**Department of Electronics and Communications Engineering**

# Electrical Load Forecasting Using Fuzzy System

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# Letter of Transmittal

To

Department of Electronics and Communication Engineering

East West University

**Subject: Submission of Project Work Report on Electrical Load Forecasting Using Fuzzy System (ETE-498)**

Dear Sir,

We are pleased to let you know that we have completed our Project work program on Electrical Load Forecasting Using Fuzzy System. The attaché contain of the Project work report that has prepared for your evaluation and consideration. The Project work has given us a great opportunity to work with the load forecasting system closely and gave us the opportunity to apply the theoretical knowledge in real life situation, which we have acquired since last four years from you and the other faculty of EWU, which would be a great help for us in future.

We are very grateful to you for your guidance throughout the Thesis period, which helped us a lot to acquire knowledge.

Thanking you.

_____          _____          _____

Mahir Faysal                     Md. Mohiuddin Murad            Md. Jahirul Islam

2015-2-55-028                   2015-2-55-027                   2015-2-55-008

# Declaration

We hereby declare that, this Project work was done under ETE 498 and has not been submitted elsewhere for requirement of any degree or diploma or for any purpose except for publication.

_____  _____  _____

Mahir Faysal  Md. Mohiuddin Murad  Md. Jahirul Islam

2015-2-55-028  2015-2-55-027  2015-2-55-008

# Acceptance

We hereby declare that this thesis is from the student's own work and best effort of us, and all other source of information used have been acknowledge. This Project work has been submitted with our approval.

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# Acknowledgement

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# Abstract

In this project work, we develop a Fuzzy system to forecast electrical load in both short and long-term basis. Here, we consider temperature, humidity, seasons of a year and time segments of a day as the parameters govern the demand of electrical load. For each of the parameter, we use several membership functions (MF) as necessary then apply Mamdani rule on MF and the output is determined by using centroid method. Finally, the surface plot reveals the real scenario of the load demand. The concept of the paper can be applied in interconnected power system of Bangladesh to reduce power loss especially when generation is higher than the demand.

***Keywords— Load forecasting; Short-term load forecasting; Long-term load forecasting; Fuzzy system;***

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# List of Abbreviations

| | |
|---|---|
| MF | Membership Function |
| ANN | Artificial Neural Network |
| ANFIS | Adaptive Neuro-Fuzzy Inference System |
| BPDB | Bangladesh Power Development Board |
| PSTCL | Punjab State Transmission Corporation Limited |
| MW | Mega-Watt |
| AME | Absolute Mean Error |
| APE | Average Percentage Error |

# List of Technical Symbols

| | |
|---|---|
| $\bar{X}$ | Center of Gravity |
| $z^{*}$ | Value of Centroid |
| $\theta$ | Angle |
| h | Height |
| µ | Membership Value |

# Chapter 1

# Introduction

**1.1 Load demand of Bangladesh on 24 hours in different seasons**

Electricity is the real source of prosperity for the greater part of a nation's financial exercises. The utility power division in Bangladesh has one national grid with somewhat sufficient amount of electricity to supply nationwide. Our country has expanded the electricity capacity day by day over the most recent nine years demonstrating powerful development in electricity and power division, yet at the same time there is such a great amount of space to make strides.

Nine years back, the nation's power capacity producing limit was not very intriguing but it happened to have increased with the passing of time over the years. Bangladesh also had to import electricity from the neighboring country, India at certain time. The amount of imported electricity has also risen compared to every passing year.

Bangladesh has introduced a certain amount of power generation limit in January 2017. Now-a-days, most of the urban populace and more than half of the country populace have electricity facilities. The number of populace who have the ability to use electricity in our country is gradually increasing. Bangladesh will have to be producing much larger amount of electricity in near future than it has been producing now.

Problems in Bangladesh's electrical power sector generally include high framework misfortunes, delays in fruition of new plants, low plant effectiveness, inconsistent influence supply, electricity burglary, power outages, and deficiencies of assets for better plant upkeep. To be honest, the nation's power generation plants have not been able to take care of the load demand over the previous decade.

We have made a comparison of 2017-2018 fiscal year maximum load demand by gathering the monthly data [1] and analyzing the mean values from each month's maximum load demand which is shown in the following figure (fig.1.1) –
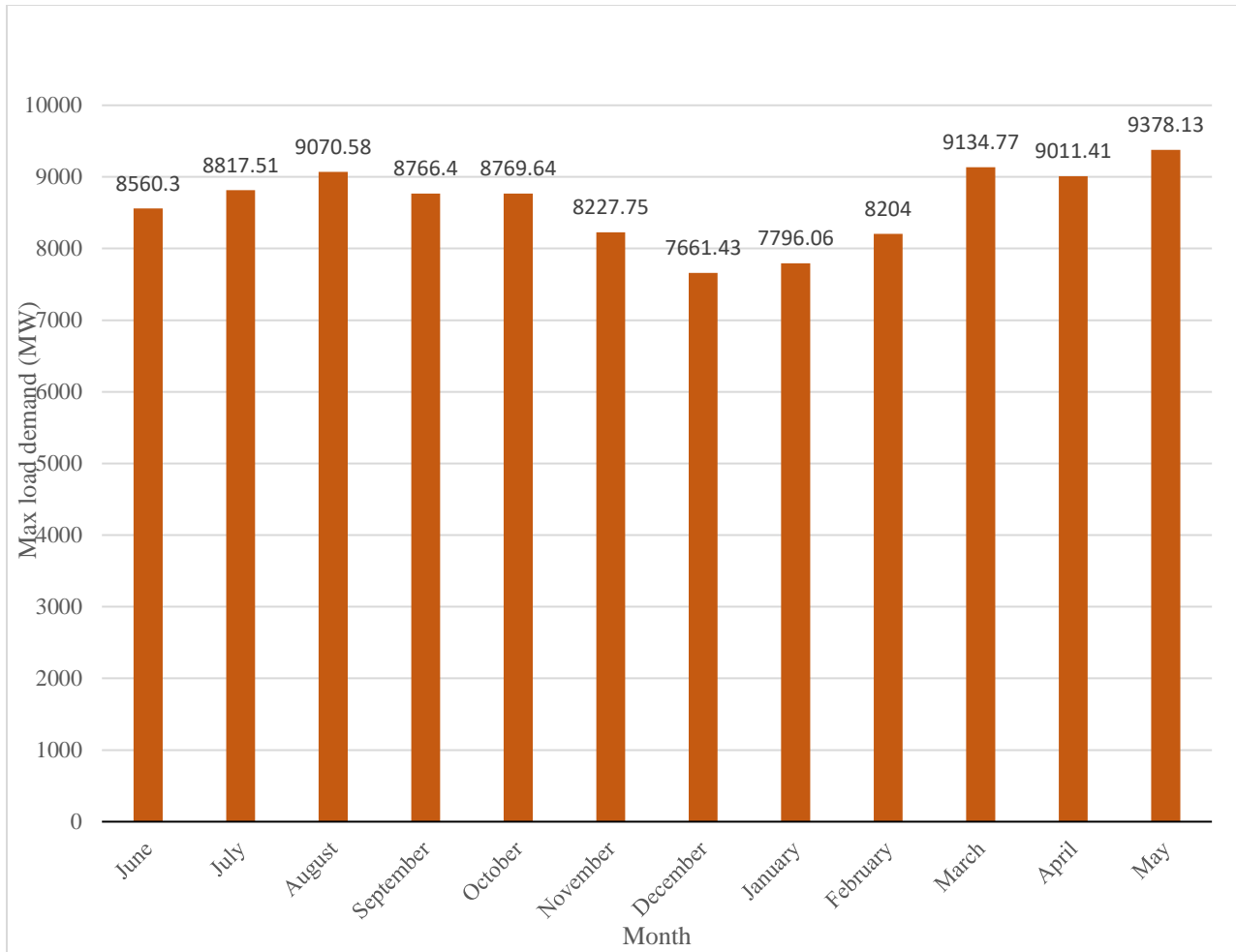
Figure 1.1: 2017-18 fiscal year data comparison of Maximum load Demand

## 1.2 Reasons for applying fuzzy rule

Electrical load forecasting is vital for utilities and power framework administrators to meet the demand in addition to the vitality lost in power frameworks. Therefore, many options are to be considered, for example, financial supporting, security investigation and upkeep arranging depending on load forecasts. The load forecasting can be done from a couple of minutes to an hour ahead or up to twenty year. Electrical load forecasting is generally divided up to four types that are long term, medium term, short term and very short term. The long term includes forecasting for one week to several years.

In this Project work, we have tried to solve the issues of load forecasting by using fuzzy inference system. Distinctive participation capacities for load parameters are utilized in particular triangular and trapezoidal membership functions in MATLAB. The prime objective here is to reduce the percentage of amount between estimated power load and actual power load. Load forecasting is an essential piece of intensity framework activity and is utilized to anticipate up to seven days ahead with the goal that everyday task of a power framework can be effectively arranged and the working expense can be minimized. However, Load estimating is not a simple task to perform. Likewise, various huge remotely influencing factors ought to be considered, for example, climate, time monetary circumstances and arbitrary disturbances.

Fuzzy inference system will help us to determine the load consumption of electricity in an efficient way. We can determine the actual and forecast of electricity consumption by analyzing the provided data. In our system, we have divided the load demand in three different seasons to compare the data precisely because in summer, there is high load demand but winter has low demand of electricity compared to summer. In addition, there is a matter of on-pick and off-pick hour, which we have considered as day peak and evening peak according to BPDB. We have collected actual data of energy consumption in twenty-four hours in a day for one fiscal year (2017-2018) to determine the pattern of consumption & analyzed them as membership functions in out fuzzy logic system. For this, we have used MATLAB fuzzy function to create rules considering four parameters that are temperature, humidity, peak hour and season. According to the input we have given into the system, we get the output from which we have designed 3D surface plots of our perception.

### 1.3 Method used by BPDB

Though we do not know the method used for load forecasting by BPDB, we have tried our best to mature our forecasting system with the help of fuzzy logic to compete with BPDB's method. Using fuzzy logic controller for our work in this case has the following advantages over the conventional controllers: the model we are creating to determine the load forecast will be cheaper to develop, it will cover a wider range of operating conditions based on our calculation and it is more readily customizable in natural language terms. So, in terms of cost and efficiency, our system might be considered better than the system used in BPDB to determine the load consumption.

## 1.4 Summary of previous similar works

Many similar works are found in recent literature. Short term electrical forecasting using fuzzy logic [2] is done to minimize actual electrical load and forecast load. The authors used data from PSTCL 220kV substation V.O.P Pakhowal, Distt. Ludhiana, Punjab. Eight Triangular membership functions are used for input time, four triangular membership function for input temperature and eight triangular membership function for output forecasted load; where input and output are linked using 'if then' conditions. Finally, a comparison is made between actual load in MW and fuzzy forecasted load graphically; where few points merge closely and few points deviate widely.

Another work is found about short term load forecasting using fuzzy logic [3] to precise electrical load loss in generation end. The authors prepared fuzzy rules based on historical data. Five triangular MF are used for input time, temperature, similar previous day load and five MF for output load forecast. The fuzzy inference system used 'if then' condition to process the input data and gives output. Finally, a comparison is given between actual load in MW, excel forecasted load and fuzzy forecasted load graphically; where the error is between +12.14% to -9.48%

A work is found about long term forecasting of power system [4] where the authors use Artificial Neural Network (ANN) and ANFIS. The authors used data from the Metrological Department of Malaysia and IEE database University Technology Malaysia. There are six number of inputs that are temperature, humidity, wind speed, rain fall, data of previous load and data of actual load. For ANN, training was set to 70%, validation was 15%, testing was 15% and number of hidden neurons are ten. Here ANFIS editor consist four types, these are load data, general fis, train fis, test fis; the load data is used for training testing and checking. The fuzzy rules are produced by grid division method. The author gives a table to compare error between ANN and ANFIS; from the table the average error was 6.7% and 0.096% respectively.

Olagoke, Ayeni and Hambali developed an ANN based model using Genetic Algorithm [5] for STLF. The paper approached for short term load forecasting with load time of a day ahead (1-24 Hours) using ANN. To generate the hidden layer of ANN they used Genetic Algorithm. They used data for training and validation of the neural network is obtained from the Transmission Company of Nigeria, National Control Center, Osogbo, Osun state, Nigeria. They used first 21 days load and temperature data for training the neural network and the remaining day's data was used for the network validation. The input variables of the system that are used in this paper is Hour of the day,

Temperature (average), Day of the week and the output of the system is Forecasted load. The methodology of the authors were data collection and preparation, data preprocessing, network structure design, network training and network validation. Mean Absolute Percentage Error (MAPE) of 4.705 for the forecasting day evaluated the result.

The authors from Iraq established another work about short-term load forecasting using ANN [6] for which they used the data from Duhok ELC (Control region of Iraq) for 2009 and 2010 years. The authors use back propagation algorithm for ANN. They created a set of models where the AME (Absolute mean error) is different. Moreover, from that when they generated the next day's forecast where they saw that the output is almost close to the actual value.

The rest of the project work is organized as chapter-2 provides theoretical analysis relevant to the project work, chapter-3 provides results based on analysis of chapter-2 and chapter-4 concludes the entire analysis.

# Chapter 2

# Centroid method of Defuzzification

## 2.1 Centroid method

This method is the most preferable and appealing of all the methods for defuzzification. This method is given by the following expression –

$$z^* = \frac{\sum A\bar{x}}{\sum A}, \qquad (2.1)$$

The figure for this method is shown in the following figure (fig.2.1) –
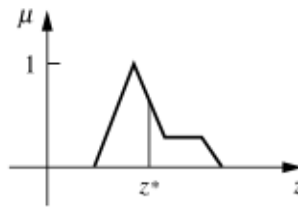


Figure 2.1: Centroid method of defuzzification

We will now apply the expression and try to calculate the centroid of the following figure (fig.2.2) which is divided into segmented areas –
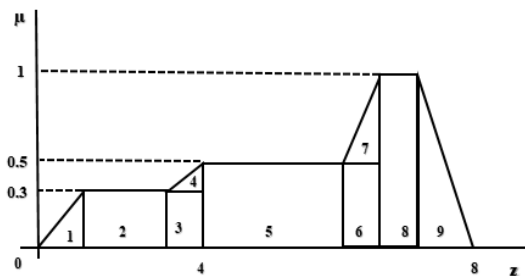


Figure 2.2: Aggregated fuzzy output as segmented areas

We will calculate $\bar{x}$ and $A\bar{x}$ for different area segments in the following table (table 2.1) –

Table 2.1: Area (A) showing the area of the segmented aggregated fuzzy set and $\bar{x}$ showing the corresponding centroid

| Area segment no. | Area (A) | $\bar{x}$ | $A\bar{x}$ |
|---|---|---|---|
| 1 | 0.5*0.3*1=0.15 | 0.67 | 0.1005 |
| 2 | 2.6*0.3=0.78 | 2.3 | 1.748 |
| 3 | 0.3*0.4=0.12 | 3.8 | 0.456 |
| 4 | 0.5*0.4*0.2=0.04 | 3.8667 | 0.1546 |
| 5 | 1.4*0.5=0.7 | 4.75 | 3.325 |
| 6 | 0.6*0.5=0.3 | 5.75 | 1.725 |
| 7 | 0.5*0.5*0.5=0.125 | 5.833 | 0.729 |
| 8 | 1*1=1 | 6.5 | 6.5 |
| 9 | 0.5*1*1=0.5 | 7.33 | 3.665 |
| | $\sum A = 3.72$ | | $\sum A\bar{x} = 18.4$ |

So, $z^* = \dfrac{\sum A\bar{x}}{\sum A} = \dfrac{18.4}{3.72} = 4.9$

From the above calculations, we can say that area segmented approach of the aggregated fuzzy output can be easily calculated using centroid method.

## 2.2 Greg Viot's Fuzzy Cruise Controller

We will now take an example of a controller that is used to maintain a vehicle at a desired speed. This system takes two fuzzy input as speed difference and acceleration and one fuzzy output that is throttle control which is shown in the following figure (fig.2.13) –
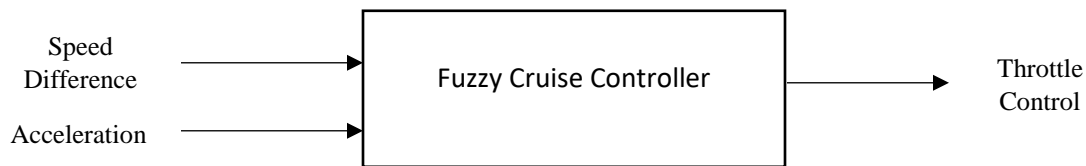


Figure 2.3: Fuzzy cruise controller

First, we are going to implement it using centroid method before applying the system in MATLAB.

## 2.3 Fuzzification of inputs

**Speed-Difference:**

**Value of NS:**

$$\tan\theta = \frac{1}{226.6-169.5}$$

$$= \frac{10}{571}$$



h= 0.46585

112.4    169.5   200    226.6

Again, $\tan \theta = \frac{h}{226.6-200}$

Or, $\frac{10h}{266} = \frac{10}{571}$
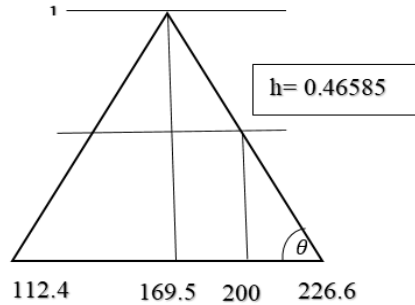
Figure 2.4: Value of NS for speed-difference

$h = 0.46585$

**Value of ZE:**

$$\tan\theta = \frac{1}{226.6-169.5}$$

$$= \frac{10}{571}$$



h= 0.53415

169.5   200    226.6      283.7

Again, $\tan\theta = \frac{h}{200-169.5}$

Or, $\frac{10h}{305} = \frac{10}{571}$

$h = 0.53415$

Figure 2.5: Value of ZE for speed-difference

## Acceleration:

### Value of NM:

$$\tan\theta = \frac{1}{169.5-112.4}$$

$$= \frac{10}{571}$$

Again, $\tan\theta = \frac{h}{169.5-150}$

Or, $\frac{2h}{39} = \frac{10}{571}$

$h = 0.34150$



h= 0.34150

55.31    112.4    150    169.5
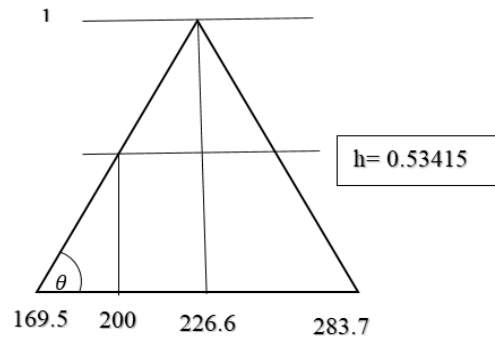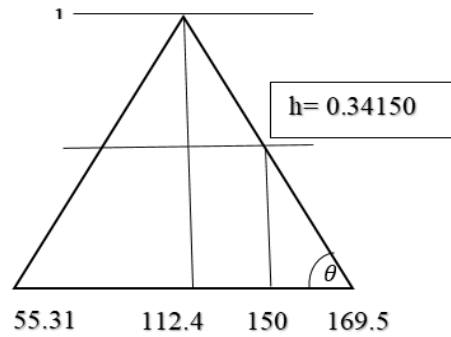
Figure 2.6: Value of NM for Acceleration

### Value of NS:

$$\tan\theta = \frac{1}{169.5-112.4}$$

$$= \frac{10}{571}$$

Again, $\tan\theta = \frac{h}{150-112.4}$

Or, $\frac{5h}{188} = \frac{10}{571}$

$h = 0.65850$



h= 0.65850

112.4    150    169.5    226.6
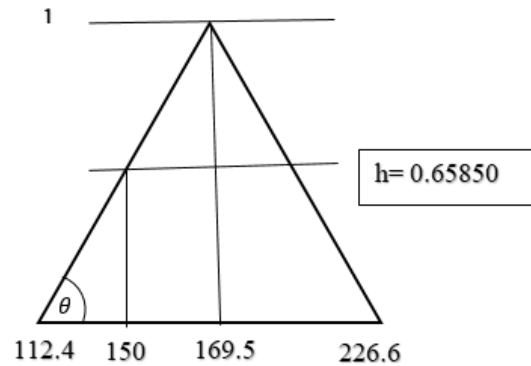
Figure 2.7: Value of NS for Acceleration

## 2.4 Defuzzification of output

The value of each input membership functions we have considered here is Speed-difference = 200 and Acceleration = 150 which is represented in the following figure (fig.2.8) –
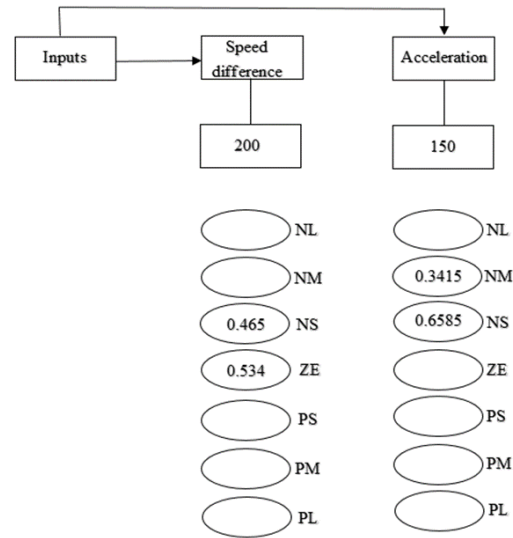


Figure 2.8: Defuzzification of output

We have used forty-nine rules to determine the throttle control. However, not all the rules affects the output. Here we have chosen some sample rule to calculate the output where the input membership functions have the value for speed-difference is equal to 200 and acceleration is equal to 150.

Rule 1: min (0, 0) = 0

Rule 2: min (0.53415, 0.65850) = 0.53415

Rule 3: min (0.53415, 0.34150) = 0.34150

Rule 4: min (0, 0) = 0

Rule 5: min (0.46585, 0) = 0

Rule 6: min (0.46585, 0.34150) = 0.34150

Rule 7: min (0.46585, 0.65850) = 0.46585

Rule 8: min (0.46585, 0) = 0

From these rules, we will now plot the aggregated fuzzy output –
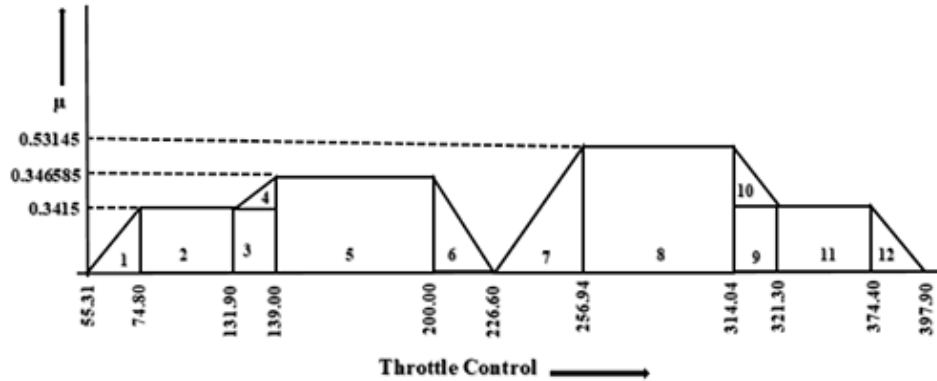


Figure 2.9: Aggregated fuzzy output of throttle control

Now, we will calculate $\bar{x}$ and $A\bar{x}$ for different area segments in the following table (table 2.2) –

Table 2.2: Area (A) showing the area of the segmented aggregated fuzzy set and $\bar{x}$ showing the corresponding centroid

| Area segment no. | Area (A) | $\bar{x}$ | $A\bar{x}$ |
|---|---|---|---|
| 1 | 0.5×19.50×0.3415=3.32 | 68.31 | 226.7892 |
| 2 | 57.09×0.3415=19.50 | 103.35 | 2015.325 |
| 3 | 7.10×0.3415=2.42 | 135.45 | 327.789 |
| 4 | 0.5×7.10×0.12435=0.50 | 136.63 | 68.315 |
| 5 | 60.10×0.46585=28.41 | 169.5 | 4815.495 |
| 6 | 0.5×26.60×0.46585=6.20 | 217.73 | 1349.926 |
| 7 | 0.5×30.34×0.53145=8.06 | 246.867 | 1989.748 |
| 8 | 57.10×0.53145=30.34 | 283.725 | 8608.217 |

| 9 | 0.5×7.25×0.19=0.70 | 317.68 | 222.376 |
|---|---|---|---|
| 10 | 7.25×0.3415=2.50 | 315.875 | 789.6875 |
| 11 | 57.10×0.3415=19.50 | 349.85 | 6822.075 |
| 12 | 0.5×19.50×0.3415=3.33 | 391.40 | 1303.362 |
| | $\sum A$ =124.78 | | $\sum A\bar{x}$=28539.10 |

Therefore, $z^* = \dfrac{\sum A\bar{X}}{\sum A} = \dfrac{28593.10}{124.78} = 229.15$

## 2.5 MATLAB Implementation

We will implement this fuzzy logic system of cruise controller in MATLAB using Mamdani method and 'if then' rules that is shown in the following figure (fig.2.10) –
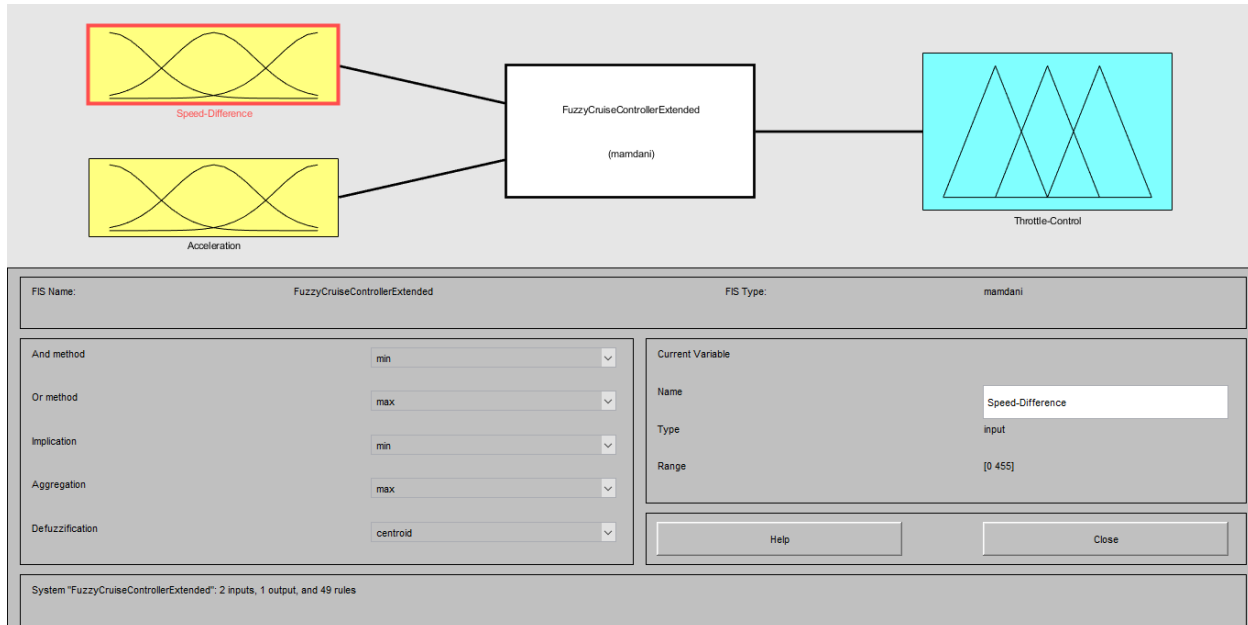


Figure 2.10: Fuzzy cruise controller system in MATLAB

## 2.6 Fuzzy rule base

Part of the forty nine rules from the rule editor for governing the cruise control is shown form the following MATLAB screenshot (fig.2.11) –
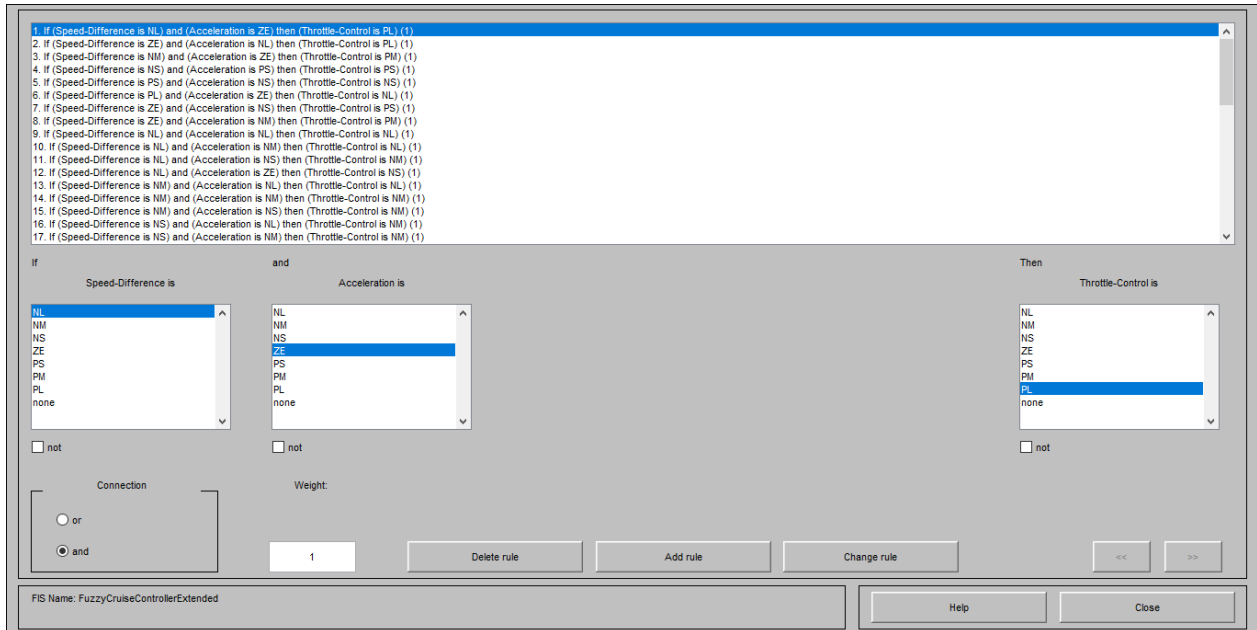


Figure 2.11: Sample cruise control rule base

The perimeters of input and output membership functions and their ranges are shown in the following table (table 2.3) –

Table 2.3: Input and output membership functions perimeters

| Perimeters | Range (0-455) |
|---|---|
| Negative large (NL) | 0-112.4 |
| Negative medium (NM) | 55.31-169.5 |
| Negative small (NS) | 112.4-226.6 |
| Zero (ZE) | 169.5-283.7 |
| Positive small (PS) | 226.6-340.8 |
| Positive medium (PM) | 283.7-397.9 |
| Positive large (PL) | 340.8-455 |

## 2.7 Fuzzy sets

The fuzzy sets considered as input and output is visualized in the following figures –
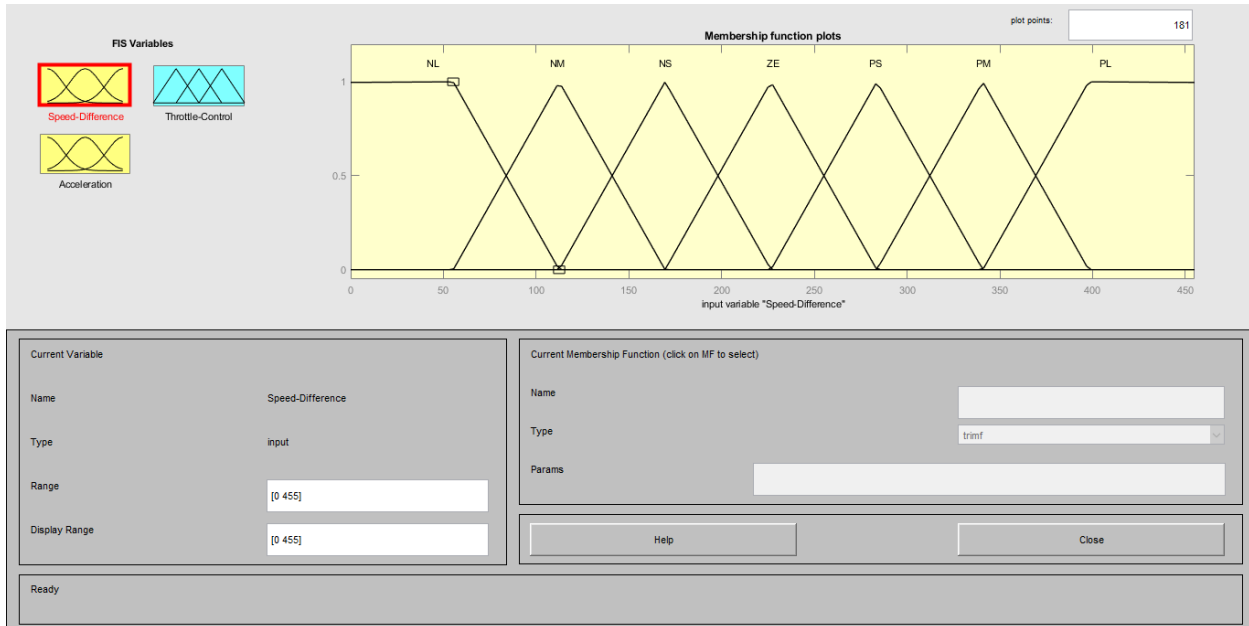


Figure 2.12: Input membership function Speed Difference
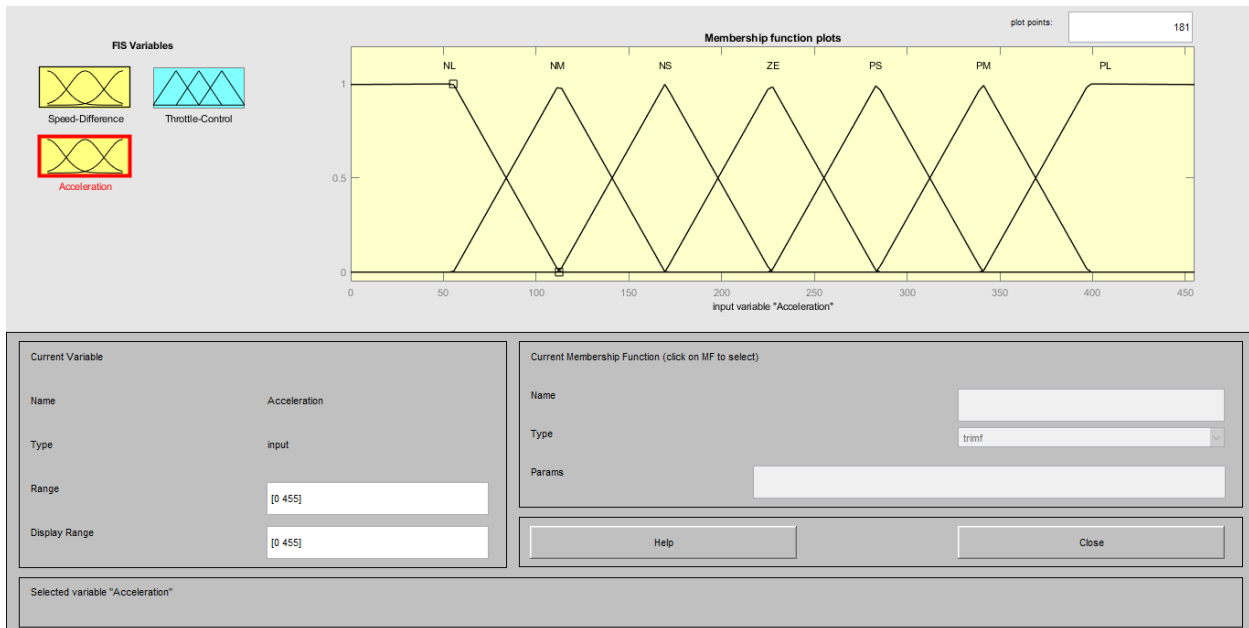


Figure 2.13: Input membership function Acceleration
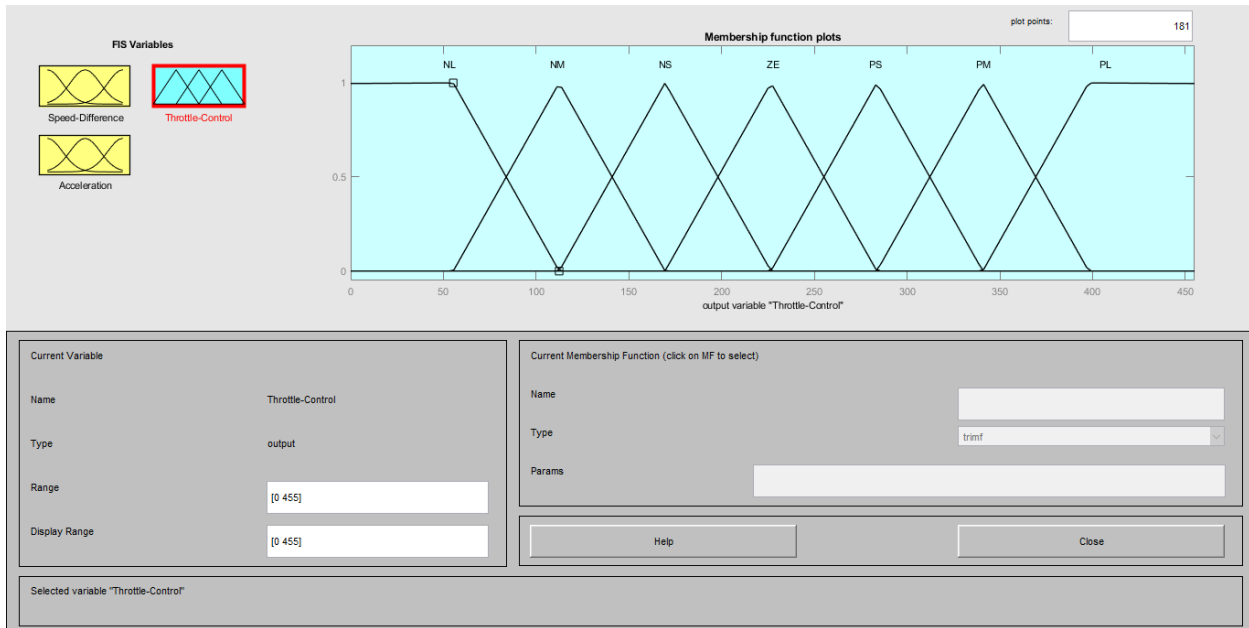
Figure 2.14: Output membership function Throttle Control

## 2.8 Rule viewer

Considering speed difference = 200 and acceleration = 150 the output throttle control result which is equal to 228 is shown in the rule viewer that we can see in the following figure (fig.2.15) –



Figure 2.15: Rule viewer in dialog box

## 2.9 Surface plot viewer

The surface plot formed from the relation of the corresponding fuzzy input and output is represented graphically in the following figures –
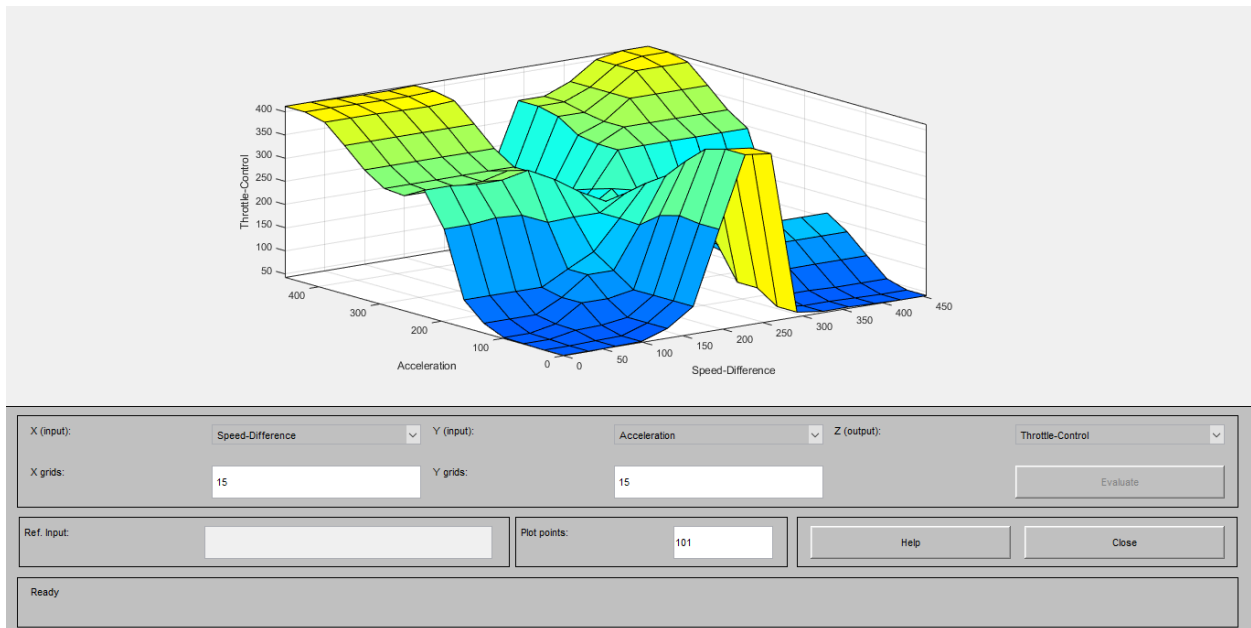


Figure 2.16: Surface plot in 3D
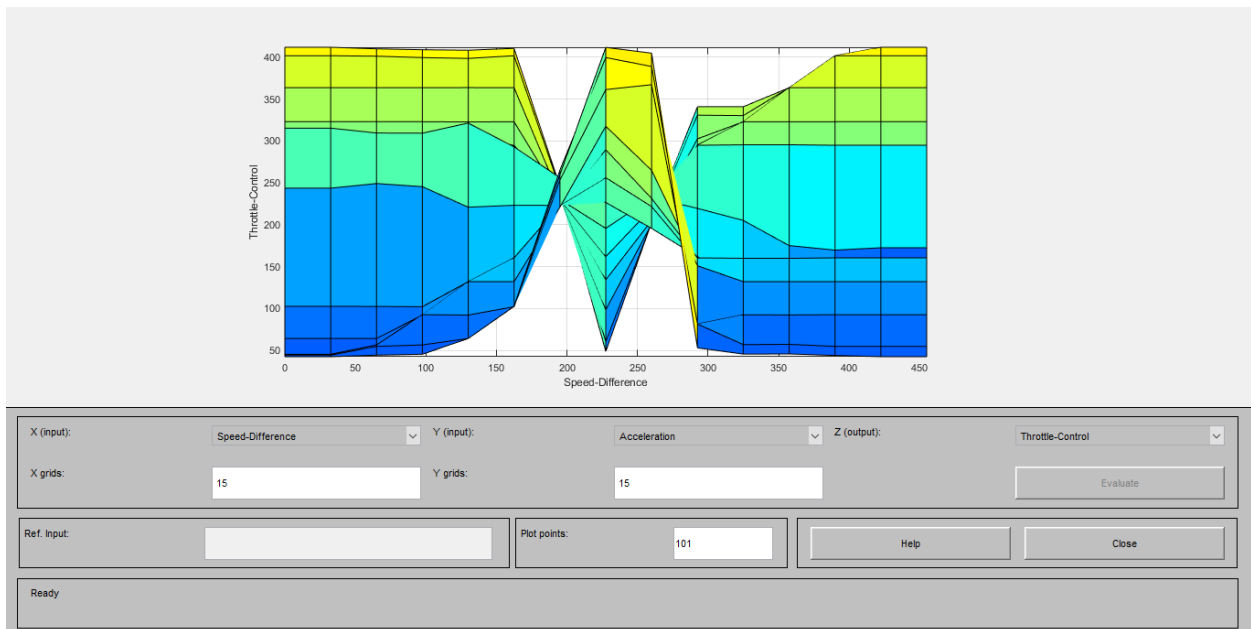


Figure 2.17: Throttle control vs. Speed difference surface plot
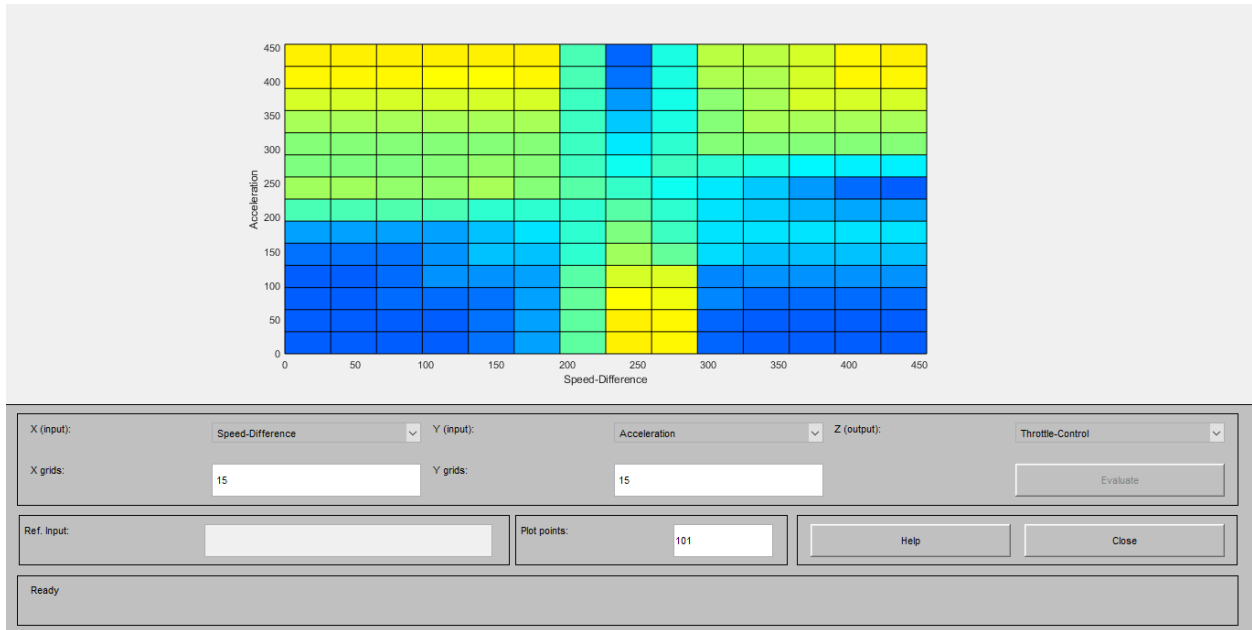
Figure 2.18: Acceleration vs. Speed Difference surface plot
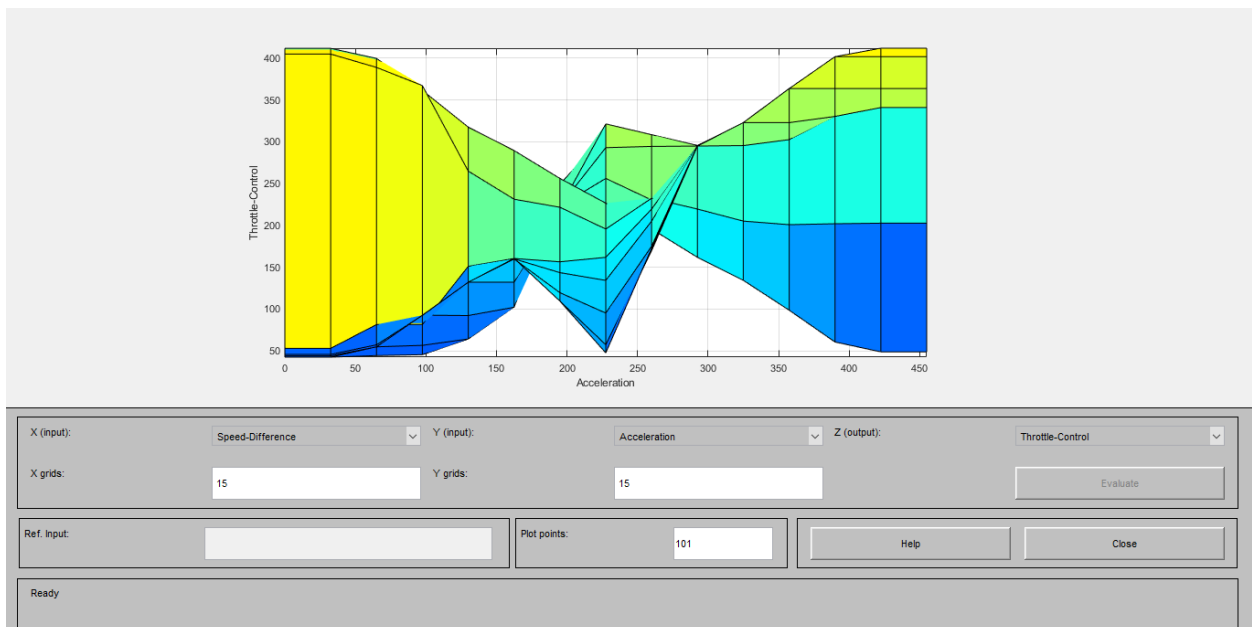


Figure 2.19: Throttle control vs. Acceleration surface plot

Comparing the centroid method's result and MATLAB output of the same input membership functions values, our percentage of error $= \frac{229.15 - 228}{229.15} * 100\% = 0.5\%$. Therefore, centroid method can be considered a very reliable method for our fuzzy load forecasting system.

# Chapter 3

# Load forecasting using fuzzy logic

## 3.1 MATLAB implementation

After elaborating the centroid method using the examples in previous chapter, now we are going to show the electrical load forecasting that we have done by utilizing the same method in MATLAB. We have gathered our preliminary data from the BPDB website that are the temperature, actual load demand, BPDB forecasted demand and the humidity was taken and calculated from a reputed [7] website (approximate calculation, not accurate). Here, Mamdani method and 'if then' rule is applied and we have considered temperature, season, humidity and pick hour as the input membership functions and maximum load demand as output membership function. We have divided normal days and holiday as two criteria for the load-forecasting scenario. First, we will demonstrate normal day criteria where we will show the input and output membership functions and their corresponding rules in rule viewer. We will also see the surface plot of each membership functions.
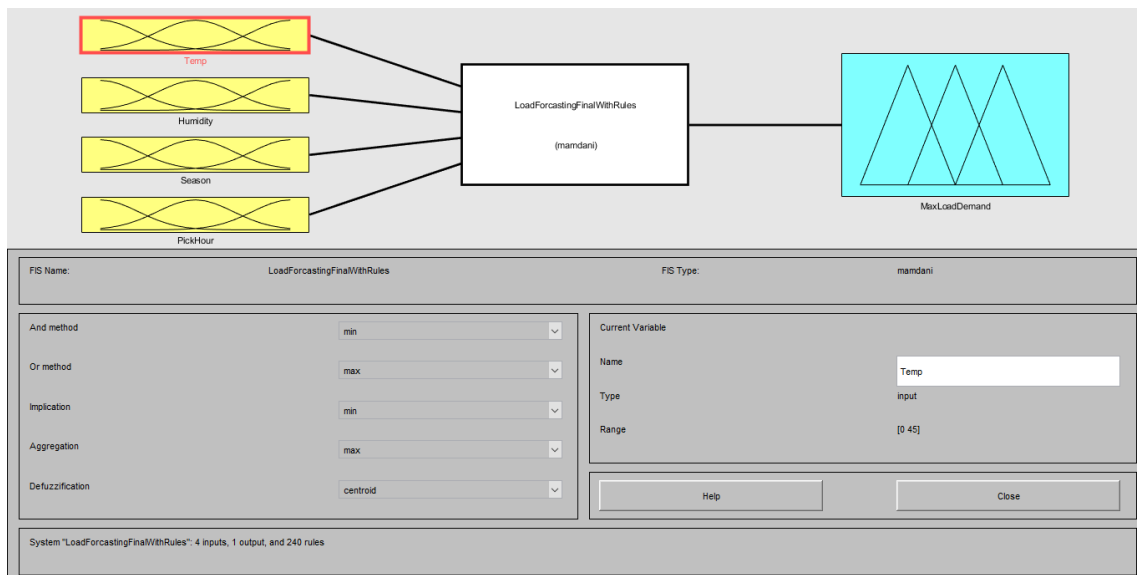


Figure 3.1: Fuzzy logic load forecasting system in MATLAB

## 3.2 Parameters used for fuzzy sets

The first input membership function is temperature and its five distinct parameters are shown in the following table (table 3.1) and figure (fig.3.2) –

Table 3.1: Input membership function temperature parameters

| Parameters | Range (in Celsius)(0-45) |
|---|---|
| Low | 0-15.5 |
| Below Average | 8-23 |
| Average | 15.5-30.5 |
| Above Average | 23-38 |
| High | 30.5-45 |
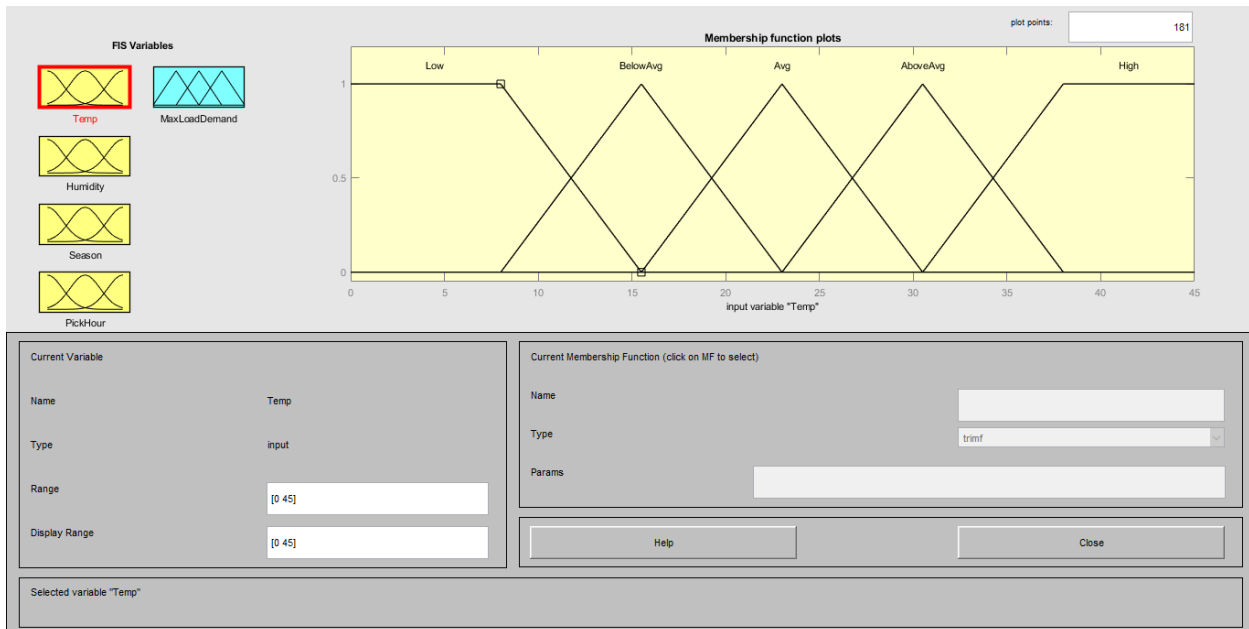


Figure 3.2: Input membership function temperature

The second input membership function is Humidity that is divided into five distinct parameters that are shown in the following table (table 3.2) and figure (fig.3.3) –

Table 3.2: Input membership function humidity parameters

| Parameters | Range (in percentage)(40-100) |
|---|---|
| Low | 40-60 |
| Below Average | 50-70 |
| Average | 60-80 |
| Above Average | 70-90 |
| High | 80-100 |
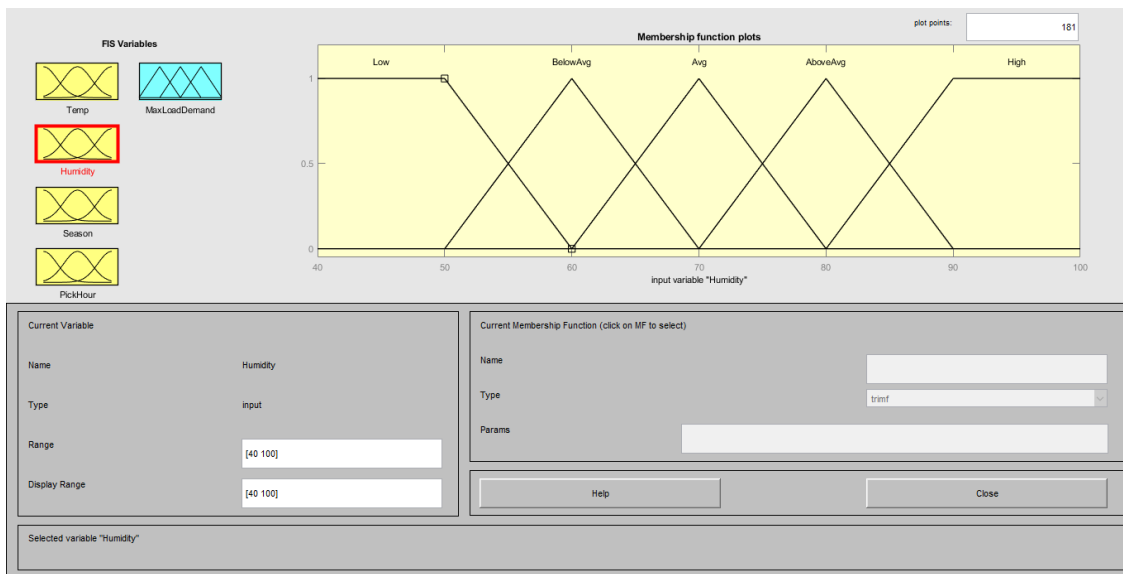


Figure 3.3: Input membership function humidity

The third input membership function is Season and its five distinct parameters are shown in the following table (table 3.3) and figure (fig.3.4) –

Table 3.3: Input membership function season parameters

| Parameters | Range (in days)(1-365) |
|---|---|
| Winter | 11-70 |
| Pre-Summer | 46-132 |
| Summer | 103-217 |
| Monsoon | 188-305 |
| Pre-Winter | 283-374 |
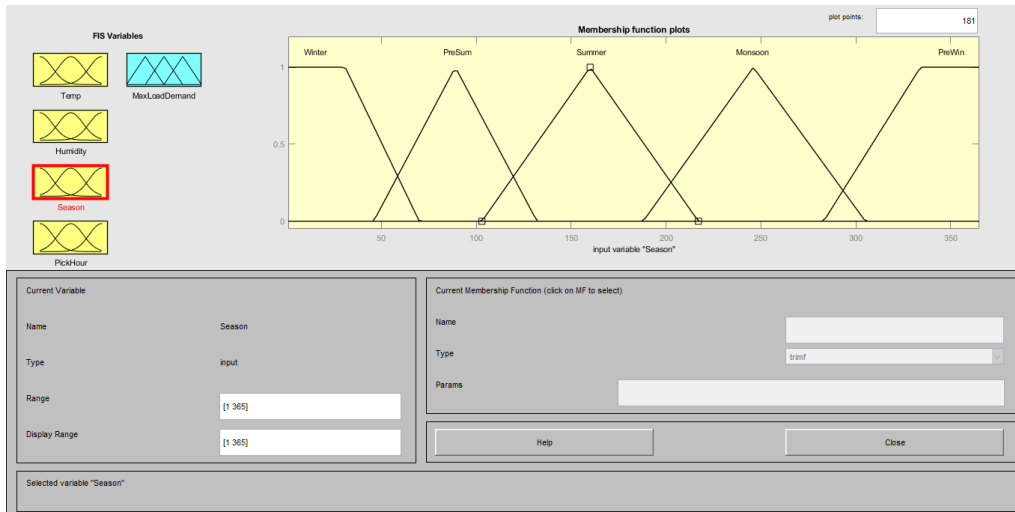
Figure 3.4: Input membership function season

The fourth input membership function is Pick hour and it has three distinct parameters that are shown in the following table (table 3.4) and figure (fig.3.5) –

Table 3.4: Input membership function pick hour parameters

| Parameters | Range (in hours)(0-23) |
|---|---|
| Off pick | 0-8 |
| Day pick | 8-16 |
| On pick | 16-23 |
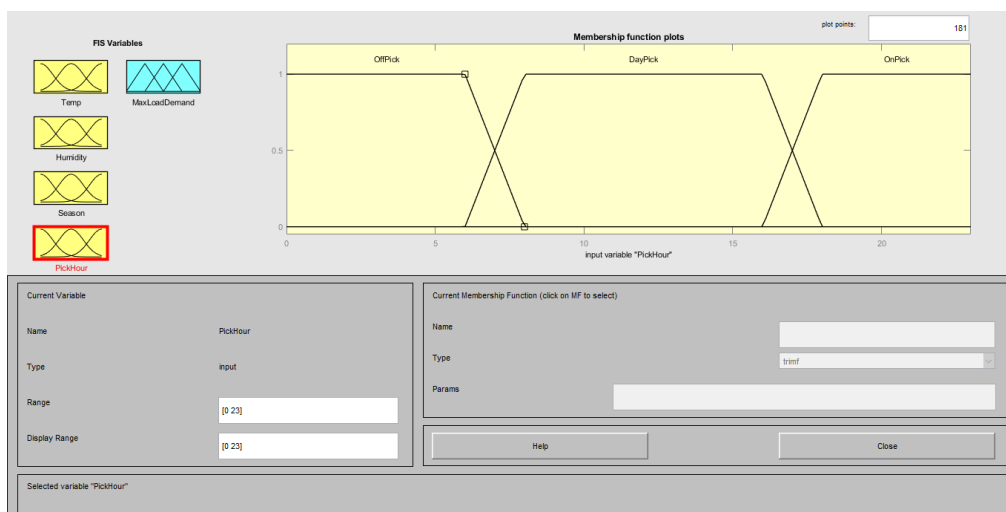


Figure 3.5: Input membership function pick hour

From the figures, we can see that temperature, humidity and season has two parameters type as trapezoidal in each of the membership functions that are low, high, low, high, winter, pre-winter respectively. All the other parameters are in triangular membership function. Only pick hour has three parameters where all of them are trapezoidal membership function. Now, output membership function that is max load demand has 10 parameters and those are shown in the following table (table 3.5) and figure (fig.3.6) below –

Table 3.5: Output membership function max load demand parameters

| Parameters | Range (in MW)(6000-12000) |
|---|---|
| Base | 6000-7200 |
| Very low | 6700-7700 |
| Low | 7200-8200 |
| Below average | 7700-8700 |
| Average | 8200-9200 |
| Above average | 8700-9700 |
| High | 9200-10200 |
| Very high | 9700-10700 |
| Extreme high | 10200-11200 |
| Forbidden | 11700-12000 |
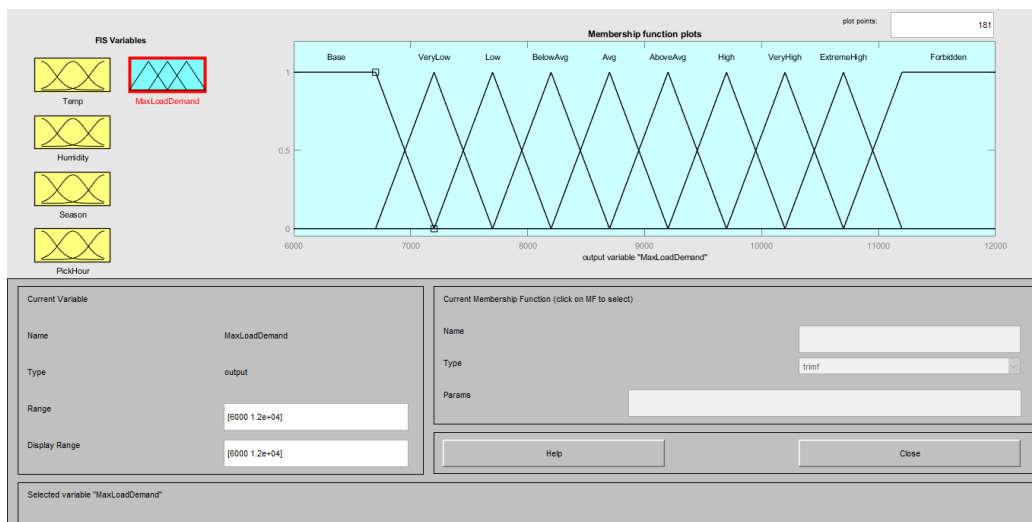


Figure 3.6: Output membership function maximum load demand

Here, the output membership function has two parameters as trapezoidal, which are base and forbidden. All the other parameters are in triangular membership function.

### 3.3 Rule viewer and editor

Using the above mentioned membership functions; we have created two hundred and forty rules. Part of the rules in rule editor are shown in the following figure (fig.3.7) –
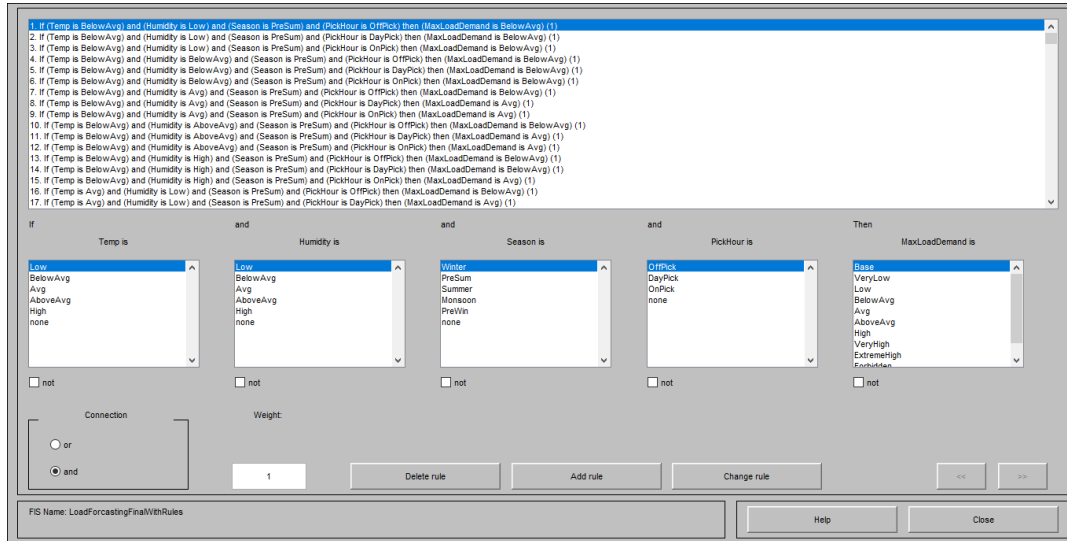


Figure 3.7: Load forecasting rules in rule editor

In rule viewer, the rules are being applied for different situations and parameters. We are going to show a figure (fig. 3.8) of the rule viewer in action –



Figure 3.8: Load forecasting rules in rule viewer

## 3.4 Surface plot viewer

In surface plot viewer, the load forecasting surface plot is graphically shown from utilizing the given rules –
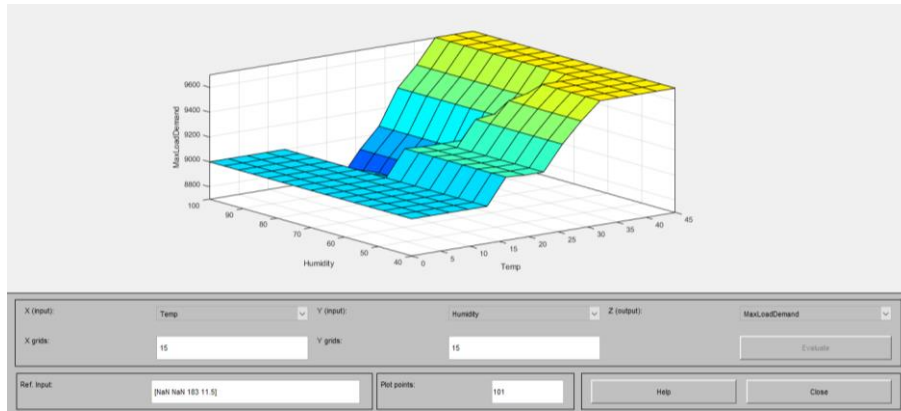


Figure 3.9: Surface plot in 3D
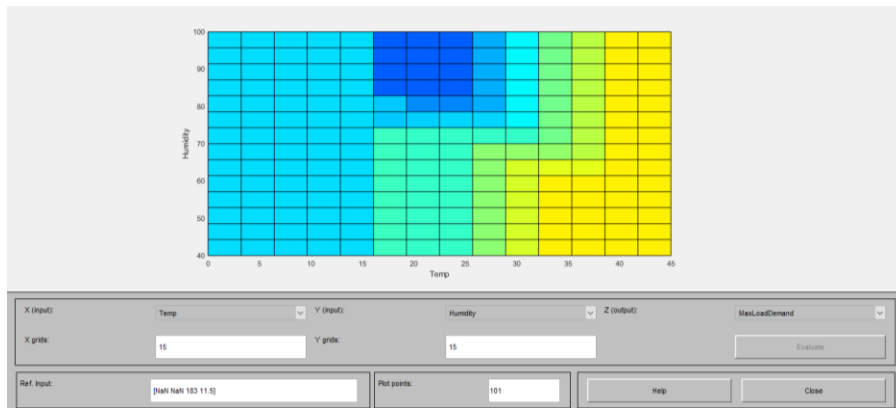


Figure 3.10: Humidity vs. Temperature surface plot
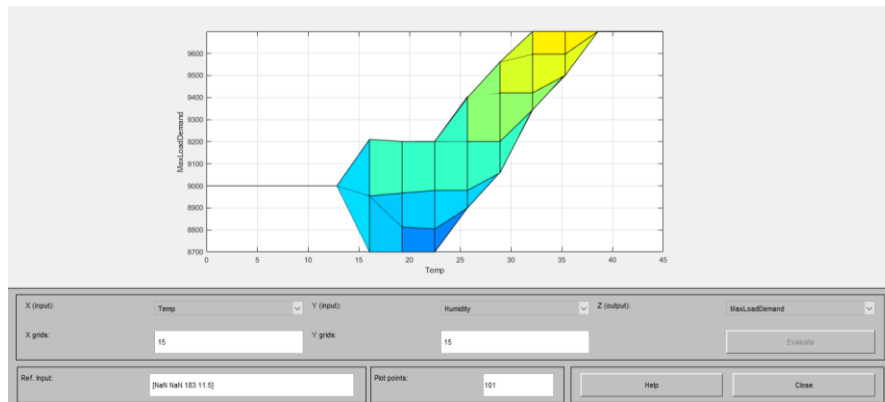


Figure 3.11: Max load demand vs. Temperature surface plot
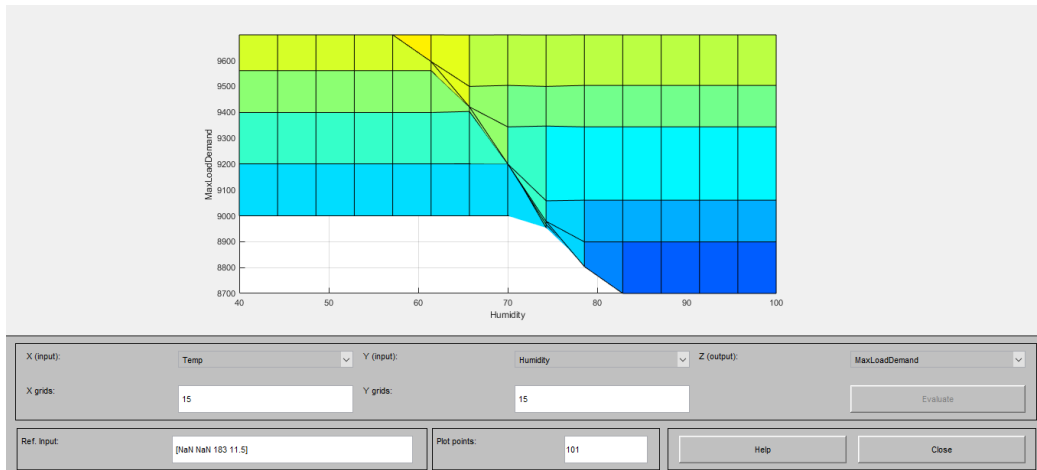
Figure 3.12: Max load demand vs. Humidity surface plot

## 3.5 Result comparison

We will now analyze some our load forecasting results with BPDB [8] for three specific seasons, which are monsoon, winter and summer. We have only selected 10 days from each of the months, as it would be lengthy and time consuming to show each day comparison.

Table 3.6: August'17 forecasted load error comparison

| Date | Forecasted Temp. (°C) | Actual Maximum Load (MW) | PDB forecasted load (MW) | Fuzzy forecasted load (MW) | APE% | APE% with fuzzy |
|------|------|------|------|------|------|------|
| 21-8-17 | 34.4 | 9318 | 9900 | 9200 | -6.24 | 1.26 |
| 22-8-17 | 33 | 9180 | 10000 | 9130 | -8.93 | 0.54 |
| 23-8-17 | 34.2 | 9129 | 9900 | 9190 | -8.44 | -0.66 |
| 24-8-17 | 34.7 | 8986 | 10000 | 9200 | -11.28 | -2.38 |
| 26-8-17 | 33.3 | 9253 | 9800 | 9200 | -5.91 | 0.57 |
| 27-8-17 | 32.6 | 9110 | 9800 | 9200 | -7.57 | 0.987 |
| 28-8-17 | 33.1 | 9084 | 9800 | 9200 | -7.88 | -1.27 |
| 29-8-17 | 32.6 | 9088 | 9800 | 9200 | -7.83 | -1.23 |
| 30-8-17 | 33.8 | 8980 | 9800 | 9200 | -9.13 | -2.45 |
| 31-8-17 | 33.3 | 8053 | 9700 | 9110 | -20.45 | -13.12 |

Table 3.7: February'18 forecasted load error comparison

| Date | Forecasted Temp. (°C) | Actual Maximum Load (MW) | PDB forecasted load (MW) | Fuzzy forecasted load (MW) | APE% | APE% with fuzzy |
|---|---|---|---|---|---|---|
| 1-2-18 | 25.8 | 8162 | 8350 | 8300 | -2.30 | -1.69 |
| 3-2-18 | 28 | 8109 | 8000 | 8200 | 1.34 | -1.12 |
| 4-2-18 | 29.7 | 8139 | 8350 | 8200 | -2.59 | -0.74 |
| 5-2-18 | 29.3 | 8247 | 8350 | 8200 | -1.24 | 0.56 |
| 6-2-18 | 28.7 | 7976 | 8400 | 8200 | -5.31 | -2.80 |
| 7-2-18 | 28.4 | 8258 | 8400 | 8360 | -1.71 | -1.25 |
| 8-2-18 | 28.3 | 8115 | 8400 | 8290 | -3.51 | -2.15 |
| 10-2-18 | 27.5 | 8144 | 8350 | 8330 | -2.52 | -2.29 |

Table 3.8: April'18 forecasted load error comparison

| Date | Forecasted Temp. (°C) | Actual Maximum Load (MW) | PDB forecasted load (MW) | Fuzzy forecasted load (MW) | APE% | APE% with fuzzy |
|---|---|---|---|---|---|---|
| 10-4-18 | 32.2 | 9355 | 9900 | 9200 | -5.82 | 1.65 |
| 11-4-18 | 33.1 | 8943 | 10000 | 9430 | -11.81 | -5.44 |
| 12-4-18 | 33.8 | 8917 | 9650 | 9560 | -8.22 | -7.21 |
| 14-4-18 | 33.4 | 7665 | 9300 | 8720 | -21.33 | -13.76 |
| 15-4-18 | 37.5 | 9961 | 9800 | 9860 | 1.61 | 1.01 |
| 16-4-18 | 36.4 | 9702 | 10100 | 9560 | -4.10 | 1.46 |
| 17-4-18 | 37 | 8464 | 10100 | 9050 | -19.32 | -6.92 |
| 18-4-18 | 37.1 | 9758 | 10000 | 9650 | -2.54 | 1.10 |
| 19-4-18 | 32.4 | 9425 | 10000 | 9300 | -6.10 | 1.32 |

## 3.6 Special case discussion

However, with our methodology, holidays load forecasting were unpredictable. BPDB forecasting method also has many flaws in terms of calculating the holidays load forecasting. For this reason, we have subtracted seven hundred MW from the output membership function's perimeter and re-created a new fuzzy logic forecasting which is only applicable for the holidays. The normal load forecasting and holiday load forecasting comparison is shown in the following tables –

Table 3.9: Holiday of August'17 forecasted load error comparison using normal and holiday case

| Date | Forecasted Temp. (°C) | Actual Maximum Load (MW) | PDB forecasted load (MW) | Fuzzy forecasted load (MW) | APE% | APE% with fuzzy |
|------|------|------|------|------|------|------|
| Normal Case | | | | | | |
| 25-8-17 | 34.7 | 8933 | 9800 | 9200 | -9.70 | -2.98 |
| Holiday Case | | | | | | |
| 25-8-17 | 34.7 | 8933 | 9800 | 8500 | -9.70 | 4.84 |

Table 3.10: Holiday of February'18 forecasted load error comparison using normal and holiday case

| Date | Forecasted Temp. (°C) | Actual Maximum Load (MW) | PDB forecasted load (MW) | Fuzzy forecasted load (MW) | APE% | APE% with fuzzy |
|------|------|------|------|------|------|------|
| Normal Case | | | | | | |
| 2-2-18 | 26.2 | 7262 | 7500 | 8200 | -3.27 | -12.91 |
| 9-2-18 | 30.4 | 7449 | 7500 | 8210 | -0.68 | -10.21 |

| Holiday Case | | | | | |
|---|---|---|---|---|---|
| 2-2-18 | 26.2 | 7262 | 7500 | 7500 | -3.27 | -3.27 |
| 9-2-18 | 30.4 | 7449 | 7500 | 7510 | -0.68 | -0.81 |

Table 3.11: Holiday of April'18 forecasted load error comparison using normal and holiday case

| Date | Forecasted Temp. (°C) | Actual Maximum Load (MW) | PDB forecasted load (MW) | Fuzzy forecasted load (MW) | APE% | APE% with fuzzy |
|---|---|---|---|---|---|---|
| Normal Case | | | | | | |
| 13-4-18 | 34.1 | 9257 | 9200 | 9420 | -0.46 | -1.76 |
| 20-4-18 | 34.1 | 8095 | 9600 | 9290 | -18.59 | -14.76 |
| Holiday Case | | | | | | |
| 13-4-18 | 34.1 | 9257 | 9200 | 8720 | -0.46 | 5.80 |
| 20-4-18 | 34.1 | 8095 | 9600 | 8590 | -18.59 | -5.15 |

# Chapter 4

# Conclusion

In this project work, we applied microscopic approach and developed fuzzy inference model applicable in short term and long term forecasting of real life problem. Here, we apply the concept in electrical load forecasting of Bangladesh, taking the practical data of BPDB. We co-relate the demand of electrical load with weather parameters and found high accuracy in winter season. In summer, the generated power is far lower than the actual demand that is mitigated by load shedding. Due to this discrepancy of demand and supply, accuracy level of forecasting model is found lower. In monsoon, the generated power is optimum in regards to the actual load demand. We found very pleasant accuracy in comparison with the traditional system in this season.

We found some uncertainties when using our fuzzy inference system for the load forecasting of the holidays. In holidays, all the schools, banks, offices and industrial sectors like garments and factories remains closed. Thus, the generated power is higher than the actual demand in these days. We tried to come up with a solution to this problem by remodeling our existing system so that this model can be used when forecasting the holiday's power demand. Still we have the scope to apply the concept of weighted Fuzzy system to segregate the data of holiday and working day. Here a large set of data record is used to acquire the Fuzzy rules. The weighting factor of data set is determine from the range of data filed and its non-overlapping part. The verification of test data is determined from weighted sum of data and weighting vector. The combination of Fuzzy system and Fuzzy C-mean clustering can be applied to observe the improvement of accuracy of load forecasting. We can also consider a simple method like fuzzy inference system model. In future, we will incorporate some additional parameters like population density, criteria of service areas, financial capacity of people of that particular region, density of households, offices etc. In addition, we will further extend our work by using Deep Learning that will utilize greater than five years of earlier forecasted load data and precisely predict the future load demand. Although deep learning is a complex algorithm and require huge process time but will help us to provide forecasted load of holiday and that of normal working day using additional input parameter.

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