

Weather Sensitive Short Term Load Forecasting using Non-fully connected Feed Forward Neural Network

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Master of Engineering

in

Power Systems & Electric Drives



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CERTIFICATE

I hereby certify that the work which is being presented in the thesis entitled "**Weather Sensitive Short Term Load Forecasting using Non-fully connected Feed Forward Neural Network**", in partial fulfillment of the requirements for the award of degree of Master of Engineering in Power systems and Electric Drives submitted in Electrical & Instrumentation Engineering Department of Thapar University, Patiala, is an authentic record of my own work carried out under the guidance of Ms. Manbir Kaur, Associate Professor, EIED.

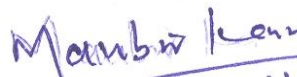
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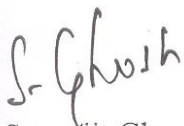
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ABSTRACT

Optimal daily operation of electric power generating plants is very essential to reduce input costs and possibly the prices of electricity in general. Load forecasting is extremely important for energy suppliers, financial institutions, and other participants in electric energy generation, transmission, distribution, and markets. An accurate and reliable electric load forecasting systems are absolutely required. Precise load forecasting helps the electric utility to make unit commitment decisions, reduce spinning reserve capacity and schedule device maintenance plan properly.

Since in power systems the next day's power generation must be scheduled every day, day-ahead short-term load forecasting (STLF) is a necessary daily task for power dispatch. Its accuracy affects the economic operation and reliability of the system greatly. Under prediction of STLF leads to insufficient reserve capacity preparation and, in turn, increases the operating cost by using expensive peaking units. On the other hand, over prediction of STLF leads to the unnecessarily large reserve capacity, which is also related to high operating cost.

This thesis presents a solution methodology using fuzzy logic approach and artificial neural network for short term load forecasting and is implemented on historical weather sensitive data i.e. temperature, humidity, wind speed and historical load data for forecasting the load. The proposed fuzzy logic approach is implemented on weather sensitive data and the accuracy of the result is compared using two different membership functions. Artificial neural network approach is implemented on the proposed non-fully connected neural network consists of five fully connected supporting networks representing weather variables, day type and load data as inputs. Jodhpur Vidyut Nigam hourly load data used for training and testing collected from State Load Dispatch and Communication Centre, Rajasthan Vidyut Parasaran Nigam. The results are obtained from two different approaches are compared and accuracy of neural network is reported as better.

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CHAPTER 1

INTRODUCTION

1.1 Overview

With the growth of power system networks and the increase in their complexity, many factors have become influential in electric power generation, demand or load management. Load forecasting is one of the critical factors for economic operation of power systems. Forecasting of future loads also plays a significant role in network planning, infrastructure development and so on. However, power system load forecasting is a two dimensional concept: consumer based forecasting and utility based forecasting and each forecast could be handled disjointedly. Consumer based forecasts are used to provide some guidelines to optimize network planning and investments, better manage risk and reduce operational costs. Undoubtedly, both utility companies and consumers are challenged to accurately predict their respective loads [1]. This challenge has been in existence for decades, thus a variety of load forecasting techniques ranging from classical to intelligent systems have been developed to date, and highlighted in a number of studies. The ultimate distinction of these methods can be drawn on the bases of forecast accuracy.

In the design stages, utilities need to plan ahead for anticipated future load growth under different possible scenarios. Their decisions and designs can affect the gain or loss of huge revenues for their companies/utilities as well as customer satisfaction and future economic growth in their area [2].

The decisions on sale-purchase, banking of power and generating electric power, load switching, and infrastructure development can be carried out with the help of load forecasting. In the market environment, precise forecasting is the basis of electrical energy trade and spot price establishment for the system to gain the minimum electricity purchasing cost [3].

Because of high complexity, the research work in the area of load forecasting is still a challenge to the electrical engineering scholars. Load forecasting with the historical data, especially in case of holidays, days with extreme weather has remained a difficulty up to now [4]. To improve the forecasting results, the new mathematical, data mining and artificial tools are implemented. The equivalent day load forecast flow diagram is shown in fig. 1.1.

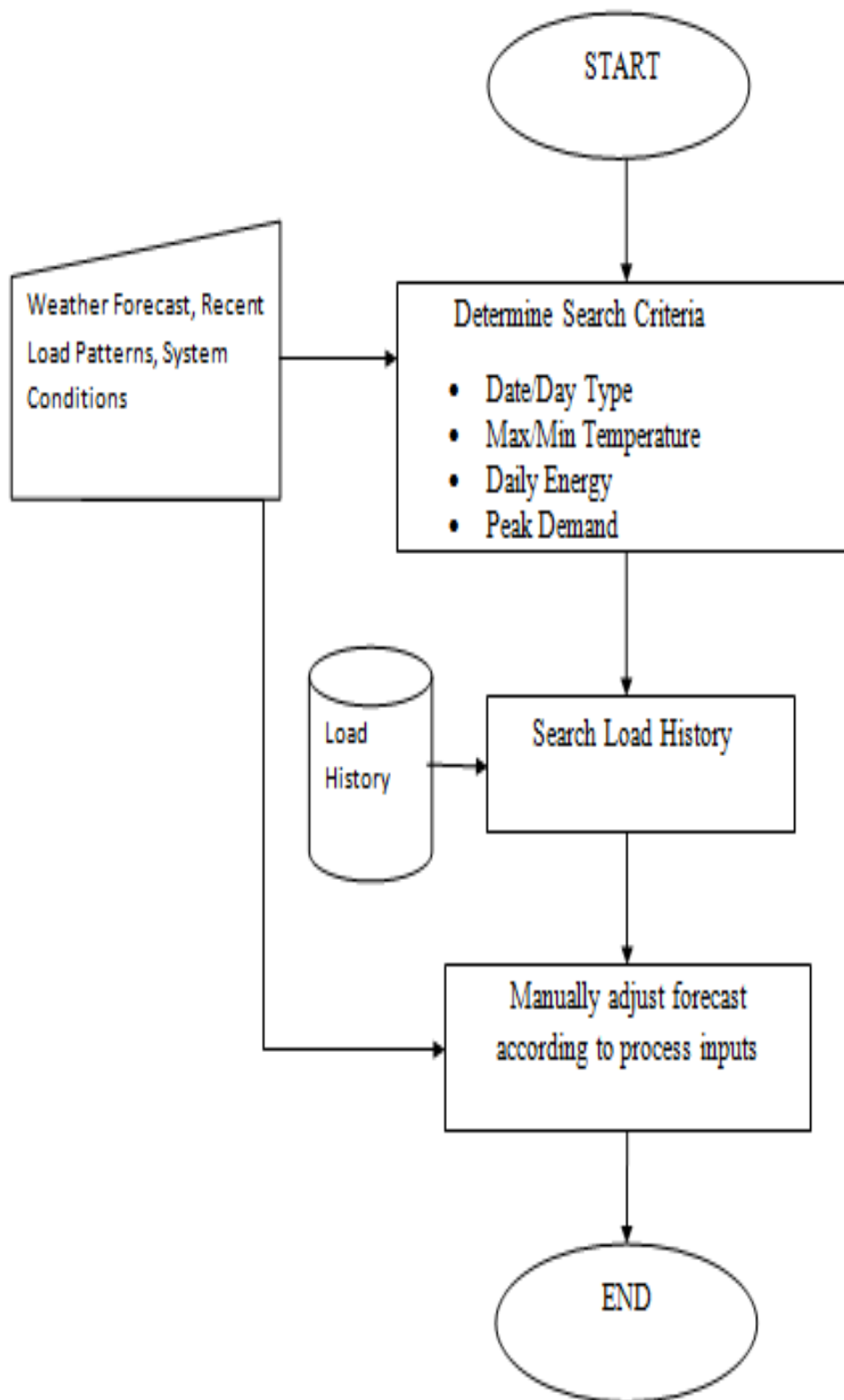


Fig 1.1 Equivalent day forecasting flowchart

1.2 Literature Review

In this section, the literature on electric load forecasting and number of techniques which have been developed for load forecasting methods is surveyed and briefly revived. This offers the background for the rest of the work.

Multiple Linear Regressions

Engle *et al.* [5] have presented several regression models. These models incorporate deterministic influences such as holidays, stochastic influences such as average loads, and exogenous influences such as weather. Moghram and Rahman *et al.* [6] have evaluated multiple regression models and compared it with other models for a 24-h load forecast. The model developed by Papalexopoulos and Hesterberg *et al.* [7] have produced an initial daily peak forecast and then uses this initial peak forecast to produce initial hourly forecasts.

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 first impetus of the approach is to accurately assemble a pattern matching available data, and then obtain the forecasted value with respect to time using the established model. Janacek *et al.*, [8] have proposed that most commonly used classical time series methods like ARMA (autoregressive moving average), ARIMA (autoregressive integrated moving average), ARMAX (autoregressive moving average with exogenous variables), and ARIMAX (autoregressive integrated moving average with exogenous variables).

Fan and McDonald [9] and Cho *et al.* [10] have described implementations of ARIMAX models for load forecasting. Yang *et al.* [11] have used an evolutionary programming (EP) approach to identify the ARMAX model parameters for one day to one week ahead hourly-load-demand-forecasting.

Expert System

An expert system is a computer program that has the ability to reason, explain, and have its knowledge base expanded as new information becomes available to it. Brown *et al.* [12] have used a knowledge based load-forecasting approach that combines existing system knowledge, load growth patterns, and horizon year data to develop multiple load growth scenarios. Rahman and Hazim *et al.* [13] have developed a site-independent technique for short-term load forecasting. Knowledge about the load and the factors affecting it are extracted and represented

in a parameterized rule base. This rule-based system has been complemented by a parameter database dependent on site. Ho *et al.* [14] have proposed a knowledge-based expert system for the short-term load forecasting of the Taiwan power system. Operators' knowledge and the hourly observation of system load over the past five years have been employed to establish eleven day types.

Similar Day Approach

The load of two days with similar impact factors such as meteorological conditions, week day type (workday or day off) is relatively close to each other too when doing short-term load forecasting. Similar day's method first selects similar historical days with similar characteristics, and then uses weighting and extrapolation to forecast the daily load. When normalizing the similarity, the similarity of each similar day has been given a processing of n^{th} power so as to increase the weight of the most similar days and less similar days, accordingly reducing the load forecast error is reported by Mu *et.al.* [15].

Fuzzy Logic

The term "fuzzy logic" has emerged in the development of the theory of fuzzy set which Dr. L.A. Zadeh has pioneered by the mid 1960's. 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. Hsu *et.al.* [16] have presented an expert system using fuzzy set theory for short term load forecasting. The expert system was used to do the updating function. Ranaweera *et. al.* [17] have developed the fuzzy rule base to produce 'fuzzy' forecasts and defuzzification has been performed to generate a point estimate for system load after converting historical load and weather data into 'fuzzy' information. Liu *et al.* [18] have observed that a fuzzy logic system has great capability in drawing similarities from huge data. Al-Anbuky *et al.* [19] have discussed the implementation of a fuzzy-logic approach to provide a structural framework for the representation, manipulation and utilization of data and information concerning the prediction of power commitments. Ismail *et.al.* [20] have used fuzzy logic approach with uncertainty data such as day types, temperature and different load pattern to forecast the daily load demand in a shorter period of time to half-hourly load demand. This has greatly benefited Tenaga Nasional Berhad (TNB) Malaysia in their management of the daily operation of electricity demand. The fuzzy logic approach proposed by Senjyu *et al.* [21] for next-day load forecasting has offered three advantages; namely, the ability to handle non-linear curves, to forecast irrespective of day type

and to provide accurate forecasts in hard-to-model situations. Mori *et al.* (1999) [22] have presented a fuzzy inference model for STLF in power systems. Their method uses the supervised learning to optimize the inference structure (i.e. number and location of fuzzy membership functions) to minimize forecast errors.

Neural Network

Artificial neural networks (ANN) based model learns to perform a desired task directly from examples using special training algorithms. Peng *et al.* [23] have proposed a neural network approach that includes a combination of linear and nonlinear terms to map past load and temperature inputs to the load forecast output. Neural networks are essentially non-linear circuits that have the demonstrated capability to do nonlinear curve fitting have been developed by Eugene *et al.* [24].

Atiya *et al.* [25] have described a river flow application that use neural network as a forecasting tool. It has used multi layer network which is trained using the back propagation algorithm. Bandyopadhyay *et al.* [26] have developed a multi-layer perceptron model with generalised data learning to predict the population of India. Learning is achieved by changing the interconnection between the processors that have been reported by Khotanzad *et al.* [27].

With the ability to approximate any continuous nonlinear function, the back propagation network has extraordinary mapping (forecasting) abilities. The back propagation network is a kind of multilayer feed forward network, and the transfer function within the network is usually a nonlinear function such as the sigmoid function. Neural Networks are widely used for load forecasting, fault diagnosis/fault location, economic load dispatch and security assessment etc. in the field of power systems have proposed by Song *et al.* [28]. A recurrent high order neural network (RHONN) have been proposed by Lu *et al.* [29]. Due to its dynamic nature, the RHONN forecasting model is able to adapt quickly to changing conditions such as important load variations or changes of the daily load pattern.

Papalexopoulos *et al.* [30] have proposed a multi-layered feed-forward ANN for short-term system load forecast with the aim to compare the forecasting accuracy of a time-series approach. In the load forecasting, accuracy mainly depends on the training and selected time period of the forecast. The feed forward neural network produced good results to forecast the load has been reported by Sharif *et al.* [31].

Adepoju *et al.* [32] have used a supervised neural network –based model to forecast the load in the Nigerian power system. The study however did not consider the influences due to weather conditions, thus the accuracy could be improved. After experimenting a variety of hidden layer neurons from 5–11, the 11 neurons were finally utilized because it offered a better model characteristic.

Satish *et al.* [33] have discussed the effect of the temperature on the load trend using an integrated ANN-based method. The study concluded that the integrated model resulted in less error of prediction. Among other weather variables, only the temperature was incorporated in the model, thus a consideration of other factors would greatly improve the result.

Rashid *et al.* [34] have presented a feed forward and feedback multi-context artificial neural network as a practical approach for load forecasting. They have proposed the use of the rate values rather than the absolute to produce better accuracy.

Al-Saba *et al.* [35] have illustrated the application of the ANN to long-term load forecasting. The model forecasted the annual peak demand of a Middle Eastern utility and repeated the process using a time-series approach. The study established that the ANN-based model produces better forecast rather classical methods (ARMA etc).

Kandil *et al.*, [36] have explored the multilayered feed-forward ANN capability to predict the load without necessary using the historical load trend, but only temperature instead. The study has reported that using estimated load values may lead to a great degree of inaccuracy in the forecast, thus only the temperature was used as an input.

Lauret *et al.* [37] have used a model called Bayesian neural network as an attempt to design an optimal network for short-term load forecasting. The Bayesian model is a new proposed methodology but also requires derivation of better noise models and uncertainties consideration. The ANN is suitable to interpolate among the load and temperature pattern data of training sets to provide the future load pattern. In order to forecast the future load from the trained ANN, we need to use the recent load and temperature data in addition to the predicted future temperature. Compared to the other regression methods, the ANN allows more flexible relationships between temperature and load pattern. The neural network typically shows higher error in the days when people have specific start-up activities such as Monday or variant activities such as during the holiday seasons. Use of additional weather variables such as cloud coverage and wind speed should yield even better results proposed by Park *et al.* [38].

Madal *et al.* [39] presented a comparison of a classical load forecasting technique with an ANN based model using actual load data. The models were used to forecast the load one-to-six hours ahead and mean absolute percentage error (MAPE) calculations have showed that the ANN-based model provided reliable forecasts. Again, the optimal network structure for better forecast was never achieved.

In addition to the three layer network and typical sigmoid function, a linear transfer function from the input layer directly to the output layer was proposed in Dillon *et al.* [40] to account for linear components of the load. Because fully connected BP networks need more training time, a non-fully connected BP model has been proposed in Djukanvic *et al.* [41], Lee *et al.* [42].

The reported results by Chen *et al.* [43] have shown that although a fully connected ANN is able to capture the load characteristics, a non-fully connected ANN is more adaptive to respond to temperature changes.

1.3 Objectives of the Thesis Work

The main objective of the work is to develop a solution methodology to forecast hourly and peak load, by incorporating weather conditions i.e. temperature, humidity, wind speed and day type information. An attempt is made to implement the above forecast using fuzzy logic approach and artificial neural network. The work presented here is divided into three steps:

1. Collection of data
2. Development of fuzzy logic model for short term hourly load forecasting using triangular and trapezoidal membership functions for weather dependent load data.
3. Development of non-fully connected feed-forward artificial neural network model for short term load forecasting for hourly load forecasting and peak load forecasting

1.4 Organization of the Thesis

The thesis is organized into six chapters. The contents of these chapters are summarized as:-

Chapter 1 includes the overview of the problem, brief summary of literature review and objectives of the work.

Chapter 2 introduces the short-term load forecasting problem and includes the forecasting methods.

Chapter 3 covers the theoretical concepts of fuzzy logic and artificial neural network techniques.

Chapter 4 summarizes the proposed methodology for short term load forecasting by training fuzzy logic and artificial neural network models. The proposed methodology is also detailed.

In Chapter 5, the effectiveness of the methodology is discussed through hourly and peak load forecasting.

In Chapter 6, the summary of conclusions and the scope of future work are detailed.

CHAPTER 2

SHORT TERM LOAD FORECASTING

2.1 Overview

Electrical load forecasting is an essential tool used to ensure that energy supplied by utilities meet the load plus the energy lost in the system. It is a central and integral process in the planning and operation of electric utilities. Load forecasting helps an electric utility to make important decisions on purchasing and generating electric power [44]. Load forecasting is extremely important for energy suppliers, independent system operator, financial institutions, and other participants in electric energy generation, transmission, distribution, and markets. It is used to control operation and decisions such as dispatch, unit commitment, and fuel allocation and off line network analysis. Timely implementations of load forecasting decisions lead to the improvement of network reliability and to the reduced occurrences of equipment failures and blackouts. With supply and demand fluctuating and the changes of weather conditions and energy prices increasing by a factor of ten or more during peak situations, load forecasting is vitally important for utilities. Load forecasting is also important for contract evaluations and evaluations of various sophisticated financial products on energy pricing offered by the market. In the deregulated economy, decisions on capital expenditures are also more important than in a non-deregulated economy when rate increases could be justified by capital expenditure projects [45].

2.2 Classification of Load Forecasting

Accurate prediction of both the magnitude and geographical location of electrical load over the different period of planning horizon is involved in the load forecasting [46]. The prediction may be just for a fraction of an hour ahead for operation purposes, or as much as 20 years into the future for planning purposes. Therefore, the forecast for different time horizon are important for different operations within a utility company as summarized in table 2.1. The natures of these forecasts are different as well. For example, for a particular region, 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 forecast are not

available. For the next year peak forecast, it is possible to provide the probability distribution of the load based on historical weather observations.

TABLE 2.1: Load Forecasts Classification

Sr. No.	Nature of forecast	Lead time	Application
1.	Very short term	A few seconds to few minutes	Generation, distribution schedules, contingency analysis for system security
2.	Short term	Half an hour to a few hours	Allocation of spinning reserve, operational planning and unit commitment, maintenance scheduling
3.	Mid term	A few days to a few weeks	Planning for seasonal peak-summer, Winter
4.	Long term	A few months to a few years	Planning generation growth

2.3 Factors Affecting Accurate Load Forecast

The accuracy of load forecast has a significant effect on load forecast on power system operation, as economy of operation and control of power system may be quite sensitive to forecasting errors as reported in literature [24], [47-48]. The four important factors affecting load forecast are :

(i) Weather Influence: Electrical load has an obvious correlation to weather. Much effort has been spent to find a viable relationship between the weather and the load so that an accurate load model could be developed. The change of the weather causes the change of consumers comfort feeling and in turn the usage of some appliances such as space heater, water heater and air conditioner. Weather-sensitive load also includes appliance of agricultural irrigation due to the need of the cultivated plants. In the areas where summer and winter have great meteorological difference, the load patterns differ greatly.

The most important weather variables in load changes are –

- I. Dry and wet bulb temperature
- II. Dew point
- III. Humidity
- IV. Wind speed / Wind direction
- V. Sunshine

Forecasted weather parameters [49] are the most important factors in short term load forecasts with its consideration as mentioned in table 2.2. Temperature and humidity are the most

commonly considered for load forecasting. People feel hotter in the environment of 35 and 70% relative humidity than in the environment of 37% and 50% relative humidity. Among the weather variables listed above, two composite weather variable functions, the THI (temperature-humidity index) and WCI (wind chill index), are broadly used by utility companies. THI is a measure of summer heat discomfort and similarly WCI is cold stress in winter.

TABLE 2.2: Components of Weather of Load Forecasting Analysis

Component	Metric	Impact on Load
Temperature	°C or °F	Load is higher whenever temperature rise or fall from a base level.
Humidity	Per cent saturation	Temperature-dependent demand variation are more extreme if humidity is higher – moisture the heat retention capability of air
Illumination	Insolation in Sols Or gross energy in kW-m ²	Load is generally greater when insolation high (sunlight $\Rightarrow$ heat $\Rightarrow$ air conditioning demand).
Wind Speed	Km/h or m/s	Variability in load in system without wind. It is site dependent.

(ii) Time factors: In forecasting model, the time factors include the time of the year, the day of the week, and the hour of the day. There are important differences in load between weekdays and weekends. The load on different weekdays also can behave differently. For example, Mondays and Fridays being adjacent to weekends, may have structurally different loads than Tuesday through Thursday. This is particularly true during the summer time. Holidays are more difficult to forecast than non- holidays because of their relative infrequent occurrence. The load variation with time reflects the arrangement of people’s daily life: working time, leisure time and sleeping time. There are some rules of load variation with time. The weekend or holiday load curve is lower than the weekday curve, due to the decrease of working load. Shifts to and from daylight savings time 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 result.

(iii) Economy: Electricity is a kind of commodity. The economic situation also influences the utilization of this commodity. Economic factors, such as the degree of industrialization, price of electricity and load management policy have significant impacts on the system load

growth/decline trend. With the development of modern electricity markets, the relationship between electricity price and load profile is even stronger. Although time-of use pricing and demand-side management had arrived before deregulation, the volatility of spot markets and incentives for consumers to adjust loads are potentially of a much greater magnitude. At low prices, elasticity is still negligible, but at times of extreme conditions, price-induced rationing is a much more likely scenario in a deregulated market compared to that under central planning.

(iv) Customer class: Most electric utilities serve customers of different types such as residential, commercial, and industrial. The electric usage pattern is different for customers that belong to different classes but is somewhat alike for customers within each class [50]. Therefore, most utilities distinguish load behavior on a class-by-class basis. The fig 2.1 depicts the load behavior in the various classes by showing the amount of peak load per customer, and the total energy.

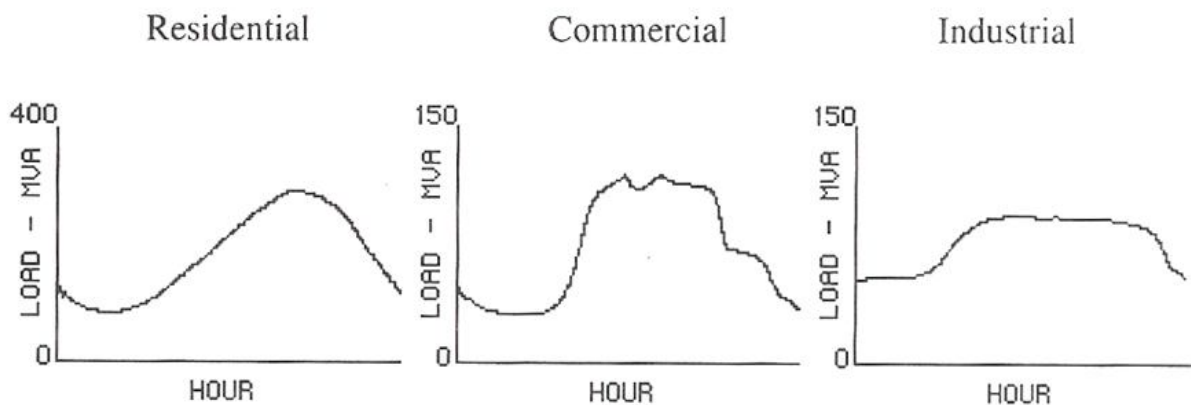


Fig. 2.1 Load Curves

2.4 Short Term Load Forecast

The term “short” to imply prediction times of the order of minutes or hours. The time boundaries are from the next hour, or possibly half-hour, up to 168 hours. The basic quantity of interest in short term load forecasting is, typically, the hourly integrated total system load. In addition to the prediction of the hourly values of the system load, the short term load forecasting (STLF) is also concerned with the forecasting of

- the daily peak system load
- the values of system load at certain times of the day
- the hourly or half-hourly values of system energy
- the daily and weekly system energy

2.5 Application of Short Term Load Forecast

STLF plays a key role in the formulation of economic, reliable, and secure operating strategies for the power system [51]. The principal objective of the STLF function is to provide the load predictions for

- the basic generation scheduling functions
- assessing the security of the power system at any time
- timely dispatcher information

The primary application of the STLF function is to drive the scheduling functions that determine the most economic commitment of generation sources consistent with reliability requirements, operational constraints and policies, and physical, environmental, and equipment limitations as represented in block diagram of fig. 2.2. For purely hydro systems, the load forecasts are required for the hydro scheduling function to determine the optimal releases from the reservoirs and generation levels in the power houses. For purely thermal systems, the load forecasts are needed by the unit commitment function to determine the minimal cost hourly strategies for the start-up and shutdown of units to supply the forecast load. For mixed hydro and thermal systems, the load forecasts are required by the hydro-thermal coordination function to schedule the hourly operation of the various resources so as to minimize production costs. The hydro schedule unit commitment/ hydro-thermal coordination function requires system load forecasts for the next day or the next week to determine the least cost operating plans subject to the various constraints imposed on system operation.

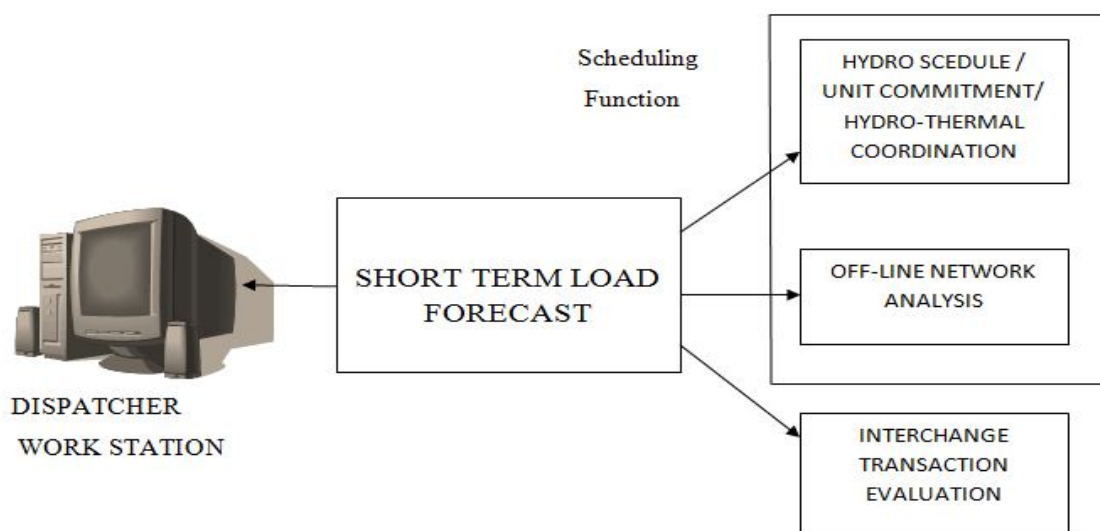


Fig 2.2 Major applications of Short term load forecasting

A second application of STLF is for predictive assessment of the power system security. The system load forecast is an essential data requirement of the off-line network analysis function for the detection of future conditions under which the power system may be vulnerable. This information permits the dispatchers to prepare the necessary corrective actions (e.g. bringing peaking units on line, load shedding, power purchases, switching operations) to operate the power systems securely.

The third application of STLF is to provide system dispatchers with timely information, i.e. the most recent load forecast, with the latest weather prediction and random behavior taken into account. The dispatchers need this information to operate the system economically and reliably.

2.6 Accuracy of Short Term Load Forecast

The evaluation of the accuracy of a model requires that the forecast error, i.e., the difference between the forecast value of the load and the "measured" (actual) value of the load, be determined at each time point of the forecasting period. It is common to measure the model accuracy statistically in terms of the standard deviation of the forecast error. Other accuracy measures, such as the maximum error or a weighted squares criterion with the heaviest weights for the peak hours and declining weights for off-peak hours, are possible but not in wide use. In practice, it is difficult to find STLF systems that have a root-mean square forecast errors of less than 2 to 3 percent of the peak load for a 24-h prediction. This may constitute a statistical limit to the goodness of fit of a model and represents by and large, the inherent noise component of the load. However, the actual 24-h prediction error will depend strongly on the type of load, that is its mix of residential, industrial, and commercial components, its geographical location and distribution, as well as the season of the year. The load dispatcher at main dispatch center must anticipate the load pattern well in advance so as to have sufficient generation to meet the load requirements. Overestimation may cause the startup of too many generating units and lead to an unnecessary increase in the reserve and the operating costs. Underestimation of the load forecast results in failure to provide the required spinning and standby reserve and stability to the system, which may lead into collapse of the power system network. Load forecast errors can yield suboptimal unit commitment decisions. With the recent trend of deregulation of electricity industry, STLF has gained more importance and greater. In the real-time dispatch operation, forecasting error causes more electricity purchasing cost or

breaking-contract penalty cost to keep the electricity supply and consumption balance. Hence accurate forecasting of the load is an essential element in power system. Both positive and negative forecasting errors resulted in increased operating costs. A 1% reduction in the average forecast error can save hundreds of thousands or even millions of rupees. As, the electric load is sensitive to several weather factors like temperature, humidity, and chill factor etc. Hence, the main difficulty in modeling load forecasting is to come up with a model that comprises only dominant factors and minimize the forecasting error [24].

2.7 Short Term Load Forecasting Techniques

A large variety of statistical and artificial intelligence techniques have been developed for short-term load forecasting, which include the methods employing similar day approach, regression models, time series, neural networks, expert systems and fuzzy logic approaches.

2.7.1 Multiple Linear Regressions

Regression is the one of most widely used statistical techniques. Consumer habits and weather behavior regression models derive linear models for the system load. The main principle behind regression is to use the common relationships between everything included in the model in order to predict the relative change in one item or variable according to changes in another item or variable. This approach is applied to short-term weather forecasting using weather data, such as temperature, humidity; day type and customer class to establish multiple variable values for the linear regression models between itself and the load. In the multiple linear regression (MLR) method, the load is found in terms of explanatory variables such as weather and non-weather variables which influence the electrical load. The load model using this method is expressed in the form as

$$y(t) = a_0 + a_1x_1(t) + \dots + a_nx_n(t) + a(t)$$

where,

$y(t)$ = electrical load.

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

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

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

The explanatory variables of this model are identified on the basis of correlation analysis on each of these (independent) variables with the load (dependent) variable. Experience about the load to be modeled helps an initial identification of the suspected influential variables. The estimation

of the regression coefficients is usually found using the least square estimation technique. In the least squares estimation technique, the model is fit such that the sum-of-squares of differences of observed and predicted values is minimized. The multi linear regression models for short term load forecasting are relatively easy to develop and update regularly. The drawback of this model is its dependency on the accuracy of previously recorded load and it is very sensitive to the fluctuation of temperature. It needs a very accurate temperature forecast, as a small change of temperature will cause a significant change in load prediction. The load characteristic is not only affected by the temperature, but also affected by the other weather factors such as humidity, cloud cover and brightness of the day [6], [7], [24].

2.7.2 Time Series

This method is defined to be an ordered set of data values of a certain variable. These models are essentially econometric models, where the only explanatory variables used are lagged values of the variable to be explained and predicted. The intuition underlying time-series processes is that the future behavior of variables is related to its past values, both actual and predicted, with some built-in adjustment to take care of how past realization deviated from the one expected. Thus, the essential prerequisite for a time-series forecasting technique is data for the last 20 to 30 time periods [54]. The approach is to accurately assemble a pattern matching available data, and then obtain the forecasted value with respect to time using the established model. The model characteristics can be formulated as:

$$\hat{L}(t) = L_n(t) + S(t) + R(t) \quad t = \dots -1, 0, 1, 2, \dots$$

where,

$L_n(t)$ = the standard load value

$S(t)$ = the seasonal term

$R(t)$ = the irregular or random component.

The advantage of time-series models is their structural simplicity. They do not require collection of data on multiple variables. Observations on the variable under study are completely sufficient. A disadvantage of these models however, is that they do not describe a cause and effect relationship. Thus a time series does not provide insights into why changes occurred in the variable. Often in the analysis of time series data, there are technical problems wherein more than one of the variables is highly correlated with another (multi-co linearity) or with its own

past values (auto-correlation). Time series may be made more accurate, but this requires large amounts of historical good quality data [52].

2.7.3 Similar Day Approach

This approach is based on searching historical data for days within one, two or three years with similar characteristics to the forecast day as shown in fig, 2.3. Similar characteristics include weather, day of the week and the date. The load of a similar day is considered as a forecast. The similar-day method may be also used for modeling the special event (e.g. holiday) component; then the search is conducted on historical data within one, two or three years. The load of a similar day is considered as a forecast and then uses weighting and extrapolation to forecast the daily load [53].

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. The disadvantage of similar day method is it uses only a similar day with minimal values of difference evaluation function for load forecasting [15].

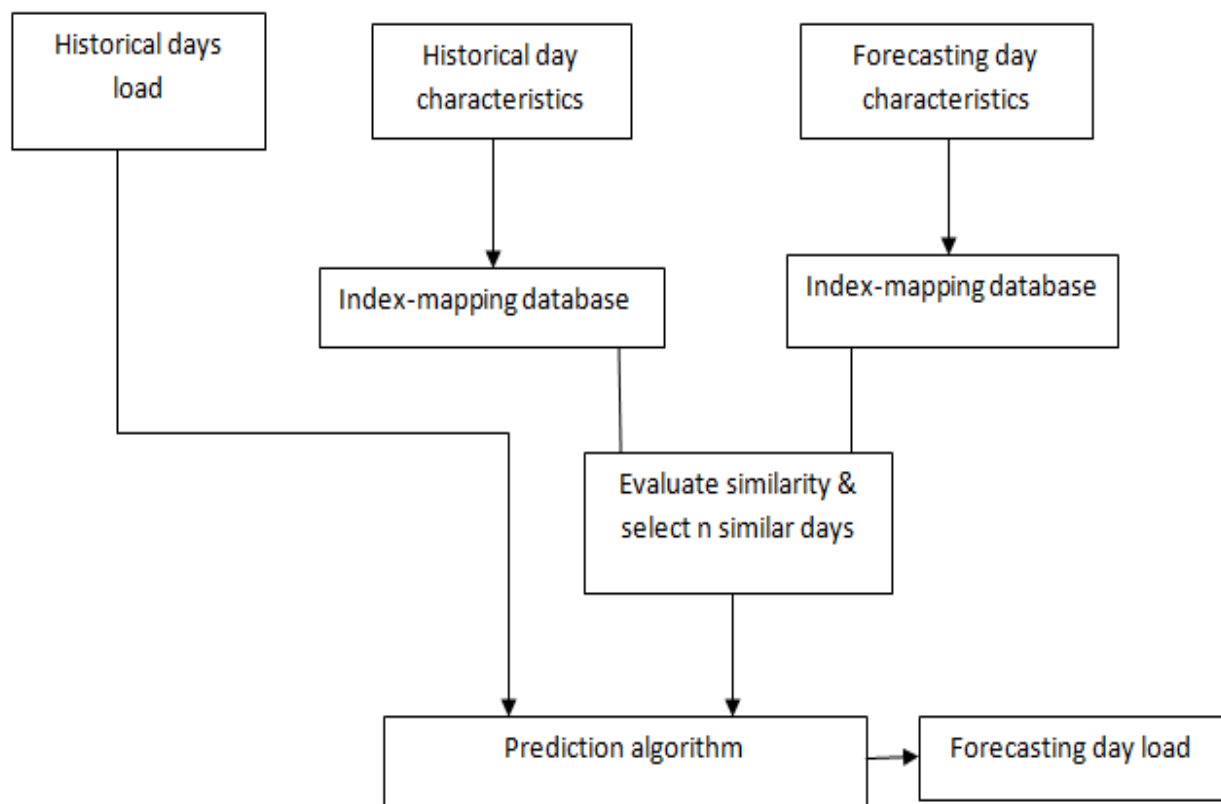


Fig 2.3 Flow Chart for Similar Day Approach

2.7.4 Expert Systems

Expert systems are new techniques that have emerged as a result of advances in the field of artificial intelligence. Expert systems, incorporates rules and procedures used by human experts in the field of interest into software that is then able to automatically make forecasts without human assistance. Expert systems work best when a human expert is available to work with software developers for a considerable amount of time in imparting the expert's knowledge to the expert system software. Knowledge about the load and the factors affecting it are extracted and represented in a parameterized rule base. The rule-base consisted of all rules taking the IF-THEN form and mathematical expressions. This rule-base is used daily to generate the forecasts. Some of the rules do not change over time, some change very slowly while others change continuously and hence are to be updated from time to time. The load model, the rules, and the parameters can be designed using no specific knowledge about any particular site. The results can be improved if operators at a particular site are consulted. It examines whether the analogical thinking that goes into the intuitive forecasting of the electric utility load can be reduced to formal steps of logic and be programmed. This method is promising, however, it is important to note that the expert opinion may not always be consistent, and the reliability of such opinion may be in question [54].

2.7.5 Fuzzy logic

Fuzzy system is another approach area which is receiving increased attention lately. In using our everyday natural language to import knowledge and information, there is a great deal of impression and vagueness. Fuzzy logic is a fascinating area of research because it does a good job of trading off between significance and precision. Fuzzy logic is a generalization of the usual Boolean logic used for digital circuit design. An input under Boolean logic takes on a truth value of "0" or "1". Under fuzzy logic an input has associated with it a certain qualitative ranges. For instance a transformer load may be "low", "medium" and "high". Fuzzy logic allows one to (logically) deduce outputs from fuzzy inputs. In this sense fuzzy logic is one of a number of techniques for mapping inputs to outputs (i.e. curve fitting). Of course in many situations an exact output (e.g. the precise 12PM load) is needed. After the logical processing of fuzzy inputs, a "defuzzification" process can be used to produce such precise outputs as shown in fig. 2.4. Fuzzy systems have been successfully applied in process control, system identification and

pattern recognition. In power system fuzzy systems have been applied in many diverse areas among which transient stability evaluation, optimal power flow and dynamic dispatch [55].

Some advantages of fuzzy set theory over conventional methods are as follows:

- i. It is based on ordinary language and is conceptually easy to understand.
- ii. The absence of a need for a mathematical model mapping inputs to outputs and the absence of a need for precise (or even noise free) inputs.
- iii. With such generic conditioning rules, properly designed fuzzy logic systems can be very robust when used for forecasting.
- iv. It resolves conflicting objectives by designing weights appropriate to the selected objectives.

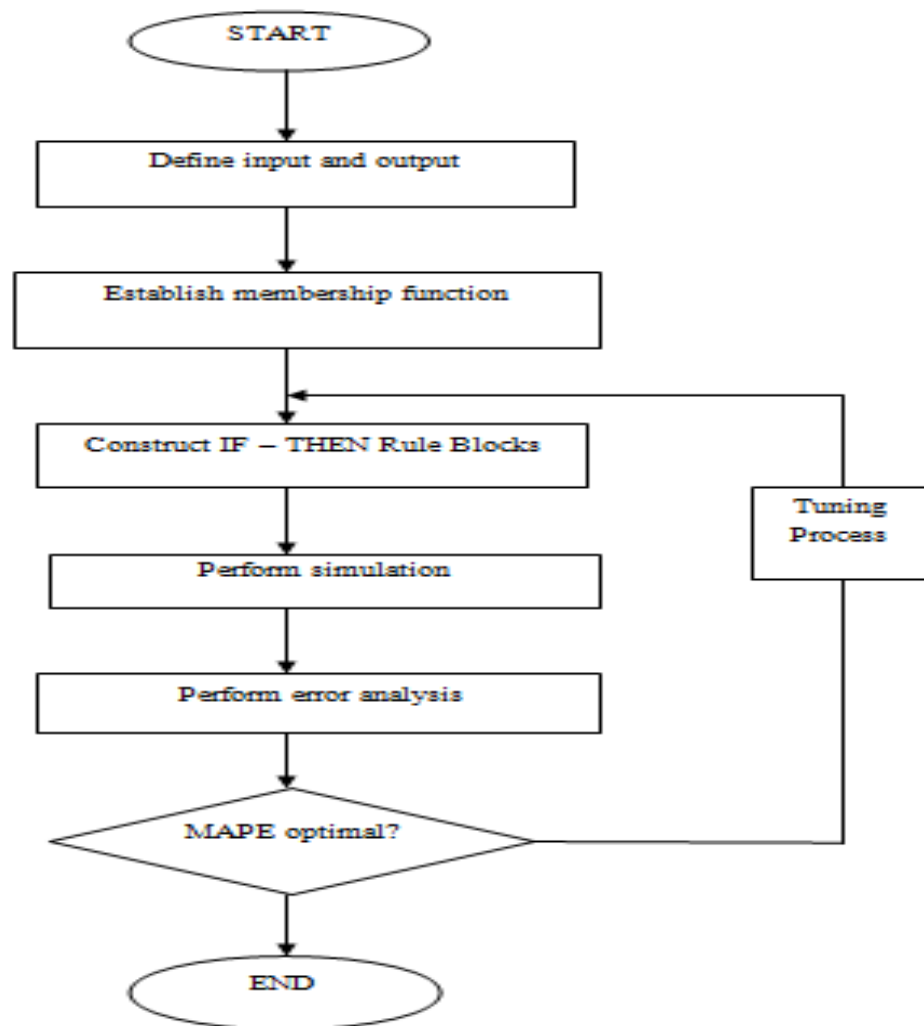


Fig 2.4 Process Flowchart of Modeling using fuzzy logic

- v. It is tolerant of imprecise data and provides capability for handling ambiguity expressed in diagnostic processes, which involves systems and causes
- vi. It develops process control as a fuzzy relation between information about the conditions of the process to be controlled.

However, the fuzzy modeling has a drawback that fuzzy rules and the fuzzy membership function are determined by experienced knowledge or trial and error. Not only is this design method time consuming since it uses trial and error to find good fuzzy rule and membership function, it is also not guaranteed to find optimal or near optimal fuzzy rules and membership function [17].

2.7.6 Artificial Neural Network

Artificial neural networks (ANN) have very wide applications because of their ability to learn. Neural networks offer the potential to overcome the reliance on a functional form of a forecasting model. The use of artificial neural networks has been a widely studied electric load forecasting technique since 1990. Neural networks are essentially non-linear circuits as its output is some linear or nonlinear mathematical function of its inputs. The inputs may be the outputs of other network elements as well as actual network inputs. In practice network elements are arranged in a relatively small number of connected layers of elements between network inputs and outputs. Feedback paths are sometimes used [56]. Fig 2.4 and 2.5 shows the importance of ANN method in power system and in types of load forecasting respectively.

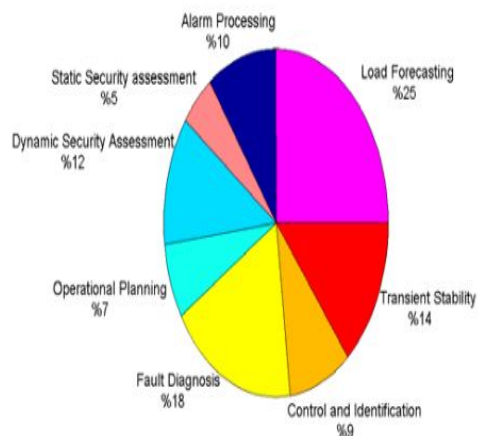


Fig.2.5 ANN application in power system

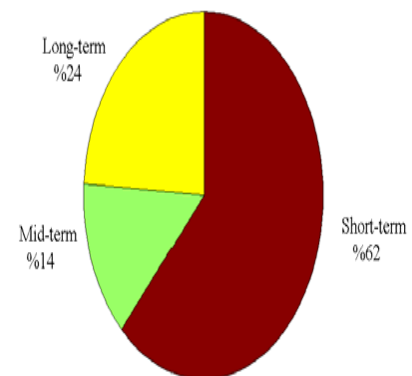


Fig 2.6 Types of load forecasting that done with ANN

In applying a neural network to electric load forecasting, one must select the architecture (e.g. feed forward or feedback), the number and connectivity of layers and elements, use of bi-directional or unidirectional links and the format (e.g. binary or continuous). The most popular

ANN architecture for electric load forecasting is multilayer employing Back Propagation (BP) algorithm. Back propagation use continuously valued functions and supervised learning. That is, under supervised learning, the actual numerical weights assigned to element inputs are determined by matching historical data (such as time and weather) to desired outputs (such as historical electric loads) in a preoperational “training session”. Artificial neural networks with unsupervised learning do not require pre-operational training [57]. The main advantage of ANN is their ability to extract the relationship among input variables and output by *learning* from the available input-output readings. A feed forward network is used for prediction of total, peak and hourly loads.

Merits of ANN

1. They are extremely powerful computational devices.
2. Massive parallelism makes them very efficient.
3. They can learn and generalize from training data – so there is no need for enormous feats of programming.
4. They are particularly fault tolerant – this is equivalent to the “graceful degradation” found in biological systems
5. They are very noise tolerant – so they can cope with situations where normal symbolic systems would have difficulty.
6. In principle, they can do anything a symbolic/logic system can do, and more

Although the BP model has been successfully applied to many fields and has solved a number of practical problems, its poor convergence features and its painful speed of convergence have been the bottleneck in using the BP model more effectively. However, the conventional artificial neural network models sometimes suffer from the local minima optimization problem. In addition to obstacles related to the mathematics of network specification and estimation, neural networks are not easily up-datable to changing conditions, e.g. a sudden change in weather or a special event on the forecasted day. The structure of a neural network is fixed for a learning process. However, a fixed structure may not provide the best performance within a given training period. If the neural network structure is too complicated, the training period will have to be long, and consequently the implementation costs will be high [58]. Fig 2.7 shows the process flowchart of modeling using ANN.

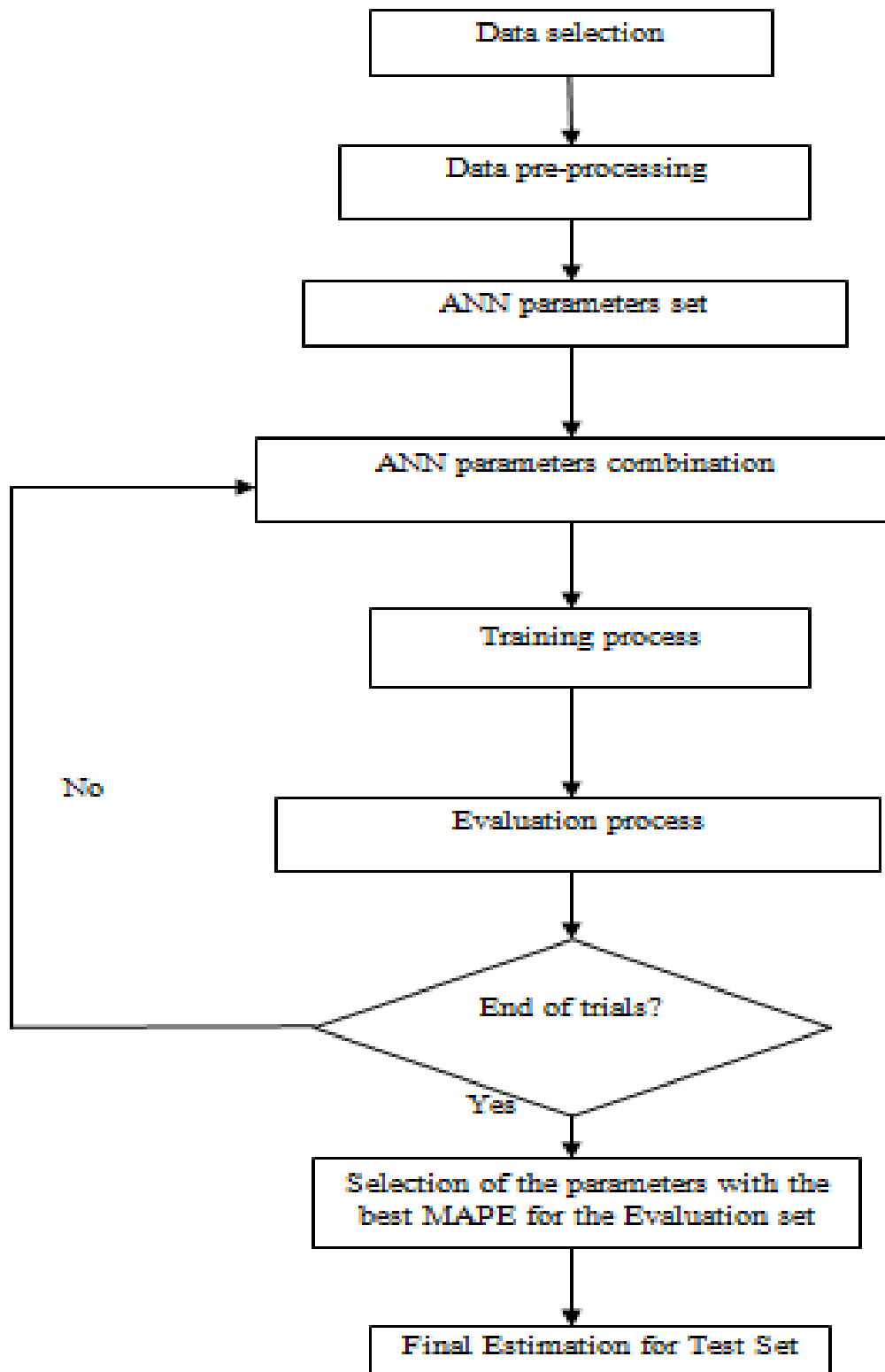


Fig 2.7 Process Flowchart of Modeling using ANN

CHAPTER 3

SHORT TERM LOAD FORECASTING USING FUZZY LOGIC

3.1 Fuzzy Logic

This section presents general information about the theory of fuzzy logic. Definition of a fuzzy set and linguistic variable conception are presented. The meaning of a fuzzy rule is explained and some rule examples are given. Fuzzy reasoning mechanism and fuzzy inference systems are also presented [59].

3.1.1 Fuzzy Sets

A fuzzy set, as the name implies, is a set without a crisp boundary. That is, the transition from “belong to a set” to “not belong to a set” is gradual, and this smooth transition is characterized by membership functions that give fuzzy sets flexibility in modeling commonly used linguistic expressions, such as “water is hot” or “the temperature is high”. A fuzzy set expresses the degree to which an element belongs to a set. Hence the characteristic function of a fuzzy set is allowed to have values between 0 and 1, which denotes the degree of membership of an element in a given set.

If X is a collection of objects denoted generally by x , then a fuzzy set A in X is defined as a set of ordered pairs:

$$A = \{(x, \mu_A(x)) \mid x \in X\} \quad \dots (3.1)$$

Where $\mu_A(x)$ is called the membership function (MF) for the fuzzy set A . The MF maps each element of X to a membership grade between 0 and 1.

The several classes of parameterized functions to define MFs with single input are triangular, trapezoidal, gaussian etc. are shown in fig 3.1 and among them most commonly used MFs is triangular.

Triangular MFs formula:

$$\text{triangle}(x, a, b, c) = \begin{cases} 0 & \text{for } x \leq a \\ (x-a)/(b-a) & \text{for } a \leq x \leq b \\ (c-x)/(c-b) & \text{for } b \leq x \leq c \\ 0 & \text{for } c \leq x \end{cases} \quad \dots(3.2)$$

Trapezoidal MFs formula:

$$\text{trapezoid}(x, a, b, c, d) = \begin{cases} 0 & \text{for } x \leq a \\ (x-a)/(b-a) & \text{for } a \leq x \leq b \\ 1 & \text{for } b \leq x \leq c \\ (d-x)/(d-c) & \text{for } c \leq x \leq d \\ 0 & \text{for } d \leq x \end{cases} \dots (3.3)$$

Gaussian MFs formula:

$$\text{gaussian}(x; c, \sigma) = e^{\frac{-(x-c)^2}{2\sigma^2}} \dots (3.4)$$

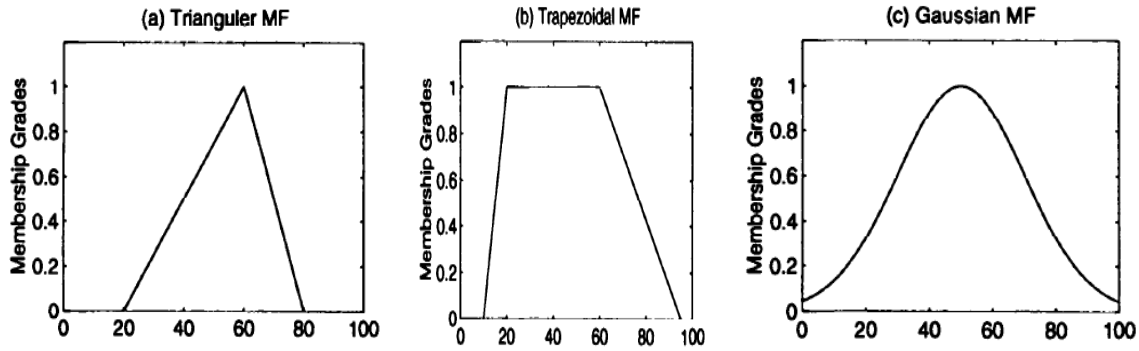


Fig 3.1 Different Shapes of Commonly Used Membership Functions

3.1.2 Linguistic Variables

The concept of linguistic variables was introduced by Zadeh (1973) to provide a basis for approximate reasoning. A linguistic variable was defined as a variable whose values are words or sentences. For instance, Age can be linguistic variable if its values are linguistic rather than numerical, i.e., young, middle aged, old that are characterized by MFs $\mu_{\text{young}}(x)$, $\mu_{\text{middleaged}}(x)$, and $\mu_{\text{old}}(x)$ respectively. Typical membership functions for the linguistic variables are shown in fig 3.2.

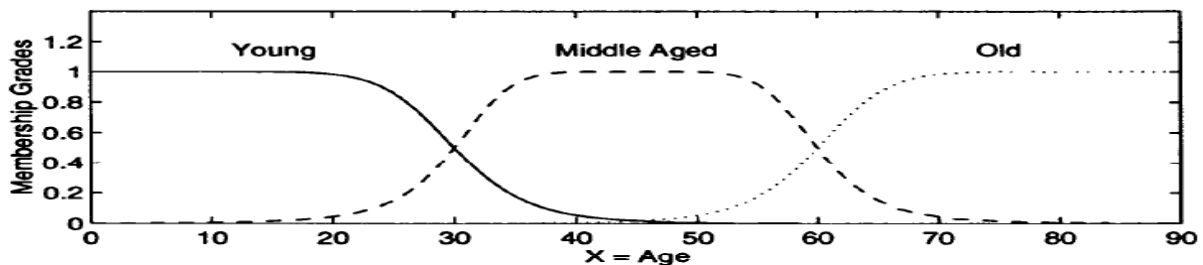


Fig 3.2 Membership functions of the term set Age

3.1.3 Fuzzy IF THEN Rules

A fuzzy if-then rule (fuzzy rule, fuzzy implication, or fuzzy conditional statement) is expressed as follow: **IF** x is A **THEN** y is B

where A and B linguistic values defined by fuzzy sets. “ x is A ” is called “antecedent” or “premise”, while “ y is B ” is called the “consequence” or “conclusion.

Some of the if-then rule examples can be given below:

- If a tomato is red, then it is ripe.
- If the road is slippery, then the driving is dangerous.

3.1.4 Fuzzy inference Systems (FIS)

The fuzzy inference system is a popular computing framework based on the concept of fuzzy set theory, fuzzy if-then rules, and fuzzy reasoning. The basic structure of a FIS shown in fig 3.3 consists of three conceptual components: a rule base, which contains a selection of fuzzy rules; a database which defines the MFs used in the fuzzy rules; and a reasoning mechanism, which performs the inference procedure upon the rules and given facts to derive a reasonable output or conclusion. Basic FIS can take either fuzzy inputs or crisp inputs, but the outputs it produces are almost always fuzzy sets. The method to extract a crisp value that best represents fuzzy sets is the defuzzification.

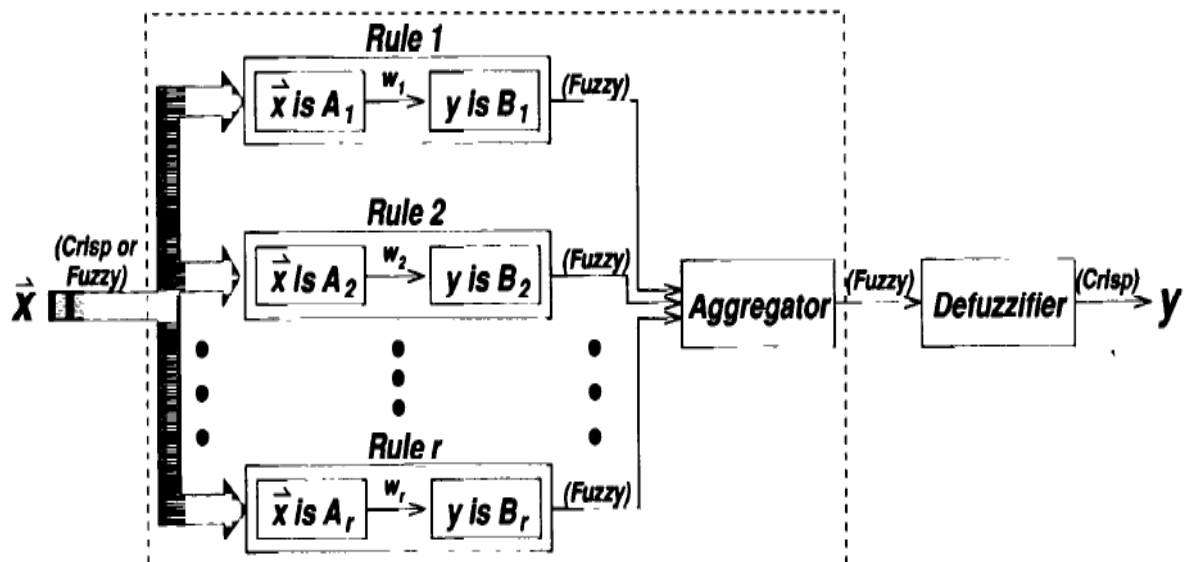


Fig 3.3 Fuzzy Inference System

Mamdani and Takagi-Sugeno fuzzy systems are the examples of fuzzy inference systems. Mamdani fuzzy inference system was first used to control a steam engine and boiler combination by a set of linguistic rules obtained from human operators. Fig 3.4 illustrates how a two rule Mamdani fuzzy inference system derives the overall output z when subjected to two numeric inputs x and y . Takagi-Sugeno fuzzy inference system was first introduced by Takagi and Sugeno. The difference of Takagi- Sugeno model is that each rule has a crisp output, and the overall output is determined as weighted average of single rules output [59]. This type of fuzzy inference system is shown in Fig 3.5.

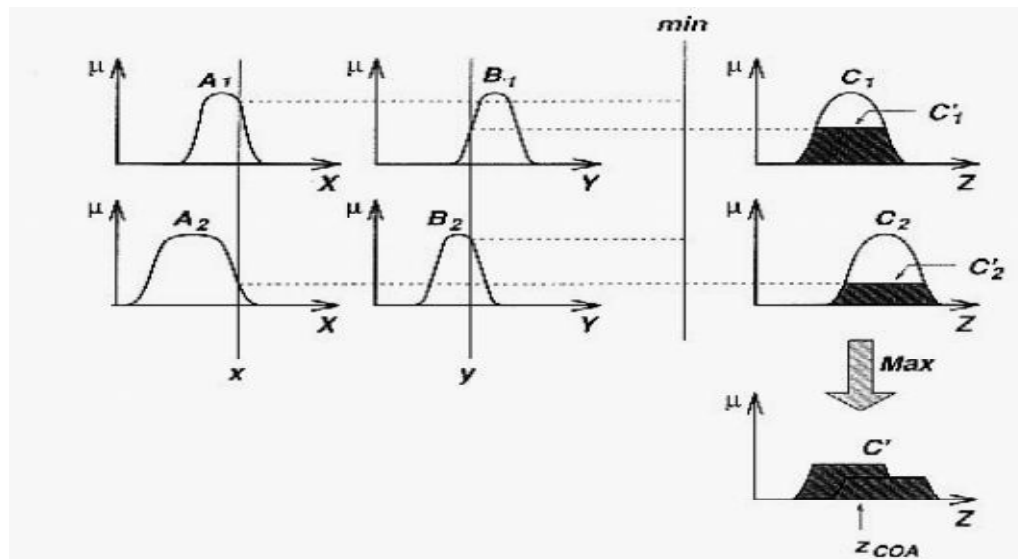


Fig 3.4 Mamdani Fuzzy Inference System

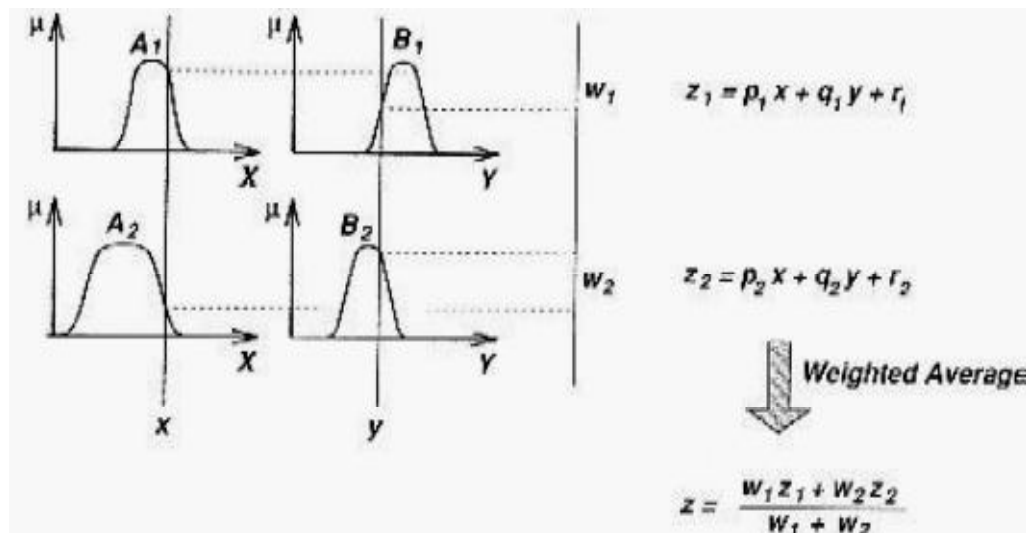


Fig 3.5 Takagi-Sugeno Fuzzy Inference System

3.2 Fuzzy Logic Technique for STLF

The proposed development and implementation of a fuzzy logic based algorithm for short term load forecasting consists of four stages

I. Design of fuzzy rule base

Based on the demonstrated success in generating forecasts, the methodology proposed by Wang [60] and Kosko [61] is used here. The approach consists of five steps as described below.

Step 1: Compile a tentative list of input and output variables using statistical analysis, engineering judgments and/or operator experience. There are four input variable that we use to forecast electricity load which are:

- i. Temperature
- ii. Humidity
- iii. Wind speed
- iv. Time

The output is forecasted load.

Step 2: Normalization of the input and output variables is defined as a graph that defines how each point in the input space is mapped to the membership value $[0,1]$. The input value is often referred as the universe of discourse or universal set (u), which contain all the possible elements of concern in each particular application. As shown in fig 3.6, 3.7, 3.8, 3.9 all the abscissa axes take on values $[0,1]$.

Step 3: Select the arbitrary shape of the fuzzy membership for each variable and change the membership function if forecasting accuracy is not good. The triangular shaped mappings shown in figure 4.1 are very common mapping, however trapezoidal with different amounts of function overlapping is used in this study.

Step 4: For each input and output variable, tentatively define the number of fuzzy membership functions. The lengths of the regions under the functions for a given variable need not be equal, nor must the number of functions for all variables be equal.

In case of triangular membership function:

Temperature data is fuzzified into three main fuzzy sets described in fig 3.6 as

1. cold
2. normal
3. hot

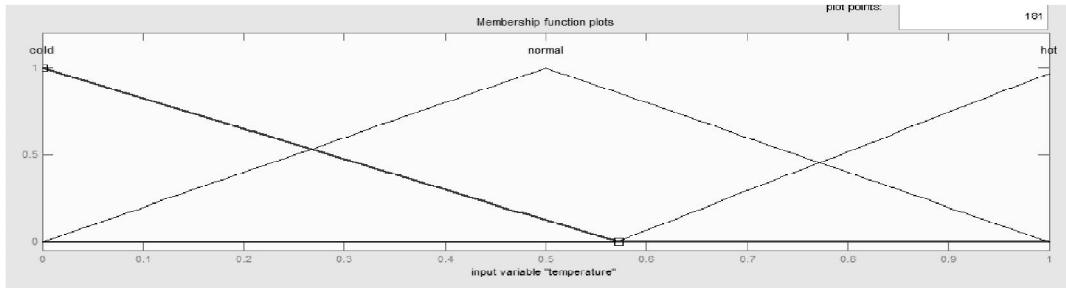


Fig 3.6 Triangular type membership function representation for temperature ($^{\circ}\text{C}$)

Fig. 3.7 depicts three main fuzzy sets for humidity described as:

1. dry
2. humid
3. very humid

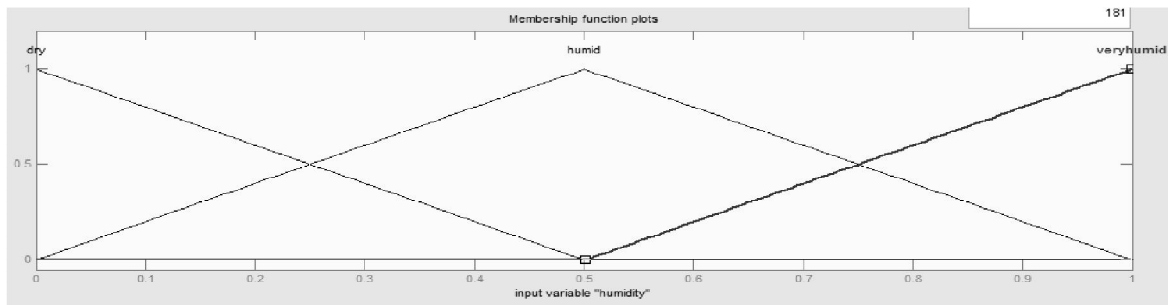


Fig 3.7 Triangular type membership function representation for humidity (%)

Fig. 3.8 depicts wind speed data fuzzified into three main fuzzy sets described as

1. below normal
2. normal
3. above normal

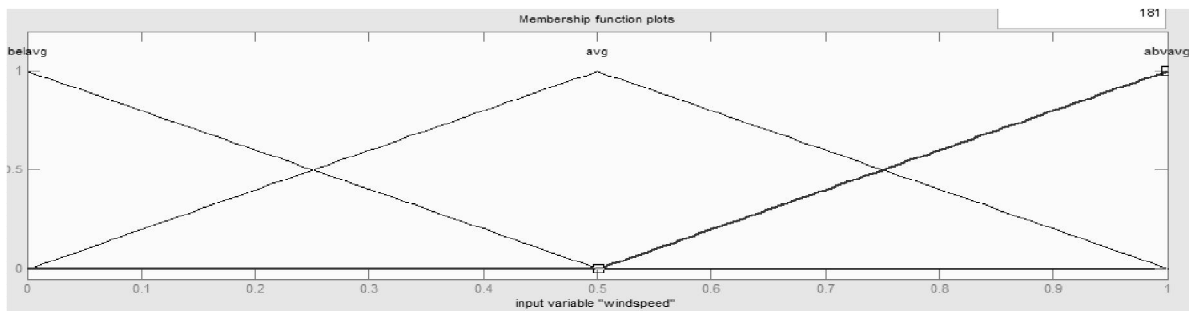


Fig 3.8 Triangular type membership function representation for wind speed (km/h)

Fig. 3.9 depicts time data fuzzified into three main fuzzy sets described as

1. morning
2. mid-day
3. night

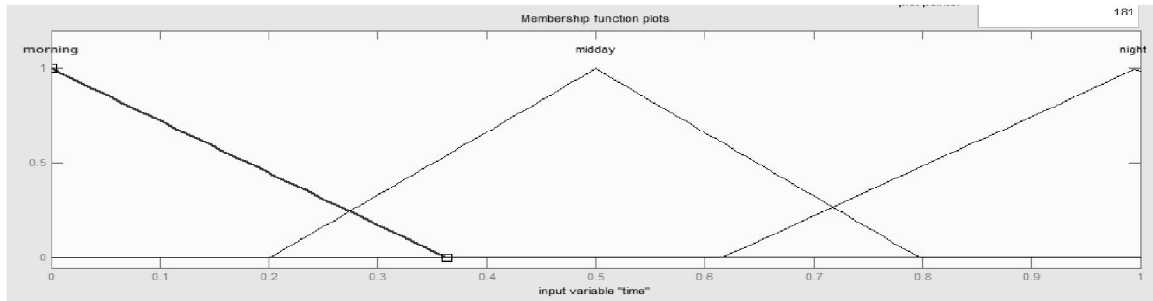


Fig 3.9 Triangular type membership function representation for time (hour)

Step 5: Construct the fuzzy rule from each pair of input-output data, also called training data as shown in fig. 3.10. For example: IF ‘temperature’ is hot and ‘humidity’ is humid and ‘wind speed’ is above average THEN ‘load’ is above average.

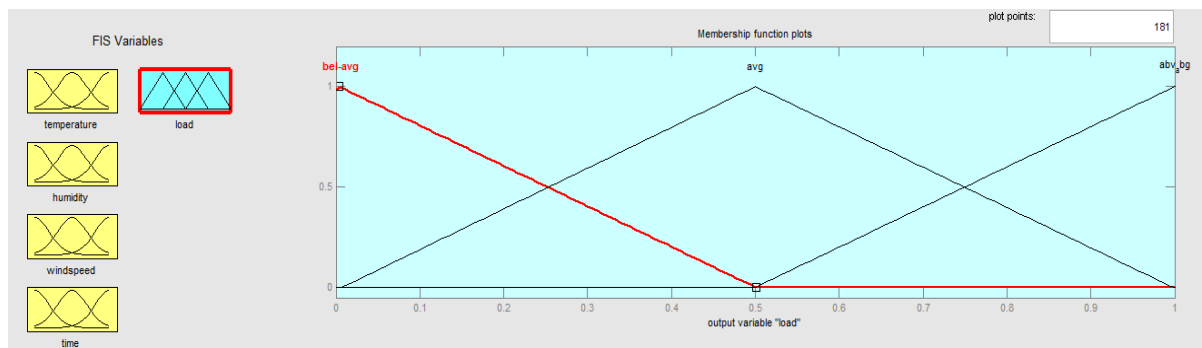


Fig 3.10 Fuzzy System Structure

In case trapezoidal membership function:

Temperature data is fuzzified into five main fuzzy sets described in fig 3.11 as

1. Very hot
2. Hot
3. Normal
4. Cold
5. Very cold

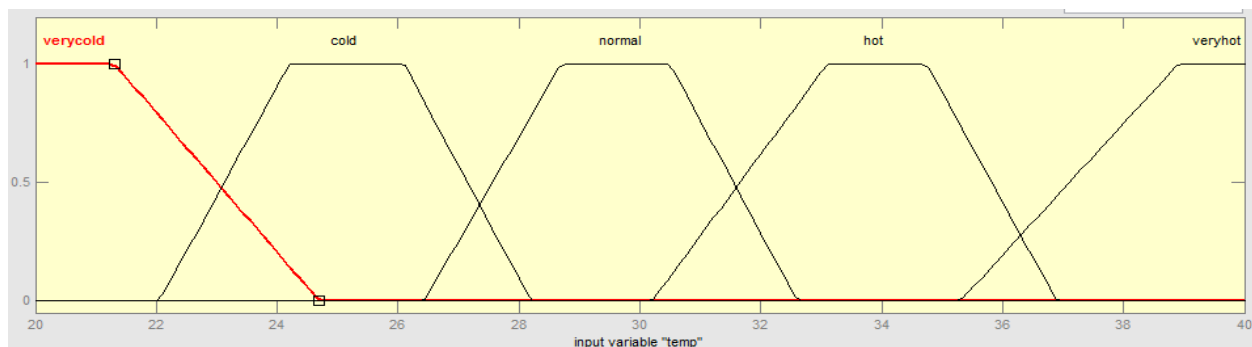


Fig 3.11 Trapezoidal type membership function representation for temperature (°C)

Fig. 3.12 depicts five main fuzzy sets for humidity described as

1. Very dry
2. Dry
3. Normal
4. Wet
5. Very wet

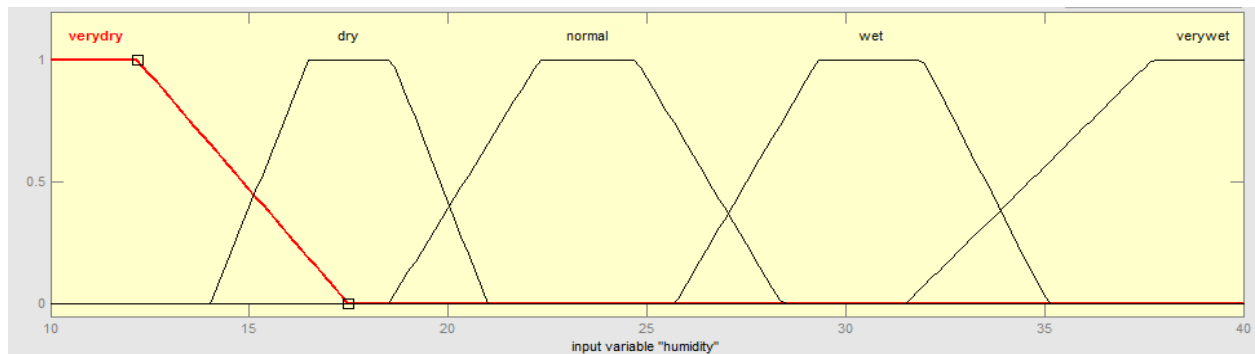


Fig 3.12 Trapezoidal type membership function representation for humidity (%)

Fig. 3.13 depicts wind speed data fuzzified into five main fuzzy sets described as

1. Very low
2. Low
3. Normal
4. High
5. Very high

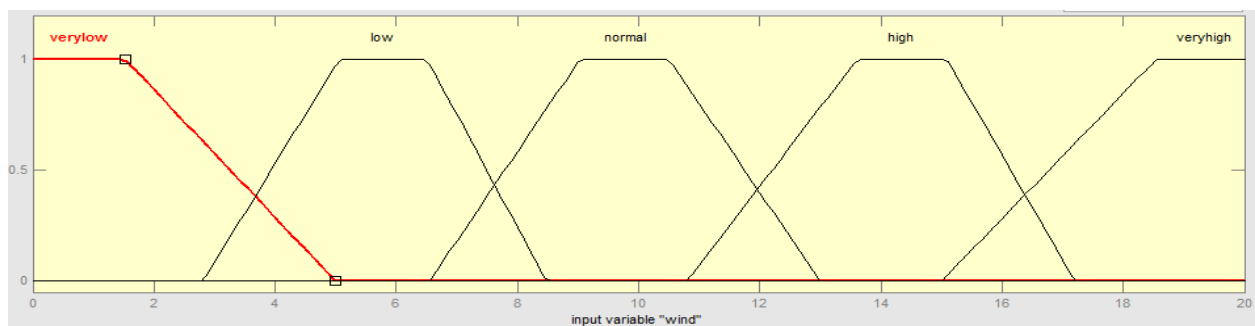


Fig 3.13 Trapezoidal type membership function representation for wind speed (km/h)

Fig. 3.14 depicts time data fuzzified into five main fuzzy sets described as

1. Midnight
2. Morning
3. Afternoon

4. Evening
5. Night

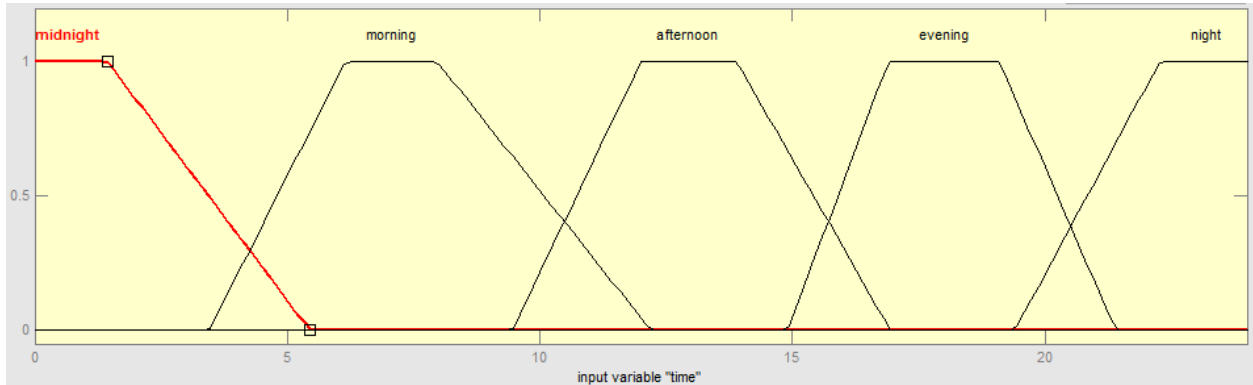


Fig 3.14 Trapezoidal type membership function representation for time (hour)

These five steps, supplemented by the resolution of conflicts and incorporation of expert opinion, constitute the construction of the fuzzy rule base for trapezoidal membership function shown in figure 3.15.

1. If (temp is normal) and (humidity is normal) and (wind is veryhigh) and (time is midnight) then (load is high) (1)
2. If (temp is normal) and (humidity is normal) and (wind is veryhigh) and (time is midnight) then (load is normal) (1)
3. If (temp is normal) and (humidity is normal) and (wind is veryhigh) and (time is midnight) then (load is low) (1)
4. If (temp is normal) and (humidity is normal) and (wind is veryhigh) and (time is morning) then (load is low) (1)
5. If (temp is normal) and (humidity is normal) and (wind is veryhigh) and (time is morning) then (load is high) (1)
6. If (temp is normal) and (humidity is wet) and (wind is veryhigh) and (time is morning) then (load is veryhigh) (1)
7. If (temp is normal) and (humidity is wet) and (wind is veryhigh) and (time is morning) then (load is high) (1)
8. If (temp is normal) and (humidity is wet) and (wind is high) and (time is morning) then (load is veryhigh) (1)
9. If (temp is normal) and (humidity is wet) and (wind is high) and (time is morning) then (load is normal) (1)
10. If (temp is hot) and (humidity is normal) and (wind is high) and (time is morning) then (load is normal) (1)
11. If (temp is hot) and (humidity is normal) and (wind is high) and (time is afternoon) then (load is normal) (1)
12. If (temp is hot) and (humidity is normal) and (wind is high) and (time is afternoon) then (load is high) (1)
13. If (temp is hot) and (humidity is dry) and (wind is normal) and (time is afternoon) then (load is normal) (1)
14. If (temp is veryhot) and (humidity is dry) and (wind is normal) and (time is afternoon) then (load is normal) (1)
15. If (temp is veryhot) and (humidity is dry) and (wind is low) and (time is afternoon) then (load is normal) (1)
16. If (temp is veryhot) and (humidity is dry) and (wind is low) and (time is afternoon) then (load is low) (1)

Fig 3.15 Fuzzy Rule Base

After the rule base is designed, the procedure described in the next stage is used to generate the point estimate forecasts for a given set of input value. Figure 3.16 shows the rule viewer of the trapezoidal membership function rule base.



Fig. 3.16 Rule Viewer

II. Compute the point forecast value

After the rule base is designed, it is ready to use for forecasting with novel inputs. A fuzzy inference system implements a nonlinear mapping from its input space to output space. Mamdani fuzzy inference system is used here.

A method called defuzzification is performed to determine the point estimate of the forecast from the fuzzy forecasts. The centroid of area method produces a numerical forecast sensitive to all the rules [59].

$$\text{Centroid of area } Z_{\text{COA}} = \frac{\int_Z \mu_A(z) z dz}{\int_Z \mu_A(z) dz}$$

where $\mu_A(z)$ is the aggregated output MF.

III. Test the performance of the rule base

After the fuzzy rule base is identified and a defuzzification algorithm is selected, forecast accuracy is tested using a different set of historical data set (test set) from the one used to obtain the rule base. If it is unsatisfactory, then the number of fuzzy membership functions and/or shape of the fuzzy membership functions can be changed and a new fuzzy rule base is obtained. The iterative process of designing the rule base, choosing a defuzzification algorithm, and testing the system performance may be repeated several times with a different number of fuzzy membership functions and/or different shapes of fuzzy memberships. The fuzzy rule base that provides the minimum error measure for the test set is selected for real time forecasting [17].

IV. Evaluate and update the fuzzy rule base

When the forecasting system is operational in real-time and new observation values are becoming available, we can also update the fuzzy rule using these new values. If the new rule designed from the new observation does not conflict with any rules already in the rule base, then the new rule can be immediately added to the fuzzy rule base. When there is a conflict, the THEN part associated with the rule may be modified based on the conflict resolution methods [55].

CHAPTER 4

SHORT TERM LOAD FORECASTING USING ARTIFICIAL NEURAL NETWORK

4.1 Neural Network

A Neural network is an artificial representation of the human brain that tries to simulate the learning process. The brain is a highly complex, nonlinear and parallel information processing system. It has the capability to organize its structural constituents, known as neurons, so as to perform certain computations many times faster than the fastest digital computer in existence today. The brain routinely accomplishes perceptual recognition tasks, e.g. recognizing a familiar face embedded in an unfamiliar scene, in approximately 100-200 ms, whereas tasks of much lesser complexity may take days on a conventional computer.

A neural network is a machine that is designed to model the way in which the brain performs a particular task. The network is implemented by using electronic components or is simulated in software on a digital computer. A neural network is a massively parallel distributed processor made up of simple processing units, which has a natural propensity for storing experimental knowledge and making it available for use. It resembles the brain in two respects:

1. Knowledge is acquired by the network from its environment through a learning process.
2. Interneuron connection strengths, known as synaptic weights, are used to store the acquired knowledge.

The procedure used to perform the learning process is called a learning algorithm, the function of which is to modify the synaptic weights of the network in an orderly fashion to attain a desired design objective [63].

4.1.1 History of Artificial Neural Network

The history is relevant because for nearly two decades the future of Neural network remained uncertain. McCulloch and Pitts (1943) are generally recognized as the designers of the first neural network. They combined many simple processing units together that could lead to an overall increase in computational power. They suggested many ideas like: a neuron has a threshold level and once that level is reached the neurons fires. It is still the fundamental way in which ANNs operate. The McCulloch and Pitt's network had a fixed set of weights. Hebb (1949) developed the first learning rule that is if two neurons are active at the same time then strength

between them should be increased. In the 1950 and 60's, many researchers (Block, Minsky, Papert, and Roenblatt worked on perceptron. The neural network model could be proved to converge to the correct weights that will solve the problem. The weight adjustment (learning algorithm) used in the perceptron was found more powerful than the learning rules used by Hebb. The neural networks research declined throughout the 1970 and until mid 80's because the perceptron could not learn certain important functions. Neural network regained importance in 1985-86. The researchers, Parker and LeCun discovered a learning algorithm for multi-layer networks called back propagation that could solve problems that were not linearly separable [63].

4.1.2 Basic Neuron Model

The model of biological neuron and artificial neuron is briefly reviewed.

Biological Neuron

A biological neuron or nerve cell main components are synapses, dendrites, the cell body and the axon [64-66]. Fig 4.1 shows schematic diagram of a Biological Neuron. The various building blocks are described as under:-

- ❖ The synapses are elementary signal processing devices
 - A synapse main objective to transform a pre-synaptic electrical signal into a chemical signal and then back into a post-synaptic electrical signal.
 - The input pulse train has its amplitude modified by parameters stored in the synapse. The nature of this modification depends on the type of the synapse, which can be either inhibitory or excitatory.
- ❖ The postsynaptic signals are summed and send along the dendrites to the cell body.
- ❖ The output neuronal signal, a spike generated by the cell body which is transferred along the axon to the synaptic terminals of other neurons.
- ❖ The frequency of firing of a neuron is proportional to the total synaptic activities and is controlled by the synaptic parameters (weights).

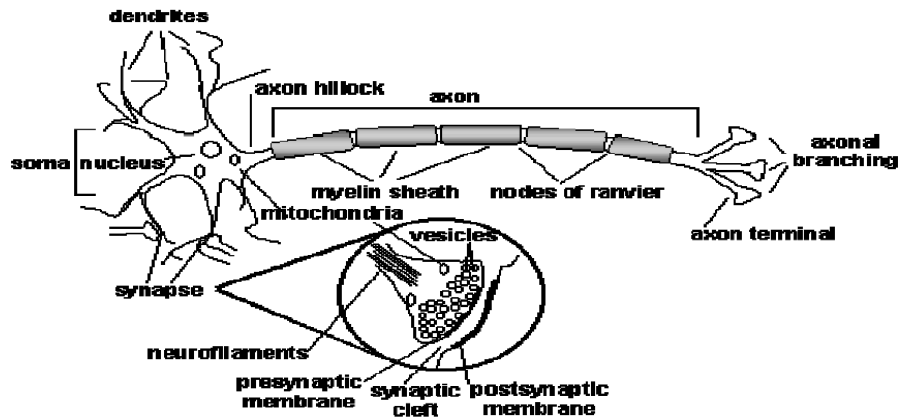


Fig 4.1: Schematic diagram of a Biological Neuron

Artificial Neuron

Neuron is the basic building block of an artificial neural network. The basic structure of an artificial neuron is shown in Fig 4.2. In this structure, the connection weights are adjusted between the neurons. Neuron u_i generates neuron inputs O_{pi} while the network is exposed to input pattern p . Each input is multiplied by a connection weight w_{ij} , where w_{ij} is the connection between neurons u_i and u_j . The connection weights correspond to the strength of the influence of each of the preceding neurons. After the inputs have been multiplied by the connection weights for input pattern p , their values are summed, net_{pj} . Included in the summation is a bias value θ_j to offset the basic level of the input to the activation function, $f(net_{pj})$, which gives the output O_{pj} . In order to establish a bias value θ_j , the bias term can appear as an input from a separate neuron with a fixed value (a value of +1 is common). Each neuron requiring a bias value will be connected to the same bias neuron. The bias values are then self-adjusted as the other neurons learn, without the need for extra considerations [67].

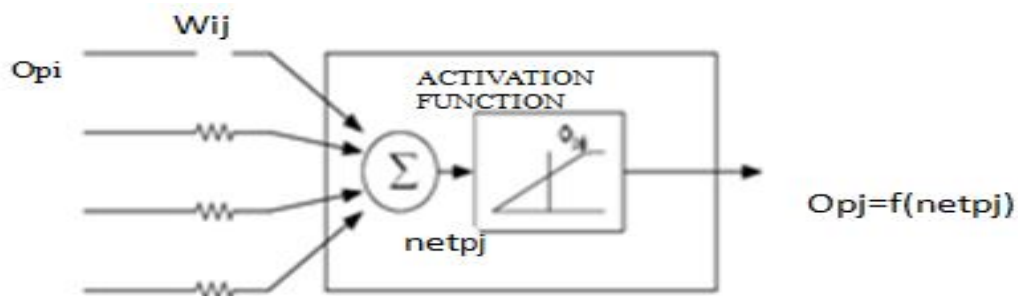


Fig 4.2: Basic Structure of an Artificial Neuron

In calculating the output of the neuron, the activation function may be in the form of a threshold function, if a threshold level is reached, the output of the neuron is +1 and 0 otherwise. The various activation functions like squashing, hyperbolic tangent, sigmoid etc. can be used. Squashing functions limit the linear output between a maximum and minimum value. Hyperbolic tangents and the sigmoid functions are similar to real neural responses; however, the hyperbolic tangent is unbounded and hard to implement in hardware.

The artificial neural network is made up of seven major components [61], [64].

These components are summarized as:-

- Weighting Factors
- Summation Function
- Transfer Function / Activation Function
- Scaling and Limiting
- Output Function
- Error Function and Back-propagated Value
- Learning Function

Weighting Factors: A neuron receives many inputs simultaneously. Each input has its own relative weight which gives the input impact that it needs on the processing element's summation function. These weights perform the same type of function as do the varying synaptic strengths of biological neurons. In both cases, some inputs are made more important than others so that they have a greater effect on the processing element as they combine to produce a neural response. These strengths can be modified in response to various training data sets and according to a network's specific topology or through its learning rules.

Summation Function: The first step in a processing element's operation is to compute the weighted sum of all of the inputs. Mathematically, the inputs and the corresponding weights can be represented as O_{pi} and w_{ij} respectively. The total input signal to the next layer neuron is the dot or inner product of these two vectors. This simplistic summation function is found by multiplying each component of the input by the corresponding component of the w_{ij} array and then adding up all the products. So, the input to the neuron of next layer is a single number, not a multi-element array.

Transfer Function / Activation Function: The activation function is denoted by $\Phi(\cdot)$. The Identity function is defined by equation (4.1).

$$g(x) = x \quad \dots(4.1)$$

It is obvious that the input units use the identity function. Sometimes a constant is multiplied by the net input to form a linear function. Fig. 4.3(a) shows identity activation function.

The Binary step function also known as threshold function or Heaviside function is shown in Fig. 4.3(b). The output of this function is limited to one of the two values as defined by equation (4.2). This kind of function is often used in single layer networks.

$$g(x) = \begin{cases} 1 & \text{if } x \geq \theta \\ 0 & \text{if } x < \theta \end{cases} \quad \dots (4.2)$$

The unipolar sigmoid and bipolar sigmoid functions are shown in Fig. 4.3(c) and 4.3(d) respectively. Equation (4.3) and (4.4) defines sigmoid and bipolar sigmoid functions respectively.

$$g(x) = \frac{1}{1 + e^{-x}} \quad \dots(4.3)$$

$$g(x) = \frac{1 - e^{-x}}{1 + e^{-x}} \quad \dots(4.4)$$

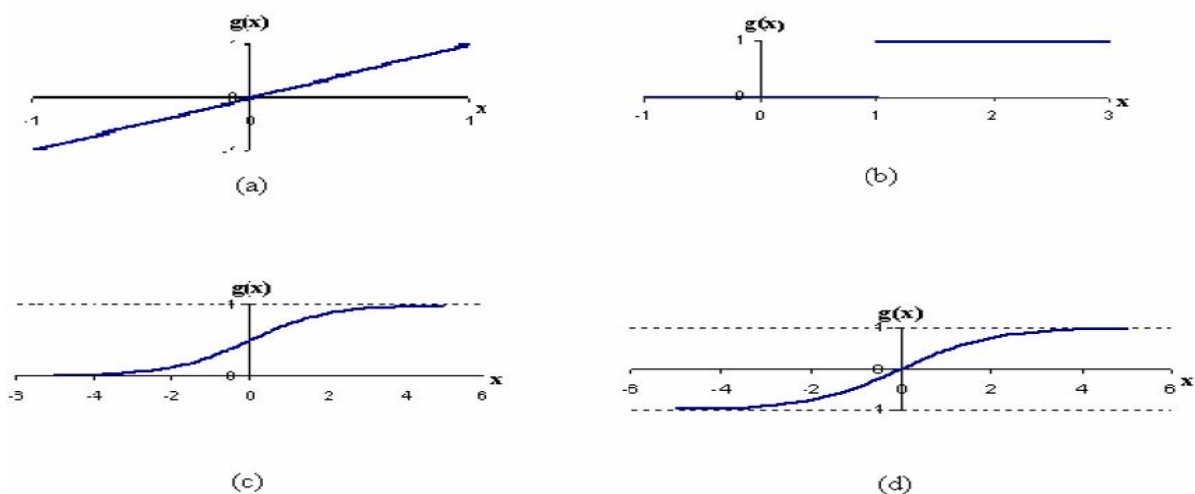


Fig 4.3: Common Activation Functions

Scaling and Limiting: After the processing element's transfer function, the result can pass through additional processes which scale and limit. This scaling simply multiplies a scale factor times the transfer value, and then adds an offset. Limiting is the mechanism which insures that the scaled result does not exceed an upper or lower bound. This limiting is in addition to the hard limits that the original transfer function may have performed.

Output Function: Each processing element is allowed one output signal which it may output to hundreds of other neurons. This is just like the biological neuron, where there are many inputs and only one output action. Normally, the output is directly equivalent to the transfer function's result. Some network topologies, however, modify the transfer result to incorporate competition among neighboring processing elements. Neurons are allowed to compete with each other, inhibiting processing elements unless they have great strength. Competition can occur at one or both of two levels. First, competition determines which artificial neuron will be active, or provides an output. Second, competitive inputs help determine which processing element will participate in the learning or adaptation process.

Error Function and Back-Propagated Value: In most learning networks the difference between the current output and the desired output is calculated. This raw error is then transformed by the error function to match particular network architecture. The most basic architectures use this error directly, but some square the error while retaining its sign, some cube the error, and other paradigms modify the raw error to fit their specific purposes. The artificial neuron's error is then typically propagated into the learning function of another processing element. This error term is sometimes called the current error. The current error is typically propagated backwards to a previous layer. Yet, this back-propagated value can be either the current error, the current error scaled in some manner (often by the derivative of the transfer function), or some other desired output depending on the network type. Normally, this back-propagated value, after being scaled by the learning function, is multiplied against each of the incoming connection weights to modify them before the next learning cycle.

Learning Function: The purpose of the learning function is to modify the variable connection weights on the inputs of each processing element according to some neural based algorithm. This process of changing the weights of the input connections to achieve some desired result can also

be called the adaption function, as well as the learning mode. There are two types of learning: supervised and unsupervised.

4.1.3 Network architectures: There are three fundamental different classes of network architectures [68]:

1) Single-layer Feed forward Network

This type of network comprises of two layers, namely the input layer and the output layer shown in fig. 4.4. The input layer neurons receive the input signals and the output layer neurons receive the output signals. The synaptic links carrying the weights connect every input neuron to the output neuron but not vice-versa. Despite the two layers, the network is termed single layer since it is the output layer, alone which perform computation.

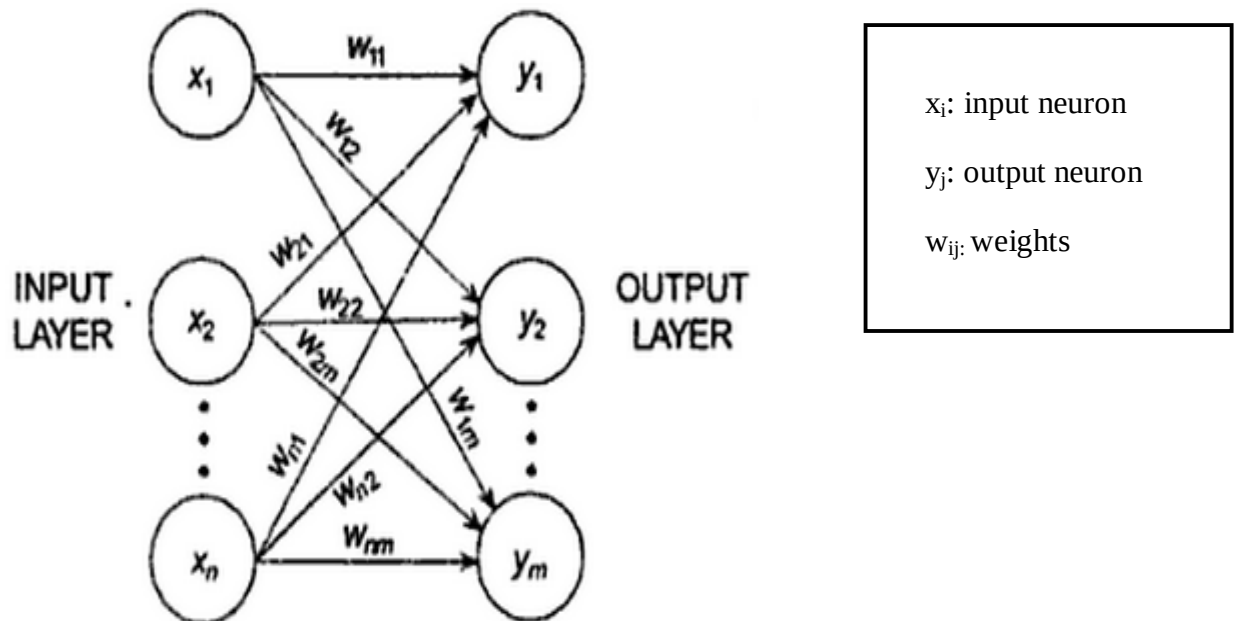
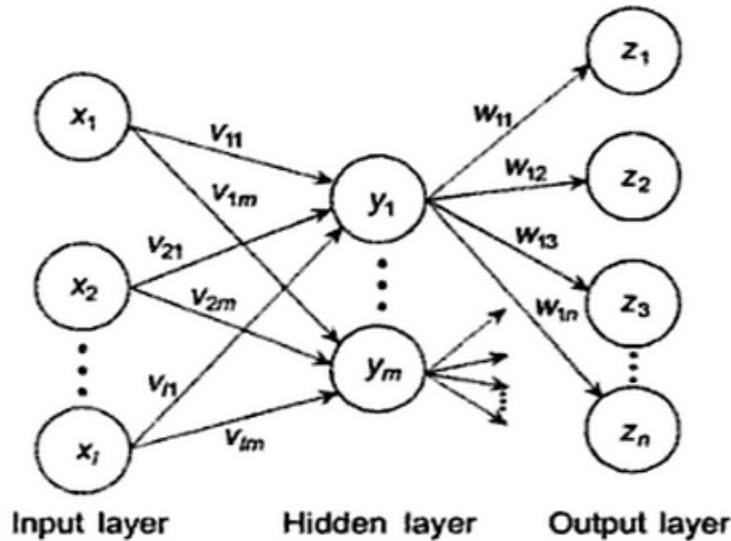


Fig 4.4 Single-layer Feed-forward Network

2) Multilayer Feedforward Networks

The second class of a Feedforward neural network shown in fig 4.5 distinguishes itself by the presence of one or more hidden layers, whose computational nodes are correspondingly called hidden neurons. The function of hidden neuron is to intervene between the external input and the network output in some useful manner. By adding more hidden layers, the network is enabled to extract higher order statistics. The input signal is applied to the neurons in the second layer. The output signal of second layer is used as inputs to the third layer, and so on for the rest of the network.



x_i : input neuron
 y_j : hidden neuron
 z_k : output neuron
 v_{ij} : input hidden layer weights
 w_{jk} : output hidden layer weights

Fig 4.5 Multi-layer Feed-forward Network

3) Recurrent networks

A recurrent neural network has at least one feedback loop. A recurrent network in fig 4.6 may consist of a single layer of neurons with each neuron feeding its output signal back to the inputs of all the other neurons. Self-feedback refers to a situation where the output of a neuron is fed back into its own input. The presence of feedback loops has a profound impact on the learning capability of the network and on its performance

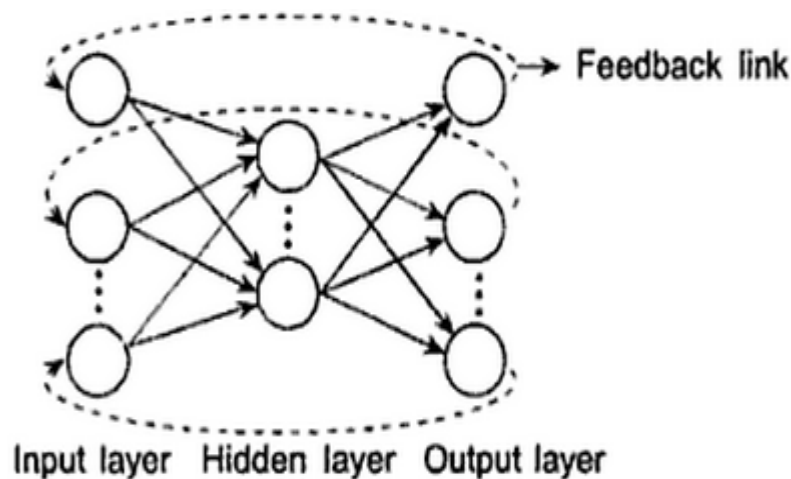


Fig 4.6 Recurrent Network

4.1.4 Teaching an artificial neural network: By learning we mean a procedure for modifying the weights and biases of a network. The purpose of learning is to train the network to perform some task. They fall into three broad categories [61], [69]:

1. Supervised learning

The learning is provided with a set of training data of proper network behavior. As the inputs are applied to the network, the network outputs are compared to the targets. The learning is then used to adjust the weights and biases of the network in order to move the network outputs closer to the targets.

2. Reinforcement learning

It is similar to supervised learning, except that, instead of being provided with the correct output for each network input, the algorithm is only given a grade. The grade is a measure of the network performance over some sequence of inputs.

3. Unsupervised learning

The weights and biases are modified in response to network inputs only. There are no target outputs available. Most of these algorithms perform some kind of clustering operation. They learn to categorize the input patterns into a finite number of classes.

4.1.5 Learning Rates: The rate at which ANNs learn depends upon several controllable factors. In selecting the approach there are many trade-offs to consider. Obviously, a slower rate means a lot more time is spent in accomplishing the off-line learning to produce an adequately trained system. With the faster learning rates, however, the network may not be able to make the fine discriminations possible with a system that learns more slowly. Network complexity, size, paradigm selection, architecture, type of learning rule or rules employed and desired accuracy must all be considered before training. These factors play a significant role in determining how long it will take to train a network. Changing any one of these factors may either extend the training time to an unreasonable length or even result in an unacceptable accuracy. Most learning functions have some provision for a learning rate, or learning constant. Usually this term is positive and between zero and one. If the learning rate is greater than one, it is easy for the learning algorithm to overshoot in correcting the weights, and the network will oscillate. Small values of the learning rate will not correct the current error as quickly, but if small steps are taken in correcting errors, there is a good chance of arriving at the best minimum convergence [70].

4.1.6 Learning Rule: Many learning rule are in common use. Most of these rules are some sort of variation of the best known and oldest learning rule, Hebb's Rule. Learning is certainly more

complex than the simplifications represented by the learning rule currently developed [71]. A few of the major rule are presented as examples.

a) Hebb's Rule

The first, and undoubtedly the best known, learning rule were introduced by Donald Hebb. The basic Hebb's rule is: If a neuron receives an input from another neuron and if both are highly active (mathematically have the same sign), the weight between the neurons should be strengthened.

The symbolic representation:

$$w_{ij} = \frac{1}{p} \sum_{k=1}^p x_i^k x_j^k \quad \dots(4.5)$$

where w_{ij} is the weight of the connection from neuron j to neuron i , p is the number of training patterns and x_i^k the k th input for neuron i , x_j^k the k th input for neuron j .

b) The Delta Rule

This rule is a further variation of Hebb's Rule. It is one of the most commonly used. This rule is based on the simple idea of continuously modifying the strengths of the input connections to reduce the difference (the delta) between the desired output value and the actual output of a processing element. This rule changes the synaptic weights in the way that minimizes the mean squared error of the network. This rule is also referred to as the Widrow-Hoff Learning Rule and the Least Mean Square (LMS) Learning Rule. The error is back propagated into previous layers one layer at a time. The process of back-propagating the network errors continues until the first layer is reached. The network type called feed forward, Back-propagation derives its name from this method of computing the error term.

The symbolic representation:

$$\Delta w_{ji} = \alpha(t_j - y_j)x_i. \quad \dots(4.6)$$

Where α is a small constant called learning rate, t_j is the target output, y_j is the actual output, x_i is the i th input.

c) The Gradient Descent Rule

This rule is similar to the Delta Rule in that the derivative of the transfer function is still used to modify the delta error before it is applied to the connection weights. Here, however, an additional proportional constant tied to the learning rate is appended to the final modifying factor

acting upon the weight. This rule is commonly used, even though it converges to a point of stability very slowly. It has been shown that different learning rates for different layers of a network help the learning process converge faster.

The symbolic representation:

$$\Delta w_{ij} = \eta \left(\frac{\partial E}{\partial w_{ij}} \right) \quad \dots(4.7)$$

Where η is the learning rate parameters and $\frac{\partial E}{\partial w_{ij}}$ is error gradient with reference to the weight w_{ij} .

4.2 ANN Technique for Short Term Load Forecasting

The artificial neural network (ANN) technique to short-term load forecasting has gained a great deal of interest and several researchers have reported the effectiveness of the ANN approach. The ANN techniques have been applied to correlate the weather information and the load variations to forecast the daily peak load and hourly load. The advantage of ANN over statistical models lies in its ability to model a multivariate problem without making complex dependency assumptions among input variables. Furthermore, the ANN extracts the implicit nonlinear relationship among input variables by "learning" from training data. The hourly historical data of the weather conditions and the load are classified according to their characteristics and are used by the ANN to create a non-linear model. These non-linear models are then used to forecast load on short-term basis.

Problem Formulation

The proposed development and implementation of new ANN based technique for the short-term load forecasting of weather sensitive loads consist of four stages. The ANN model used a non-fully-connected neural network consisting of one main and four supporting neural network.

I. Data selection and analysis

Papalexopoulos A.D. *et al.*, [72] state that, for selection of number of input variables there is no basic rule. It is carried out almost entirely on hit and trial basis. According to Wang X. *et al.*, [73], for most customers belong to different classes e.g. residential, industrial etc. historical data is essential for estimating demand in STLF. The required input parameters are the historical load and weather data, forecasted average daily weather, indices listing the day of the week and the time of the day, and the most recent load and weather data. Here, weather data include temperature (°C), humidity (%), Windspeed (km/h). The suggested input vector to the ANN specifies the time and weather data for the hour to be forecasted, and associated load data.

Typically, it is configured from day type, temperature, humidity, wind speed and hourly load data from today, yesterday and the same two days of the previous week are required. The daily loads are strongly influenced by the recent temperature, humidity, wind speed and the average daily temperature, humidity, wind speed. Since the most recent three hours load data points are considered as part of the inputs, the corresponding three hour temperatures, humidity, and wind speed are included. The average daily temperature, humidity, wind speed is treated as part of the input set to reflect the daily variations. In order to reflect this characteristic, the average daily temperatures, humidity, wind speed of the two days before the forecasting day is taken into consideration also. In total, the temperature, humidity, wind speed data points account for six input variables.

In general, the daily loads are divided into two categories: weekdays and weekends. Weekends tend to have a low average load than weekdays. The load range fluctuates with the climatic conditions. In order to accommodate differences between these two categories, the day of the week is presented by one to one coding scheme. To represent the day of the week seven input nodes are required. Only one node is set to a nonzero value at any given input set. Since the weekday patterns occur more frequently than the weekend patterns, different input values are assigned to the weekday and weekend indices to aid the learning process. In this model, a value assigned to weekday input nodes is 1; and a value assigned to weekend input nodes is 0.5 [42].

There are twelve input nodes represent hourly load variables in which three nodes represent the load from the previous three hours which occur prior to the forecasting time, three nodes represent the load from the same three hours of yesterday and the final six inputs nodes are the loads from the same hours of the previous week.

Therefore, input vector consist of 37 inputs which include weather information (16 nodes), day type (7 nodes) and load data (12 nodes).

II. Data normalization

Normalization is the process of organizing data in a database. It makes the data more flexible. Before training, the input and the output values are normalized such that all the data falls within the range from 0.15 to 0.85. This is done to prevent the simulated neurons from being driven too far into saturation.

III. ANN Architecture

Network configuration mainly depends on

- Input variable selection
- Number of hidden layers
- Number of neurons in each hidden layer

A fully connected ANN comprises three layer architecture is not readily adaptive enough to the weather variation. By increasing the size of hidden layers and hidden nodes gives no effective improvement [74]. To overcome these problems, a non-fully-connected ANN model is proposed. The model consists of one fully connected primary ANN and four secondary fully connected ANNs as shown in fig 4.7, 4.8, 4.9, 4.10, 4.11. These five ANNs are then combined to form the proposed non-fully-connected ANN as shown in fig 4.12.

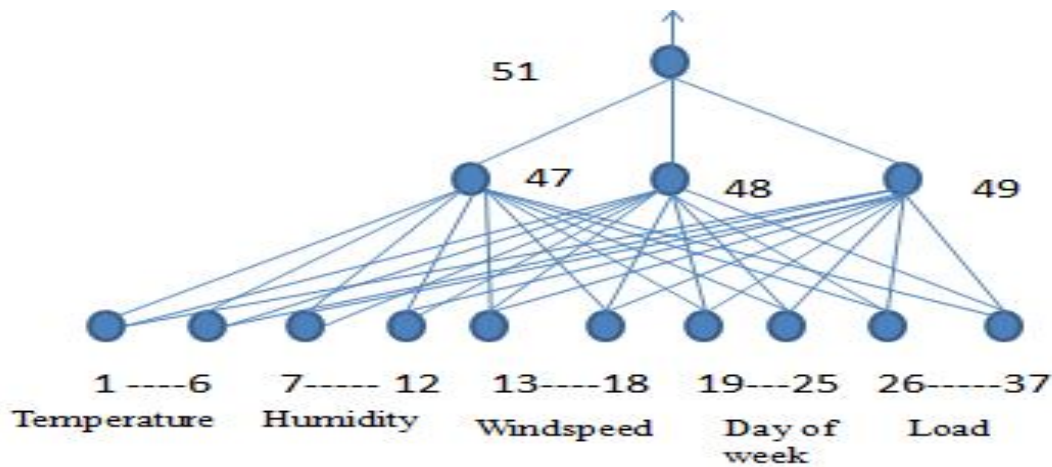


Fig 4.7 Primary network I

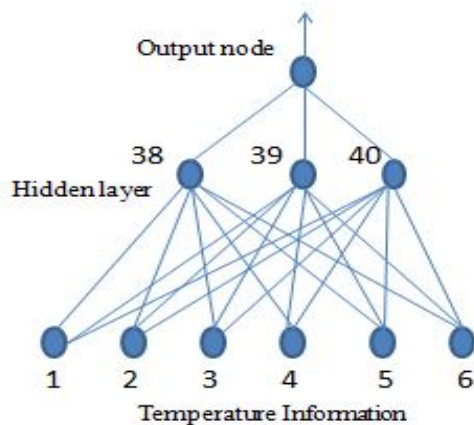


Fig 4.8 Secondary network (Temperature)

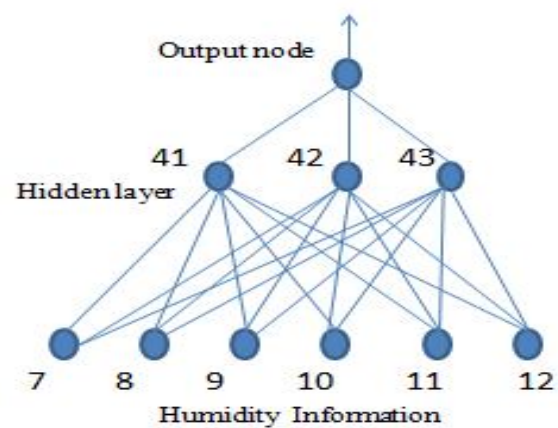


Fig 4.9 Secondary network (Humidity)

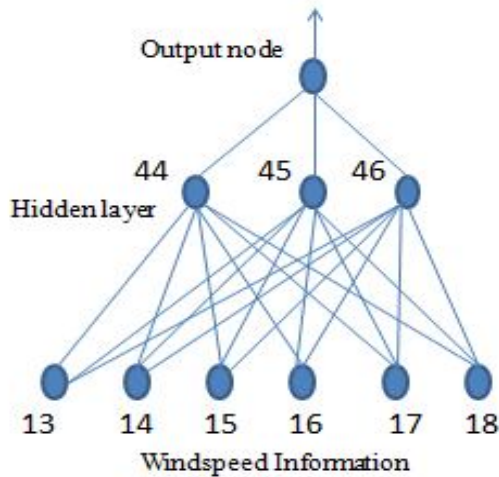


Fig 4.10 Secondary network (Wind speed)

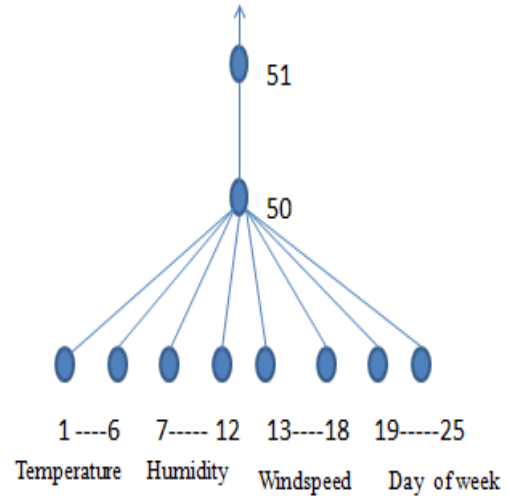


Fig 4.11 Primary network II

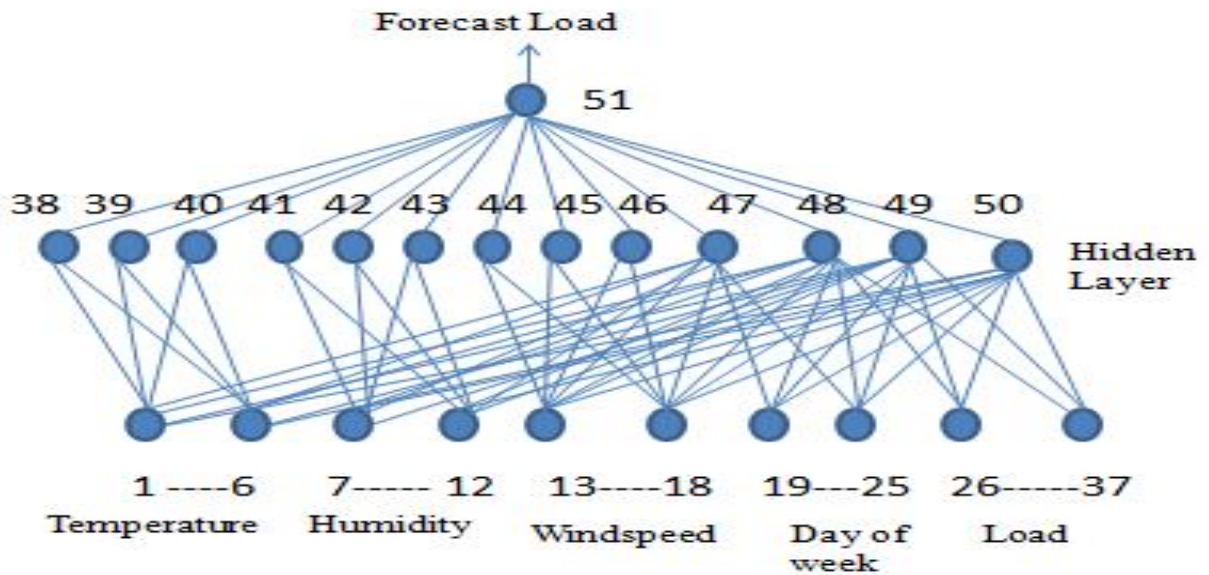


Fig 4.12 Non-fully-connected ANN primary network III

The primary ANN, it is a basic forecasting reference includes all the input variables. The secondary neural network is used to provide additional learning capacity to the primary ANN. It allows the model to correlate the relationship between temperature information and forecasted load; humidity information and forecasted load; Windspeed information and forecasted load. The temperature input variables are fully connected to the hidden nodes 38, 39 and 40. The humidity input variables are fully connected to the hidden nodes 41, 42 and 43.

The wind speed input variables are fully connected to the hidden nodes 44, 45 and 46. These hidden nodes are then connected to the output of the base ANN. The secondary neural network

IV is used to capture the correlation between the variation of the load curve and the temperature, humidity, wind speed for different days of the week. This local ANN uses temperature information (nodes 1 through 6), humidity information (nodes 7 through 12), Windspeed information (nodes 13 through 18) and the day of the week index (nodes 19 through 25) as inputs. These inputs are fully connected to the hidden node 50. The output of the hidden node is then connected to the output node of the main ANN.

IV Training and Testing

The non-fully connected ANN architecture used in this study, consist of three-Layered Feed forward network using a back-propagation algorithm with gradient delta learning rule.

Back propagation learning algorithm is used at the learning stage. Steps for Backpropagation learning algorithm are as follows:

Assumptions:

q = feed-forward layers ($q= 1, 2 \dots Q$)

k = number of data set ($k= 1, 2 \dots K$)

${}^q \text{net}_i$ = net input in the q th layer

${}^q y_i$ = net output in the q th layer

m =input nodes

n =output nodes

${}^q w_{ij}$ = connection weight from j th node in $(q-1)$ th layer to i th node in q th layer i.e. ${}^{q-1}y_j$ to ${}^q y_i$

input and output data set: $\{x^{(k)}, d^{(k)}\}$

Step 1: Set learning rate $\eta > 0$, $E_{\max}$ (maximum tolerable error)

Also, set initial error, $E = 0$ and data set, $k = 1$

Step 2: Apply k th input pattern to input layer ($q=1$)

$${}^q y_i = {}^1 y_i = x_i^{(k)} \text{ for all } i$$

Step 3: Forward propagation: propagate the signal forward through the network

$${}^q y_i = a ({}^q \text{net}_i) = a \left(\sum_j w_{ij}^q * y_j^{q-1} \right)$$

a = activation function

In this work activation function used is sigmoidal.

Step 4: Compute the error value and error signals ${}^Q \partial_i$ for the output.

$$E = \frac{1}{2} \sum_{i=1}^n (d_i^{(k)} - y_i^Q)^2$$

$${}^Q\delta_i = (d_i^{(k)} - y_i^Q) a'(\text{net}_i^Q)$$

Step 5: Propagate the errors backward to update the weights and compute the error signals

${}^{Q-1}\delta_i$ for the preceding layers:-

$$\Delta w_{ij}^q = \eta * \delta_i^q * y_j^{q-1}$$

$$w_{ij}^{q\text{ new}} = w_{ij}^{q\text{ old}} + \Delta w_{ij}^q$$

$$\delta_i^{q-1} = a'(\text{net}_i^{q-1}) \sum_j w_{ij}^q * \delta_j^q \quad \text{for } q=Q, Q-1, \dots, 2, 1$$

Step 6: check whether the whole set of training data has been cycled once

If $k < K$ then $k = k + 1$, go to step1, otherwise go to step 6.

Step 7: Total error checking: check whether the current total error is acceptable. If $E < E_{\max}$, then terminate the training process and output the final weights.

For each ANN, the sigmoid activation function is used. The initial network connection weights are set to equal small random numbers commonly ranges between 0 and 0.4 [74]. The training of neural network to forecast hourly loads is based upon the classified data. The flowchart for training and load forecasting is shown in fig 4.12

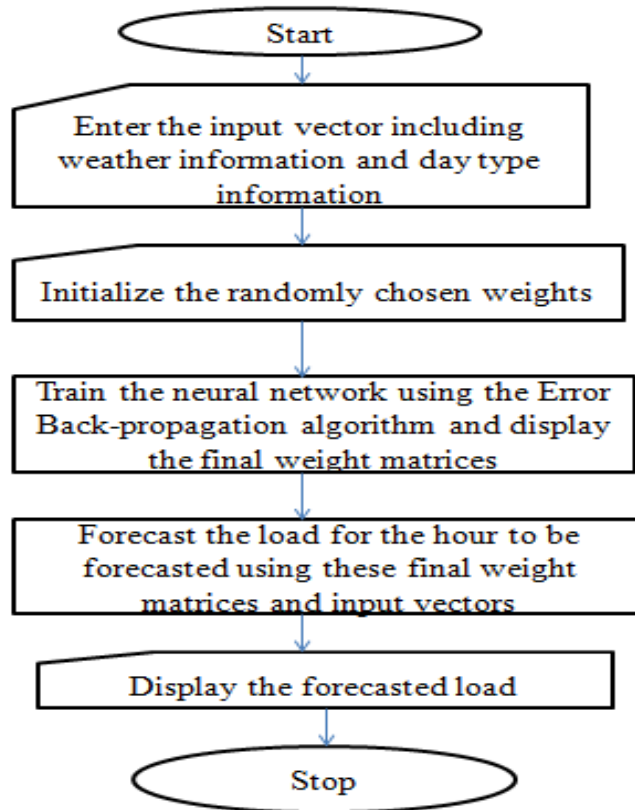


Fig 4.13 Flowchart for Training and Load forecasting

4.3 Accuracy of Forecasts

To ensure the system accuracy, the relative error between the forecasted load and the actual load consumption are obtained on daily basis. A positive value of error will indicate an over forecast, means that the forecasted load is larger than the actual load. In contrast, a negative value indicates under forecast, where the forecasted load value is less than the actual value [55].

$$\text{Absolute Percentage Error (APE)} = \frac{|Forecast\ load - Actual\ load|}{Actual\ load} * 100$$

$$\text{Mean Absolute Percentage Error (MAPE)} = \left(\frac{1}{N}\right) \sum_{i=1}^N \frac{|Forecast\ load - Actual\ load|}{Actual\ load} * 100$$

CHAPTER 5

RESULTS

The dissertation work has been focused on the preliminary investigation of feasibility and performance of fuzzy logic model and artificial neural network model to carry out short term load forecasting on hourly basis and peak load demand prediction for weekdays and weekend days. Real time data that includes historical hourly load demand over a week, and weather data in terms of temperature, humidity, wind speed, is collected from Jodhpur State Load Dispatch and Communication Center, Rajasthan Vidyut Parasaran Nigam (JVN). The forecasted load is compared with the actual load and average percentage error is calculated.

Three months data of JVN collected for training and test data to carry out forecasting load demand is given in appendix.

The following five cases are investigated to validate the proposed methodology of fuzzy logic model and artificial neural network model and the results are compared and reported.

- I. Hourly load forecast of a weekday(Wednesday)
- II. Hourly load forecast of a pre-holiday (Saturday)
- III. Hourly load forecast of a holiday (Sunday)
- IV. Hourly load forecast of a post-holiday(Monday)
- V. Peak load forecast of a weekdays and weekends

5.1 Fuzzy Logic Model

Fuzzy logic model includes the mapping of input variables to output values using IF-THEN rules with approximate reasoning. The rules are developed from numerical data in combination with expert opinion. The proposed methodology of implementation follows the procedure as:

1. Generate a list of input and output variables representing correlation of physical variables namely temperature, wind speed, humidity with previous hour/s load demand or previous day/s peak load for a day type as input variables and a single output of hourly load demand or peak load demand.
2. Normalize the input and output data within the permissible range.
3. Assign the membership functions to each input and output variables. The proposed methodology of fuzzy logic model is investigated with two different shapes of membership functions namely triangular and trapezoidal with 50% of overlapping.

4. Define number of fuzzy functions for each input and output variable.(In this study, five fuzzy membership functions are selected for each variable)
5. Construct the training fuzzy rule set from each pair of input output data. The conflict among the input-output pairs is resolved by selecting a pair of high degree evaluated using rule of confidence. The number of rules in the rule base used for training in the range of 22 to 27.
6. For given inputs of the selected fuzzy rule base, the membership value of output function is computed and a point estimate is calculated by de-fuzzification of computed output function using centroid method.
7. Forecasted output value accuracy is tested on a different set of historical data and forecast accuracy is computed. The calculated average percentage error is tabulated in table 5.1.
8. The results obtained for hourly load forecast for different week days indexed as weekday, post-holiday, pre-holiday and holiday, with two different shapes of membership functions viz. triangular and trapezoidal membership functions are plotted as shown in fig. 5.1, 5.2, 5.3 and 5.4.

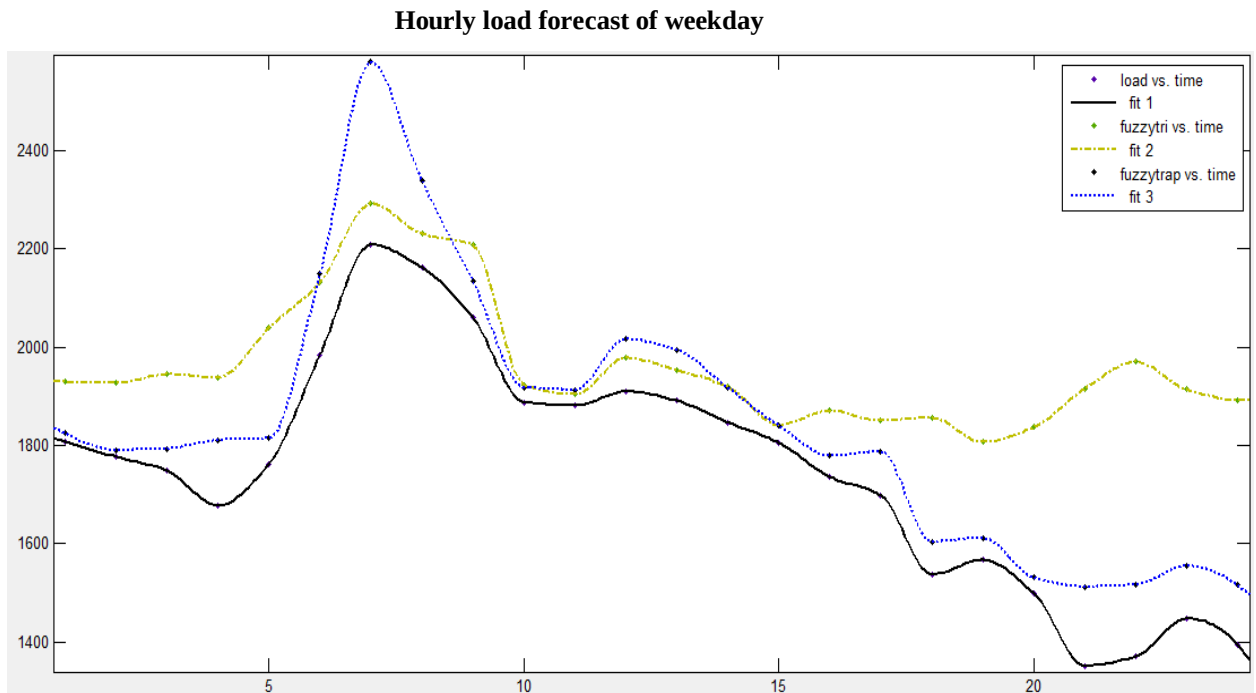


Fig 5.1: Comparison between Actual and Fuzzy Logic Forecasted Loads for weekday (using triangular and trapezoidal membership function with $K=5$)

Black bar – actual load Vs time; Green bar – F.L (triangular MF, $k=5$) Vs time; Blue bar – FL (with trapezoidal MF, $k=5$) Vs time

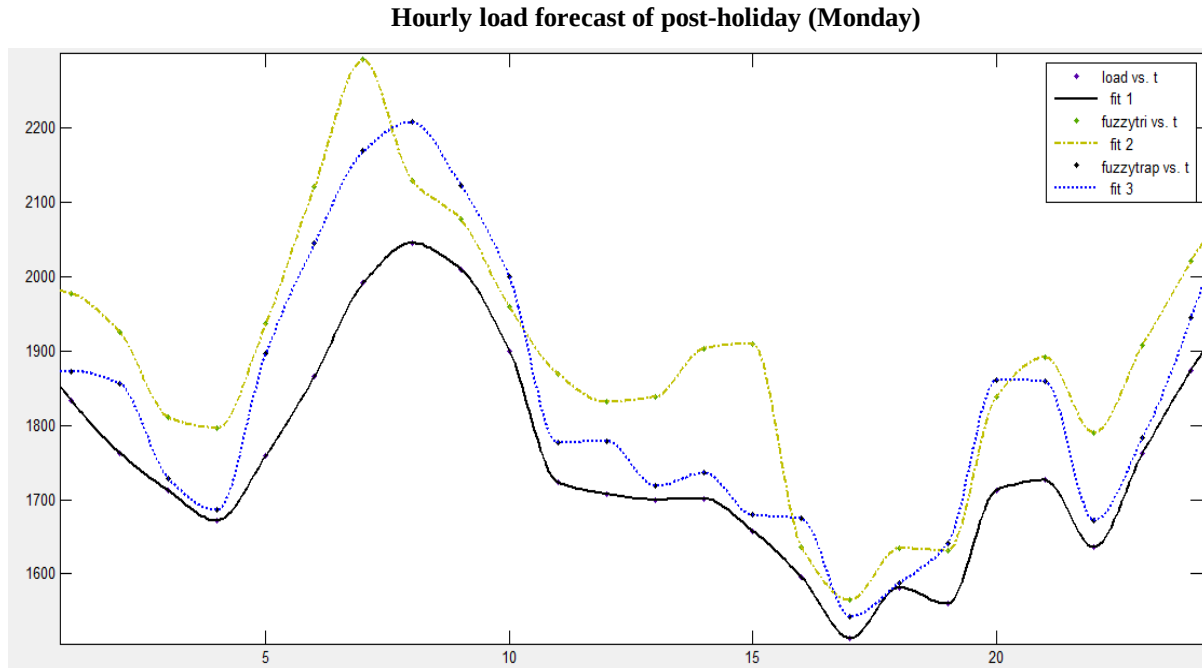


Fig 5.2: Comparison between Actual and Fuzzy Logic Forecasted Loads for post-holiday (using triangular and trapezoidal membership function with $K=5$)

Black bar – actual load Vs time; Green bar – F.L (with triangular MF, $k=5$) Vs time; Blue bar – F.L (with trapezoidal MF, $k=5$) Vs time

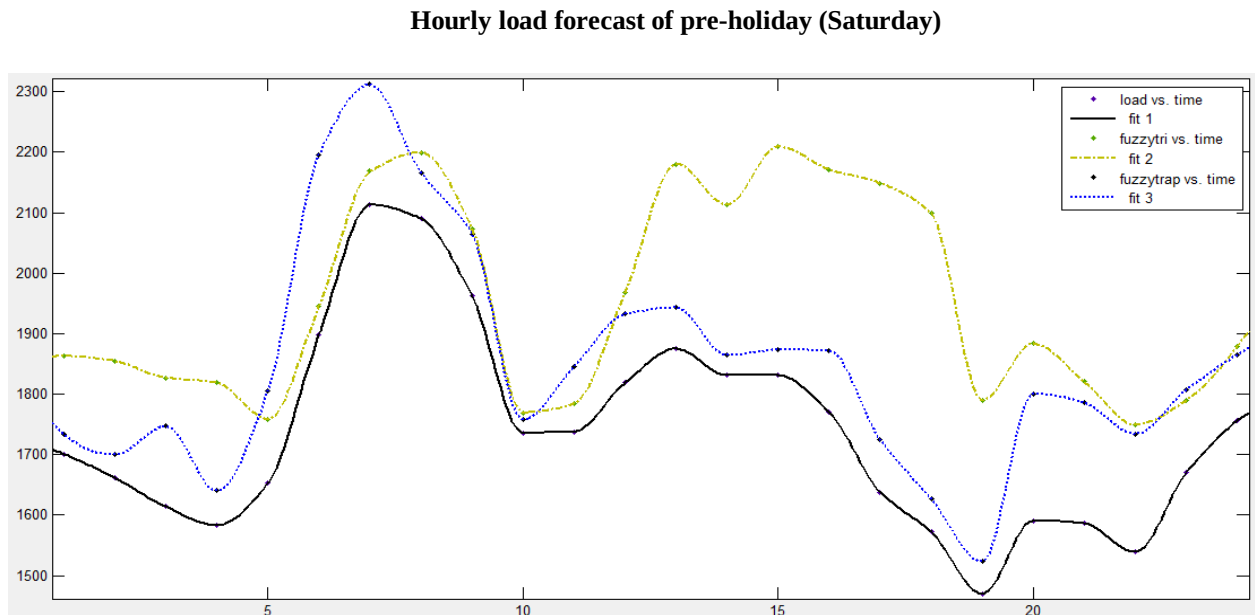


Fig 5.3: Comparison between Actual and Fuzzy Logic Forecasted Loads for preholiday (using triangular and trapezoidal membership function with $K=5$)

Black bar – actual load Vs time; Green bar – F.L (with triangular MF, $k=5$) Vs time; Blue bar – F.L (with trapezoidal MF, $k=5$) Vs time.

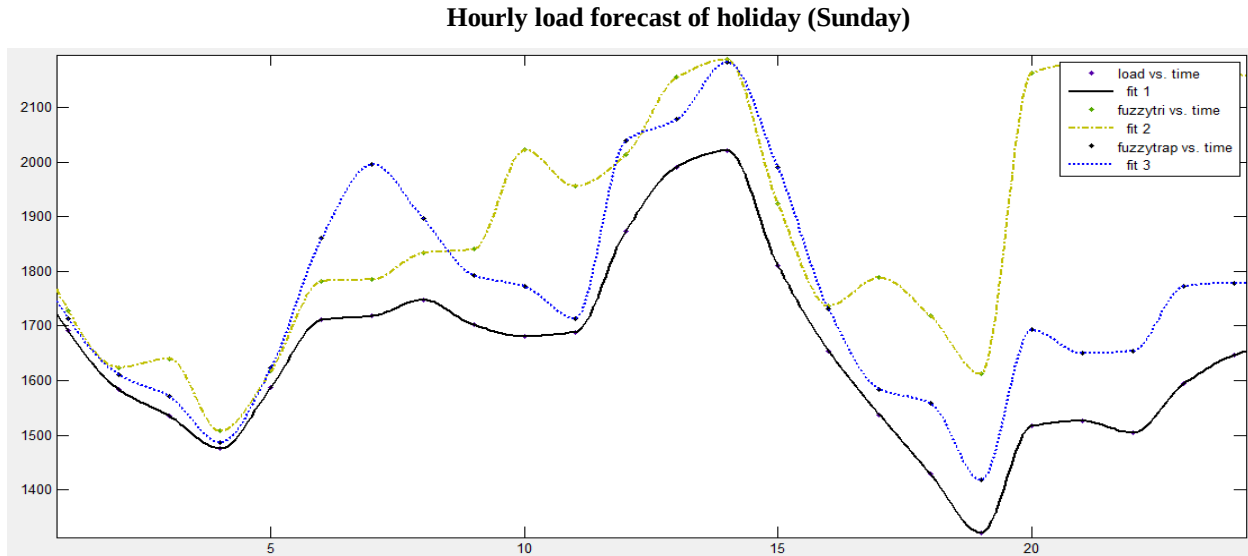


Fig 5.4: Comparison between Actual and Fuzzy logic Forecasted Loads for holiday (using triangular and trapezoidal membership function with $K=5$)

Black bar – actual load Vs time; Green bar – F.L (with triangular MF, $k=5$) Vs time; Blue bar – F.L (with trapezoidal MF, $k=5$) Vs time

5.2 Artificial Neural Network Model

The proposed methodology of artificial neural network model consists of non-fully connected feed-forward back propagation network configuration and is investigated with an objective to reduce computational time and storage space. The network basically consists of input layer, hidden layer and output layer and is detailed in chapter 4. The development and implementation of the proposed network follows the procedure as:

1. Select a feed forward back propagation network architecture with one hidden layer.
2. Build the training data set includes load data, time of the day, type of the day, and physical weather data of temperature, humidity, and wind speed strongly influencing the load data, indexed as input parameters to which input layer is subjected to. The load data set is selected using ARIMA procedure which basically represents the correlation of hourly load data over the days in the consecutive hours.
3. Initialize the weights of connecting links to small random values so as to avoid saturation of model.
4. Compute the activated output using summation principle at a neuron.
5. Implement back propagation learning algorithm and train the network for given number of iterations.

6. Test the trained model on the test data.
7. Forecasted output value accuracy is tested on a different set of historical data and forecast accuracy is computed. The calculated average percentage error is tabulated in table 5.1.
8. The results obtained for hourly load forecast for different week days indexed as weekday, post-holiday, pre-holiday and holiday are plotted as shown under various cases of study.
9. Train and test the network for peak load forecast.
10. The results obtained for peak load forecasting are plotted as shown in fig.

5.2.1 Case-I: Hourly Load Forecasting For Post Holiday

In this case, hourly load for JVN is forecasted for a post-holiday i.e. Monday (2 April). Training data is given in appendix (table 1 & 2) that includes temperature (°C), humidity (%), wind speed (km/h) and load (MW) information. The actual load and forecasted load with absolute percentage error for ANN using lambda (sigmoidal constant) = 1, learning constant = .01 and compared with fuzzy logic model is reported in table 5.1. The forecasted hourly load demand obtained from ANN model is plotted as shown in fig. 5.5 and compared with results obtained from fuzzy logic model as shown in fig. 5.6.

TABLE 5.1: Conventional load and absolute percentage error calculation for case -I

Time (hours)	Actual load (MW)	Back Propagation Neural Network Model		Fuzzy Logic Rule base Model			
		Number of iteration/s		Membership Function with fuzzy sets K=5			
		500	APE	Triangular	APE	trapezoidal	APE
1	1834	1838.95	0.27	1977.8	7.84	1872.7	2.11
2	1763	1770.58	0.43	1925.4	9.21	1856.1	5.28
3	1712	1715.93	0.23	1811.0	5.78	1728.8	.98
4	1672	1674.50	0.15	1796.6	7.45	1685.5	.81
5	1759	1761.99	0.17	1936.7	10.1	1896.7	7.83
6	1866	1868.79	0.15	2121.6	13.7	2044.4	9.56
7	1991	1995.18	0.21	2291.6	15.1	2168.8	8.93
8	2045	2049.70	0.23	2129.7	4.14	2207.6	7.95
9	2010	2013.61	0.18	2076.9	3.33	2122.8	5.61
10	1900	1903.99	0.21	1959.5	3.13	1999.4	5.23
11	1723	1727.30	0.25	1869.3	8.49	1776.1	3.08

12	1708	1712.61	0.27	1831.8	7.25	1779.1	4.16
13	1700	1702.55	0.15	1838.2	8.13	1718.4	1.08
14	1701	1702.53	0.09	1903.4	11.9	1735.9	2.05
15	1658	1658.99	0.06	1910.0	15.2	1679.2	1.28
16	1596	1598.23	0.14	1636.9	2.56	1674.4	4.91
17	1514	1516.27	0.15	1565.3	3.39	1542.9	1.91
18	1582	1585.32	0.21	1634.7	3.33	1587.8	.366
19	1560	1563.27	0.21	1631.4	4.58	1641.1	5.20
20	1713	1717.79	0.28	1838.2	7.31	1860.8	8.63
21	1726	1731.35	0.31	1892.0	9.62	1859.4	7.73
22	1636	1642.21	0.38	1789.9	9.41	1672.5	2.23
23	1762	1769.92	0.45	1907.4	8.25	1782.6	1.17
24	1874	1882.99	0.48	2020.4	7.81	1944.1	3.74

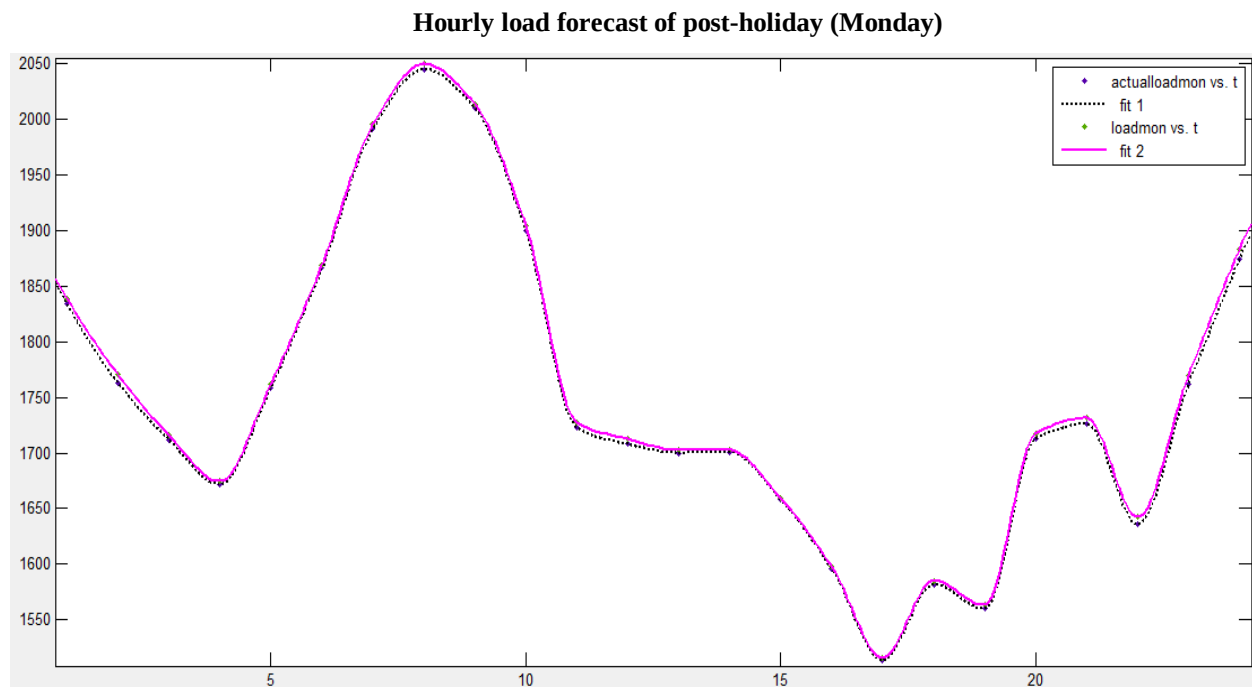


Fig 5.5: Comparison between Actual and ANN Forecasted Loads (using iteration 500)

Black bar – actual load Vs time; Pink bar – F.L (with 500 iterations)

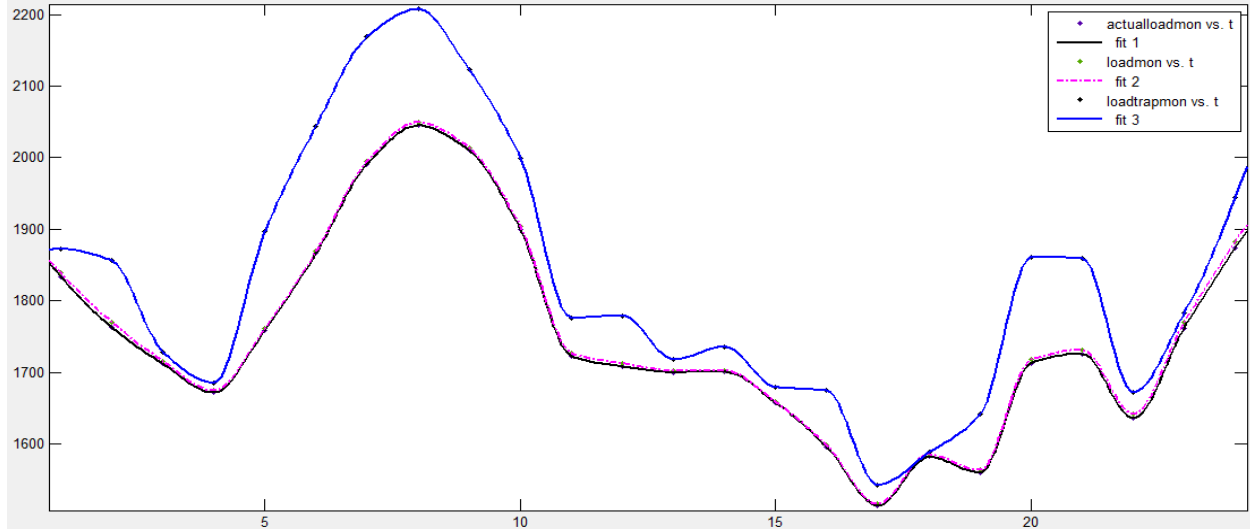


Fig 5.6: Comparison between ANN (using 500 iteration) and Fuzzy Logic (trapezoidal membership function)
 Black bar – actual load Vs time; Blue bar – F.L (trapezoidal MF, k=5) Vs time; Pink bar – ANN (with 500 iterations)

5.2.2 Case-II: Hourly Load Forecasting For Pre-Holiday

In this case, hourly load for JVN is forecasted for a pre-holiday i.e. Saturday (7th april). Training data used for this case is given in appendix table 3 and 4. The results in comparison with fuzzy logic model are summarized in table 5.2. The forecasted hourly load demand obtained from ANN model is plotted as shown in fig. 5.7 and compared with results obtained from fuzzy logic model as shown in fig. 5.8.

TABLE 5.2: Conventional load and absolute percentage error calculation for case -II

Time (hours)	Actual load (MW)	Back Propagation Neural Network Model		Fuzzy Logic Rule base Model			
		Number of iteration/s		Membership Function with fuzzy sets K=5			
		500	APE	Triangular	APE	trapezoidal	APE
1	1701	1708.65	0.45	1862.8	9.51	1734.0	1.94
2	1662	1670.47	0.51	1854.8	11.6	1700.4	2.31
3	1614	1617.71	0.23	1827.0	13.2	1747.0	8.24
4	1583	1587.90	0.31	1818.9	14.9	1640.1	3.61
5	1653	1657.46	0.27	1759.0	6.41	1805.9	9.25
6	1898	1901.22	0.17	1945.1	2.48	2196.0	15.7
7	2113	2115.95	0.14	2168.6	2.63	2312.3	9.43
8	2090	2093.34	0.16	2199.3	5.23	2165.7	3.62
9	1962	1965.53	0.18	2073.6	5.69	2064.2	5.21

10	1736	1740.86	0.28	1769.5	1.93	1757.7	1.25
11	1738	1740.60	0.15	1784.6	2.68	1845.9	6.21
12	1819	1822.09	0.17	1967.8	8.18	1932.3	6.23
13	1875	1878.56	0.19	2180.6	16.3	1942.9	3.62
14	1831	1832.64	0.09	2113.0	15.4	1864.1	1.81
15	1831	1832.28	0.07	2210.0	20.7	1873.3	2.31
16	1770	1773.01	0.17	2171.8	22.7	1872.0	5.76
17	1638	1645.69	0.47	2149.1	31.2	1725.0	5.31
18	1572	1577.50	0.35	2098.6	33.5	1626.7	3.48
19	1470	1474.55	0.31	1790.5	21.8	1523.1	3.61
20	1591	1594.81	0.24	1883.7	18.4	1801.0	13.2
21	1586	1590.28	0.27	1820.7	14.8	1785.8	12.6
22	1539	1543.77	0.31	1749.8	13.7	1734.5	12.7
23	1670	1675.51	0.33	1789.9	7.18	1807.1	8.21
24	1756	1763.37	0.42	1879.1	7.01	1865.4	6.23

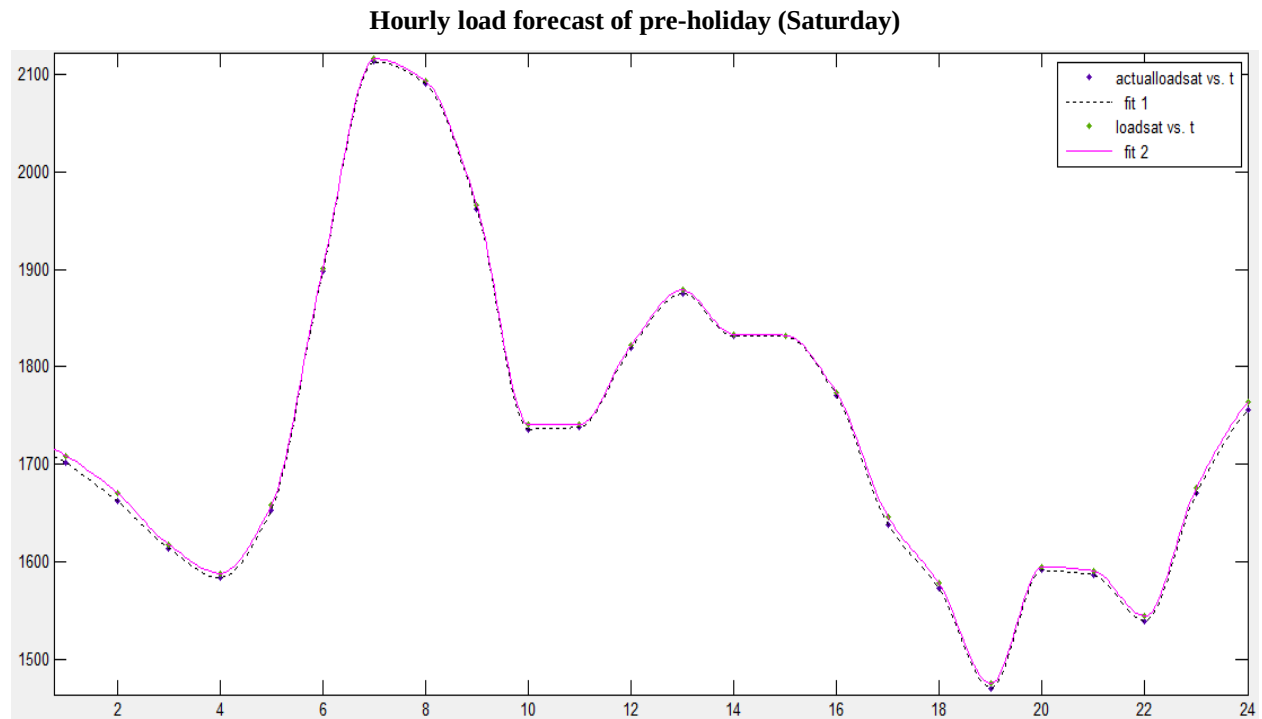


Fig 5.7: Comparison between Actual and ANN Forecasted Loads (using iteration 500)

Black bar – actual load Vs time; Pink bar – F.L (with 500 iterations)

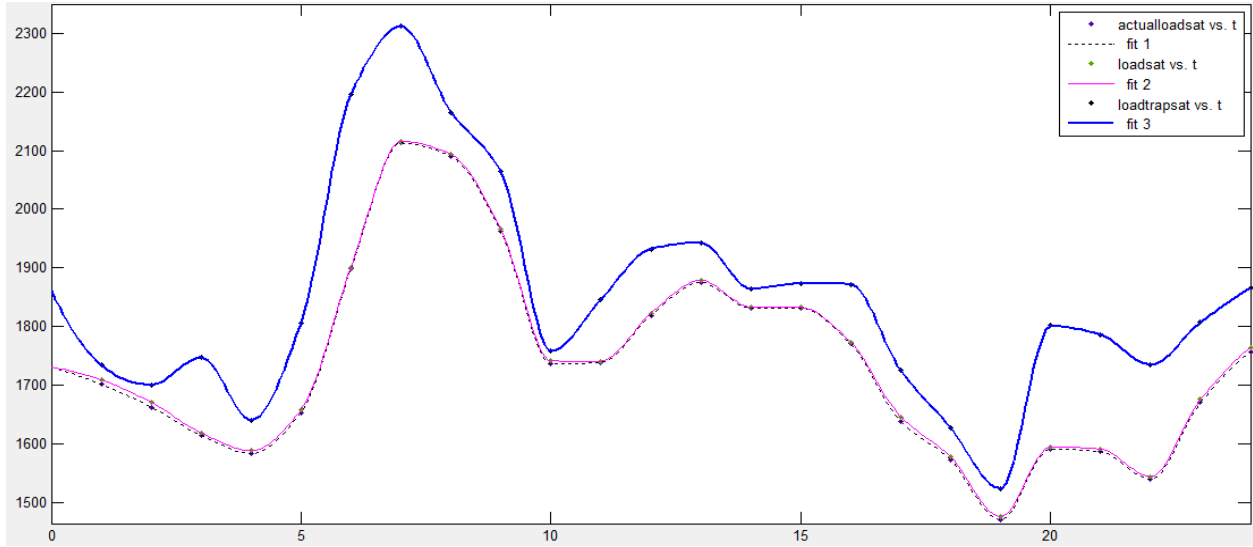


Fig 5.8: Comparison between ANN (using 500 iteration) and Fuzzy Logic (trapezoidal membership function $K=5$)
 Black bar – actual load Vs time; Blue bar – F.L (trapezoidal MF, $k=5$) Vs time; Pink bar – ANN (500 iterations)

5.2.3 Case -III: Hourly Load Forecasting For Weekday

In this case, among four weekdays i.e. Tuesday, Wednesday, Thursday, Friday hourly load for JVN is forecasted for Wednesday (4th april). Training and testing data used for this case is given in appendix Table 5 and 6. The actual load and forecasted load with absolute percentage error for ANN using lambda (sigmoidal constant) = 1, $\eta = .01$ and fuzzy logic is given in table 5.3. The forecasted hourly load demand obtained from ANN model is plotted as shown in fig. 5.9 and are compared with results obtained from fuzzy logic model as shown in fig. 5.10.

TABLE 5.3: Conventional load and absolute percentage error calculation for case -III

Time (hours)	Actual load (MW)	Back Propagation Neural Network Model		Fuzzy Logic Rule base Model			
		Number of iteration/s		Membership Function with fuzzy sets $K=5$			
		500	APE	Triangular	APE	trapezoidal	APE
1	1807	1810.07	0.17	1929.5	6.78	1824.9	.992
2	1777	1780.73	0.21	1926.8	8.43	1790.9	.783
3	1749	1751.62	0.15	1944.9	11.2	1793.8	2.56
4	1678	1679.84	0.11	1938.1	15.5	1811.1	7.93
5	1763	1768.64	0.32	2039.8	15.7	1815.0	2.95
6	1985	1991.94	0.35	2132.5	7.43	2149.4	8.28
7	2209	2218.94	0.45	2292.5	3.78	2580.1	16.8
8	2162	2173.24	0.52	2230.8	3.18	2338.0	8.14

9	2060	2062.47	0.12	2207.3	7.15	2133.7	3.58
10	1888	1892.34	0.23	1923.7	1.89	1918.8	1.63
11	1881	1883.82	0.15	1903.8	1.21	1913.5	1.73
12	1910	1914.58	0.24	1978.0	3.56	2016.2	5.56
13	1891	1895.72	0.25	1953.0	3.28	1994.8	5.49
14	1847	1850.32	0.18	1920.0	3.95	1917.6	3.82
15	1806	1807.80	0.10	1841.8	1.98	1840.7	1.92
16	1736	1739.81	0.22	1870.5	7.75	1778.7	2.46
17	1699	1703.24	0.25	1850.6	8.92	1788.2	5.25
18	1538	1538.76	0.05	1856.4	20.7	1604.4	4.32
19	1567	1568.88	0.12	1806.8	15.3	1612.3	2.89
20	1500	1502.70	0.18	1837.5	22.5	1531.5	2.10
21	1352	1354.29	0.17	1915.8	41.7	1512.9	11.9
22	1371	1372.09	0.08	1970.1	43.7	1517.7	10.7
23	1448	1449.30	0.09	1914.3	32.2	1555.2	7.40
24	1395	1396.53	0.11	1891.6	35.6	1516.2	8.69

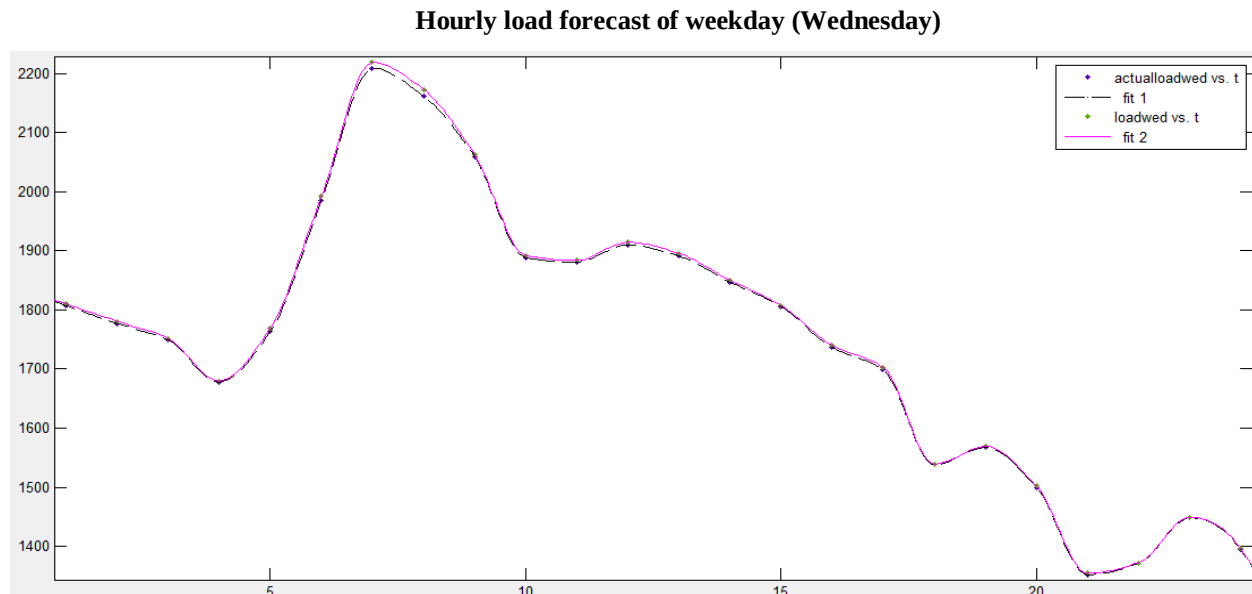


Fig 5.9: Comparison between Actual and ANN Forecasted Loads (using iteration 500)

Black bar – actual load Vs time; Pink bar – F.L (with 500 iterations)

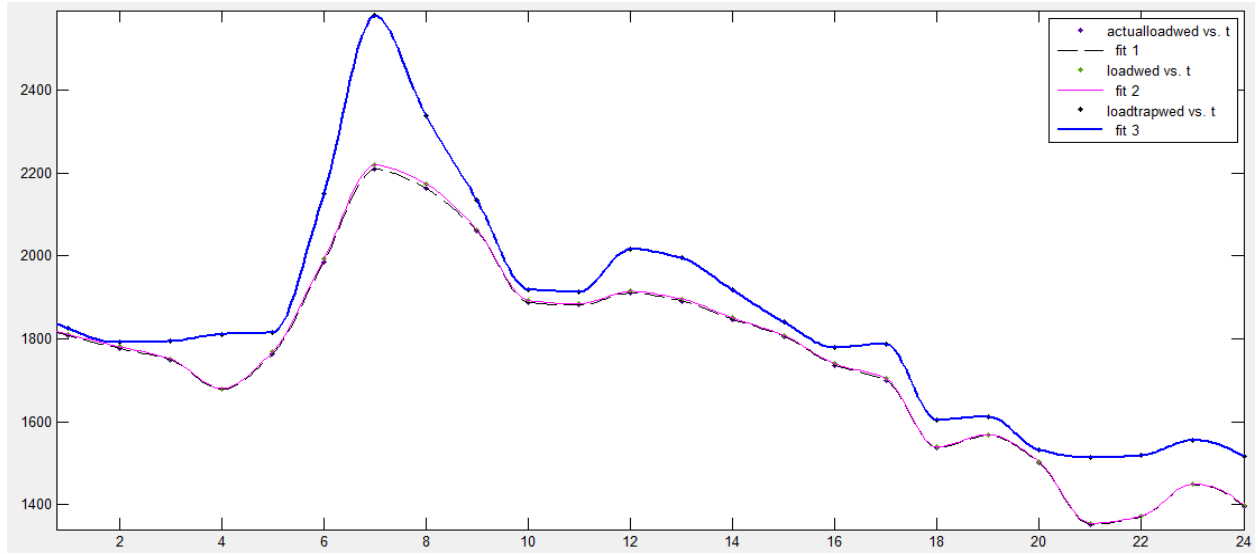


Fig 5.10: Comparison between ANN (using 500iteration) and Fuzzy Logic (trapezoidal membership function K=5)
Black bar – actual load Vs time; Blue bar – F.L (trapezoidal MF, k=5) Vs time; Pink bar – ANN (500 iterations)

5.2.4 Case –IV: Hourly Load Forecasting For Holiday

In this case, hourly load for JVN is forecasted for a holiday i.e. Sunday (8th april) . Training data used for this case is given in appendix table 7 and 8. The table includes temperature (°C), humidity (%), windspeed (km/h) and load (MW) information. The actual load and forecasted load with absolute percentage error for ANN using lambda (sigmoidal constant) = 1, eta = .01 and fuzzy logic is given in table 5.4. The forecasted hourly load demand obtained from ANN model is plotted as shown in fig. 5.11 and are compared with results obtained from fuzzy logic model as shown in fig. 5.12.

TABLE 5.4: Conventional load and absolute percentage error calculation for case -IV

Time (hours)	Actual load (MW)	ANN		Fuzzy Logic			
		Number of iteration		Membership Function			
		500	APE	Triangular	APE	Trapezoidal	APE
1	1691	1698.10	0.42	1728.4	2.21	1713.5	1.33
2	1584	1592.39	0.53	1624.1	2.53	1610.6	1.68
3	1535	1539.75	0.31	1640.5	6.87	1570.9	2.34
4	1476	1481.16	0.35	1507.9	2.16	1486.8	.732
5	1588	1592.44	0.28	1618.0	1.89	1622.8	2.19
6	1711	1715.27	0.25	1782.0	4.15	1861.2	8.78
7	1718	1722.12	0.24	1785.3	3.92	1996.3	16.2

8	1748	1750.97	0.17	1833.3	4.88	1896.8	8.51
9	1702	1705.06	0.18	1840.2	8.12	1792.5	5.32
10	1681	1683.18	0.13	2022.2	20.3	1772.3	5.43
11	1689	1691.53	0.15	1955.9	15.8	1714.0	1.48
12	1874	1879.43	0.29	2013.6	7.45	2039.5	8.83
13	1991	1997.17	0.31	2154.9	8.23	2077.4	4.34
14	2021	2025.85	0.24	2187.3	8.23	2183.3	8.03
15	1810	1814.88	0.27	1922.8	6.23	1989.4	9.91
16	1654	1657.47	0.21	1736.9	5.01	1730.4	4.62
17	1538	1542.30	0.28	1788.7	16.3	1584.8	3.04
18	1430	1432.14	0.15	1718.9	20.2	1559.0	9.02
19	1322	1323.58	0.12	1612.8	22.0	1418.1	7.27
20	1517	1519.57	0.17	2163.2	42.6	1693.0	11.6
21	1526	1528.13	0.14	2179.1	42.8	1649.6	8.10
22	1505	1507.71	0.18	2034.8	35.2	1654.1	9.91
23	1594	1597.02	0.19	2129.6	33.6	1772.5	11.2
24	1647	1649.79	0.17	2160.9	31.2	1778.9	8.01

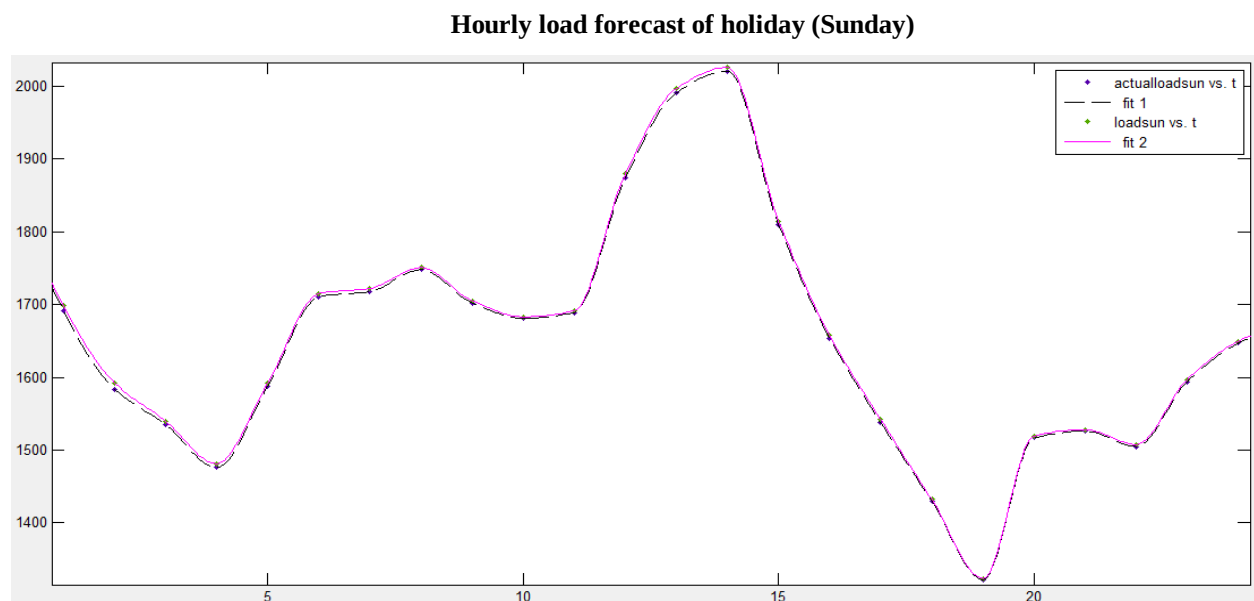


Fig 5.11: Comparison between Actual and ANN Forecasted Loads (using iteration 500)

Black bar – actual load Vs time; Pink bar – F.L (with 500 iterations)

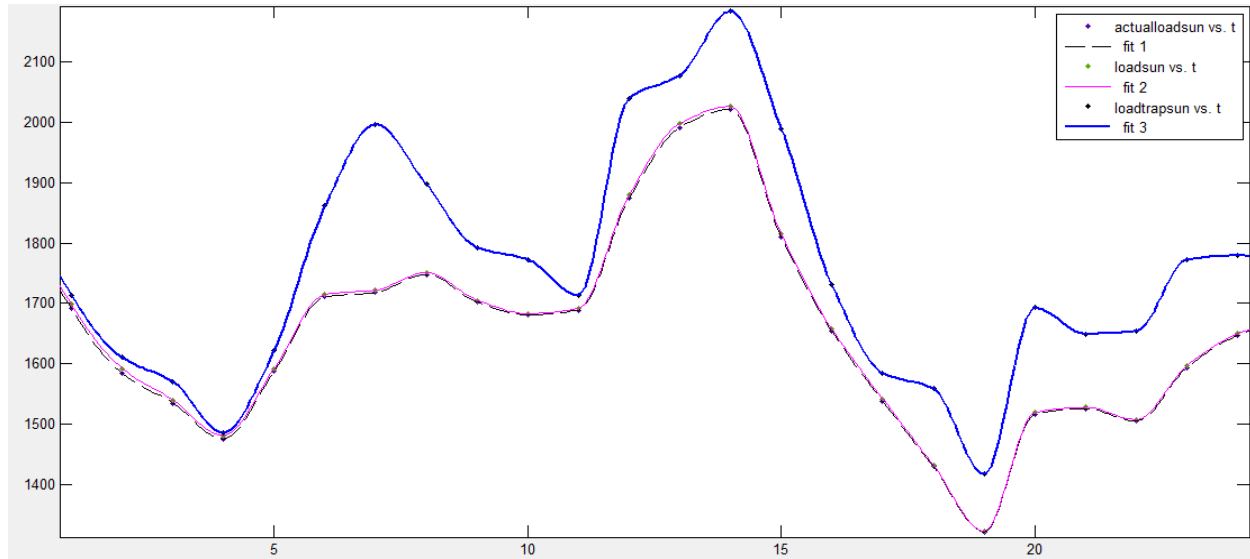


Fig 5.12: Comparison between ANN (500 iteration) and Fuzzy Logic (trapezoidal membership function $K=5$)
 Black bar – actual load Vs time; Blue bar – F.L (trapezoidal MF, $k=5$) Vs time; Pink bar – ANN (500 iterations)
 The mean percentage error in hourly load forecasting calculated over different days of the week is tabulated in table 5.5 along with comparison with results obtained from fuzzy logic model.

TABLE 5.5: Mean Absolute Percentage Errors (MAPE) for the predicted days

Day	MAPE with ANN (For number of iteration)			MAPE with Fuzzy Logic	
	200	300	500	Triangular	Trapezoidal
MONDAY	2.06	1.42	0.23	7.79	4.24
SATURDAY	1.72	1.35	0.26	12.7	6.32
WEDNESDAY	2.40	1.43	0.20	13.4	5.32
SUNDAY	1.85	1.40	0.24	14.6	6.02

5.2.5 Case –V: Peak Load Forecasting

In this case, peak hourly load for JVN is forecasted for weekdays and weekends i.e. from 23rd april to 29th april 201 with varying learning constant for 200, 100 and 50 iterations are summarized in table 5.6, 5.7, 5.8 respectively.

TABLE 5.6: Conventional load and absolute percentage error calculation for 200 iterations

Day	Actual Load(MW)	Learning Rate (η), number of iterations =200							
		.005	APE	.007	APE	.01	APE	.03	APE
MON	1784	1822.8	2.18	1813.2	1.64	1803.9	1.12	1784.8	0.05
TUE	1775	1811.7	2.07	1801.1	1.47	1791.1	0.91	1776.2	0.07
WED	1741	1778.6	2.16	1767.8	1.54	1757.7	0.96	1742.4	0.08

THUR	1661	1694.5	2.02	1683.9	1.38	1675.6	0.88	1661.6	0.04
FRI	1847	1888.0	2.22	1878.4	1.70	1868.2	1.15	1848.3	0.07
SAT	1772	1812.9	2.31	1801.9	1.69	1791.3	1.09	1773.4	0.08
SUN	1762	1803.9	2.38	1792.3	1.72	1781.0	1.08	1763.4	0.08

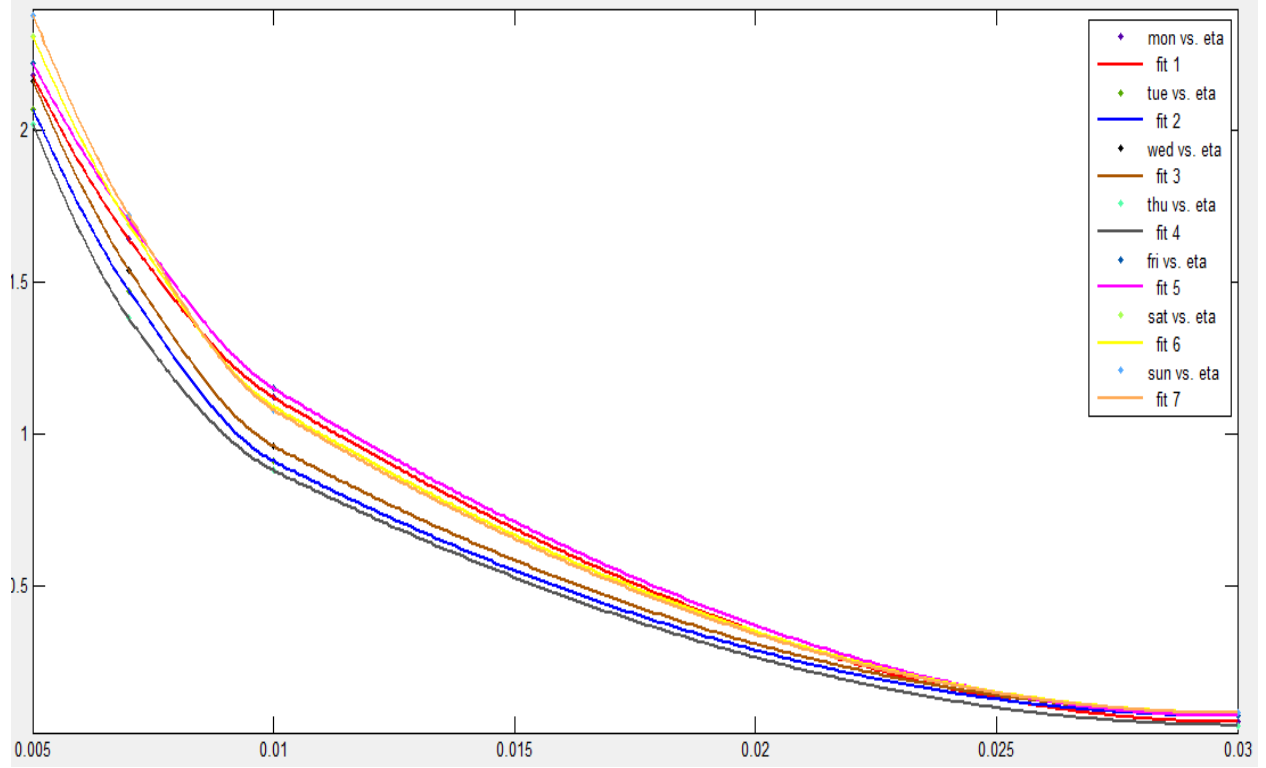


Fig 5.13: Comparison between Absolute percentage error and eta (learning rate) for iterations 200 (using learning rate $\eta = .005, .007, .01, .03$)

TABLE 5.7: Conventional load calculation for 100 iterations

Week	Actual load(MW)	Learning Rate (η), number of iterations =100				
		.005	.007	.01	.03	.05
MON	1784	1837.2	1831.3	1818.7	1790.7	1786.5
TUE	1775	1832.7	1823.1	1811.7	1782.8	1777.3
WED	1741	1799.8	1790.1	1778.7	1749.2	1743.3
THUR	1661	1719.5	1705.8	1698.2	1669.9	1664.5
FRI	1847	1895.7	1891.8	1882.3	1853.3	1850.3
SAT	1772	1820.7	1816.8	1813.8	1780.3	1775.0
SUN	1762	1826.5	1816.3	1804.1	1771.3	1764.6

Table 5.8: Absolute percentage error calculation for 100iterations

Week	APE($\eta=.005$)	APE($\eta=.007$)	APE ($\eta=.01$)	APE ($\eta=.03$)	APE ($\eta=.05$)
MON	2.98	2.65	1.95	0.38	0.14
TUE	3.25	2.71	2.07	0.44	0.13
WED	3.38	2.82	2.17	0.47	0.13
THUR	3.52	2.70	2.24	0.54	0.21
FRI	2.64	2.43	1.91	0.34	0.18
SAT	2.75	2.53	2.36	0.47	0.17
SUN	3.66	3.08	2.39	0.53	0.15

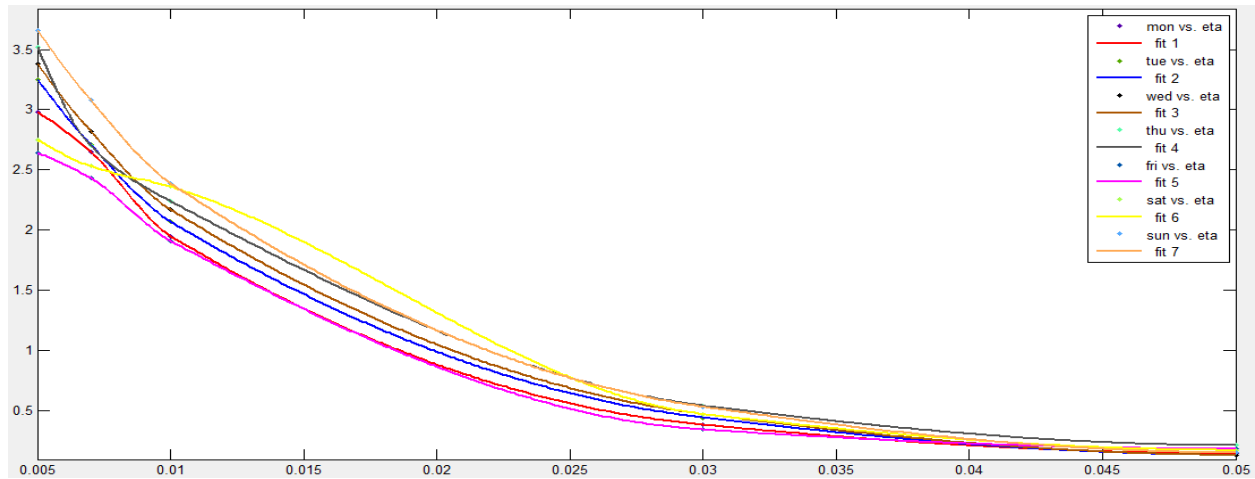


Fig 5.14: Comparison between Absolute percentage error and eta (learning rate) for 100 iterations

TABLE 5.9: Conventional load calculation for 50 iterations

Week	Actual load(MW)	Learning Rate (η), number of iterations =50				
		.005	.007	.01	.03	.05
MON	1784	1866.9	1864.8	1845.5	1816.6	1793.4
TUE	1775	1848.3	1841.5	1832.8	1799.3	1786.2
WED	1741	1815.3	1808.7	1800.0	1766.1	1752.6
THUR	1661	1734.5	1721.3	1713.8	1679.7	1672.9
FRI	1847	1934.2	1926.6	1912.0	1881.1	1854.9
SAT	1772	1853.6	1847.3	1836.6	1798.9	1781.9
SUN	1762	1842.6	1835.8	1862.6	1790.2	1775.2

Table 5.10: Absolute percentage error calculation for 50 iterations

Week	APE($\eta=.005$)	APE($\eta=.007$)	APE ($\eta=.01$)	APE ($\eta=.03$)	APE ($\eta=.05$)
MON	4.65	4.53	3.45	1.83	0.53
TUE	4.13	3.75	3.26	1.37	0.63
WED	4.27	3.89	3.39	1.44	0.67
THUR	4.43	3.63	3.18	1.13	0.72
FRI	4.72	4.31	3.52	1.85	0.43
SAT	4.61	4.25	3.65	1.52	0.56
SUN	4.58	4.19	3.67	1.60	0.75

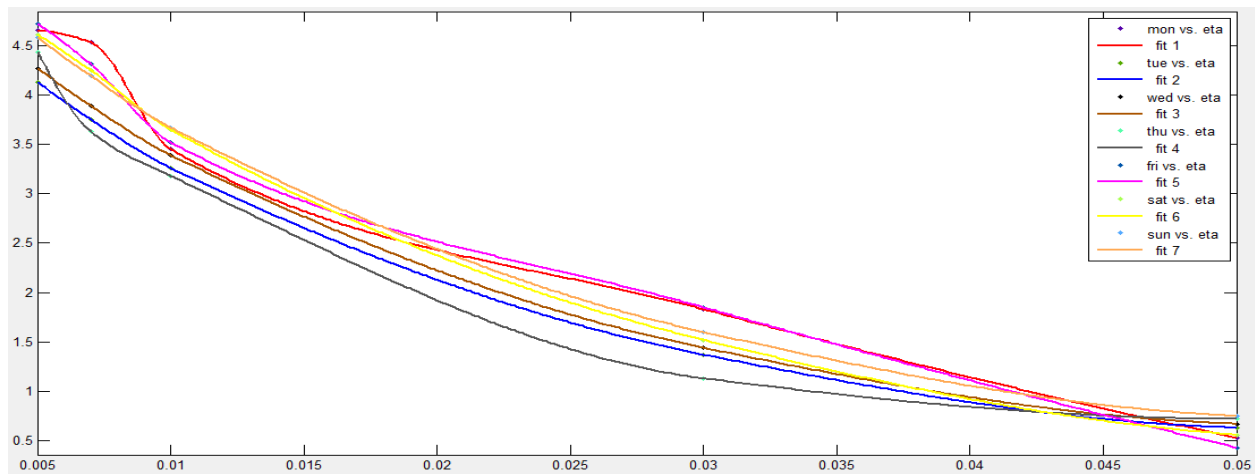


Fig 5.15: Comparison between Absolute percentage error and eta (learning rate) for iterations 50 (using learning rate $\eta = .005, .007, .01, .03, .05, .07$)

From the above discussed cases I, II, III, IV, it is observed on the bases of APE and MAPE, the ANN technique with 500 iterations is more effective and gives a better hourly forecast accuracy. The figures 5.13, 5.14 and 5.15 show that the APE varying dramatically with the change in the number of iterations. Also, it is concluded from the results that proposed artificial neural network approach is better than fuzzy logic approach based on forecast accuracy although the network configuration takes more computational time.

In case V, the result shows with the increase in learning rate the average percentage error (APE) reduces but with the decrease in number of iterations, the error increases.

CHAPTER 6

CONCLUSIONS AND FUTURE SCOPE OF WORK

6.1 Conclusions

The results of fuzzy logic and artificial neural network technique for short term hourly load forecasting for the Jodhpur city, are investigated and shows that the proposed non-fully connected artificial neural network technique gives a good performance and reasonable prediction accuracy is achieved. Its forecasting reliabilities were evaluated by computing the mean absolute error between the exact and predicted values. The mean absolute percentage error is in the range of .05% to .55% using artificial neural network with 500 iterations in comparison of using fuzzy logic with triangular and trapezoidal membership function.

In case of short term peak load forecasting, the absolute percentage error suggest that by increasing learning rate and number of iterations using artificial neural network gives the higher degree of accurate result.

6.2 Future Scope of Work

The mean absolute percentage error in the forecasting the load can even be lowered if a large and accurate training data is used to train artificial the neural network. The absolute percentage error can be reduced further by combining the fuzzy system with the artificial neural network structure. Future studies on this work can incorporate additional information such as season of the year and other weather parameters like wind speed, sky cover and rainfall etc. into the network so as to obtain a more representative forecast of future load.

PUBLICATIONS

1. Gupta M., Kaur M., “Weather sensitive short term load forecasting using fuzzy logic reasoning”, 15th Punjab Science Congress, Guru Nanak Dev University, Amritsar Feb 7-9, 2012. (presented)
2. Gupta M., Kaur M., “Artificial Neural Network approach for short term weather dependent load forecasting” ,IEEE Sponsored 2nd International Conference on Power, Control and Embedded Systems, 2012, Allahabad. (communicated)

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APPENDIX

The results are obtained by using the data set given below in table.

The data set for case -1 is given below:-

TABLE 1. Weather data for case –1 with first four data set for training and fifth data set for testing.

T1, H1, W1 –represents temperature, humidity, Windspeed for 5th march.

T2, H2, W2 –represents temperature, humidity, Windspeed for 12th march.

T3, H3, W3 –represents temperature, humidity, Windspeed for 19th march.

T4, H4, W4 –represents temperature, humidity, Windspeed for 26th march.

T5, H5, W5 –represents temperature, humidity, Windspeed for 2nd april.

t	T1	T2	T3	T4	T5	H1	H2	H3	H4	H5	W1	W2	W3	W4	W5
1	25	19	26	25	29	29	26	37	13	20	24	13	0	7	6
2	24	19	25	24	28	31	26	36	14	21	23	15	0	4	6
3	23	19	23	23	28	34	28	47	15	21	22	19	0	3	6
4	22	18	22	25	27	36	34	44	16	21	20	17	0	2	7
5	22	18	22	24	28	39	34	41	17	21	20	15	0	1	8
6	21	17	21	23	28	41	37	46	19	20	19	19	0	4	9
7	21	17	21	22	29	43	39	46	16	19	21	17	0	6	9
8	21	17	21	20	30	44	37	46	17	17	22	17	0	9	9
9	22	17	21	19	32	43	35	50	17	16	23	22	0	8	10
10	23	18	22	24	34	42	33	47	16	15	24	19	13	8	10
11	25	19	26	25	35	37	29	39	16	13	26	20	11	8	9
12	27	20	29	26	37	31	18	31	14	12	28	28	11	8	9
13	29	22	30	28	38	27	19	31	12	12	29	24	9	8	9
14	30	26	33	30	39	23	19	28	11	11	30	20	9	8	9
15	31	28	34	32	39	20	20	26	11	11	31	20	9	9	10
16	32	28	34	34	38	18	19	23	12	11	29	17	13	9	10
17	32	28	35	36	38	17	19	22	12	12	28	19	9	9	10
18	31	29	36	36	36	18	20	19	13	12	27	19	9	10	11
19	30	29	37	36	34	18	20	17	13	14	22	17	17	12	10
20	28	28	37	36	33	20	20	18	12	14	18	15	9	13	9
21	27	28	37	35	32	22	20	15	12	15	13	15	4	14	9
22	25	28	33	24	31	24	20	18	12	16	10	9	0	15	7

23	24	27	31	34	30	26	21	18	12	17	8	13	9	16	5
24	22	27	28	33	30	29	21	18	12	19	8	13	9	16	4

TABLE 2. Load data for case –1 with data set for training and testing.

L1, L2 –represents load for 26th and 27thfebruary.

L3, L4 -represents load for 5th and 6th march.

L5, L6 -represents load for 12th and 13th march.

L7, L8 -represents load for 19th and 20th march.

L9, L10 -represents load for 26th and 27th march.

L11, L12 -represents load for 4th and 5thapril.

t	L1	L2	L3	L4	L5	L6	L7	L8	L9	L10	L11	L12
1	1868	2067	2022	2041	1944	2070	2144	2106	1939	1800	1837	1834
2	1917	2036	2010	1956	1922	2031	2134	2057	1909	1980	1780	1763
3	1894	1964	2001	1872	1904	2027	2108	2020	1880	1940	1750	1712
4	1779	1899	1916	1754	1785	1864	2067	1917	1773	1910	1688	1672
5	1701	1874	1821	1728	1702	1770	1997	1946	1749	1843	1692	1759
6	1851	1963	1919	1941	1832	1729	2024	2013	1862	1959	1790	1866
7	2149	2181	2030	2201	2070	1887	2198	2240	2134	2193	1862	1991
8	2217	2218	2034	2156	2138	1952	2262	2244	2162	2201	1893	2045
9	2122	2224	1998	2146	2107	2017	2245	2142	2103	2136	1903	2010
10	2172	2059	1932	2135	2017	1907	2182	2003	2059	2087	1936	1900
11	2215	2051	2119	2153	2007	1959	2133	2009	2100	2080	1981	1723
12	2303	1954	2007	2188	2071	2117	2103	2045	2072	2067	2064	1708
13	2303	2001	2070	2105	2047	2159	2230	2073	2120	2125	2053	1700
14	2187	2038	2238	2091	2036	2085	2120	2020	2009	2059	1959	1701
15	2142	1951	2071	2031	1969	1968	2004	1902	1898	2000	2045	1658
16	2070	1902	1872	1961	1866	1882	2061	1724	1892	1923	1961	1596
17	1859	1967	1945	1816	1833	1808	1985	1681	1872	1794	1865	1514
18	1744	1885	1918	1737	1677	1688	1816	1615	1704	1621	1720	1582
19	1701	1795	1862	1784	1594	1614	1676	1795	1611	1538	1630	1560
20	1844	1955	1986	2006	1824	1789	1865	1767	1790	1740	1770	1713

21	1737	1772	1809	1916	1774	1671	1792	1929	1809	1728	1730	1726
22	1896	1966	1863	2115	1845	1837	1938	1814	1839	1836	1725	1636
23	2094	2051	2097	2135	2034	2054	2000	2094	1872	1968	1859	1762
24	2035	2131	2001	2226	2113	2109	2160	2128	1856	2020	1912	1874

The data set for case -2 is given below:-

TABLE 3.Weather data for case –2 with first four data set for training and fifth data set for testing.

T1, H1, W1 –represents temperature, humidity, Windspeed for 10th march.

T2, H2, W2 –represents temperature, humidity, Windspeed for 17th march.

T3, H3, W3 –represents temperature, humidity, Windspeed for 24th march.

T4, H4, W4 –represents temperature, humidity, Windspeed for 31st march.

T5, H5, W5 –represents temperature, humidity, Windspeed for 7th april.

t	T1	T2	T3	T4	T5	H1	H2	H3	H4	H5	W1	W2	W3	W4	W5
1	15	25	25	27	32	31	20	9	21	21	6	5	12	9	5
2	15	25	24	26	31	31	21	10	23	20	4	8	12	6	5
3	16	25	24	25	30	27	24	11	25	19	4	11	12	4	3
4	13	25	23	25	30	36	28	11	27	24	0	14	12	3	2
5	11	25	23	25	29	38	30	12	29	22	0	14	12	3	2
6	12	25	23	25	29	35	31	12	31	26	0	14	12	2	2
7	10	25	23	25	28	43	33	13	32	33	0	14	13	3	3
8	15	25	23	25	28	31	34	14	26	31	7	14	13	4	3
9	17	21	23	26	31	30	38	14	24	26	9	14	13	5	3
10	18	25	24	27	29	30	36	14	23	37	11	14	13	5	3
11	20	25	25	28	30	28	34	12	21	30	13	14	13	6	3
12	21	25	26	29	32	29	31	11	18	25	11	14	13	6	5
13	23	26	28	31	36	20	28	9	16	16	11	14	11	5	5
14	25	28	30	33	37	15	24	8	13	12	9	14	10	5	6
15	25	29	31	34	39	15	20	7	12	10	6	13	9	4	8
16	26	30	31	34	41	16	18	8	12	18	6	13	9	4	8

17	25	30	30	33	40	17	17	8	12	8	4	13	9	4	10
18	24	30	30	33	39	16	17	8	12	9	4	13	9	4	10
19	23	30	29	32	38	19	17	9	13	9	0	12	10	5	10
20	19	29	29	30	36	24	18	9	15	9	0	11	12	6	11
21	20	28	28	30	35	23	19	10	14	10	2	10	13	8	10
22	20	28	28	30	34	23	19	10	15	10	9	9	14	9	10
23	19	27	27	30	34	24	20	11	16	10	9	8	14	10	10
24	17	27	26	29	32	27	20	12	17	11	11	8	15	11	10

TABLE 4. Load data for case –2 with data set for training and testing.

L1, L2 –represents load for 2nd and 3rd march.

L3, L4 -represents load for 9th and 10th march.

L5, L6 -represents load for 16th and 17th march.

L7, L8 -represents load for 23rd and 24th march.

L9, L10 -represents load for 30th and 31st march.

L11, L12 -represents load for 6th and 7th april.

t	L1	L2	L3	L4	L5	L6	L7	L8	L9	L10	L11	L12
1	1892	2083	1998	2137	2190	2019	2044	1917	1967	1801	1846	1701
2	1901	2064	1985	2108	2146	2054	2019	1983	1959	1790	1791	1662
3	1903	2015	1967	2094	2131	2058	1945	1976	1930	1866	1718	1614
4	1911	2012	1874	1988	2038	1959	1855	1904	1885	1830	1636	1583
5	1855	1940	1799	1874	1939	1891	1764	1850	1852	1797	1684	1653
6	1862	2102	1977	1814	1997	2023	1907	1923	1855	1847	1883	1898
7	2009	2258	2147	2011	2030	2114	1985	2049	2093	2084	2093	2113
8	2054	2387	2261	2230	2264	2248	2103	2165	2146	1984	2092	2090
9	1989	2352	2164	2193	2116	2193	2028	2091	2072	2059	2002	1962
10	2001	2223	2034	1975	2041	2064	1999	2000	2080	2004	1760	1736
11	1877	2177	2125	1956	2181	2141	1925	2063	2132	2039	1757	1738
12	1942	2096	2115	2052	2164	2164	1939	2081	2016	2066	1871	1819

13	1952	2138	2123	2039	2213	1997	1924	2079	2088	2054	1903	1875
14	2051	2150	2045	2007	2147	1985	2065	2078	2121	2067	1885	1831
15	1836	2111	1975	1870	2091	1891	2039	1942	2037	1892	1908	1831
16	1755	2002	1879	1811	2021	2023	1995	1815	1942	1957	1805	1770
17	1848	1869	1743	1811	1943	2037	1811	1828	1886	1944	1672	1638
18	1909	1856	1631	1722	1770	1906	1708	1798	1776	1832	1612	1572
19	1859	1785	1574	1637	1614	1778	1610	1698	1592	1732	1546	1470
20	1970	1921	1786	1788	1823	1914	1788	1856	1801	1838	1645	1591
21	1871	1793	1753	1707	1799	1873	1794	1833	1787	1813	1653	1586
22	1954	1923	1895	1845	1948	2013	1836	1839	1898	1785	1739	1539
23	2118	2216	2124	2090	1926	1900	1889	1886	1906	1900	1780	1670
24	2067	2196	2201	1942	2023	2026	2004	1873	1826	1876	1793	1756

The data set for case -3 is given below:-

TABLE 5.Weather data for case –3 with first four data set for training and fifth data set for testing.

T1, H1, W1 –represents temperature, humidity, Windspeed for 7th march.

T2, H2, W2 –represents temperature, humidity, Windspeed for 14th march.

T3, H3, W3 –represents temperature, humidity, Windspeed for 21st march.

T4, H4, W4 –represents temperature, humidity, Windspeed for 28th march.

T5, H5, W5 –represents temperature, humidity, Windspeed for 4th april.

t	T1	T2	T3	T4	T5	H1	H2	H3	H4	H5	W1	W2	W3	W4	W5
1	21	19	13	28	30	20	30	38	15	20	17	0	17	19	18
2	20	18	12	27	29	19	32	38	18	21	17	0	17	13	18
3	19	18	10	26	28	18	32	37	34	22	18	0	16	11	18
4	19	17	10	25	28	17	34	36	35	23	18	6	16	9	18
5	18	15	10	25	28	17	39	35	35	24	17	0	16	6	17
6	18	16	9	25	28	19	42	34	36	26	16	7	16	0	17
7	18	14	9	26	28	21	51	35	37	27	15	0	16	6	17
8	18	13	9	26	27	22	59	38	37	30	14	0	16	17	16

9	19	16	10	27	28	22	48	38	38	29	13	0	15	9	16
10	21	18	12	30	28	22	46	37	35	28	13	7	16	13	15
11	24	21	16	31	30	19	38	34	29	26	11	7	16	7	15
12	25	24	18	33	31	17	27	31	28	24	9	6	16	4	14
13	25	25	24	34	33	16	18	27	24	21	8	4	16	7	12
14	26	27	25	34	34	15	15	25	26	18	8	7	17	6	10
15	26	27	25	35	36	13	15	23	27	16	8	9	17	9	9
16	27	27	25	35	35	12	17	25	25	16	8	9	17	19	8
17	27	28	25	35	35	12	15	30	20	16	9	9	17	13	8
18	26	27	25	34	35	12	17	37	25	15	9	13	17	11	8
19	25	27	20	33	34	13	17	42	24	16	10	7	16	6	11
20	24	25	18	33	34	15	19	46	23	15	9	11	16	7	14
21	24	24	17	32	33	16	22	46	22	15	8	7	15	7	17
22	23	23	16	31	33	16	23	47	21	16	8	7	15	7	17
23	23	19	14	30	32	17	28	48	20	16	11	0	15	0	16
24	21	20	13	30	31	18	28	51	20	18	14	0	15	6	16

TABLE 6. Load data for case –3 with data set for training and testing.

L1, L2 –represents load for 28th and 29thfebruary.

L3, L4 -represents load for 6th and 7th march.

L5, L6 -represents load for 13th and 14th march.

L7, L8 -represents load for 20th and 21st march.

L9, L10 -represents load for 27th and 28th march.

L11, L12 -represents load for 3rd and 4thapril.

t	L1	L2	L3	L4	L5	L6	L7	L8	L9	L10	L11	L12
1	2118	2100	2187	2180	2001	2111	2209	2121	1838	1817	1687	1807
2	2127	2128	2141	2165	2006	2078	2181	1995	1852	1800	1658	1777
3	2150	2107	2167	2165	1987	2046	2121	1952	1831	1916	1598	1749
4	2094	2043	2123	2176	1916	1948	2031	1862	1781	1873	1515	1678

5	2067	1909	2026	2059	1896	1830	2011	1799	1744	1793	1587	1763
6	1979	1894	2092	2124	2055	1924	2168	1978	1888	1837	1736	1985
7	2143	2162	2302	2210	2271	2042	2326	2168	2024	2182	2137	2209
8	2237	2239	2165	2282	2301	2169	2257	2156	2156	2129	2137	2162
9	2305	2253	2278	2301	2212	2089	2164	2129	2052	2019	2079	2060
10	2249	2149	2224	2205	2108	1951	2098	2098	2032	1945	1869	1888
11	2083	2109	2234	2121	2015	1969	2065	2031	2092	2010	1944	1881
12	2132	2139	2215	2161	2095	2095	2118	2002	2133	2011	1846	1910
13	2218	2233	2178	2143	2035	2205	2107	2024	2217	2014	1750	1891
14	2167	2127	2131	2023	1910	2032	2065	2029	2149	1956	1869	1847
15	2018	1989	2083	1854	1828	2009	2036	1993	2094	1788	1729	1806
16	1975	1931	2023	1776	1875	1969	1965	1933	2039	1916	1796	1736
17	1926	1861	1898	1648	1938	1995	1855	1800	1916	1889	1759	1699
18	1870	1762	1792	1542	1817	1845	1779	1713	1789	1813	1774	1538
19	1806	1686	1702	1576	1714	1771	1911	1597	1691	1747	1650	1567
20	1955	1866	1900	1800	1862	1866	1857	1770	1897	1877	1818	1500
21	1880	1715	1809	1702	1822	1799	1935	1764	1875	1811	1750	1352
22	2016	1808	1989	1861	1952	1857	2093	1874	1988	1861	1666	1371
23	2144	2078	1914	2001	1999	2142	2151	1896	2087	2017	1774	1448
24	2062	2118	1933	2033	2200	2225	2232	1941	1884	1837	1850	1395

The data set for case -4 is given below:-

TABLE 7. Weather data for case -4 with first four data set for training and fifth data set for testing.

T1, H1, W1 –represents temperature, humidity, Windspeed for 11th march.

T2, H2, W2 –represents temperature, humidity, Windspeed for 18th march.

T3, H3, W3 –represents temperature, humidity, Windspeed for 25th march.

T4, H4, W4 –represents temperature, humidity, Windspeed for 1st april.

T5, H5, W5 –represents temperature, humidity, Windspeed for 8th april.

t	T1	T2	T3	T4	T5	H1	H2	H3	H4	H5	W1	W2	W3	W4	W5
1	18	26	25	27	30	28	25	9	19	36	11	7	14	8	0
2	18	26	24	26	29	30	26	11	21	31	15	9	14	4	0
3	18	26	24	25	28	30	28	12	23	27	15	12	14	1	0
4	13	26	24	25	28	30	29	13	26	35	13	12	14	3	0
5	13	25	24	25	28	44	30	14	28	29	6	12	13	4	0
6	13	25	24	25	27	41	32	15	26	31	9	12	12	6	0
7	16	25	24	27	25	39	34	16	22	40	7	12	12	7	0
8	18	25	24	28	25	41	38	17	21	35	9	11	11	9	2
9	18	25	24	30	28	34	36	17	21	28	13	10	10	10	3
10	20	25	24	31	29	32	34	16	19	42	19	10	9	10	3
11	21	26	25	33	30	32	31	14	17	34	19	10	9	10	3
12	23	27	27	35	32	30	28	12	15	28	15	10	8	11	5
13	25	09	28	36	37	31	23	11	14	15	17	10	7	12	3
14	27	31	30	37	39	25	19	9	12	12	13	10	6	12	5
15	26	32	31	36	40	18	17	9	11	10	15	10	5	13	6
16	26	32	31	36	40	13	16	9	11	14	15	10	5	12	5
17	27	32	31	35	31	15	16	9	12	21	13	10	6	12	3
18	26	31	31	33	30	13	16	9	12	21	11	10	7	11	5
19	26	30	30	32	30	12	17	10	13	19	13	8	9	10	5
20	23	29	29	31	30	13	18	10	15	18	9	7	10	10	5
21	21	28	29	30	31	13	19	10	15	17	7	5	12	9	5
22	20	28	29	29	28	16	20	11	16	21	9	5	13	8	6
23	20	27	28	28	29	20	21	11	17	21	13	5	13	7	6
24	22	27	27	27	30	21	22	12	18	22	13	5	14	6	8

TABLE 8. Load data for case –4 with data set for training and testing.

L1, L2 –represents load for 3rd and 4th march.

L3, L4 -represents load for 10th and 11th march.

L5, L6 -represents load for 17th and 18th march.

L7, L8 -represents load for 24rd and 25th march.

L9, L10 -represents load for 31st march and 1st april.

L11, L12 -represents load for 7th and 8th april.

t	L1	L2	L3	L4	L5	L6	L7	L8	L9	L10	L11	L12
1	2083	2022	2137	1944	2019	2144	1917	1939	1801	1837	1701	1691
2	2064	2010	2108	1922	2054	2134	1983	1909	1790	1780	1662	1584
3	2015	2001	2094	1904	2058	2108	1976	1880	1866	1750	1614	1535
4	2012	1916	1988	1785	1959	2067	1904	1773	1830	1688	1583	1476
5	1940	1821	1874	1702	1891	1997	1850	1749	1797	1692	1653	1588
6	2102	1919	1814	1832	2023	2024	1923	1862	1847	1790	1898	1711
7	2258	2030	2011	2070	2114	2198	2049	2134	2084	1862	2113	1718
8	2387	2034	2230	2138	2248	2262	2165	2162	1984	1893	2090	1748
9	2352	1998	2193	2107	2193	2245	2091	2103	2059	1903	1962	1702
10	2223	1932	1975	2017	2064	2182	2000	2059	2004	1936	1736	1681
11	2177	2119	1956	2007	2141	2133	2063	2100	2039	1981	1738	1689
12	2096	2007	2052	2071	2164	2103	2081	2072	2066	2064	1819	1874
13	2138	2070	2039	2047	1997	2230	2079	2120	2054	2053	1875	1991
14	2150	2238	2007	2036	1985	2120	2078	2009	2067	1959	1831	2021
15	2111	2071	1870	1969	1891	2004	1942	1898	1892	2045	1831	1810
16	2002	1872	1811	1866	2023	2061	1815	1892	1957	1961	1770	1654
17	1869	1945	1811	1833	2037	1985	1828	1872	1944	1865	1638	1538
18	1856	1918	1722	1677	1906	1816	1798	1704	1832	1720	1572	1430
19	1785	1862	1637	1594	1778	1676	1698	1611	1732	1630	1470	1322
20	1921	1986	1788	1824	1914	1865	1856	1790	1838	1770	1591	1517
21	1793	1809	1707	1774	1873	1792	1833	1809	1813	1730	1586	1526
22	1923	1863	1845	1845	2013	1938	1839	1839	1785	1725	1539	1505
23	2216	2097	2090	2034	1900	2000	1886	1872	1900	1859	1670	1594
24	2196	2001	1942	2113	2026	2160	1873	1856	1876	1912	1756	1647