the next day using AR and ANN models was performed separately while the results of the AR analysis was used as input to different ANN models, which are feed forward Backpropagation Network (BPN) and cascade forward BPN. In the first approach, AR model was used for load forecasting with different NN structures. All the NN structures comprised of six neurons in the input and one neuron in the output. Cascade forward backpropagation was found to be more efficient than feed forward backpropagation method. Also the ANN was corrected by applying the result of the AR model to their inputs.

He et al (2006) applied the use of computational intelligent methods to STLF and proposed Elman recurrent neural network model based on fuzzy classification and entropy theory. Entropy was used to select relevant factors among many available data before the load data was processed. Then considering the features of load and reduced influential factors, the use of fuzzy classification rules was to divide the past load data into different network property. Then the representative historical load data samples were selected as the training set for NN which had the same weather characteristic as the certain forecasting day. Finally, intelligent computational technique Elman recurrent neural network forecasting model was developed for daily load forecasting problem.

Hinojosa et al (2010) described Fuzzy Inductive Reasoning (FIR) to the problem of STLF in power systems. The FIR model learns both past and future relations from the load and the temperature. The proposed optimization model used an evolutionary algorithm based on local random controlled search Simulated Rebounding Algorithm (SRA) to choose the inputs to the
FIR model. Using an optimization method to determine linear and nonlinear relationships between the variables, a parsimonious set of input variables was identified to improve the accuracy of the forecast. The input variables were updated when a new load pattern happened or when relative errors were unacceptable. The FIR and SRA methodology was applied to the Ecuadorian power system.

Hippert et al (2001) reviewed various NN models that were published during 1991 to 1999 for STLF. The author highlights the use of BP algorithm which is a steepest descent technique used by many researchers for forecasting although many algorithms were available. The use of multilayer feed forward architecture was projected, since it is popular and widely used than the other networks with large number of designs. The input classification and various parameters used by researchers for load forecasting with NN were discussed. The number of research work on NN for load forecasting with input variables like load, type of day and temperature was more. Few works were on using humidity as additional parameter and few more on using load parameters other than hourly load. The number of research work using the NN architecture which includes the type of forecast, activation function and the number of neurons at input-output-hidden layer was also reviewed.

Holger Maier et al (2000) discussed the steps in the development of ANN to predict and forecast water resources variables. These include the choice of performance criteria, the division and pre processing of the available data, the determination of appropriate model inputs and network architecture, optimization of the connection weights (training) and model validation. The options available to modelers at each of these steps are discussed and the issues that should be considered was highlighted. The vast majority of these networks are trained by BPN. Issues in relation to the
optimal division of the available data, data pre processing and the choice of appropriate model inputs are seldom considered.

Huang et al (2010) proposed a Modified GA with BP to inherit the strengths of Standard GA and BP to overcome their weaknesses. The modified model was applied to daily load forecast. In comparison with the other models, this prediction model corresponds well with the actual value and the forecast accuracy reaches 98.7%. Especially, with regard to prediction accuracy and running time etc., the performance of MGA in load forecasting is better than other techniques, such as BP and Particle swarm optimization.

Kelo et al (2011) used Maharashtra’s load consumption profile to predict the load patterns considering various short term memory structures of Focused Time Lag Recurrent Neural Network (FTLRNN) such as gamma, laguarre and multi channel tapped delay line based Time Lag Recurrent Neural Network (TRNN). The parameter wise optimization training process was implemented to achieve the optimal configuration of the applied NNs. Conventional and advanced adaptive algorithms were tested to achieve the optimal performance of the applied recurrent neural network. Experimental results indicate that the dynamic NN model including FTLRNN based TDNN memory filter consistently performs well in all the seasons, months, and on daily basis and has indeed outperformed the gamma and laguarre based short term memory structures. The empirical results obtained in this study demonstrate that the FTLRNN based TDNN as a multi channel tapped delay line short term memory structure offers a pragmatic alternative to solve short term load prediction problem of a practical system as considered in this paper.

Kher et al (2003) presented a new approach with functional link network for STLF. The STLF was carried out for one hour ahead using the tensor model of functional link network. The tensor model was used to
produce additional inputs to be given to the input and forecasting for the next
day. This was used to increase the network capability.

Laurence Fausett (2004), Zurada (1997), Freeman et al (2000) and
Chin et al (1996) described on various ANN techniques which are used to
solve problems in many areas. The main aim is to train the network to achieve
a balance between the ability to respond correctly to the input patterns that are
used for training. Different activation functions and networks were described
with their training algorithms. This also clarifies the differences in the
capabilities of different networks.

Liao et al (2006) applied a fuzzy NN combined with a chaos search
 genetic algorithm and simulated annealing. A Fuzzy Hyper Rectangular
Composite Neural Network (FHCNN) was adopted for the initial load
forecasting. An integrated chaos genetic algorithm and fuzzy system and
simulated annealing were used to find the optimal FHCNN parameters instead
of the ones with the BP method. The Chaos method holds good for global
search capability but poor local search ability. On the contrary, the simulated
annealing method possesses a good local optimal search capability.

Ling et al (2003) proposed a STLF by a Neural Fuzzy Network
(NFN) and a modified GA. Based on the benchmark De Jong’s test function,
it was shown that the modified GA performs better than the traditional GA.
An NFN was proposed in which a switch was introduced in each fuzzy rule.
Thus, the number of rules can be optimized by applying the modified GA.
The cost of implementing the NFN can be reduced. The optimal number of
rules and the network parameters was tuned by the modified GA.

Manohar et al (2008) developed a software package for obtaining
and studying STLF using ANN. It presented the results of investigation
carried out with data collected from a 220 KV / 132 KV / 33 KV / 11 KV
Renigunta substation, A.P, India. Calculations were done based on the hourly data of active power variations obtained over a period of one month. The active powers were used as input quantities for training the ANN and obtained the respective output active powers for the corresponding day. Based on the results the NN based forecasting was much faster than the conventional methods.

Maria et al (2006) discusses about load forecasting with data mining combined with NN and comparing with statistical methods. This forecasting was focused on electricity trading based on which the electricity prices are determined. Forecasting the load based on competitive market rather than for the operation of power plant was carried out.

Misra et al (2008) employed AIS Algorithm for STLF. It was observed that the proposed Hybrid AIS algorithm trained by NN had better accuracy than conventional AIS trained by NN. This training approach required a leaner network than BP to reach at the almost same level of accuracy. GA & particle swarm optimization trained networks required 150 iterations & 36 data sets, where as hybrid AIS required hardly 6 iterations & 21 data sets to converge to the same extent. The proposed approach had good convergence.

Misra et al (2009) carried out a comparative study between Wilcoxon NN with Wilcoxon norm cost function and a Multi layer perceptron network with least mean square cost function. It was found that in case of regression or forecasting problem, containing few data sets, Multi layer perceptron network provided better performance than Wilcoxon NN in terms of MAPE. Then a novel Wilcoxon NN was proposed to improve the MAPE forecasting and to reduce computational complexity.
Mosalman et al (2011) proposed a method based on the development of ANN for STLF. Days of year with average temperature was divided in this method. In addition, groups are divided according to the linearity rate of curve. Then, with considering weekday and weekend, the ultimate forecast load was obtained for each group. Moreover, investigation was made on the effect of temperature and humidity on consuming curve. The forecasting load curve of holidays was at first pick and valley, then the NN forecast was reshaped with the new data. The ANN based load models was trained and tested using hourly historical load data of Yazd utility with daily historical max/min temperature and humidity data.

Osofisan et al (2010) proposed an ANN based STLF method that used a four layered feed forward neural network and a BP algorithm. It was proposed to increase the efficiency of NN for load forecasting in general and in the energy management of power holding company of Nigeria. It has thus been proven that ANN is capable of numeric approximation of any continuous function with the desired accuracy as well as being computationally fast. The temperature, pressure and other weather conditions were not taken for consideration.

Othman et al (2009) presented an AR Box Jenkins model for STLF using the Malaysian hourly peak load study. The AR Box Jenkins model used for STLF was selected based on the behaviors of Sample Auto Correlation and Sample Partial Auto Correlation functions. Both the correlation represents the behavior of the stationary past hourly peak loads, first differences of the time series or second differences of the time series. The first differences of the past hourly peak loads was performed in order to obtain the stationary form of time series. If the time series is still a non stationary then, the second differences of the past hourly peak loads was performed in order to obtain the
stationary form of time series. This was proposed to be more efficient than ARIMA Box Jenkins model.

Othman et al (2012) proposed a method to increase accuracy of STLF by considering only one input data that is the univariate time series of chronological hourly peak loads. The proposed method comprised of ANN model incorporating with feature extraction of multiple time lags of input data and stationary output. Also it was emphasized to accurately specify the total number of lagging time interval, K, for the input data of ANN which may significantly affect the performance of ANN. The ANN with stationary output provides better results compared to the ANN with non stationary output for STLF.

Paras et al (2006) proposed an ANN combined with similar day approach which was most commonly used in traditional methods for forecasting the load for similar weather conditions. A weight factor was used to evaluate the similarity between the forecasted day and the previous day of similar pattern which was used with ANN to forecast the load.

Park et al (1991) proposed an ANN approach to electric load forecasting. The ANN was used to learn the relationship among past, current and future temperature and loads. In order to provide the forecasted load, the ANN interpolates among the load and temperature data in a training data set. The forecast was carried for one hour to 24 hour, to compare with currently used forecasting technique applied to the same data. The temperature information was only used while additional weather variables such as cloud coverage and wind speed were not used.

Patel el al (2005) proposed a novel ANN model the RBFN, for STLF is presented as an alternative to multilayered feed forward network. The
ANN was first designed by using historical load data and then the designed network, produces the load forecast when forecast pattern is presented to it. STLF of 220 KV GSS, Jodhpur was used to propose RBFN. The proposed RBFN can yield the hourly electric load forecast very efficiently and accurately. Moreover, for finding neurons weights and biases, there is no training required in the proposed RBFN. It is believed that forecasting using RBFN can be further improved if weather data such as temperature, humidity, sky cover etc., are included in training and forecasting patterns.

Paulraj et al (2010) conducted a study to develop a simple system for classrooms speech intelligibility prediction. In the study, several classrooms properties such as size, signal-to-noise ratio and speech transmission index were collected from different types of classrooms in Universiti Malaysia Perlis (UniMAP). A dataset was obtained from the measurement and was used to develop the system. To develop the system, several process were implemented which included the statistical analysis, data cleaning and preprocessing, network development, training and classification. In that study, Elman network was selected to develop the system for its robustness in prediction application. Also the network performances were dependent to the normalization method.

Peng et al (1992) proposed an improved NN approach to STLF for selecting the training cases for the NN. The approach used a minimum distance measurement to identify the appropriate historical patterns of load and temperature values used in the estimation of the network weights. This approach had the advantage of circumventing the problem of holidays and drastic changes in weather patterns. In addition, an improved NN was proposed which included a combination of linear and nonlinear terms, to map the past load and temperature inputs to the load forecast output. The proposed method was tested with two years of utility data and had self learning
capability, providing significant advantage over other methods in circumventing the need for a separate adaptive algorithm.

Peng et al (1993) proposed a NN approach for one week ahead forecasting using ADALINE. The various load components were used to decompose using digital filters which were used to forecast with ADALINE. Later with weight vectors the network was trained and the corresponding outputs were obtained.

Ranaweera et al (1995) proposed a RBFN model and a BPN model to provide peak and total load forecasts for the next day. Both models were tested with real data. The results strongly indicated that the RBFN model performed better than the BPN model. The RBFN model also computes reliability measures which is an added advantage. The measures provided confidence intervals for the forecasts and an extrapolation index to determine when the model is extrapolating beyond its original training data. These reliability measures are very useful to the operators and provide a reasonable solution to an unmet need in the industry. Furthermore, the training time for the RBFN model was much less than that for the BPN model.

Rashid et al (2005) proposed a modified network which was a part of the recurrent networks family called as Feed Forward and Feedback Multi Context Artificial Neural Network using daily energy peak load forecasting approach. The main positive result was the change in weather components over time, leading to better performance than using current absolute weather components for power plant peak load forecasting. The results indicated that the network using different data sets were steady and provided positive results.
Salama et al (2007) suggested few choices of ANN structures to be applied with changing the input data. The network performance examined only the simulation of the network while the performance of some networks achieved the expected goal, but the estimated errors were not satisfied. For successful ANN more attention for the study of the load curve, the current and the historical curves which may extend to five years ago to identify and specify the effective growth rate of them are very essential. The results were compared with the actual load of Egyptian electrical utility.

Sanjay Kelo et al (2012) proposed a novel combination of wavelet and Elman network of recurrent neural network to predict one day ahead electrical power load under the influence of temperature. Using wavelet multi-resolution analysis, the load series was decomposed to different sub series, showing different frequency characteristics of the load. Elman network was designed and trained using standard BP algorithm. Feasibility of Daubechies wavelet at different scales with suitable number of decomposition levels was investigated to choose the best order for different seasonal load series. The estimated models were evaluated over different temperature and humidity in order to examine their impact on accurate load prediction. The reliability and consistency in prediction by the adopted technique was maintained even in the presence of controlled Gaussian noise to the predicted temperature series and have minimum MAPE.

Seker et al (2003) proposed recurrent neural nets for condition monitoring and diagnosis in nuclear power plant systems and rotating machinery. In the first application, recurrent neural nets was used for detecting anomalies introduced from the simulated power operation of a high temperature gas cooled nuclear reactor. In the second, it was used to detect the motor bearing damage using a coherence function approach, which was
defined between the motor current and vibration signals, for induction motors. The Elman neural network training algorithm was structured on the classical BP algorithm using the context layer. Due to which it exhibited a high level performance in following the dynamical changes with the special topological structure. It was observed that Elman network had better performance capability in reflecting the physical changes considered with two different engineering systems.

Salman Quaiyum et al (2011) proposed few NN models for STLF. The accuracy of the forecast model showed that particle swarm optimized Elman recurrent neural network was better for 168 hours ahead load forecasting. The author suggested that these types of networks were efficient in terms of predicting future loads. Though the simulations seemed very promising, the models developed needed to be tested on data sets from other sources, so that reliability of these models can be verified for other load patterns. Weather parameters like temperature, wind speed, rainfall were not considered.

Siddarameshwara et al (2010) discussed Elman recurrent network model by using matlab software to simulate the load forecasting. The work included comparing the results obtained by weather sensitive model and a non weather sensitive model. The work was specifically limited to offline training. But for real time applications, few more matters are still need to be carefully addressed during model development process. The existence of bad data (outliers) in the historical load curve as well as in the weather data can affect the accuracy of the forecast negatively. In that work, a manually based strategy for detecting and replacing bad data was employed. However, the approach was inappropriate for real time implementation, thus a technique aimed at identifying and replacing abnormal data in the input variable curves needs to be automated.
Sivanandam et al (1997) and Paulraj (2002) and (2004) described about the Stability of BP NN system using various activation functions. Also improvements in BPN network using slope parameter has been analyzed which gives the basic idea to introduce with the BPN network. The STLF was carried out for half hourly load using BPN for real time data. The systole activation function was also used in the training of the network. The performance of the network was improved by these methods.

Song et al (2005) proposed a new fuzzy linear regression method for the short term 24 hourly loads forecasting during holidays. The concept of a fuzzy linear regression was employed in the STLF. The proposed fuzzy linear regression model was based on Tanaka’s approach using based fuzzy arithmetic operations where both input data and output data are fuzzy numbers. Due to dissimilar load patterns of the holidays compared with those of weekdays, relatively big load forecasting errors of the holidays were considerably improved. In addition, the relative coefficient is introduced to the proposed fuzzy linear regression algorithm in the case of load forecasting for holidays falling on Saturday or Monday and a great enhancement of the accuracy of the load forecasting was achieved. The algorithm was proposed to increase the accuracy.

Soozanchi et al (2010) explored the use of Adaptive Neural Fuzzy Inference System (ANFIS) to study the design of STLF systems for Iran power system. While reviewing the probability of chaos and predictability of electricity load curve by Lyapunov exponent, it used the load from multi ANFIS. Entries of the presented model of ANFIS included the date of the day, temperature and the previous day’s consumption. The importance of temperature was emphasized since it had important role in load forecast.
Srinivasan et al (1995) proposed a hybrid fuzzy neural technique combining NN modeling, techniques from fuzzy logic and fuzzy set theory for electric load forecasting. The strengths of the powerful technique lied in its ability to forecast accurately on weekdays, as well as, on weekends, public holidays, and days before and after public holidays. Furthermore, use of fuzzy logic effectively handled the load variations due to special events. The Fuzzy NN was extensively tested on actual data obtained from a power system for 24-hour ahead prediction based on forecast weather information. The approach avoided complex mathematical calculations and training on many years of data, and was simple to implement on a personal computer.

Su et al (2007) proposed dynamic nonlinear characteristics in power systems for STLF model based on Wiener model, and Elman recursive NN to fit into its nonlinear part proposed by. H_{\infty} filter was introduced to overcome the unknown disturbance and noise in the linear part of the systems during forecasting, and then, Elman dynamic NN was applied to implement the nonlinear loads prediction. Compared with normal Kalman filter and BP NN, the proposed method possessed high learning efficiency, strong adaptability, high forecasting accuracy and good forecasting behavior.

Subburaj et al (2008) presented a new approach using Combined Artificial Neural Network module (CANN) for daily peak load forecasting. Five different computational techniques were used, Constrained method, unconstrained method, Evolutionary Programming, Particle Swarm Optimization, and GA to identify the CANN module for peak load forecasting. A set of NN was trained with different architecture and training parameters. A set of better trained conventional ANNs was selected to develop a CANN module using different algorithms instead of using one best conventional ANN.
Sun et al (2011) used DB wavelet and the BPN method for STLF. First, the load sequence was decomposed into different sub sequences by using the wavelet transform, high frequency son sequence and low frequency son sequence. Then these sub sequences were forecasted by ANN. Finally, the load forecasting sequence was obtained by the reconstruction of the forecasted results from the sub sequences. The hebei baoding areas historical load data was used to compare the algorithm with BPN. The DB wavelet with BPN was carried out to increase forecasting accuracy.

Taylor et al (2002) investigated the use of weather ensemble predictions in the application of ANNs to load forecasting for lead times from one to ten days ahead. A weather ensemble prediction consisted of multiple scenarios for a weather variable. The results showed that the average of the load scenarios is a more accurate than traditional weather forecasts. The load scenarios were used to estimate the uncertainty in the ANN load forecast. In view of this, the variance of the load scenarios was rescaled before using it as an estimator of the load forecast error variance. The resulting estimator compared favorably with benchmark estimators based purely on historical forecast error. Using the same variance estimator as a basis for estimating prediction intervals also compared well with benchmark methods. The work emphasized a strong potential with the use of weather ensemble predictions in ANN load forecasting.

Tomonobu et al (2002) discussed about forecasting the load based on forecasted temperature since temperature has a major role in the load profile. This additional forecast information was given as input to the network to be trained. To forecast the temperature, similar day data was used based on which the load forecasting was carried out and the NN structure reduced along with training time.
Yun et al (2008) used the RBFN based method for load forecasting. The self learning and nonlinear mapping ability of the RBFN gave the forecasting results without considering the influence of the electricity price. Aiming at the uncertainty of the real time price and its effect on load, an ANFIS based adjustment was proposed. The supplement reflected the relationship between price fluctuation and load change and consequently improved the accuracy of predictions.

Zhang et al (1998) highlighted the use of ANN for load forecasting with various NN model taken into consideration. The use of ANN to different problems were discussed and compared with statistical methods. Training the network and the problems with overfitting were stressed.

Zhihang Tang et al (2011) proposed an improved Elman NN, Hybrid feedback Elman network, for short HF Elman, to give a sufficient condition for the convergence of the new network and constructed the corresponding training algorithm based on chaotic mechanism. The model introduced chaos mechanism to train the improved network, thus the shortcomings of local extreme caused by the traditional gradient algorithm could be eliminated effectively, and either the network’s learning efficiency or the forecast accuracy can be enhanced greatly. Results indicate that, the HF Elman network performed better to the modeling of high order, delay, and nonlinear chemical dynamic system.

1.8 OBJECTIVE OF THE WORK

The increase of error in load forecasting makes the network unreliable which increases the operation cost. Forecasting started with traditional methods with a high percentage of error and later the error was minimized with the use of intelligent techniques. The reduction in error could
be reduced further which in turn increased better utility operation. Both overprediction and underprediction results in high percentage of error.

The first objective is to develop models trained by Backpropagation algorithm with modification to reduce the training time and improve the network performance.

The network is normally trained by BP algorithm and activated by an activation function; so training the BPN and the proposed models with various activation functions and making a comparative study to indicate the best among them would be the next objective.

While developing the models to forecast the comparison should not within a single network like feed forward network, the work should be extended to recurrent network also which would be the next objective.

The last objective is to test the developed models for various activation functions with a real time data.

The requirements for Load forecasting application are derived from its intended use within an EMS. There are some properties, which are considered important:

- The model should be automatic and able to adapt quickly to changes in the load behavior.
- The model is intended for use in many different cases. This requires generality.
- Updating the forecast with new available data should be possible.
The model should be reliable, even in exceptional circumstances it should not give rise to unreasonable forecasts.

- Difficult weather conditions should be taken into account.
- The model should be easily attachable to an EMS.

1.9 SCOPE OF THE WORK

This research work focuses on a specific area of load forecasting, the short term load forecasting. The forecasts are carried using ANN based models of feed forward network and recurrent networks simulated with MATLAB. The models are then tested for the actual load data of the Load Dispatch Centre of Tamil Nadu Generation and Distribution Corporation for Chennai city, India. The application of actual data to the models is done to validate the approach.

Similarly the models are focused on feed forward and recurrent network for load forecasting. In the feed forward network the connections between the units do not form a directed cycle while the feedback is available in recurrent network. A Multi layer Perceptron of feed forward network and Elman network of recurrent neural network are used in developing the models.

The activation function plays a major role in the training of the network. The research work focuses on four activation function such as Log sigmoid, Tan sigmoid, Radial Basis and Log sigmoid with slope parameter which would help the investigations on selection of activation function. The training of the network is carried with the supervised learning.
1.10 THESIS OUTLINE

This thesis is composed of seven chapters. The following chapter concentrates on the subject of load forecasting in general and outlines the work to be carried out. The methods used in load forecasting by various researches are given a brief study to understand the idea and their proposed method. This helps us to have a clear scope of the research. The overall organization of rest of the chapters is as follows:

Chapter 2 gives a detailed study of ANN and the standard BPN used for load forecasting. The proposed model for load forecasting, the Minimized BPN is discussed to minimize the training time, the network is trained and tested with load data.

Chapter 3 discusses the proposed model Functional Link Network. In this the Functional Link concept, additional input generation and feed forward of input with training and testing are discussed so as to increase the performance of the network.

Chapter 4 discusses the combination of Functional Link Network model and Minimized BPN model. The proposed model is to increase the network performance as well as reduce the training time.

Chapter 5 discusses the Recurrent Neural Network. The Elman Network model is proposed with minimized BPN and standard Elman Network is also discussed.

Chapter 6 discusses the proposed model of Functional Link Network with minimized Elman Network. The Functional Link Network is introduced with Elman Network to test the performance of forecasting in Recurrent Neural Network.
Chapter 7 discusses the proposed models with results and effectiveness of the network. Also it identifies some area for future work.

In this thesis the following conventions are employed

- In all the proposed models and the compared network the training is carried with four activation function such as Log sigmoid, Tan sigmoid, Radial Basis and Log sigmoid with slope parameter.
- The networks are trained and tested with real time load data of Chennai city, India obtained from Load Dispatch Centre of Tamil Nadu Generation and Distribution Corporation.
- Mean Square Error is employed to measure the error of the networks.