

SHORT TERM LOAD FORECASTING USING TYPE-II FUZZY LOGIC SYSTEMS

Dissertation submitted in partial fulfilment for the award of degree of

MASTER OF ENGINEERING IN POWER SYSTEMS

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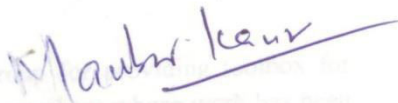
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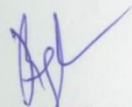
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ABSTRACT

The main objective of short term load forecasting (STLF) is to provide load predictions for generation scheduling, economic load dispatch and security assessment at any time.

This dissertation presents a solution methodology using Type-1 Fuzzy Logic approach and Type-2 Fuzzy Logic approach for short term load forecasting and is implemented on historical data that includes temperature, humidity, wind speed and load data for forecasting the load. The proposed Type-2 Fuzzy Logic approach has been implemented on weather sensitive data and the accuracy of the results has been compared with Type-1 Fuzzy Logic approach.

Jaipur Vidyut Nigam hourly load data is collected from State Load Dispatch and Communication Centre, Rajasthan Vidyut Parasaran Nigam. The results are obtained from two different approaches are compared and the accuracy of Type-2 Fuzzy Logic approach is reported as better.

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1.1 Overview

Load forecasting is an integral element of power system operation and planning that involves the prediction of the future load demand to serve as the basis of both supply side and demand side planning. The load requirements are to be predicted in advance so that the power system operates effectively and efficiently [1].

Load forecasting helps us to estimate load flows and to make decisions that can prevent overloading of power system. Economic and reliable operations of an electric utility depend to a significant extent on the accuracy of the load forecast. The load dispatcher at main dispatch centre must predict the load pattern well in advance so as to have sufficient generation to meet the customer needs. Overestimation may cause the start up 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 to collapse of the power system network [2].

In power systems many uncertainties arises due to various factors like aging of machines, unexpected load, fluctuations, losses in transmission lines, voltage and frequency instability and change of weather conditions. These factors are difficult to deal with many power system problems through straight mathematical formulations alone. Therefore, fuzzy set theory based approach, in recent years has emerged as a complement tool to mathematical approach for solving power system problems. The wonderful world of fuzzy logic is a powerful new paradigm, helping us to analyse unknown and complicated systems [3]. Owing to the importance of fuzzy logic various methods have been reported, that includes linear regression, exponential smoothing, stochastic process, ARIMA models [4], etc. In this dissertation, we propose an approach for short term load forecasting problem, using type-1 and type-2 fuzzy logic approach. These approaches has an advantage of dealing with non linear parts of the forecasted load curves, and also has the ability to deal with the abrupt change in the weather variables such as temperature, humidity, wind speed etc.

1.2 Literature Review

Load forecasting is the prediction of the power usage for a chosen area at a particular instant of time, which can be implemented using several different techniques that include:

- Statistical methods (Such as regression models, time series models, ARIMA).
- Expert methods (ANN; fuzzy logic systems; evolutionary algorithm).
- Hybrid methods.

1.2.1 Statistical Models

The statistical category includes multiple linear regression [5], stochastic time series [6], general exponential smoothing [7], state space [8], etc. Recently support vector regression (SVR) [6, 7], which is a very promising statistical learning method, has also been applied to short-term load

forecasting and has shown good results. Usually statistical methods can predict the load curve of ordinary days very well, but they lack the ability to analyze the load property of holidays and other anomalous days, due to the inflexibility of their structure.

Regression Methods

Regression is one of most widely used statistical techniques. For load forecasting regression methods are usually employed to model the relationship of load consumption and other factors such as weather, day type and customer class. A.D et al. [5] presented several regression models for the next day load forecasting. Their models incorporate deterministic influences such as holidays, stochastic influences such as average loads, and exogenous influences such as weather. [6], [7], [8] and [9] describe other applications of regression models applied to load forecasting.

Time Series

Time series methods are based on the assumption that the data have an internal structure, such as autocorrelation, trend or seasonal variation. The methods detect and explore such a structure. Time series have been used for decades in such fields as economics, digital signal processing, as well as electric load forecasting [6].

Autoregressive Integrated Moving Average (ARIMA)

In particular, ARMA (auto regressive moving average), ARIMA (autoregressive integrated moving average) and ARIMAX (autoregressive integrated moving average with exogenous variables) are the most often used classical time series methods. ARMA models are usually used for stationary processes while ARIMA is an extension of ARMA to non stationary processes. ARMA and ARIMA use the time and load as the only input parameters. Since load generally depends on the weather and time of the day, ARIMAX is the most natural tool for load forecasting among the classical time series models. Cho et al. [8] described implementations of ARIMAX models for load forecasting. Yang et al. [9] used an evolutionary programming (EP) approach to identify the ARMAX model parameters for one day to one week ahead hourly-load-demand-forecasting. The evolutionary programming is a method for simulating evolution and constitutes a stochastic optimization algorithm. Yang and Huang [9] proposed a fuzzy autoregressive moving average with exogenous input variables (FARMAX) for one day ahead hourly load forecasting.

1.2.2 Expert Methods

Artificial Neural Networks

The use of artificial neural networks (ANN or simply NN) has been a widely studied load forecasting technique since 1990 [10]. Neural networks are non-linear circuits that have the demonstrated capability to do non-linear curve fitting. The outputs of an artificial neural network are some linear or non-linear 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. In applying a neural network to load forecasting, one must select one out of a number of architectures (e.g. Hopfield, back propagation, Boltzmann machine), the number and connectivity of

layers and elements, use of bi-directional or uni-directional links and the number format (e.g. binary or continuous) to be used by inputs and outputs [10]. The most popular artificial neural network architecture for load forecasting is back propagation. This network uses 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 output. Artificial neural networks with unsupervised learning do not require pre-operational training. In the development they used a fully connected three-layer feed forward ANN and a back propagation algorithm was used for training. Input variables include historical hourly load data, temperature, and the day of week. The model can forecast load profiles from one to seven days. Also Papalexopoulos et al. [11] developed and implemented a multi-layered feed forward ANN for short-term system load forecasting. In the model three types of variables are used as inputs to the neural networks: seasonal related inputs, weather related inputs, and historical loads. Khotanzad et al [12] described a load forecasting system known as ANNSTLF. It is based on multiple ANN strategy that captures various trends in the data. In the development they used a multilayer perceptron trained with an error back propagation algorithm. ANN STLF can consider the effect of temperature and relative humidity on the load. It also contains forecasters that can generate the hourly temperature and relative humidity forecasts needed by the system. An improvement of the above system was described in [13]. In the new generation, ANNSTLF includes two ANN forecasters: one predicts the base load and the other forecasts the change in load. The final forecast is computed by adaptive combination of these forecasts. The effect of humidity and wind speed are considered through a linear transformation of temperature. At the time it was reported in [12], ANNSTLF was being used by 35 utilities across the USA and Canada. Chen et al. [14] also developed a three layer fully connected feed forward neural network and a back propagation algorithm was used as the training method. Their ANN though considers electricity price as one of the main characteristics of the system load. Many published studies use artificial neural networks in conjunction with other forecasting techniques such as time series [15] and fuzzy logic [16].

Expert Systems Rule-based forecasting makes use of rules, which are often heuristic in nature, to do accurate forecasting. Expert systems incorporate 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. Ho et al. [17] 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 are employed to establish eleven day-types. Weather parameters were also considered. Rahman and Hazim [18] developed a site-independent technique for short-term load forecasting. Knowledge about the load and the factors affecting it is extracted and represented in a parameterized rule base. This rule-based system is complemented by a parameter database that varies from site to site. The technique is tested in different sites in the United States with low forecasting errors. The load model, the rules and the parameters presented in the paper have been designed using no specific knowledge about any particular site.

Fuzzy Logic

Fuzzy logic is a generalization of the usual Boolean logic used for digital circuit design. An input under Boolean logic takes on a value of “True” or “False”. Under fuzzy logic an input is associated with certain qualitative ranges. For instance the temperature of a day may be “low”, “medium” or “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 [19]. Among the advantages of the use of fuzzy logic is the absence of a need for a mathematical model for mapping inputs to outputs and the absence of a need for precise inputs. With such generic conditioning rules, properly designed fuzzy logic systems can be very robust when used for forecasting. Of course in many situations an exact output is needed. After the logical processing of fuzzy inputs, a “defuzzification” can be used to produce such precise outputs. [20], [21] and [22] describe applications of fuzzy logic to load forecasting.

1.2.3 Hybrid Methods

There are hybrid methods that combine at least two of the methods mentioned to improve the results. Two common combinations of methods include the hybrid fuzzy-regression and the hybrid fuzzy-neural networks [23].

1.3 Objectives of the Dissertation

The main objective of the work is to develop a solution methodology to forecast hourly load by incorporating weather conditions i.e. temperature, humidity, wind-speed and day type information. An attempt is made to short term load forecasting using type-1 fuzzy logic approach and type-2 fuzzy logic approach. The work presented here is divided into four steps:

1. Collection of data
2. Development of type-1 fuzzy logic model for short term hourly load forecasting using triangular membership functions for weather dependent load data.
3. Development of type-2 fuzzy logic model for short term hourly load forecasting using triangular membership functions for weather dependent load data.
4. Comparison of Results.

1.4 Organization of the Dissertation

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

1. Chapter 1 includes the overview of the proposed work, brief summary of literature review and objective of the work.
2. Chapter 2 describes the type-1 fuzzy logic basics.
3. Chapter 3 describes the type-2 fuzzy logic basics.
4. Chapter 4 includes problem formulation using type-1 and type-2 fuzzy logic.
5. Chapter 5 includes test system results
6. Chapter 6 includes conclusion and future scope of the work.

2.1 Introduction

The concept of fuzzy logic was developed by Lotfi A. Zadeh, a professor at University of California, Berkeley, in the mid 1960's as a way of processing data based on linguistic descriptions [24]. Unlike Boolean logic or classical logic, which assumes that every fact is either entirely true or false, fuzzy logic extends Boolean logic to handle vague and imprecise expressions. According to Zadeh, the essential characteristics of fuzzy logic are:

1. Exact reasoning is viewed as a limiting case of approximate reasoning
2. Everything is a matter of degree
3. Any logic system can be fuzzified
4. Knowledge is interpreted as a collection of equivalent and fuzzy constraints on collection of variables.
5. Inference is viewed as a process of propagation of fuzzy constraints [25].

2.2 Fuzzy Sets and Membership Functions

2.2.1 Fuzzy Set

Let X be a set of objects, called the universe of discourse, whose elements are denoted by x . Membership in a subset A of x is the membership function, $\mu_A(x)$ from X to the real interval $[0, 1]$. The universe is all the possible elements of concern in the particular context [26].

\tilde{A} is called a fuzzy set and is a subset of X that has no sharp boundary. $\mu_A(x)$ is the grade of membership x in \tilde{A} . The closer the value of $\mu_A(x)$ is to 1, the more x belongs to \tilde{A} . The total allowable universe of values is called the domain of the fuzzy set [26]. The domain is a set of real numbers, increasing monotonically from left to right where the values can be both positive and negative. \tilde{A} is completely characterized by the set of pairs defined as:-

$$\tilde{A} = \{(x, \mu_A(x)), x \in X\} \quad (2.1)$$

or

$$\tilde{A} = \int_X \mu_A(x)/x \quad (2.2)$$

2.2.2 Membership Functions

Membership values can be expressed in different types of fuzzy membership functions. The most common representations are the triangular and the trapezoidal membership functions. Instead of using triangular and trapezoidal membership functions Gaussian, Sigmoidal, Gaussian bell membership functions can be used [27]. Figure 2.1 shows an example of a triangular membership function, which is expressed by (a_1, a_2, a_3) , where a_1, a_2 and a_3 are the abscissa of the three points of the triangle.

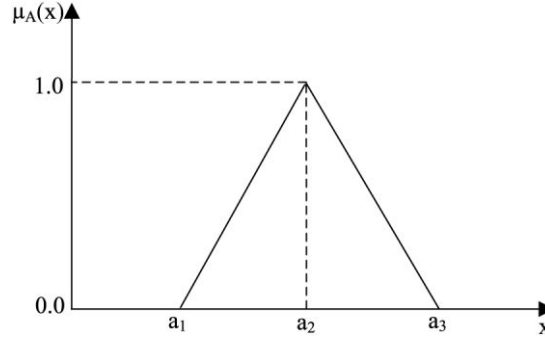


Figure 2.1 Triangular Fuzzy Membership Function

2.3 Operations on Fuzzy Sets:-

(i) **Union:** The union of two fuzzy sets \tilde{A} and \tilde{B} is a new fuzzy set $\tilde{A} \cup \tilde{B}$ also on X with a membership defined as

$$\mu_{\tilde{A} \cup \tilde{B}}(x) = \max(\mu_A(x), \mu_B(x)) \quad (2.3)$$

(ii) **Intersection:** The intersection of two fuzzy sets \tilde{A} and \tilde{B} is a new fuzzy set $\tilde{A} \cap \tilde{B}$ also on X with a membership defined as

$$\mu_{\tilde{A} \cap \tilde{B}}(x) = \min(\mu_A(x), \mu_B(x)) \quad (2.4)$$

(iii) **Complement:** The complement of a fuzzy set \tilde{A} is a new fuzzy set \tilde{A}^c with a membership function defined as

$$\mu_{\tilde{A}^c}(x) = 1 - \mu_{\tilde{A}}(x) \quad (2.5)$$

(iv) **Product of two Fuzzy Sets:** The product of two fuzzy sets \tilde{A} and \tilde{B} is a new fuzzy set $\tilde{A} * \tilde{B}$ whose membership function is defined as

$$\mu_{\tilde{A} * \tilde{B}}(x) = \mu_{\tilde{A}}(x) * \mu_{\tilde{B}}(x) \quad (2.6)$$

2.4 Fuzzy Inference System

Fuzzy inference system is the process of formulating the mapping from a given input to an output using fuzzy logic. Fuzzy inference systems are essentially knowledge-based systems that utilize all of the concepts such as fuzzy logic, fuzzy IF-THEN rules and membership functions. In other words, A Fuzzy Inference System (FIS) is a way of mapping an input space to an output space using fuzzy logic [28]. A FIS tries to formalize the reasoning process of human language by means of fuzzy logic (that is, by building fuzzy IF-THEN rules).

Fuzzy inference system can be implemented in MATLAB environment and a possible input – output relationships can be visualized. In MATLAB environment a fuzzy inference system can be implemented by typing “fuzzy” in command window, after the execution of command graphical user interface (GUI) of fuzzy inference system can be visualized. One can add or edit the input-output membership functions and rules based on his own knowledge. Figure 2.2 shows the components of a fuzzy inference system:

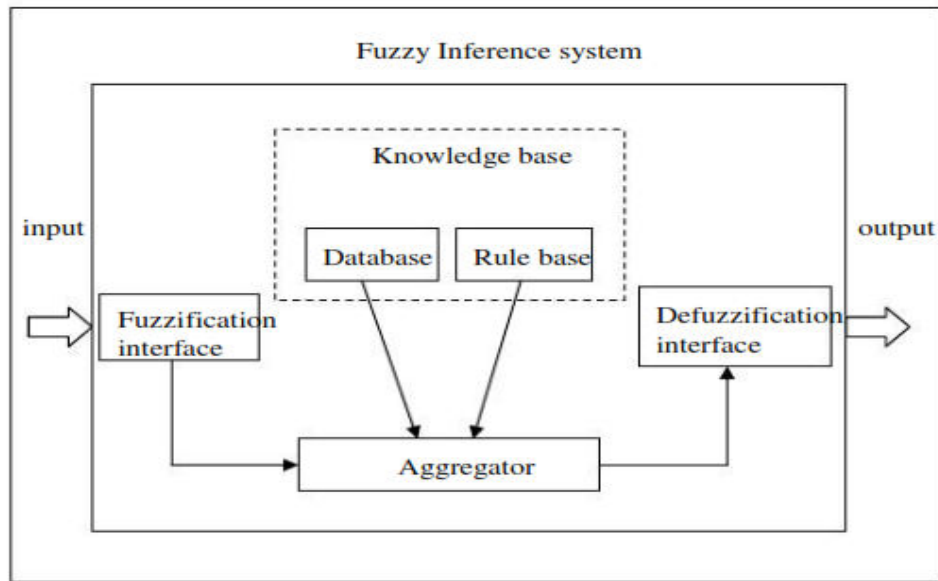


Figure 2.2 Fuzzy Inference System

A fuzzy inference system is made up of five functional blocks:-

1. A fuzzification interface which transforms the crisp inputs into degrees of match with linguistic values
2. An aggregator which performs the inference operation based on the rules
3. A database which defines the membership functions
4. A rule base containing a number of fuzzy IF-THEN rules
5. A defuzzification interface which converts the fuzzy results into crisp outputs.

Six Basic Implications followed in Type-1 fuzzy inference system:-

1. And method: Choose min, prod, or Custom, for a custom operation.
2. Or method: Choose max or Custom, for a custom operation.
3. Implication method: Choose min, prod, or Custom, for a custom operation. This selection is not available for Sugeno-style fuzzy inference.
4. Aggregation method: Choose max, sum, or Custom, for a custom operation. This selection is not available for Sugeno-style fuzzy inference.
5. Defuzzification method: For Mamdani-style inference, choose centroid or Custom, for a custom operation. For Sugeno-style inference, choose wtaver (weighted average) or wtsum (weighted sum).

2.4.1 Types of Fuzzy Inference System

There are a number of inference techniques used in a fuzzy inference system as:

(i) Mamdani Inference System: One of the techniques that is used mostly in various practical applications is the Mamdani inference technique. The Mamdani technique was introduced by Professor Ebrahim Mamdani of London University in 1975 to control kiln temperature in a cement factory [29]. To come up with the technique, he applied a set of fuzzy rules supplied by experienced human operators rather than using theoretical formula. The technique takes the form of:

IF $\langle x \text{ is } A \rangle$ AND $\langle y \text{ is } B \rangle$
 THEN $\langle z \text{ is } C \rangle$

where A, B are fuzzy sets in the premise and C is a fuzzy set in the consequence. Mamdani-type inference as defined for the toolbox, expects the output membership functions to be fuzzy sets. After the aggregation process, there is a fuzzy set for each output variable that needs defuzzification.

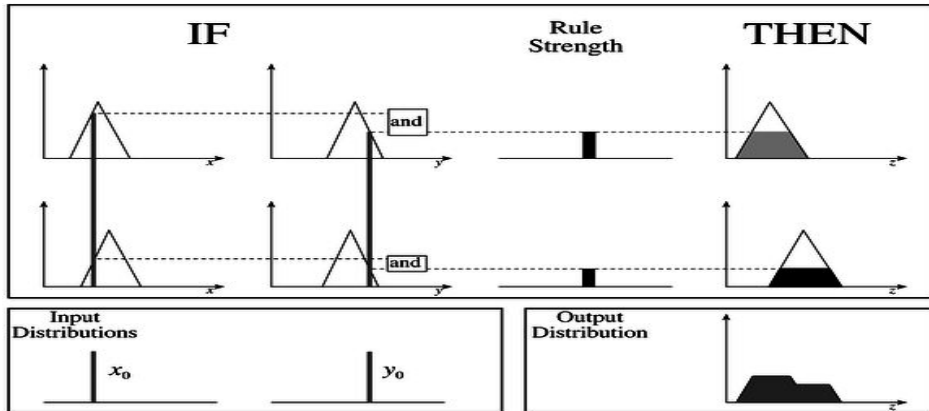


Figure 2.3 Mamdani Fuzzy Inference System

(ii) Sugeno Inference System: Takagi-Sugeno-Kang, method of fuzzy inference was introduced in 1985, it is similar to the Mamdani method in many respects. The primary difference is that the output consequence is not computed by clipping an output membership function at the rule strength. In fact, in the Sugeno FIS there is no output membership function at all. Instead the output is a crisp number computed by multiplying each input by a constant and then adding up the results [30]. The first two parts of the fuzzy inference process, fuzzifying the inputs and applying the fuzzy operator, are exactly the same. The main difference between Mamdani and Sugeno is that the Sugeno output membership functions are either linear or constant.

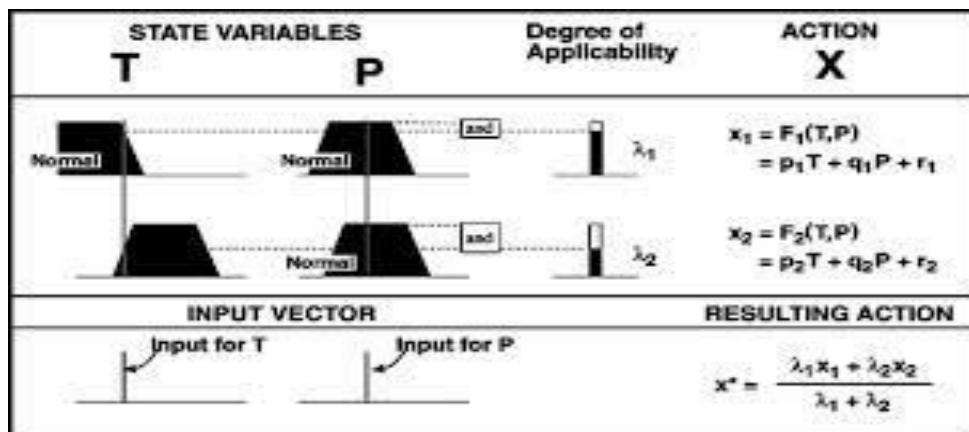


Figure 2.4 Takagi Sugeno Inference System

2.5 Fuzzy Logic System

A fuzzy logic system is constructed completely by fuzzy sets. It contains four components as shown in figure 2.5

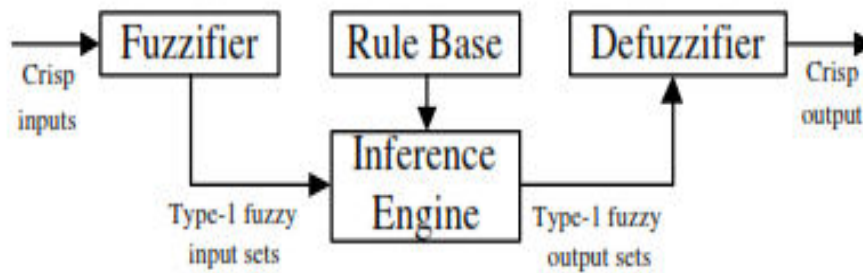


Figure 2.5 Fuzzy Logic System

2.5.1 Fuzzifier

The fuzzifier performs a mapping from crisp inputs $x = (x_1, x_2 \dots \dots x_n)$ into fuzzy sets. These input variables should be such that, they represent the dynamical system completely. Then the function of the fuzzifier comes into picture. As we know that instead of using numerical variables, fuzzy logic uses linguistic variables for processing information. But since the inputs to the fuzzy logic system are in the form of numerical variables (or in other words, crisp sets), they need to be converted into linguistic variables. This function of converting these crisp sets into fuzzy sets (linguistic variables) is performed by the Fuzzifier and the process is called as fuzzification. The fuzzification technique involves outlining the membership functions for the inputs [31]. These membership functions should cover the whole universe of discourse and each one represents a fuzzy set or a linguistic variable. The crisp inputs are thus transformed into fuzzy sets. Triangular MF, Trapezoidal MF, Bell MF, Generalized Bell MF or Sigmoidal MF can be used. Even a hybrid of any of the above Membership Functions can be used for fuzzification.

2.5.2 Rule Base

The Rule Base is a collection of IF- THEN statements in the form of

IF **X** is **A** and **Y** is **B** THEN **Z** is **C**

Or

IF the **water level** is **low** and **pressure** is **high** THEN **open the valve a little**

The IF- part of a rule is its antecedent, and the THEN-part is its consequent.

The application of fuzzy logic in real world systems is mainly used with fuzzy IF-THEN rules. In this application, conditional statements take the form of:

IF < premise > THEN < consequence >

Where by both premise and consequences are characterized by fuzzy or linguistic elements respectively. An example that illustrates this relationship is: IF < food is excellent > THEN < tip is high >

Where, ‘excellent’ and ‘high’ are linguistic variables that can be characterized by membership functions.

Through the use of linguistic inputs and membership functions, fuzzy IF-THEN rules can easily capture the spirit of “rule of thumb” used by humans. This is done by incorporating them in fuzzy inference systems.

2.5.3. Inference Engine

In the fuzzy inference engine, fuzzy logic principles are used to combine the fuzzy IF-THEN rules in the fuzzy rule base into a mapping from the fuzzy sets in one form to fuzzy sets in other form.

2.5.4. Defuzzification

A defuzzifier performs the exact opposite function of a fuzzifier. It transforms the fuzzy variables (which are obtained as output after processing of the inputs) to crisp sets. The defuzzifier is necessary because in the real world the crisp values can only be taken as inputs to the other systems.

A defuzzifier is generally required only when the Mamdani fuzzy model is used for designing a controller [32]. There are five basic defuzzification strategies and they are defined as follows:

(i) Centroid of Area (COA): It is one of the most popular techniques used for defuzzification, as it is important for the calculation of expected values of probability distributions. It can be defined as follows:

$$z_{COA} = \frac{\int_z \mu_A(z)zdz}{\int_z \mu_A(z)dz} \quad 2.7$$

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

(ii) Mean of Maximum (MOM): z_{MOM} is the average of the maximizing z at which the MF reaches a maximum μ^* . It can be represented as follows:

$$z_{MOM} = \frac{\int_z zdz}{\int_z dz} \quad 2.8$$

(iii) Smallest of Minimum (SOM): z_{SOM} is the minimum of the maximizing z (in terms of magnitude).

(iv) Largest of Maximum (LOM): z_{LOM} is the maximum of the maximizing z (in terms of magnitude).

The various defuzzification techniques have been explained with the help of the figure 2.6 shown above. The smallest of minimum (SOM) and largest of maximum (LOM) defuzzification techniques are rarely used because of their biased nature. The most widely used technique is the Centroid of Area (COA) method.

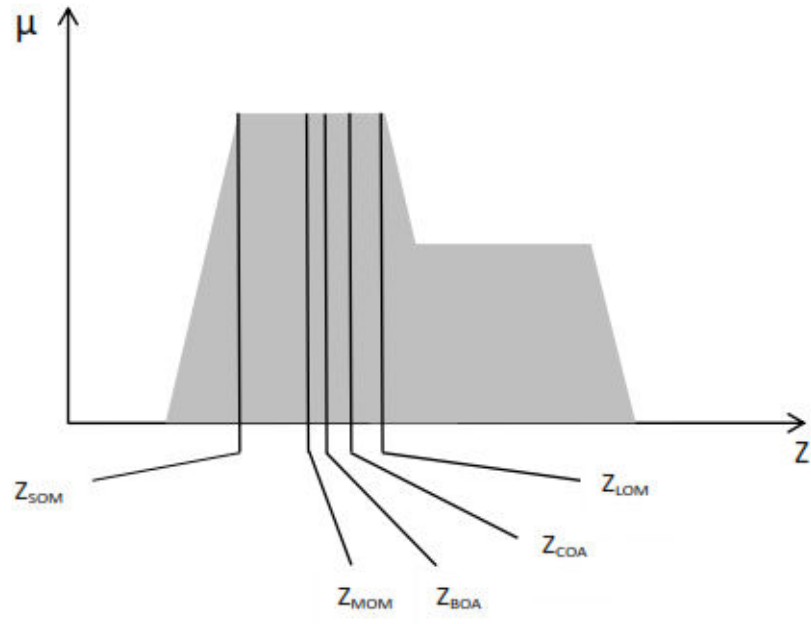


Figure 2.6 Various defuzzification techniques and their optimisation

3.1 Introduction

The concept of type-2 fuzzy sets was introduced by Zadeh as an extension of the concept of an ordinary fuzzy set (called as type-1 fuzzy set) [33]. A type-2 fuzzy set is characterized by a type-2 fuzzy membership function, i.e., the membership value for each element of this set is a fuzzy number in $[0, 1]$. Such sets can be used in situations where there is uncertainty about the membership grades themselves, e.g., an uncertainty in the shape of the membership function or in some of its parameters. Type-2 fuzzy logic is able to handle uncertainties because it can model them and minimize their effects.

The uncertainty is the imperfection of knowledge about the natural process or natural state. The statistical uncertainty is the randomness or error that comes from different sources as we use it in a statistical methodology. There are different sources of uncertainty in the evaluation and calculus process. The five types of uncertainty that emerge from the imprecise knowledge natural state are [34]:

1. **Measurement uncertainty-** It is the error on observed quantities.
2. **Process uncertainty-** It is the dynamic randomness.
3. **Model uncertainty-** It is the wrong specification of the model structure.
4. **Estimate uncertainty-** It is the one that can appear from any of the previous uncertainties or a combination of them, and it is called inexactness and imprecision.
5. **Implementation uncertainty-** It is the consequence of the variability that results from sorting politics, i.e. in capacity to reach the exact strategic objective.

Frequently asked questions regarding type-2 fuzzy sets

1. **Why did it take so long for the concept of a type-2(T2) fuzzy sets (FS) to emerge?**
It seems that science moves in progressive ways where one theory is eventually replaced or supplemented by another, and then another. Learning about type-1 (T1) FSs before T2 FSs fits a similar learning model. So, from this point of view it was natural for fuzzy logic developers to develop type-1 FS. Only by doing so was it possible to see the shortcomings of such FSs when one tries to use them to the situations where uncertainties abound [35].
2. **Why didn't T2 FSs immediately become popular?** Although Zadeh introduced T2 FSs in 1975, very little was published about them until the mid-to late nineties. Until then they were studied by only a relatively small number of people, including:. In the 1970s people were first learning what to do with T1 FSs, e.g. fuzzy logic control. Once it was clear what could be done with T1 FSs, it was only natural for people to then look at more challenging problems [35].
3. **Why do we believe that by using T2 FSs we will outperform the use of T1 FSs?**
T2 FSs are described by membership functions (MFs) that are characterized by more parameters than the MFs of T1 FSs. Hence, T2 FSs provide us with more design degrees of freedom; so using T2 FSs has the potential to outperform using T1 FSs,

especially when there are uncertainties in the model. At present, there is no theory that guarantees that a T2 FS will always do this [35].

3.2 Type-2 Fuzzy Sets and Membership Function

3.2.1 Type-2 Fuzzy Sets

Assume that primary variable x is sampled to N values, $(x_1, x_2, x_3 \dots x_n)$ and at each of these values its primary memberships u_i is sampled at M_i values, $u_{i1}, u_{i2}, u_{i3} \dots u_{iM_i}$ [36].

Let \overline{A}_i^j denote the type-2 fuzzy set then

$$\overline{A}_i^j = \left\{ \left(x_i, \left(u_i^j, f_{x_i}(u_i^j) \right) \right), u_i^j \in \{u_{ik}, k = 1 \dots M_i\}, i = 1 \dots n \right\} \quad (3.1)$$

In which $f_{x_i}(u_i^j)$ is the secondary grade at u_i^j . Note that \overline{A}_i^j can also be expressed as

$$\overline{A}_i^j = \sum_{i=1}^n [f_{x_i}(u_i^j)/u_i^j] / x_i, u_i^j \in \{u_{ik}, k = 1 \dots M_i\} \quad (3.2)$$

3.2.2 Types of Type-2 Fuzzy Sets (T2FS)

(i) Interval Type-2 Fuzzy Sets (IT2FS): An interval type-2 fuzzy Set (IT2FS) is the most widely used kind of T2FS. It can be considered as a special case of T2FS, wherein an IT2FS is one in which the membership grade of every domain point is a crisp set whose domain is the interval that lies in the interval $[0,1]$. The membership grade of an IT2FS is an interval set with a unity value for each secondary grade in that set. IT2 Takagi-Sugeno-Kang (TSK) FLSs are TSK fuzzy models, where antecedent MFs are IT2 FSs or consequent parameters are intervals. As per this definition, three classes of models can be formed [33]:

- i. A2-C1:2 Antecedents are IT2 FSs, and consequents are interval T1 FSs.
- ii. A2-C0: Antecedents are similar to the case of A2-C1 model, however, consequent parameters are crisp (similar to the case of traditional type-1 TSK fuzzy models).
- iii. A1-C1: Antecedents and consequents are both type-1 fuzzy sets.

Classes A2-C1 and A2-C0 use IT2 FSs, and hence have a more general form of IT2 TSK FLS models with the greater degrees of freedom. The extra flexibility of these models allows for efficient handling of uncertainties and minimizing their effects on the quality of forecasts.

(ii) General Type-2 Fuzzy Sets (GT2FS): A general type-2 fuzzy set is a three dimensional fuzzy set and have three dimensional FOU, thus imparting great complexity to the system.

3.2.3 Difference b/w Type-1, Interval and General Type-2 Fuzzy Sets

The difference between T1, IT2FS, GT2FS can be visualized in terms of degrees of membership. In Figure (3.1), the same input p is applied to the three different types of fuzzy sets (type-1 fuzzy set in Figure (3.1 a), interval type-2 fuzzy set in Figure (3.1 b) and general type-2 fuzzy set in Figure (3.1c), resulting in a degree of membership which is specific to the type of fuzzy set [38].

The amount of uncertainty that is associated with the degree is shown in colour in Figure (3.1) and is explained in Figure (3.2). It shows the secondary Membership Functions (MFs) (third dimension) of the type-1 fuzzy set in Figure (3.2 a), the interval type-2 fuzzy set in Figure (3.2 b) and the general type-2 fuzzy set in Figure (3.2 c) as induced by the same input p as shown in Figure (3.1). Figure (3.2) is visualising the y - z plane [38].

In type-1 fuzzy sets the secondary MF has only one value in its domain in Figure (3.2 a) corresponding to the primary membership value at which the secondary grade equals 1. Hence, in type-1 fuzzy sets, for each x value (in our case p), there is no uncertainty associated with the primary membership value.

In interval type-2 fuzzy sets as shown in Figure (3.2 b), there is maximum uncertainty associated with the secondary membership function as the primary membership is taking values within the interval $[a, b]$, where each point in this interval is having an associated secondary membership of 1.

In general type-2 fuzzy sets as shown in Figure (3.2 c), the uncertainty can be modelled with any degree between type-1 and interval type-2 fuzzy sets, for example by the triangular secondary membership function shown in Figure (3.2 c).

Hence it is concluded that general type-2 fuzzy sets can model the uncertainty in the third dimension from nearly no uncertainty in type-1 fuzzy sets to maximum in interval type-2, where the uncertainty is equally spread in the third dimension [38].

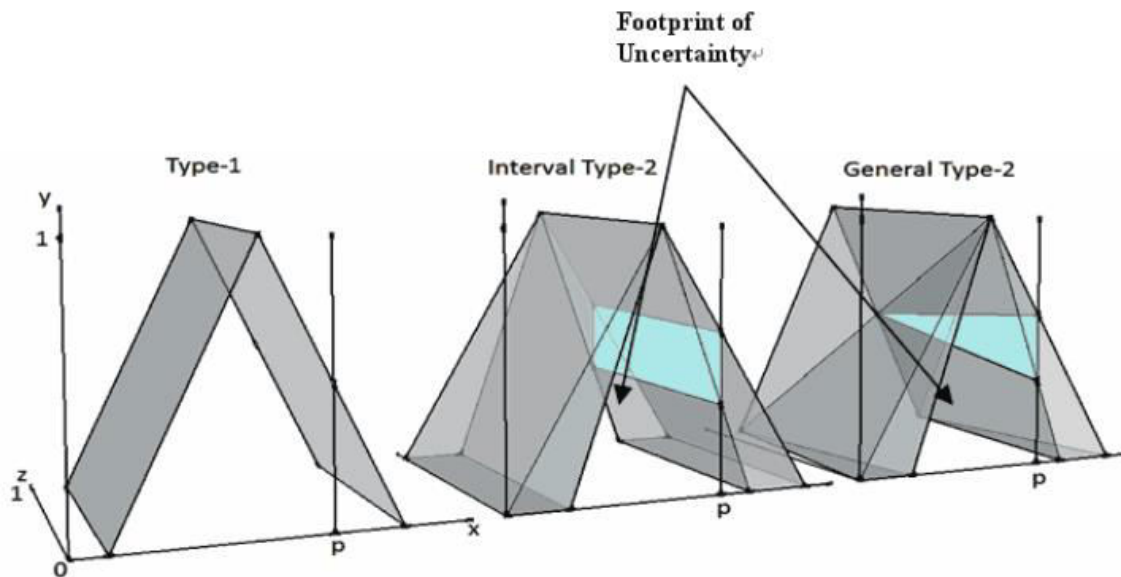


Figure 3.1 An example of the three types of fuzzy sets.

(a) Type-1 fuzzy set. (b) Interval type-2 fuzzy set. (c) General type-2 fuzzy set.

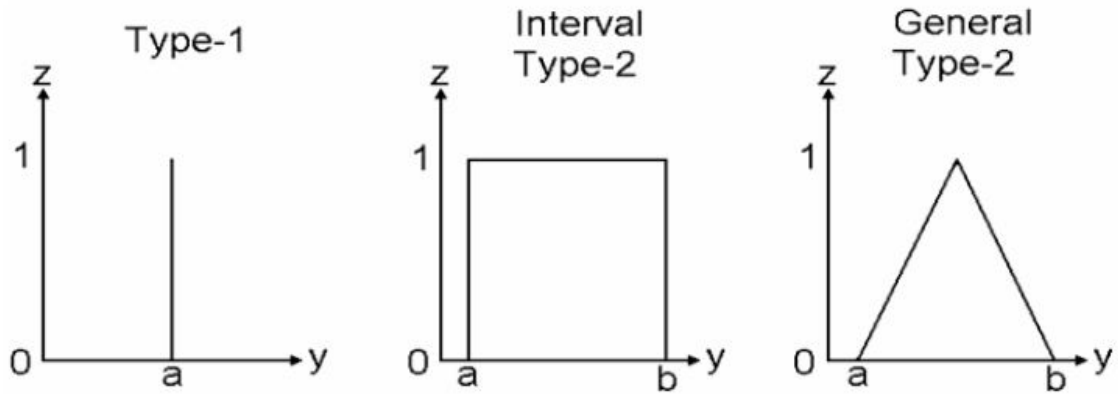


Figure 3.2 View of the secondary membership functions (third dimensions)
 (a) Type-1 fuzzy set. (b) Interval Type-2 fuzzy set. (c) General type-2 sets.

3.2.4 Type-2 Membership Functions

(i) **Gaussian Membership Function:** A type-2 membership function (MF) is actually a three dimensional membership function that characterizes a type-2 fuzzy set. The shaded region is known as footprint of uncertainty (FOU). It is the union of all primary membership grades [39].

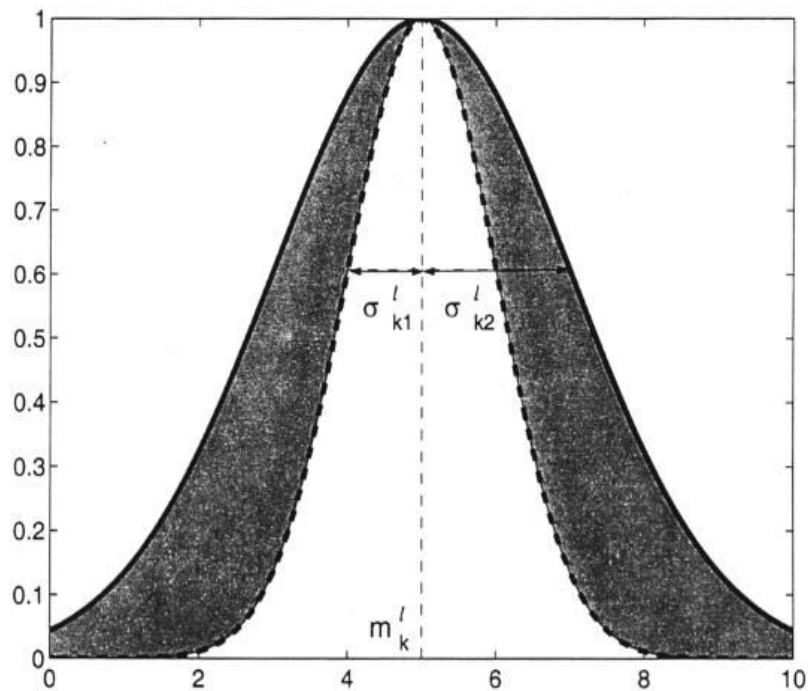


Figure 3.3 Type-2 Gaussian membership function

(ii) **Triangular Membership Function:** An upper MF and a lower MF are two type-1 MFs that are bounds for the footprint of uncertainty of triangular type-2 MF. The upper MF is a subset that has the maximum membership grade of the footprint of uncertainty; and the lower MF is a subset that has the minimum membership grade of the footprint of uncertainty [39].

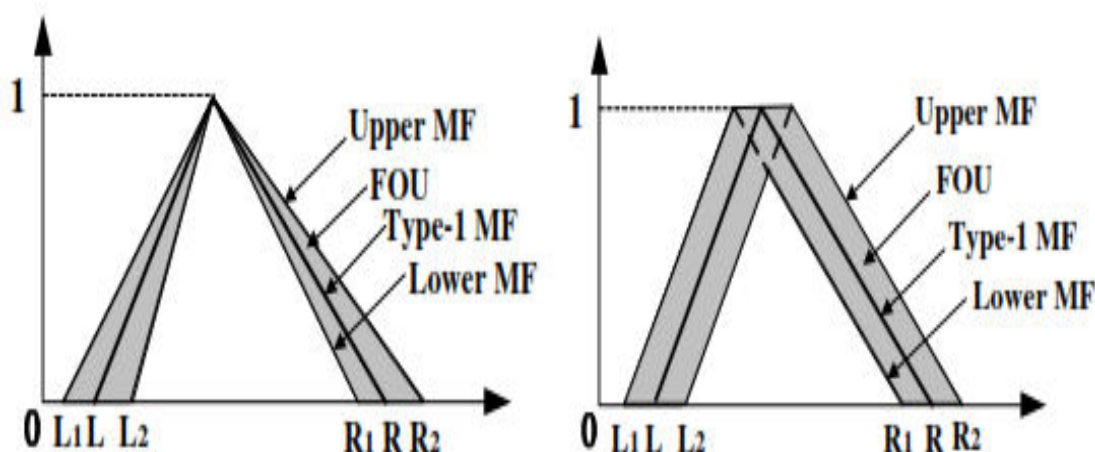


Figure 3.4 Type-2 Triangular membership function

3.3 Operations on Type-2 Fuzzy Sets (T2FS's)

(i) **Union:** The union of two type-2 fuzzy sets \tilde{A} and \tilde{B} is a new fuzzy set $\tilde{A} \cup \tilde{B}$ also on X with a membership defined as

$$\mu_{\tilde{A} \cup \tilde{B}}(x) = 1 / [\underline{\mu}_{\tilde{A}}(x) \vee \underline{\mu}_{\tilde{B}}(x), \overline{\mu}_{\tilde{A}}(x) \vee \overline{\mu}_{\tilde{B}}(x)] \quad \forall x \in X \quad (3.3)$$

Where

$\underline{\mu}_{\tilde{A}}(x)$ – lower bounding MF of \tilde{A}

$\underline{\mu}_{\tilde{B}}(x)$ – lower bounding MF of \tilde{B}

$\overline{\mu}_{\tilde{A}}(x)$ – upper bounding MF of \tilde{A}

$\overline{\mu}_{\tilde{B}}(x)$ – upper bounding MF of \tilde{B}

(ii) **Intersection:** The intersection of two type-2 fuzzy sets \tilde{A} and \tilde{B} is a fuzzy set $\tilde{A} \cap \tilde{B}$ also on X with a membership defined as

$$\mu_{\tilde{A} \cap \tilde{B}}(x) = 1 / [\underline{\mu}_{\tilde{A}}(x) \wedge \underline{\mu}_{\tilde{B}}(x), \overline{\mu}_{\tilde{A}}(x) \wedge \overline{\mu}_{\tilde{B}}(x)] \quad \forall x \in X \quad (3.4)$$

(iii) **Complement:** The complement of a type-2 fuzzy set $\tilde{A}, \overline{\tilde{A}}$, is

$$\overline{\tilde{A}} = 1 / [1 - \underline{\mu}_{\tilde{A}}(x), 1 - \overline{\mu}_{\tilde{A}}(x)] \quad \forall x \in X \quad (3.5)$$

Or

$$\overline{\tilde{A}} = 1 / \text{FOU}(\tilde{A}) \quad (3.6)$$

3.4 Type-2 Fuzzy Inference System

Type-2 fuzzy inference systems are essentially knowledge-based systems that utilize all of the concepts such as fuzzy logic, fuzzy IF-THEN rules and membership functions. The inference process in a type-2 FLS is very similar to that in a type-1 FLS. The rules are combined by the inference engine that provides a mapping from input type-2 fuzzy sets to output type-2 fuzzy sets. In order to do this, intersections, unions and compositions of type-2 fuzzy sets are required [40].

In a type-1 FLS, a crisp output is produced by the defuzzifier from the output of the inference engine, which is actually a fuzzy set. On the other hand, in a type-2 FLS, the output of the inference engine is normally a type-2 fuzzy set. Using the Zadeh's extension principle, a type-reduced set, that is a type-1 fuzzy set, is obtained from the type-2 output sets of the FLS. This operation is called type reduction. The type reduction is an important calculation for type-2 FLSs.

Six Basic Implications followed in Type-2 Fuzzy Inference System:-

1. And method: Choose min, prod, or Custom, for a custom operation.
2. Or method: Choose max or Custom, for a custom operation.
3. Implication method: Choose min, prod, or Custom, for a custom operation. This selection is not available for Sugeno-style fuzzy inference.
4. Aggregation method: Choose max, sum, or Custom, for a custom operation. This selection is not available for Sugeno-style fuzzy inference.
5. Type reduction method: Karnik Mendel algorithm is used.
6. Defuzzification method: For Mamdani-style inference, choose centroid or Custom, for a custom operation. For Sugeno-style inference, choose wtaver (weighted average) or wtsum (weighted sum).

3.5 Type-2 Fuzzy Logic System (T2FLS)

Zadeh introduced type-2 fuzzy logic system (T2FLS) as an extension to type-1 fuzzy logic system (T1FLS). T2FLS are able to handle uncertainty in a much better way, which make T2FLS ideal for control applications. The fuzzifier maps the crisp input into a fuzzy set. This fuzzy set can, in general, be a type-2 set, however, in this dissertation, we consider only singleton fuzzification, for which the input fuzzy set has only a single point of nonzero membership [41].

The structure of a type-2 FLS is shown in Figure 3.5. It is very similar to the structure of a type-1 FLS. Only the difference is, for a type-1 FLS, the output processing block contains only the defuzzifier, and in case of type-2 FLS one additional block is type-reducer along with defuzzifier.

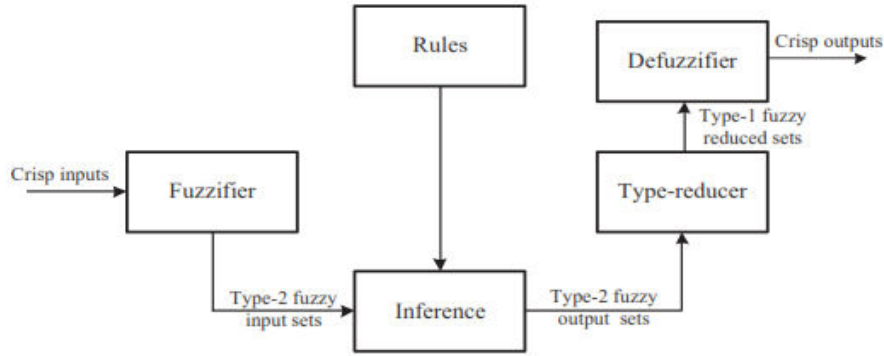


Figure 3.5 Type-2 Fuzzy Logic System

3.5.1 Fuzzification

The fuzzifier maps the crisp input into a fuzzy set. This fuzzy set will, in general, be a type-2 set in the case of a type-2 FLS; however, for now, we consider only singleton fuzzification, i.e., in the input fuzzy set, only a single point has a non-zero membership and this membership is equal to 1 [41].

3.5.2. Inference Engine

The inference engine matches the fuzzy singletons with the fuzzy rules in the rule base. To compute unions and intersections of type-2 sets, compositions of type-2 relations are needed. Just as the sup-star composition is the backbone computation for a type-1 FLS, the extended sup-star composition is the backbone for a type-2 FLS.

3.5.3 Rule Base: Consider the rule base of a type-2 FLS consisting of N rules assuming the following form:

$$\text{If } x_1 \text{ is } \overline{X}_1^l \text{ and } x_p \text{ is } \overline{X}_p^l \text{ then } y \text{ is } \overline{Y}_1^l \quad (3.7)$$

Where \overline{X}_1^l , \overline{X}_p^l and \overline{Y}_1^l are type-2 fuzzy sets called as antecedents and consequent respectively.

3.5.4. Type Reducer

Since the output of the inference engine are type-2 fuzzy sets, they must be type reduced before the defuzzifier can be used to generate a crisp output. This process is called as type-reduction.

Numerous algorithms are developed for type reduction. One of the commonly used algorithm in type reduction is the Karnik Mendel algorithm explained below [42].

Karnik-Mendel Algorithm:

Few Notations:

- \tilde{X} – Type – 2 fuzzy set notation of input variable
- \bar{X} – Upeer MF of input variable

- \underline{X} – Lower MF of input variable
- \overline{X}^i – Upper MF corresponding to i th element
- \underline{X}^i – Lower MF corresponding to i th element
- FOU – Footprint of unncertainty (area between upper MF and lower MF)
- Y^n – Output variable corresponding to n th element
- \underline{y}^n – Lower MF value of Y^n
- \overline{y}^n – Upper MF value of Y^n
- f^n – firing interval corresponding to n th rule
- \underline{f}^n – lower MF of firing interval corresponding to n th rule
- \overline{f}^n – lower MF of firing interval corresponding to n th rule

Computations of Interval Type-2 FLS:

Consider the rule base of an IT2 FLS consisting of N rules:

$$R^n: \text{If } x_1 \text{ is } \tilde{X}_1^n \text{ and } x_i \text{ is } \tilde{X}_i^n \text{ then } y \text{ is } Y^n \quad (3.8)$$

Where

$$Y^n = [\underline{y}^n, \overline{y}^n] \quad (3.9)$$

In general

$$Y^n = [\underline{y}^n + \overline{y}^n]/2 \quad (3.10)$$

Assume the input vector $x' = (x'_1, x'_2 \dots \dots x'_i)$

KM algorithm for Type Reduction:

Computation of $[y_l]$:

Step1: Sort \underline{y}^n ($n = 1, 2, 3 \dots N$) in increasing order such that

$$\underline{y}^1 \leq \underline{y}^2 \leq \underline{y}^3 \dots \dots \dots \leq \underline{y}^n \quad (3.11)$$

Match the corresponding weights $f^n(x')$

Step2: Initialize f^n by setting

$$f^n = [\underline{f}^n + \overline{f}^n]/2 \quad (3.12)$$

For $n = 1, 2, 3 \dots \dots \dots N$

Compute

$$y = \frac{\sum_{n=1}^N \underline{y}^n f^n}{\sum_{n=1}^N f^n} \quad (3.13)$$

Step3: Find a switch point K such that

$$\underline{y}^k \leq y \leq \overline{y}^{k+1} \quad (3.14)$$

Step4: Set

$$f^n = \begin{cases} \overline{f}^n & n \leq k \\ \underline{f}^n & n > k \end{cases} \quad (3.15)$$

And Compute

$$y = \frac{\sum_{n=1}^N y^n f^n}{\sum_{n=1}^N f^n} \quad (3.16)$$

Step5: check if $y' = y$ if yes then stop

And set $y_L = y$

And

$L=K$

Step6: Set $y = y'$

Computation of $[y_r]$:

Step1: Sort $\bar{y}^n (n = 1, 2, \dots, 3)$ in increasing order such that

$$\bar{y}^1 \leq \bar{y}^2 \leq \dots \leq \bar{y}^n \quad (3.17)$$

Match their corresponding weights

Now follow the same procedure for the computation of y_r .

3.5.5 Defuzzification

In case of type-2 FLS, a type-2 defuzzification gives a type-1 set from a type-2 set (which is the output of the inference engine). We call this process type-reduction rather than defuzzification. The type reduced set can further be defuzzified to obtain a crisp output. Various defuzzification techniques are explained below [43]:

(i) Centroid method: The centroid type-reducer combines all the rule-output type-2 fuzzy sets by finding their union as:-

$$\mu_{\tilde{B}}(y) = \bigcup_{i=1}^M \mu_{\tilde{B}^i}(y) \quad \forall y \in Y \quad (3.18)$$

Where, $\mu_{\tilde{B}^i}$ is the secondary membership function for the i th rule. Finding the union of type-2 fuzzy sets requires computing the join of their secondary membership functions. This method involves an enormous amount of computation, as the Centroid and membership computations have to be repeated numerous times. Equation used by the Centroid type-reducer to calculate the Centroid of \tilde{B} is given as:

$$Y_c(x) = \int_{\theta_1 \in J_{y_1}} \dots \int_{\theta_N \in J_{y_N}} [f_{y_1}(\theta_1) * \dots * f_{y_N}(\theta_N)] / \frac{\sum_{i=1}^N y_i \theta_i}{\sum_{i=1}^N \theta_i} \quad (3.19)$$

Where $i=1, 2, \dots, N$, and $\theta_N, j_{y_i}, f_{y_i}$ are associated with $\mu_{\tilde{B}^i}(y)$.

(ii) Centre-of-Sums method: The centre of sums type-reducer combines the type-2 rule output sets by adding their secondary membership functions by using and then finds the Centroid of the resulting type-2 set using above equation.

$$\mu_{\tilde{B}}(y) = \sum_{i=1}^M \mu_{\tilde{B}^i}(y) \quad \forall y \in Y \quad (3.20)$$

Where, $\mu_{\tilde{B}^i}$ is the secondary membership function for the i th rule.

(iii) Height method: The height type-reducer replaces each type-2 output set by a type-2 fuzzy set whose y-domain consists of a single point (\bar{y}), the secondary membership function of which is a type-1 fuzzy set as in (7). This single point is chosen to be the point having the highest primary membership in the principal membership function of the output set.

$$Y_h(x) = \int_{\theta_1 \in J_{\bar{y}^1}} \dots \int_{\theta_M \in J_{\bar{y}^M}} [f_{\bar{y}^1}(\theta_1) \star \dots \star f_{\bar{y}^M}(\theta_M)] / \frac{\sum_{l=1}^M \bar{y}^l \theta_l}{\sum_{l=1}^M \bar{y}^l} \quad (3.21)$$

Where \bar{y}^l is the point having maximum membership in the l th output set and $\theta_l, J_{\bar{y}^l}, f_{\bar{y}^l}$ are associated with $\mu_{\bar{B}^l}(y^l)$.

(iv) Centre of sets method: The centre of sets type-reducer replaces each type-2 consequent set, by its Centroid, and finds a weighted average of these centroids.

3.5.6 Difference between various type-2 defuzzification techniques:

There are important differences between the generalised centroid and centre of sums method. The generalised Centroid breaks the defuzzification problem down into many smaller defuzzification problems and aggregates them.

This results in a type-reduced set. This set gives a measure of the uncertainty propagated through the fuzzy system. The centre of sums tackles the problem in one go, translating directly from a type-2 fuzzy set to a crisp number, giving no measure of uncertainty. The two operations are also identifying different properties.

The generalised centroid finds an average of the centroids of the embedded fuzzy sets that make up the type-2 set. The centre of sums finds the centre of the area encompassed by the membership function of the type-2 fuzzy set. These are two quite distinct notions. If it were ever needed, then both operations could be easily extended to take account of a further degree of freedom. However, Centroid method suffers from lower complexities than centre of sums.

4.1 Type-1 Fuzzy Logic Technique for STL

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

I. Design of fuzzy model and rule base

Based on the demonstrated success in generating forecasts, the methodology proposed by Wang [44] and Kosko [45] 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. Choose the appropriate range and for each input and output variable. There are four input variable that we use to forecast electricity load namely:

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

The output is forecasted load. The model is depicted in fig 4.1

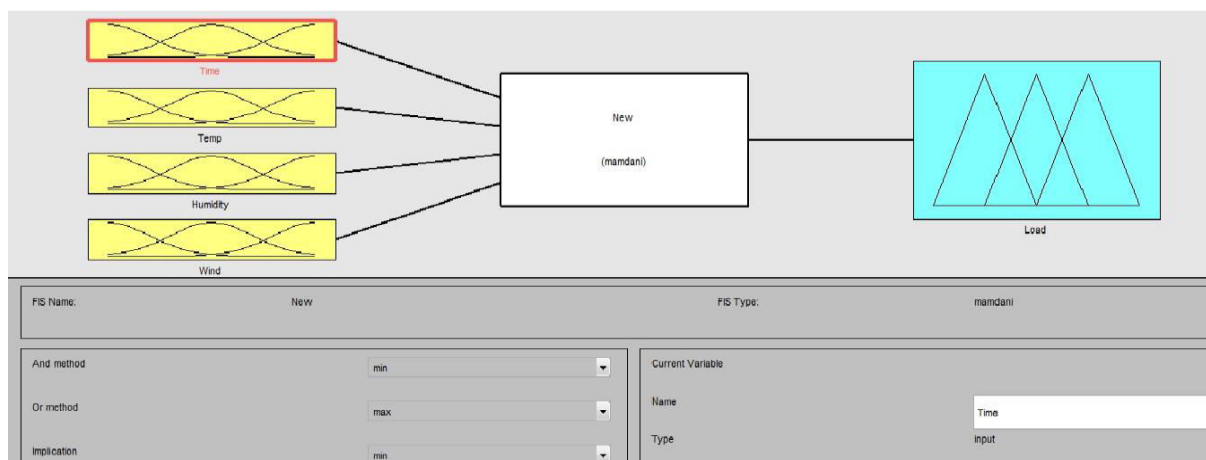


Figure 4.1 Fuzzy Logic Model for STL

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 $[0, 1]$.

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 4.2 are used in this model.

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:

Time data is fuzzified into five fuzzy sets depicted in fig 4.2 as

- i. Midnight
- ii. Morning
- iii. Noon
- iv. Evening
- v. Night

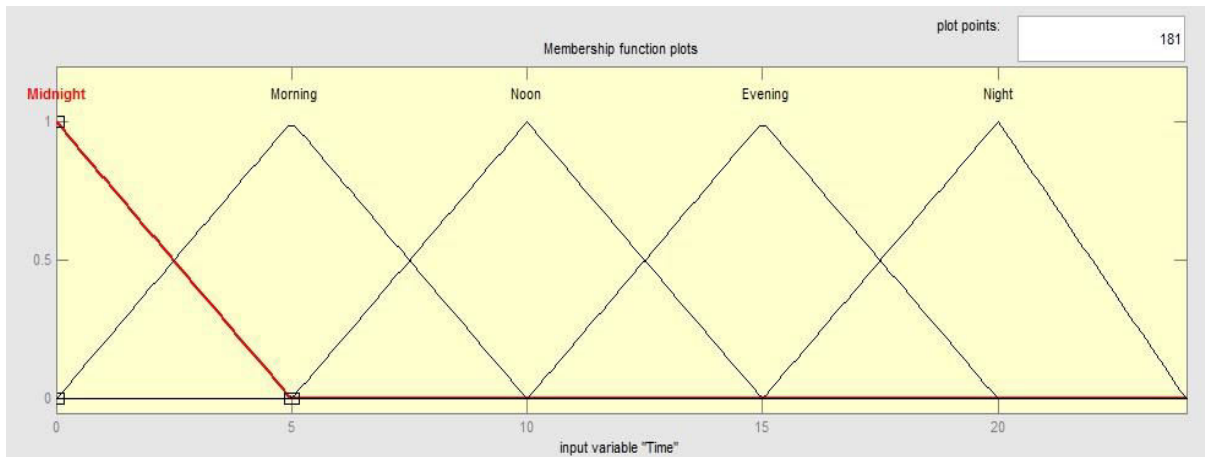


Figure 4.2 Fuzzy Membership Function for Input Variable Time

Temperature data is fuzzified into six fuzzy sets depicted in fig 4.3 as

- i. Very low
- ii. Low
- iii. Normal
- iv. High
- v. Moderate high
- vi. Very high

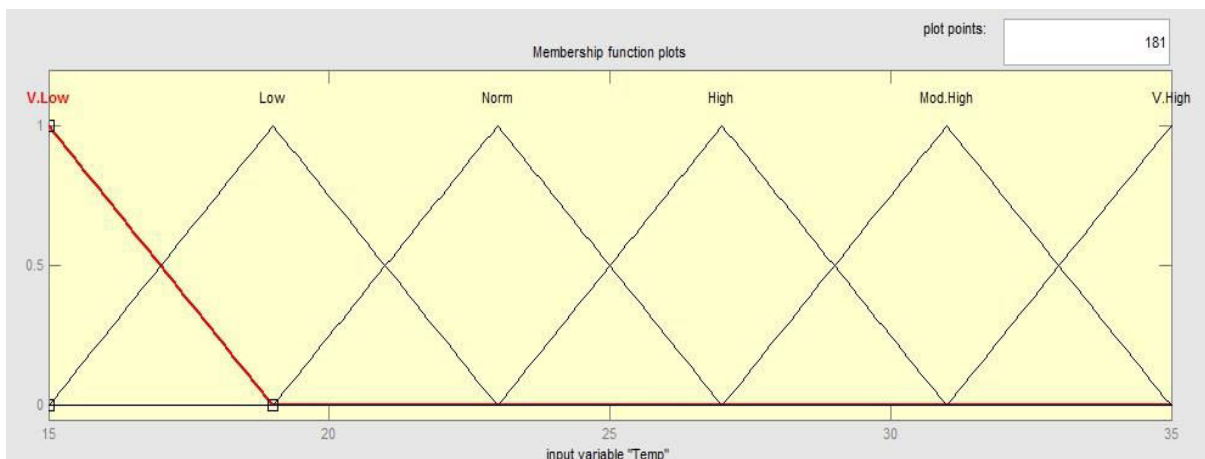


Figure 4.3 Fuzzy Membership Function for Input Variable Temperature

Humidity data is fuzzified into six fuzzy sets depicted in fig 4.4 as

- i. Very low
- ii. Low
- iii. Normal
- iv. High

- v. Moderate high
- vi. Very high

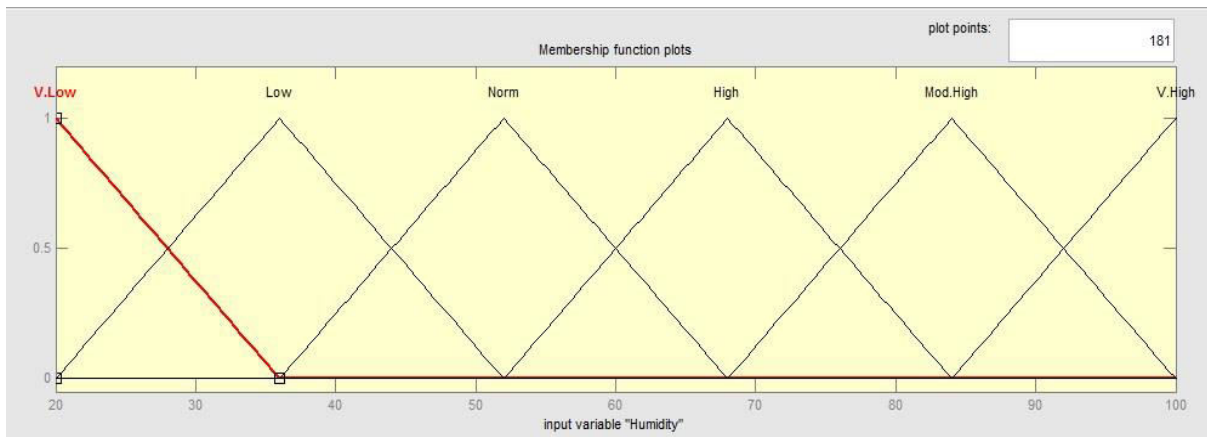


Figure 4.4 Fuzzy Membership Function for Input Variable Humidity

Wind speed data is fuzzified into six fuzzy sets depicted in fig 4.5 as

- i. Very low
- ii. Low
- iii. Normal
- iv. High
- v. Moderate high
- vi. Very high

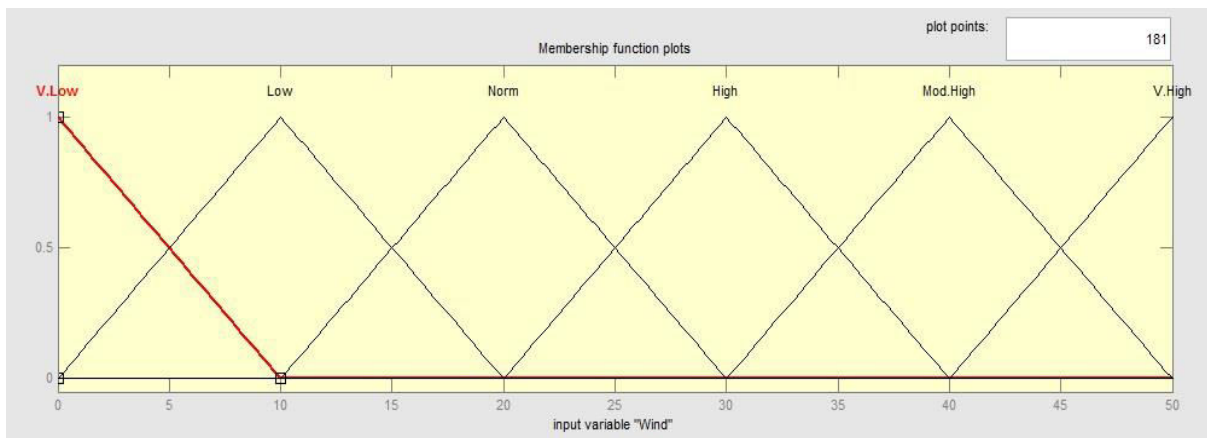


Figure 4.5 Fuzzy Membership Function for Input Variable Wind Speed

Load data is fuzzified into five fuzzy sets depicted in fig 4.6 as

- i. Very low
- ii. Low
- iii. Normal
- iv. High
- v. Very high

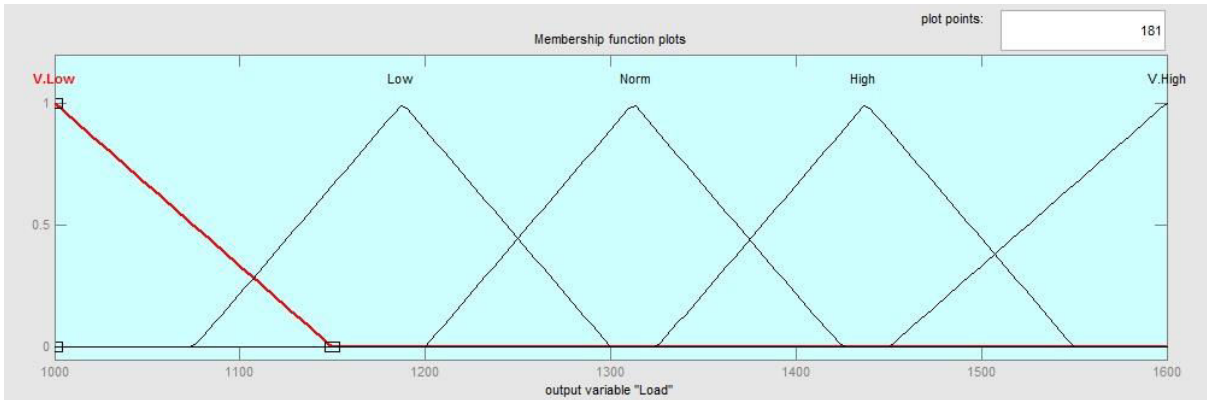


Figure 4.6 Fuzzy Membership Function for Output Variable Forecasted Load

Step 5: Construct the fuzzy rule from each pair of input-output data. For example: IF ‘time’ is midnight and ‘temperature’ is very low and ‘humidity’ is normal and ‘wind speed’ is high THEN ‘load’ is normal.

These five steps, supplemented by the resolution of conflicts and incorporation of expert opinion, constitute the construction of the fuzzy rule base for triangular membership function shown in fig 4.7

1. If (Time is Morning) and (Temp is V.Low) and (Humidity is Mod.High) and (Wind is V.Low) then (Load is V.Low) (1)
2. If (Time is Morning) and (Temp is Low) and (Humidity is Mod.Hgr) and (Wind is Low) then (Load is Norm) (1)
3. If (Time is Morning) and (Temp is Low) and (Humidity is Mod.Hgr) and (Wind is Low) then (Load is Norm) (1)
4. If (Time is Morning) and (Temp is Norm) and (Humidity is High) and (Wind is Low) then (Load is Low) (1)
5. If (Time is Morning) and (Temp is Norm) and (Humidity is High) and (Wind is Low) then (Load is Norm) (1)
6. If (Time is Noon) and (Temp is Norm) and (Humidity is Hgr) and (Wind is Low) then (Load is Norm) (1)
7. If (Time is Noon) and (Temp is High) and (Humidity is Norm) and (Wind is V.Low) then (Load is Norm) (1)
8. If (Time is Noon) and (Temp is High) and (Humidity is Norm) and (Wind is Low) then (Load is High) (1)
9. If (Time is Noon) and (Temp is Mod.High) and (Humidity is Low) and (Wind is Low) then (Load is Hgr) (1)
10. If (Time is Noon) and (Temp is Mod.Hgr) and (Humidity is V.Low) and (Wind is Low) then (Load is High) (1)
11. If (Time is Evening) and (Temp is Mod.High) and (Humidity is Low) and (Wind is V.Low) then (Load is Norm) (1)
12. If (Time is Evening) and (Temp is Mod.High) and (Humidity is Norm) and (Wind is V.Low) then (Load is Norm) (1)
13. If (Time is Evening) and (Temp is Mod.High) and (Humidity is V.Low) and (Wind is Norm) then (Load is Norm) (1)
14. If (Time is Evening) and (Temp is High) and (Humidity is Low) and (Wind is Hgr) then (Load is High) (1)
15. If (Time is Night) and (Temp is Low) and (Humidity is Norm) and (Wind is High) then (Load is V.High) (1)
16. If (Time is Night) and (Temp is Low) and (Humidity is Norm) and (Wind is Mod.High) then (Load is Hgr) (1)
17. If (Time is Night) and (Temp is Low) and (Humidity is High) and (Wind is Mod.High) then (Load is High) (1)

Figure 4.7 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 4.8 shows the rule viewer of the triangular membership function rule base.



Figure 4.8 Rule Viewer for Triangular Membership Function

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.

Centroid of area

$$z_{COA} = \frac{\int_z \mu_A(z)zdz}{\int_z \mu_A(z)dz} \quad 4.1$$

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. 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 [46].

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 [47].

4.2 Type-2 Fuzzy Logic Technique for STLF

The proposed development and implementation of a type-2 fuzzy logic based algorithm for short term load forecasting consists of four stages

I. Design of type-2 fuzzy model and rule base

The approach consists of four steps as described below.

Step 1: Compile a tentative list of input and output variables using statistical analysis, engineering judgments and/or operator experience. Choose the appropriate range and Discretization for each input and output variable as shown in table 1. There are four input variable that we use to forecast electricity load which are:

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

The output is forecasted load. Schematic representation of the model is shown in fig 4.9

Table 4.1 Type-2 Fuzzy Model for STLF Specifications

Variable Type	Variable Name	Range	Discretization
Input Variable	Time	[0;24]	0.5
	Temperature	[15;39]	0.5
	Humidity	[16,100]	0.5
	Wind Speed	[0;48]	0.25
Output Variable	Forecasted Load	[1100;1600]	0.5

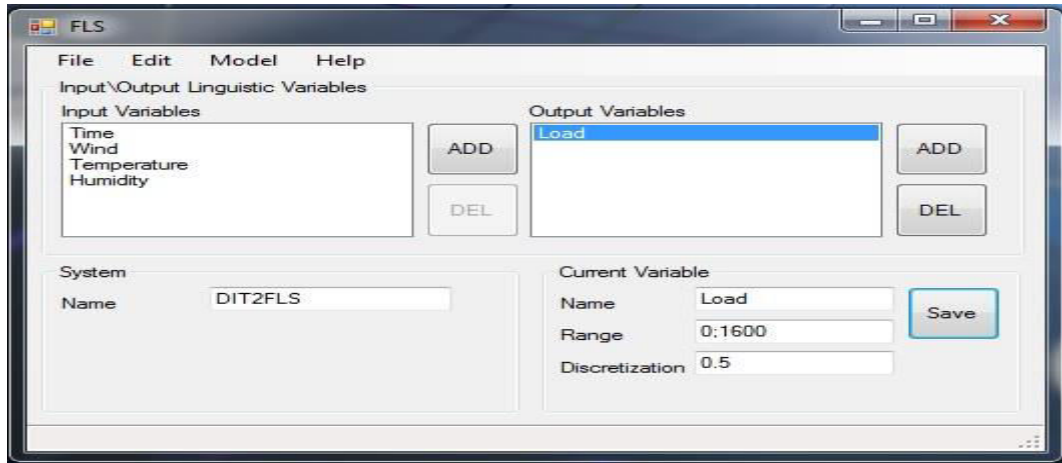


Figure 4.9 Discrete Interval Type-2 Fuzzy Model for STLF

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].

Step 3: Select the arbitrary shape of the type-2 fuzzy membership for each variable and change the membership function if forecasting accuracy is not good. The type-2 triangular shaped mappings shown in figure 4.10 are used.

Step 4: For each input and output variable, tentatively define the number of type-2 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 type-2 triangular membership function:

Time data is fuzzified into five type-2 fuzzy sets described in fig 4.10 as

- i. Midnight
- ii. Morning
- iii. Noon
- iv. Evening
- v. Night

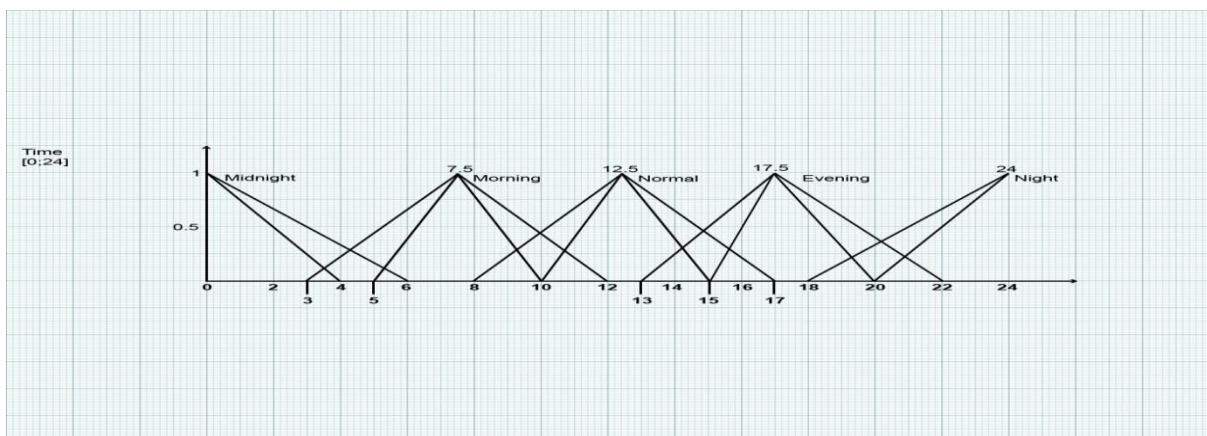


Figure 4.10 Type-2 Fuzzy Membership Function for Input Variable Time

Temperature data is fuzzified into five type-2 fuzzy sets described in fig 4.11 as

- i. Very low
- ii. Low

- iii. Normal
- iv. High
- v. Very high

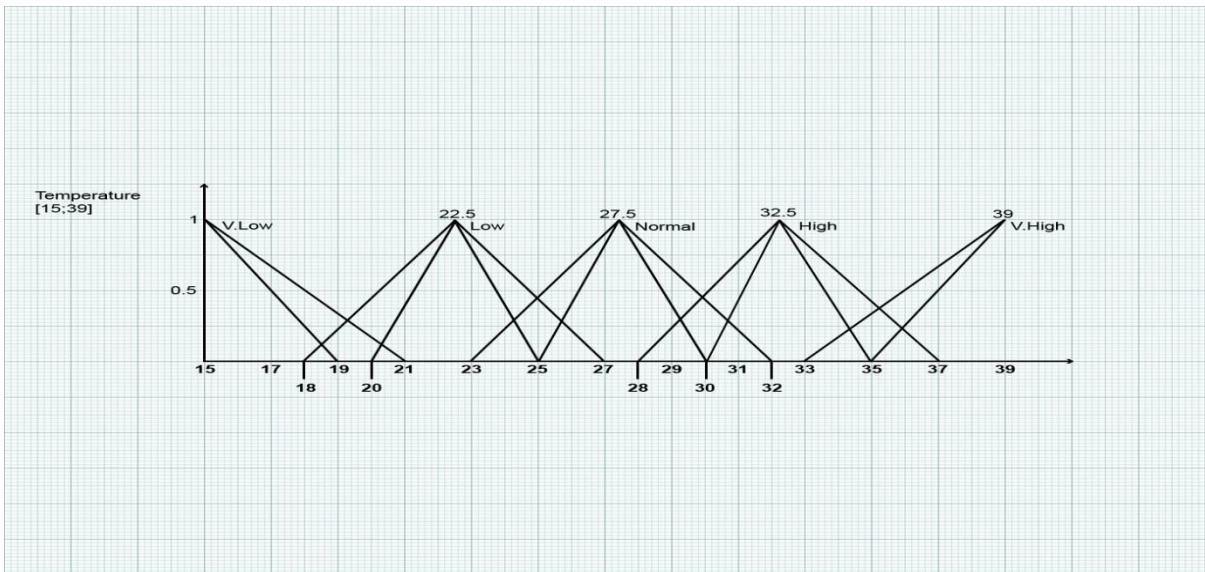


Figure 4.11 Type-2 Fuzzy Membership Function for Input Variable Temperature

Humidity data is fuzzified into five type-2 fuzzy sets described in fig 4.12 as

- i. Very low
- ii. Low
- iii. Normal
- iv. High
- v. Very high

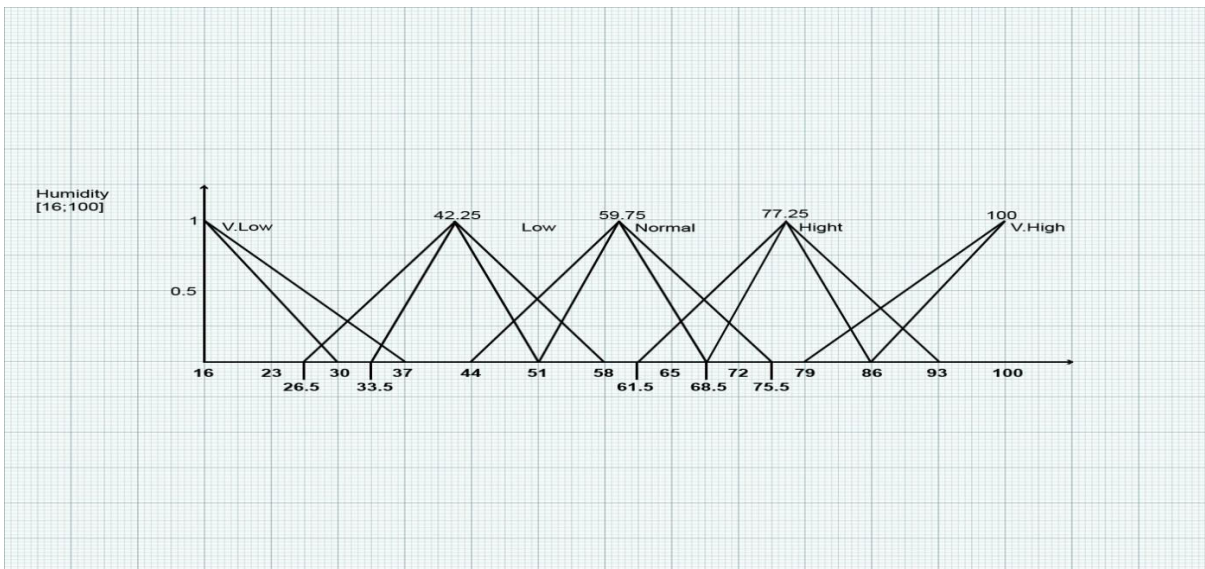


Figure 4.12 Type-2 Fuzzy Membership Function for Input Humidity

Wind speed data is fuzzified into six type-2 fuzzy sets described in fig 4.13 as

- i. Very low

- ii. Low
- iii. Normal
- iv. High
- v. Very high

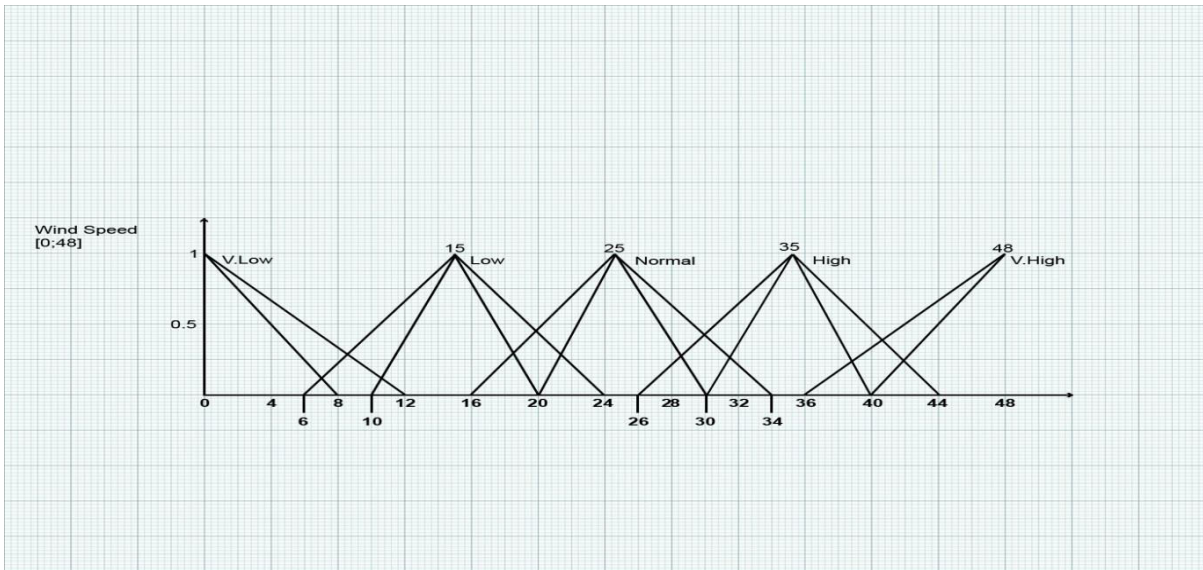


Figure 4.13 Type-2 Fuzzy Membership Function for Input Variable Wind Speed

Load data is fuzzified into five type-2 fuzzy sets described in fig 4.14 as

- i. Very low
- ii. Low
- iii. Normal
- iv. High
- v. Very high

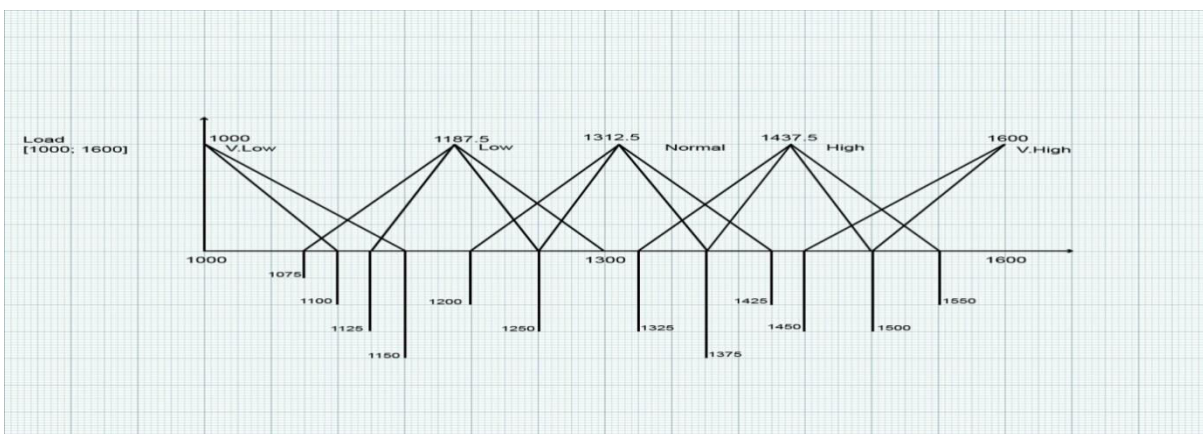


Figure 4.14 Type-2 Fuzzy Membership Function for Output Variable Forecasted Load

Step 5: Construct the fuzzy rule from each pair of input-output data, also called training data. For example: IF ‘time’ is midnight and ‘temperature’ is very low and ‘humidity’ is normal and ‘wind speed’ is high THEN ‘load’ is high. 86 rules are created for type-2 fuzzy logic model for short term load forecasting.

These five steps, supplemented by the resolution of conflicts and incorporation of expert opinion, constitute the construction of the fuzzy rule base for triangular membership function shown in fig 4.15.

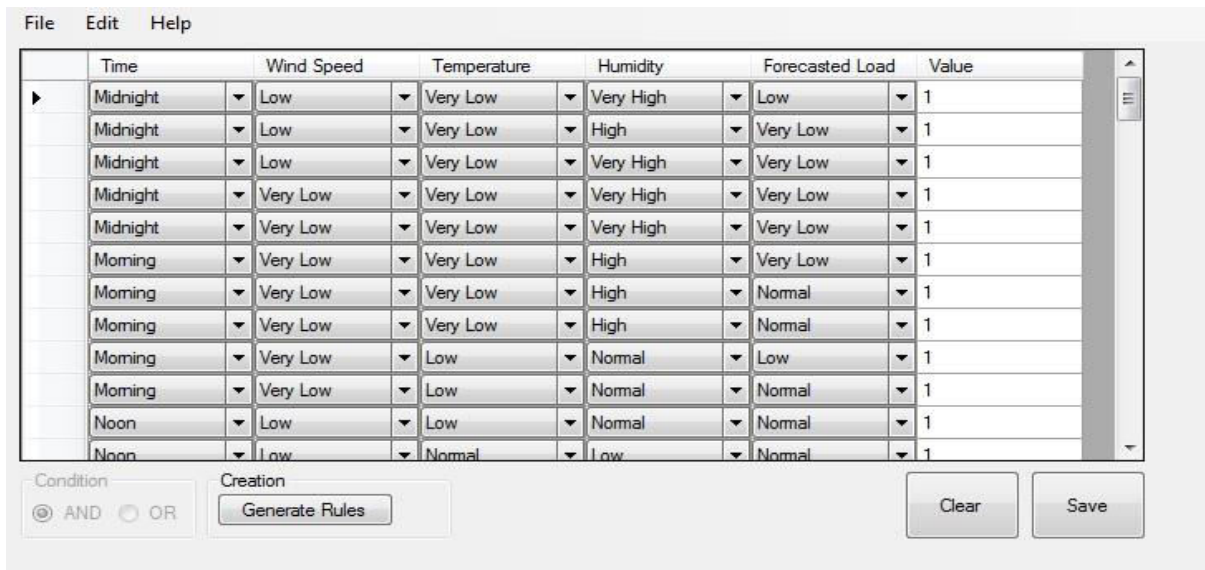


Figure 4.15 Type-2 Fuzzy Rule Base

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 4.16 shows the running model interface of type-2 fuzzy model for short term load forecasting.

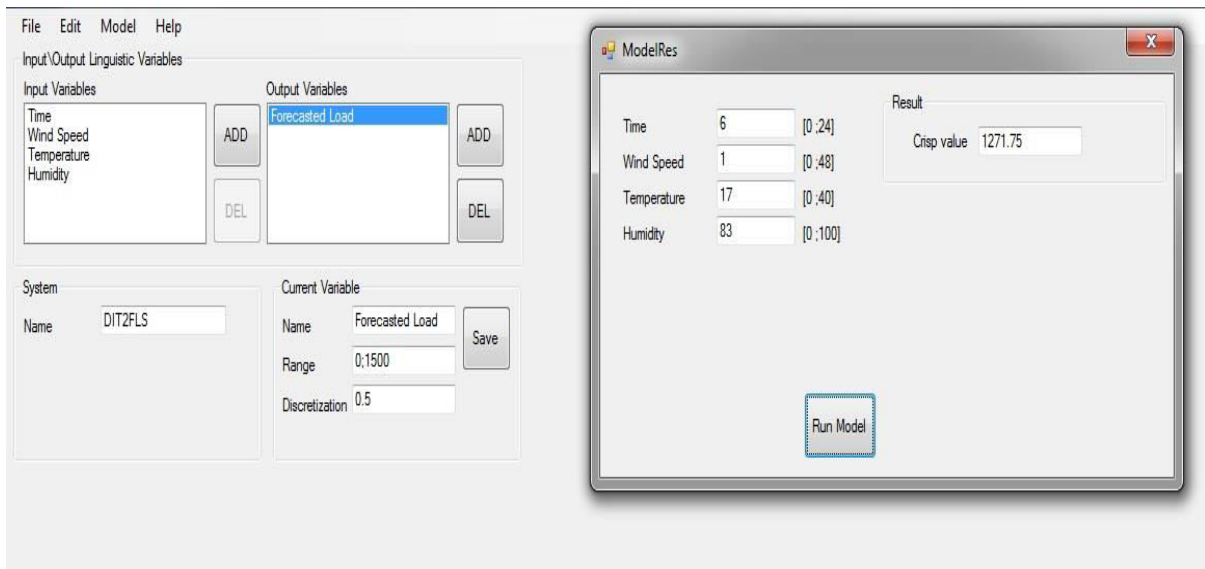


Figure 4.16 Type-2 Fuzzy Model for STLF Running Interface

II. Compute the point forecast value

After the rule base is designed, it is ready to use for forecasting with novel inputs. A type-2 fuzzy inference system implements a nonlinear mapping from its input space to output space. Discrete interval type-2 Takagi-Sugeno-Kang fuzzy inference system is used here. Since output of the type-2 fuzzy inference engine are type-2 fuzzy sets, they must be type reduced

before the defuzzifier can be used to generate a crisp output. This process is called as type-reduction. Numerous algorithms are developed for type reduction. One of the commonly used algorithm in type reduction is the Karnik Mendel algorithm [41] is used explained in Chapter 3 under the section 3.5.4.

In case of type-2 FLS, a type-2 defuzzification gives a type-1 set from a type-2 set (which is the output of the inference engine). We call this process type-reduction rather than defuzzification. The type reduced set can further be defuzzified to obtain a crisp output. The centroid type-reducer combines all the rule-output type-2 fuzzy sets by finding their union [42] explained in section 3.5.5.

III. Test the performance of the rule base

After the fuzzy rule base is identified and a type reduction algorithm and 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.

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.

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 [46].

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

$$\text{Mean absolute percentage error (MAPE)} = \left(\frac{1}{n}\right) \sum_{i=1}^n \frac{|\text{actual load} - \text{forecasted load}|}{\text{actual load}} * 100$$

The dissertation work has been focused on the preliminary investigation of feasibility and performance of type-1 fuzzy logic model and type-2 fuzzy logic model to carry out short term load forecasting on hourly basis daily load 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 State Load Dispatch and Communication Center, Rajasthan Vidyut Parasaran Nigam of Jaipur (Rajasthan).

The forecasted load is compared with the actual load and average percentage error is calculated. 28 days data of Jaipur is collected for training and test data to carry out forecasting load demand is given in appendix.

The following seven cases are investigated to validate the proposed methodology of type-1 fuzzy logic model and type-2 fuzzy logic model and the results are compared and reported.

- i. Hourly load forecast for week 1
- ii. Hourly load forecast for week 2
- iii. Hourly load forecast for week 3
- iv. Hourly load forecast for week 4

5.1 Type-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 time, temperature, wind speed and humidity as input variables and hourly load demand as single output.
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 triangular membership functions with 50% of overlapping.
4. Define number of fuzzy functions for each input and output 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.
8. The results obtained for hourly load forecast for different week days and weekends are indexed as weekday and weekend, using triangular membership functions are plotted.

5.2 Type-2 Fuzzy Logic Model

Type-2 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 time, temperature, wind speed and humidity as input variables and hourly load demand as single output.
2. Normalize the input and output data within the permissible range.
3. Assign the type-2 fuzzy membership functions to each input and output variables. The proposed methodology of fuzzy logic model is investigated with triangular membership functions with 30% of overlapping and 44% uncertainty level.
4. Define number of fuzzy functions for each input and output variable. In case of type-2 fuzzy membership function each variable has five type-2 fuzzy sets.
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 115-127.
6. For given inputs of the selected fuzzy rule base, the type-2 membership value of output function is computed and a point estimate is calculated by type reduction using Karnik Mendel algorithm followed 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.
8. The results obtained for hourly load forecast for different week days and weekends are indexed as weekday and weekend, using triangular membership functions are plotted.

5.3 Calculations for MAPE for Week 1

5.3.1 Hourly Load Forecasting for Weekday (Monday)

Table 5.1 Hourly Load Forecasting for Week 1 of Weekday (Monday)

Time	10-Mar	Forecasted(MW)		APE(MW)	
	(MW)	Type-I	Type-II	Type-I	Type-II
06:00	1526	1300	1544	14.83	-1.16
07:00	1513	1530	1551	-1.10	-2.49
08:00	1524	1540	1551	-1.06	-1.78
09:00	1488	1530	1545	-2.83	-3.84
10:00	1434	1300	1479	9.33	-3.16
11:00	1404	1300	1374	7.40	2.13
12:00	1338	1300	1428	2.86	-6.70
13:00	1330	1300	1429	2.27	-7.43
14:00	1325	1300	1329	1.88	-0.31
15:00	1325	1300	1374	1.88	-3.71
16:00	1328	1310	1358	1.37	-2.25
17:00	1317	1340	1428	-1.74	-8.42
18:00	1333	1310	1301	1.69	2.37
19:00	1470	1310	1378	10.87	6.24
20:00	1487	1300	1437	12.58	3.37
21:00	1418	1310	1351	7.58	4.69
22:00	1379	1300	1358	5.70	1.49
23:00	1369	1300	1304	5.05	4.76
00:00	1399	1300	1315	7.07	6.00
01:00	1468	1530	1551	-4.19	-5.62
02:00	1437	1540	1546	-7.13	-7.55
03:00	1432	1530	1538	-6.82	-7.38
04:00	1432	1540	1546	-7.52	-7.94
05:00	1471	1300	1549	11.60	-5.33

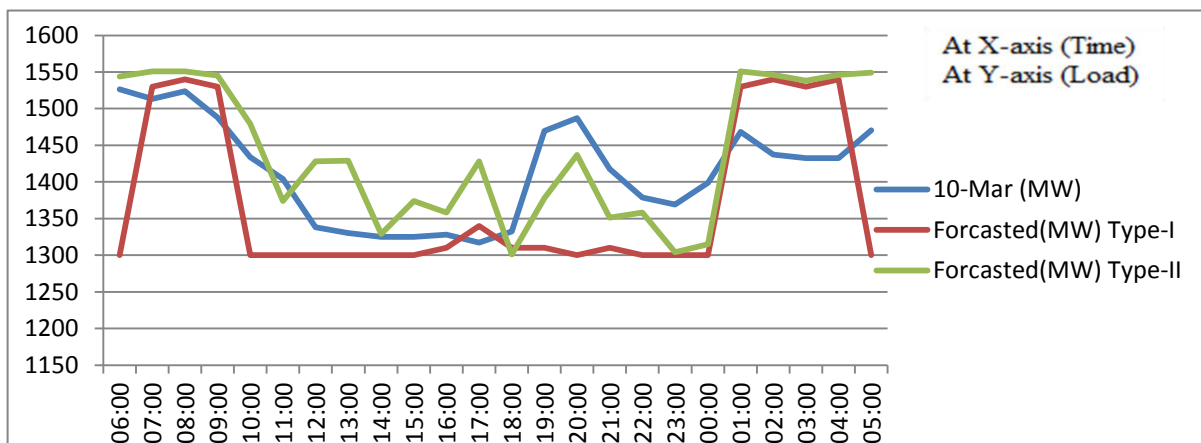


Figure 5.1 Comparison b/w Actual Load and Forecasted Load for week 1 weekday using Type-1 & Type-2 Fuzzy Logic Model

5.3.2 Hourly Load Forecasting for Weekday (Tuesday)

Table 5.2 Hourly Load Forecasting for Week1 of Weekday (Tuesday)

Time	11-Mar	Forecasted(MW)		APE(MW)	
	(MW)	Type-I	Type-II	Type-I	Type-II
06:00	1547	1530	1545	1.11	0.15
07:00	1488	1540	1551	-3.48	-4.21
08:00	1423	1530	1551	-7.51	-8.99
09:00	1327	1530	1543	-15.34	-16.32
10:00	1306	1300	1542	0.44	-18.09
11:00	1287	1300	1546	-1.02	-20.14
12:00	1316	1300	1303	1.20	0.97
13:00	1350	1300	1305	3.73	3.36
14:00	1350	1300	1426	3.69	-5.65
15:00	1350	1300	1375	3.67	-1.89
16:00	1350	1310	1301	2.93	3.60
17:00	1336	1300	1367	2.72	-2.30
18:00	1343	1300	1364	3.20	-1.57
19:00	1481	1300	1358	12.21	8.29
20:00	1491	1300	1312	12.80	11.99
21:00	1406	1300	1299	7.52	7.59
22:00	1376	1300	1302	5.51	5.36
23:00	1401	1300	1428	7.24	-1.90
00:00	1434	1300	1308	9.32	8.77
01:00	1457	1540	1551	-5.66	-6.42
02:00	1435	1540	1546	-7.30	-7.72
03:00	1426	1540	1538	-8.02	-7.88
04:00	1425	1540	1536	-8.06	-7.78
05:00	1445	1540	1542	-6.57	-6.71

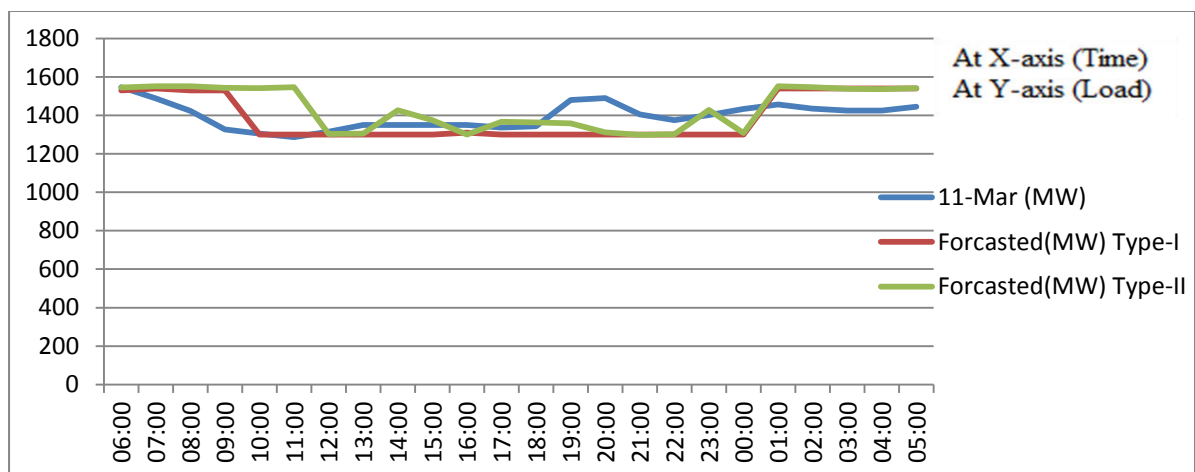


Figure 5.2 Comparison b/w Actual Load and Forecasted Load for week 1 weekday using Type-1 and Type-2 Fuzzy Logic Model

5.3.3 Hourly Load Forecasting for Weekday (Wednesday)

Table 5.3 Hourly Load Forecasting for Week 1 of Weekday (Wednesday)

Time	12-Mar	Forecasted(MW)		APE(MW)	
	(MW)	Type-I	Type-II	Type-I	Type-II
06:00	1561	1300	1543	16.72	1.16
07:00	1573	1300	1550	17.38	1.49
08:00	1512	1300	1550	14.00	-2.54
09:00	1419	1530	1545	-7.84	-8.90
10:00	1398	1300	1549	7.01	-10.80
11:00	1367	1300	1344	4.91	1.69
12:00	1381	1300	1303	5.86	5.64
13:00	1380	1300	1305	5.77	5.41
14:00	1411	1300	1364	7.89	3.36
15:00	1411	1300	1375	7.87	2.55
16:00	1423	1310	1374	7.95	3.45
17:00	1417	1310	1371	7.57	3.27
18:00	1368	1310	1303	4.27	4.78
19:00	1495	1300	1400	13.02	6.33
20:00	1479	1310	1323	11.44	10.56
21:00	1448	1300	1299	10.23	10.29
22:00	1406	1300	1302	7.56	7.42
23:00	1393	1300	1365	6.69	2.03
00:00	1418	1300	1430	8.31	-0.86
01:00	1464	1300	1430	11.22	2.34
02:00	1464	1540	1546	-5.18	-5.59
03:00	1445	1540	1538	-6.56	-6.43
04:00	1443	1530	1549	-6.00	-7.31
05:00	1486	1300	1549	12.55	-4.21

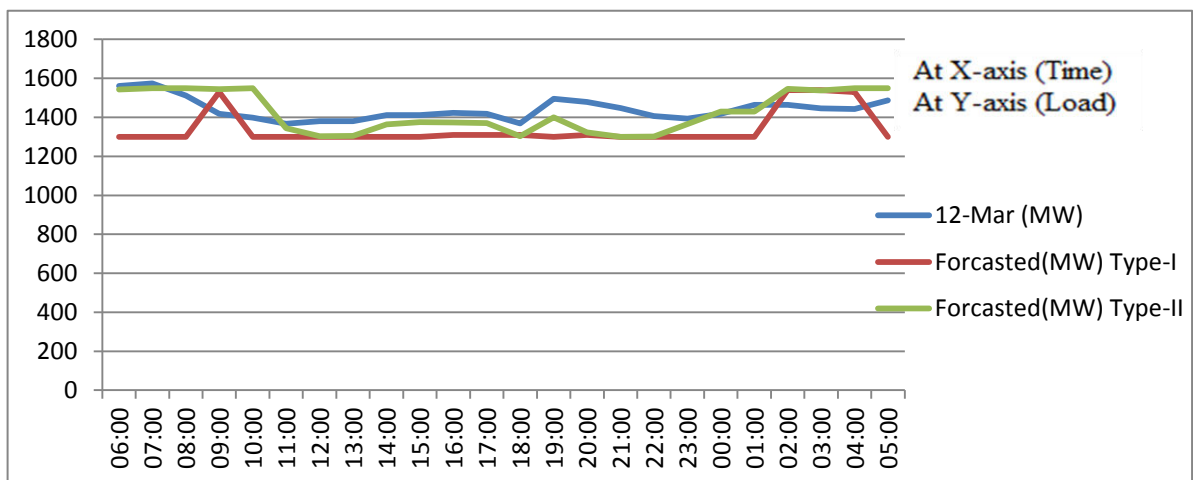


Figure 5.3 Comparison b/w Actual Load and Forecasted Load for week1 of weekday using Type-1 and Type-2 Fuzzy Logic Model.

5.3.4 Hourly Load Forecasting for Weekday (Thursday)

Table 5.4 Hourly Load Forecasting for Week 1 of Weekday (Thursday)

Time	13-Mar	Forecasted(MW)		APE(MW)	
	(MW)	Type-I	Type-II	Type-I	Type-II
06:00	1593	1540	1544	3.35	3.10
07:00	1609	1540	1551	4.29	3.61
08:00	1540	1540	1550	0.01	-0.64
09:00	1529	1300	1547	15.9	-1.17
10:00	1476	1300	1546	11.91	-4.76
11:00	1412	1300	1445	7.90	-2.37
12:00	1397	1300	1429	6.94	-2.29
13:00	1371	1300	1429	5.17	-4.25
14:00	1402	1300	1426	7.26	-1.73
15:00	1407	1300	1373	7.58	2.39
16:00	1405	1300	1437	7.50	-2.25
17:00	1405	1310	1304	6.76	7.19
18:00	1343	1300	1303	3.19	2.96
19:00	1469	1300	1374	11.52	6.48
20:00	1455	1300	1312	10.62	9.80
21:00	1399	1300	1423	7.06	-1.73
22:00	1385	1300	1427	6.13	-3.04
23:00	1413	1300	1440	7.99	-1.92
00:00	1453	1300	1366	10.55	6.01
01:00	1479	1530	1550	-3.42	-4.78
02:00	1479	1530	1545	-3.42	-4.43
03:00	1460	1300	1424	10.95	2.45
04:00	1466	1300	1546	11.32	-5.46
05:00	1496	1540	1546	-2.94	-3.34

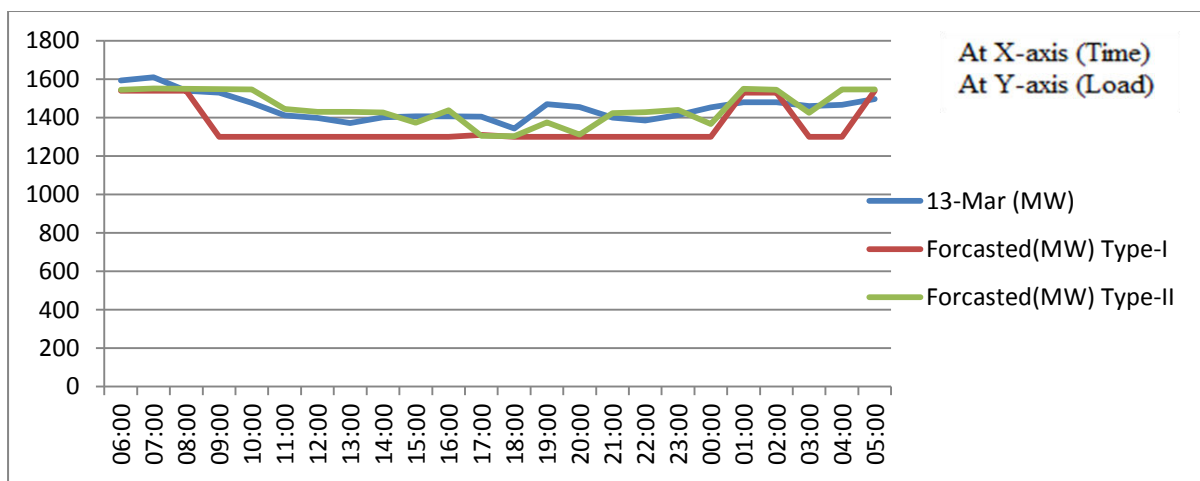


Figure 5.4 Comparison b/w Actual Load and Forecasted Load for Week 1 of weekday using Type-1 and Type-2 Fuzzy Logic Model

5.3.5 Hourly Load Forecasting for Weekday (Friday)

Table 5.5 Hourly Load Forecasting for Week 1 of Weekday (Friday)

Time	14-Mar	Forecasted(MW)		APE(MW)	
	(MW)	Type-I	Type-II	Type-I	Type-II
06:00	1591	1300	1545	18.31	2.91
07:00	1590	1300	1551	18.21	2.42
08:00	1550	1540	1551	0.64	-0.07
09:00	1544	1530	1475	0.92	4.49
10:00	1480	1300	1549	12.17	-4.65
11:00	1419	1300	1345	8.38	5.21
12:00	1405	1300	1365	7.48	2.86
13:00	1378	1300	1367	5.67	0.80
14:00	1377	1300	1329	5.62	3.51
15:00	1379	1300	1375	5.72	0.28
16:00	1371	1380	1358	-0.69	0.91
17:00	1358	1370	1367	-0.86	-0.64
18:00	1341	1360	1364	-1.39	-1.69
19:00	1463	1310	1358	10.48	7.20
20:00	1505	1310	1375	12.97	8.65
21:00	1430	1310	1343	8.40	6.09
22:00	1432	1300	1302	9.20	9.06
23:00	1426	1300	1303	8.85	8.64
00:00	1483	1300	1303	12.35	12.15
01:00	1503	1300	1550	13.51	-3.12
02:00	1468	1300	1427	11.45	2.80
03:00	1464	1300	1423	11.19	2.79
04:00	1464	1300	1479	11.18	-1.05
05:00	1488	1300	1548	12.66	-4.00

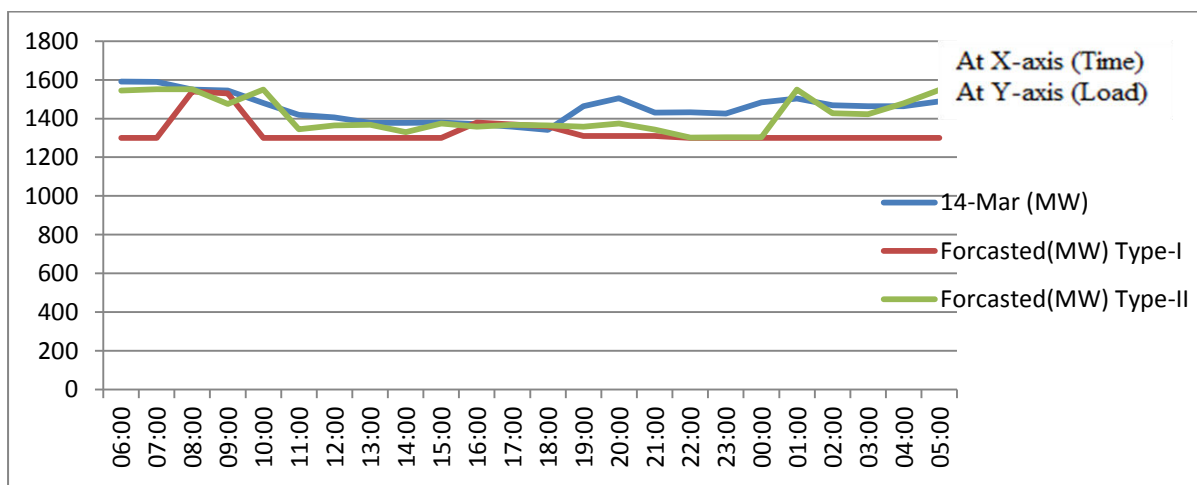


Figure 5.5 Comparison b/w Actual Load and Forecasted Load for Week 1 of weekday using Type-1 and Type-2 Fuzzy Logic Model

5.3.6 Hourly Load Forecasting for Weekday (Saturday)

Table 5.6 Hourly Load Forecasting for Week 1 of Weekend (Saturday)

Time	15-Mar	Forecasted(MW)		APE(MW)	
	(MW)	Type-I	Type-II	Type-I	Type-II
06:00	1575	1300	1544	17.45	1.95
07:00	1561	1300	1550	16.73	0.71
08:00	1539	1300	1550	15.53	-0.71
09:00	1495	1300	1398	13.07	6.52
10:00	1448	1300	1406	10.21	2.89
11:00	1395	1300	1374	6.82	1.51
12:00	1379	1300	1366	5.71	0.92
13:00	1330	1300	1428	2.28	-7.34
14:00	1334	1300	1426	2.56	-6.88
15:00	1321	1300	1375	1.58	-4.10
16:00	1321	1380	1426	-4.47	-7.95
17:00	1322	1380	1364	-4.40	-3.19
18:00	1305	1390	1428	-6.55	-9.46
19:00	1433	1350	1358	5.80	5.24
20:00	1501	1310	1375	12.72	8.38
21:00	1435	1300	1359	9.40	5.29
22:00	1377	1300	1302	5.60	5.45
23:00	1365	1300	1386	4.76	-1.54
00:00	1418	1300	1366	8.30	3.65
01:00	1529	1530	1550	-0.04	-1.34
02:00	1471	1530	1545	-4.01	-5.03
03:00	1479	1540	1538	-4.11	-3.97
04:00	1479	1300	1541	12.12	-4.17
05:00	1504	1300	1475	13.58	1.95

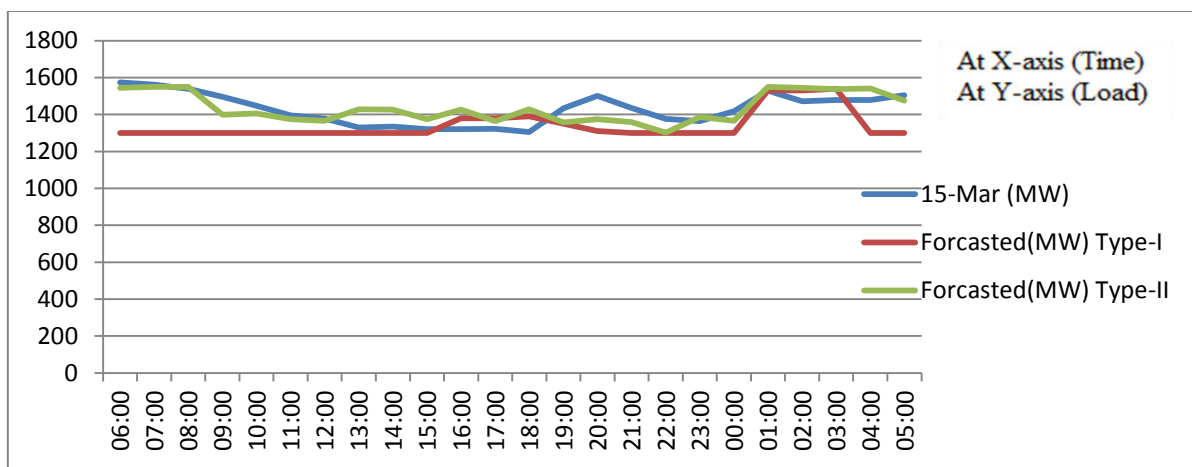


Figure 5.6 Comparison b/w Actual Load and Forecasted Load for Week 1 of weekend using Type-1 and Type-2 Fuzzy Logic Model

5.3.7 Hourly Load Forecasting for Weekday (Sunday)

Table 5.7 Hourly Load Forecasting For Week 1 of Weekend (Sunday)

Time	16-Mar	Forecasted(MW)		APE(MW)	
	(MW)	Type-I	Type-II	Type-I	Type-II
06:00	1475	1300	1545	11.88	-4.73
07:00	1499	1300	1550	13.27	-3.41
08:00	1447	1530	1551	-5.72	-7.17
09:00	1440	1300	1418	9.75	1.56
10:00	1426	1300	1415	8.84	0.78
11:00	1428	1300	1289	8.99	9.76
12:00	1425	1370	1364	3.87	4.29
13:00	1384	1380	1300	0.29	6.07
14:00	1375	1420	1357	-3.25	1.33
15:00	1359	1380	1375	-1.53	-1.17
16:00	1349	1390	1363	-3.07	-1.06
17:00	1343	1430	1429	-6.44	-6.37
18:00	1296	1390	1365	-7.26	-5.33
19:00	1442	1310	1358	9.15	5.82
20:00	1491	1310	1343	12.13	9.91
21:00	1426	1310	1338	8.15	6.18
22:00	1374	1310	1371	4.66	0.22
23:00	1354	1310	1375	3.28	-1.52
00:00	1428	1300	1368	8.96	4.20
01:00	1428	1530	1551	-7.13	-8.60
02:00	1439	1530	1547	-6.30	-7.48
03:00	1426	1300	1538	8.82	-7.87
04:00	1426	1300	1541	8.84	-8.06
05:00	1445	1300	1545	10.01	-6.95

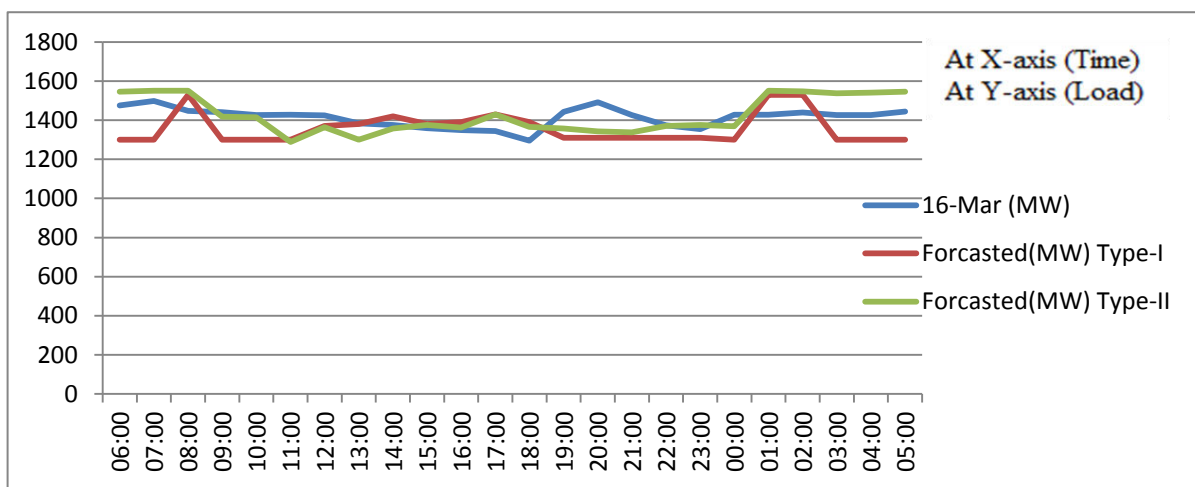


Figure 5.7 Comparison b/w Actual Load and Forecasted Load for Week 1 of weekend using Type-1 and Type-2 Fuzzy Logic Model

5.3.8 Comparison of Type-1 and Type-2 Fuzzy Logic Models in terms of MAPE for Week 1:

Table 5.8 MAPE in case of Type-1 and Type-2 Fuzzy Logic Models for Week 1

Days	Type-1 (MAPE)	Type-2 (MAPE)
Monday	5.68	3.86
Tuesday	5.84	6.98
Wednesday	8.90	4.93
Thursday	6.79	3.67
Friday	8.68	4.00
Saturday	7.82	4.17
Sunday	7.14	4.99

5.4 Calculations for MAPE for Week 2

5.4.1 Hourly Load Forecasting for Weekday (Monday)

Table 5.9 Hourly Load Forecasting for Week 2 of Weekday (Monday)

Time	17-Mar	Forecasted(MW)		APE(MW)	
	(MW)	Type-I	Type-II	Type-I	Type-II
06:00	1516	1530	1544	-0.90	-1.83
07:00	1553	1530	1551	1.49	0.13
08:00	1529	1300	1551	14.96	-1.46
09:00	1485	1300	1426	12.47	3.98
10:00	1440	1300	1437	9.73	0.22
11:00	1399	1300	1357	7.05	2.97
12:00	1324	1380	1364	-4.26	-3.05
13:00	1318	1370	1364	-3.97	-3.52
14:00	1303	1360	1301	-4.35	0.18
15:00	1292	1310	1312	-1.43	-1.58
16:00	1281	1310	1327	-2.23	-3.56
17:00	1271	1310	1366	-3.08	-7.48
18:00	1260	1300	1364	-3.13	-8.21
19:00	1434	1410	1426	1.68	0.57
20:00	1421	1310	1437	7.84	-1.10
21:00	1344	1310	1338	2.51	0.43
22:00	1314	1300	1302	1.09	0.93
23:00	1316	1300	1303	1.24	1.01
00:00	1371	1300	1303	5.15	4.93
01:00	1548	1540	1550	0.50	-0.15
02:00	1503	1550	1546	-3.13	-2.86
03:00	1523	1540	1538	-1.13	-1.00
04:00	1504	1530	1538	-1.76	-2.29
05:00	1491	1300	1540	12.81	-3.28

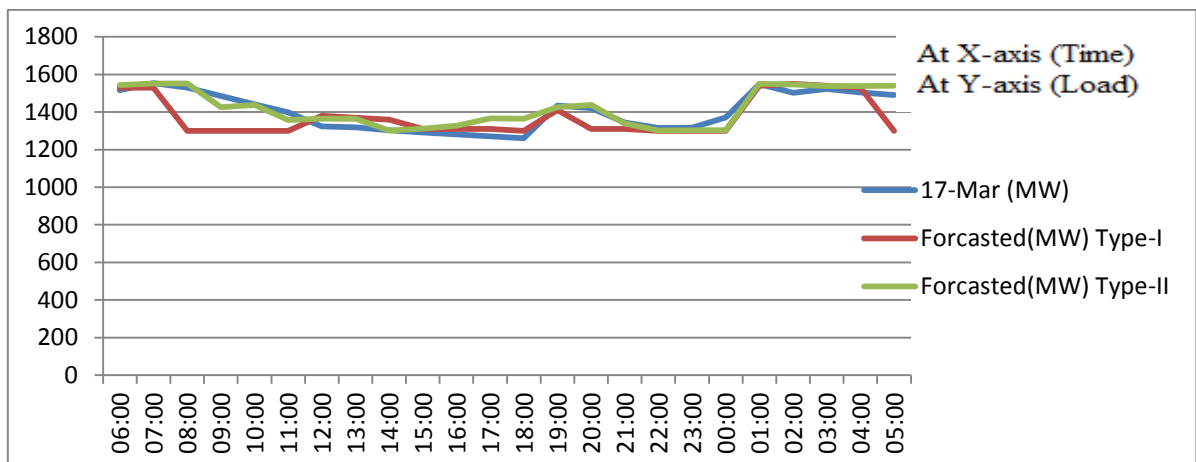


Figure 5.8 Comparison b/w Actual Load and Forecasted Load for Week 2 of weekday using Type-1 and Type-2 Fuzzy Logic Model

5.4.2 Hourly Load Forecasting for Weekday (Tuesday)

Table 5.10 Hourly Load Forecasting for Week 2 of Weekday (Tuesday)

Time	18-Mar	Forecasted(MW)		APE(MW)	
	(MW)	Type-I	Type-II	Type-I	Type-II
06:00	1546	1530	1544	1.04	0.13
07:00	1584	1540	1551	2.77	2.08
08:00	1588	1530	1516	3.67	4.55
09:00	1539	1300	1481	15.53	3.77
10:00	1474	1300	1471	11.82	0.23
11:00	1431	1300	1437	9.13	-0.45
12:00	1329	1300	1305	2.18	1.80
13:00	1308	1330	1304	-1.64	0.34
14:00	1306	1360	1301	-4.16	0.35
15:00	1302	1410	1312	-8.31	-0.78
16:00	1293	1310	1325	-1.30	-2.46
17:00	1287	1310	1378	-1.78	-7.06
18:00	1338	1300	1365	2.84	-2.02
19:00	1468	1300	1426	11.47	2.89
20:00	1441	1310	1437	9.11	0.29
21:00	1370	1310	1424	4.39	-3.93
22:00	1346	1310	1360	2.69	-1.03
23:00	1351	1300	1428	3.78	-5.70
00:00	1365	1300	1304	4.75	4.45
01:00	1487	1530	1551	-2.88	-4.30
02:00	1480	1530	1547	-3.37	-4.52
03:00	1510	1530	1541	-1.32	-2.04
04:00	1509	1540	1538	-2.04	-1.91
05:00	1497	1300	1546	13.18	-3.25

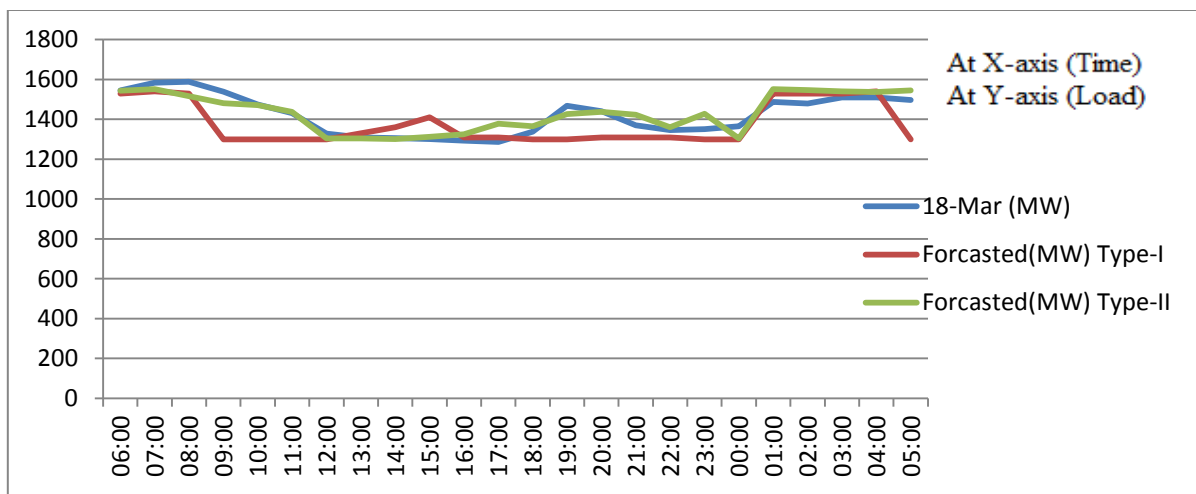


Figure 5.9 Comparison b/w Actual Load and Forecasted Load for Week 2 of weekday using Type-1 and Type-2 Fuzzy Logic Model

5.4.3 Hourly Load Forecasting for Weekday (Wednesday)

Table 5.11 Hourly Load Forecasting for Week 2 of Weekday (Wednesday)

Time	19-Mar	Forecasted(MW)		APE(MW)	
	(MW)	Type-I	Type-II	Type-I	Type-II
06:00	1533	1300	1543	15.18	-0.67
07:00	1530	1300	1551	15.01	-1.40
08:00	1540	1300	1428	15.57	7.26
09:00	1471	1300	1471	11.62	-0.01
10:00	1394	1300	1437	6.74	-3.08
11:00	1387	1300	1426	6.28	-2.80
12:00	1374	1390	1364	-1.15	0.74
13:00	1348	1330	1365	1.32	-1.28
14:00	1320	1360	1301	-3.02	1.45
15:00	1314	1310	1312	0.34	0.18
16:00	1315	1300	1329	1.16	-1.04
17:00	1309	1300	1303	0.71	0.49
18:00	1368	1300	1303	5.01	4.79
19:00	1508	1300	1426	13.82	5.47
20:00	1510	1380	1437	8.60	4.82
21:00	1442	1310	1423	9.14	1.30
22:00	1398	1300	1428	7.00	-2.16
23:00	1371	1300	1429	5.20	-4.20
00:00	1393	1300	1399	6.65	-0.46
01:00	1574	1550	1551	1.52	1.45
02:00	1553	1300	1546	16.27	0.43
03:00	1531	1540	1539	-0.57	-0.51
04:00	1499	1530	1477	-2.08	1.46
05:00	1545	1300	1542	15.85	0.18

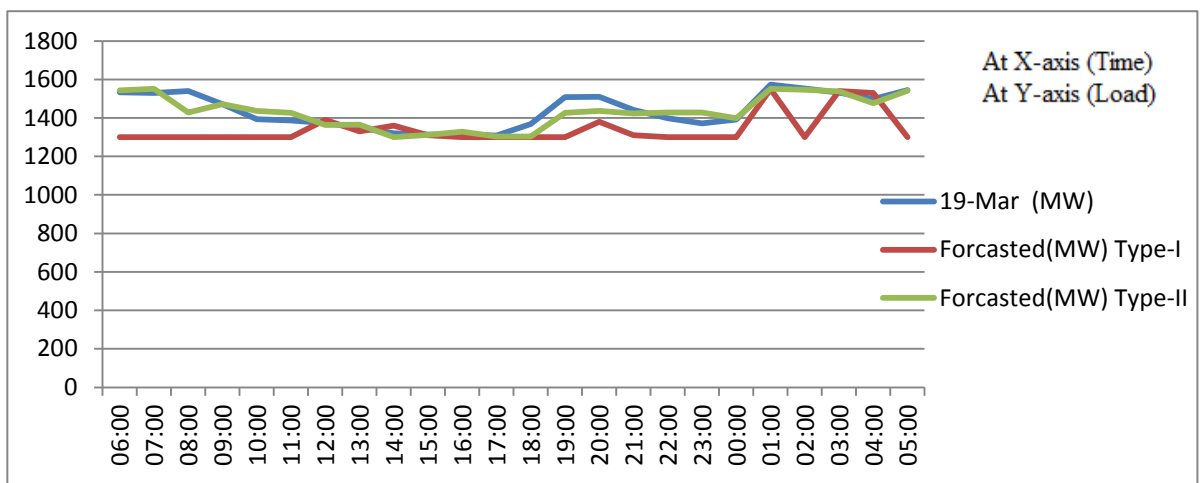


Figure 5.10 Comparison b/w Actual Load and Forecasted Load for Week 2 of weekday using Type-1 and Type-2 Fuzzy Logic Model

5.4.4 Hourly Load Forecasting for Weekday (Thursday)

Table 5.12 Hourly Load Forecasting for Week 2 of Weekday (Thursday)

Time	20-Mar	Forecasted(MW)		APE(MW)	
	(MW)	Type-I	Type-II	Type-I	Type-II
06:00	1449	1540	1544	-6.30	-6.57
07:00	1436	1540	1581	-7.21	-10.07
08:00	1450	1300	1428	10.35	1.53
09:00	1459	1300	1474	10.91	-1.01
10:00	1365	1300	1415	4.75	-3.68
11:00	1356	1300	1374	4.12	-1.34
12:00	1353	1300	1363	3.93	-0.73
13:00	1320	1300	1370	1.52	-3.79
14:00	1292	1380	1329	-6.77	-2.82
15:00	1303	1380	1374	-5.88	-5.42
16:00	1309	1310	1357	-0.07	-3.66
17:00	1259	1380	1428	-9.57	-13.38
18:00	1285	1390	1428	-8.16	-11.12
19:00	1424	1300	1359	8.73	4.59
20:00	1412	1300	1435	7.94	-1.62
21:00	1330	1300	1423	2.27	-6.97
22:00	1316	1300	1399	1.20	-6.32
23:00	1328	1310	1428	1.34	-7.55
00:00	1389	1300	1429	6.41	-2.87
01:00	1491	1300	1428	12.84	4.25
02:00	1469	1300	1427	11.50	2.85
03:00	1442	1300	1424	9.82	1.22
04:00	1474	1530	1480	-3.79	-0.40
05:00	1502	1530	1540	-1.84	-2.50

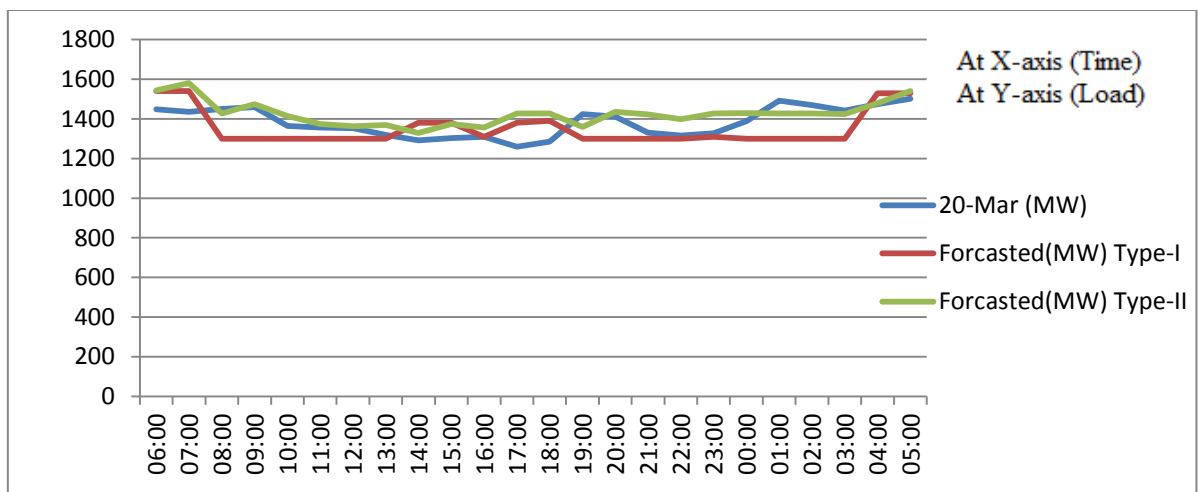


Figure 5.11 Comparison b/w Actual Load and Forecasted Load for Week 2 of weekday using Type-1 and Type-2 Fuzzy Logic Model

5.4.5 Hourly Load Forecasting for Weekday (Friday)

Table 5.13 Hourly Load Forecasting for Week 2 of Weekday (Friday)

Time	21-Mar	Forecasted(MW)		APE(MW)	
	(MW)	Type-I	Type-II	Type-I	Type-II
06:00	1482	1530	1545	-3.27	-4.28
07:00	1477	1530	1551	-3.58	-5.00
08:00	1464	1540	1550	-5.21	-5.90
09:00	1453	1530	1544	-5.30	-6.26
10:00	1363	1300	1536	4.61	-12.70
11:00	1344	1300	1426	3.28	-6.10
12:00	1335	1300	1428	2.59	-7.00
13:00	1314	1380	1364	-4.99	-3.77
14:00	1310	1360	1301	-3.79	0.72
15:00	1306	1360	1375	-4.13	-5.28
16:00	1294	1330	1360	-2.77	-5.09
17:00	1291	1300	1367	-0.69	-5.87
18:00	1235	1300	1428	-5.23	-15.59
19:00	1413	1350	1426	4.49	-0.89
20:00	1430	1310	1437	8.41	-0.47
21:00	1347	1310	1353	2.78	-0.41
22:00	1324	1310	1354	1.04	-2.28
23:00	1357	1310	1428	3.49	-5.21
00:00	1403	1300	1429	7.31	-1.86
01:00	1459	1550	1551	-6.27	-6.33
02:00	1507	1540	1545	-2.18	-2.51
03:00	1495	1540	1540	-2.99	-2.99
04:00	1509	1540	1546	-2.08	-2.47
05:00	1489	1540	1546	-3.42	-3.82

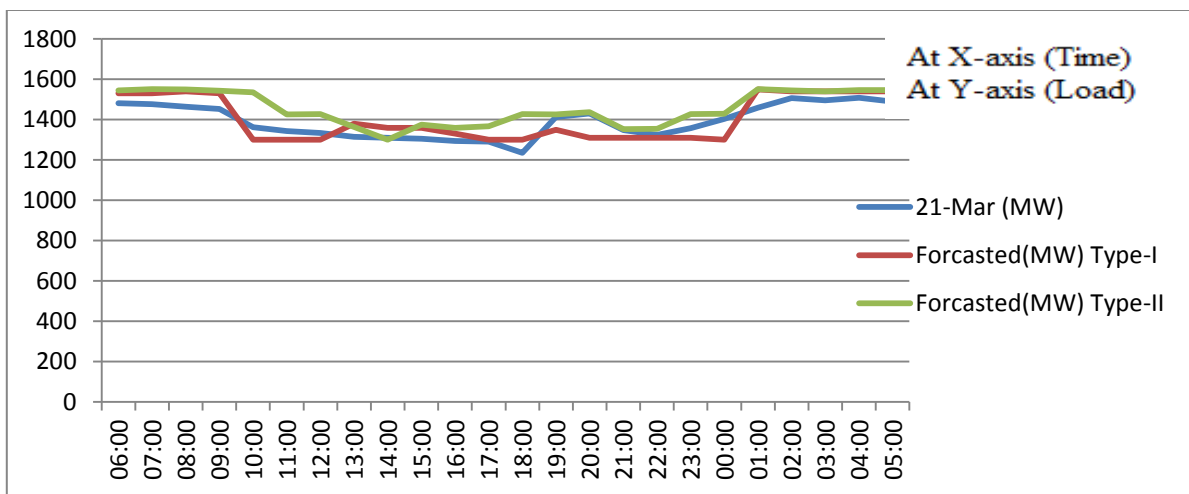


Figure 5.12 Comparison b/w Actual Load and Forecasted Load for Week 2 of weekday using Type-1 and Type-2 Fuzzy Logic Model

5.4.6 Hourly Load Forecasting for Weekend (Saturday)

Table 5.14 Hourly Load Forecasting for Week 2 of Weekend (Saturday)

Time	22-Mar	Forecasted(MW)		APE(MW)	
	(MW)	Type-I	Type-II	Type-I	Type-II
06:00	1446	1540	1544	-6.51	-6.78
07:00	1380	1530	1551	-10.83	-12.36
08:00	1352	1540	1551	-13.94	-14.76
09:00	1329	1300	1544	2.20	-16.16
10:00	1295	1300	1549	-0.42	-19.65
11:00	1280	1300	1445	-1.60	-12.93
12:00	1289	1300	1428	-0.84	-10.76
13:00	1299	1300	1303	-0.10	-0.33
14:00	1311	1300	1358	0.81	-3.62
15:00	1295	1310	1375	-1.16	-6.18
16:00	1271	1370	1358	-7.82	-6.88
17:00	1262	1430	1428	-13.31	-13.15
18:00	1282	1400	1428	-9.18	-11.36
19:00	1390	1340	1426	3.61	-2.58
20:00	1434	1300	1437	9.37	-0.18
21:00	1381	1300	1423	5.89	-3.02
22:00	1315	1300	1427	1.12	-8.55
23:00	1306	1300	1428	0.44	-9.36
00:00	1409	1300	1429	7.74	-1.42
01:00	1448	1540	1550	-6.39	-7.08
02:00	1427	1540	1546	-7.90	-8.32
03:00	1397	1540	1541	-10.23	-10.30
04:00	1383	1300	1536	6.01	-11.06
05:00	1395	1300	1540	6.79	-10.42

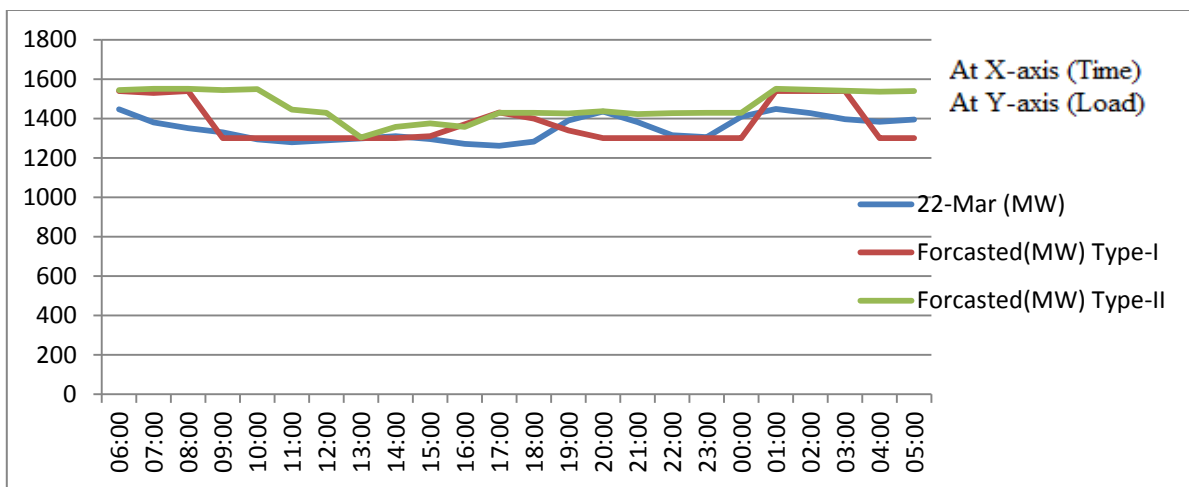


Figure 5.13 Comparison b/w Actual Load and Forecasted Load for Week 2 of weekend using Type-1 and Type-2 Fuzzy Logic Model

5.4.7 Hourly Load Forecasting for Weekend (Sunday)

Table 5.15 Hourly Load Forecasting for Week 2 of Weekend (Sunday)

Time	23-Mar	Forecasted(MW)		APE(MW)	
	(MW)	Type-I	Type-II	Type-I	Type-II
06:00	1396	1530	1544	-9.57	-10.58
07:00	1394	1300	1551	6.72	-11.29
08:00	1404	1300	1479	7.43	-5.32
09:00	1377	1300	1489	5.56	-8.17
10:00	1331	1300	1413	2.36	-6.12
11:00	1320	1300	1329	1.50	-0.70
12:00	1315	1300	1303	1.14	0.91
13:00	1326	1300	1364	1.98	-2.85
14:00	1326	1300	1358	1.96	-2.41
15:00	1332	1380	1375	-3.64	-3.26
16:00	1324	1420	1365	-7.25	-3.10
17:00	1324	1430	1428	-8.04	-7.89
18:00	1306	1380	1428	-5.70	-9.37
19:00	1470	1300	1427	11.54	2.90
20:00	1466	1300	1437	11.34	1.99
21:00	1407	1300	1423	7.61	-1.13
22:00	1381	1300	1427	5.87	-3.33
23:00	1388	1300	1428	6.34	-2.88
00:00	1436	1300	1429	9.50	0.52
01:00	1363	1550	1551	-13.73	-13.81
02:00	1350	1540	1547	-14.04	-14.55
03:00	1344	1540	1538	-14.61	-14.46
04:00	1348	1530	1549	-13.51	-14.92
05:00	1359	1300	1542	4.36	-13.44

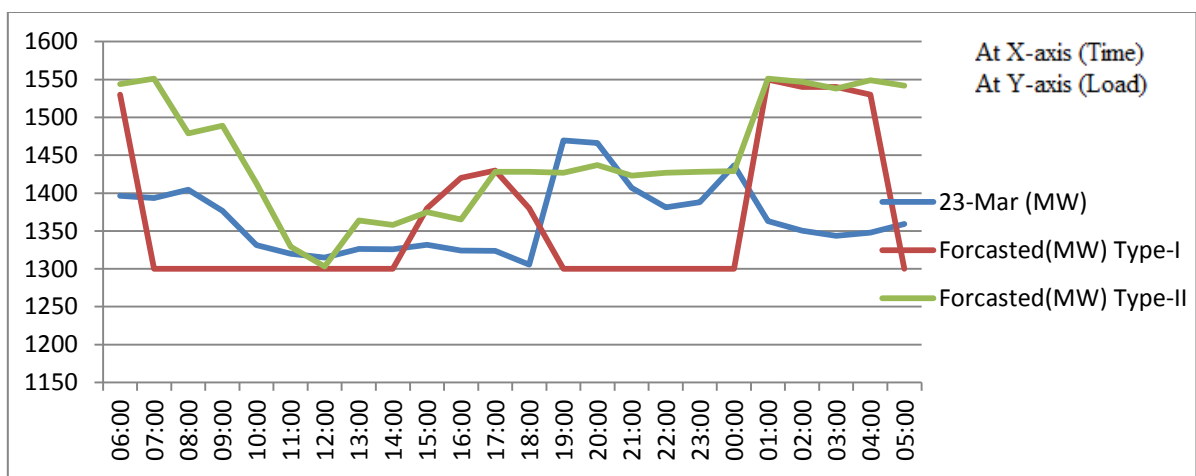


Figure 5.14 Comparison b/w Actual Load and Forecasted Load for Week 2 of weekend using Type-1 and Type-2 Fuzzy Logic Model

5.4.8 Comparison of Type-1 and Type-2 Fuzzy Logic Models in terms of MAPE for Week 2:

Table 5.16 MAPE in case of Type-1 and Type-2 Fuzzy Logic Models for Week 2

Days	Type-1 (MAPE)	Type-2 (MAPE)
Monday	4.50	2.36
Tuesday	5.21	2.51
Wednesday	7.07	1.98
Thursday	5.88	4.42
Friday	4.31	4.69
Saturday	5.59	8.63
Sunday	7.30	6.49

5.5 Calculations for MAPE for Week 3

5.5.1 Hourly Load Forecasting for Weekday (Monday)

Table 5.17 Hourly Load Forecasting for Week 3 Weekday (Monday)

Time	24-Mar	Forecasted(MW)		APE(MW)	
	(MW)	Type-I	Type-II	Type-I	Type-II
06:00	1392	1540	1544	-10.63	-10.92
07:00	1394	1540	1550	-10.51	-11.23
08:00	1424	1300	1493	8.73	-4.82
09:00	1403	1300	1471	7.32	-4.87
10:00	1336	1300	1469	2.69	-9.97
11:00	1332	1300	1368	2.38	-2.72
12:00	1324	1300	1364	1.81	-3.03
13:00	1330	1380	1364	-3.76	-2.56
14:00	1322	1420	1357	-7.42	-2.66
15:00	1322	1300	1437	1.64	-8.72
16:00	1322	1390	1426	-5.17	-7.90
17:00	1316	1390	1428	-5.60	-8.49
18:00	1308	1410	1428	-7.78	-9.16
19:00	1446	1350	1426	6.65	1.40
20:00	1474	1310	1395	11.10	5.33
21:00	1392	1310	1372	5.92	1.46
22:00	1369	1300	1399	5.06	-2.17
23:00	1388	1300	1401	6.33	-0.95
00:00	1415	1300	1429	8.15	-0.96
01:00	1403	1530	1551	-9.09	-10.58
02:00	1373	1530	1546	-11.42	-12.59
03:00	1358	1540	1538	-13.37	-13.22
04:00	1362	1530	1539	-12.32	-12.98
05:00	1382	1300	1540	5.96	-11.40

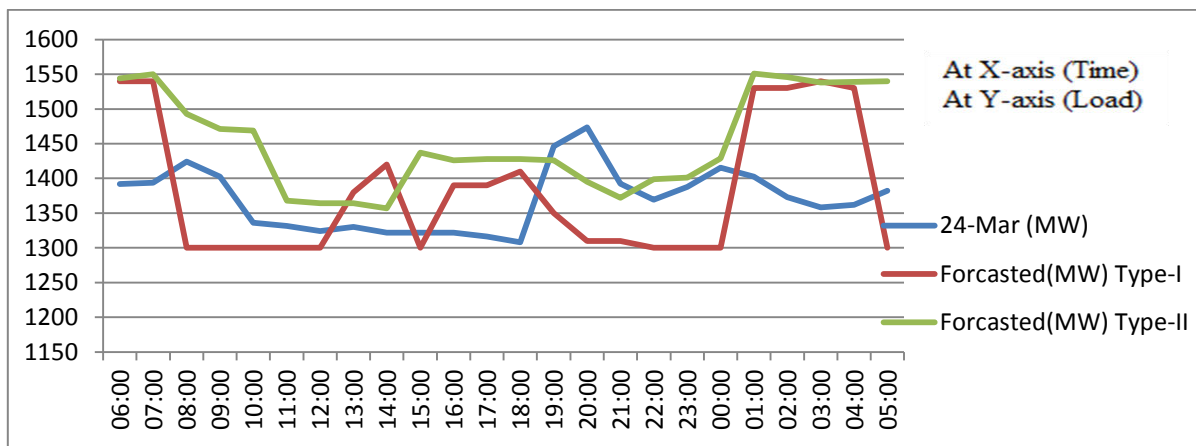


Figure 5.15 Comparison b/w Actual Load and Forecasted Load for Week 3 weekday using Type-1 and Type-2 Fuzzy Logic Model

5.5.2 Hourly Load Forecasting for Weekday (Tuesday)

Table 5.18 Hourly Load Forecasting for Week 3 Weekday (Tuesday)

Time	25-Mar	Forecasted(MW)		APE(MW)	
	(MW)	Type-I	Type-II	Type-I	Type-II
06:00	1491	1540	1544	-3.29	-3.44
07:00	1486	1550	1551	-4.27	-4.16
08:00	1463	1300	1551	11.11	-5.70
09:00	1442	1300	1476	9.83	-2.33
10:00	1344	1300	1411	3.26	-4.76
11:00	1356	1300	1357	4.09	-0.11
12:00	1354	1300	1428	3.97	-5.20
13:00	1359	1380	1364	-1.54	-0.36
14:00	1359	1370	1329	-0.81	2.26
15:00	1307	1310	1375	-0.26	-4.97
16:00	1301	1300	1357	0.09	-4.12
17:00	1288	1300	1428	-0.91	-9.78
18:00	1299	1300	1428	-0.06	-9.02
19:00	1452	1300	1426	10.46	1.82
20:00	1463	1310	1437	10.49	1.84
21:00	1383	1310	1347	5.30	2.70
22:00	1335	1310	1427	1.90	-6.42
23:00	1352	1300	1428	3.85	-5.32
00:00	1377	1300	1429	5.62	-3.61
01:00	1405	1550	1549	-10.31	-9.28
02:00	1376	1540	1547	-11.88	-11.03
03:00	1356	1540	1541	-13.58	-12.02
04:00	1345	1530	1543	-13.75	-12.83
05:00	1355	1530	1519	-12.88	-10.77

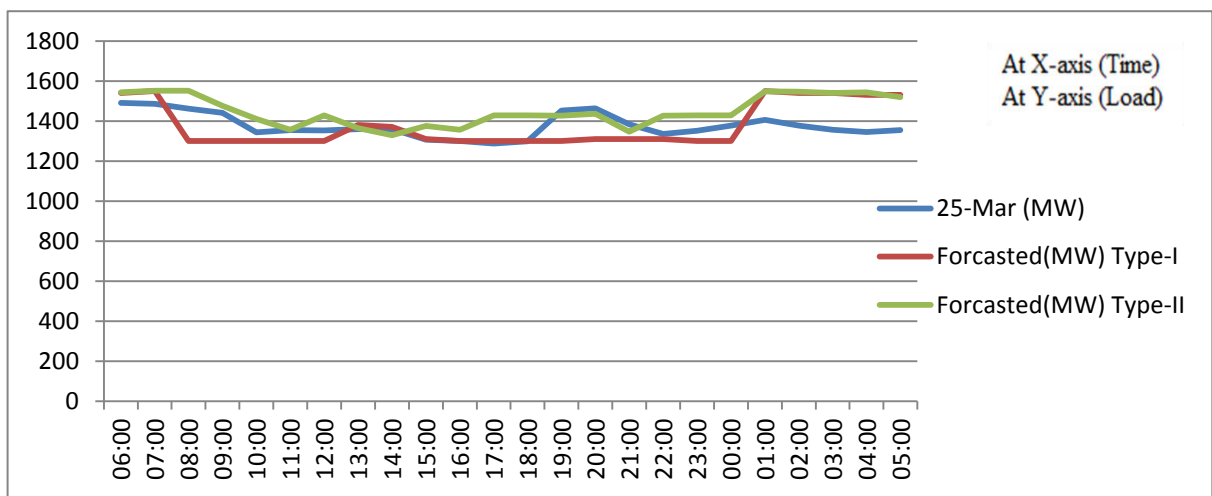


Figure 5.16 Comparison b/w Actual Load and Forecasted Load for Week 3 weekday using Type-1 and Type-2 Fuzzy Logic Model

5.5.3 Hourly Load Forecasting for Weekday (Wednesday)

Table 5.19 Hourly Load Forecasting for Week 3 Weekday (Wednesday)

Time	26-Mar	Forecasted(MW)		APE(MW)	
	(MW)	Type-I	Type-II	Type-I	Type-II
06:00	1526	1540	1544	-0.93	-1.19
07:00	1525	1530	1551	-0.30	-1.67
08:00	1512	1300	1500	14.04	0.81
09:00	1479	1300	1426	12.13	3.61
10:00	1302	1300	1374	0.18	-5.50
11:00	1315	1300	1358	1.14	-3.27
12:00	1314	1300	1428	1.09	-8.64
13:00	1353	1300	1364	3.95	-0.78
14:00	1366	1350	1358	1.14	0.55
15:00	1365	1310	1374	4.06	-0.63
16:00	1332	1300	1357	2.43	-1.85
17:00	1295	1300	1364	-0.35	-5.29
18:00	1295	1300	1428	-0.42	-10.30
19:00	1444	1390	1426	3.75	1.26
20:00	1470	1310	1437	10.91	2.27
21:00	1409	1310	1298	7.04	7.89
22:00	1345	1310	1302	2.63	3.22
23:00	1428	1310	1375	8.29	3.74
00:00	1464	1300	1356	11.18	7.35
01:00	1533	1530	1551	0.20	-1.17
02:00	1506	1540	1546	-2.24	-2.64
03:00	1488	1540	1540	-3.52	-3.52
04:00	1473	1530	1546	-3.89	-4.97
05:00	1478	1300	1542	12.06	-4.32

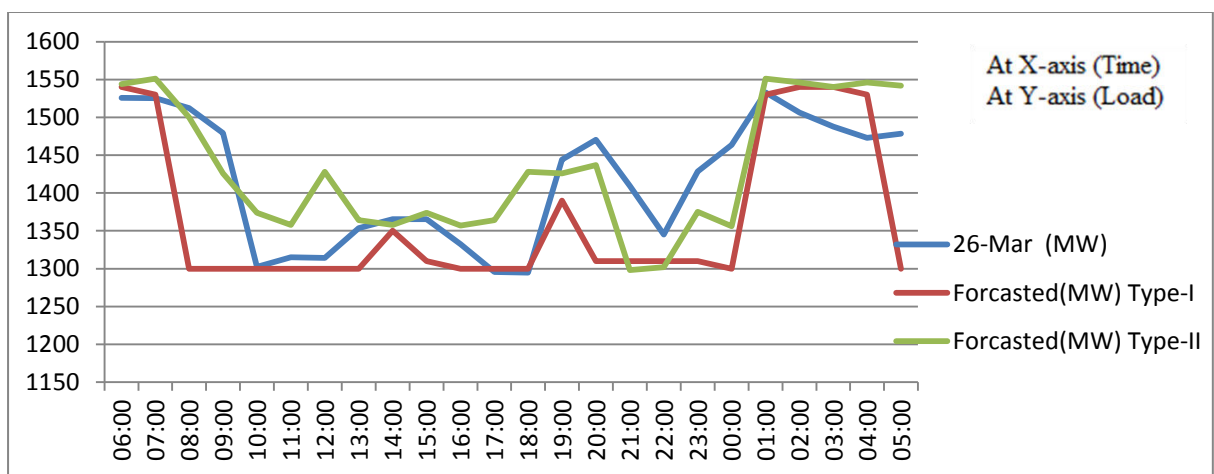


Figure 5.17 Comparison b/w Actual Load and Forecasted Load for Week 3 weekday using Type-1 and Type-2 Fuzzy Logic Model

5.5.4 Hourly Load Forecasting for Weekday (Thursday)

Table 5.20 Hourly Load Forecasting for Week 3 Weekday (Thursday)

Time	27-Mar	Forecasted(MW)		APE(MW)	
	(MW)	Type-I	Type-II	Type-I	Type-II
06:00	1508	1540	1544	-2.10	-2.37
07:00	1518	1530	1551	-0.79	-2.17
08:00	1528	1300	1551	14.94	-1.49
09:00	1413	1300	1544	7.99	-9.29
10:00	1276	1300	1480	-1.87	-15.98
11:00	1282	1300	1358	-1.41	-5.93
12:00	1313	1300	1303	0.99	0.76
13:00	1334	1380	1303	-3.43	2.35
14:00	1342	1370	1301	-2.07	3.07
15:00	1315	1310	1375	0.37	-4.58
16:00	1319	1310	1329	0.67	-0.77
17:00	1278	1300	1428	-1.73	-11.74
18:00	1262	1430	1428	-13.30	-13.14
19:00	1389	1300	1426	6.43	-2.63
20:00	1459	1300	1437	10.93	1.54
21:00	1398	1300	1437	6.98	-2.82
22:00	1346	1380	1302	-2.52	3.28
23:00	1394	1380	1428	1.00	-2.45
00:00	1415	1300	1429	8.11	-1.00
01:00	1583	1540	1550	2.73	2.10
02:00	1558	1540	1546	1.14	0.75
03:00	1542	1540	1546	0.15	-0.24
04:00	1516	1540	1542	-1.57	-1.70
05:00	1529	1530	1542	-0.09	-0.88

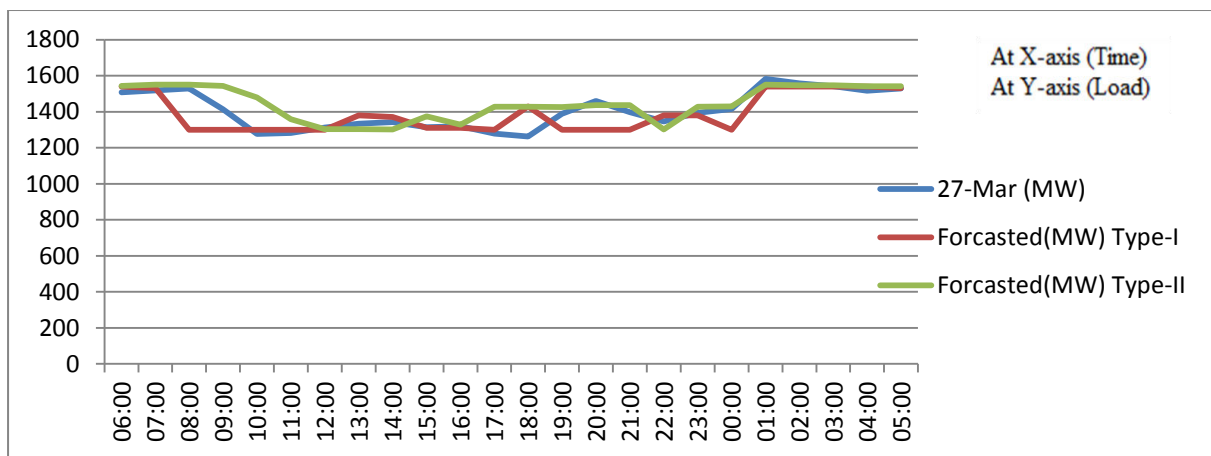


Figure 5.18 Comparison b/w Actual Load and Forecasted Load for Week 3 weekday using Type-1 and Type-2 Fuzzy Logic Model

5.5.5 Hourly Load Forecasting for Weekday (Friday)

Table 5.21 Hourly Load Forecasting for Week 3 Weekday (Friday)

Time	28-Mar	Forecasted(MW)	Forecasted(MW)	APE(MW)	APE(MW)
	(MW)	Type-I	Type-II	Type-I	Type-II
06:00	1535	1300	1426	15.31	7.10
07:00	1575	1300	1551	17.44	1.50
08:00	1525	1300	1500	14.73	1.61
09:00	1533	1300	1427	15.17	6.89
10:00	1378	1300	1476	5.68	-7.09
11:00	1309	1300	1307	0.71	0.17
12:00	1294	1380	1364	-6.61	-5.37
13:00	1304	1370	1364	-5.10	-4.64
14:00	1305	1370	1301	-4.96	0.32
15:00	1299	1310	1375	-0.85	-5.85
16:00	1267	1310	1357	-3.40	-7.11
17:00	1263	1310	1303	-3.69	-3.14
18:00	1263	1300	1363	-2.93	-7.92
19:00	1419	1400	1426	1.31	-0.53
20:00	1432	1390	1437	2.92	-0.37
21:00	1362	1380	1437	-1.32	-5.51
22:00	1329	1300	1427	2.15	-7.40
23:00	1430	1300	1428	9.08	0.13
00:00	1448	1300	1353	10.22	6.56
01:00	1567	1540	1549	1.73	1.15
02:00	1555	1530	1547	1.58	0.48
03:00	1530	1540	1537	-0.65	-0.46
04:00	1531	1530	1471	0.07	3.92
05:00	1547	1530	1549	1.12	-0.11

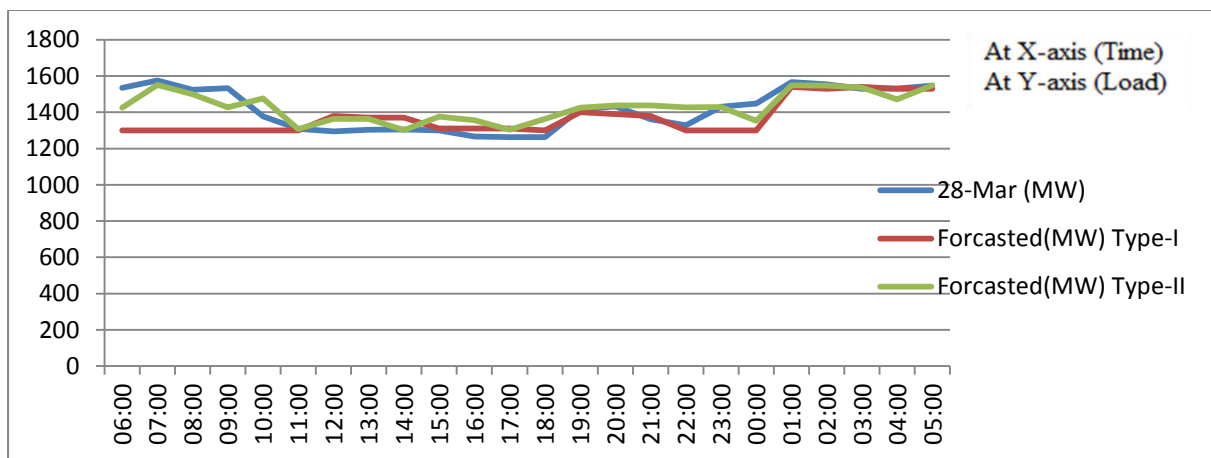


Figure 5.19 Comparison b/w Actual Load and Forecasted Load for Week 3 weekday using Type-1 and Type-2 Fuzzy Logic Model

5.5.6 Hourly Load Forecasting for Weekday (Saturday)

Table 5.22 Hourly Load Forecasting for Week 3 Weekend (Saturday)

Time	29-Mar	Forecasted(MW)		APE(MW)	
	(MW)	Type-I	Type-II	Type-I	Type-II
06:00	1511	1530	1544	-1.28	-2.20
07:00	1526	1540	1551	-0.92	-1.64
08:00	1520	1300	1550	14.46	-1.99
09:00	1456	1300	1572	10.72	-7.96
10:00	1369	1300	1412	5.02	-3.16
11:00	1344	1300	1360	3.26	-1.21
12:00	1332	1300	1303	2.38	2.15
13:00	1308	1370	1303	-4.75	0.38
14:00	1314	1340	1301	-2.01	0.96
15:00	1284	1360	1312	-5.96	-2.22
16:00	1267	1310	1301	-3.36	-2.65
17:00	1268	1310	1364	-3.32	-7.58
18:00	1259	1300	1364	-3.27	-8.35
19:00	1406	1400	1357	0.42	3.48
20:00	1449	1300	1374	10.30	5.20
21:00	1423	1300	1353	8.63	4.91
22:00	1371	1300	1302	5.16	5.01
23:00	1415	1300	1428	8.14	-0.90
00:00	1496	1300	1429	13.12	4.50
01:00	1527	1540	1549	-0.88	-1.47
02:00	1502	1550	1546	-3.18	-2.91
03:00	1483	1540	1540	-3.85	-3.85
04:00	1478	1530	1549	-3.52	-4.81
05:00	1490	1530	1549	-2.66	-3.94

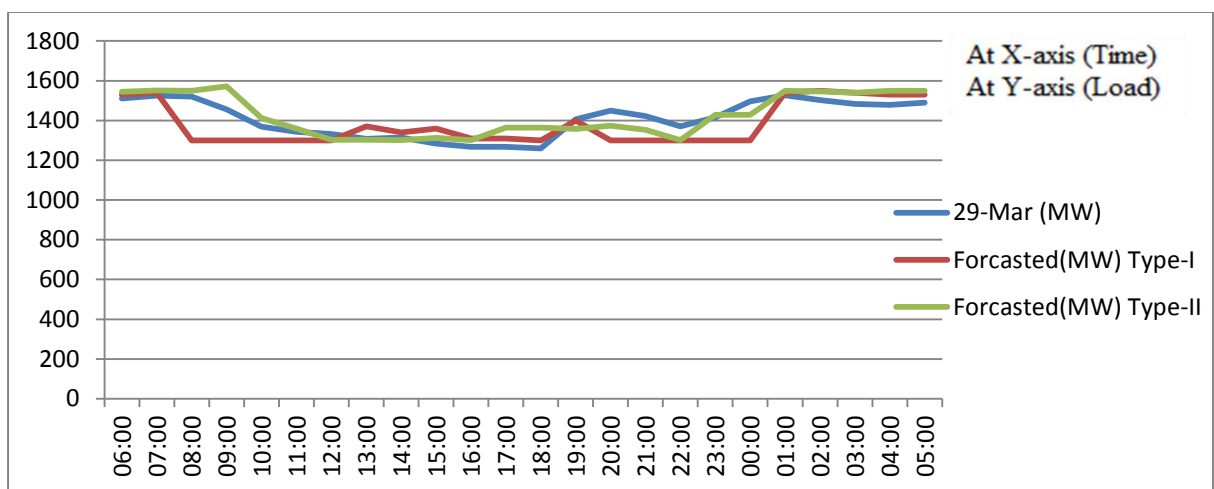


Figure 5.20 Comparison b/w Actual Load and Forecasted Load for Week 3 weekend using Type-1 and Type-2 Fuzzy Logic Model

5.5.7 Hourly Load Forecasting for Weekend (Sunday)

Table 5.23 Hourly Load Forecasting For Week 3 Weekend (Sunday)

Time	30-Mar	Forecasted(MW)		APE(MW)	
	(MW)	Type-I	Type-II	Type-I	Type-II
06:00	1525	1530	1545	-0.33	-1.32
07:00	1585	1530	1551	3.46	2.13
08:00	1543	1540	1551	0.17	-0.54
09:00	1504	1300	1543	13.54	-2.63
10:00	1361	1300	1476	4.48	-8.45
11:00	1235	1300	1357	-5.25	-9.86
12:00	1229	1300	1303	-5.81	-6.06
13:00	1190	1370	1299	-15.14	-9.17
14:00	1250	1360	1358	-8.77	-8.61
15:00	1283	1310	1312	-2.12	-2.27
16:00	1286	1310	1359	-1.85	-5.66
17:00	1257	1310	1366	-4.19	-8.64
18:00	1258	1300	1365	-3.30	-8.47
19:00	1380	1300	1359	5.76	1.49
20:00	1438	1300	1374	9.61	4.47
21:00	1402	1300	1354	7.26	3.41
22:00	1343	1300	1427	3.23	-6.22
23:00	1406	1300	1428	7.54	-1.56
00:00	1468	1300	1428	11.44	2.72
01:00	1572	1540	1550	2.01	1.37
02:00	1548	1550	1546	-0.12	0.14
03:00	1524	1530	1541	-0.36	-1.08
04:00	1509	1530	1479	-1.42	1.96
05:00	1523	1300	1475	14.64	3.15

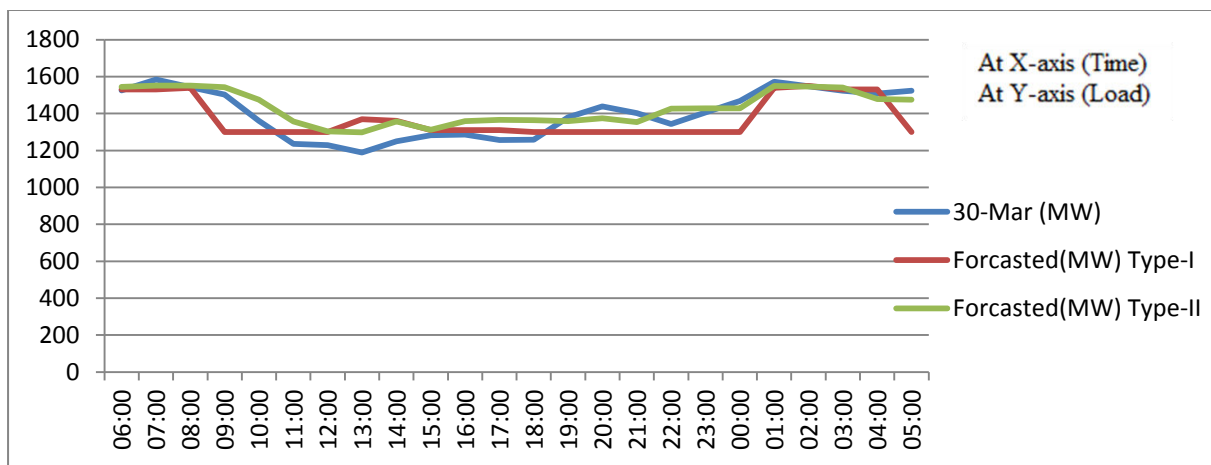


Figure 5.21 Comparison b/w Actual Load and Forecasted Load for Week 3 weekend using Type-1 and Type-2 Fuzzy Logic Model

5.5.8 Comparison of Type-1 and Type-2 Fuzzy Logic Models in terms of MAPE for Week 3:

Table 5.24 MAPE in case of Type-1 and Type-2 Fuzzy Logic Models for Week 3

Days	Type-1 (MAPE)	Type-2 (MAPE)
Monday	7.12	8.67
Tuesday	5.98	5.58
Wednesday	4.49	3.60
Thursday	3.88	3.87
Friday	5.36	3.55
Saturday	5.02	3.48
Sunday	5.49	4.22

5.6 Calculations for MAPE for Week 4

5.6.1 Hourly Load Forecasting for Weekday (Monday)

Table 5.25 Hourly Load Forecasting for Week 4 Weekday (Monday)

Time	March.31	Forecasted(MW)		APE(MW)	
	(MW)	Type-I	Type-II	Type-I	Type-II
06:00	1200	1300	1217	-8.33	-1.42
07:00	1220	1300	1260	-6.56	-3.28
08:00	1315	1300	1260	1.14	4.18
09:00	1308	1300	1300	0.61	0.61
10:00	1227	1300	1266	-5.95	-3.18
11:00	1240	1300	1255	-4.84	-1.21
12:00	1285	1310	1261	-1.95	1.87
13:00	1311	1340	1303	-2.21	0.61
14:00	1316	1300	1255	1.22	4.64
15:00	1318	1300	1308	1.37	0.76
16:00	1306	1310	1300	-0.31	0.46
17:00	1277	1390	1385	-8.85	-8.46
18:00	1233	1300	1259	-5.43	-2.11
19:00	1338	1390	1265	-3.89	5.46
20:00	1434	1300	1321	9.34	7.88
21:00	1364	1300	1385	4.69	-1.54
22:00	1280	1300	1416	-1.56	-10.63
23:00	1283	1300	1467	-1.33	-14.34
00:00	1327	1300	1468	2.03	-10.63
01:00	1134	1300	1193	-14.64	-5.20
02:00	1199	1300	1202	-8.42	-0.25
03:00	1092	1300	1130	-19.05	-3.48
04:00	1089	1300	1180	-19.38	-8.36
05:00	1090	1300	1198	-19.27	-9.91

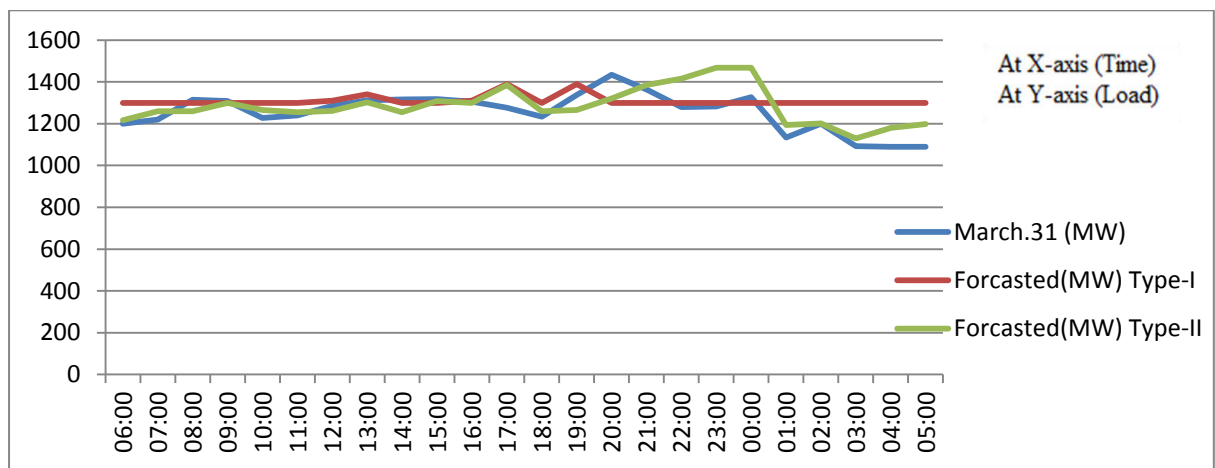


Figure 5.22 Comparison b/w Actual Load and Forecasted Load for Week 4 weekday using Type-1 and Type-2 Fuzzy Logic Model

5.6.2 Hourly Load Forecasting for Weekday (Tuesday)

Table 5.26 Hourly Load Forecasting for Week 4 Weekday (Tuesday)

Time	Apr. 1	Forecasted(MW)		APE(MW)	
	(MW)	Type-I	Type-II	Type-I	Type-II
06:00	1306	1270	1281	2.76	1.91
07:00	1402	1270	1302	9.42	7.13
08:00	1385	1270	1303	8.30	5.92
09:00	1379	1390	1308	-0.80	5.15
10:00	1322	1390	1308	-5.14	1.06
11:00	1323	1390	1301	-5.06	1.66
12:00	1323	1350	1303	-2.04	1.51
13:00	1316	1390	1302	-5.62	1.06
14:00	1328	1320	1308	0.60	1.51
15:00	1327	1310	1308	1.28	1.43
16:00	1313	1310	1301	0.23	0.91
17:00	1297	1300	1302	-0.23	-0.39
18:00	1292	1300	1302	-0.62	-0.77
19:00	1414	1390	1384	1.70	2.12
20:00	1489	1300	1411	12.69	5.24
21:00	1401	1300	1385	7.21	1.14
22:00	1341	1390	1416	-3.65	-5.59
23:00	1352	1390	1386	-2.81	-2.51
00:00	1376	1300	1386	5.52	-0.73
01:00	1364	1270	1220	6.89	10.56
02:00	1321	1270	1218	3.86	7.80
03:00	1235	1270	1217	-2.83	1.46
04:00	1230	1270	1273	-3.25	-3.50
05:00	1230	1270	1281	-3.25	-4.15

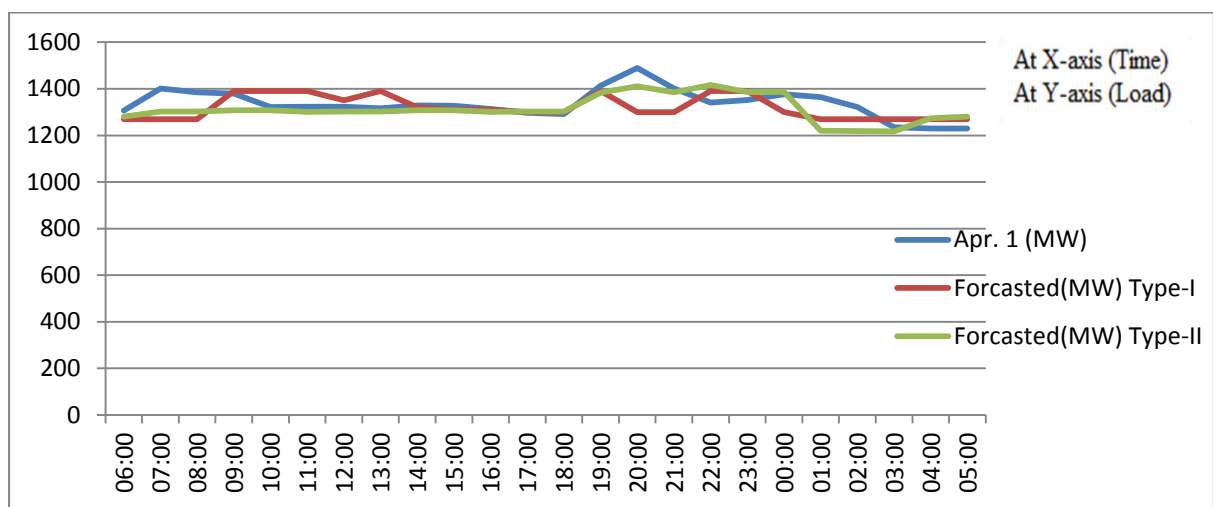


Figure 5.23 Comparison b/w Actual Load and Forecasted Load for Week 4 weekday using Type-1 and Type-2 Fuzzy Logic Model

5.6.3 Hourly Load Forecasting for Weekday (Wednesday)

Table 5.27 Hourly Load Forecasting for Week 4 Weekday (Wednesday)

Time	Apr. 2	Forecasted(MW)		APE(MW)	
	(MW)	Type-I	Type-II	Type-I	Type-II
06:00	1386	1310	1290	5.48	6.93
07:00	1350	1310	1297	2.96	3.93
08:00	1338	1270	1385	5.08	-3.51
09:00	1299	1310	1292	-0.85	0.54
10:00	1230	1350	1266	-9.76	-2.93
11:00	1301	1340	1300	-3.00	0.08
12:00	1323	1370	1302	-3.55	1.59
13:00	1324	1350	1302	-1.96	1.66
14:00	1301	1320	1304	-1.46	-0.23
15:00	1301	1310	1308	-0.69	-0.54
16:00	1298	1310	1308	-0.92	-0.77
17:00	1298	1310	1302	-0.92	-0.31
18:00	1313	1310	1302	0.23	0.84
19:00	1443	1310	1360	9.22	5.75
20:00	1500	1310	1369	12.67	8.73
21:00	1405	1310	1364	6.76	2.92
22:00	1379	1300	1416	5.73	-2.68
23:00	1380	1300	1306	5.80	5.36
00:00	1415	1300	1387	8.13	1.98
01:00	1373	1300	1386	5.32	-0.95
02:00	1349	1300	1217	3.63	9.79
03:00	1319	1300	1299	1.44	1.52
04:00	1314	1300	1289	1.07	1.90
05:00	1327	1250	1240	5.80	6.56

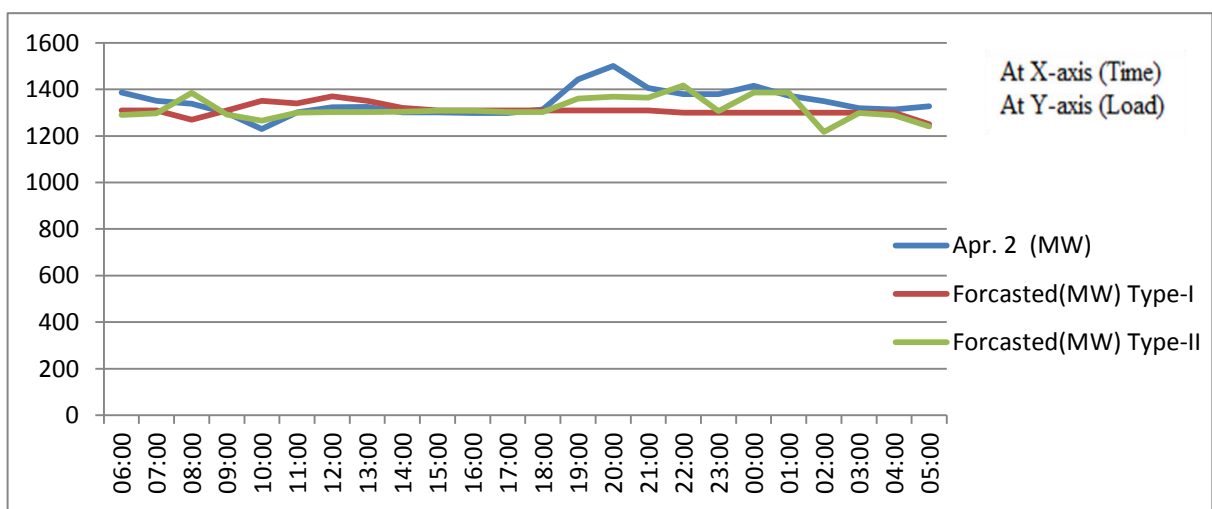


Figure 5.24 Comparison b/w Actual Load and Forecasted Load for Week 4 weekday using Type-1 and Type-2 Fuzzy Logic Model

5.6.4 Hourly Load Forecasting for Weekday (Thursday)

Table 5.28 Hourly Load Forecasting for Week 4 Weekday (Thursday)

Time	Apr. 3	Forecasted(MW)		APE(MW)	
	(MW)	Type-I	Type-II	Type-I	Type-II
06:00	1306	1310	1271	-0.31	2.68
07:00	1389	1180	1280	15.05	7.85
08:00	1389	1280	1311	7.85	5.62
09:00	1372	1270	1281	7.43	6.63
10:00	1309	1310	1308	-0.08	0.08
11:00	1309	1310	1259	-0.08	3.82
12:00	1308	1300	1302	0.61	0.46
13:00	1302	1300	1302	0.15	0.00
14:00	1302	1330	1300	-2.15	0.15
15:00	1305	1310	1308	-0.38	-0.23
16:00	1301	1300	1360	0.08	-4.53
17:00	1301	1300	1367	0.08	-5.07
18:00	1294	1310	1367	-1.24	-5.64
19:00	1429	1300	1360	9.03	4.83
20:00	1472	1300	1372	11.68	6.79
21:00	1388	1300	1353	6.34	2.52
22:00	1358	1300	1416	4.27	-4.27
23:00	1362	1300	1386	4.55	-1.76
00:00	1386	1300	1387	6.20	-0.07
01:00	1360	1300	1386	4.41	-1.91
02:00	1318	1240	1224	5.92	7.13
03:00	1297	1300	1218	-0.23	6.09
04:00	1268	1260	1240	0.63	2.21
05:00	1247	1310	1276	-5.05	-2.33

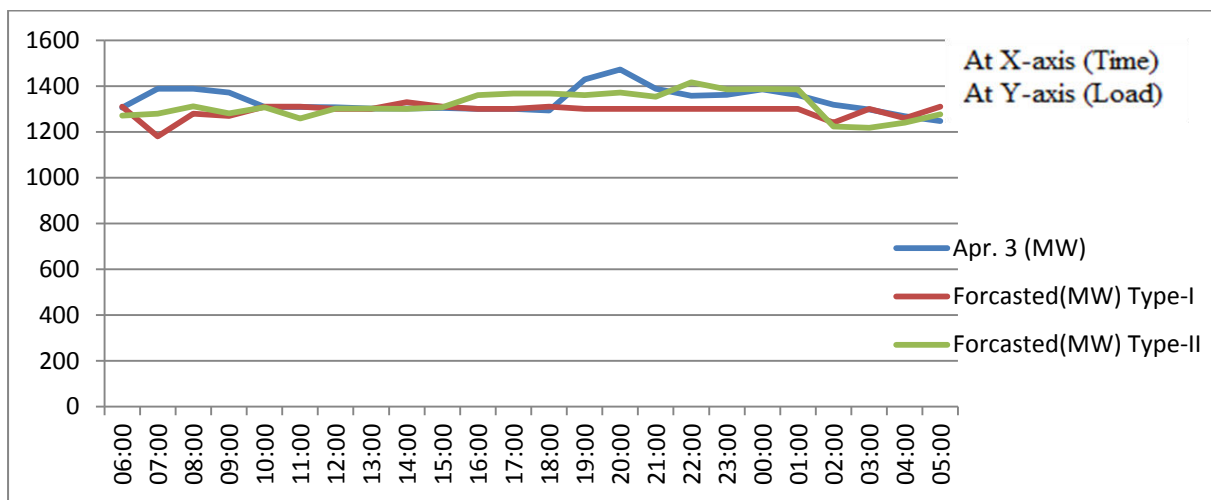


Figure 5.25 Comparison b/w Actual Load and Forecasted Load for Week 4 weekday using Type-1 and Type-2 Fuzzy Logic Model

5.6.5 Hourly Load Forecasting for Weekday (Friday)

Table 5.29 Hourly Load Forecasting For Week 4 Weekday (Friday)

Time	Apr. 4	Forecasted(MW)		APE(MW)	
	(MW)	Type-I	Type-II	Type-I	Type-II
06:00	1354	1300	1272	3.99	6.06
07:00	1407	1310	1288	6.89	8.46
08:00	1396	1280	1259	8.31	9.81
09:00	1349	1360	1256	-0.82	6.89
10:00	1307	1360	1266	-4.06	3.14
11:00	1297	1350	1262	-4.09	2.70
12:00	1275	1360	1302	-6.67	-2.12
13:00	1258	1300	1219	-3.34	3.10
14:00	1255	1300	1217	-3.59	3.03
15:00	1270	1300	1225	-2.36	3.54
16:00	1270	1300	1256	-2.36	1.10
17:00	1192	1300	1302	-9.06	-9.23
18:00	1188	1300	1302	-9.43	-9.60
19:00	1330	1360	1265	-2.26	4.89
20:00	1393	1350	1308	3.09	6.10
21:00	1331	1350	1299	-1.43	2.40
22:00	1275	1340	1302	-5.10	-2.12
23:00	1280	1320	1303	-3.13	-1.80
00:00	1297	1300	1386	-0.23	-6.86
01:00	1269	1270	1219	-0.08	3.94
02:00	1265	1270	1218	-0.40	3.72
03:00	1260	1230	1215	2.38	3.57
04:00	1261	1240	1253	1.67	0.63
05:00	1266	1270	1271	-0.32	-0.39

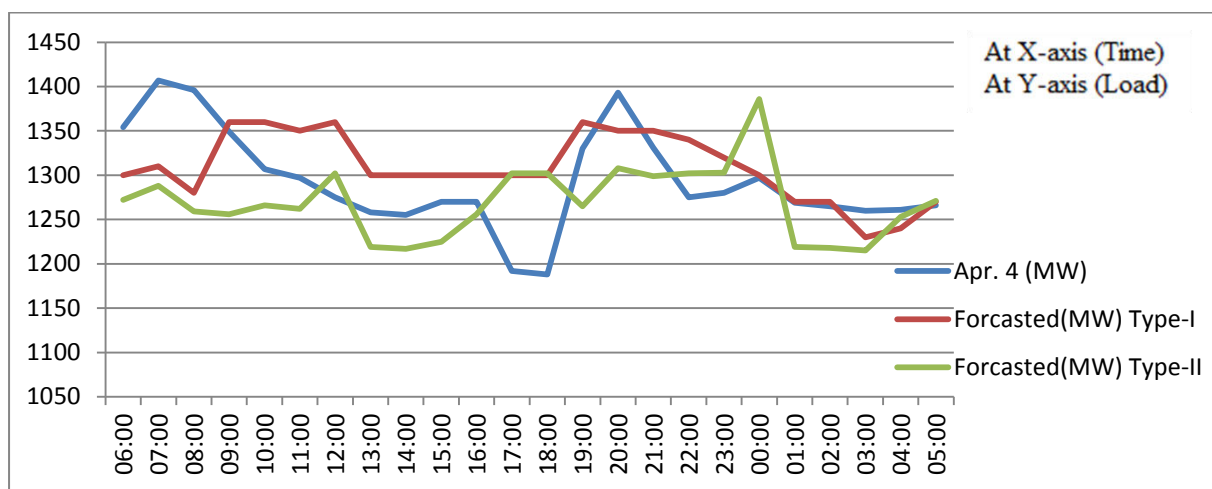


Figure 5.26 Comparison b/w Actual Load and Forecasted Load for Week 4 weekday using Type-1 and Type-2 Fuzzy Logic Model

5.6.6 Hourly Load Forecasting for Weekend (Saturday)

Table 5.30 Hourly Load Forecasting for Week 4 Weekend (Saturday)

Time	Apr. 5	Forecasted(MW)		APE(MW)	
	(MW)	Type-I	Type-II	Type-I	Type-II
06:00	1162	1180	1271	-1.55	-9.38
07:00	1284	1280	1284	0.31	0.00
08:00	1295	1310	1297	-1.16	-0.15
09:00	1259	1250	1296	0.71	-2.94
10:00	1218	1310	1308	-7.55	-7.39
11:00	1290	1310	1290	-1.55	0.00
12:00	1285	1390	1302	-8.17	-1.32
13:00	1279	1330	1302	-3.99	-1.80
14:00	1298	1370	1314	-5.55	-1.23
15:00	1314	1310	1308	0.30	0.46
16:00	1309	1310	1360	-0.08	-3.90
17:00	1281	1310	1302	-2.26	-1.64
18:00	1278	1310	1302	-2.50	-1.88
19:00	1397	1390	1368	0.50	2.08
20:00	1458	1460	1458	-0.14	0.00
21:00	1426	1470	1410	-3.09	1.12
22:00	1360	1390	1416	-2.21	-4.12
23:00	1351	1410	1419	-4.37	-5.03
00:00	1294	1190	1303	8.04	-0.70
01:00	1173	1210	1227	-3.15	-4.60
02:00	1162	1220	1229	-4.99	-5.77
03:00	1119	1240	1217	-10.81	-8.76
04:00	1119	1210	1291	-8.13	-15.37
05:00	1127	1180	1291	-4.70	-14.55

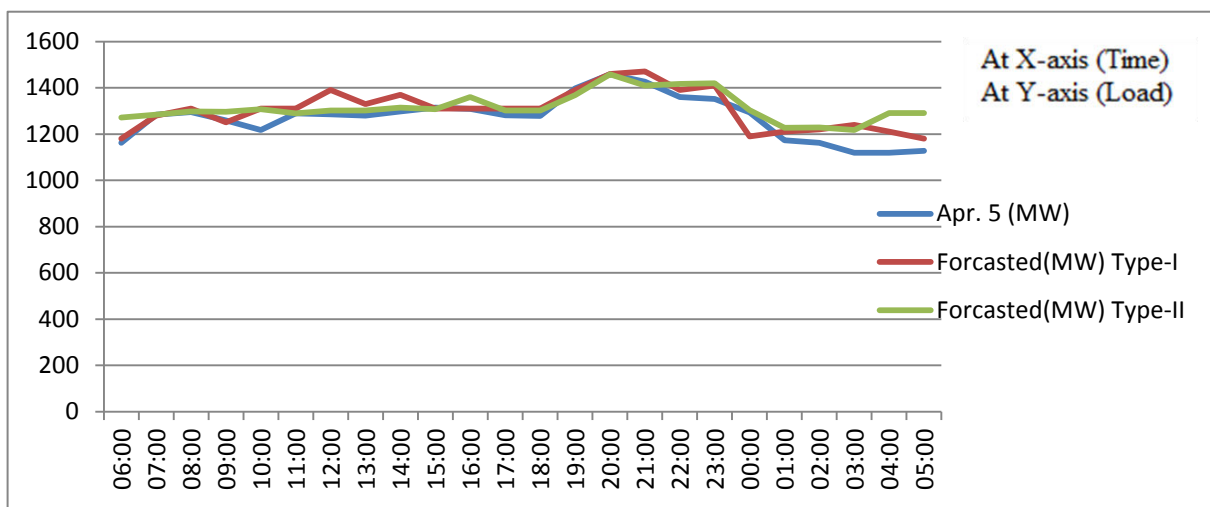


Figure 5.27 Comparison b/w Actual Load and Forecasted Load for Week 4 weekend using Type-1 and Type-2 Fuzzy Logic Model

5.6.7 Hourly Load Forecasting for Weekday (Sunday)

Table 5.31 Hourly Load Forecasting for Week 4 Weekend (Sunday)

Time	Apr.6	Forecasted(MW)		APE(MW)	
	(MW)	Type-I	Type-II	Type-I	Type-II
06:00	1051	1300	1300	-23.69	-23.69
07:00	1174	1300	1302	-10.73	-10.90
08:00	1175	1300	1128	-10.64	4.00
09:00	1218	1270	1256	-4.27	-3.12
10:00	1169	1390	1266	-18.91	-8.30
11:00	1231	1300	1277	-5.61	-3.74
12:00	1221	1380	1302	-13.02	-6.63
13:00	1215	1380	1302	-13.58	-7.16
14:00	1224	1340	1314	-9.48	-7.35
15:00	1235	1310	1369	-6.07	-10.85
16:00	1234	1310	1360	-6.16	-10.21
17:00	1205	1310	1374	-8.71	-14.02
18:00	1206	1310	1367	-8.62	-13.35
19:00	1337	1310	1360	2.02	-1.72
20:00	1386	1300	1370	6.20	1.15
21:00	1326	1300	1308	1.96	1.36
22:00	1270	1300	1416	-2.36	-11.50
23:00	1277	1300	1302	-1.80	-1.96
00:00	1284	1300	1419	-1.25	-10.51
01:00	1078	1270	1252	-17.81	-16.14
02:00	1033	1270	1253	-22.94	-21.30
03:00	1015	1270	1250	-25.12	-23.15
04:00	1016	1300	1240	-27.95	-22.05
05:00	1017	1300	1139	-27.83	-12.00

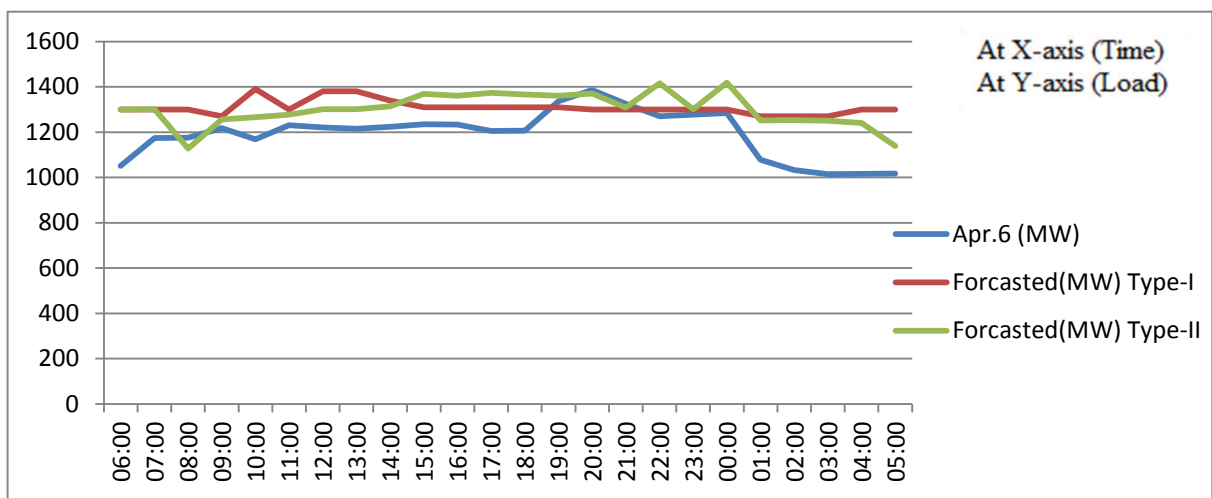


Figure 5.28 Comparison b/w Actual Load and Forecasted Load for Week 4 weekday using Type-1 and Type-2 Fuzzy Logic Model

5.6.8 Comparison of Type-1 and Type-2 Fuzzy Logic Models in terms of MAPE for Week 4:

Table 5.32 MAPE in case of Type-1 and Type-2 Fuzzy Logic Models for Week 4

Days	Type-1 (MAPE)	Type-2 (MAPE)
Monday	6.35	4.60
Tuesday	3.99	3.13
Wednesday	4.27	2.99
Thursday	3.9	3.45
Friday	3.54	4.38
Saturday	3.57	3.92
Sunday	11.5	10.25

5.7 Comparison of Type-1 and Type-2 Fuzzy Logic Models in terms of Average MAPE

Table 5.33 Average MAPE in case of Type-1 and Type-2 Fuzzy Logic Models

Days	Type-1 (MAPE)	Type-2 (MAPE)
Monday	5.91	4.87
Tuesday	5.25	4.55
Wednesday	6.18	3.39
Thursday	5.11	3.85
Friday	5.47	4.15
Saturday	5.5	5.05
Sunday	7.05	6.48

6.1 Conclusions

The results of type-1 and type-2 fuzzy logic model are investigated for short term hourly load forecasting of the Jaipur city from 10th, March 2008 to 6th, April 2008 and results shows that in case of the proposed type-2 fuzzy logic model for STLF, a good performance and reasonable prediction accuracy is achieved. Its forecasting reliabilities were evaluated by computing the mean absolute percentage error between the exact and predicted values. The mean absolute percentage error is in the range of 1.98%-6.98% and 3.48%-10.25% for weekdays and weekends respectively using type-2 fuzzy logic model in comparison with type-1 fuzzy logic model for which absolute percentage error is in the range of 3.54%-10.38% and 3.57%- 11.5% for weekdays and weekends. In case of short term load forecasting, it is concluded that by increasing number of rules and increasing the footprint of uncertainty in case of type-2 fuzzy logic model, a great accuracy can be achieved

6.2 Future Scope of Work

The mean absolute percentage error in forecasting the load can even be lowered that by increasing number of rules and increasing the footprint of uncertainty in case of type-2 fuzzy logic model. The absolute percentage error can be reduced further by combining the type-2 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, intensity of sun light, dew point and rainfall etc. into the network in order to obtain a more accurate forecast of the future load.

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Table 1 Hourly Load Data from 10th-16th March 2008

Time	10-Mar	11-Mar	12-Mar	13-Mar	14-Mar	15-Mar	16-Mar
	(MW)	(MW)	(MW)	(MW)	(MW)	(MW)	(MW)
06:00	1526	1547	1561	1593	1591	1575	1475
07:00	1513	1488	1573	1593	1590	1561	1499
08:00	1524	1423	1512	1540	1550	1539	1447
09:00	1488	1327	1419	1529	1544	1495	1440
10:00	1434	1306	1398	1476	1480	1448	1426
11:00	1404	1287	1367	1412	1419	1395	1428
12:00	1338	1316	1381	1397	1405	1379	1425
13:00	1330	1350	1380	1371	1378	1330	1384
14:00	1325	1350	1411	1402	1377	1334	1375
15:00	1325	1350	1411	1407	1379	1321	1359
16:00	1328	1350	1423	1405	1371	1321	1349
17:00	1317	1336	1417	1405	1358	1322	1343
18:00	1333	1343	1368	1343	1341	1305	1296
19:00	1470	1481	1495	1469	1463	1433	1442
20:00	1487	1491	1479	1455	1505	1501	1491
21:00	1418	1406	1448	1399	1430	1435	1426
22:00	1379	1376	1406	1385	1432	1377	1374
23:00	1369	1401	1393	1413	1426	1365	1354
00:00	1399	1434	1418	1453	1483	1418	1428
01:00	1468	1457	1464	1479	1503	1529	1428
02:00	1437	1435	1464	1479	1468	1471	1439
03:00	1432	1426	1445	1460	1464	1479	1426
04:00	1432	1425	1443	1466	1464	1479	1426
05:00	1471	1445	1486	1496	1488	1504	1445

Table 2 Hourly Load Data from 17th-23rd March 2008

Time	17-Mar	18-Mar	19-Mar	20-Mar	21-Mar	22-Mar	23-Mar
	(MW)	(MW)	(MW)	(MW)	(MW)	(MW)	(MW)
06:00	1516	1546	1533	1449	1482	1446	1396
07:00	1553	1584	1530	1436	1477	1380	1394
08:00	1529	1588	1540	1450	1464	1352	1404
09:00	1485	1539	1471	1459	1453	1329	1377
10:00	1440	1474	1394	1365	1363	1295	1331
11:00	1399	1431	1387	1356	1344	1280	1320
12:00	1324	1329	1374	1353	1335	1289	1315
13:00	1318	1308	1348	1320	1314	1299	1326

14:00	1303	1306	1320	1292	1310	1311	1326
15:00	1292	1302	1314	1303	1306	1295	1332
16:00	1281	1293	1315	1309	1294	1271	1324
17:00	1271	1287	1309	1259	1291	1262	1324
18:00	1260	1338	1368	1285	1235	1282	1306
19:00	1434	1468	1508	1424	1413	1390	1470
20:00	1421	1441	1510	1412	1430	1434	1466
21:00	1344	1370	1442	1330	1347	1381	1407
22:00	1314	1346	1398	1316	1324	1315	1381
23:00	1316	1351	1371	1328	1357	1306	1388
00:00	1371	1365	1393	1389	1403	1409	1436
01:00	1548	1487	1574	1491	1459	1448	1363
02:00	1503	1480	1553	1469	1507	1427	1350
03:00	1523	1510	1531	1442	1495	1397	1344
04:00	1504	1509	1499	1474	1509	1383	1348
05:00	1491	1497	1545	1502	1489	1395	1359

Table 3 Hourly Load Data from 24th-30th March 2008

Time	24-Mar	25-Mar	26-Mar	27-Mar	28-Mar	29-Mar	30-Mar
	(MW)	(MW)	(MW)	(MW)	(MW)	(MW)	(MW)
06:00	1392	1491	1526	1508	1535	1511	1525
07:00	1394	1486	1525	1518	1575	1526	1585
08:00	1424	1463	1512	1528	1525	1520	1543
09:00	1403	1442	1479	1413	1533	1456	1504
10:00	1336	1344	1302	1276	1378	1369	1361
11:00	1332	1356	1315	1282	1309	1344	1235
12:00	1324	1354	1314	1313	1294	1332	1229
13:00	1330	1359	1353	1334	1304	1308	1190
14:00	1322	1359	1366	1342	1305	1314	1250
15:00	1322	1307	1365	1315	1299	1284	1283
16:00	1322	1301	1332	1319	1267	1267	1286
17:00	1316	1288	1295	1278	1263	1268	1257
18:00	1308	1299	1295	1262	1263	1259	1258
19:00	1446	1452	1444	1389	1419	1406	1380
20:00	1474	1463	1470	1459	1432	1449	1438
21:00	1392	1383	1409	1398	1362	1423	1402
22:00	1369	1335	1345	1346	1329	1371	1343
23:00	1388	1352	1428	1394	1430	1415	1406
00:00	1415	1377	1464	1415	1448	1496	1468
01:00	1403	1405	1533	1583	1567	1527	1572
02:00	1373	1376	1506	1558	1555	1502	1548
03:00	1358	1356	1488	1542	1530	1483	1524

04:00	1362	1345	1473	1516	1531	1478	1509
05:00	1382	1355	1478	1529	1547	1490	1523

Table 4 Hourly Load Data from 31st-6th April 2008

Time	31-Mar	01-Apr	02-Apr	03-Apr	04-Apr	05-Apr	06-Apr
	(MW)	(MW)	(MW)	(MW)	(MW)	(MW)	(MW)
06:00	1200	1306	1386	1306	1354	1162	1051
07:00	1220	1402	1350	1389	1407	1284	1174
08:00	1315	1385	1338	1389	1396	1295	1175
09:00	1308	1379	1299	1372	1349	1259	1218
10:00	1227	1322	1230	1309	1307	1218	1169
11:00	1240	1323	1301	1309	1297	1290	1231
12:00	1285	1323	1323	1308	1275	1285	1221
13:00	1311	1316	1324	1302	1258	1279	1215
14:00	1316	1328	1301	1302	1255	1298	1224
15:00	1318	1327	1301	1305	1270	1314	1235
16:00	1306	1313	1298	1301	1270	1309	1234
17:00	1277	1297	1298	1301	1192	1281	1205
18:00	1233	1292	1313	1294	1188	1278	1206
19:00	1338	1414	1443	1429	1330	1397	1337
20:00	1434	1489	1500	1472	1393	1458	1386
21:00	1364	1401	1405	1388	1331	1426	1326
22:00	1280	1341	1379	1358	1275	1360	1270
23:00	1283	1352	1380	1362	1280	1351	1277
00:00	1327	1376	1415	1386	1297	1294	1284
01:00	1134	1364	1373	1360	1269	1173	1078
02:00	1199	1321	1349	1318	1265	1162	1033
03:00	1092	1235	1319	1297	1260	1119	1015
04:00	1089	1230	1314	1268	1261	1119	1016
05:00	1090	1230	1327	1247	1266	1127	1017

Table 5 Hourly Weather Data from 10th-16th March 2008

Time	10-Mar			11-Mar			12-Mar			13-Mar			14-Mar		
	T1	H1	W1	T2	H2	W2	T3	H3	W3	T4	H4	W4	T5	H5	W5
06:00	19	56	7.4	22	43	1	19	69	1	21	60	3.7	16	80	5.6
07:00	20	50	1	22	43	11.1	19	65	3.7	21	60	3.7	16	82	7.4
08:00	21	49	3.7	23	35	3.7	19	60	3.7	22	55	5.6	22	42	7.4
09:00	25	41	1	24	41	5.6	21	53	1	22	50	5.6	23	47	1
10:00	28	20	7.4	25	39	5.6	26	50	1	23	50	3.7	24	42	1
11:00	30	20	11.1	25	39	3.7	28	21	3.7	21	60	1	27	20	5.6
12:00	29	21	5.6	27	22	1	28	24	3.7	25	50	5.6	29	22	5.6
13:00	31	26	1	28	21	11.1	28	30	7.4	24	49	5.6	31	25	3.7

14:00	26	21	3.7	29	20	1	29	29	3.7	23	48	5.6	31	21	7.4
15:00	24	19	3.7	29	25	7.4	29	30	7.4	24	53	3.7	31	24	7.4
16:00	29	20	7.4	27	20	5.6	28	32	1	23	57	3.7	31	21	7.4
17:00	30	25	1	25	25	11.1	25	29	9.3	25	41	5.6	31	26	5.6
18:00	27	19	5.6	24	19	5.6	25	39	1	24	44	3.7	30	29	5.6
19:00	28	28	7.4	20	20	7.4	25	39	11.1	22	53	11.1	29	19	5.6
20:00	27	30	14.8	21	43	9.3	25	36	5.6	22	42	11.1	27	22	3.7
21:00	25	29	5.6	22	50	1	24	41	1	21	46	14.8	26	34	3.7
22:00	24	31	5.6	21	55	3.7	24	41	3.7	21	56	14.8	23	44	1
23:00	23	41	7.4	20	60	1	23	50	3.7	19	64	11.1	21	33	3.7
00:00	23	50	11.1	23	41	9.3	19	64	5.4	21	53	3.7	20	30	3.7
01:00	23	50	11.1	22	43	9.3	19	64	11.1	20	56	3.7	18	50	3.7
02:00	22	34	14.8	22	43	3.7	21	46	9.3	20	56	5.6	17	77	11.1
03:00	20	32	11.1	21	46	9.3	21	37	7.4	19	60	7.4	17	73	11.1
04:00	22	46	3.7	21	46	9.3	20	49	1	19	60	3.7	16	70	7.4
05:00	19	43	1	21	46	5.6	19	56	1	21	48	3.7	15	79	9.3

Table 5 Continued..

Time	15-Mar			16-Mar		
	T6	H6	W6	T7	H7	W7
06:00	17	68	3.7	15	60	11.1
07:00	17	68	1	17	63	11.1
08:00	18	64	1	20	52	11.1
09:00	25	24	1	27	28	11.1
10:00	27	32	9.3	28	20	9.3
11:00	31	25	7.4	34	20	18.5
12:00	31	24	7.4	35	18	11.1
13:00	32	20	5.6	35	22	22.2
14:00	33	18	5.6	36	17	5.6
15:00	33	28	9.3	36	17	9.3
16:00	33	25	5.6	35	18	5.6
17:00	32	21	9.3	34	26	5.6
18:00	32	20	5.6	34	23	9.3
19:00	30	21	5.6	29	20	7.4
20:00	26	22	7.4	28	23	3.7
21:00	24	24	7.4	27	34	1
22:00	23	30	5.6	26	36	7.4
23:00	22	36	9.3	25	39	7.4
00:00	21	46	3.7	22	46	5.6
01:00	20	52	3.7	21	49	11.1
02:00	20	41	5.6	20	43	1
03:00	20	52	5.6	18	46	3.7

04:00	18	59	3.7	18	48	3.7
05:00	18	64	5.6	17	52	1

Table 6 Hourly Weather Data from 17th-23rd March 2008

Time	17-Mar			18-Mar			19-Mar			20-Mar			21-Mar		
	T1	H1	W1	T2	H2	W2	T3	H3	W3	T4	H4	W4	T5	H5	W5
06:00	21	33	11.1	20	49	9.3	21	31	4.8	22	50	11.1	22	53	1
07:00	20	35	11.1	22	41	11.1	23	27	18.5	24	42	14.8	21	56	1
08:00	27	18	1	27	36	7.4	26	22	14.8	25	24	22.2	23	50	5.6
09:00	28	20	14.8	28	32	11.1	28	21	11.1	27	28	11.1	26	33	3.7
10:00	31	19	14.8	30	30	11.1	30	19	13	31	22	9.3	28	30	5.6
11:00	34	18	18.5	32	33	14.8	32	18	1	31	20	9.3	32	22	9.3
12:00	35	18	18.5	34	30	14.8	35	20	1	32	31	9.3	33	18	7.4
13:00	36	20	18.5	36	28	9.3	36	22	9.3	33	28	11.1	35	20	5.6
14:00	37	22	14.8	36	26	13	36	23	14.8	35	20	14.8	36	22	14.8
15:00	37	26	13	37	26	1	37	23	14.8	35	19	5.6	36	24	7.4
16:00	36	25	18.5	36	30	24.1	34	21	27.8	35	18	11.1	36	26	9.3
17:00	35	24	11.1	36	32	11.1	34	19	18.5	35	20	3.7	34	25	11.1
18:00	34	21	11.1	34	22	11.1	34	18	14.8	33	24	1	33	23	11.1
19:00	32	18	5.6	31	18	11.1	32	18	11.1	31	24	14.8	30	22	7.4
20:00	28	17	1	29	20	5.6	30	19	9.3	27	19	14.8	28	21	5.6
21:00	25	34	1	28	18	5.6	29	24	3.7	27	30	14.8	27	32	7.4
22:00	23	41	1	25	34	7.4	27	28	14.8	27	30	11.1	27	34	5.6
23:00	23	31	1	25	17	11.1	27	28	22.2	25	24	5.6	27	21	9.3
00:00	23	44	3.7	23	44	1	25	28	11.1	27	26	29.6	26	25	11.1
01:00	23	44	3.7	22	46	1	24	29	9.3	27	26	27.8	25	30	11.1
02:00	23	33	11.1	21	49	1	26	24	22.2	26	22	29.6	24	35	5.6
03:00	23	29	7.6	21	49	1	26	24	11.1	26	19	33.3	22	39	3.7
04:00	22	31	7.4	21	49	7.4	26	24	9.3	25	32	18.5	22	39	3.7
05:00	22	31	11.1	20	52	3.7	25	26	5.6	22	35	14.8	22	39	3.7

Table 6 Continued..

22-Mar			23-Mar		
T6	H6	W6	T7	H7	W7
21	43	11.1	20	37	14.8
20	49	1	23	31	7.6
22	38	3.7	26	22	7.6
24	21	3.7	26	32	9.3
26	18	5.6	30	25	11.1
30	17	9.3	32	21	14.8
30	18	11.1	32	18	14.8
32	19	14.8	34	19	9.3

34	21	11.1	34	19	9.3
35	22	11.1	35	22	5.6
36	21	7.4	34	23	5.6
34	20	5.6	34	24	3.7
33	22	3.7	32	25	9.3
30	22	5.6	33	28	14.8
29	21	14.8	30	23	14.8
29	23	18.5	29	25	27.8
28	22	14.8	28	21	11.1
28	23	11.1	27	26	14.8
26	24	9.3	27	17	14.8
26	23	7.4	23	31	7.4
26	23	9.3	23	21	9.3
25	19	5.6	22	33	7.4
22	38	22.2	22	33	1
21	29	11.1	21	35	5.6

Table 7 Hourly Weather Data from 24th-30th March 2008

Time	24-Mar			25-Mar			26-Mar			27-Mar			28-Mar		
	T1	H1	W1	T2	H2	W2	T3	H3	W3	T4	H4	W4	T5	H5	W5
06:00	22	41	14.8	23	47	3.7	22	41	9.3	22	48	9.6	22	43	25.9
07:00	23	38	5.6	23	47	9.3	23	36	9.3	20	52	9.3	23	38	22.2
08:00	24	30	8.2	27	22	3.7	25	32	18.5	27	15	3.7	25	32	14.8
09:00	26	24	9.3	28	30	9.3	27	17	14.8	28	21	3.7	28	28	14.8
10:00	31	22	5.6	30	28	9.3	31	21	14.8	30	18	5.6	30	25	5.6
11:00	33	22	7.4	32	17	9.3	33	22	11.1	34	22	11.1	30	25	18.5
12:00	34	21	3.7	33	22	5.6	33	20	3.7	34	21	14.8	35	19	18.5
13:00	35	20	3.7	35	21	5.6	34	18	5.6	37	20	22.2	36	18	22.2
14:00	36	17	3.7	36	17	14.8	35	21	9.3	37	18	11.1	37	19	27.8
15:00	33	18	5.6	35	18	14.8	36	22	16.7	36	18	7.4	36	18	22.2
16:00	32	18	5.6	34	18	14.8	34	20	14.8	36	20	29.6	35	22	22.2
17:00	32	20	1	33	19	11.1	34	17	18.5	33	20	11.1	35	18	25.9
18:00	32	18	3.7	33	20	11.1	32	18	18.5	34	18	5.6	34	19	18.5
19:00	30	20	5.6	30	22	11.1	32	20	5.6	33	18	11.1	32	18	7.4
20:00	29	27	9.3	29	18	1	28	24	5.6	32	22	11.1	33	19	7.4
21:00	29	27	9.3	28	28	1	27	37	5.6	32	17	14.8	33	18	9.3
22:00	28	28	11.1	27	26	9.3	25	37	5.6	32	17	9.3	30	17	11.1
23:00	28	28	11.1	27	28	14.8	26	39	7.4	31	19	9.3	28	20	11.1
00:00	27	26	14.8	27	28	14.8	24	31	1	27	24	3.7	26	36	3.7
01:00	26	28	18.5	26	26	9.3	25	32	1	25	22	5.6	26	36	5.6
02:00	25	27	19.3	26	20	5.6	26	30	14.8	22	32	3.7	27	18	3.7
03:00	23	28	14.8	25	20	5.6	26	30	3.7	22	43	3.7	27	28	13

04:00	22	28	11.1	24	25	1	23	36	3.7	22	40	5.6	26	30	9.3
05:00	22	29	11.1	23	35	1	22	28	5.6	21	35	5.6	24	38	1

Table 7 Continued..

29-Mar			30-Mar		
T6	H6	W6	T7	H7	W7
20	52	7.4	25	39	1
21	43	14.8	24	40	1
25	32	5.6	24	41	11.1
28	25	9.3	28	30	3.7
30	27	11.1	30	26	5.6
33	26	18.5	34	17	18.5
35	25	14.8	35	18	14.8
36	25	14.8	36	20	22.2
37	23	11.1	36	22	18.5
37	22	14.8	37	23	16.7
37	21	22.2	36	23	14.8
35	20	14.8	35	24	14.8
33	19	11.1	34	22	16.7
32	18	7.4	32	23	16.7
31	19	14.8	30	21	18.5
31	19	11.1	30	25	18.5
39	22	11.1	28	22	11.1
28	24	14.8	27	20	11.1
27	26	9.3	27	22	11.1
27	26	9.3	21	24	11.1
25	32	9.3	26	28	11.1
25	22	7.4	26	17	11.1
22	43	1	26	21	14.8
21	49	1	25	27	14.8

Table 8 Hourly Weather Data from 31st-6th March 2008

Time	Mar-31			Apr-01			Apr-02			Apr-03			Apr-04		
	T1	H1	W1	T2	H2	W2	T3	H3	W3	T4	H4	W4	T5	H5	W5
06:00	23	41	18.5	20	75	7.4	19	83	1	17	88	11.1	19	68	9.3
07:00	23	41	5.6	20	73	18.5	19	88	1	17	88	1	19	78	9.3
08:00	24	36	5.6	21	68	5.6	22	78	1	20	78	5.6	24	48	7.4
09:00	25	24	5.6	26	42	18.5	24	65	1	20	71	7.4	25	52	6.3
10:00	27	32	13	27	39	18.5	26	57	5.6	22	65	8.3	25	50	7.2
11:00	31	17	31.5	28	39	14.8	27	45	3.7	23	61	1	26	47	5.6
12:00	31	25	29.6	29	35	5.6	30	35	14.8	25	33	9.3	27	45	7.4

13:00	34	30	18.5	29	42	16.6	31	35	5.6	26	35	7.2	23	58	50.2
14:00	35	18	37	30	23	18.5	32	33	1	27	45	1	21	61	140.8
15:00	36	17	22.2	32	23	8.6	34	32	3.7	29	40	3.7	21	73	33.3
16:00	30	22	11.1	23	35	5.6	33	34	5.6	29	37	11.1	23	62	7.2
17:00	24	46	29.6	23	36	46.3	32	23	7.4	28	39	14.8	24	53	1
18:00	23	60	11.1	28	25	41.2	30	35	5.6	28	42	9.3	24	40	1
19:00	22	64	18.5	27	30	28.2	29	42	7.4	27	45	13	22	70	12.5
20:00	23	52	19	25	36	25.9	28	35	11.1	25	44	9.3	19	78	18.5
21:00	25	44	14.8	25	34	11.1	28	45	7.4	24	57	9.3	18	75	7.2
22:00	26	42	9.2	21	64	46.3	26	40	8.2	23	53	7.6	19	78	5.6
23:00	27	45	11.1	19	76	33.3	20	82	23.2	22	51	5.6	19	83	9.3
00:00	27	30	11.1	23	53	11.1	19	76	46.3	19	83	46.3	22	60	5.6
01:00	26	32	7.4	22	55	7.8	18	78	29.6	18	90	37	22	60	5.6
02:00	25	36	9.3	22	57	7.4	19	68	11.1	18	94	18.5	21	68	1
03:00	24	26	14.8	22	59	9.3	19	64	1	19	67	11.1	21	70	1
04:00	24	28	16	21	60	10	19	64	3.7	18	77	11.1	20	73	18.5
05:00	23	30	18.5	20	62	11.1	18	73	3.7	17	82	11.1	20	73	18.5

Table 8 Continued..

Apr-05			Apr-06		
T6	H6	W6	T7	H7	W7
17	83	1	19	64	20.4
18	82	8.3	19	68	22.2
19	78	1	18	64	27.8
22	64	5.6	20	56	9.3
22	63	7.2	29	30	18.5
23	61	11.1	26	31	14.8
26	47	14.8	27	42	9.3
27	42	1	29	33	9.3
29	35	9.3	30	31	7.4
30	22	5.6	30	31	14.8
30	30	11.1	30	31	11.1
29	37	1	29	27	18.5
29	21	3.7	29	29	14.8
25	35	20.2	28	30	9.3
20	42	27.8	27	28	8.2
20	52	29.6	26	26	7.4
19	60	42.6	25	39	14.8
20	60	37	15	72	11.1
19	83	11.1	20	56	29.6

18	86	11.1	20	56	1
19	83	9.3	20	56	5.6
18	88	9.3	20	56	7.4
18	88	1	18	68	1
17	88	1	18	68	27.8

T- Temperature
H- Humidity
W- Wind Speed

References

1. Hourly Load Data is collected from Jaipur Vidyut Nigam State Load Dispatch and Communication Centre, Rajasthan Vidyut Parasaran Nigam.
2. Weather Data is collected from <http://www.wunderground.com/>.