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Load Forecasting Using Fuzzy Inference

Submitted in Partial Fulfillment of the Requirement
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Master of Technology

In

Software Technology

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DECLARATION

I hereby want to declare that the thesis entitled "**Load Forecasting Using Fuzzy Inference"** which is being submitted to the **Delhi Technological University**, in partial fulfillment of the requirements for the award of degree in **Master of Technology in Software Technology** is an authentic work carried out by me. The material contained in this thesis has not been submitted to any institution or university for the award of any degree.

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ABSTRACT

Forecasting is the process of making statements about events whose actual outcomes have not yet been observed. Power companies uses load forecasting technique to anticipate the amount of the power needed to supply the demand, which helps them utilizing the power generation system more efficiently. Therefore it is important to forecast the future load requirement accurately for efficient operation of power system.

Some of the approaches of load forecasting are based on similar day selection. Loads of past similar days are used to forecast load of future day. The main goal of this work is to study fuzzy inference system based approach applied after considering various factors which impacts in similar day selection methods used for the short term load forecasting process. This report work analyzes the impact of similar weather and time factors in selecting similar day. Based on the results obtained, the combined approach of maximum-minimum temperature and classification of days in seven unique types we get better results for the forecasting purpose. Fuzzy logic is used to modify the load curves of the selected similar days.

The comparison of results obtained in various methods is done by comparing forecast error. The forecast error is the difference between the actual value and the forecast value for the corresponding period. Some of the examples of measuring the aggregate errors are MAE (Mean Absolute Error), MAPE (Mean Absolute percentage Error). I use MAPE to compare results in various approaches

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CHAPTER 1: INTRODUCTION

Forecasting is the process of making statements about events whose actual outcomes have not yet been observed. Load forecasting is used by the power companies to anticipate the amount of the power needed to supply the demand. The main goal of this report work is to propose and show the results of fuzzy inference system for short term load forecasting.

This report proposes the methods which should be applied for better similar days selection resulting into better forecasting results.

1.1. GENERAL

Forecasting: It is the process of making statements about events whose actual outcomes (typically) have not yet been observed.

Load Forecasting: It is used by the power companies to anticipate the amount of the power needed to meet the demand.

Types of Forecasting:

- **Short-term load forecasting:**

  The main strategy in the short term load Forecasting is to predict the hourly, daily, weekly loads. In case of short term load forecasting the estimated load for each hour and the daily peak load is calculated.

- **Medium-term load forecasting:**

  In case of the medium term load forecasting it deals with the estimation of the load from a week to the year ahead.

- **Long-term load forecasting:**

That knows the load consumption pattern of the present and thus predicting the load consumption pattern from a week to the year ahead.

The Prediction of the system Load over an interval ranging from one hour to one week which is very important in the online scheduling and security functions of an energy management system (EMS). Hence we get the title as short term load forecasting.

The forecast error is the difference between the actual value and the forecast value for the corresponding period. There are many dxiifferent measures of the aggregate error. Some of the examples of measuring the aggregate errors are MAE (Mean Absolute Error), MAPE (Mean Absolute percentage Error).

Forecasting greatly depends upon the degree of similarity between target day and past similar days. Load demand varies depending upon weather conditions and day type. In this report similarity of days is considered based on temperature, humidity and day of week.

1.2. MOTIVATION

The electrical energy is the type of the energy that cannot be stored in bulk, it must be generated shipped to the point where it's needed and immediately consumed. It is used for determining the load demand in future because the electrical energy cannot be stored appropriately and correct load forecasting is necessary for the correct investments.

The variation of load demand varies with change in weather condition. So it is very imperative to study the relationship between load demand and weather factors. Another important factor in observing the electric load demand is the day type. On week-ends the demand is generally less than weed-days when offices are open. This motivated to study the relation between load demand, weather and day type and establish a model which could forecast the load demand.

1.3. PROBLEM STATEMENT

From the forgoing section we can see that future electric load demand can be predicted if we could find out the days similar to the forecasting day. Electric load of the similar days need to be corrected further for reducing error in forecasting.

This leads to the approach of detailed study of weather and day type based similarity and applying the Fuzzy inference system to correct the load prediction.

This thesis aims at studying various factors which could enhance the similar day selection and applying Fuzzy logic to forecast the electric load.

To establish the similarity, regression analysis is carried out, it's a statistical technique used to find relationships between the variables for the purpose of predicting the future values. Regression analysis includes any techniques for modeling and analyzing several variables, when the focus is on the relationship between a dependent variable and one or more independent variables.

More specifically, regression analysis helps us understand how the typical value of the dependent variable changes when any one of the independent variables is varied, while the

other independent variables are held fixed. The fuzzy logic based approach is used to get the load Forecasting. Fuzzy logic is used to modify the load curves of the selected similar days. A commonplace example might be estimation of the expected value for some variable of interest at some specified future date. Prediction is a similar, but more general term. The forecasting may not necessarily give the correct values. Hence there is the need for the calculation of the accuracy level.

1.4. SCOPE OF THE THESIS

The scope of this thesis is to study the individual and combined impact of weather and time factors on similar day selection and hence analyzing the impact of same on MAPE in load forecasting.

Thesis proposes combination of weather and time factors in determining most similar day to the forecasting day. The correction in load of similar days is achieved by applying fuzzy inference system. The relation between weather and time factors and that of load is calculated using regression technique. Once a relationship is established between load and dependent variables, the coefficients are used to calculate Euclidean norm in determining the most similar days.

The Euclidean norm alone is not sufficient for the load forecast as the selected similar days for the forecast day have considerably large mean absolute percentage error (MAPE). Assuming same trends of relationships between the previous forecast day and previous similar days as that of the forecast day and its similar days, the similar days can thus be evaluated by analyzing the previous forecast day and its previous similar days.

1.5. THESIS ORGANIZATION

Chapter 1 begins with General introduction and related work. It addresses the topics like Motivation, Problem Statement, Scope, Related work and thesis organization.

Chapter 2 provides a detailed description about electric load forecasting techniques and gives a brief about the pros-cons and accuracy level of same.

Chapter 3 presents the proposed research methodology which explains the detailed model of fuzzy inference system used in correction load of selected similar days.

Chapter 4 shows the implementation of the proposed methodology also the tools used in it.

Chapter 5 presents the results and analysis part of the proposed methodology.

Chapter 6 concludes the thesis.

CHAPTER 2: LITERATURE REVIEW

2.1. Forecasting Techniques

The forecasting techniques can be classified into two types.

- Statistical Technique
- Artificial Intelligence algorithms

The methods generally used for the Short term load forecasting include similar day approach, various regression models, time series, statistical learning models, fuzzy logic and expert systems. The accuracy of the load forecasting not only depends on the load forecasting techniques but also on the accuracy of the forecasted weather scenario. The weather forecast error also contributes to the errors developed in the load forecasting as well. A large variety of statistical and artificial intelligence techniques have been developed for the short term load forecasting some of them are mentioned below.

2.2. Similar-day approach

The approach searches historical load data containing hourly weather information within one, two or three years with characteristics based on weather similarity to forecast day. Similar weather characteristics include day type, temperature, humidity and day. The load of similar day is considered for forecast. In order to improve the accuracy, instead of considering single day for similarity, several days can be selected based on these similarity techniques. The coefficients of trend may be applied for similar day in past years.

2.3. Regression Methods

Regression is the one of the most widely used statistical techniques. For electric load forecasting regression methods are usually used to model the relationship of the load consumption and the other factors such as weather, day type, and customer class. Their models incorporate deterministic influences such as holidays, stochastic influences such as average loads and exogenous influences such as weather.

2.4. Time Series

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

2.5. Important Factors of the forecast

The factors that should be considered for the short term load forecasting are

- **Time factor**

  It includes the time of the year, the day of the week and the hour of the day. The load consumption pattern in weekdays and weekends behave differently.

- **Weather data**

  It includes the humidity and the temperature values.

2.6. Weather Variables

The forecasted weather parameters are most important factors in the short term load forecast. Various weather variables can be considered for the short term load forecasting. The temperature and the humidity are the commonly used load predictors.

2.7. Graphs and Relations between the variables

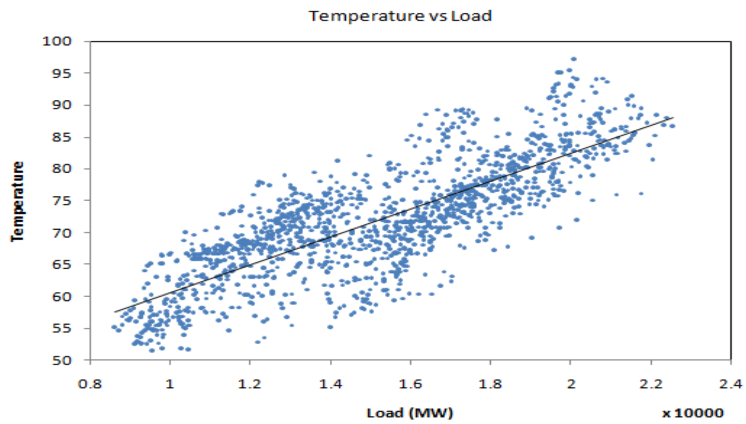

Figure 1 Plot between load and temperature (+ ve Correlation)

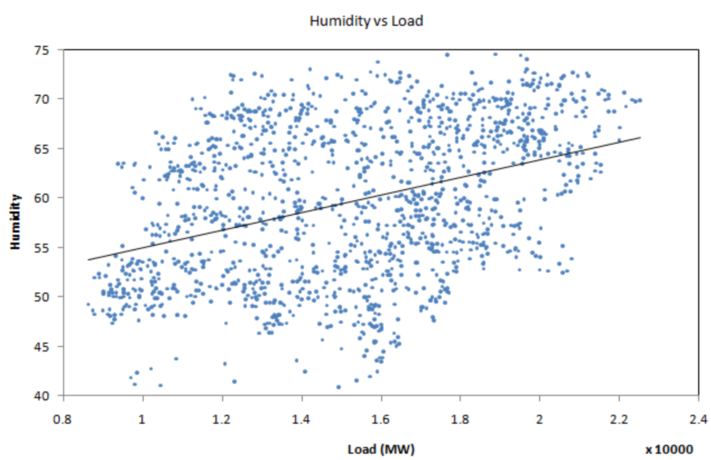

Figure 2 Plot between load and humidity (+ve Correlation)

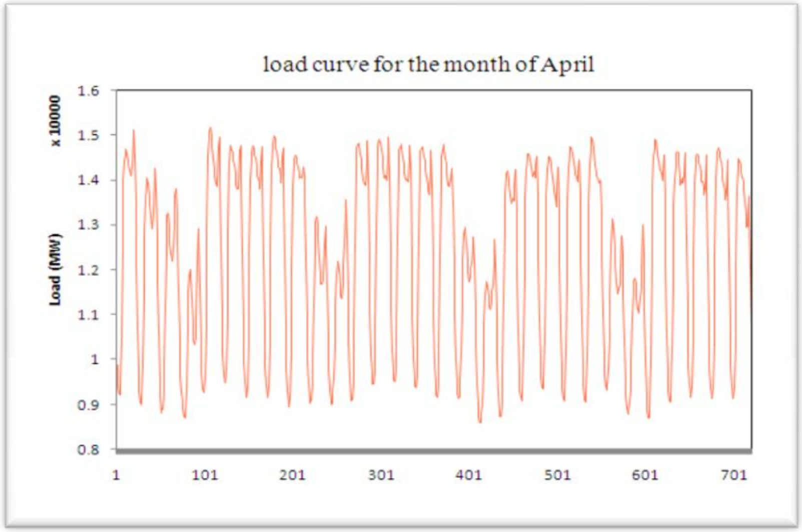

Figure 3 Plot between load and time (Cyclic Trend)

CHAPTER 3: METHODOLOGY

3.1. Fuzzy Logic

Fuzzy logic is a form of many-valued logic derived from fuzzy set theory to deal with reasoning that is fluid or approximate rather than fixed and exact. In contrast with "crisp logic", where binary sets have two-valued logic, fuzzy logic variables may have a truth value that ranges in degree between 0 and 1. Put more simply, fuzzy logic is a superset of conventional (Boolean) logic that has been extended to handle the concept of partial truth, where the truth value may range between completely true and completely false.

A basic application might characterize various sub-ranges of a continuous variable. For instance, a temperature measurement for anti-lock brakes might have several separate membership functions defining particular temperature ranges needed to control the brakes properly. Each function maps the same temperature value to a truth value in the 0 to 1 range. These truth values can then be used to determine how the brakes should be controlled.

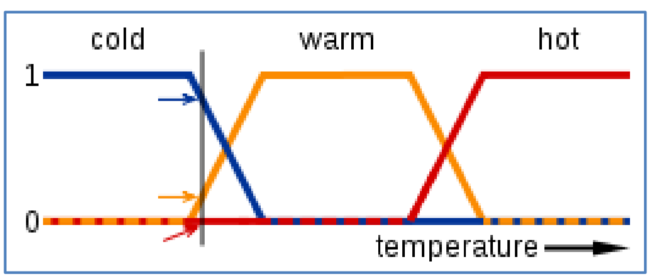

Figure 4: Fuzzy Logic Example

In this image, the meanings of the expressions cold, warm, and hot are represented by functions mapping a temperature scale. A point on that scale has three "truth values" — one for each of the three functions. The vertical line in the image represents a particular temperature that the three arrows (truth values) gauge. Since the red arrow points to zero, this temperature may be interpreted as "not hot". The orange arrow (pointing at 0.2) may describe it as "slightly warm" and the blue arrow (pointing at 0.8) "fairly cold".

Furthermore, when linguistic variables are used, these degrees may be managed by specific functions. Fuzzy logic and probabilistic logic are mathematically similar – both have truth values ranging between 0 and 1 – but conceptually distinct, due to different interpretations—see interpretations of probability theory. Fuzzy logic corresponds to "degrees of truth", while probabilistic logic corresponds to "probability, likelihood"; as these differ, fuzzy logic and probabilistic logic yield different models of the same real-world situations.

3.2. Fuzzy Inference System

A fuzzy inference system (FIS) is a system that uses fuzzy set theory to map inputs (features in the case of fuzzy classification) to outputs (classes in the case of fuzzy classification).

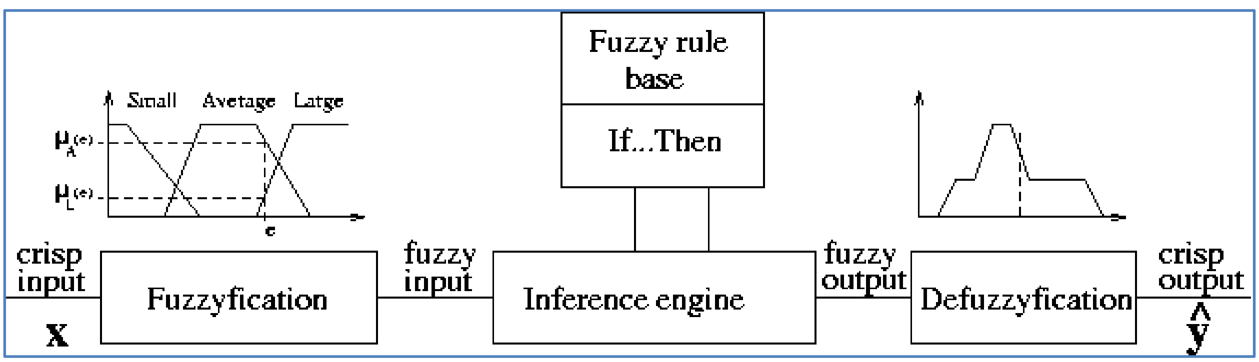

Figure 5: Fuzzy Inference System

A fuzzy inference system is composed of three blocks, as shown in above Figure. The first block is the fuzzification block. It transforms numerical values into membership degrees to the different fuzzy sets of the partition. The second block is the inference engine, with the rule base. The third one implements the defuzzification stage if necessary. It yields a crisp value from the rule aggregation result.

3.3. Fuzzy Rule

Fuzzy set theory defines fuzzy operators on fuzzy sets. The problem in applying this is that the appropriate fuzzy operator may not be known. For this reason, fuzzy logic usually uses IF-THEN rules, or constructs that are equivalent, such as fuzzy associative matrices.

Rules are usually expressed in the form: IF variable IS property THEN action, for example we can have a rule such as IF temperature IS very cold THEN stop fan.

3.4. FIS for Load Correction

Since the actual load data for the day before is known hence the errors to those similar days are calculated and FIS system is used to obtain the w_k=correction factor values. Since there are 5 similar days which are calculated hence we get the 5 correction factors namely w1 to w5.The load of the present hour depends on the load on previous hour and also on the load of the same hour of the previous day. The Fuzzy inference system is used to evaluate the similarity between the previous forecast day and previous similar day. To get the degree of similarity 3 input variables are defined:

$$E_L^k = L_p - L_{ps}^k \qquad (1)$$

$$E_T^k = T_p - T_{ps}^k \qquad (2)$$

$$E_H^k = H_p - H_{ps}^k \qquad (3)$$

L=load, T=temperature, H=humidity .There are 3 fuzzy set values used they are Low, Medium and High. Now each of this corrected values are used in the below equation to get the forecasted load for the day which is needed.

- **INPUT variable membership functions**

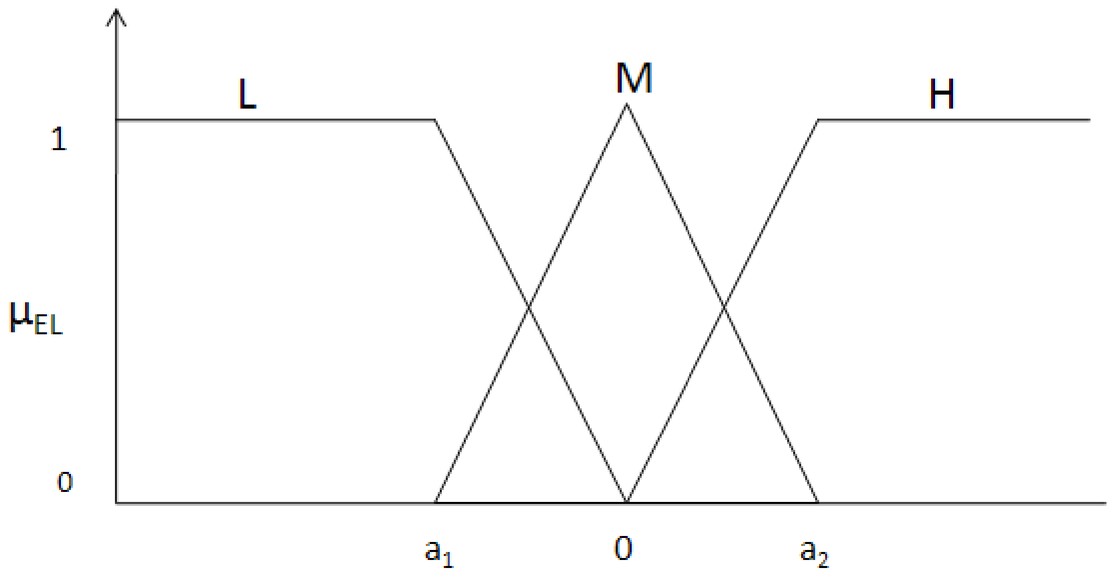

Figure 6 Membership function of Load

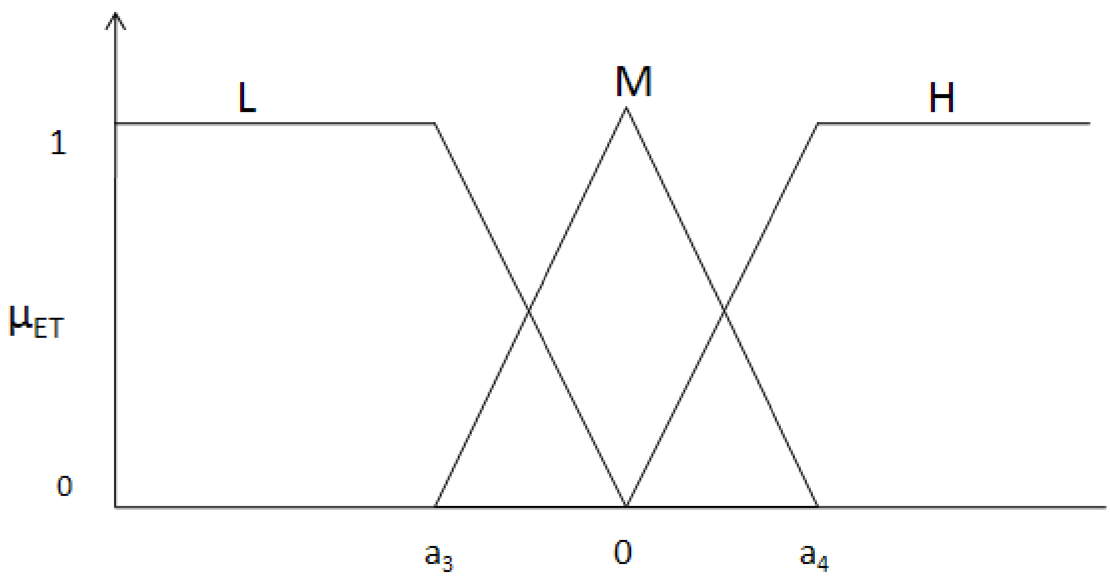

Figure 7 Membership function of Temperature

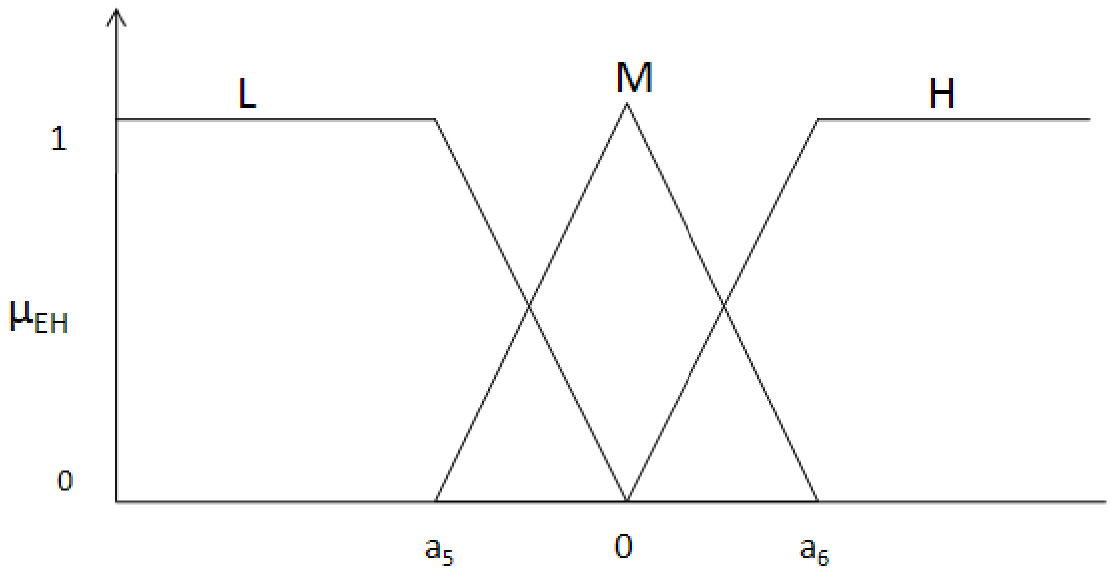

Figure 8 Membership functino of Humidity

- **OUTPUT variable membership function**

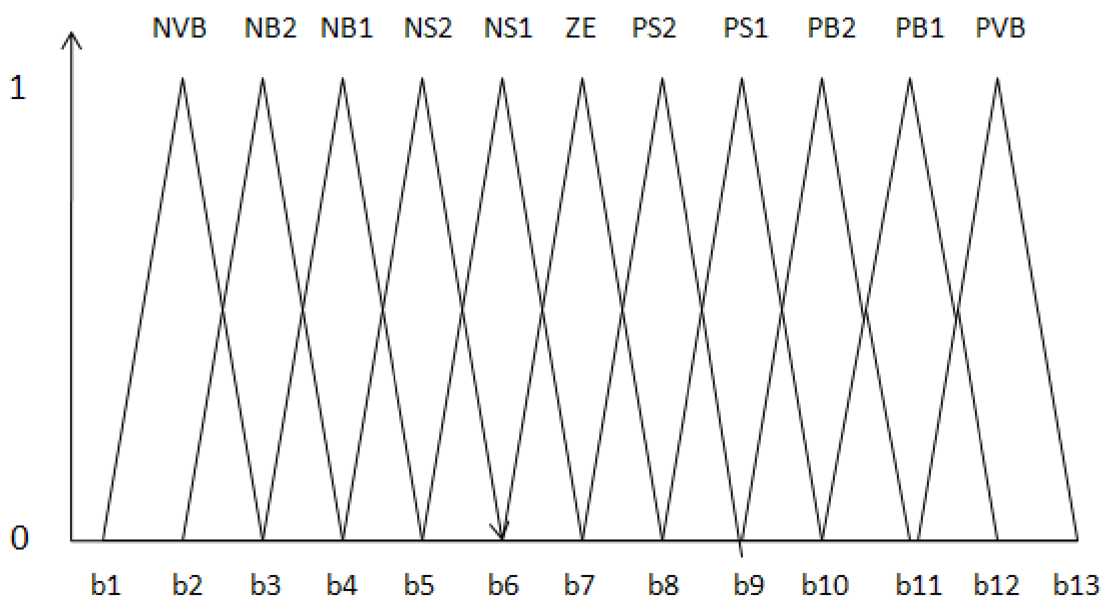

Figure 9 Membership function of output variable

3.5. Fuzzy Evaluation

In the FIS used after the fuzzyfication of the input the second step is the rule table evaluation. The rules can be made based on some of the observations of the load values. This step comes under the rule table evaluation. For the de-fuzzification the centroid rule is used to get the crisp value output. The centroid rule for the de-fuzzyfication process used is:

$$W_k = \frac{\sum_{i=1}^{27} \alpha_i \square_i^k}{\sum_{i=1}^{27} \square_i^k} \qquad (4)$$

Where there are 27 rules which are used in the rule table evaluation. After applying the centroid rule there is one crisp output which is obtained which is the correction factor for k^{ith} similar day [12].

$$L(t) = \frac{1}{N}\left[\sum_{i=1}^{N}(1 + W_k)L_s^k(t)\right] \qquad (5)$$

Here the value of N=5 corrected factors are added to the corresponding similar days of the forecast day and averaged.w1, w2, w3 which are the weights can not only be obtained by the regression method but they can be obtained through any other normalizing method also, the main purpose is scaling. For each hour same process is applied to get the forecast load of that particular hour of the day.

After the weight factors are calculated from the fuzzy inference system then the load of every hour is calculated and the corresponding mean absolute percentage error can also be determined. Now this fuzzy inference system that was made could be optimized using the ant colony optimization to get new memberships and refined rules. Then the same process could be repeated to get the weight factors w1 to w5 and get the corresponding hourly load values.

CHAPTER 4: SIMULATION, RESULTS AND DISCUSSIONE

Load forecasting analysis is done using seven months hourly data of electric load. This hourly data contains electric load, temperature and humidity of every hour. First six months data is used to carry out regression to establish relation between load and temperature and humidity. This relation is calculated in terms of regression coefficients. These regression coefficients are further used to find out similar days with forecasting day.

4.1. Regression Using MATLAB

Regression is done using MATLAB to establish relationship between electric load and weather and time variables. Six months hourly data of electric load with temperature and humidity is used to carry out regression. The coefficients calculated in regression are used in Euclidean norm calculation (Appendix I)

Load can be represented as linearly dependent upon temperature, humidity and time

L=w1*Temp + w2*Humidity + w3*Day

The regression coefficients are calculated as below:

Table 1 Regression Coefficients

SN	Weight	Value
1	W1	77.0
2	W2	76.0
3	W3	1075

4.2. Euclidean Norm and similar days calculation

Euclidean norm calculation and similar day selection is done in C language. (Appendix II)

$$En = \sqrt{W1 * (\Delta T)^2 + W2 * (\Delta H)^2 + W3 * (\Delta D)^2}$$

ΔT = Temperature difference

ΔH = Humidity difference

ΔD = Day type difference

W1, W2, W3 are weights as calculated in regression method.

In this report, result of difference of Temperature has been compared by taking maximum, average, and combination of maximum-minimum temperature.

Similarly, the day type field has been analyzed considering 2, 4 and 7 day types.

Euclidean norm and similar days for 30-July:

Table 2 Euclidean Norm and Similar Day of 30-July

Avg Load	Max Temp	Min Temp	Avg Temp	Avg Humi	Day Type	Date	EN
17725.5	84.7	68.5	76.0917	68.1417	1	30	0
16180.9	80.9	70.9	75.6417	68.9125	1	2	7.75
17409.9	86.7	67.7	77.1917	65.7708	1	23	22.8
17273.5	84.6	66.9	76.0333	65.2375	1	27	25.32
17709	83.6	66.2	73.5958	66.6625	1	19	25.4
16518	84.2	66.7	74.7458	64.4333	1	22	34.41

4.3. FIS input variables calculation

FIS input variables calculation is done in C (Appendix III).

$$E_L^k = L_p - L_{ps}^k \qquad (1)$$

$$E_T^k = T_p - T_{ps}^k \qquad (2)$$

$$E_H^k = H_p - H_{ps}^k \qquad (3)$$

Table 3 FIS input variables of 30-July

	(E_L^k)	(E_T^k)	(E_H^k)
(set 1)	[1544.6;	0.45;	0.7708]
(set 2)	[315.6;	-1.1;	2.3709]
(set 3)	[452;	0.0584;	2.9042]
(set 4)	[16.5;	2.4959;	1.4792]
(set 5)	[1207.5;	1.3459;	3.7084]

4.4. FIS simulation using MATLAB

FIS is simulated using fuzzy tool box available in MATLAB (TODO appendix).

MAMDANI FIS is used to simulate load forecasting model. Input membership function parameters

(a1, a2) --> for Load (-1200, + 1200)

(a3, a4) --> for Temp (-10, 10)

(a5, a6) --> for Humi (-10, 10)

Table 4 FIS membership function

(a1, a2)	(a3, a4)	(a5, a6)
(-1200, 1200)	(-10, 10)	(-10, 10)

4.5. MAPE calculation

MAPE calculation is done in C. The correction variables obtained in FIS are used to correct the load of similar selected days. MAPE calculation is done for below cases:

- **2_DT_MAX:** Similarity based upon 2 day types and maximum temperature
- **7_DT_MAX:** Similarity based upon 7 day types and maximum temperature
- **2_DT_MAX_MIN:** Similarity based upon 2 day types and maximum-minimum temperature
- **7_DT_MAX_MIN:** Similarity based upon 7 day types and maximum-minimum temperature

Table 5 MAPE in Different Methods

		MAPE			
SN	**Date**	**2_DT_MAX**	**7_DT_MAX**	**2_DT_MAX_MIN**	**7_DT_MAX_MIN**
1	24-July	3.27	2.91	2.8	2.71
2	25-July	1.05	1.05	1.1	0.65
3	26-July	2.93	3.18	3.05	2.85
4	27-July	1.87	1.44	1.34	0.95

From the table 5, we can see that MAPE is reduced when we use seven day type and maximum and minimum temperature.

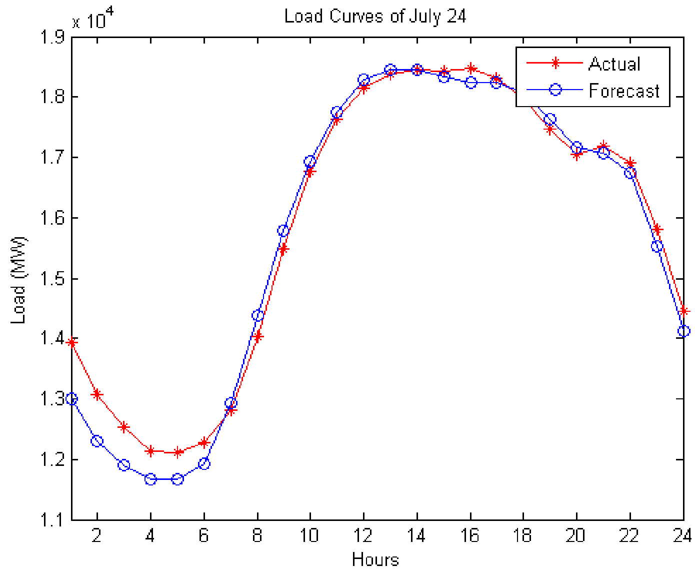

Figure 10 Load Curve for 24th July

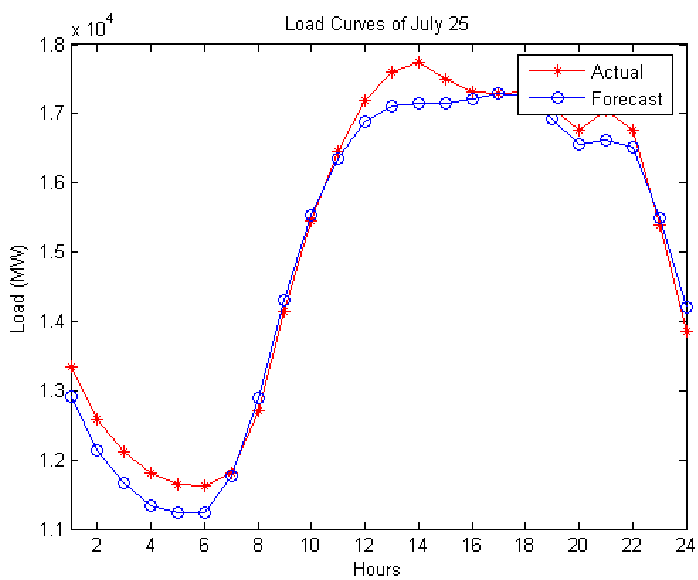

Figure 11 Load Curve for 25th July

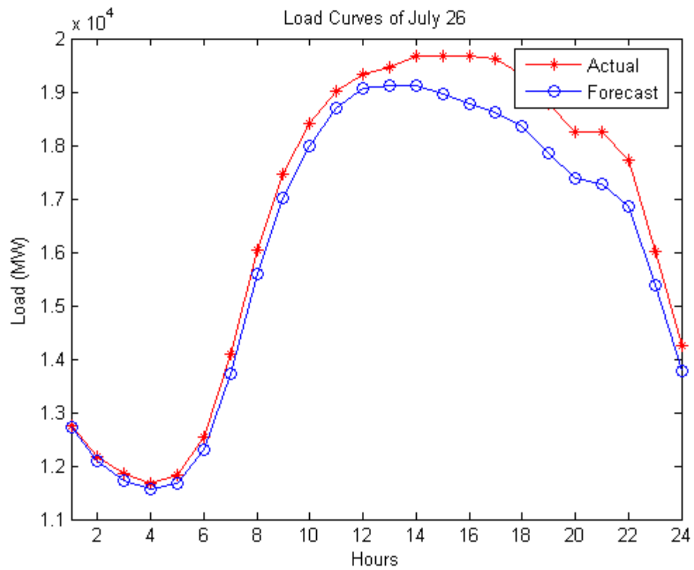

Figure 12 Load Curve for 26th July

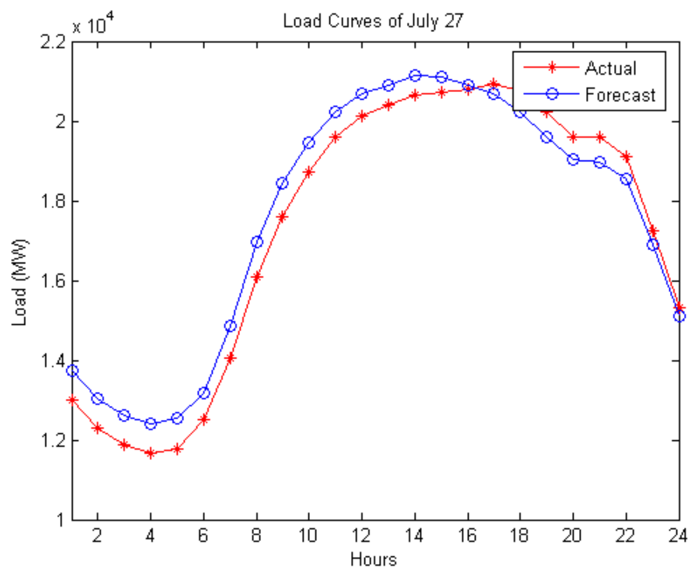

Figure 13 Load Curve for 27th July

CHAPTER 5: CONCLUSION & FUTURE WORK

5.1 CONCLUSION:

In this project similarity parameters in choosing near day to forecast day is consider and fuzzy logic is used to forecast the load. The system takes into account the effect of humidity as well as temperature on load and a fuzzy logic based method is used to correct the similar day load curves of the forecast day to obtain the load forecast. Also, a Euclidean norm with weight factors is used for the selection of similar days. Fuzzy logic is used to calculate the correction factors of the selected similar day to the forecast day using the information of the previous forecast day and the previous similar days.

The analysis combination of maximum-minimum temperature and seven days type gives best results in load forecasting.

To verify the forecasting ability of the proposed method, simulation is done to do the load forecasting for the month of July in a data set of 7 months and the result for the four representative days of a week in the month of July are given. The results thus obtained from the simulation show that the proposed method used for load forecasting, which proposes the use of weather variables i.e. temperature as well as humidity gives the load forecasting results with reasonable accuracy.

5.2 Future work

This may form the future work on load forecasting. The method to be followed for load forecasting is as follows. Fuzzy parameters can be optimized to give better forecasting results. Optimization can be done using meta heuristic algorithms.

Frequency Response (FR) analysis can be done of weekly load for several weeks. Establishing similarity between successive weekly loads by comparing FR characteristics using Neural Network in Frequency Domain and deducing empirical relation for similarity. Determination of data in frequency domain for any week to be predicted by empirical formula thus derived.

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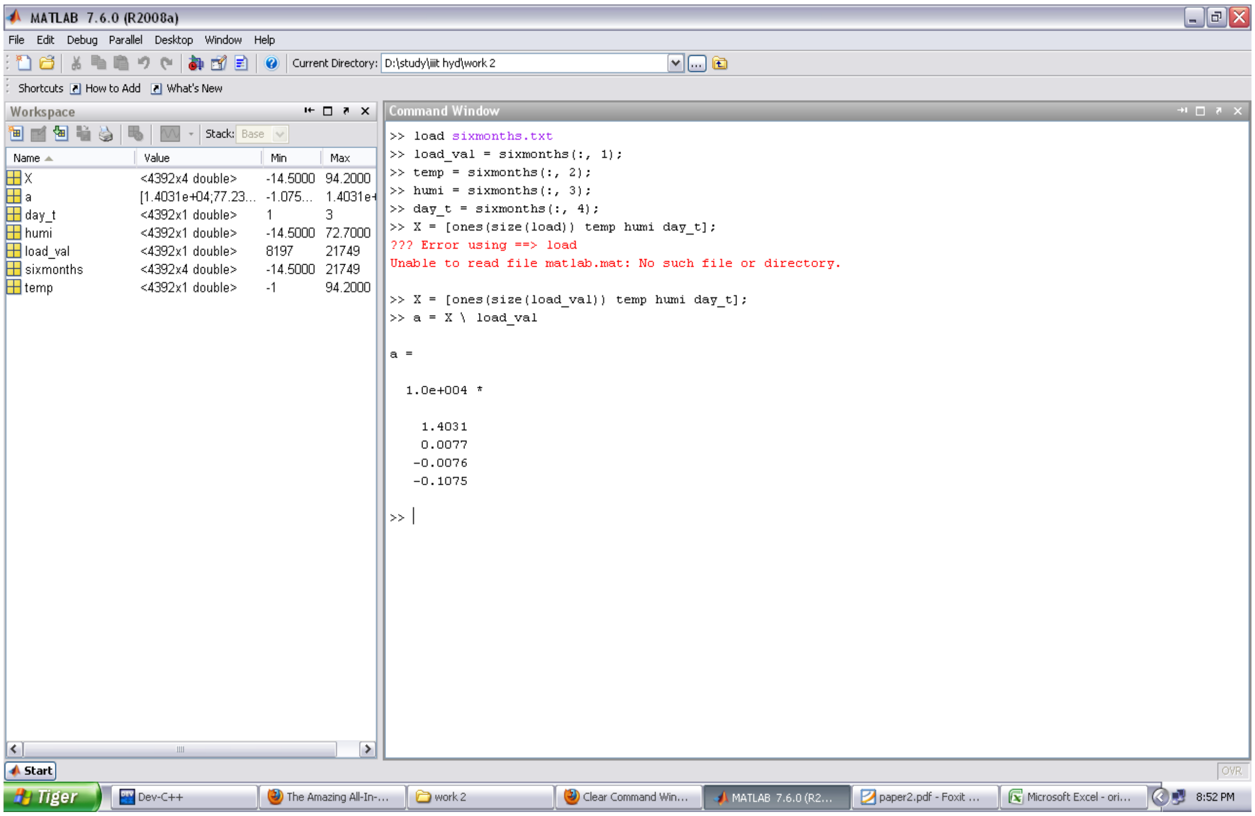
APPENDIX I: Regression



APPENDIX II: Euclidean Norm and Similar Days

- **2_DT_MAX: Similarity based upon 2 day types and maximum temperature**

23-July:

Avg Load	Max Temp	Min Temp	Avg Temp	Avg Humi	Day Type	Date	EN
17409.9	86.7	67.7	77.1917	65.7708	1	23	0
17273.5	84.6	66.9	76.0333	65.2375	1	27	11.14
17725.5	84.7	68.5	76.0917	68.1417	1	30	22.8
16518	84.2	66.7	74.7458	64.4333	1	22	24.39
17377.2	91.3	66.2	79.5792	63.5417	1	16	28.55
16180.9	80.9	70.9	75.6417	68.9125	1	2	30.56

24-July:

Avg Load	Max Temp	Min Temp	Avg Temp	Avg Humi	Day Type	Date	EN
15826.4	85.4	70	75.9792	69.4583	2	24	0
16402.1	85.4	68.9	77.0625	69.475	2	31	9.49
15107.3	84	69.2	75.6792	66.3292	2	25	27.39
16180.9	80.9	70.9	75.6417	68.9125	1	2	33.24
14533.4	89.3	72.8	79.4833	70.9417	2	4	33.35
17725.5	84.7	68.5	76.0917	68.1417	1	30	34.73

25-July:

Avg Load	Max Temp	Min Temp	Avg Temp	Avg Humi	Day Type	Date	EN
15107.3	84	69.2	75.6792	66.3292	2	25	0
15826.4	85.4	70	75.9792	69.4583	2	24	27.39
16402.1	85.4	68.9	77.0625	69.475	2	31	29.98
14660.8	87.2	66.2	77.4542	62.9583	2	3	33.24
17273.5	84.6	66.9	76.0333	65.2375	1	27	34.26
17409.9	86.7	67.7	77.1917	65.7708	1	23	35.69

26-July:

Avg Load	Max Temp	Min Temp	Avg Temp	Avg Humi	Day Type	Date	EN
16575.2	78.3	66.8	71.9125	65.9458	1	26	0
17709	83.6	66.2	73.5958	66.6625	1	19	16.03
15487.8	73.1	65.1	69.2083	65.9583	1	1	23.73
16518	84.2	66.7	74.7458	64.4333	1	22	28.12
17273.5	84.6	66.9	76.0333	65.2375	1	27	36.67
17725.5	84.7	68.5	76.0917	68.1417	1	30	41.35

- **7_DT_MAX: Similarity based upon 7 day types and maximum temperature**

23-July:

Avg Load	Max Temp	Min Temp	Avg Temp	Avg Humi	Day Type	Date	EN
17409.9	86.7	67.7	77.1917	65.7708	5	23	0
17725.5	84.7	68.5	76.0917	68.1417	5	30	22.8
17377.2	91.3	66.2	79.5792	63.5417	5	16	28.55
16180.9	80.9	70.9	75.6417	68.9125	5	2	30.56
16518	84.2	66.7	74.7458	64.4333	4	22	40.87
14660.8	87.2	66.2	77.4542	62.9583	6	3	41

24-July:

Avg Load	Max Temp	Min Temp	Avg Temp	Avg Humi	Day Type	Date	EN
15826.4	85.4	70	75.9792	69.4583	6	24	0
16402.1	85.4	68.9	77.0625	69.475	6	31	9.49
16180.9	80.9	70.9	75.6417	68.9125	5	2	33.24
17725.5	84.7	68.5	76.0917	68.1417	5	30	34.73
15107.3	84	69.2	75.6792	66.3292	7	25	42.72
14533.4	89.3	72.8	79.4833	70.9417	7	4	46.77

25-July:

Avg Load	Max Temp	Min Temp	Avg Temp	Avg Humi	Day Type	Date	EN
15107.3	84	69.2	75.6792	66.3292	7	25	0
15826.4	85.4	70	75.9792	69.4583	6	24	42.72
16402.1	85.4	68.9	77.0625	69.475	6	31	44.43
14660.8	87.2	66.2	77.4542	62.9583	6	3	46.69
14533.4	89.3	72.8	79.4833	70.9417	7	4	52.25
16837.6	93.1	73.2	82.0625	67.25	7	18	56.58

26-July:

Avg Load	Max Temp	Min Temp	Avg Temp	Avg Humi	Day Type	Date	EN
16575.2	78.3	66.8	71.9125	65.9458	1	26	0
17709	83.6	66.2	73.5958	66.6625	1	19	16.03
17273.5	84.6	66.9	76.0333	65.2375	2	27	49.19
18695.8	88.4	72.8	80	69.8083	2	6	85.11
15732.3	78.3	62.9	70.4417	56.6208	2	20	88.59
15487.8	73.1	65.1	69.2083	65.9583	4	1	101.18

- **2_DT_MAX_MIN: Similarity based upon 2 day types and maximum-minimum temperature**

23-July:

Avg Load	Max Temp	Min Temp	Avg Temp	Avg Humi	Day Type	Date	EN
17409.9	86.7	67.7	77.1917	65.7708	1	23	0
17273.5	84.6	66.9	76.0333	65.2375	1	27	20.22
16518	84.2	66.7	74.7458	64.4333	1	22	26.32
17725.5	84.7	68.5	76.0917	68.1417	1	30	28
17709	83.6	66.2	73.5958	66.6625	1	19	31.18
15107.3	84	69.2	75.6792	66.3292	2	25	42.8

24-July:

Avg Load	Max Temp	Min Temp	Avg Temp	Avg Humi	Day Type	Date	EN
15826.4	85.4	70	75.9792	69.4583	2	24	0
16402.1	85.4	68.9	77.0625	69.475	2	31	9.64
15107.3	84	69.2	75.6792	66.3292	2	25	30.71
17725.5	84.7	68.5	76.0917	68.1417	1	30	37.63
14533.4	89.3	72.8	79.4833	70.9417	2	4	44.06
18695.8	88.4	72.8	80	69.8083	1	6	48.79

25-July:

Avg Load	Max Temp	Min Temp	Avg Temp	Avg Humi	Day Type	Date	EN
15107.3	84	69.2	75.6792	66.3292	2	25	0
16402.1	85.4	68.9	77.0625	69.475	2	31	30.13

15826.4	85.4	70	75.9792	69.4583	2	24	30.71
17725.5	84.7	68.5	76.0917	68.1417	1	30	37.39
17273.5	84.6	66.9	76.0333	65.2375	1	27	39.99
17709	83.6	66.2	73.5958	66.6625	1	19	42.28

26-July:

Avg Load	Max Temp	Min Temp	Avg Temp	Avg Humi	Day Type	Date	EN
16575.2	78.3	66.8	71.9125	65.9458	1	26	0
17709	83.6	66.2	73.5958	66.6625	1	19	47.2
15487.8	73.1	65.1	69.2083	65.9583	1	1	48
16180.9	80.9	70.9	75.6417	68.9125	1	2	49.82
16518	84.2	66.7	74.7458	64.4333	1	22	53.41
17273.5	84.6	66.9	76.0333	65.2375	1	27	55.62

- **7_DT_MAX_MIN: Similarity based upon 7 day types and maximum-minimum temperature**

23-July:

Avg Load	Max Temp	Min Temp	Avg Temp	Avg Humi	Day Type	Date	EN
17409.9	86.7	67.7	77.1917	65.7708	5	23	0
17725.5	84.7	68.5	76.0917	68.1417	5	30	28
16518	84.2	66.7	74.7458	64.4333	4	22	42.05
14660.8	87.2	66.2	77.4542	62.9583	6	3	43.22
17377.2	91.3	66.2	79.5792	63.5417	5	16	46.68
16402.1	85.4	68.9	77.0625	69.475	6	31	48.55

24-July:

Avg Load	Max Temp	Min Temp	Avg Temp	Avg Humi	Day Type	Date	EN
15826.4	85.4	70	75.9792	69.4583	6	24	0
16402.1	85.4	68.9	77.0625	69.475	6	31	9.64
17725.5	84.7	68.5	76.0917	68.1417	5	30	37.63
15107.3	84	69.2	75.6792	66.3292	7	25	44.92
17409.9	86.7	67.7	77.1917	65.7708	5	23	51.43
16180.9	80.9	70.9	75.6417	68.9125	5	2	52.13

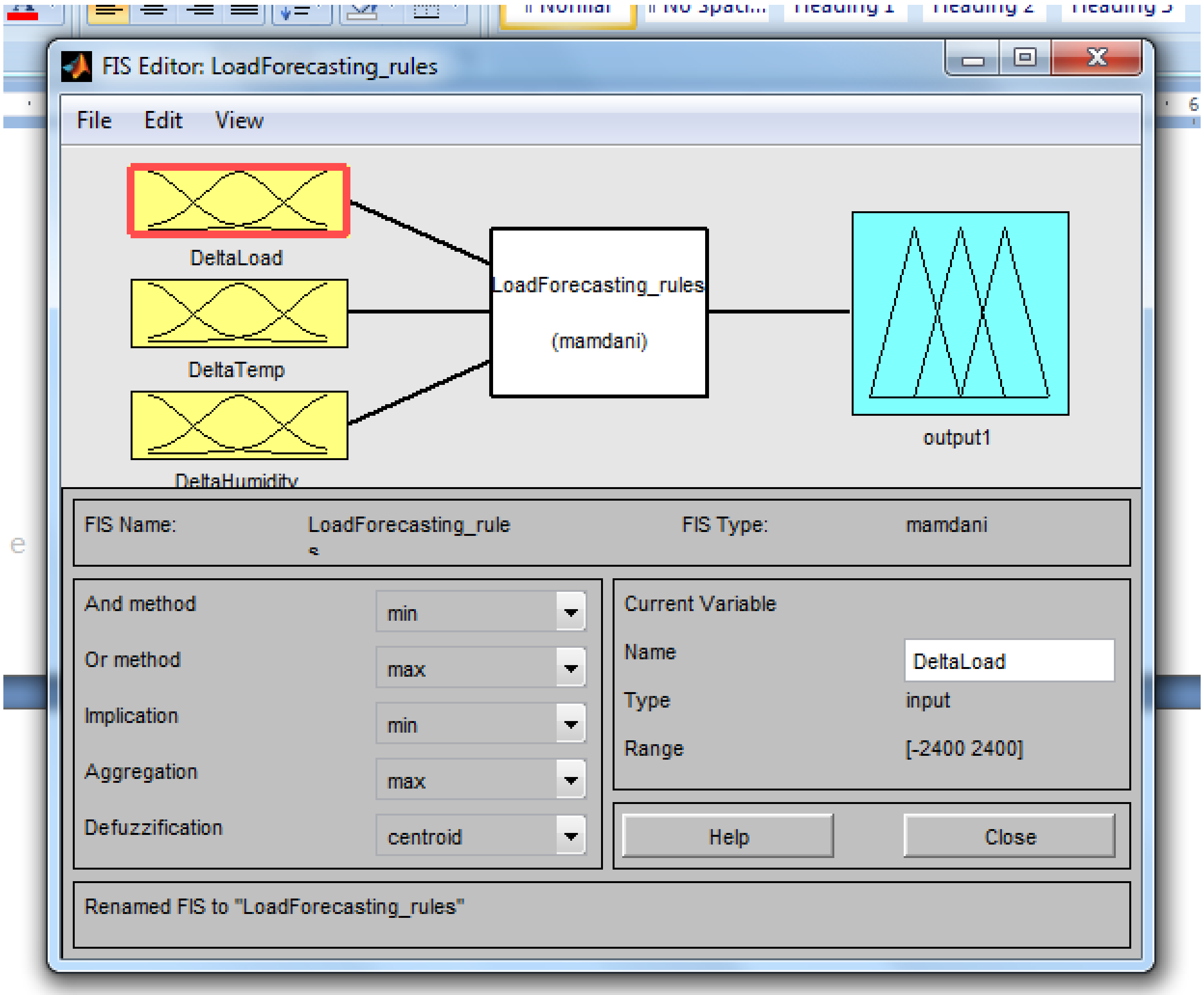
25-July:

Avg Load	Max Temp	Min Temp	Avg Temp	Avg Humi	Day Type	Date	EN
15107.3	84	69.2	75.6792	66.3292	7	25	0
16402.1	85.4	68.9	77.0625	69.475	6	31	44.53
15826.4	85.4	70	75.9792	69.4583	6	24	44.92
14660.8	87.2	66.2	77.4542	62.9583	6	3	58.47
17725.5	84.7	68.5	76.0917	68.1417	5	30	67.99
14533.4	89.3	72.8	79.4833	70.9417	7	4	69.1

26-July:

Avg Load	Max Temp	Min Temp	Avg Temp	Avg Humi	Day Type	Date	EN
16575.2	78.3	66.8	71.9125	65.9458	1	26	0
17709	83.6	66.2	73.5958	66.6625	1	19	47.2
17273.5	84.6	66.9	76.0333	65.2375	2	27	64.57
15732.3	78.3	62.9	70.4417	56.6208	2	20	94.1
15487.8	73.1	65.1	69.2083	65.9583	4	1	109.45
16690	83.9	68.6	76.1083	57.7792	3	7	109.69

APPENDIX III: FUZZY INFERENCE SYSTEM



Input variables

- **2_DT_MAX: Similarity based upon 2 day types and maximum temperature**

23-July:

	(E_L^k)	(E_T^k)	(E_H^k)
(set 1)	[136.4;	1.1584;	0.5333]
(set 2)	[-315.6;	1.1;	-2.3709]
(set 3)	[891.9;	2.4459;	1.3375]
(set 4)	[32.7;	-2.3875;	2.2291]
(set 5)	[1229;	1.55;	-3.1417]

24-July:

	(E_L^k)	(E_T^k)	(E_H^k)
(set 1)	[-575.7;	-1.0833;	-0.0167]
(set 2)	[719.1;	0.3;	3.1291]
(set 3)	[-354.5;	0.3375;	0.5458]
(set 4)	[1293;	-3.5041;	-1.4834]
(set 5)	[-1899.1;	-0.1125;	1.3166]

25-July:

	(E_L^k)	(E_T^k)	(E_H^k)
(set 1)	[-1133.8;	-1.6833;	-0.7167]
(set 2)	[1087.4;	2.7042;	-0.0125]
(set 3)	[57.2;	-2.8333;	1.5125]

(set 4)	[-698.3;	-4.1208;	0.7083]
(set 5)	[-1150.3;	-4.1792;	-2.1959]

26-July:

	(E_L^k)	(E_T^k)	(E_H^k)
(set 1)	[-719.1;	-0.3;	-3.1291]
(set 2)	[-1294.8;	-1.3833;	-3.1458]
(set 3)	[446.5;	-1.775;	3.3709]
(set 4)	[-2166.2;	-0.3541;	1.0917]
(set 5)	[-2302.6;	-1.5125;	0.5584]

- **7_DT_MAX: Similarity based upon 7 day types and maximum temperature**

23-July:

	(E_L^k)	(E_T^k)	(E_H^k)
(set 1)	[-315.6;	1.1;	-2.3709]
(set 2)	[32.7;	-2.3875;	2.2291]
(set 3)	[1229;	1.55;	-3.1417]
(set 4)	[891.9;	2.4459;	1.3375]
(set 5)	[2749.1;	-0.2625;	2.8125]

24-July:

	(E_L^k)	(E_T^k)	(E_H^k)
(set 1)	[-575.7;	-1.0833;	-0.0167]

(set 2)	[-354.5;	0.3375;	0.5458]
(set 3)	[-1899.1;	-0.1125;	1.3166]
(set 4)	[719.1;	0.3;	3.1291]
(set 5)	[1293;	-3.5041;	-1.4834]

25-July:

	(E_L^k)	(E_T^k)	(E_H^k)
(set 1)	[-719.1;	-0.3;	-3.1291]
(set 2)	[-1294.8;	-1.3833;	-3.1458]
(set 3)	[446.5;	-1.775;	3.3709]
(set 4)	[573.9;	-3.8041;	-4.6125]
(set 5)	[-1730.3;	-6.3833;	-0.9208]

26-July:

	(E_L^k)	(E_T^k)	(E_H^k)
(set 1)	[-1133.8;	-1.6833;	-0.7167]
(set 2)	[-698.3;	-4.1208;	0.7083]
(set 3)	[-2120.6;	-8.0875;	-3.8625]
(set 4)	[842.9;	1.4708;	9.325]
(set 5)	[1087.4;	2.7042;	-0.0125]

- **2_DT_MAX_MIN: Similarity based upon 2 day types and maximum-minimum temperature**

23-July:

	(E_L^k)	(E_T^k)	(E_H^k)
(set 1)	[136.4;	1.1584;	0.5333]
(set 2)	[891.9;	2.4459;	1.3375]
(set 3)	[-315.6;	1.1;	-2.3709]
(set 4)	[-299.1;	3.5959;	-0.8917]
(set 5)	[2302.6;	1.5125;	-0.5584]

24-July:

	(E_L^k)	(E_T^k)	(E_H^k)
(set 1)	[-575.7;	-1.0833;	-0.0167]
(set 2)	[719.1;	0.3;	3.1291]
(set 3)	[-1899.1;	-0.1125;	1.3166]
(set 4)	[1293;	-3.5041;	-1.4834]
(set 5)	[-2869.4;	-4.0208;	-0.35]

25-July:

	(E_L^k)	(E_T^k)	(E_H^k)
(set 1)	[-1294.8;	-1.3833;	-3.1458]
(set 2)	[-719.1;	-0.3;	-3.1291]
(set 3)	[-2618.2;	-0.4125;	-1.8125]
(set 4)	[-2166.2;	-0.3541;	1.0917]
(set 5)	[-2601.7;	2.0834;	-0.3333]

26-July:

	(E_L^k)	(E_T^k)	(E_H^k)
(set 1)	[-1133.8;	-1.6833;	-0.7167]
(set 2)	[1087.4;	2.7042;	-0.0125]
(set 3)	[394.3;	-3.7292;	-2.9667]
(set 4)	[57.2;	-2.8333;	1.5125]
(set 5)	[-698.3;	-4.1208;	0.7083]

- **7_DT_MAX_MIN: Similarity based upon 7 day types and maximum-minimum temperature**

23-July:

	(E_L^k)	(E_T^k)	(E_H^k)
(set 1)	[-315.6;	1.1;	-2.3709]
(set 2)	[891.9;	2.4459;	1.3375]
(set 3)	[2749.1;	-0.2625;	2.8125]
(set 4)	[32.7;	-2.3875;	2.2291]
(set 5)	[1007.8;	0.1292;	-3.7042]

24-July:

	(E_L^k)	(E_T^k)	(E_H^k)
(set 1)	[-575.7;	-1.0833;	-0.0167]
(set 2)	[-1899.1;	-0.1125;	1.3166]
(set 3)	[719.1;	0.3;	3.1291]
(set 4)	[-1583.5;	-1.2125;	3.6875]
(set 5)	[-354.5;	0.3375;	0.5458]

25-July:

	(E_L^k)	(E_T^k)	(E_H^k)
(set 1)	[-1294.8;	-1.3833;	-3.1458]
(set 2)	[-719.1;	-0.3;	-3.1291]
(set 3)	[446.5;	-1.775;	3.3709]
(set 4)	[-2618.2;	-0.4125;	-1.8125]
(set 5)	[573.9;	-3.8041;	-4.6125]

26-July:

	(E_L^k)	(E_T^k)	(E_H^k)
(set 1)	[-1133.8;	-1.6833;	-0.7167]
(set 2)	[-698.3;	-4.1208;	0.7083]
(set 3)	[842.9;	1.4708;	9.325]
(set 4)	[1087.4;	2.7042;	-0.0125]
(set 5)	[-114.8;	-4.1958;	8.1666]

Output variables

TABLE II. OUTPUT MEMBERSHIP FUNCTION PARAMETERS

(b1,b2,b3)	(-0.3,-0.25,-0.2)
(b3,b4,b5)	(-0.2,-0.15,-0.10)
(b4,b5,b6)	(-0.15,-0.10,-0.05)
(b5,b6,b7)	(-0.10,-0.05,0)
(b6,b7,b8)	(-0.05,0,0.05)
(b7,b8,b9)	(0,0.05,0.1)
(b8,b9,b10)	(0.05,0.1,0.15)
(b9,b10,b11)	(0.1,0.15,0.2)
(b10,b11,b12)	(0.15,0.2,0.25)
(b11,b12,b13)	(0.2,0.25,0.3)

FIS Rules

Input Variable 1 : (Load Difference) (mf1)

Input Variable 2 : (Temperature Difference) (mf2)

Input Variable 3 : (Humidity Difference) (mf3)

Rules are of the Form : "IF variable IS property THEN action"

TOTAL RULES POSSIBLE = 3 * 3 * 3 = 27 These Rules are defined before and are made on the generalised Knowledge.

Rule 1	IF mf1 is HIGH AND mf2 is HIGH AND mf3 is HIGH THEN OUTPUT is HIGH
Rule 2	IF mf1 is HIGH AND mf2 is HIGH AND mf3 is MEDIUM THEN OUTPUT is MEDIUM
Rule 3	IF mf1 is HIGH AND mf2 is HIGH AND mf3 is LOW THEN OUTPUT is MEDIUM
Rule 4	IF mf1 is HIGH AND mf2 is MEDIUM AND mf3 is HIGH THEN OUTPUT is HIGH
Rule 5	IF mf1 is HIGH AND mf2 is MEDIUM AND mf3 is MEDIUM THEN OUTPUT is MEDIUM
Rule 6	IF mf1 is HIGH AND mf2 is MEDIUM AND mf3 is LOW THEN OUTPUT is MEDIUM
Rule 7	IF mf1 is HIGH AND mf2 is LOW AND mf3 is HIGH THEN OUTPUT is HIGH
Rule 8	IF mf1 is HIGH AND mf2 is LOW AND mf3 is MEDIUM THEN OUTPUT is MEDIUM
Rule 9	IF mf1 is HIGH AND mf2 is LOW AND mf3 is LOW THEN OUTPUT is LOW
Rule 10	IF mf1 is MEDIUM AND mf2 is HIGH AND mf3 is HIGH THEN OUTPUT is HIGH
Rule 11	IF mf1 is MEDIUM AND mf2 is HIGH AND mf3 is MEDIUM THEN OUTPUT is MEDIUM
Rule 12	IF mf1 is MEDIUM AND mf2 is HIGH AND mf3 is LOW THEN OUTPUT is MEDIUM
Rule 13	IF mf1 is MEDIUM AND mf2 is MEDIUM AND mf3 is HIGH THEN OUTPUT is MEDIUM
Rule 14	IF mf1 is MEDIUM AND mf2 is MEDIUM AND mf3 is MEDIUM THEN OUTPUT is MEDIUM
Rule 15	IF mf1 is MEDIUM AND mf2 is MEDIUM AND mf3 is LOW THEN OUTPUT is MEDIUM
Rule 16	IF mf1 is MEDIUM AND mf2 is LOW AND mf3 is HIGH THEN OUTPUT is LOW
Rule 17	IF mf1 is MEDIUM AND mf2 is LOW AND mf3 is MEDIUM THEN OUTPUT is LOW
Rule 18	IF mf1 is MEDIUM AND mf2 is LOW AND mf3 is LOW THEN OUTPUT is LOW
Rule 19	IF mf1 is LOW AND mf2 is HIGH AND mf3 is HIGH THEN OUTPUT is MEDIUM
Rule 20	IF mf1 is LOW AND mf2 is HIGH AND mf3 is MEDIUM THEN OUTPUT is LOW
Rule 21	IF mf1 is LOW AND mf2 is HIGH AND mf3 is LOW THEN OUTPUT is LOW
Rule 22	IF mf1 is LOW AND mf2 is MEDIUM AND mf3 is HIGH THEN OUTPUT is MEDIUM
Rule 23	IF mf1 is LOW AND mf2 is MEDIUM AND mf3 is MEDIUM THEN OUTPUT is LOW
Rule 24	IF mf1 is LOW AND mf2 is MEDIUM AND mf3 is LOW THEN OUTPUT is LOW
Rule 25	IF mf1 is LOW AND mf2 is LOW AND mf3 is HIGH THEN OUTPUT is MEDIUM
Rule 26	IF mf1 is LOW AND mf2 is LOW AND mf3 is MEDIUM THEN OUTPUT is LOW
Rule 27	IF mf1 is LOW AND mf2 is LOW AND mf3 is LOW THEN OUTPUT is LOW