# Short Term Load Forecasting Using Fuzzy Logic In UiTM Shah Alam

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***Abstract* – This paper explains the load forecasting using fuzzy logic method. This technique allows a qualitative description of the system's characteristics and data without the need for exact mathematical formulations. It is demonstrated that Fuzzy Logic technique achieves a logical and practical answer of short-term load forecasting. The data of the load demand and temperature in this thesis are obtained from the Unit of Facilities in UiTM Shah Alam. The special day like forecast like religious festival were not assigned. Load forecasting is very important to the operation of Electricity companies such as Tenaga Nasional Berhad (TNB). From the load forecasting analysis and study, we can increase the energy efficiency and also the reliable operation of power system. By forecasting the load demand data, it will be an important component in planning generation schedules in a power system. In this paper, we focus on fuzzy logic based short term load forecasting. The purposed technique for implementing fuzzy logic based forecasting is by identification of the specific day and**

***Keywords – Fuzzy Logic, Short-term load forecasting, Fuzzy Membership Function, Rule based***

## I. INTRODUCTION

Load forecasting is a central and integral process in the planning and operation of electric utilities. Precise load forecasting helps the electric utility to make electrical consumption prediction, reduce usage of the energy and schedule device maintenance plan properly. Electric companies have mainly used simple forecasting models, like linear regression [1], genetic algorithms [2], econometric models [3]. Besides playing a key role in reducing the generation cost, it is also necessary to the reliability of power systems. With the recent development of new mathematical, data mining and artificial intelligence tools, it is possible to improve the forecasting result. With the recent trend of deregulation of electricity markets, short term load forecasting has gained more importance and bigger challenges.

Recently, application of artificial intelligence techniques has also been applied to midterm energy forecasting using either neural network [4],[5]. Traditional short-term load forecasting methods include classical multiply linear regression, automatic regressive moving average (ARMA), data mining models, time-series models and exponential smoothing models [6,7,8] . The use of fuzzy logic has received increased attention in recent years because of its usefulness in reducing the need for complex mathematical models in problem solving [9]. Fuzzy Logic's strong abilities in finding solutions made it easy to approximate any complicated non-linear relations. The ability of fuzzy logic to capture system dynamics qualitatively and execute this qualitative idea in a real time situation is an attractive feature for short-term load forecasting. In this paper the simulation was demonstrated with the fuzzyTECH 5.54 software [10].

## II. METHODOLOGY

Figure shows the flowchart for overall methods or steps that has been applied throughout the project.

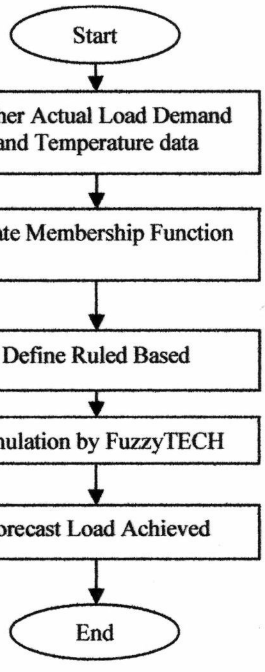


Figure 2.1. Flowchart of Overall Methods

*A. Short Term Load Forecasting Model*

This paper basically forecast the day load of the Menara S&T UiTM Shah Alam. Using FuzzyTECH 5.54 software, the model for study was developed, simulated, and analysed. The model have 3 input and 1 output, with ruled blocks.

**Input**

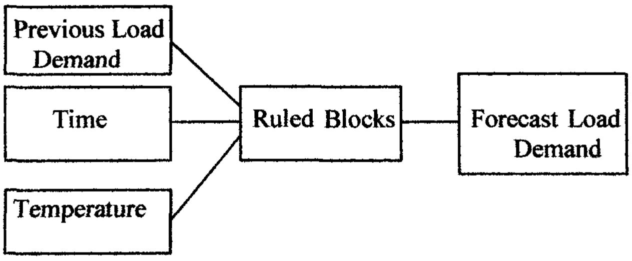


Figure 2.2. The model of short-term load forecasting

The previous load demand, temperature and time were specified as the input to the model. The output is load demand, which is the forecasted load demand at a given time variable. The input membership functions were assigned as follows: membership functions for the particular previous load demand were presented as, Prev {small, medium, large}. For the hourly temperature, the membership functions were reported as temp {low_temp, medium, high_temp}. There were 24 memberships for time, which indicated hourly time from midnight to next midnight, and this was represented as time {t00,t01 ...t23}.

The short-term load-forecasting model was applied for the task of hourly electrical load forecasting. Since the task is to forecast hourly, the input parameters are concerned with previous load demand, temperature and time. By following all the steps in Figure 2.2, the results of membership functions for all inputs were carried out. This data was classified as the input data. The output was presented as load demand. Table below shows the number of membership functions that were used in this model.

TABLE 2.1: MEMBERSHIP FUNCTION OF THE INPUT AND THE OUTPUT

| | |
|---|---|
| **Input** | |
| Previous load demand | 3 |
| Temperature | 3 |
| Time | 24 |
| **Output** | |
| Load demand | 3 |

*B. Fuzzy Sets of Input and Output*

After identifying the fuzzy variables related with input and output, the fuzzy sets defining these variables were selected and normalized between 0 and 1. The sets defining the input and output variables were as follows:

Previous load demand (MW)
= { small, medium, large }

Temperature (°C)
= {low_temp, medium_temp, high_temp}

Time (Hours) = {t00, t01, t02, ..., t22, t23}

Load Demand (MW)
= { small, medium, large}

The triangular and trapezoidal shapes are chosen for each fuzzy input and output variable for the membership functions. For convenience, approximately 25% to 50% is the suggested overlap between neighbouring sets.

*C. Rule Blocks*

Once these sets were established, the input variables were then related to the output variables by the If-Then rules. Generally, each rule can be represented in the following mode:

*If* (antecedent) *then* (consequence)

Previous load demand, temperature and time were considered as input variables and load demand as the output variable. For example:

*If* (previous load demand is small and temperature is low_temp and time is 00) then (load demand is small)

This relation can also be written as:

Load demand = {Previous load demand} *and* {Temperature} *and* {Time}

All steps taken in this method is performed through the fuzzyTECH. In this paper, the centroid or centre of gravity method was chosen to be the method for the defuzzification process. This method finds the point where a vertical line would slice the aggregate set into two equal masses.

Based on the relationship between input and output, total 628 rules were obtained. From 628, only 216 rules that usable in the thesis. In this thesis, the rules blocks that is usable is sets based on the rule blocks wizard in the fuzzyTECH software. Because of the time input that have no effect in this thesis, here are 9 rules that been implemented in this thesis. The sets of rules used here to derive the output are:

1. When time is 00, temperature is low and the previous load demand is small, then load demand is small.
2. When time is 00, temperature is low and the previous load demand is medium, then the load demand is medium.
3. When time is 00, temperature is low and the previous load demand is large, then the load demand is medium.
4. When time is 00, temperature is medium and the previous load demand is small, then the load demand is medium. .
5. When time is 00, temperature is medium and the previous load demand is medium, then the load demand is medium.
6. When time is 00, temperature is medium and the previous load demand is large, then the load demand is large
7. When time is 00, temperature is high and the previous load demand is small, then the load demand is medium.
8. When time is 00, temperature is high and the previous load demand is medium, then the load demand is medium.
9. When time is 00, temperature is high and the previous load demand is large, then the load demand is large

The rules that been set is same if the time is 00,01,02...23. So only 9 rules that's been used in this thesis.

TABLE 2.2: FUZZY RULES IN MATRIX FORM

| TEMP / LOAD | SMALL | MEDIUM | LARGE |
|---|---|---|---|
| LOW | SMALL | MEDIUM | MEDIUM |
| MED | MEDIUM | MEDIUM | LARGE |
| HIGH | MEDIUM | MEDIUM | LARGE |

## III. RESULT AND DISCUSSION

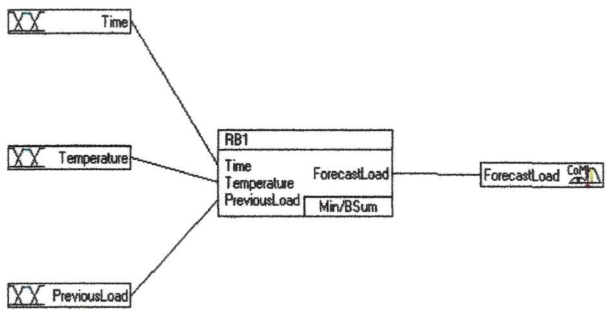


Figure 3.1. Diagram of Fuzzy Inferences in fuzzyTECH

As illustrated in figure 3.1, 3 inputs that is time, temperature and previous load have been used to determine the forecast load in Menara S&T UiTM Shah Alam. Between the input and the output is the rule blocks where we set the rules.

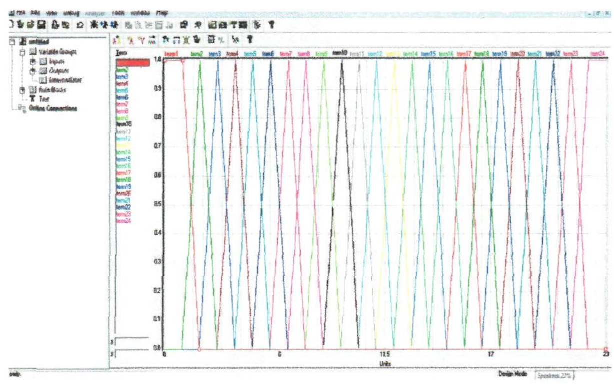

Figure 3.2. Input fuzzy variable 1, Time

Figure 3.2 shows the input for time. There are 24 terms in the time input that is 00,01,02,03...23 that corresponded to time. In the rule blocks, time doesn't have influence to the output. For example, if time is 00, temperature is low and previous load demand is small, then the forecast load is small and it's the same result if the time is 01,02,03...23.

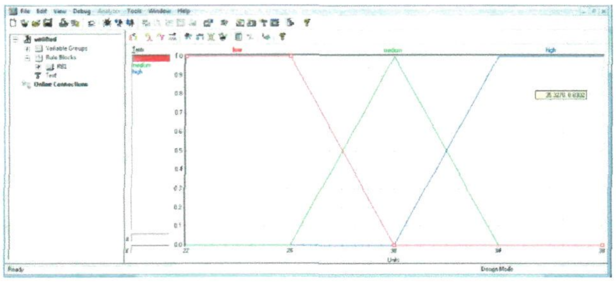

Figure 3.3. Input fuzzy variable 2, Temperature

Figure 3.3 shows the second input variable that is temperature. In the rule blocks the influence of the temperature to the forecast load is positive. In this input we set the range from low to high temperature from 22 to 38 C.

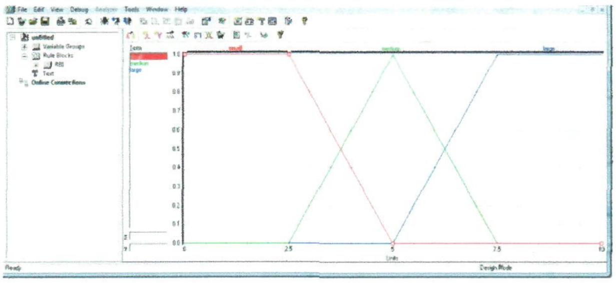

Figure 3.4. Input fuzzy variable 3, previous load demand

Figure 3.4 shows the third input variable that give the most influence to the output that is previous load demand. In fuzzyTECH, we set the range of load from 1 to 10.

This paper forecast the load of Menara S&T on Monday, February 18, 2013. The result of the forecast load is shown in the table 3.1 below. RE (Relative Error) and MAPE (Mean Absolute Percentage Error) were used to evaluate the result error.

$$FL = \frac{FL-AL}{FL} x100\% \quad (1)$$

$$MAPE = \frac{1}{n}\left[\frac{FL-AL}{FL}\right] x100\% \quad (2)$$

Where FL was the forecast load, AL was the actual load and n was the number of hours.

TABLE 2.3 : ERROR ANALYSIS ON MONDAY (18FEBRUARY 2013)

| Monday 18 February 2013(Hours) | Forecast Load (kW) | Actual Load(kW) | Relative Error(%) |
|---|---|---|---|
| 0000 | 1162 | 1178 | -1.38 |
| 0100 | 1123 | 1098 | 2.23 |
| 0200 | 1117 | 1045 | 6.45 |
| 0300 | 1106 | 1034 | 6.51 |
| 0400 | 1089 | 1095 | -0.55 |
| 0500 | 1063 | 1084 | -1.98 |
| 0600 | 1134 | 1109 | 2.20 |
| 0700 | 1178 | 1156 | 1.87 |
| 0800 | 1200 | 1189 | 0.92 |
| 0900 | 1213 | 1219 | -0.49 |
| 1000 | 1244 | 1223 | 1.68 |
| 1100 | 1278 | 1290 | -0.94 |
| 1200 | 1390 | 1378 | 0.86 |
| 1300 | 1423 | 1399 | 1.69 |
| 1400 | 1462 | 1423 | 2.67 |
| 1500 | 1498 | 1476 | 1.47 |
| 1600 | 1390 | 1413 | -1.65 |
| 1700 | 1376 | 1398 | -1.59 |
| 1800 | 1365 | 1334 | 2.27 |
| 1900 | 1298 | 1285 | 1.00 |
| 2000 | 1343 | 1298 | 3.35 |
| 2100 | 1356 | 1368 | -0.88 |
| 2200 | 1290 | 1309 | -1.47 |
| 2300 | 1284 | 1299 | -1.17 |
| | | MAPE (%) | 0.96 |

From the table above. The average error is 0.96%, with the highest error at 0300 hour which is 6.51 % (under forecast) and lowest error at 0500 hour which is 0.55% (under forecast). For error at peak hour which is 1100 to 1400 are considerably low. To find MAPE (%) we use equation (2).

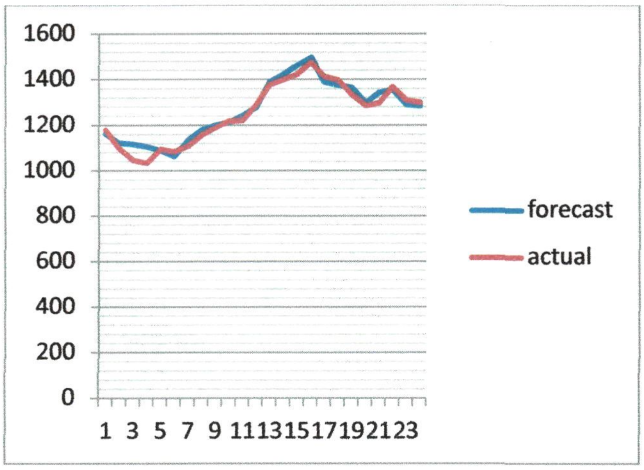


Figure 3.5. Curve for actual load and forecast load demand versus time (24hours)

## IV. CONCLUSION

Short-term load forecasting plays an important role in the planning and operations of power systems. The accuracy of this forecast value is important to decide when and where the station should shut-down or start-up. From this thesis, the work have been demonstrated using fuzzyTECH software and its shown by using this software, fuzzy logic method can be easily compute. Besides that it was demonstrated that the fuzzy logic technique could be alternative method to solve short term load forecast value.

## V. RECOMMENDATION

For future recommendation, this project could use other forecast technique such as artificial neural network (ANN), regression method or data mining. If possible, the input of the fuzzy can be add to improve the accuracy of the load forecast value.

## ACKNOWLEDGMENT

Firstly, I would like to thank my supervisor, Ir Harizan Bin Che Mat Haris for the all the guidance, teaching, and encouragement from the beginning of this project until it is done. Besides that, I also very thankful to all my friends for giving me support in morale and finance. Lastly, I offer my regards and blessing to my parents and those who were helping me in completing this project.

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