# LOAD FORECASTING USING AI TECHNIQUES

A DISSERTATION SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF THE DEGREE OF

**MASTER OF TECHNOLOGY**

**IN**

**POWER SYSTEM**

SUBMITTED BY:


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UNDER THE SUPERVISION OF

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## DECLARATION

I hereby certify that the work which is presented in the Major Project – II entitled "Load Forecasting using AI Techniques" in fulfilment of the requirement for the award of the Degree of Master of Technology in Power System and submitted to the Department of Electrical Engineering, Delhi Technological University, Delhi is an authentic record of my own, carried out during a period from January to October 2021, under the supervision of Dr. M. Rizwan.

The matter presented in this report has not been submitted by me for the award of any other degree of this or any other Institute/University. The work has been accepted in peer reviewed Scopus indexed conference with the following details:

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## SUPERVISOR'S CERTIFICATE

To the best of my knowledge this work has not been submitted in part or full for any Degree or Diploma to this University or elsewhere. I, further certify that the publication and indexing information given by the student is correct.

Place: Delhi
Date: 29/10/2021

Dr. M. Rizwan
SUPERVISOR
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# ABSTRACT

Electricity is the greatest gift of science to mankind. World have reached a point of civilization when electricity is used for all purposes. In India, the demand for electricity is increasing day by day. As on 30th September 2021, the total installed capacity is 3,88,848 MW of India. The reason for increase in consumption of electricity is due to urbanization, increasing population. It can be concluded that in the upcoming time this demand will keep on increasing. Electricity is generated on the basis of demand. It is, consequently, basic for the electric force utilities that the heap on their frameworks ought to be assessed ahead of time. This assessment of burden ahead of time is ordinarily known as load forecasting. As different constraints of regular methodologies, the accentuation has gradually moved to the use of Artificial Intelligence based methodologies. Fuzzy logic speculation is one of transcendent advancement in artificial intelligence. Its application in load estimating depends on periodical comparability of electric burden, where the information factors, yield factors and rules are the central issue.

Load forecasts are additionally used to set up obtainment arrangements for development capital energy estimates, which are expected to decide future fuel necessities. Hence, a decent conjecture, mirroring the present and future patterns, is the way in to all arranging. The term forecast alludes to projected burden prerequisites decided utilizing an efficient cycle of characterizing future needs in adequate quantitative detail to allow significant framework extension choices to be made. Dismally, the customer load is basically disorderly albeit minor varieties can be influenced by frequency control and all the more radically by load shedding. The variety in load shows certain every day and yearly example.

This dissertation work “Load Forecasting using AI Techniques”, focus is on short term load forecasting which is substantial for controlling and operation in real time of the power system. The proposition is the use of artificial intelligence techniques like fuzzy logic, artificial neural network and adaptive neuro-fuzzy inference system. All three models are studied for the set of data considered and the results are analysed. Also, the results obtained from above methods is compared to the desired output and the mean absolute percentage error is calculated.

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# LIST OF ABBREVIATIONS

| | |
|---|---|
| AI | Artificial intelligence |
| ANFIS | Adaptive neural-fuzzy inference system |
| ANN | Artificial neural network |
| ARE | Absolute relative error |
| ARMA | Auto-regressive moving average |
| FL | Fuzzy logic |
| LTLF | Long term load forecasting |
| MIS | Madami inference system |
| MPPT | Maximum power point tracking |
| MSE | Mean square error |
| MTLF | Medium term load forecasting |
| NARX | Nonlinear auto-regressive exogenous model |
| NN | Neural network |
| PV | Photovoltaic |
| STLF | Short term load forecasting |

# LIST OF SYMBOLS

| | |
|---|---|
| $L_{max}$ | Maximum load value |
| $L_{min}$ | Minimum load value |
| L | Load to be converted |
| $L_S$ | Normalized value |
| O (1, i) | Output of first layer |
| $\mu_{Ai}$ | Membership function |
| O (2, i) | Output of second layer |
| O (3, i) | Output of third layer |
| $w_i'$ | Normalize of weight function |
| O (4, i) | Output of fourth layer |
| $p_i, q_i, r_i$ | Consequent parameters of node |
| O (5, i) | Output of fifth layer |
| $P_{desired}$ | Target load |
| $P_{forecasted}$ | Forecast load |

# CHAPTER 1

# INTRODUCTION

## 1.1 : General

Electrical energy cannot be stored. It has to be generated whenever there is a demand for it. It is, therefore, imperative for the electric power utilities that the load on their systems should be estimated in advance. This estimation of load in advance is commonly known as load forecasting. It is necessary for power system planning. Power structure expansion foreseeing begin with a speculation of future or upcoming load prediction. There is a developing inclination towards unbundling the electricity network. This is ceaselessly going up against the various areas of the business (generating, transmission, and conveyance) with expanding desire on activities of the organization and management planning. For the purpose of planning and operations in power system organisation, it is important to have a satisfactory model for the determination of demand in the future.

Forecasting helps a power company to settle on ends in regards to the choice on production and purchasing of electricity, switching loads, voltage control, reconfiguration of network and improvements in framework. Electrical load estimating is utilized to conjecture future electric burden, given recorded load and climate data and flow and determined climate data. In the previous few decades, a few models have been created to estimate electrical load all the more precisely. With the development of non-interference of power field, numerous new difficulties have been experienced by the power market members. Estimating of wind power, electrical loads and energy costs has become a significant issue in power frameworks.

## 1.2 : Load Forecasting

Forecasting power loads has arrived at the condition of development. Short term (a couple of moments, hours, or days ahead) to long term (as long as 20 years ahead) figures have gotten progressively significant since the rebuilding of power networks. Following the requirements of the market, different methods are utilized to estimate wind power, energy cost and demand in power. The market hazard identified with exchanging is significant because of the outrageous unpredictability of power costs. Considering the questionable idea of future costs in competitive power markets, value estimates are utilized by market members in their functional arranging activities. Furthermore, guaranteeing the protected activity of the power system at some upcoming time requires the investigation of its conduct under an assortment of hypothesized possibility conditions.

Demand expectation is a significant angle in the advancement of any model for power planning, particularly in the present improving power framework structure. The type of the interest relies upon the kind of preparation and precision that is required. Dependent upon the time locale of planning strategies the forecasting of load can be classified into the following three types specifically:

- Short term load forecasting (STLF): In this method, generally the time period ranges from an hour to a week. It can direct us to surmised load flow and then leads to making choices that can block excess loading. Transient determining is utilized to give mandatory data for managing system of day by day activities and unit responsibility.
- Medium term load forecasting (MTLF): In this method the period of time range is from a week to a year. The figures for various time horizons are significant for various tasks inside a utility organization. Medium term estimating is utilized to plan fuel supplies and unit the board.
- Long term load forecasting (LTLF): In this method the time range is more than a year. It is utilized to supply electric service organization with précised expectation of future requirements for extension, hardware buys or staff employing.

## 1.3 : Advantages of Load Forecasting

- Empowers the service organization to design well since they have a comprehension of things to come in future for utilization or demand of load.
- Limits the dangers for the service organization. Comprehension of the future long-term load assists the organization with planning and making the financially practical choices as to group of people yet to come and transmission investment.
- Assists with deciding the necessary assets, for example, fuel needed to work the generating plants just as other sources that are expected to guarantee continuous but conservative age and circulation of the power to the customers. This is significant for short, medium, and long-term arrangement.

- The load forecasting helps in arranging the future as far as the size, area and kind of generation plant. By deciding regions or areas with high or developing interest, the utilities will probably produce the power close to demand. This limits the transmission and distribution architecture in addition to related losses.
- Helps in choosing and anticipating upkeep of the power networks. By assimilation of the demand, the utility can realize when to complete the support and guarantee that it minimally affects the buyers. For instance, they may choose to do upkeep on residential locations during the day when many people are in offices and demand is extremely low.
- Most utilization of power generating plants. The forecasting eschews over generation or under generation.

## 1.4 : Challenges of Load Forecasting

- Forecasting depends on expected conditions like climate. Sadly, the climate is in some cases flighty and the estimating may hence be diverse when the real time climate varies from what was anticipated.
- What's more, various areas may encounter diverse climatic conditions which will influence the power demand. This may adversely affect incomes, particularly assuming the utility produces more to satisfy anticipated significant need and, it just so happens, the consumption is substantially less than what was created either utilizing costly strategies like fuel generators and so on.
- The vast majority of the accomplished utility forecasters utilize manual techniques that depend on an intensive comprehension of a wide scope of contributing aspects dependent on forthcoming occasions or a specific dataset. Depending on manual forecasting isn't economical because of the expanding number and intricacy of the forecasting. Utilities should hence search for technology that can precisely provide results and dispose of issues that may happen whenever experienced forecasters resign or leave work.
- The use conduct changes between purchasers utilizing various kinds of meters and particularly between the smart and customary meters just as various taxes. The utility should get this and foster separate estimate model for every one of the metering frameworks and afterward add them up for the final estimating value. Else, they will acquire inaccurate forecast.

- Troubles getting precise information on utilization behaviour because of changes in elements, for example, price and the comparing demand dependent on such a value change.
- It is a troublesome task because of the complicated nature of demands which may change depending upon the seasons and complete consumption of two akin seasons may differ.
- Sometimes it is difficult to precisely fit the various complicated factors that influence the demand in electricity in the models that are used for forecasting. Moreover, it might not be difficult to get an accurate forecast of demand depending on factors like temperature change, humidity and further aspects that impact the consumption.
- The utility may endure misfortunes if it is not comprehended and then settle for bearable margin of buffer in STLF.

## 1.5 : Outline of Dissertation

This dissertation consists of:

**Chapter 1:** In this chapter introduction to the term load forecasting is done along with its importance, advantages and limitations.

**Chapter 2:** This shows the literature review done for the project "Load Forecasting using AI Techniques". This chapter gives the understanding of the different techniques used in forecasting of load of different applications or situations.

**Chapter 3:** This chapter focus on understanding of Fuzzy Logic. Along with its basic structure, it also focuses on application, advantages and disadvantages.

**Chapter 4:** This chapter focus on understanding of ANN. Along with its basic structure, it also focuses on application, advantages and disadvantages.

**Chapter 5:** This chapter focus on understanding of ANFIS. Along with its basic structure, it also focuses on application, advantages and disadvantages.

**Chapter 6:** In this chapter, all the models of each methods used for forecasting are explained along with their results.

**Chapter 7:** This chapter summarizes the result obtained through the models and also acknowledges the future work that can be done.

# CHAPTER 2

# LITERATURE REVIEW

## 2.1: Introduction

In this chapter, research papers related to Load Forecasting and different techniques using AI are reviewed. Research paper related to Fuzzy, ANN, ANFIS, etc are discussed.

## 2.2: Load Forecasting using Various Techniques

In [2] importance of load forecasting and issues regarding load forecasting are focused. Various methodologies of artificial intelligence that can be used in forecasting are explained like fuzzy, ANN, statistical, spatial, etc. It highlights the importance of these various intelligent system approach and helps in recognising various aspects of research in these methods. In [3] priority vector-based technique for load forecasting is used. Records of almost two years of load at every hour and weather is extracted and the relation between them is drawn and categorized based on that. It is an adaptive technique as it generates relationship coefficient between weather parameters and load continuously. As these relations changes from time to time, it automatically updates the changed coefficient between these two parameters. It is used to predict forecast of load of one week. In [4] knowledge based expert system is used for short term load forecasting (STLF). The expert system developed in this method is written using 5-years of historical data in PROLOG. Distinct load shapes and their load calculations are done. Various categories of load usage according to the observation are set like low level of load during Chinese New Year or at the time of typhoon. With the help of these observations, new rules or information are made or set for the purpose of short term load forecasting. In [5] linear regression-based method or model is used for STLF is described. This model takes care of many area such as innovative model of building, with the help of weighted least-squares in linear regression techniques estimation of parameters is done, with the use of reverse errors-in-variables techniques effect of potential errors on load forecasts can be relieved and to differentiate between daily time independent peak load forecast and maximum hourly peak load forecast from negative bias.

## 2.3: Load Forecasting with Fuzzy Logic

Methodology for STLF problem with the help of fuzzy logic approach is presented in [6]. Load forecast for the next day is obtained using FL. It is used for modification of load curves on similar selected days. New Euclidean norm along weight factor is presented for selecting similar days. Fuzzy Logic is used for the purpose of load forecasting in [7]. Two input variables are taken into consideration in this paper, namely temperature and time. Output variable is forecasted load. The input time variable is divided into eight triangular membership function and the input variable temperature is divided into four triangular membership function. Output is divided into eight triangular membership function i.e., forecasted load. These fuzzy logic forecasted load values are compared to conventional forecast load value. Also, in [8] FL is used for STLF purpose. The data of input and output are normalized value that is scaled down in the range of (0.1-0.9). It is done to avoid convergence problem. Historical data of consecutive four days of every hour load consumption are used as input in fuzzy. Forecasted load is obtained for $5^{th}$ day of every hour through fuzzy model. The load obtained from fuzzy is compared to the actual data of the day. Also, mean absolute percentage error is calculated.

## 2.4: Load Forecasting Modelling with ANN Technique

In [10] ANN is studied in context of its strength in field of power system and its application. Also, its application in various problems of power system are briefly discussed. An overview of ANN based models for STLF is presented in [11]. Review of paper published during 1991 and 1999 is done. These papers that are reviewed are application of NN used for STLF purpose. Each paper is critically reviewed to properly understand the use of NN in forecasting. A further developed NN approach is produced for STLF purpose in [12]. An approach that is befitting for selection of training cases in the NN is suggested. This approach has benefit of circumventing the issue of holidays and sudden changes in weather patterns, which makes it difficult for training of network. Additionally, an improved algorithm for neural network is presented. In [13], the practicality of utilizing simple NN for STLF is researched. The combination of non linear and linear neural network is created. The estimates are computed utilizing weights that are reestimated using recent observations. In [15] ANN based model is developed in forecasting of solar radiation with input data as aerosol index. It is very difficult to estimate solar photovoltaic (PV) power. It is important to predict the solar PV for the purpose of proper control and operations in renewable energy. With the help of weather classification, ANN using Nonlinear auto-regressive for exogenous inputs (NARX) manner for forecasting of next day three hours solar radiation outputs. This model is designed by keeping various data into consideration like humidity, temperature, wind speed and direction. Also, mean square error (MSE) is calculated.

## 2.5: ANFIS Technique for Load Forecasting

In [18], adaptive neural-fuzzy inference system (ANFIS) is used for the purpose of studying STLF design. In this paper, consumed load is forecasted with the help of multi ANFIS. Sections of the presenting model are into the multi ANFIS which includes maximum and minimum temperature, date of day, condition of climate and consumed load of previous day and its output is forecast of load consumption of power. In [19], ANFIS model is developed for short term load forecasting purpose. It is the combination of both fuzzy and ANN. Factors like data types and weather, etc are used in this model. The training of the model is done by historical load data. ANFIS based approach of load forecasting is used for small regions with low consumption in [20]. Record of every hour load demand is to be predicted in this model. Only consumption parameter is required. With the help of using a predicted sixth order polynomial curve in MPPT techniques is designed for tracking highest maximum power point in [21]. These results are compared with ANFIS based model results. In [22], neural network-based approach and fuzzy neural network-based modelling is done for PV.

## 2.6: Comparision of Models

In [23], for predicting wind power, models based on fuzzy, ANN, ANFIS are developed. The models proposed easily can incorporate nonlinearity and uncertainties related with climatic factors. In [24], approach that is different from conventional algorithm which are based on deterministic computations. Techniques like fuzzy, ANN, ANFIS are developed so that important feature are extracted from coefficients of wavelet MRA regarding fault location. In [25], auto-regressive moving average (ARMA), neuro-fuzzy and neural network models are created with historical consumption of electricity time series data to forecast demand of future.

## 2.7: Conclusion

The literature review is done in this chapter in the relevant area for the present work “Load Forecasting using AI Techniques” in detail. Literature review is carried out to realize the scope of each method and to understand each technique for the purpose of load forecasting.

# CHAPTER 3

# LOAD FORECASTING USING FUZZY LOGIC

## 3.1: Introduction

The fuzzy logic concept was introduced by Professor Lotfi A. Zadeh. Truth is certainly not an outright idea. Fuzzy Logic gives an approach to address levels of conviction. It is a technique for thinking that looks like human thinking. The methodology of FL impersonates the method of dynamic in people that includes all middle of the road prospects between advanced qualities YES and NO. The conventional block of logic that a PC can comprehend takes exact information and produces an unequivocal yield as TRUE or FALSE, which is identical to human's YES or NO. The designer of FL saw that not at all like PCs, the human dynamic incorporates a scope of other range of outcomes among YES and NO, for example:

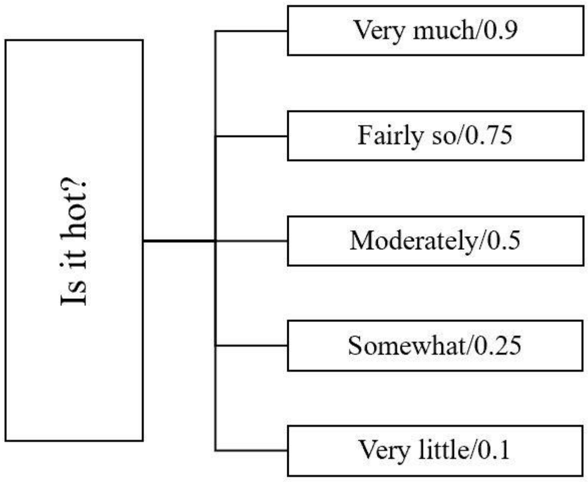


Figure 3.1: Degrees of Truth with Fuzzy Logic

The FL deals with the degrees of potential outcomes of contribution to accomplish the output.

## 3.2: Architecture

Figure 3.2 shows the block diagram of fuzzy logic. The methodology of FL impersonates the method of dynamic in people that includes all middle of the road prospects between computerized values YES and NO. The four main parts can be explained as:

1) Fuzzifier: It is used to change over contributions for instance new numbers into fuzzy sets. New information sources are on a very basic level the particular

information sources assessed by sensors and passed into the control system for getting ready, similar to weather conditions.

2) Fuzzy Rule Base: It contains the course of action of rules and the IF-THEN conditions given by the experts to direct the unique structure, in view of linguistic information. Late upgrades in feathery speculation offer a couple of fruitful strategies for the arrangement and tuning of fuzzy controllers. Most of these headways decline the number of fuzzy rules.
3) Fuzzy Inference System: It chooses the organizing with level of the current fuzzy information concerning every norm and picks which rules are to be ended by the data field. At that point, the ended standards are joined to outline the control exercises.
4) Defuzzifier: It is used to change over the fuzzy sets obtained by induction engine into a new worth. There are a couple of defuzzification procedures available and the most proper one is used with a specific expert system to decrease the botch.

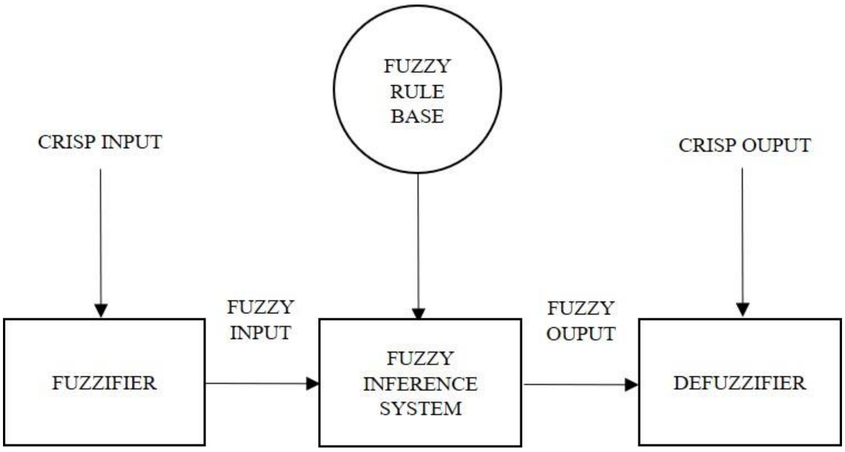


Figure 3.2: Fuzzy Logic Block Diagram

## 3.3: Fuzzy Logic

It tends to be executed in frameworks with different sizes and capacities going from little micro-controllers to huge, organized, workstation, network-based control system. It tends to be executed in hardware, programming, or a blend of both. It can be useful for both practical and commercial purposes:

- It can handle machines and products used by customers.
- It may not give exact reasoning, yet justifiable reasoning.
- It assists with managing the vulnerability in designing.

## 3.4: Membership Functions

A membership function for a fuzzy set A on the universe of discourse X is defined as $\mu_A:X \rightarrow [0,1]$, where each element of X is mapped to a value between 0 and 1. This value, called membership value or degree of membership, quantifies the grade of membership of the element in X to the fuzzy set A. Zadeh proposed a series of membership functions that could be classified into two groups: those made up of straight lines being "**linear**" ones, and the "**curved**" or "**nonlinear**" ones.

Membership functions allow us to graphically represent a fuzzy set. The *x* axis represents the universe of discourse, whereas the *y* axis represents the degrees of membership in the [0,1] interval.

Simple functions are used to build membership functions. Because we are defining fuzzy concepts, using more complex functions does not add more precision. There different kinds of membership function:

1) Triangular Function
2) Trapezoidal Function
3) Gaussian Function

## 3.5: Applications of FL

It can be used in various fields:

- In aerospace fields, it can be used for altitude supervision of satellite and spacecraft.
- In automotive systems, it can control the traffic and speed.
- It can also be used in support systems utilized for decision making and personal judgement in large organizations.
- In chemical industry, it can be used to control chemical distillation, drying process, PH.
- It can be used with Neural Network.
- It can be used in domestic goods such as, washing machines, refrigerators, ovens, etc.

## 3.6: Advantages of FL

- Fuzzy Logic is easy to make and understandable.

- It is very flexible system. Rules can be modified easily either by adding or deleting them. Modifications can be done at ease.
- Mathematical conception in fuzzy are simpler.
- Fuzzy can take distorted, imprecise or noisy input.
- It is a simple solution for complex issues in various fields.

## 3.7: Disadvantages of FL

- It can be confused with probability theories.
- Setting of rules, membership function is a challenge.
- It may not provide accuracy for all the problems.

## 3.8: Fuzzy Model Development

Generalized flowchart for fuzzy is shown in Figure 3.3. The average of data of a location at every 15 mins. The data of input and output are normalized value that is scaled down in the range of (0.1-0.9). It is done to avoid convergence problem. The collected data taken into consideration can be seen in Table 3.1. The normalized values of the data can be seen in Table 3.2. Fuzzy logic is basically the general Boolean Logic that are used in design of digital circuits. It takes only two values i.e., false (0) or true (1). But in this the input can take the values in between 0 and 1 also. It chips away at the degrees of potential result for contribution to attain the definite output. The actual data is scaled down using the equation below:

$$\mathrm{L_S} = \frac{(\mathrm{Y_{max}} - \mathrm{Y_{min}})}{(\mathrm{L_{max}} - \mathrm{L_{min}})}\,(\mathrm{L} - \mathrm{L_{min}}) + \mathrm{Y_{min}} \qquad (3.1)$$

Where,

$Y_{max}$ is 0.9

$Y_{min}$ is 0.1

$L_{max}$ is maximum load value

$L_{min}$ is minimum load value

L is load to be converted

$L_S$ is normalized value

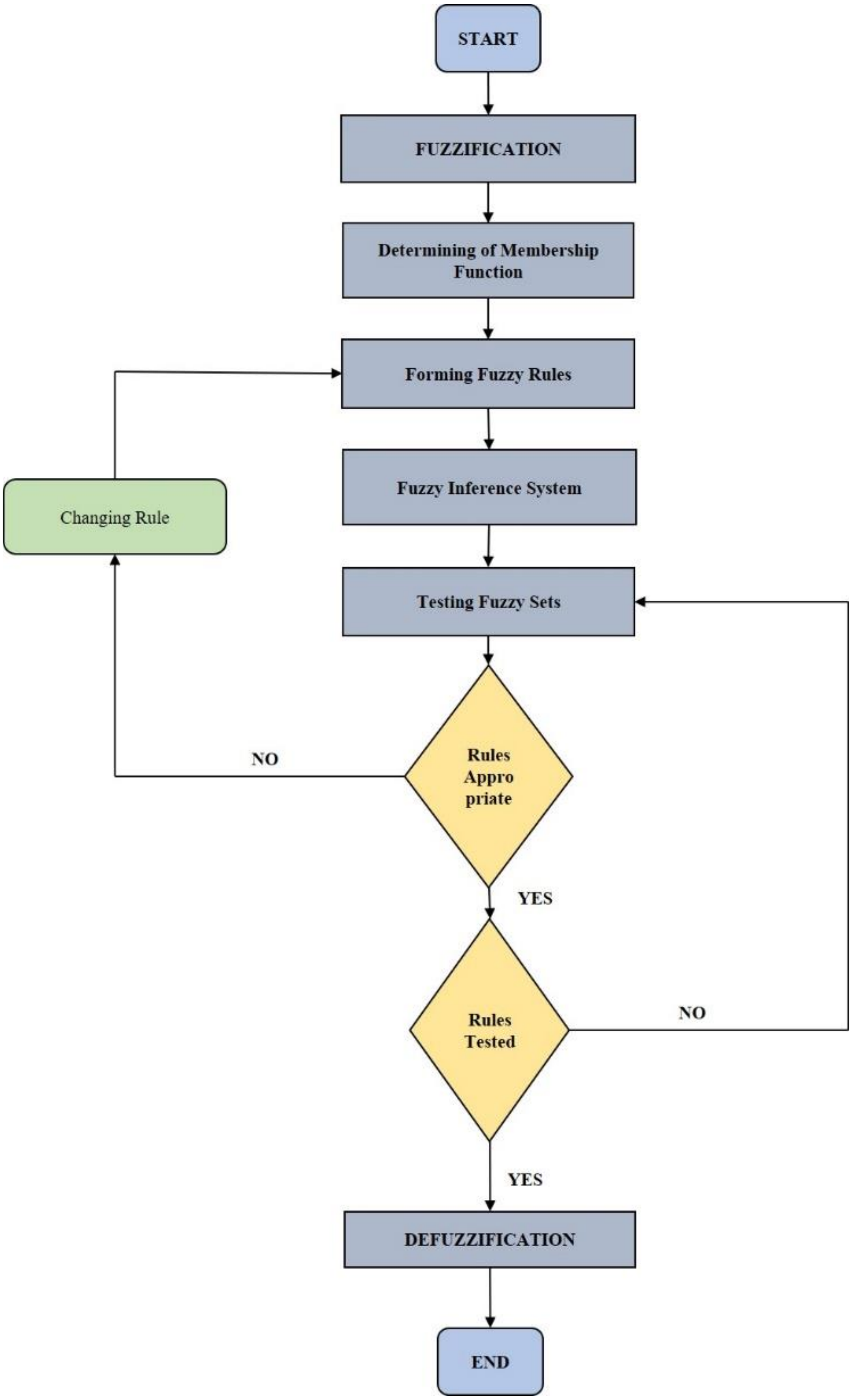


Figure 3.3: Flowchart for Fuzzy Logic

In this thesis work is done on fuzzy inference system in which the result of the rules in fuzzy is communicated in fresh number. One of the appealing highlights is that in fuzzy logic, the fuzzy rule is prepared to do effectively add on the new participation's capacity to the current ones.

Table 3.1: Collected Data of Hospital in MW

| Time | Day 1 | Day 2 | Day 3 | Day 4 | Day 5 | Day 6 |
|---|---|---|---|---|---|---|
| 00:15 | 24.9 | 27.24 | 32.93 | 32.3 | 35.5 | 36.4 |
| 00:30 | 23.68 | 25.4 | 31.1 | 30.51 | 35.5 | 34.72 |
| 00:45 | 23.29 | 25.17 | 31.1 | 27.2 | 34.52 | 30 |
| 01:00 | 22.95 | 23.3 | 29.94 | 27.2 | 30.6 | 35.61 |
| 01:15 | 22.8 | 23.3 | 29 | 27.2 | 30.6 | 35.7 |
| 01:30 | 22.59 | 23.3 | 29 | 27.2 | 30.6 | 35.7 |
| 01:45 | 22.51 | 23.3 | 29.45 | 27.2 | 30.6 | 35.7 |
| 02:00 | 22.88 | 23.3 | 29.1 | 27.2 | 30.6 | 32.72 |
| 02:15 | 22.46 | 23.3 | 29.1 | 27.2 | 30.6 | 29.7 |
| 02:30 | 22.52 | 23.3 | 29.1 | 27.2 | 30.6 | 29.7 |
| 02:45 | 22.5 | 23.3 | 29.1 | 27.2 | 30.6 | 29.7 |
| 03:00 | 22.79 | 23.3 | 29.1 | 27.2 | 30.44 | 29.7 |
| 03:15 | 22.39 | 23.3 | 29.1 | 27.2 | 28.1 | 29.7 |
| 03:30 | 22.56 | 21.65 | 29.1 | 27.2 | 28.1 | 29.7 |
| 03:45 | 22.65 | 22.51 | 28.84 | 27.2 | 28.1 | 29.7 |
| 04:00 | 22.9 | 23.1 | 26.7 | 27.2 | 28.1 | 29.7 |
| 04:15 | 22.7 | 21.9 | 26.7 | 26.46 | 28.1 | 29.7 |
| 04:30 | 22.47 | 21.64 | 26.7 | 25.1 | 28.1 | 29.31 |
| 04:45 | 22.55 | 22.12 | 26.7 | 25.1 | 28.1 | 27.7 |
| 05:00 | 22.22 | 22.33 | 26.7 | 25.78 | 28.1 | 27.7 |
| 05:15 | 22.99 | 23.4 | 26.7 | 25.6 | 29.59 | 27.7 |
| 05:30 | 23.23 | 23.4 | 26.7 | 25.6 | 29.74 | 27.7 |
| 05:45 | 23.67 | 23.4 | 26.7 | 25.6 | 28.1 | 27.7 |
| 06:00 | 23.26 | 23.4 | 26.7 | 25.6 | 28.1 | 27.7 |
| 06:15 | 22.71 | 23.4 | 25.26 | 25.6 | 28.1 | 27.7 |
| 06:30 | 22.27 | 23.4 | 27.35 | 25.6 | 26.2 | 26.5 |
| 06:45 | 22.51 | 26.84 | 26.89 | 23.51 | 27.08 | 28.59 |
| 07:00 | 22.68 | 28.53 | 26.8 | 26.89 | 31.6 | 33.42 |
| 07:15 | 22.86 | 27.8 | 26.8 | 29.69 | 31.6 | 33.65 |
| 07:30 | 23.23 | 27.8 | 27.14 | 29.33 | 32.38 | 34.1 |
| 07:45 | 23.01 | 27.8 | 30.92 | 29.7 | 33.8 | 34.1 |
| 08:00 | 22.81 | 28.2 | 31.9 | 29.7 | 35.46 | 34.74 |
| 08:15 | 24.23 | 27.8 | 32.07 | 31.21 | 37.09 | 36.2 |
| 08:30 | 24.15 | 27.36 | 33.9 | 31.9 | 38.08 | 37.83 |
| 08:45 | 24.48 | 25.8 | 35.18 | 33.94 | 39.2 | 39.08 |
| 09:00 | 25.01 | 25.8 | 38.59 | 35.43 | 40.52 | 40.53 |
| 09:15 | 25.97 | 25.66 | 36.84 | 34.2 | 42.26 | 42.82 |
| 09:30 | 28.15 | 24.42 | 43.28 | 32.37 | 34.96 | 47.39 |
| 09:45 | 25.24 | 29.81 | 50.44 | 42.56 | 52.32 | 49.11 |
| 10:00 | 30.69 | 33.74 | 51.7 | 45.53 | 52.9 | 49.37 |
| 10:15 | 31.93 | 33.86 | 51.7 | 47.21 | 53.2 | 45.3 |
| 10:30 | 32.52 | 33.74 | 51.7 | 48.99 | 55.2 | 46.75 |
| 10:45 | 32.69 | 34.2 | 53.6 | 51.7 | 55.2 | 47.1 |
| 11:00 | 33.04 | 26.89 | 53.9 | 52.6 | 57.16 | 48.42 |
| 11:15 | 33.16 | 30.68 | 53.9 | 53.25 | 58.18 | 54.34 |
| 11:30 | 33.1 | 30.71 | 53.9 | 53.21 | 57.54 | 58.49 |
| 11:45 | 32.77 | 30.38 | 53.9 | 52.08 | 58.52 | 57.6 |
| 12:00 | 33.53 | 28.7 | 54.67 | 50.6 | 57.78 | 56.39 |

| Time | Day 1 | Day 2 | Day 3 | Day 4 | Day 5 | Day 6 |
|---|---|---|---|---|---|---|
| 12:15 | 33.05 | 29.51 | 54.9 | 49.33 | 55.95 | 55.16 |
| 12:30 | 32.3 | 28.84 | 53.58 | 49.52 | 57.3 | 55.08 |
| 12:45 | 32.3 | 29.34 | 52.6 | 51.88 | 57.3 | 54.4 |
| 13:00 | 32.3 | 29.23 | 52.6 | 52.77 | 57.3 | 54.26 |
| 13:15 | 32.3 | 28 | 51.47 | 50.69 | 53.98 | 54.2 |
| 13:30 | 30.71 | 28 | 51.51 | 43.8 | 46.11 | 52.21 |
| 13:45 | 30.34 | 28 | 52.35 | 42.31 | 51.42 | 52.1 |
| 14:00 | 29.85 | 28.76 | 52.17 | 41.66 | 52.8 | 52.6 |
| 14:15 | 29.76 | 30 | 51.9 | 39.6 | 52.8 | 52.81 |
| 14:30 | 29.7 | 28.23 | 51 | 41.83 | 52.8 | 53.77 |
| 14:45 | 29.7 | 32.48 | 50.63 | 49 | 50.51 | 54.8 |
| 15:00 | 29.7 | 34.19 | 46.78 | 49.21 | 50 | 54.8 |
| 15:15 | 29.7 | 22.36 | 43.18 | 50.87 | 50 | 53.69 |
| 15:30 | 29.66 | 30.47 | 35.04 | 50.5 | 48.99 | 52 |
| 15:45 | 27.7 | 28.2 | 33 | 50.95 | 47.52 | 51.18 |
| 16:00 | 26.45 | 29.46 | 33 | 45.23 | 42.71 | 47.11 |
| 16:15 | 25.6 | 29.6 | 33 | 42.07 | 39.15 | 38.89 |
| 16:30 | 25.52 | 13.71 | 33 | 34.76 | 38.7 | 35.57 |
| 16:45 | 28.5 | 24 | 32.73 | 31.95 | 39.33 | 33.3 |
| 17:00 | 28.84 | 23.07 | 32.29 | 32.31 | 40.36 | 33.38 |
| 17:15 | 28.64 | 22.3 | 30.7 | 30.75 | 32.14 | 34.62 |
| 17:30 | 28.5 | 23.21 | 28.84 | 29.88 | 31.61 | 33.5 |
| 17:45 | 28.5 | 21.79 | 29.27 | 28.66 | 30.84 | 31.31 |
| 18:00 | 28.5 | 21.81 | 29.1 | 28.46 | 29.96 | 31.3 |
| 18:15 | 24.54 | 22.26 | 27.84 | 27.89 | 27.1 | 29.98 |
| 18:30 | 22.8 | 23.56 | 28.95 | 26.4 | 27.1 | 29.4 |
| 18:45 | 22.84 | 19.73 | 33.29 | 26.52 | 27.1 | 29.71 |
| 19:00 | 24.93 | 22.9 | 35.5 | 26.39 | 27.1 | 31.3 |
| 19:15 | 25.95 | 22.2 | 35.5 | 26.31 | 27.1 | 36.02 |
| 19:30 | 25.5 | 22.73 | 35.5 | 26.61 | 27.77 | 34.3 |
| 19:45 | 24.17 | 27.4 | 35.5 | 28.26 | 29.3 | 34.43 |
| 20:00 | 23.48 | 28.28 | 35.92 | 32.34 | 29.3 | 34.1 |
| 20:15 | 23.92 | 30.1 | 37.6 | 32.5 | 29.3 | 34.1 |
| 20:30 | 23.9 | 29.4 | 37.43 | 32.5 | 29.3 | 34.46 |
| 20:45 | 24.82 | 28 | 35.6 | 32.5 | 29.3 | 36.2 |
| 21:00 | 24.8 | 28.48 | 35.6 | 33.29 | 29.43 | 37.98 |
| 21:15 | 24.71 | 28.69 | 35.6 | 34.6 | 31.4 | 37.9 |
| 21:30 | 24.71 | 28.2 | 36.76 | 34.6 | 31.4 | 37.9 |
| 21:45 | 25.1 | 27.96 | 37.7 | 34.6 | 31.4 | 37.9 |
| 22:00 | 25.1 | 24.67 | 37.7 | 34.6 | 31.4 | 37.9 |
| 22:15 | 25.1 | 24 | 37.7 | 34.6 | 31.4 | 37.9 |
| 22:30 | 25.1 | 25.49 | 36.86 | 34.6 | 31.4 | 37.9 |
| 22:45 | 25.1 | 29.4 | 35.7 | 34.6 | 31.4 | 37.9 |
| 23:00 | 25.1 | 29.4 | 35.7 | 34.32 | 31.4 | 37.9 |
| 23:15 | 25.1 | 29.4 | 32.69 | 34.36 | 32.71 | 37.9 |
| 23:30 | 25.1 | 29.4 | 31 | 33.2 | 38.5 | 37.9 |
| 23:45 | 25.1 | 29.4 | 31 | 32.3 | 35.5 | 37.9 |
| 00:00 | 23.3 | 29.4 | 31 | 30.51 | 35.5 | 37.9 |

Table 3.2: Normalized Value

| Time | Inputs | | | | | | Output |
|---|---|---|---|---|---|---|---|
| | **Day 1** | **Day 2** | **Day 3** | **Day 4** | **Day 5** | **Day 6** | |
| 00:15 | 0.3 | 0.34 | 0.44 | 0.43 | 0.48 | 0.50 | 0.54 |
| 00:30 | 0.27 | 0.30 | 0.41 | 0.4 | 0.48 | 0.47 | 0.54 |
| 00:45 | 0.27 | 0.30 | 0.41 | 0.34 | 0.47 | 0.39 | 0.54 |
| 01:00 | 0.26 | 0.27 | 0.39 | 0.34 | 0.40 | 0.49 | 0.54 |
| 01:15 | 0.26 | 0.27 | 0.37 | 0.34 | 0.40 | 0.49 | 0.54 |
| 01:30 | 0.25 | 0.27 | 0.37 | 0.34 | 0.40 | 0.49 | 0.51 |
| 01:45 | 0.25 | 0.27 | 0.38 | 0.34 | 0.40 | 0.49 | 0.39 |
| 02:00 | 0.26 | 0.27 | 0.37 | 0.34 | 0.40 | 0.43 | 0.39 |
| 02:15 | 0.25 | 0.27 | 0.37 | 0.34 | 0.40 | 0.38 | 0.39 |
| 02:30 | 0.26 | 0.27 | 0.37 | 0.34 | 0.40 | 0.38 | 0.39 |
| 02:45 | 0.25 | 0.27 | 0.37 | 0.34 | 0.40 | 0.38 | 0.39 |
| 03:00 | 0.26 | 0.27 | 0.37 | 0.34 | 0.39 | 0.38 | 0.39 |
| 03:15 | 0.25 | 0.27 | 0.37 | 0.34 | 0.35 | 0.38 | 0.39 |
| 03:30 | 0.25 | 0.24 | 0.37 | 0.34 | 0.35 | 0.38 | 0.39 |
| 03:45 | 0.26 | 0.25 | 0.37 | 0.34 | 0.35 | 0.38 | 0.39 |
| 04:00 | 0.26 | 0.26 | 0.33 | 0.34 | 0.35 | 0.38 | 0.39 |
| 04:15 | 0.26 | 0.24 | 0.33 | 0.32 | 0.35 | 0.38 | 0.39 |
| 04:30 | 0.25 | 0.24 | 0.33 | 0.30 | 0.35 | 0.37 | 0.39 |
| 04:45 | 0.25 | 0.25 | 0.33 | 0.30 | 0.35 | 0.35 | 0.39 |
| 05:00 | 0.25 | 0.25 | 0.33 | 0.31 | 0.35 | 0.35 | 0.39 |
| 05:15 | 0.26 | 0.27 | 0.33 | 0.31 | 0.38 | 0.35 | 0.39 |
| 05:30 | 0.27 | 0.27 | 0.33 | 0.31 | 0.38 | 0.35 | 0.39 |
| 05:45 | 0.27 | 0.27 | 0.33 | 0.31 | 0.35 | 0.35 | 0.39 |
| 06:00 | 0.27 | 0.27 | 0.33 | 0.31 | 0.35 | 0.35 | 0.39 |
| 06:15 | 0.26 | 0.27 | 0.30 | 0.31 | 0.35 | 0.35 | 0.36 |
| 06:30 | 0.25 | 0.27 | 0.34 | 0.31 | 0.32 | 0.32 | 0.35 |
| 06:45 | 0.25 | 0.33 | 0.33 | 0.27 | 0.33 | 0.36 | 0.35 |
| 07:00 | 0.26 | 0.36 | 0.33 | 0.33 | 0.41 | 0.45 | 0.44 |
| 07:15 | 0.26 | 0.35 | 0.33 | 0.38 | 0.41 | 0.45 | 0.45 |
| 07:30 | 0.27 | 0.35 | 0.34 | 0.37 | 0.43 | 0.46 | 0.46 |
| 07:45 | 0.26 | 0.35 | 0.40 | 0.38 | 0.45 | 0.46 | 0.48 |
| 08:00 | 0.26 | 0.35 | 0.42 | 0.38 | 0.48 | 0.47 | 0.52 |
| 08:15 | 0.28 | 0.35 | 0.42 | 0.41 | 0.51 | 0.50 | 0.53 |
| 08:30 | 0.28 | 0.34 | 0.46 | 0.42 | 0.53 | 0.53 | 0.56 |
| 08:45 | 0.29 | 0.31 | 0.48 | 0.46 | 0.55 | 0.55 | 0.61 |
| 09:00 | 0.30 | 0.31 | 0.54 | 0.48 | 0.57 | 0.57 | 0.63 |
| 09:15 | 0.31 | 0.31 | 0.51 | 0.46 | 0.61 | 0.61 | 0.56 |
| 09:30 | 0.35 | 0.29 | 0.62 | 0.43 | 0.47 | 0.70 | 0.64 |
| 09:45 | 0.30 | 0.38 | 0.75 | 0.61 | 0.78 | 0.73 | 0.68 |
| 10:00 | 0.40 | 0.45 | 0.77 | 0.66 | 0.8 | 0.73 | 0.79 |
| 10:15 | 0.42 | 0.46 | 0.77 | 0.69 | 0.8 | 0.66 | 0.84 |
| 10:30 | 0.43 | 0.45 | 0.77 | 0.73 | 0.84 | 0.69 | 0.87 |
| 10:45 | 0.43 | 0.46 | 0.81 | 0.77 | 0.84 | 0.69 | 0.88 |
| 11:00 | 0.44 | 0.33 | 0.81 | 0.79 | 0.87 | 0.72 | 0.88 |
| 11:15 | 0.44 | 0.40 | 0.81 | 0.80 | 0.89 | 0.82 | 0.88 |
| 11:30 | 0.44 | 0.40 | 0.81 | 0.80 | 0.88 | 0.89 | 0.88 |
| 11:45 | 0.44 | 0.39 | 0.81 | 0.78 | 0.9 | 0.88 | 0.88 |

| Time | Day 1 | Day 2 | Day 3 | Day 4 | Day 5 | Day 6 | Output |
|---|---|---|---|---|---|---|---|
| 12:00 | 0.45 | 0.36 | 0.83 | 0.75 | 0.88 | 0.86 | 0.87 |
| 12:15 | 0.44 | 0.38 | 0.83 | 0.73 | 0.85 | 0.84 | 0.86 |
| 12:30 | 0.43 | 0.37 | 0.81 | 0.73 | 0.87 | 0.83 | 0.84 |
| 12:45 | 0.43 | 0.37 | 0.79 | 0.78 | 0.87 | 0.82 | 0.8 |
| 13:00 | 0.43 | 0.37 | 0.79 | 0.79 | 0.87 | 0.82 | 0.78 |
| 13:15 | 0.43 | 0.35 | 0.77 | 0.76 | 0.81 | 0.82 | 0.75 |
| 13:30 | 0.40 | 0.35 | 0.77 | 0.67 | 0.67 | 0.78 | 0.74 |
| 13:45 | 0.39 | 0.35 | 0.79 | 0.61 | 0.77 | 0.78 | 0.75 |
| 14:00 | 0.38 | 0.36 | 0.78 | 0.59 | 0.79 | 0.79 | 0.74 |
| 14:15 | 0.38 | 0.39 | 0.78 | 0.56 | 0.79 | 0.79 | 0.77 |
| 14:30 | 0.38 | 0.35 | 0.76 | 0.60 | 0.79 | 0.81 | 0.85 |
| 14:45 | 0.38 | 0.43 | 0.75 | 0.73 | 0.75 | 0.83 | 0.85 |
| 15:00 | 0.38 | 0.46 | 0.69 | 0.73 | 0.74 | 0.83 | 0.83 |
| 15:15 | 0.38 | 0.25 | 0.62 | 0.76 | 0.74 | 0.81 | 0.80 |
| 15:30 | 0.38 | 0.39 | 0.48 | 0.75 | 0.73 | 0.78 | 0.78 |
| 15:45 | 0.35 | 0.35 | 0.44 | 0.76 | 0.70 | 0.76 | 0.73 |
| 16:00 | 0.32 | 0.38 | 0.44 | 0.66 | 0.83 | 0.69 | 0.67 |
| 16:15 | 0.31 | 0.38 | 0.44 | 0.60 | 0.55 | 0.54 | 0.51 |
| 16:30 | 0.31 | 0.1 | 0.44 | 0.47 | 0.54 | 0.49 | 0.44 |
| 16:45 | 0.36 | 0.28 | 0.44 | 0.42 | 0.55 | 0.45 | 0.40 |
| 17:00 | 0.02 | 0.26 | 0.43 | 0.43 | 0.57 | 0.45 | 0.40 |
| 17:15 | 0.36 | 0.25 | 0.40 | 0.40 | 0.42 | 0.47 | 0.43 |
| 17:30 | 0.36 | 0.27 | 0.37 | 0.38 | 0.42 | 0.45 | 0.43 |
| 17:45 | 0.36 | 0.24 | 0.37 | 0.36 | 0.40 | 0.41 | 0.44 |
| 18:00 | 0.36 | 0.24 | 0.37 | 0.36 | 0.39 | 0.41 | 0.44 |
| 18:15 | 0.29 | 0.25 | 0.35 | 0.35 | 0.33 | 0.39 | 0.41 |
| 18:30 | 0.26 | 0.27 | 0.37 | 0.32 | 0.33 | 0.38 | 0.40 |
| 18:45 | 0.26 | 0.20 | 0.45 | 0.32 | 0.33 | 0.38 | 0.37 |
| 19:00 | 0.3 | 0.26 | 0.48 | 0.32 | 0.33 | 0.41 | 0.37 |
| 19:15 | 0.31 | 0.25 | 0.48 | 0.32 | 0.33 | 0.49 | 0.38 |
| 19:30 | 0.31 | 0.26 | 0.48 | 0.33 | 0.35 | 0.46 | 0.38 |
| 19:45 | 0.28 | 0.34 | 0.48 | 0.36 | 0.37 | 0.47 | 0.40 |
| 20:00 | 0.27 | 0.36 | 0.49 | 0.43 | 0.37 | 0.46 | 0.42 |
| 20:15 | 0.28 | 0.39 | 0.52 | 0.43 | 0.37 | 0.46 | 0.41 |
| 20:30 | 0.28 | 0.38 | 0.52 | 0.43 | 0.37 | 0.47 | 0.38 |
| 20:45 | 0.29 | 0.35 | 0.49 | 0.43 | 0.37 | 0.50 | 0.40 |
| 21:00 | 0.29 | 0.36 | 0.49 | 0.45 | 0.38 | 0.53 | 0.50 |
| 21:15 | 0.29 | 0.36 | 0.49 | 0.47 | 0.41 | 0.53 | 0.53 |
| 21:30 | 0.29 | 0.35 | 0.51 | 0.47 | 0.41 | 0.53 | 0.56 |
| 21:45 | 0.30 | 0.35 | 0.52 | 0.47 | 0.41 | 0.53 | 0.56 |
| 22:00 | 0.30 | 0.29 | 0.52 | 0.47 | 0.41 | 0.53 | 0.57 |
| 22:15 | 0.30 | 0.28 | 0.52 | 0.47 | 0.41 | 0.53 | 0.56 |
| 22:30 | 0.30 | 0.31 | 0.51 | 0.47 | 0.41 | 0.53 | 0.56 |
| 22:45 | 0.30 | 0.38 | 0.49 | 0.47 | 0.41 | 0.53 | 0.53 |
| 23:00 | 0.30 | 0.38 | 0.49 | 0.46 | 0.41 | 0.53 | 0.52 |
| 23:15 | 0.30 | 0.38 | 0.43 | 0.46 | 0.43 | 0.53 | 0.52 |
| 23:30 | 0.30 | 0.38 | 0.40 | 0.44 | 0.54 | 0.53 | 0.52 |
| 23:45 | 0.30 | 0.38 | 0.40 | 0.43 | 0.48 | 0.53 | 0.51 |
| 00:00 | 0.27 | 0.38 | 0.40 | 0.4 | 0.48 | 0.53 | 0.49 |

Fuzzy methodology that is put forward can be utilized as a guide to forecasting the heaps with various time arrangement. An accurate fuzzy system can be made by dividing into various intervals. The basic fuzzy logic model used for STLF for the data can be seen in Figure 3.4. The span of input as well as output is divided into thirteen triangular membership functions that is presented in Figure 3.5.

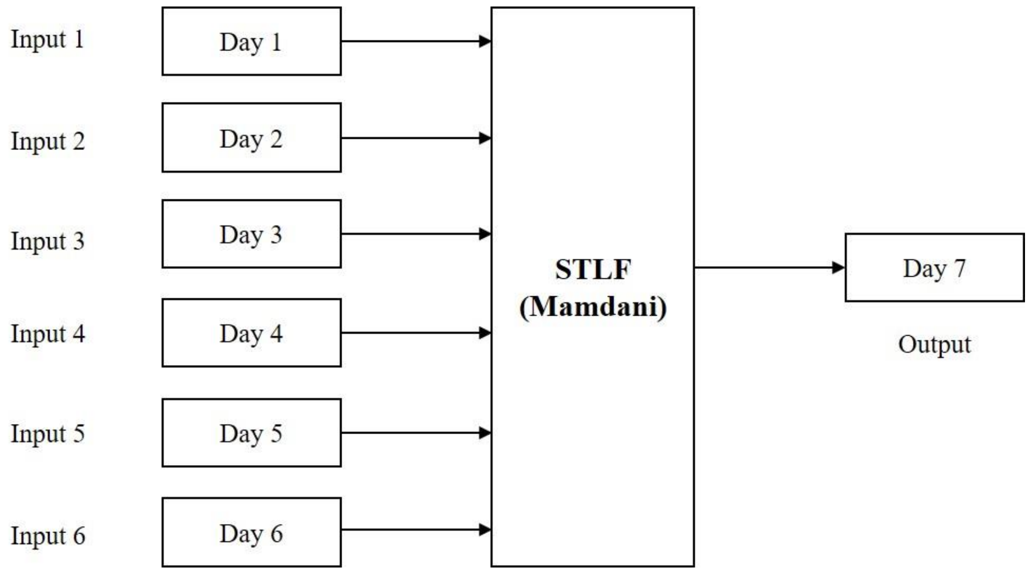


Figure 3.4: Model of Fuzzy Logic for STLF

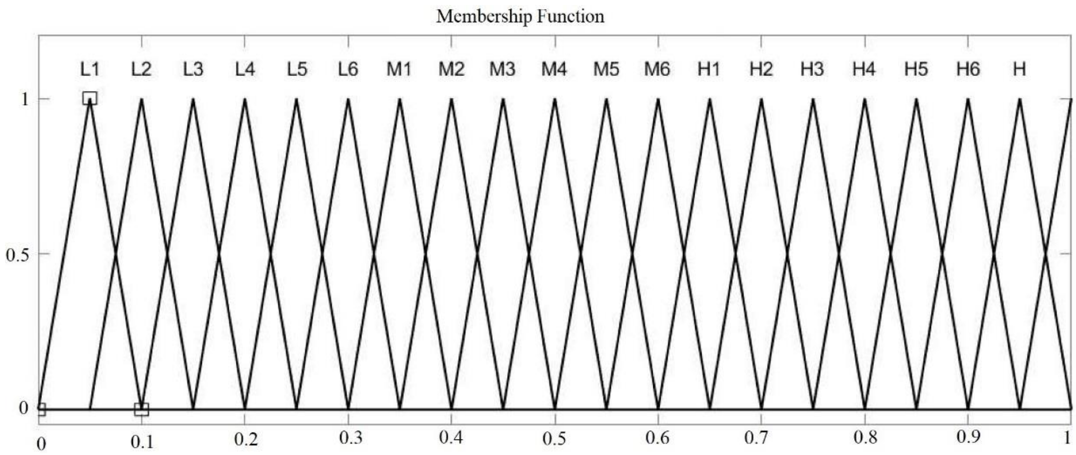


Figure 3.5: Input and output Triangular Membership Function

## 3.9: Fuzzy Results

The triangular membership functions are utilized where the help of the participation work is settled based on the gathered information. The arrangement of the creation rules depends on the basic semantic learning, and is the essential premise for the forecast model. The output of the model will exclusively rely upon this, and subsequently after primer investigation of the informational collection, the accompanying creation rules is utilized, anyway the equivalent might be distinctive for another arrangement of information. Together the triangular membership functions as well as fuzzy rules are intended to give a simpler technique in which we can implement instinct and experience directly into a PC program. Fuzzy rules applied for the data set is shown in Table 3.3.

Basically, we are able consider the possibilities between complete true and complete false. Each fuzzy set values of input variables are tested for all fuzzy rules and the appropriate rule is set for the model. All fuzzy rules (IF-THEN) are tested and then only decided that which rule is most suitable for the accurate output obtained.

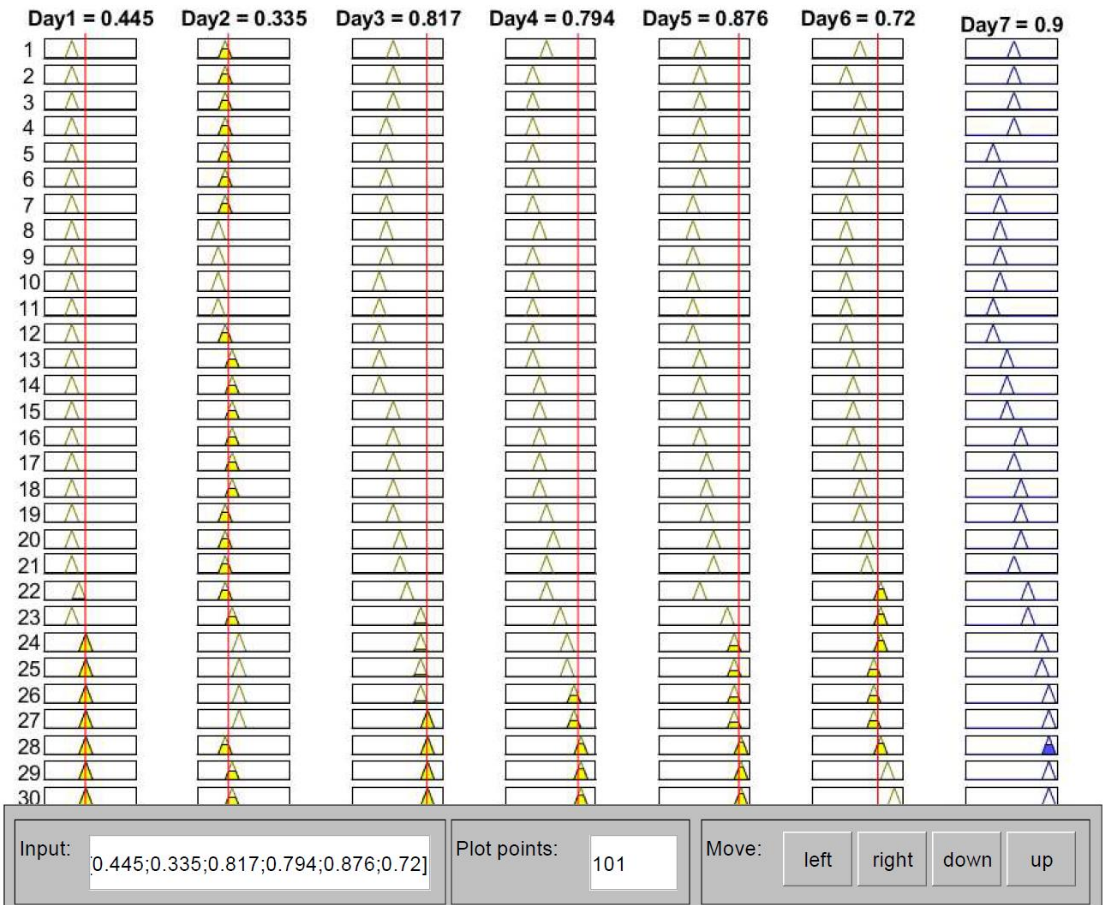


Figure 3.6: Rule Viewer for 28th Rule

With advantages in fuzzy logic, there is also the absence for the requirement to map the inputs with outputs in the mathematical model and also the for the input to be precise. The key idea of uncertainty is targeted through fuzzy logic. Fuzzy Logic recognizes the importance of the incomplete truth. With such conventional moulding rules, appropriately planned fuzzy logic system can be robust to design when utilized for STLF.

Table 3.3: Fuzzy Rules for STLF

| Time | Inputs | | | | | | Output |
|---|---|---|---|---|---|---|---|
| | **Day 1** | **Day 2** | **Day 3** | **Day 4** | **Day 5** | **Day 6** | |
| 00:15 | L4 | L4 | M2 | M2 | M2 | M3 | M3 |
| 00:30 | L4 | L4 | M2 | M2 | M2 | M3 | M3 |
| 00:45 | L4 | L4 | M2 | L4 | M2 | M1 | M3 |
| 01:00 | L4 | L4 | M2 | L4 | M2 | M3 | M3 |
| 01:15 | L4 | L4 | M1 | L4 | M2 | M3 | M3 |
| 01:30 | L4 | L4 | M1 | L4 | M2 | M3 | M3 |
| 01:45 | L4 | L4 | M1 | L4 | M2 | M3 | L4 |
| 02:00 | L4 | L4 | M1 | L4 | M2 | M2 | M1 |
| 02:15 | L4 | L4 | M1 | L4 | M2 | M2 | M1 |
| 02:30 | L4 | L4 | M1 | L4 | M2 | M2 | M1 |
| 02:45 | L4 | L4 | M1 | L4 | M2 | M2 | M1 |
| 03:00 | L4 | L4 | M1 | L4 | M1 | M1 | M1 |
| 03:15 | L4 | L4 | M1 | L4 | M1 | M1 | M1 |
| 03:30 | L4 | L3 | M1 | M1 | M1 | M1 | M2 |
| 03:45 | L4 | L3 | M1 | M1 | M1 | M1 | M2 |
| 04:00 | L4 | L3 | M1 | M1 | M1 | M1 | M2 |
| 04:15 | L4 | L3 | M1 | M1 | M1 | M1 | M2 |
| 04:30 | L4 | L3 | M1 | L4 | M1 | M1 | M1 |
| 04:45 | L4 | L3 | M1 | L4 | M1 | M1 | M1 |
| 05:00 | L4 | L3 | M1 | L4 | M1 | M1 | M1 |
| 05:15 | L4 | L3 | M1 | L4 | M1 | M1 | M1 |
| 05:30 | L4 | L3 | M1 | L4 | M1 | M1 | M1 |
| 05:45 | L4 | L3 | M1 | L4 | M1 | M1 | M1 |
| 06:00 | L4 | L3 | M1 | L4 | M1 | M1 | M1 |
| 06:15 | L4 | L3 | L4 | L4 | M1 | M1 | M1 |
| 06:30 | L4 | L3 | L4 | L4 | M1 | M1 | L4 |
| 06:45 | L4 | L4 | L4 | L4 | M1 | M1 | L4 |
| 07:00 | L4 | M1 | L4 | L4 | M2 | M2 | M2 |
| 07:15 | L4 | M1 | L4 | M1 | M2 | M2 | M2 |
| 07:30 | L4 | M1 | L4 | M1 | M2 | M2 | M2 |
| 07:45 | L4 | M1 | M2 | M1 | M2 | M2 | M2 |
| 08:00 | L4 | M1 | M2 | M1 | M2 | M2 | M4 |
| 08:15 | L4 | M1 | M2 | M1 | M3 | M3 | M3 |
| 08:30 | L4 | M1 | M2 | M1 | M3 | M3 | M4 |
| 08:45 | L4 | L4 | M2 | M2 | M3 | M3 | M4 |
| 09:00 | L4 | L4 | M3 | M3 | M4 | M4 | M4 |
| 09:15 | L4 | L4 | M3 | M2 | M4 | M4 | M3 |
| 09:30 | M1 | L4 | M4 | M2 | M2 | H2 | H1 |
| 09:45 | L4 | M1 | H2 | M4 | H2 | H2 | H1 |
| 10:00 | M2 | M2 | H2 | H1 | H3 | H2 | H3 |
| 10:15 | M2 | M2 | H2 | H1 | H3 | H1 | H3 |
| 10:30 | M2 | M2 | H2 | H2 | H3 | H1 | H4 |
| 10:45 | M2 | M2 | H3 | H2 | H3 | H1 | H4 |
| 11:00 | M2 | L4 | H3 | H3 | H4 | H2 | H1 |
| 11:15 | M2 | M1 | H3 | H3 | H4 | H3 | H4 |
| 11:30 | M2 | M1 | H3 | H3 | H4 | H4 | H4 |
| 11:45 | M2 | M1 | H3 | H3 | H4 | H4 | H4 |

| Time | Day 1 | Day 2 | Day 3 | Day 4 | Day 5 | Day 6 | Output |
|---|---|---|---|---|---|---|---|
| 12:00 | M2 | M1 | H3 | H2 | H4 | H4 | H4 |
| 12:15 | M2 | M1 | H3 | H2 | H4 | H4 | H4 |
| 12:30 | M2 | M1 | H3 | H2 | H4 | H3 | H3 |
| 12:45 | M2 | M1 | H3 | H2 | H4 | H3 | H2 |
| 13:00 | M2 | M1 | H2 | H2 | H4 | H3 | H1 |
| 13:15 | M2 | M1 | H2 | H2 | H3 | H3 | H2 |
| 13:30 | M2 | M1 | H2 | H1 | H1 | H2 | H2 |
| 13:45 | M1 | M1 | H2 | M4 | H2 | H2 | H2 |
| 14:00 | M1 | M1 | H2 | M4 | H2 | H2 | H2 |
| 14:15 | M1 | M1 | H2 | M3 | H2 | H2 | H3 |
| 14:30 | M1 | M1 | H2 | M4 | H2 | H3 | H4 |
| 14:45 | M1 | M2 | H2 | H2 | H2 | H3 | H4 |
| 15:00 | M1 | M2 | H1 | H2 | H2 | H3 | H3 |
| 15:15 | M1 | L3 | H1 | H2 | H2 | H3 | H3 |
| 15:30 | M1 | M1 | M2 | H2 | H2 | H2 | H2 |
| 15:45 | M1 | L4 | M2 | H2 | H2 | H2 | H2 |
| 16:00 | L4 | M1 | M2 | H1 | H3 | H1 | H1 |
| 16:15 | L4 | M1 | M2 | M4 | M3 | M3 | M3 |
| 16:30 | L4 | L1 | M2 | M2 | M3 | M3 | M2 |
| 16:45 | M1 | L4 | M2 | M2 | M3 | M2 | M1 |
| 17:00 | L1 | L4 | M2 | M2 | M4 | M2 | M2 |
| 17:15 | M1 | L3 | M2 | M2 | M2 | M2 | M2 |
| 17:30 | M1 | L3 | M1 | M1 | M2 | M2 | M2 |
| 17:45 | M1 | L3 | M1 | M1 | M2 | M2 | M2 |
| 18:00 | M1 | L3 | M1 | M1 | M2 | M2 | M2 |
| 18:15 | L4 | L3 | M1 | M1 | L4 | M2 | M2 |
| 18:30 | L4 | L3 | M1 | M1 | L4 | M1 | M1 |
| 18:45 | L4 | L3 | M2 | M1 | L4 | M1 | M1 |
| 19:00 | L4 | L3 | M2 | M1 | L4 | M1 | M1 |
| 19:15 | L4 | L3 | M2 | M1 | L4 | M2 | M1 |
| 19:30 | L4 | L3 | M2 | M1 | L4 | M2 | M1 |
| 19:45 | L4 | L4 | M2 | M1 | M1 | M2 | M2 |
| 20:00 | L4 | L4 | M1 | M2 | M1 | M2 | M2 |
| 20:15 | L4 | M1 | M3 | M2 | M1 | M2 | M2 |
| 20:30 | L4 | M1 | M3 | M2 | M1 | M2 | M1 |
| 20:45 | L4 | M1 | M3 | M2 | M1 | M2 | M1 |
| 21:00 | L4 | M1 | M3 | M2 | M1 | M3 | M3 |
| 21:15 | L4 | M1 | M3 | M2 | M1 | M3 | M3 |
| 21:30 | L4 | M1 | M3 | M2 | M1 | M3 | M4 |
| 21:45 | L4 | M1 | M3 | M2 | M1 | M3 | M4 |
| 22:00 | L4 | L4 | M3 | M2 | M1 | M3 | M4 |
| 22:15 | L4 | L4 | M3 | M2 | M1 | M3 | M3 |
| 22:30 | L4 | L4 | M3 | M2 | M1 | M3 | M3 |
| 22:45 | L4 | M1 | M3 | M2 | M1 | M3 | M3 |
| 23:00 | L4 | M1 | M3 | M2 | M1 | M3 | M2 |
| 23:15 | L4 | M1 | M2 | M2 | M1 | M3 | M3 |
| 23:30 | L4 | M1 | M2 | M2 | M3 | M3 | M3 |
| 23:45 | L4 | M1 | M2 | M2 | M3 | M3 | M3 |
| 00:00 | L4 | M1 | M2 | M2 | M3 | M3 | M2 |

After the crisp input is applied with logical reasoning or through the fuzzy inference system an output is obtained to which the defuzzification process can be applied and the crisp output can be obtained. One of the outputs for the 28th rule is seen in Figure 3.6. The output obtained from the model is then compared to the actual load which can be seen in Figure 3.7.

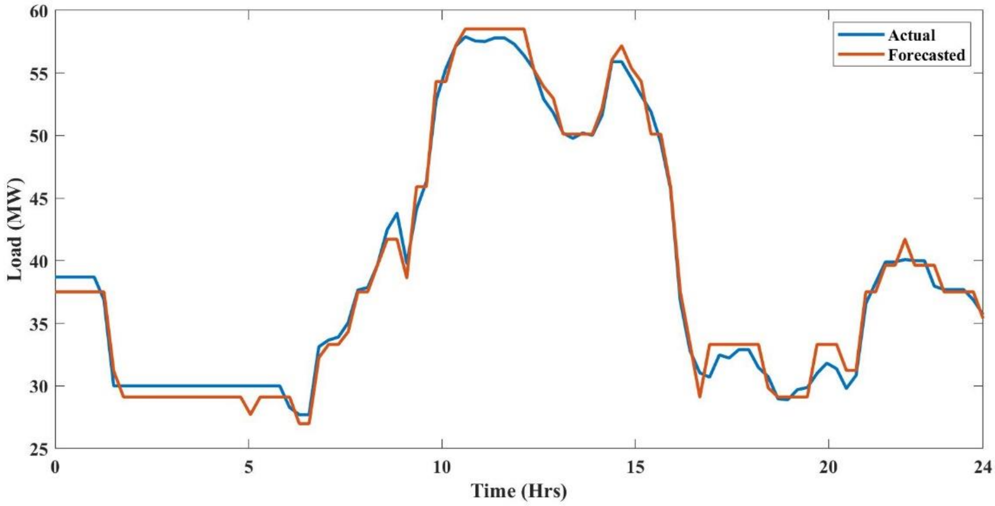


Figure 3.7: Actual Load Vs Forecasted Load Using FL

Then absolute relative error (ARE) is calculated with the help of formula given below:

$$\text{ARE} = \frac{\text{P}_{\text{desired}} - \text{P}_{\text{forecasted}}}{\text{P}_{\text{desired}}} \times 100 \qquad (3.2)$$

Where, $\text{P}_{\text{desired}}$ is the target load and $\text{P}_{\text{forecasted}}$ is the forecast load through fuzzy logic model for STLF. The error obtained can be observed in figure 3.8.

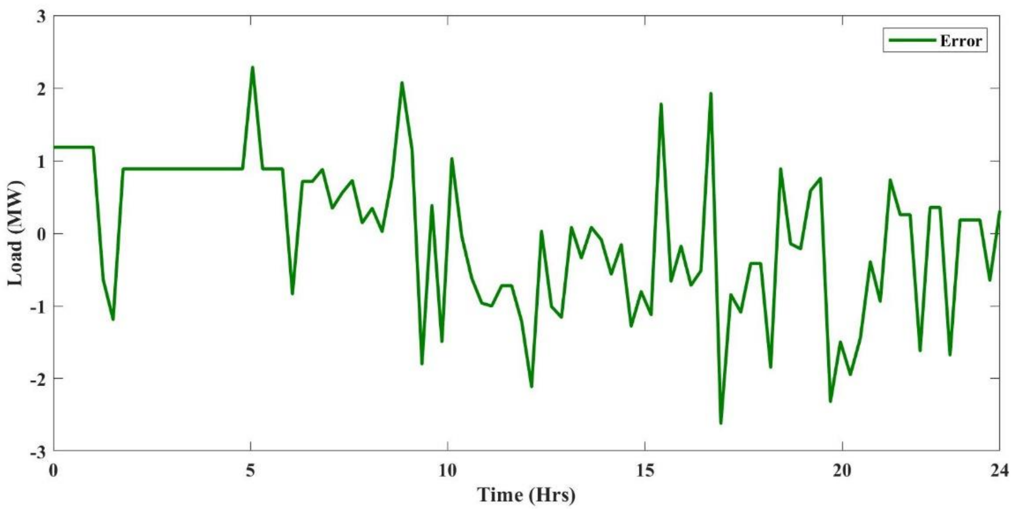


Figure 3.8: Error Obtained in Fuzzy

Table 3.4: Comparison of the Result Obtained using Fuzzy

| Time | Target Load (MW) | Forecasted Load (MW) | Error | %ARE |
|---|---|---|---|---|
| 00:15 | 38.700 | 37.515 | 1.185 | 3.062 |
| 00:30 | 38.700 | 37.515 | 1.185 | 3.062 |
| 00:45 | 38.700 | 37.515 | 1.185 | 3.062 |
| 01:00 | 38.700 | 37.515 | 1.185 | 3.062 |
| 01:15 | 38.700 | 37.515 | 1.185 | 3.062 |
| 01:30 | 36.880 | 37.515 | -0.635 | 1.721 |
| 01:45 | 30.000 | 31.186 | -1.186 | 3.953 |
| 02:00 | 30.000 | 29.113 | 0.887 | 2.956 |
| 02:15 | 30.000 | 29.113 | 0.887 | 2.956 |
| 02:30 | 30.000 | 29.113 | 0.887 | 2.956 |
| 02:45 | 30.000 | 29.113 | 0.887 | 2.956 |
| 03:00 | 30.000 | 29.113 | 0.887 | 2.956 |
| 03:15 | 30.000 | 29.113 | 0.887 | 2.956 |
| 03:30 | 30.000 | 29.113 | 0.887 | 2.956 |
| 03:45 | 30.000 | 29.113 | 0.887 | 2.956 |
| 04:00 | 30.000 | 29.113 | 0.887 | 2.956 |
| 04:15 | 30.000 | 29.113 | 0.887 | 2.956 |
| 04:30 | 30.000 | 29.113 | 0.887 | 2.956 |
| 04:45 | 30.000 | 29.113 | 0.887 | 2.956 |
| 05:00 | 30.000 | 29.113 | 0.887 | 2.956 |
| 05:15 | 30.000 | 27.713 | 2.287 | 7.623 |
| 05:30 | 30.000 | 29.113 | 0.887 | 2.956 |
| 05:45 | 30.000 | 29.113 | 0.887 | 2.956 |
| 06:00 | 30.000 | 29.113 | 0.887 | 2.956 |
| 06:15 | 28.280 | 29.113 | -0.833 | 2.945 |
| 06:30 | 27.700 | 26.985 | 0.715 | 2.581 |
| 06:45 | 27.700 | 26.985 | 0.715 | 2.581 |
| 07:00 | 33.130 | 32.250 | 0.88 | 2.656 |
| 07:15 | 33.660 | 33.314 | 0.346 | 1.027 |
| 07:30 | 33.900 | 33.314 | 0.559 | 1.648 |
| 07:45 | 35.050 | 34.323 | 0.727 | 2.074 |
| 08:00 | 37.660 | 37.515 | 0.145 | 0.385 |
| 08:15 | 37.860 | 37.515 | 0.345 | 0.911 |
| 08:30 | 39.670 | 39.644 | 0.026 | 0.065 |
| 08:45 | 42.480 | 41.716 | 0.764 | 1.798 |
| 09:00 | 43.790 | 41.716 | 2.074 | 4.736 |
| 09:15 | 39.790 | 38.636 | 1.154 | 2.9 |
| 09:30 | 44.120 | 45.917 | -1.797 | 4.072 |
| 09:45 | 46.300 | 45.917 | 0.383 | 0.827 |
| 10:00 | 52.830 | 54.319 | -1.489 | 2.818 |
| 10:15 | 55.350 | 54.319 | 1.031 | 1.862 |
| 10:30 | 57.130 | 57.176 | -0.046 | 0.08 |
| 10:45 | 57.900 | 58.52 | -0.62 | 1.07 |
| 11:00 | 57.560 | 58.52 | -0.96 | 1.667 |
| 11:15 | 57.520 | 58.52 | -1 | 1.738 |
| 11:30 | 57.800 | 58.52 | -0.72 | 1.245 |
| 11:45 | 57.800 | 58.52 | -0.72 | 1.245 |
| 12:00 | 57.310 | 58.52 | -1.21 | 2.111 |

| Time | Targeted Load (MW) | Forecasted Load (MW) | Error | %ARE |
|---|---|---|---|---|
| 12:15 | 56.410 | 58.52 | -2.11 | 3.74 |
| 12:30 | 55.300 | 55.271 | 0.029 | 0.052 |
| 12:45 | 52.920 | 53.927 | -1.007 | 1.902 |
| 13:00 | 51.820 | 52.975 | -1.155 | 2.228 |
| 13:15 | 50.200 | 50.118 | 0.082 | 0.163 |
| 13:30 | 49.780 | 50.118 | -0.338 | 0.678 |
| 13:45 | 50.200 | 50.118 | 0.082 | 0.163 |
| 14:00 | 50.030 | 50.118 | -0.088 | 0.175 |
| 14:15 | 51.630 | 52.191 | -0.561 | 1.086 |
| 14:30 | 55.900 | 56.055 | -0.155 | 0.277 |
| 14:45 | 55.900 | 57.176 | -1.276 | 2.282 |
| 15:00 | 54.580 | 55.383 | -0.803 | 1.471 |
| 15:15 | 53.200 | 54.319 | -1.119 | 2.103 |
| 15:30 | 51.900 | 50.118 | 1.782 | 3.433 |
| 15:45 | 49.460 | 50.118 | -0.658 | 1.33 |
| 16:00 | 45.740 | 45.917 | -0.177 | 0.386 |
| 16:15 | 36.800 | 37.515 | -0.715 | 1.94 |
| 16:30 | 32.800 | 33.314 | -0.514 | 1.567 |
| 16:45 | 31.040 | 29.113 | 1.927 | 6.208 |
| 17:00 | 30.700 | 33.314 | -2.614 | 8.514 |
| 17:15 | 32.470 | 33.314 | -0.844 | 2.599 |
| 17:30 | 32.230 | 33.314 | -1.084 | 3.363 |
| 17:45 | 32.900 | 33.314 | -0.414 | 1.258 |
| 18:00 | 32.900 | 33.314 | -0.414 | 1.258 |
| 18:15 | 31.470 | 33.314 | -1.844 | 5.85 |
| 18:30 | 30.730 | 29.842 | 0.888 | 2.88 |
| 18:45 | 28.970 | 29.113 | -0.143 | 0.493 |
| 19:00 | 28.900 | 29.113 | -0.213 | 0.737 |
| 19:15 | 29.700 | 29.113 | 0.587 | 1.976 |
| 19:30 | 29.870 | 29.113 | 0.757 | 2.534 |
| 19:45 | 31.000 | 33.314 | -2.314 | 7.464 |
| 20:00 | 31.820 | 33.314 | -1.494 | 4.695 |
| 20:15 | 31.370 | 33.314 | -1.944 | 6.197 |
| 20:30 | 29.800 | 31.242 | -1.442 | 4.838 |
| 20:45 | 30.850 | 31.242 | -0.392 | 1.27 |
| 21:00 | 36.580 | 37.515 | -0.935 | 2.556 |
| 21:15 | 38.250 | 37.515 | 0.735 | 1.921 |
| 21:30 | 39.900 | 39.644 | 0.256 | 0.641 |
| 21:45 | 39.900 | 39.644 | 0.256 | 0.641 |
| 22:00 | 40.100 | 41.716 | -1.616 | 4.029 |
| 22:15 | 40.000 | 39.644 | 0.356 | 0.89 |
| 22:30 | 40.000 | 39.644 | 0.356 | 0.89 |
| 22:45 | 37.970 | 39.644 | -1.674 | 4.408 |
| 23:00 | 37.700 | 37.515 | 0.185 | 0.491 |
| 23:15 | 37.700 | 37.515 | 0.185 | 0.491 |
| 23:30 | 37.700 | 37.515 | 0.185 | 0.491 |
| 23:45 | 36.870 | 37.515 | -0.645 | 1.749 |
| 00:00 | 35.700 | 35.387 | 0.313 | 0.876 |
| **Avg. ARE %** | | | | 2.376 |

The comparison is done to check the accuracy of the fuzzy logic model developed for the STLF. It can be observed that the load forecasted is nearby the actual demand data. This ARE is seen in the Table 3.4. Average absolute relative error is also calculated.

## 3.10: Conclusion

In this chapter fuzzy logic is explained in detail. Every block of fuzzy is discussed for better understanding of the technique. Madami Inference System (MIS) is selected in this model. Also, triangular membership function is used in this model for STLF purpose. In table 3.3, it can be seen that minimum ARE is 0.052% and maximum ARE is 8.514%. The Average absolute Relative Error calculated is 2.376%. It can be concluded that the error is low. Hence, the fuzzy model developed for the purpose of STLF for this data is accurate.

# CHAPTER 4

# DEVELOPING ARTIFICAL NEURAL NETWORK MODEL FOR LOAD FORECASTING

## 4.1: Introduction

It is also known as neural network (NN). It is a machine acts like human brain with learning capacity and speculation as its attributes. ANNs make them learn capacities that empower them to deliver better outcomes as more information opens up. It is the establishment of AI and tackles issues that would demonstrate outlandish or troublesome by human or measurable norms. They are basically non-linear mathematical processing networks. They are being used in fields like image recognition, load forecasting, speech recognition, energy consumption prediction, data retrieval, mine dam water level prediction and monitoring.

ANN endeavour to rearrange and impersonate this behaviour of brain. They can be prepared in an administered or un-administered way. In a managed ANN, the structure is prepared by giving coordinated information of input output samples, determined to get the ANN to give the ideal output for provided input. Unaided learning in ANN is an endeavour to get the ANN to "comprehend" the construction of the given input information "all alone".

## 4.2: Architecture

ANNs are made out of different node, which mimic natural neurons of human mind. The neurons are associated by connections and they communicate with one another. The hubs can take input information and perform straightforward procedure on the information. The outcome of these activities is passed to different neurons. The yield at every hub is called its initiation or node value. It consists of three layers:

i) Input Layer: It’s the first layer. In enters the external input data in the network.

ii) Hidden Layer: It is the second layer. It is layer between output and input. All sorts of calculation are performed in this to determine any pattern or hidden feature.

iii) Output Layer: It is the final layer. After going through some transformation series in hidden layer, which provides an output is conveyed by this layer.

Every arrow speaks for an association between the two neurons and shows the pathway for the progression of data. Every association has a weight, a whole number that controls the sign between two neurons. In the event that the organization creates a "great or wanted" outputs, there is no compelling reason to change the loads. Be that as it may, assuming the organization creates a "poor or undesired" error or an output, the framework modifies the loads to work on ensuing outcomes. Its basic structure cane be seen in figure 4.1.

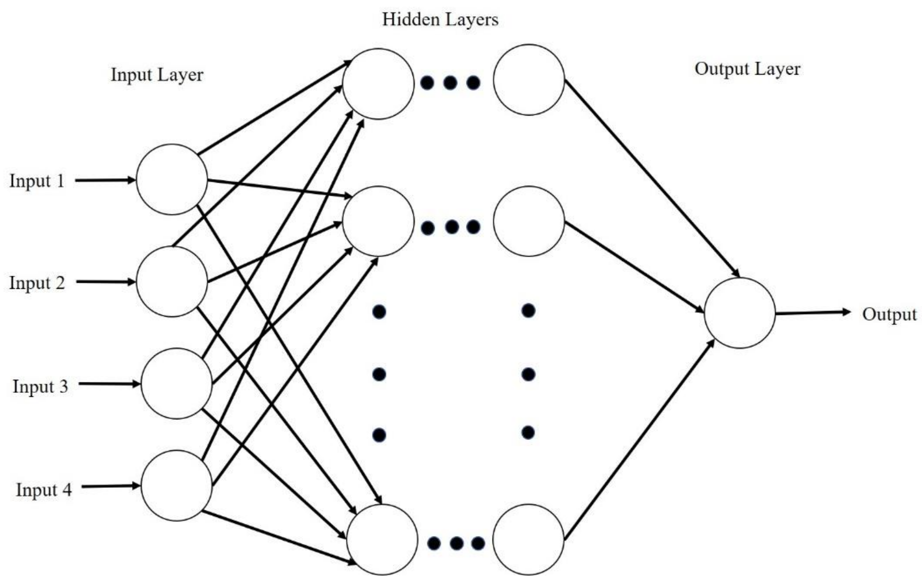


Figure 4.1: Basic structure of ANN

## 4.3: Benefits of ANN

It is obvious that a neural organization determines its registering power through, first, its greatly parallelly distributed network and second, its capacity to learn and in this way generalize. So, it can be said that it has following capacities or strengths:

- Non-Linearity: A artificial neuron can either be nonlinear or linear. A neural network is comprised of an interconnection in non-linear neurons, which itself is nonlinear. In addition, the nonlinearity is of a unique kind as in it is appropriated all through the network.
- Adaptive: In Neural network, they have an implicit capacity to adjust their synaptic loads to changes in the environment surrounding. Specifically, a neural organization prepared to work in a particular environment can be effortlessly retrained to manage minor changes in the working conditions. In addition, when it is working in nonstationary surroundings (i.e., one where insights change

with time), a neural network might be intended to change its synaptic loads with time.

- Response: The NN can be intended to give data regarding which specific pattern to choose as well as about the trust in the choice made. This latter data might be utilized to dismiss equivocal examples, should they emerge, and consequently further develop the order execution of the network.
- Tolerance: ANN executed in equipment form, can possibly inherit tolerance for fault or equipped for robust calculation, as in its presentation debases smoothly under adverse working conditions.
- Mapping: A well-known worldview of learning, called learning with an educator, or managed learning, includes adjustment of the synaptic loads of ANN by applying a bunch of labels task examples.

## 4.4: Applications of ANN

They can be applied in many fields:

- They can be used in military weapons such as tracking of targets, facial recognition.
- It can be used in automobiles in their guidance systems.
- It can be used in speech such as recognition, classification, conversion.
- It can be used in signal processing.
- It can be used in time series prediction.

## 4.5: Disadvantages of ANN

- To determine the structure in ANN, there are no specific guidelines. For accomplishment of appropriate or correct structure of network, it is done through trail and error and experience.
- When some testing solutions are produced by ANN, it do not give reasons concerning how and why. This results in decrease of trust in network.
- ANN requires processors having parallel processing capability according to their structure. So, realisation of apparatus is dependent.
- ANNs can work with mathematical information. Problem should be changed over into mathematical values prior to being acquainted with ANN. The show component to be settled here will affect directly the exhibition of network. It depends on the user's capacities.

- The structure is diminished to a particular value of error, and this worth doesn't give us ideal outputs or results.

## 4.6: ANN Model Development

For the development of ANN Model, MATLAB 2018 software is used. With the help of 'nftool' ANN model is developed. Feed forward network type of ANN is used here. Training of network is done by using 'Levenberg-Marquardt backpropagation algorithm'.

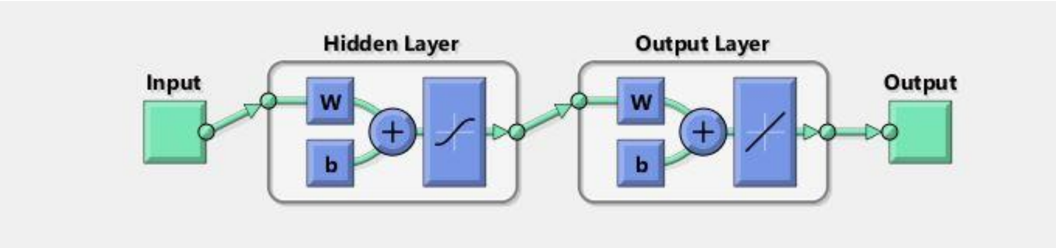


Figure 4.2: ANN Model in MATLAB

Using the algorithm discussed through flowchart in Figure 4.4 the forecasted load data for the 7$^{th}$ day for the location is generated through ANN.

## 4.7: ANN Model Results

Figure 4.3 represents the regression plot obtained during ANN model training and testing. Figure 4.5 is comparing of actual load and forecasted load from ANN model. Figure 4.6 is the error plot obtained by ANN and Table 4.1 shows the data obtained through this model.

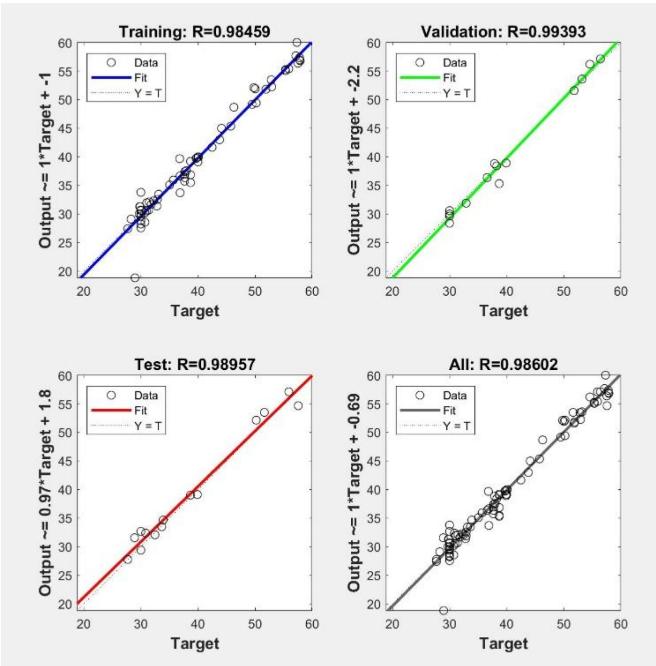


Figure 4.3: Regression plot while implementing ANN model

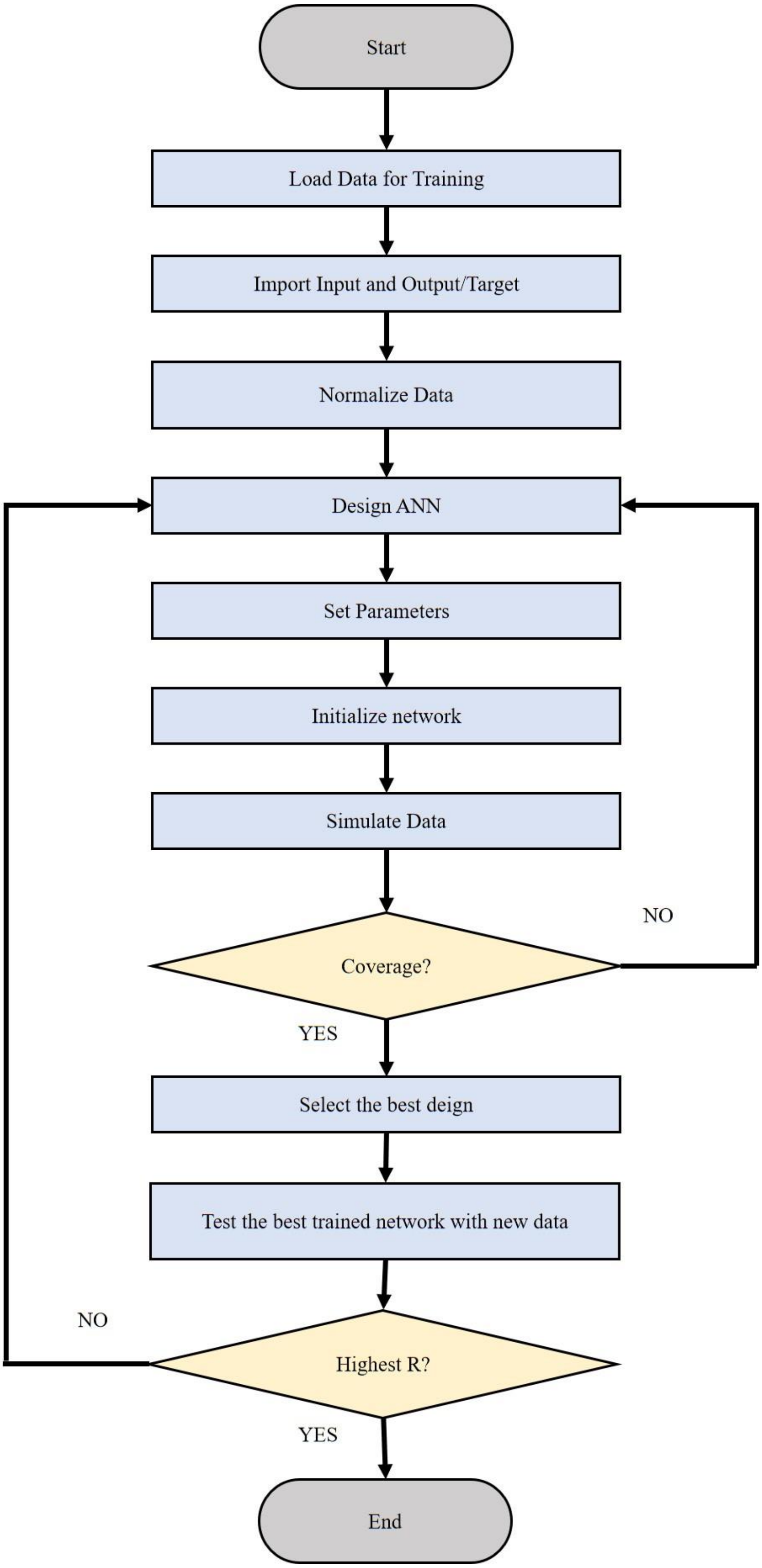


Figure 4.4: Flowchart of ANN algorithm

Table 4.1: Comparison of the Result Obtained using ANN

| Time | Actual Load (MW) | Predicted Load (MW) | Error | % ARE |
|---|---|---|---|---|
| 00:15 | 38.7 | 39.030 | 0.330 | 0.852 |
| 00:30 | 38.7 | 39.195 | 0.495 | 1.280 |
| 00:45 | 38.7 | 36.865 | 1.835 | 4.742 |
| 01:00 | 38.7 | 35.484 | 3.216 | 8.309 |
| 01:15 | 38.7 | 35.313 | 3.387 | 8.753 |
| 01:30 | 36.88 | 33.711 | 3.169 | 8.593 |
| 01:45 | 30 | 32.682 | 2.682 | 8.939 |
| 02:00 | 30 | 33.792 | 3.792 | 12.640 |
| 02:15 | 30 | 30.611 | 0.611 | 2.038 |
| 02:30 | 30 | 30.666 | 0.666 | 2.220 |
| 02:45 | 30 | 30.649 | 0.649 | 2.163 |
| 03:00 | 30 | 30.598 | 0.598 | 1.992 |
| 03:15 | 30 | 27.578 | 2.422 | 8.072 |
| 03:30 | 30 | 28.388 | 1.612 | 5.372 |
| 03:45 | 30 | 28.850 | 1.150 | 3.832 |
| 04:00 | 30 | 29.640 | 0.360 | 1.199 |
| 04:15 | 30 | 29.999 | 0.001 | 0.002 |
| 04:30 | 30 | 29.410 | 0.590 | 1.966 |
| 04:45 | 30 | 29.655 | 0.345 | 1.150 |
| 05:00 | 30 | 28.240 | 1.760 | 5.868 |
| 05:15 | 30 | 29.648 | 0.352 | 1.175 |
| 05:30 | 30 | 30.008 | 0.008 | 0.027 |
| 05:45 | 30 | 30.698 | 0.698 | 2.328 |
| 06:00 | 30 | 30.033 | 0.033 | 0.111 |
| 06:15 | 28.28 | 29.110 | 0.830 | 2.936 |
| 06:30 | 27.7 | 27.777 | 0.077 | 0.280 |
| 06:45 | 27.7 | 27.433 | 0.267 | 0.964 |
| 07:00 | 33.13 | 33.460 | 0.330 | 0.995 |
| 07:15 | 33.66 | 33.498 | 0.162 | 0.480 |
| 07:30 | 33.9 | 34.665 | 0.765 | 2.257 |
| 07:45 | 35.05 | 35.080 | 0.030 | 0.086 |
| 08:00 | 37.66 | 35.745 | 1.915 | 5.084 |
| 08:15 | 37.86 | 38.816 | 0.956 | 2.526 |
| 08:30 | 39.67 | 39.711 | 0.041 | 0.104 |
| 08:45 | 42.48 | 41.662 | 0.818 | 1.925 |
| 09:00 | 43.79 | 42.986 | 0.804 | 1.837 |
| 09:15 | 39.79 | 39.825 | 0.035 | 0.087 |
| 09:30 | 44.12 | 44.994 | 0.874 | 1.981 |
| 09:45 | 46.3 | 48.666 | 2.366 | 5.110 |
| 10:00 | 52.83 | 53.457 | 0.627 | 1.187 |
| 10:15 | 55.35 | 55.063 | 0.287 | 0.518 |
| 10:30 | 57.13 | 57.663 | 0.533 | 0.933 |
| 10:45 | 57.9 | 56.791 | 1.109 | 1.915 |
| 11:00 | 57.56 | 54.661 | 2.899 | 5.037 |
| 11:15 | 57.52 | 56.361 | 1.159 | 2.015 |
| 11:30 | 57.8 | 56.948 | 0.852 | 1.475 |
| 11:45 | 57.8 | 57.339 | 0.461 | 0.798 |
| 12:00 | 57.31 | 60.004 | 2.694 | 4.700 |

| Time | Actual Load (MW) | Predicted Load (MW) | Error | % ARE |
|---|---|---|---|---|
| 12:15 | 56.41 | 57.122 | 0.712 | 1.262 |
| 12:30 | 55.3 | 55.246 | 0.054 | 0.097 |
| 12:45 | 52.92 | 52.248 | 0.672 | 1.269 |
| 13:00 | 51.82 | 51.581 | 0.239 | 0.462 |
| 13:15 | 50.2 | 49.417 | 0.783 | 1.560 |
| 13:30 | 49.78 | 52.094 | 2.314 | 4.648 |
| 13:45 | 50.2 | 52.136 | 1.936 | 3.856 |
| 14:00 | 50.03 | 51.896 | 1.866 | 3.730 |
| 14:15 | 51.63 | 53.495 | 1.865 | 3.612 |
| 14:30 | 55.9 | 55.390 | 0.510 | 0.912 |
| 14:45 | 55.9 | 57.100 | 1.200 | 2.147 |
| 15:00 | 54.58 | 56.192 | 1.612 | 2.953 |
| 15:15 | 53.2 | 53.593 | 0.393 | 0.739 |
| 15:30 | 51.9 | 51.818 | 0.082 | 0.158 |
| 15:45 | 49.46 | 49.164 | 0.296 | 0.598 |
| 16:00 | 45.74 | 45.368 | 0.372 | 0.814 |
| 16:15 | 36.8 | 39.680 | 2.880 | 7.825 |
| 16:30 | 32.8 | 31.401 | 1.399 | 4.266 |
| 16:45 | 31.04 | 31.972 | 0.932 | 3.004 |
| 17:00 | 30.7 | 30.191 | 0.509 | 1.660 |
| 17:15 | 32.47 | 32.091 | 0.379 | 1.169 |
| 17:30 | 32.23 | 32.299 | 0.069 | 0.214 |
| 17:45 | 32.9 | 32.573 | 0.327 | 0.994 |
| 18:00 | 32.9 | 31.899 | 1.001 | 3.044 |
| 18:15 | 31.47 | 32.114 | 0.644 | 2.047 |
| 18:30 | 30.73 | 28.566 | 2.164 | 7.043 |
| 18:45 | 28.97 | 18.848 | 10.122 | 34.939 |
| 19:00 | 28.9 | 31.564 | 2.664 | 9.218 |
| 19:15 | 29.7 | 30.009 | 0.309 | 1.041 |
| 19:30 | 29.87 | 31.297 | 1.427 | 4.778 |
| 19:45 | 31 | 30.559 | 0.441 | 1.423 |
| 20:00 | 31.82 | 31.683 | 0.137 | 0.430 |
| 20:15 | 31.37 | 30.685 | 0.685 | 2.185 |
| 20:30 | 29.8 | 31.309 | 1.509 | 5.065 |
| 20:45 | 30.85 | 32.386 | 1.536 | 4.980 |
| 21:00 | 36.58 | 36.371 | 0.209 | 0.571 |
| 21:15 | 38.25 | 38.418 | 0.168 | 0.439 |
| 21:30 | 39.9 | 39.125 | 0.775 | 1.943 |
| 21:45 | 39.9 | 38.917 | 0.983 | 2.463 |
| 22:00 | 40.1 | 39.984 | 0.116 | 0.290 |
| 22:15 | 40 | 39.120 | 0.880 | 2.201 |
| 22:30 | 40 | 39.968 | 0.032 | 0.080 |
| 22:45 | 37.97 | 37.585 | 0.385 | 1.013 |
| 23:00 | 37.7 | 37.414 | 0.287 | 0.760 |
| 23:15 | 37.7 | 36.921 | 0.779 | 2.066 |
| 23:30 | 37.7 | 36.364 | 1.336 | 3.545 |
| 23:45 | 36.87 | 36.649 | 0.221 | 0.600 |
| 00:00 | 35.7 | 35.937 | 0.237 | 0.664 |
| **AVG. %ARE** | | | | 2.913 |

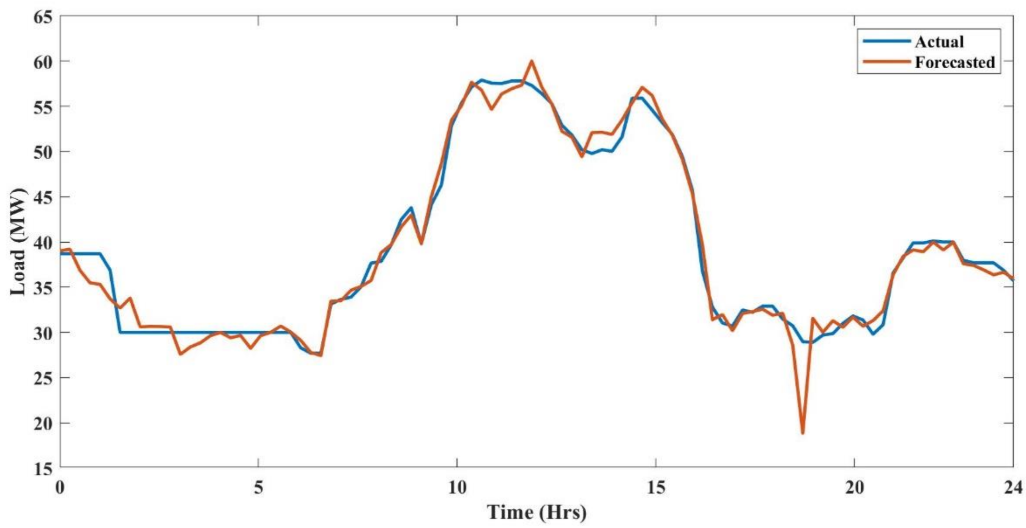


Figure 4.5: Actual Vs Forecasted Load through ANN

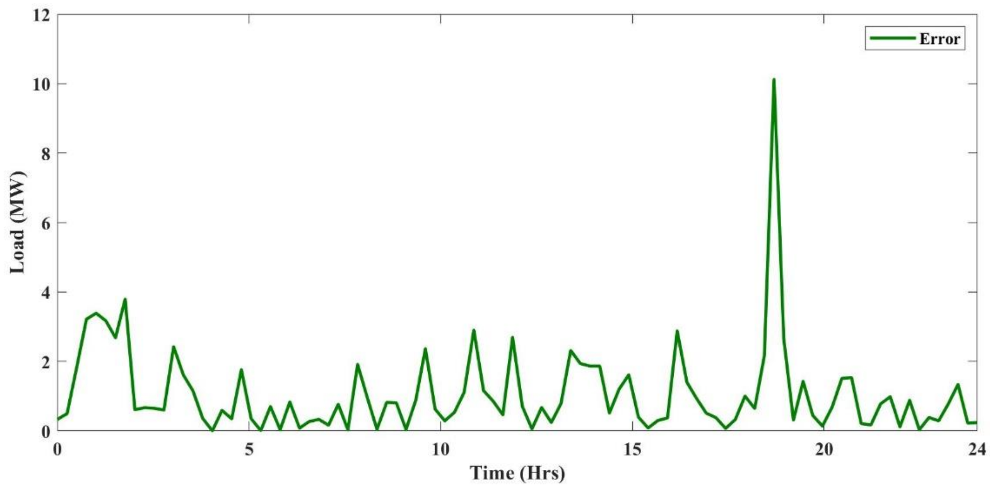


Figure 4.6: Error obtained using ANN

## 4.8: Conclusion

In this chapter the technique artificial neural network is discussed in detail. In this multilayer NN is used for the development of model. Every layer of ANN is discussed for better understanding. Table 4.1 shows the error of every 15 min load forecasted using this model. The average absolute relative error calculated is 2.913%. It is slightly more than fuzzy model error but accurate enough for the purpose of STLF.

# CHAPTER 5

# LOAD FORECASTING WITH ADAPTIVE NEURO-FUZZY INTERFERENCE SYSTEM

## 5.1: Introduction

ANFIS can address any sort of non-linear and complex issues successfully by adding the benefits of ANN and FUZZY. It merges the mathematical and linguistic information by using fuzzy methods. It additionally utilizes the ANN's capacity of classification of data and identifying the pattern. Also, the ANFIS causes less retention error and is more noticeable to user in comparison of ANN.

It is a combination of both ANN and fuzzy logic (FL). Hence, it has advantages of both the methods overcoming their flaws. FL cannot gain any information from the data. ANN have absence of information representability and logic. ANFIS can also be used in applications like PV plants maximum power point tracking, load forecasting, photovoltaics model optimization.

## 5.2: Architecture of ANFIS

ANFIS consists of five layers of neurons as shown in figure 5.1. Every layer has their own behaviour. Layers 2, 3 and 5 consists of constant behaviour. Whereas layer 1 and layer 4 have varying parameters, in these modifications are done for training. These five layers are:

1) Layer 1 - Fuzzification

In this layer, process known as fuzzification is carried out. Degrees in which every input is belonged to fuzzy space are the given the values in between 0 and 1. Every node in this layer is adaptive node. The input and output relation of this node can be given as:

$$O(1, i) = \mu_{Ai}(x), \qquad i = 1,2 \qquad (5.1)$$

2) Layer 2 - Fuzzy Rule

Every node is fixed and addressed with a rule. Every node of this layer duplicates the input signal which can show degrees to which the sources of incoming signal fulfil the membership function. The result of the information signs to every node of this layer addresses the terminating strength of a rule. The output for this can be defined as follows:

$$O(2, i) = \mu_{Ai}(x) \text{ X } \mu_{Bi}(y), \qquad i = 1,2 \qquad (5.2)$$

3) Layer 3 - Normalization

In this layer, fixed nodes are named as N. Output in this layer is normalization of the weight work or summation of every rule firing strength as follows:

$$O(3, i) = w_i' = \frac{w_i}{w_1 + w_2}, \qquad i = 1,2 \qquad (5.3)$$

4) Layer 4 – Defuzzification

Every node registers the weighted subsequent value of every rule which addresses the contribution of every rule to the output overall. These are adaptive nodes other than the nodes in fuzzy layer. In this layer, nodes calculate output of rules base on subsequent parameters as follows:

$$O(4, i) = w_i' f_i = w_i'(p_i x + q_i y + r_i), \qquad i = 1,2 \qquad (5.4)$$

5) Layer 5 - Output

It is final layer. By summing all the incoming signals, it provides the output as below:

$$O(5, i) = \sum_{i=1}^{2} w_i' f_i, \qquad i = 1,2 \qquad (5.5)$$

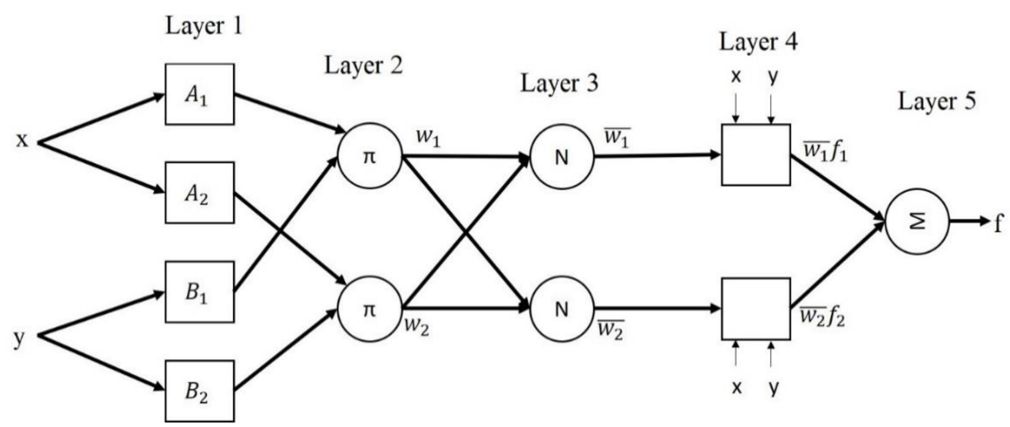


Figure 5.1: Basic Structure of ANFIS

## 5.3: Benefits and Limitations of ANFIS

Various advantages of ANFIS are as follows:

- It allows parallel computation.
- It has better ability of learning.
- It allows better integration with other design of control methods.
- It has highly generalization capability.

It also has some disadvantages. It has high computational cost due to high complexity in structure and gradient learning. The establishment between accuracy and interpretability is critical problem. With increase in number of inputs its complexity increases.

## 5.4: Applications of ANFIS

The ANFIS controller is generally utilized for controlling the systems that are non-linear. It is one of the best controllers in comparison to PID or other types of controller. It can be used to control the temperature of water bath. It can also be used in planes for controlling such as intelligent planes in which it can learn to take off or do the landing.

## 5.5: ANFIS Model Development

For the development of ANFIS Model, MATLAB 2018 software is used. With the help of ‘anfisedit’ ANFIS model is developed. Approximately 70% data is trained and 30% data is tested in this model. Using the algorithm discussed through flowchart in Figure 5.3 the forecasted load data for the 7$^{th}$ day for the location is generated through ANFIS.

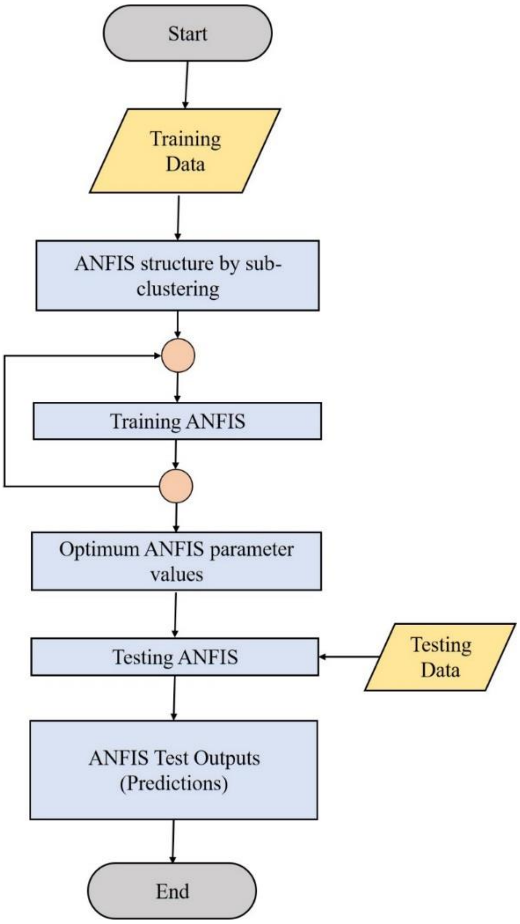

Figure 5.3: Flowchart for ANFIS algorithm

## 5.6: ANFIS Model Result

Figure 5.4 is comparing of actual load and forecasted load from ANFIS model. Figure 5.5 is the error plot obtained by ANFIS. Table 5.1 shows the data obtained through this model.

Table 5.1: Comparison of the Result Obtained using ANFIS

| Time | Actual Load (MW) | Forecasted Load (MW) | Error | %ARE |
|---|---|---|---|---|
| 00:15 | 38.7 | 38.692 | 0.008 | 0.021 |
| 00:30 | 38.7 | 38.648 | 0.052 | 0.135 |
| 00:45 | 38.7 | 38.690 | 0.010 | 0.025 |
| 01:00 | 38.7 | 37.717 | 0.983 | 2.541 |
| 01:15 | 38.7 | 38.250 | 0.450 | 1.162 |
| 01:30 | 36.88 | 35.052 | 1.828 | 4.958 |
| 01:45 | 30 | 31.497 | 1.497 | 4.990 |
| 02:00 | 30 | 33.474 | 3.474 | 11.579 |
| 02:15 | 30 | 29.997 | 0.003 | 0.010 |
| 02:30 | 30 | 29.929 | 0.071 | 0.237 |
| 02:45 | 30 | 29.997 | 0.003 | 0.010 |
| 03:00 | 30 | 28.394 | 1.606 | 5.353 |
| 03:15 | 30 | 30.167 | 0.167 | 0.556 |
| 03:30 | 30 | 30.120 | 0.120 | 0.399 |
| 03:45 | 30 | 29.741 | 0.259 | 0.865 |
| 04:00 | 30 | 29.953 | 0.047 | 0.156 |
| 04:15 | 30 | 30.087 | 0.087 | 0.291 |
| 04:30 | 30 | 29.958 | 0.042 | 0.140 |
| 04:45 | 30 | 30.030 | 0.030 | 0.100 |
| 05:00 | 30 | 29.932 | 0.068 | 0.228 |
| 05:15 | 30 | 30.375 | 0.375 | 1.251 |
| 05:30 | 30 | 29.583 | 0.417 | 1.392 |
| 05:45 | 30 | 30.090 | 0.090 | 0.300 |
| 06:00 | 30 | 29.900 | 0.100 | 0.332 |
| 06:15 | 28.28 | 28.330 | 0.050 | 0.177 |
| 06:30 | 27.7 | 27.715 | 0.015 | 0.054 |
| 06:45 | 27.7 | 27.694 | 0.006 | 0.021 |
| 07:00 | 33.13 | 33.131 | 0.001 | 0.003 |
| 07:15 | 33.66 | 33.645 | 0.015 | 0.044 |
| 07:30 | 33.9 | 33.916 | 0.016 | 0.047 |
| 07:45 | 35.05 | 35.087 | 0.037 | 0.107 |
| 08:00 | 37.66 | 37.644 | 0.016 | 0.043 |
| 08:15 | 37.86 | 37.872 | 0.012 | 0.033 |
| 08:30 | 39.67 | 39.662 | 0.008 | 0.020 |
| 08:45 | 42.48 | 42.503 | 0.023 | 0.054 |
| 09:00 | 43.79 | 43.784 | 0.006 | 0.014 |
| 09:15 | 39.79 | 39.789 | 0.001 | 0.003 |
| 09:30 | 44.12 | 44.126 | 0.006 | 0.013 |
| 09:45 | 46.3 | 46.298 | 0.002 | 0.004 |
| 10:00 | 52.83 | 52.829 | 0.001 | 0.002 |
| 10:15 | 55.35 | 55.351 | 0.001 | 0.002 |
| 10:30 | 57.13 | 57.128 | 0.002 | 0.004 |
| 10:45 | 57.9 | 57.900 | 0.000 | 0.000 |
| 11:00 | 57.56 | 57.559 | 0.001 | 0.002 |
| 11:15 | 57.52 | 57.523 | 0.003 | 0.005 |

| Time | Actual Load (MW) | Forecasted Load (MW) | Error | %ARE |
|---|---|---|---|---|
| 11:30 | 57.8 | 57.798 | 0.002 | 0.003 |
| 11:45 | 57.8 | 57.798 | 0.002 | 0.003 |
| 12:00 | 57.31 | 57.310 | 0.000 | 0.001 |
| 12:15 | 56.41 | 56.411 | 0.001 | 0.001 |
| 12:30 | 55.3 | 55.297 | 0.003 | 0.005 |
| 12:45 | 52.92 | 52.936 | 0.016 | 0.030 |
| 13:00 | 51.82 | 51.809 | 0.011 | 0.021 |
| 13:15 | 50.2 | 50.199 | 0.001 | 0.001 |
| 13:30 | 49.78 | 49.784 | 0.004 | 0.007 |
| 13:45 | 50.2 | 50.184 | 0.016 | 0.032 |
| 14:00 | 50.03 | 50.058 | 0.028 | 0.056 |
| 14:15 | 51.63 | 51.623 | 0.007 | 0.014 |
| 14:30 | 55.9 | 55.892 | 0.008 | 0.014 |
| 14:45 | 55.9 | 55.898 | 0.002 | 0.004 |
| 15:00 | 54.58 | 54.581 | 0.001 | 0.002 |
| 15:15 | 53.2 | 53.199 | 0.001 | 0.002 |
| 15:30 | 51.9 | 51.898 | 0.002 | 0.004 |
| 15:45 | 49.46 | 49.461 | 0.001 | 0.002 |
| 16:00 | 45.74 | 45.739 | 0.001 | 0.003 |
| 16:15 | 36.8 | 27.372 | 9.428 | 25.619 |
| 16:30 | 32.8 | 42.800 | 10.000 | 30.488 |
| 16:45 | 31.04 | -14.501 | 45.541 | 146.718 |
| 17:00 | 30.7 | -38.019 | 68.719 | 223.842 |
| 17:15 | 32.47 | 23.178 | 9.292 | 28.617 |
| 17:30 | 32.23 | 2.918 | 29.312 | 90.948 |
| 17:45 | 32.9 | -29.795 | 62.695 | 190.563 |
| 18:00 | 32.9 | -22.324 | 55.224 | 167.855 |
| 18:15 | 31.47 | 7.260 | 24.210 | 76.930 |
| 18:30 | 30.73 | 31.263 | 0.533 | 1.734 |
| 18:45 | 28.97 | 34.072 | 5.102 | 17.611 |
| 19:00 | 28.9 | 88.650 | 59.750 | 206.746 |
| 19:15 | 29.7 | 257.177 | 227.477 | 765.916 |
| 19:30 | 29.87 | 160.565 | 130.695 | 437.545 |
| 19:45 | 31 | 40.457 | 9.457 | 30.507 |
| 20:00 | 31.82 | 2.216 | 29.604 | 93.036 |
| 20:15 | 31.37 | 9.957 | 21.413 | 68.259 |
| 20:30 | 29.8 | 6.780 | 23.020 | 77.248 |
| 20:45 | 30.85 | 19.106 | 11.744 | 38.067 |
| 21:00 | 36.58 | 11.697 | 24.883 | 68.024 |
| 21:15 | 38.25 | 11.501 | 26.749 | 69.932 |
| 21:30 | 39.9 | 9.122 | 30.778 | 77.138 |
| 21:45 | 39.9 | 13.824 | 26.076 | 65.353 |
| 22:00 | 40.1 | 52.131 | 12.031 | 30.003 |
| 22:15 | 40 | 60.142 | 20.142 | 50.355 |
| 22:30 | 40 | 41.733 | 1.733 | 4.333 |
| 22:45 | 37.97 | 16.837 | 21.133 | 55.658 |
| 23:00 | 37.7 | 18.239 | 19.461 | 51.620 |
| 23:15 | 37.7 | 20.684 | 17.016 | 45.136 |
| 23:30 | 37.7 | 24.243 | 13.457 | 35.695 |
| 23:45 | 36.87 | 26.701 | 10.169 | 27.580 |
| 00:00 | 35.7 | 21.034 | 14.666 | 41.080 |
| **AVG. %ARE** | | | | **1.953** |

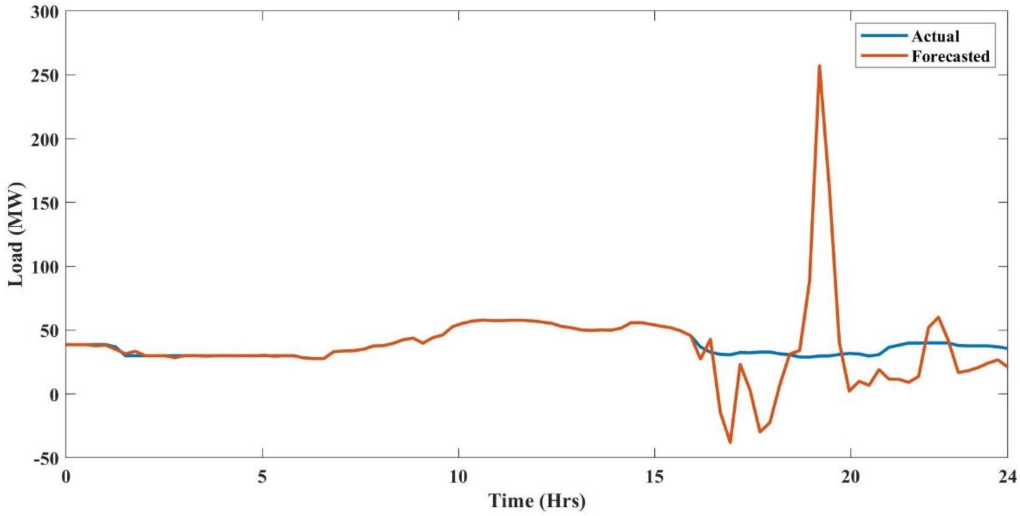


Figure 5.4: Actual Vs Forecasted Load through ANFIS

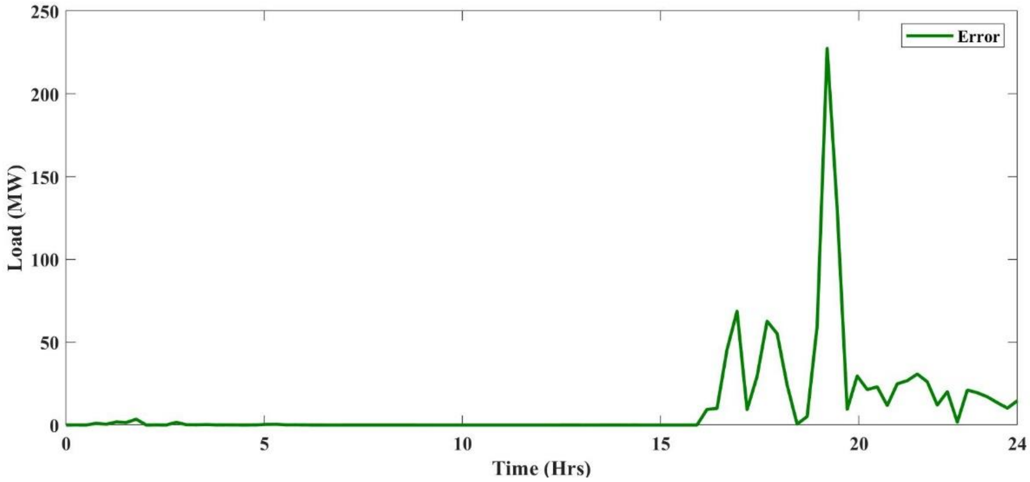


Figure 5.5: Error obtained using ANFIS

## 5.7: Conclusion

In this chapter, adaptive neuro-fuzzy inference system (ANFIS) is discussed in detail. Every layer of ANFIS is explained for better understanding. The Average absolute relative error calculated is 1.953%. It is less that fuzzy and ANN model. It can be said that the model developed is accurate for load forecasting.

# CHAPTER 6

# CONCLUSION AND FUTURE SCOPE

## 6.1: Conclusion

The importance of short-term load forecasting is increasing with increase in the utilization of electricity. In electricity load forecasting, machine learning techniques are demonstrating to be quite useful. These are frequently being used as one of the most forward-looking approaches during the time of generation of electricity, market planning activities and also in planning for development in the distribution network.

In fuzzy model, it is observed that at 12:30 pm the accuracy of the model developed is 100%. The rest are nearby values for the actual load. The average absolute relative error calculated is 2.376%. So, it can be concluded that the model developed for the STLF is quite accurate.

Efficiency in load forecasting is the issue that needs to be considered as important issue while planning. Error for each method is calculated and then compared. The result of all the techniques are shown in table 6.1. It can also be observed from the table that in ANFIS the error is very less than zero from 8 AM to 4 PM. In table 6.2 it can be observed that average ARE while using ANN is 2.913% and through ANFIS is 1.953% which is less than other two techniques used for STLF. So, it can be concluded that ANFIS model is more efficient than ANN and Fuzzy model.

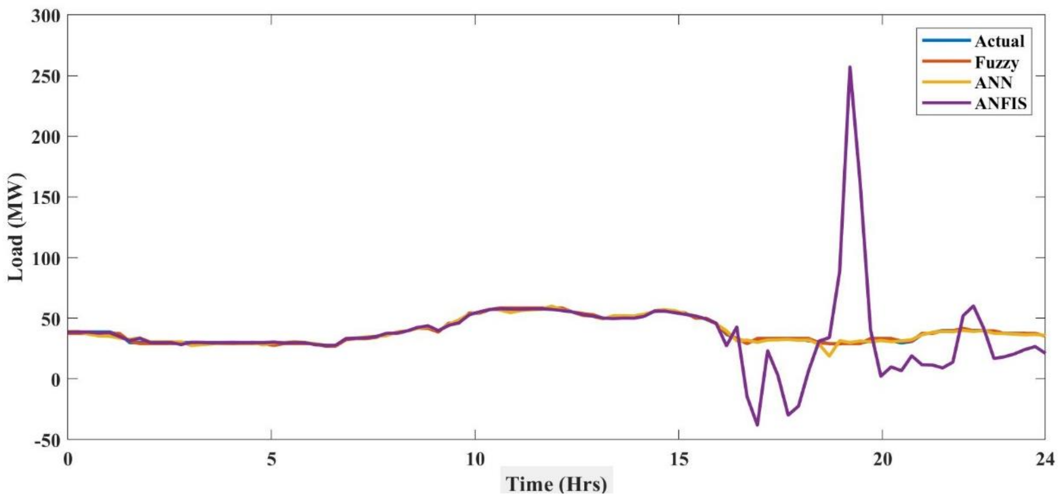


Figure 6.1: Comparision of Actual Load with all the Techniques used

Table 6.1: Results of all the Techniques

| Time | Target Load (MW) | Fuzzy Logic | | ANN | | ANFIS | |
|---|---|---|---|---|---|---|---|
| | | Forecasted Load (MW) | %ARE | Forecasted Load (MW) | % ARE | Forecasted Load (MW) | %ARE |
| 00:15 | 38.700 | 37.515 | 3.062 | 39.030 | 0.852 | 38.692 | 0.021 |
| 00:30 | 38.700 | 37.515 | 3.062 | 39.195 | 1.280 | 38.648 | 0.135 |
| 00:45 | 38.700 | 37.515 | 3.062 | 36.865 | 4.742 | 38.690 | 0.025 |
| 01:00 | 38.700 | 37.515 | 3.062 | 35.484 | 8.309 | 37.717 | 2.541 |
| 01:15 | 38.700 | 37.515 | 3.062 | 35.313 | 8.753 | 38.250 | 1.162 |
| 01:30 | 36.880 | 37.515 | 1.721 | 33.711 | 8.593 | 35.052 | 4.958 |
| 01:45 | 30.000 | 31.186 | 3.953 | 32.682 | 8.939 | 31.497 | 4.990 |
| 02:00 | 30.000 | 29.113 | 2.956 | 33.792 | 12.640 | 33.474 | 11.579 |
| 02:15 | 30.000 | 29.113 | 2.956 | 30.611 | 2.038 | 29.997 | 0.010 |
| 02:30 | 30.000 | 29.113 | 2.956 | 30.666 | 2.220 | 29.929 | 0.237 |
| 02:45 | 30.000 | 29.113 | 2.956 | 30.649 | 2.163 | 29.997 | 0.010 |
| 03:00 | 30.000 | 29.113 | 2.956 | 30.598 | 1.992 | 28.394 | 5.353 |
| 03:15 | 30.000 | 29.113 | 2.956 | 27.578 | 8.072 | 30.167 | 0.556 |
| 03:30 | 30.000 | 29.113 | 2.956 | 28.388 | 5.372 | 30.120 | 0.399 |
| 03:45 | 30.000 | 29.113 | 2.956 | 28.850 | 3.832 | 29.741 | 0.865 |
| 04:00 | 30.000 | 29.113 | 2.956 | 29.640 | 1.199 | 29.953 | 0.156 |
| 04:15 | 30.000 | 29.113 | 2.956 | 29.999 | 0.002 | 30.087 | 0.291 |
| 04:30 | 30.000 | 29.113 | 2.956 | 29.410 | 1.966 | 29.958 | 0.140 |
| 04:45 | 30.000 | 29.113 | 2.956 | 29.655 | 1.150 | 30.030 | 0.100 |
| 05:00 | 30.000 | 29.113 | 2.956 | 28.240 | 5.868 | 29.932 | 0.228 |
| 05:15 | 30.000 | 27.713 | 7.623 | 29.648 | 1.175 | 30.375 | 1.251 |
| 05:30 | 30.000 | 29.113 | 2.956 | 30.008 | 0.027 | 29.583 | 1.392 |
| 05:45 | 30.000 | 29.113 | 2.956 | 30.698 | 2.328 | 30.090 | 0.300 |
| 06:00 | 30.000 | 29.113 | 2.956 | 30.033 | 0.111 | 29.900 | 0.332 |
| 06:15 | 28.280 | 29.113 | 2.945 | 29.110 | 2.936 | 28.330 | 0.177 |
| 06:30 | 27.700 | 26.985 | 2.581 | 27.777 | 0.280 | 27.715 | 0.054 |
| 06:45 | 27.700 | 26.985 | 2.581 | 27.433 | 0.964 | 27.694 | 0.021 |
| 07:00 | 33.130 | 32.250 | 2.656 | 33.460 | 0.995 | 33.131 | 0.003 |
| 07:15 | 33.660 | 33.314 | 1.027 | 33.498 | 0.480 | 33.645 | 0.044 |
| 07:30 | 33.900 | 33.314 | 1.648 | 34.665 | 2.257 | 33.916 | 0.047 |
| 07:45 | 35.050 | 34.323 | 2.074 | 35.080 | 0.086 | 35.087 | 0.107 |
| 08:00 | 37.660 | 37.515 | 0.385 | 35.745 | 5.084 | 37.644 | 0.043 |
| 08:15 | 37.860 | 37.515 | 0.911 | 38.816 | 2.526 | 37.872 | 0.033 |
| 08:30 | 39.670 | 39.644 | 0.065 | 39.711 | 0.104 | 39.662 | 0.020 |
| 08:45 | 42.480 | 41.716 | 1.798 | 41.662 | 1.925 | 42.503 | 0.054 |
| 09:00 | 43.790 | 41.716 | 4.736 | 42.986 | 1.837 | 43.784 | 0.014 |
| 09:15 | 39.790 | 38.636 | 2.9 | 39.825 | 0.087 | 39.789 | 0.003 |
| 09:30 | 44.120 | 45.917 | 4.072 | 44.994 | 1.981 | 44.126 | 0.013 |
| 09:45 | 46.300 | 45.917 | 0.827 | 48.666 | 5.110 | 46.298 | 0.004 |
| 10:00 | 52.830 | 54.319 | 2.818 | 53.457 | 1.187 | 52.829 | 0.002 |
| 10:15 | 55.350 | 54.319 | 1.862 | 55.063 | 0.518 | 55.351 | 0.002 |
| 10:30 | 57.130 | 57.176 | 0.08 | 57.663 | 0.933 | 57.128 | 0.004 |
| 10:45 | 57.900 | 58.52 | 1.07 | 56.791 | 1.915 | 57.900 | 0.000 |
| 11:00 | 57.560 | 58.52 | 1.667 | 54.661 | 5.037 | 57.559 | 0.002 |
| 11:15 | 57.520 | 58.52 | 1.738 | 56.361 | 2.015 | 57.523 | 0.005 |
| 11:30 | 57.800 | 58.52 | 1.245 | 56.948 | 1.475 | 57.798 | 0.003 |
| 11:45 | 57.800 | 58.52 | 1.245 | 57.339 | 0.798 | 57.798 | 0.003 |

| Time | Target Load (MW) | Fuzzy Logic | | ANN | | ANFIS | |
|---|---|---|---|---|---|---|---|
| | | Forecasted Load (MW) | %ARE | Forecasted Load (MW) | % ARE | Forecasted Load (MW) | %ARE |
| 12:00 | 57.310 | 58.52 | 2.111 | 60.004 | 4.700 | 57.310 | 0.001 |
| 12:15 | 56.410 | 58.52 | 3.74 | 57.122 | 1.262 | 56.411 | 0.001 |
| 12:30 | 55.300 | 55.271 | 0.052 | 55.246 | 0.097 | 55.297 | 0.005 |
| 12:45 | 52.920 | 53.927 | 1.902 | 52.248 | 1.269 | 52.936 | 0.030 |
| 13:00 | 51.820 | 52.975 | 2.228 | 51.581 | 0.462 | 51.809 | 0.021 |
| 13:15 | 50.200 | 50.118 | 0.163 | 49.417 | 1.560 | 50.199 | 0.001 |
| 13:30 | 49.780 | 50.118 | 0.678 | 52.094 | 4.648 | 49.784 | 0.007 |
| 13:45 | 50.200 | 50.118 | 0.163 | 52.136 | 3.856 | 50.184 | 0.032 |
| 14:00 | 50.030 | 50.118 | 0.175 | 51.896 | 3.730 | 50.058 | 0.056 |
| 14:15 | 51.630 | 52.191 | 1.086 | 53.495 | 3.612 | 51.623 | 0.014 |
| 14:30 | 55.900 | 56.055 | 0.277 | 55.390 | 0.912 | 55.892 | 0.014 |
| 14:45 | 55.900 | 57.176 | 2.282 | 57.100 | 2.147 | 55.898 | 0.004 |
| 15:00 | 54.580 | 55.383 | 1.471 | 56.192 | 2.953 | 54.581 | 0.002 |
| 15:15 | 53.200 | 54.319 | 2.103 | 53.593 | 0.739 | 53.199 | 0.002 |
| 15:30 | 51.900 | 50.118 | 3.433 | 51.818 | 0.158 | 51.898 | 0.004 |
| 15:45 | 49.460 | 50.118 | 1.33 | 49.164 | 0.598 | 49.461 | 0.002 |
| 16:00 | 45.740 | 45.917 | 0.386 | 45.368 | 0.814 | 45.739 | 0.003 |
| 16:15 | 36.800 | 37.515 | 1.94 | 39.680 | 7.825 | 27.372 | 25.619 |
| 16:30 | 32.800 | 33.314 | 1.567 | 31.401 | 4.266 | 42.800 | 30.488 |
| 16:45 | 31.040 | 29.113 | 6.208 | 31.972 | 3.004 | -14.501 | 146.718 |
| 17:00 | 30.700 | 33.314 | 8.514 | 30.191 | 1.660 | -38.019 | 223.842 |
| 17:15 | 32.470 | 33.314 | 2.599 | 32.091 | 1.169 | 23.178 | 28.617 |
| 17:30 | 32.230 | 33.314 | 3.363 | 32.299 | 0.214 | 2.918 | 90.948 |
| 17:45 | 32.900 | 33.314 | 1.258 | 32.573 | 0.994 | -29.795 | 190.563 |
| 18:00 | 32.900 | 33.314 | 1.258 | 31.899 | 3.044 | -22.324 | 167.855 |
| 18:15 | 31.470 | 33.314 | 5.85 | 32.114 | 2.047 | 7.260 | 76.930 |
| 18:30 | 30.730 | 29.842 | 2.88 | 28.566 | 7.043 | 31.263 | 1.734 |
| 18:45 | 28.970 | 29.113 | 0.493 | 18.848 | 34.939 | 34.072 | 17.611 |
| 19:00 | 28.900 | 29.113 | 0.737 | 31.564 | 9.218 | 88.650 | 206.746 |
| 19:15 | 29.700 | 29.113 | 1.976 | 30.009 | 1.041 | 257.177 | 765.916 |
| 19:30 | 29.870 | 29.113 | 2.534 | 31.297 | 4.778 | 160.565 | 437.545 |
| 19:45 | 31.000 | 33.314 | 7.464 | 30.559 | 1.423 | 40.457 | 30.507 |
| 20:00 | 31.820 | 33.314 | 4.695 | 31.683 | 0.430 | 2.216 | 93.036 |
| 20:15 | 31.370 | 33.314 | 6.197 | 30.685 | 2.185 | 9.957 | 68.259 |
| 20:30 | 29.800 | 31.242 | 4.838 | 31.309 | 5.065 | 6.780 | 77.248 |
| 20:45 | 30.850 | 31.242 | 1.27 | 32.386 | 4.980 | 19.106 | 38.067 |
| 21:00 | 36.580 | 37.515 | 2.556 | 36.371 | 0.571 | 11.697 | 68.024 |
| 21:15 | 38.250 | 37.515 | 1.921 | 38.418 | 0.439 | 11.501 | 69.932 |
| 21:30 | 39.900 | 39.644 | 0.641 | 39.125 | 1.943 | 9.122 | 77.138 |
| 21:45 | 39.900 | 39.644 | 0.641 | 38.917 | 2.463 | 13.824 | 65.353 |
| 22:00 | 40.100 | 41.716 | 4.029 | 39.984 | 0.290 | 52.131 | 30.003 |
| 22:15 | 40.000 | 39.644 | 0.89 | 39.120 | 2.201 | 60.142 | 50.355 |
| 22:30 | 40.000 | 39.644 | 0.89 | 39.968 | 0.080 | 41.733 | 4.333 |
| 22:45 | 37.970 | 39.644 | 4.408 | 37.585 | 1.013 | 16.837 | 55.658 |
| 23:00 | 37.700 | 37.515 | 0.491 | 37.414 | 0.760 | 18.239 | 51.620 |
| 23:15 | 37.700 | 37.515 | 0.491 | 36.921 | 2.066 | 20.684 | 45.136 |
| 23:30 | 37.700 | 37.515 | 0.491 | 36.364 | 3.545 | 24.243 | 35.695 |
| 23:45 | 36.870 | 37.515 | 1.749 | 36.649 | 0.600 | 26.701 | 27.580 |
| 00:00 | 35.700 | 35.387 | 0.876 | 35.937 | 0.664 | 21.034 | 41.080 |

Table 6.2: Comparision of Results

| **Method** | Fuzzy Logic | ANN | ANFIS |
|---|---|---|---|
| **Avg. %ARE** | 2.376 | 2.913 | 1.953 |

## 6.2: Future Scope

Efficiency in load forecasting is the issue that needs to be considered as important factor while planning. Electrical load forecasting is a complex activity that deals with diverse data set. Factors like weather conditions such as humidity and temperature, holidays and working days, especial occasion days, etc can also be considered to generated more better results.

As discussed in literature review, there are different methods for predicting the load. To predict with more accuracy, optimizing techniques like Particle Swarm Optimization, Artificial Bee Colony, Genetic Algorithm can be used with ANN and ANFIS. Hybrid models can also be created to study load forecasting and how they help in energy conservation.

# LIST OF PUBLICATIONS

On the premise of work presented in this dissertation two conference paper are written and presented in SCOPUS indexed conference:

1) Arshi Khan and M. Rizwan, "Fuzzy Logic Based Simplified Approach For Short Term Load Forecasting", *International Conference on Smart Grids Structures and Materials (ICSGSM-21)*, K L University, Andhra Pradesh, April 19-20, 2021.
2) Arshi Khan and M. Rizwan, "ANN and ANFIS Based Approach for Very Short Term Load Forecasting: A Step Towards Smart Energy Management System", *8$^{th}$ IEEE International Conference on Signal Processing and Integrated Networks (SPIN-21)*, Amity University, Uttar Pradesh, Aug. 26-27, 2021.

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