APPLICATION OF FUZZY LOGIC FOR SHORT TERM LOAD DEMAND FORECASTING

By

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FINAL YEAR PROJECT REPORT

Submitted to the Electrical & Electronics Engineering Programme
In Partial Fulfillment of the Requirements
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CERTIFICATION OF APPROVAL

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Approved:

Dr Nidal Kamel
Project Supervisor

UNIVERSITI TEKNOLOGI PETRONAS
TRONOH, PERAK

DECEMBER 2006

CERTIFICATION OF ORIGINALITY

This is to certify that I am responsible for the work submitted in this project, that the original work is my own except as specified in the references and acknowledgements, and that the original work contained herein have not been undertaken or done by unspecified sources or persons.

Norazlin Makhtar

ABSTRACT

This Final Year Project report presents the implementation of Fuzzy Logic techniques in designing the short term load demand forecasting model for Gas District Cooling (GDC) of Universiti Teknologi PETRONAS and New South Wales, Australia. The implementation of Fuzzy Logic technique was carried out by FuzzyTECH software. The performance of the forecast model is evaluated through the prediction for the days in the year 2005. The fuzzy forecasted load values are compared with the actual load to get the forecast accuracy. From the model error analysis, the Mean Absolute Percentage Error (MAPE) is about 1% to 6%. It shows that the forecast models still need an improvement in order to reduce errors until reach the acceptable accuracy level. The meteorological variables such as weather temperature, humidity is required in order to achieve high precision of STLF model.

ACKNOWLEDGEMENTS

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LIST OF ABBREVIATIONS

UTP	Universiti Teknologi PETRONAS
NSW	New South Wales
GDC	Gas District Cooling
STLF	Short Term Load Forecasting
FL	Fuzzy Logic
RB	Rule Block
MAPE	Mean Absolute Percentage Error
MBF	Membership Function

CHAPTER 1
INTRODUCTION

1.1 BACKGROUND OF STUDY

This thesis explores and implements the existing techniques for load forecasting in the electricity market. The study is more toward the load and analysis of the historical data and implementation of Fuzzy Logic technique in designing the load forecasting model. Case studies have been carried out for the Gas District Cooling (GDC) of Universiti Teknologi PETRONAS (UTP) and New South Wales, Australia.

1.2 PROBLEM STATEMENT

1.2.1 Problem Identification

In power system, it is essential to have accurate models to forecast the future load demand. Load demand forecasting is significant for efficient network operation, network planning, economic scheduling of generation units and also maintenance activities. However, forecasting problem can be complicated since many uncertainties in load demand arises due to fluctuation, losses in transmission line and change of weather conditions. These facts make it complex to deal with the power system problem only through mathematical formulation alone. Thus, introduction of Fuzzy Logic approach is the effective way to deal with these uncertainties.

1.2.2 Project Significant

Short term load demand forecasting is essential for the power system operation and planning since accurate forecast can improve the efficiency of daily operation. Throughout this project, the short-term load forecasting model will be designed using Fuzzy Logic technique.

1.3 OBJECTIVES AND SCOPE OF STUDY

1.3.1 Objectives of the project

The objectives of this project are:

1. To analyze the load behavior of Universiti Teknologi PETRONAS (UTP) and New South Wales, Australia
2. To design the accurate short term load forecasting model (STLF) using Fuzzy Logic approach

1.3.2 Scope of Study

Generally, the scope of study will cover the following areas;

1. Load demand in Universiti Teknologi PETRONAS and New South Wales, Australia
2. Electrical load demand forecasting model
3. Fuzzy Logic

1.4 PROJECT FEASIBILITY

This project takes two semesters to be completed. The first semester will be on research and study. The second semester will be concentrated on load analysis and model development. The adequate data for load forecasting will be obtained from Gas District Cooling (GDC) of UTP and lecturer. The time frame for this project in completing this project has been divided equally and feasible for the whole 2 semesters.

CHAPTER 2

LITERATURE REVIEW AND THEORY

2.1 LOAD DEMAND FORECASTING

Prediction of future events and conditions are called forecasts, and the act of making such predictions is called ***forecasting.*** Forecasting is a key element of decision making.

The major aim of short term load forecasting (STLF) is to provide load prediction for generation scheduling, economic load dispatch and security assessment at any time [1]. In broad terms, load demand forecasting can be categorized into long term and short term functions. Long-term load forecasting usually covers from one to ten years ahead (monthly and yearly values), which is used for applications in capacity expansion of generation and transmission, and long-term capital investment return studies.

While STLF is normally carried out from one day to one week ahead. Information derived from the STLF is vital to the system management of weekly, daily and hourly operation and generation units scheduling [1].

2.1.1 Parameter of Load Forecasting

There are several factors that give rise to load forecasting, which can be classified to three key factors;

1. Time factor
2. Meteorological condition
3. Random factor

Time factor includes time of year, day of the week and hour of the day. It is essential because there are cyclic behavior (daily and weekly rhythms) as well as occurrences of public holiday. The load on weekdays also behaves differently due to synchronous behavior of people during the day [2]. Meteorological conditions such as temperature, humidity and wind speed also can lead to variation of the load demand [3].

Random factors also cause the instability in load forecasting [3]. The possibility of unexpected events, like equipment breakdown or strikes can cause large unpredictable disturbances in the load level. In the case of UTP load usage, the social and behavioral factors such as big event, holiday and study week affects the load.

2.1.2 Load Demand Forecasting Techniques

Due to increasing pressure on the need for accurate load forecasts, numerous models have been proposed for the short-term load forecasting problem. It can be classified into to basic types; time series and expert systems.

Time series model

Time series methods are based on the assumption that the data have internal structure such as autocorrelation, trend and seasonal variation. The example of time series model are ARIMA (autoregressive integrated moving average ARMA (autoregressive moving average. Time series models are typically more accurate, but are also more complex and require large amounts of historical data. Additionally, careful effort must be made to insure an accurate time line throughout the data collection, filtering, modeling, and recall processes

Expert system [2]

Expert system has been also used in load forecasting. These systems are heuristic models that usually can include both quantitative and qualitative factors. A typical approach is trying to imitate the reasoning of a human operator. A popular techniques has been developed is based on Fuzzy Logic. Another technique is Neural Network. Neural network train the network using real load data from the past.

2.2 FUZZY LOGIC TECHNIQUE

Fuzzy Logic theory was first introduced by Professor Lotfi A. Zadeh in 1965. Fuzzy system based on the concepts of fuzzy set theory, fuzzy if then rules and fuzzy reasoning. Fuzzy Logic is based on **IF X AND Y THEN Z** approach [4]. A fuzzy rule can be defined as conditional statement in the form:

If x is A

Then y is B

Where x and y are linguistic variables, A and B are *linguistic values* determines by fuzzy sets on the universe of discourses x and Y, respectively [4]. These terms are imprecise and yet very descriptive of what must actually happen. The structure of fuzzy inference consists of three conceptual components, namely;

1. Rule Base containing a selection of fuzzy rules
2. Database defining the membership function
3. Reasoning mechanism that performs the inference procedure upon the rules and fact and derives a reasonable output.

In Fuzzy Logic system, the De-Fuzzification method is performed to extract a crisp value that represents the fuzzy output. With such crisp input and outputs, a fuzzy logic system implements a non-linear mapping from input to output. This mapping is accomplished by IF-THEN rules that describe the behavior of mapping. Figure 1 below illustrates this clearly.

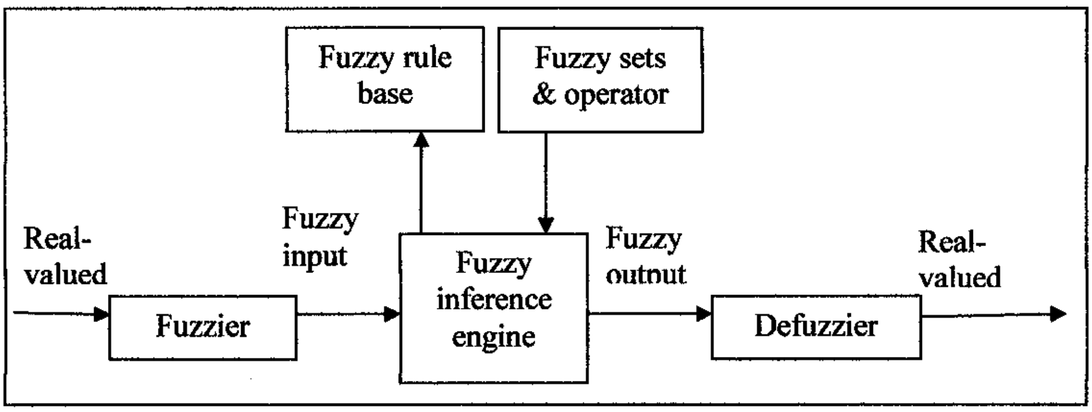

FIGURE 1: Basic Components of Fuzzy System

CHAPTER 3

METHODOLOGY

The proposed development and implementation of fuzzy logic based algorithm for load forecasting consists of several stages. In computing the Fuzzy Logic, a software called FuzzyTECH is required. This software provides simple yet powerful user interface for developing the forecasting model. FuzzyTECH can be linked together with Microsoft Excel for data interfacing.

3.1 Design Fuzzy Rule Base

This stage consists of six steps as follows;

1. Define the objectives and criteria required
2. Identify the list of input and output variables using load analysis and operator experience.
3. Select the shape of fuzzy membership function for each variables
4. For each input and output variables, defined the number of fuzzy membership function
5. Use the fuzzy membership function to determine the membership values for each variable.
6. Construct the fuzzy rule from each pair of input and output variables, based on IF THEN rules.

3.2 Compute the Point Forecast Value

After the rule base is assigned, it is ready to use forecasting. A method called defuzzification is performed to determine the point estimate of the forecast from the fuzzy forecasts. This approach produces a numerical forecast sensitive to all the rules.

3.3 Test the Performance of Rule Base

After the fuzzy rule base is identified and a defuzzification algorithm is selected, forecast accuracy is tested using historical data set from the one used to obtain the rule base. If it is unsatisfactory, then number of fuzzy membership and/or shape of fuzzy membership functions can be changed and new fuzzy rule base is obtained. Testing system performance can be done for several times until get the minimum error for the test set.

The error analysis requires the calculation of percentage of absolute error using the formula below;

$$\% \text{ Absolute Error} = \frac{|\text{Actual Load} - \text{Forecasted Load}|}{\text{Actual Load}} \times 100\%$$

To evaluate the whole performance of forecast result, the Mean Absolute Percentage Error (MAPE) is used. The formula given by;

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{P_A^i - P_F^i}{P_A^i}\right| \; x \; 100\%$$

Where PA is the actual load, PF is the forecasted load and N is the number of data points.

3.4 Real Time Forecasting

Real time forecasting is performed in several steps. First, the operator will obtain the historical value of maximum and minimum load demand of previous day and it will be used as the input for forecasting system. Second, the values of fuzzy membership functions are computed for each input values. Then, by each rule, the fuzzy membership values of the output function are computed. Then, the load forecast is obtained.

Figure below simplifies the system design approach of this project.

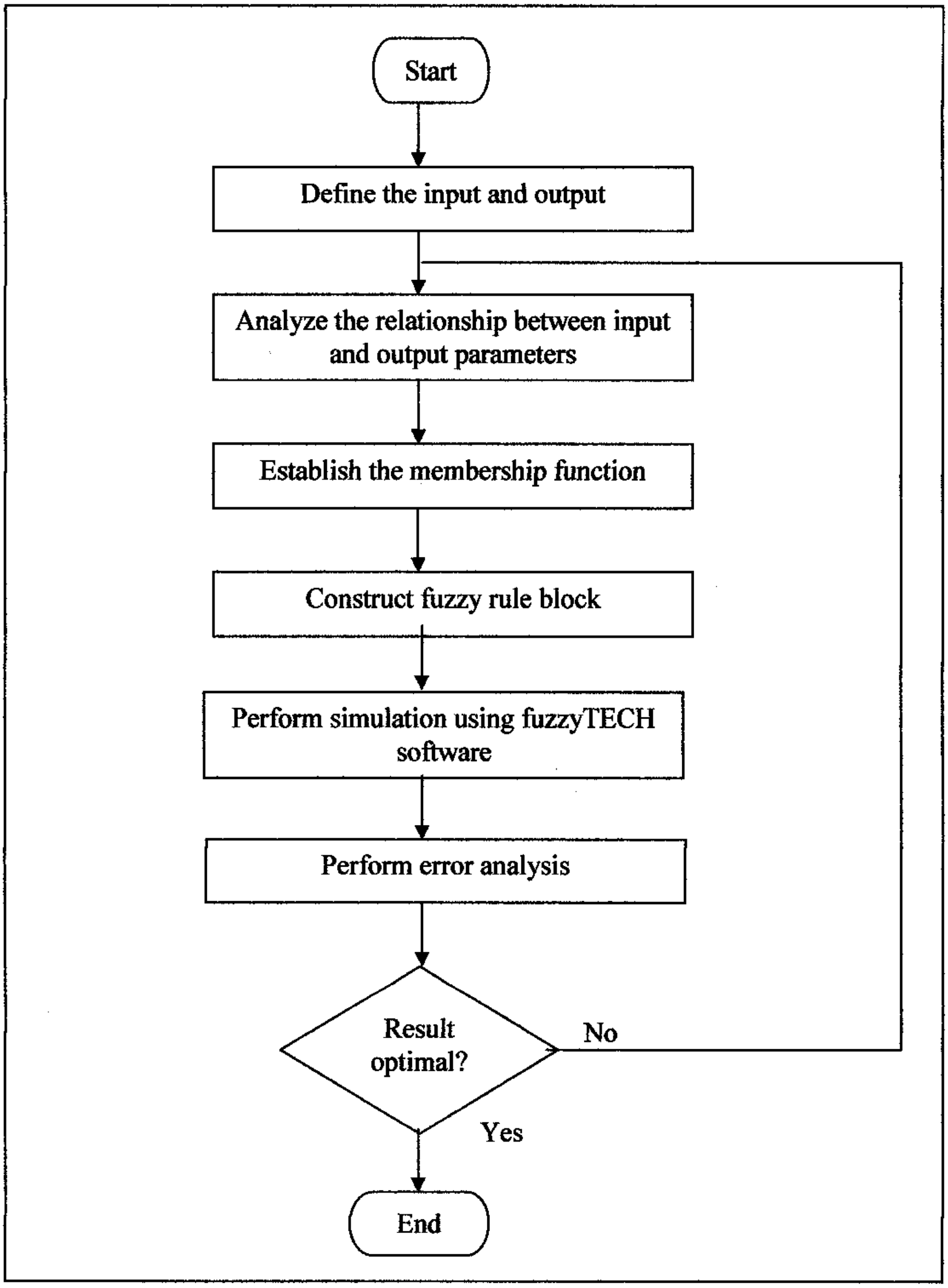

FIGURE 2: Design Flowchart of Fuzzy Logic

CHAPTER 4

RESULTS AND DISCUSSION

The outcome of this project is involved the data analysis and STLF model for two separate part, which are UTP and New South Wales, Australia.

4.1 UTP LOAD DATA ANALYSIS

The data used for analysis validation go from April 2005 to September 2005. Load pattern is not constant for 24hours in a day, see Figure 3. It keeps changing from hour to hour. It has overnight minimum, mid day peak, evening peak, and late high.

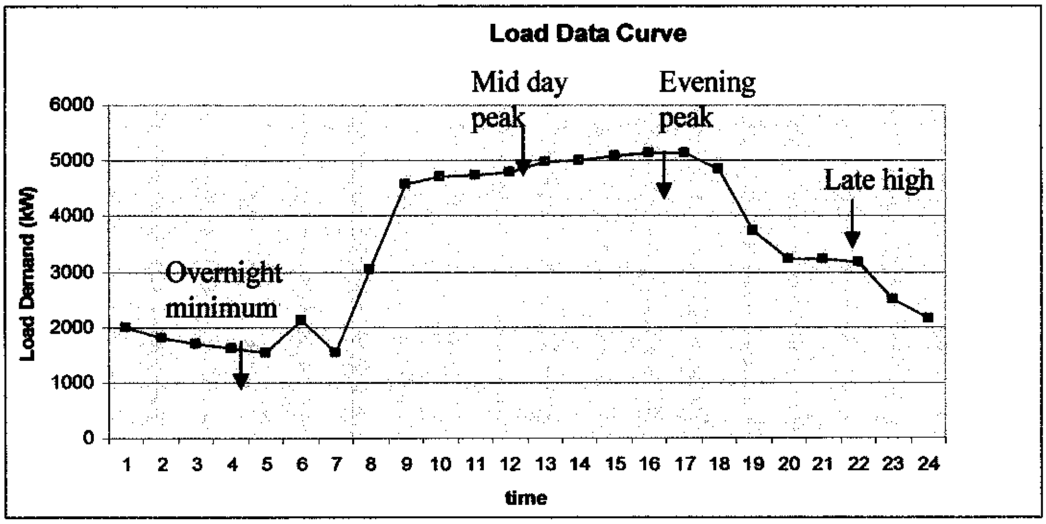

FIGURE 3: Typical load curve pattern for a day

Similarly, the week load is not constant for all 7days. It changes from weekdays to weekdays. However, there are cyclic effects for the load data, see Figure 3 It can be observed starting from working day; the weekend rhythm is followed by most people. The Monday to Friday, which is weekdays has the similar patterns. From the Figure 4, it shown that the load is higher during working days compared to Saturday and Sunday. Saturday and Sunday display lower demands than workdays, with Sunday having lowest demand. A closer inspection of the data reveals that there is slightly variation during workdays. There are generally less demand on Friday that other workdays. The daily rhythm takes place because of the synchronous behavior of people during the day. Most of people sleep at night; consequently the load is low during night hours. Moreover during the day, many activities tend to be simultaneous for most people.

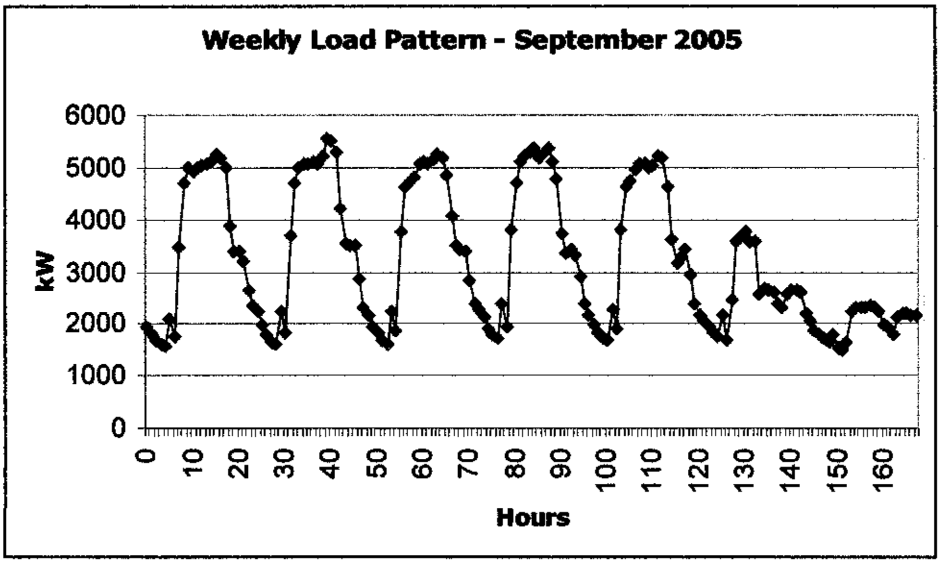

FIGURE 4: Weekly Load Pattern

Based on the monthly demand of load during September 2005, the same weekly pattern is repeated.

4.2 NEW SOUTH WALES LOAD DATA ANALYSIS

The sample data used in this analysis included the value of 24hours load demand in MW from December 2004 to December 2005. Located in the southern hemisphere and known as an island continent, Australia has diverse range of climatic zones, which are spring, summer, autumn and winter. The load data shows four distinct seasons. Each season is characterized by a distinct load behavior.

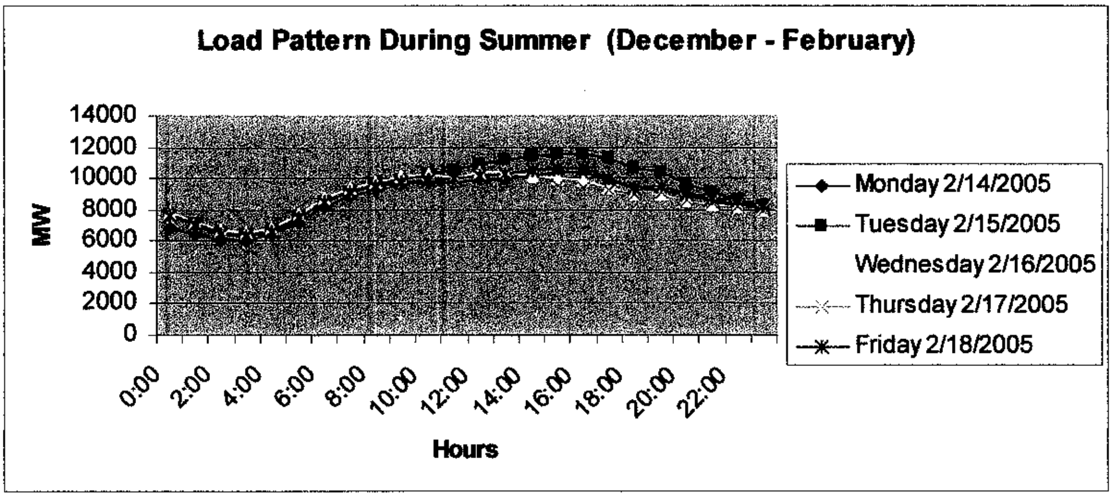

FIGURE 5: Load Pattern during Summer Season

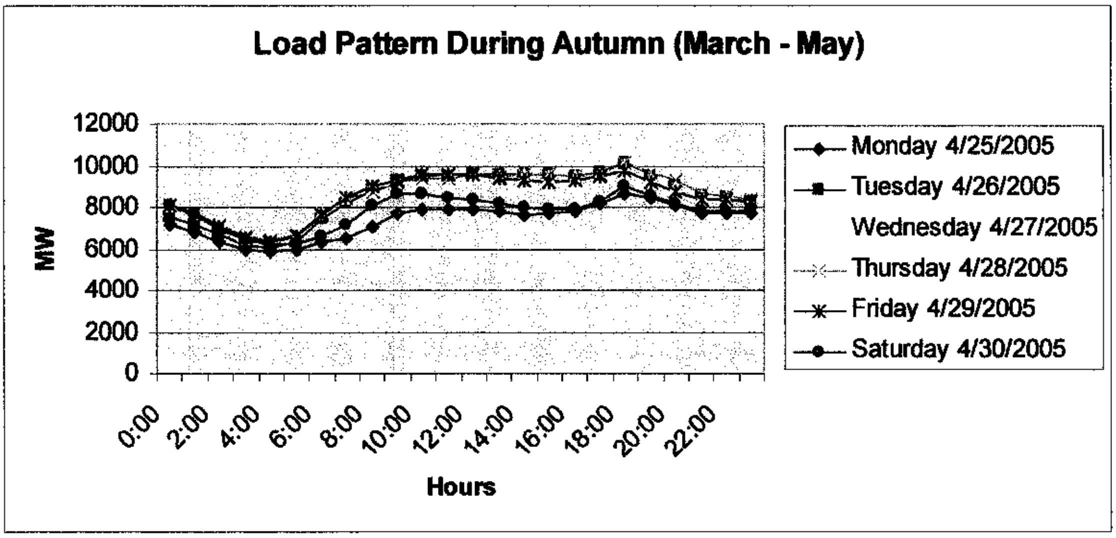

FIGURE 6: Load Pattern during Autumn Season

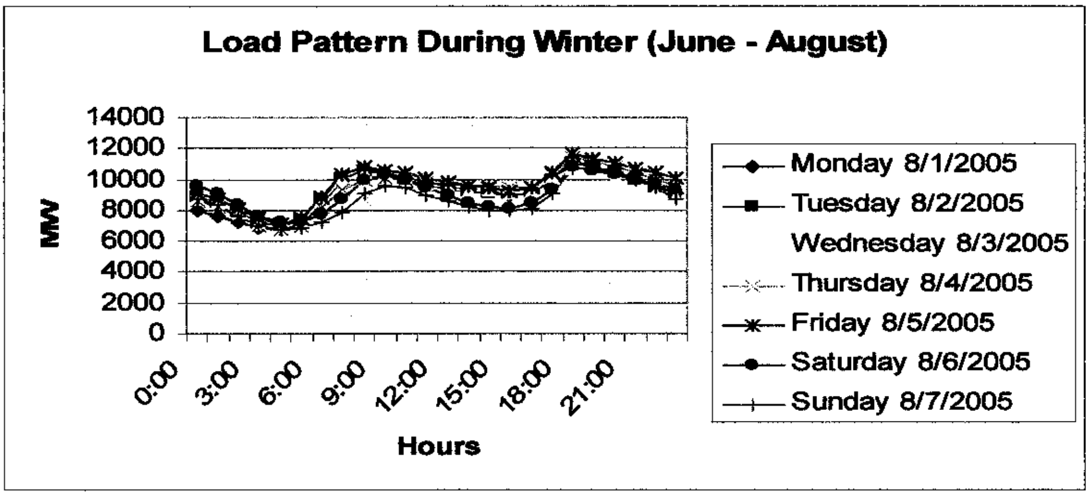

FIGURE 7: Load Pattern during Winter Season

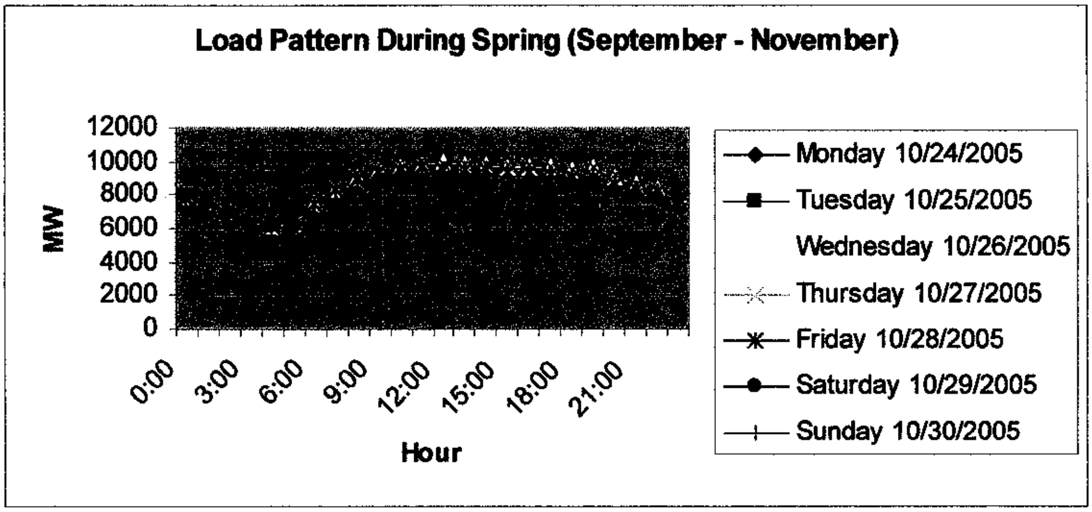

FIGURE 8: Load Pattern during Winter Spring

Based on the graph shown above, it can be observed that load pattern is not constant for 24hours in a day [1]. It varies throughout days of the week and seasons. However, for load behavior for each seasons are following the usual seasonal pattern.

4.3 FUZZY LOGIC IMPLEMENTATION

Using FuzzyTECH software, the short-term load forecasting model is designed & tested. One of the attractive features in FuzzyTECH software is that the fuzzy rule is capable of easily created and adding the membership function of each variable to the existing one.

There are separates model designed for each load analysis which are, GDC of UTP and New South Wales, Australia. For UTP load analysis, there are one model is designed to complement the days in a week. While for New South Wales, there are separate model for every seasons

For each model, it consists of 3 parts, which are;

- Fuzzy Input
- Fuzzy Rule Block
- Fuzzy Output

For each fuzzy input and output variables, its has own membership function. Each membership function is defined for any input value by the degree of membership function. An input variable may consist of more than one term and all terms are associated together and displayed in one graph.

Fuzzy Rule Block is the heart of the fuzzy system where the control strategy is lies within. Using linguistic variable, the operator will be able to determine how the input affect the output, based on the IF-THEN rule. All the rule is based on the analysis of previous load data with expert opinion. The fuzzyTECH software simplifies the operation by having the operator only to manipulate the linguistic variables.

4.3.1 UTP Model Structure

Fuzzy Logic approach proposed can be used to aid forecast a week ahead of 24hours basis load demand (kW) during weekdays (Monday to Friday) which are from 10th October until 14th October 2005. October 2005 is the latest data that author obtained from GDC.

There is one model (Weekday Model) to complement the forecast for 5days in a week. Only one model is used to forecast 5days because it has similar day pattern as shown in the load analysis earlier. 2months historical data of August 2005 and September 2005 are used to forecast the load demand during October 2005. The forecast model which is generated at the FuzzyTECH software is shown in the Figure 9.

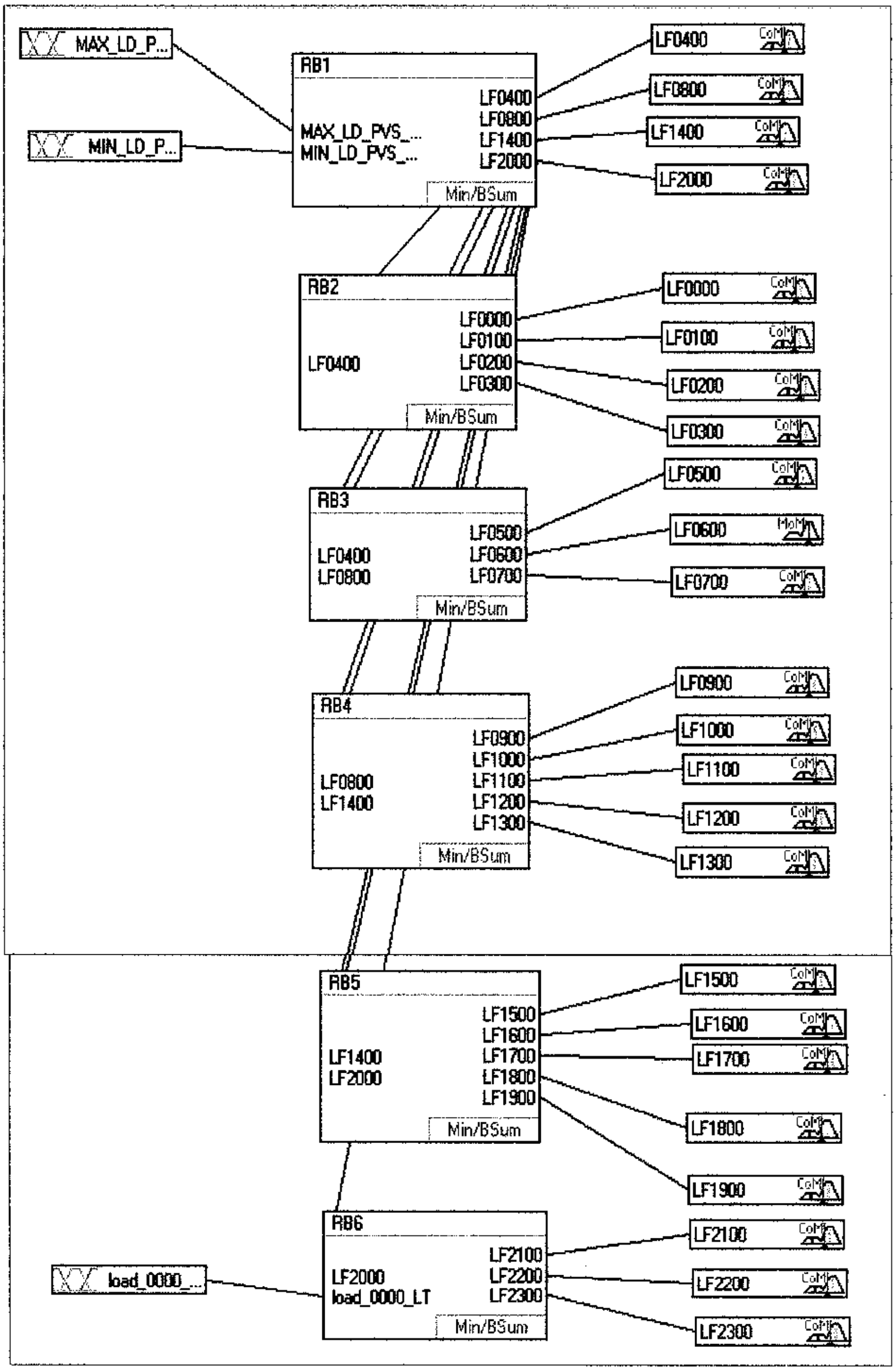

FIGURE 9: STLF Model structure for UTP Forecast

This system has in total three input and 24 hours output variables. The input variables are;

I. Maximum Load Demand of Previous Day

II. Minimum Load Demand of Previous Day

III. Load Demand at 12am of 6days earlier

Input variables of **I** and **II** are used to forecast at the 0400, 0800, 1400, and 2000. These four points are considered as important hours based on the load analysis. Meanwhile, the output variables are the load forecast for 24hours basis. The minimum and maximum output values for each parameter are based on the data from the past two months.

4.3.2 New South Wales, Australia Model Structure

There are 4 models used to forecast the load demand for seasonal load. The data from December 2004 to December 2005 is used to develop the model that forecast weekdays in each seasons. The models below are used to forecast the following date;

- Summer (December – February) The date chosen for forecast is 14^{th} to 18^{th} February 2005
- Autumn (March – May) The date chosen for forecast is 2^{nd} to 6th May 2005
- Winter (June - August) The date chosen for forecast is 8^{th} to 12^{th} August 2005
- Spring (September – November) The date chosen for forecast is 10^{th} to 14^{th} November 2005

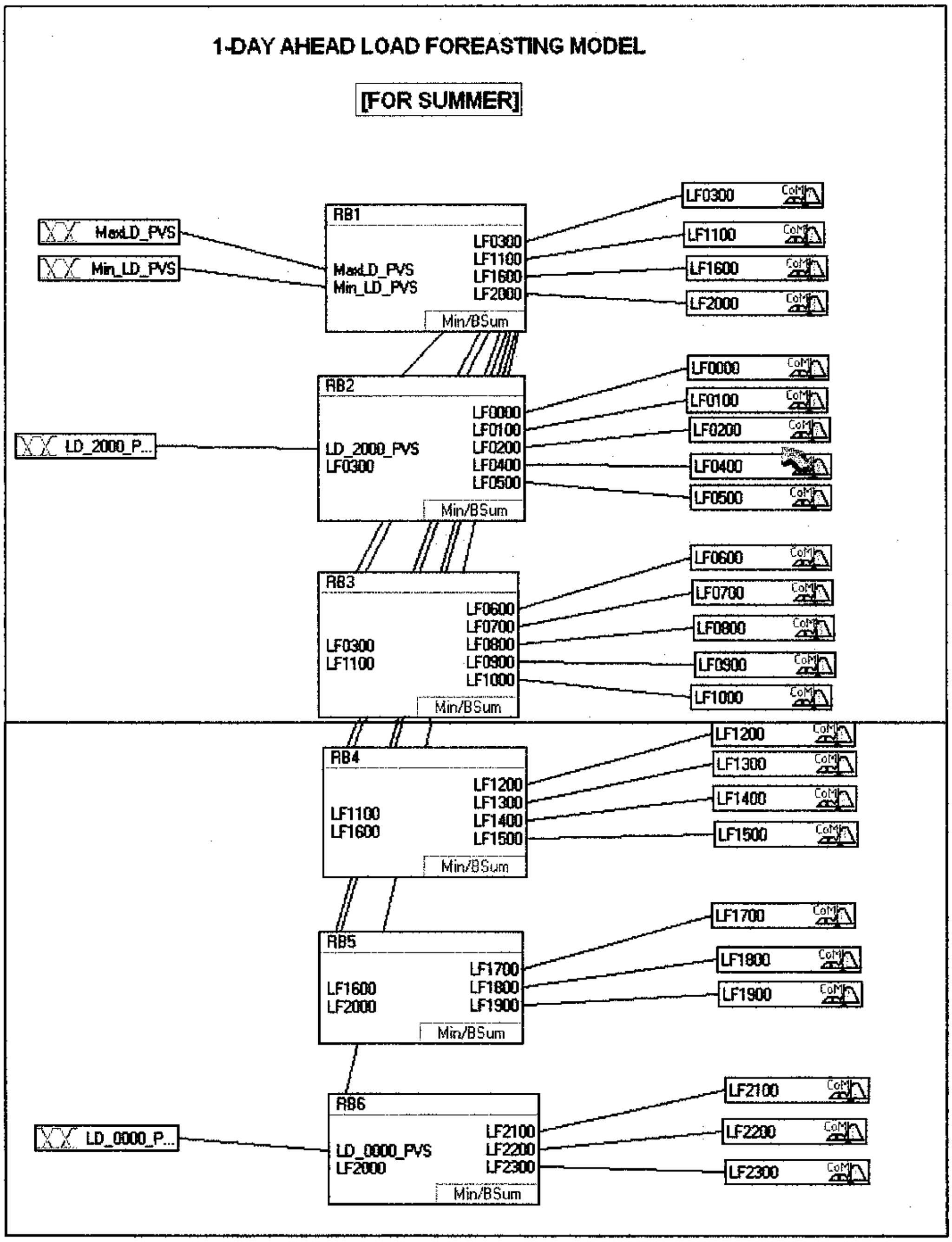

FIGURE 10: STLF Model structure for Summer Forecast

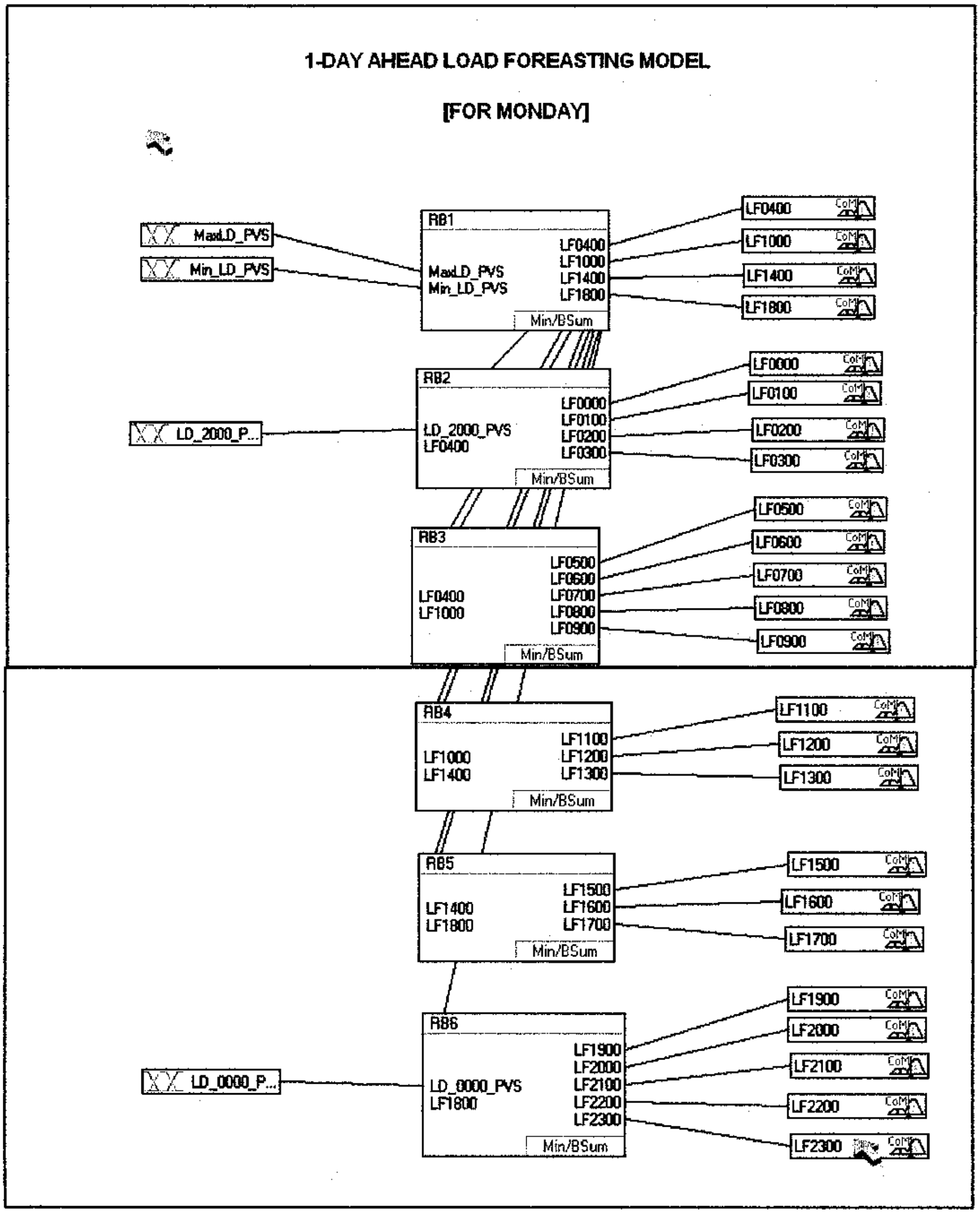

FIGURE 11: STLF Model structure for Autumn Forecast

The forecast model for summer, autumn, winter and spring have the same model pattern since they have relatively similar load pattern.

Each system has in total 3 input variables and 24 output variables altogether. The inputs variables are;

I. Maximum Load Demand of Previous Day
II. Minimum Load Demand of Previous Day
III. Load Demand at 12am of 6days earlier
IV. Load Demand at 2000 of Previous Day

For each seasonal model, input variables of **I** and **II** are used to forecast at the four points (e.g. for summer model, the four points are 0400, 0900, 1300, 1900) that considered as important hours based on the load analysis. The reason for input no. **IV** is to be able to forecast the load demand of next day on the night before. The output variables are the load forecast for 24hours basis.

4.4 FORECAST RESULTS

To ease results simulation for all users, a DDE (Dynamic Data Exchange) Link user interface is created from FuzzyTECH to Microsoft EXCEL. The user interface is shown below. This interface requires the user to enter the necessary value of model input variables before producing the output, which is the forecasted load demand. Below is the DDE Link at the Microsoft Excel

USER INTERFACE OF 1 DAY AHEAD LOAD FORECASTING MODEL

PLEASE ENTER THE FORECAST DATE (mm/dd/yy) :		5/3/2005
PLEASE ENTER THE MAXIMUM DEMAND OF	**May 2, 2005**	8744
PLEASE ENTER THE MINIMUM DEMAND OF	**May 2, 2005**	5886
PLEASE ENTER THE DEMAND ON 00:00 OF	**April 27, 2005**	[redacted]
PLEASE ENTER THE DEMAND ON 20:00 OF	**May 2, 2005**	[redacted]

FIGURE 12: DDE Links

4.4.1 UTP Model Forecast Results

Input Variables

The model will present the forecasting results from Monday (10th October 2005) to Friday (14th October 2005).

TABLE 1: Input Parameters, UTP

Input Variable	Values (kW)				
	Monday	Tuesday	Wednesday	Thursday	Friday
Maximum load demand (previous day)	2640	5160	5111	5108	5324
Minimum load demand (previous day)	1914	1935	2023	2052	1993
Load demand at 0000 (Last Saturday)	2206	2284	2377	2199	2198

Comparison between forecast values and actual values determine from the load analysis also can be observed in the same graph.

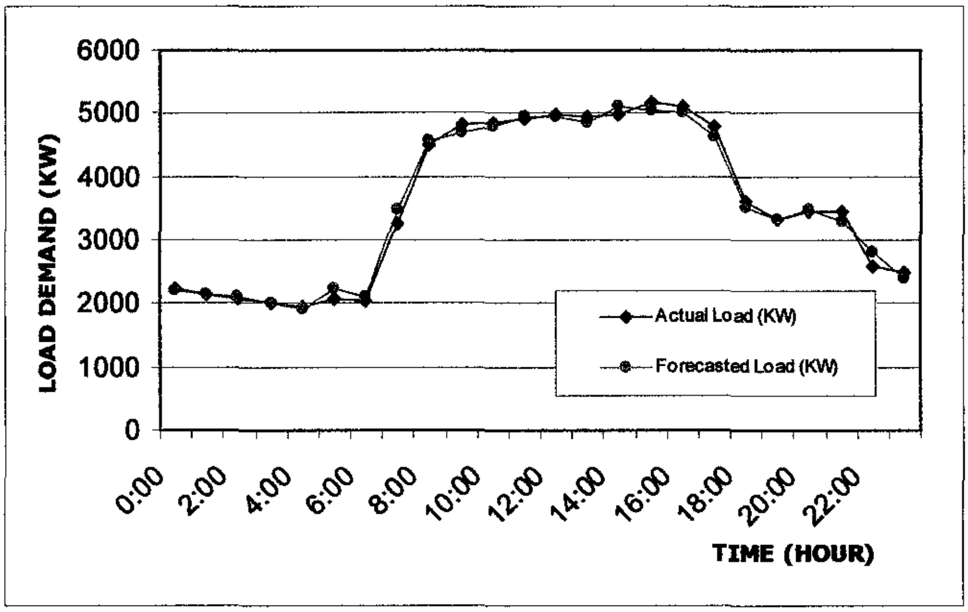

FIGURE 13: Forecasted and Actual Load for Monday 10th October 2005

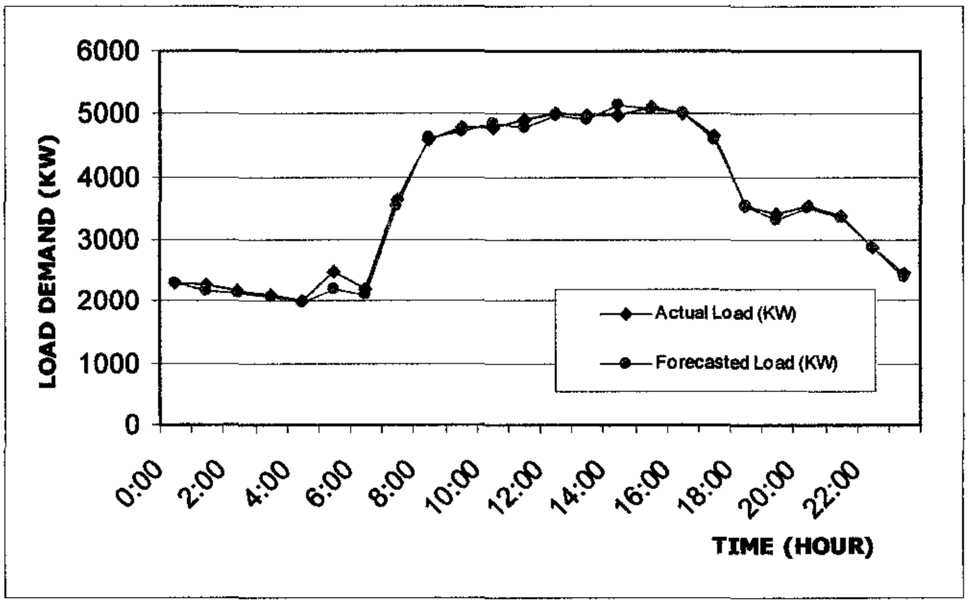

FIGURE 14: Forecasted and Actual Load for Tuesday 11th October 2005

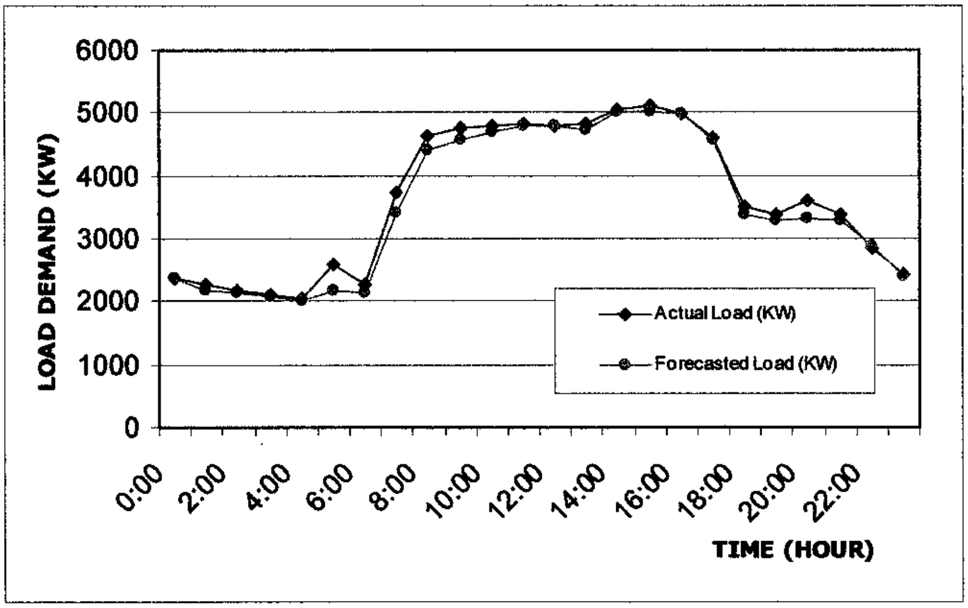

FIGURE 15: Forecasted and Actual Load for Wednesday 12th October 2005

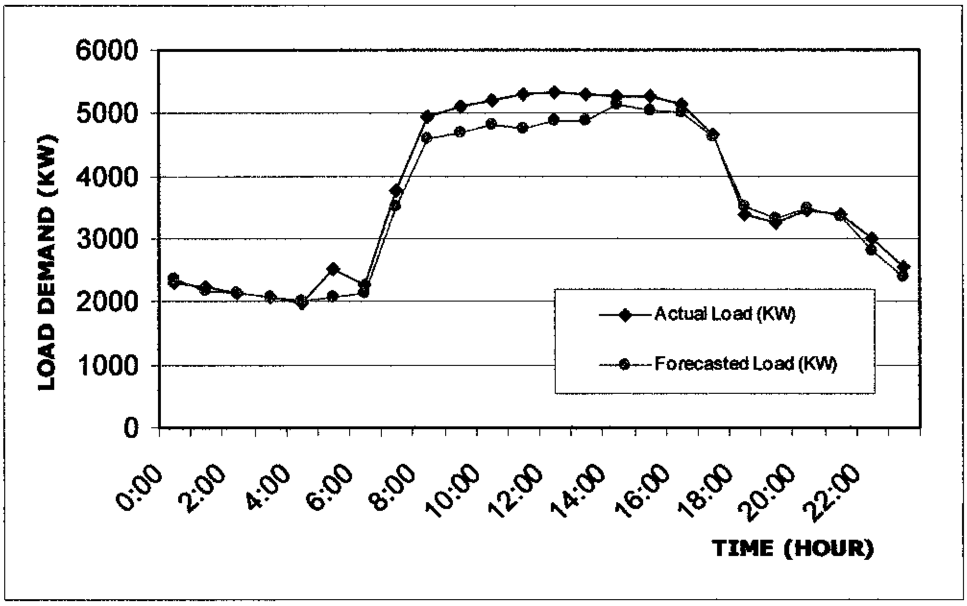

FIGURE 16: Forecasted and Actual Load for Thursday 13th October 2005

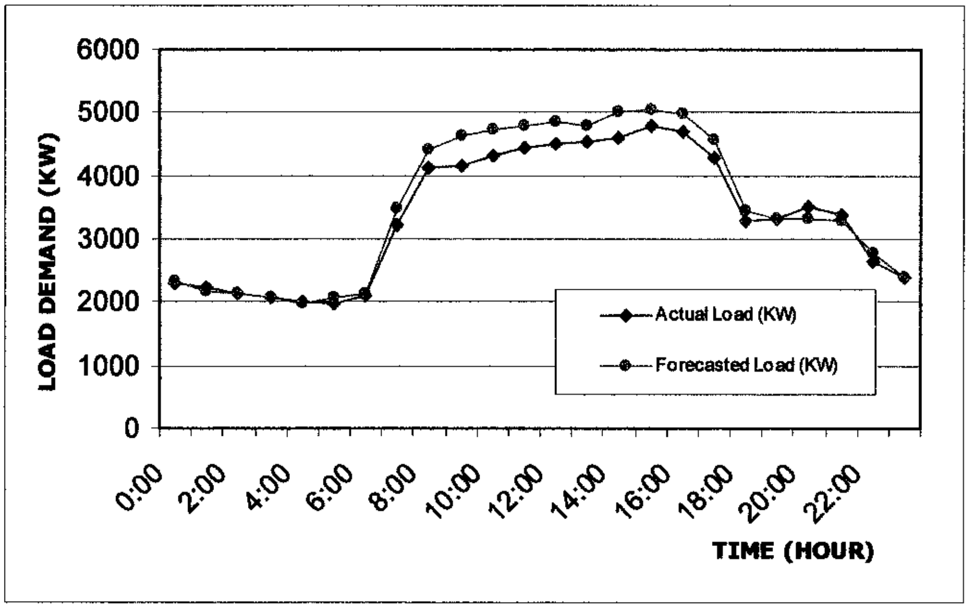

FIGURE 17: Forecasted and Actual Load for Friday 14th October 2005

4.4.2 New South Wales, Australia Model Forecast Results

__Input Variables__

The model will present the forecasting results for the following days;

- Summer (December – February) The date chosen for forecast is 14th to 18th February 2005
- Autumn (March – May) The date chosen for forecast is 2nd to 6th May 2005
- Winter (June - August) The date chosen for forecast is 8th to 12th August 2005
- Spring (September – November) The date chosen for forecast is 10th to 14th November 2005

TABLE 2: Input Parameters, NSW

Date	Input Variables			
	Max Load Demand (previous day)	Min Load Demand (previous day)	Load Demand at 2000 (previous day)	Load Demand at 0000 (6days earlier)
14-02-05	8008	5914	7914	7734
15-02-05	10394	6040	8910	8182
16-02-05	11588	6378	9636	7592
17-02-05	10366	6526	8592	7518
18-02-05	9614	6364	8640	7514
02-05-05	8698	5934	8386	7508
03-05-05	10104	6082	9176	8076
04-05-05	10038	6344	9156	8080
05-05-05	9994	6310	9032	8098
06-05-05	9988	6326	9176	8106
01-08-05	9994	6480	9744	8838
02-08-05	11158	6696	10486	8838
03-08-05	11036	6974	10492	8906
04-08-05	10718	6836	10016	9090
05-08-05	11158	6696	10846	9152
10-10-05	8744	5886	8412	7386
11-10-05	9366	6144	8892	7944
12-10-05	9418	6394	8972	7966
13-10-05	9478	6326	9058	8008
14-10-05	9536	6336	9048	8120

Comparison between forecast values and actual values determine from the load analysis also can be observed in the same graph.

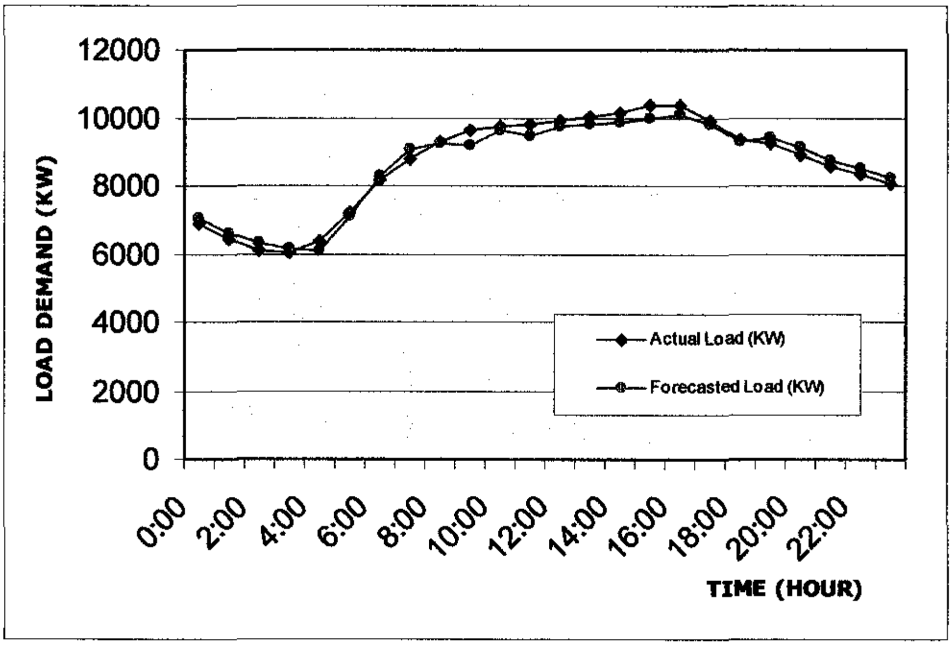

FIGURE 18: Forecasted and Actual Load for Monday 14th February 2005

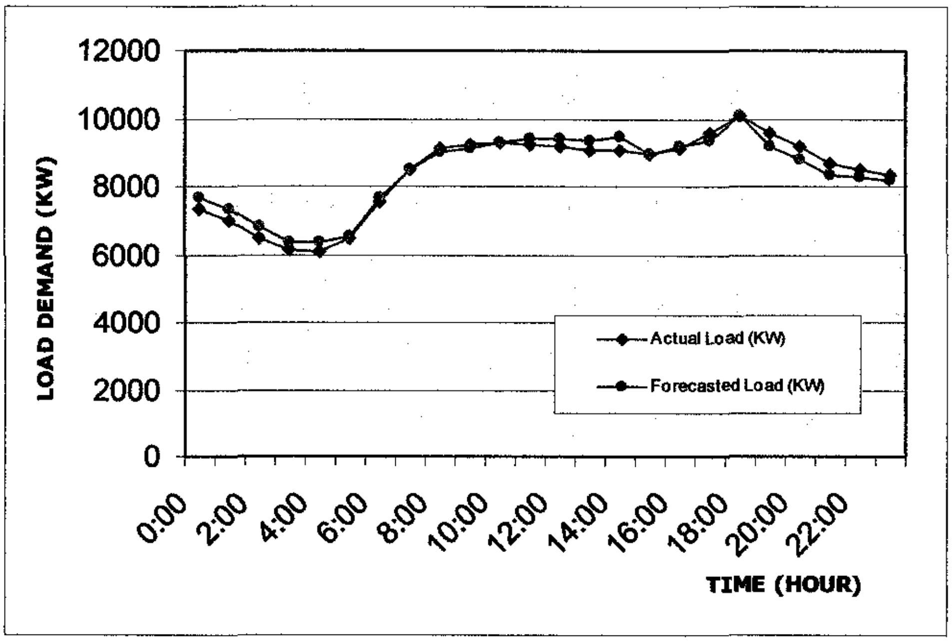

FIGURE 19: Forecasted and Actual Load for Monday 2nd May2005

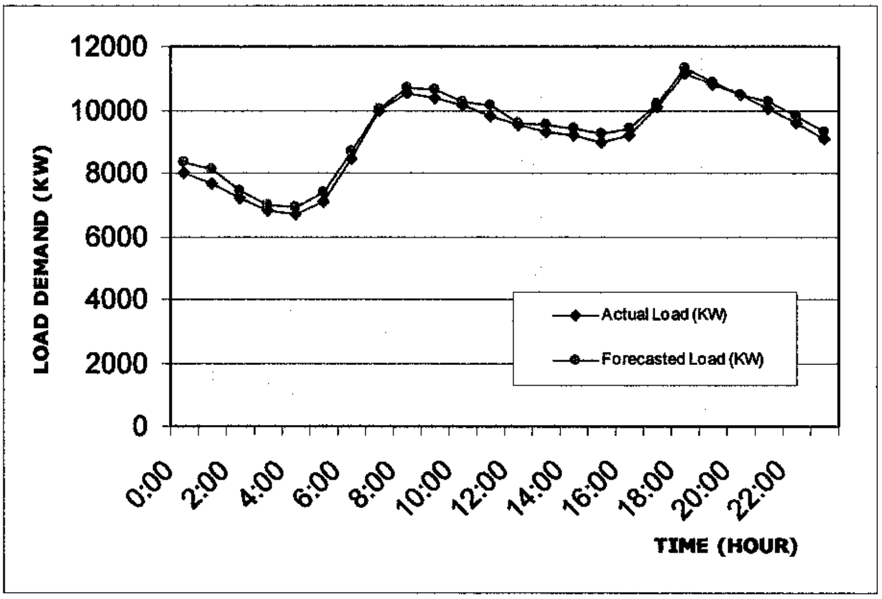

FIGURE 20: Forecasted and Actual Load for Monday 2nd August 2005

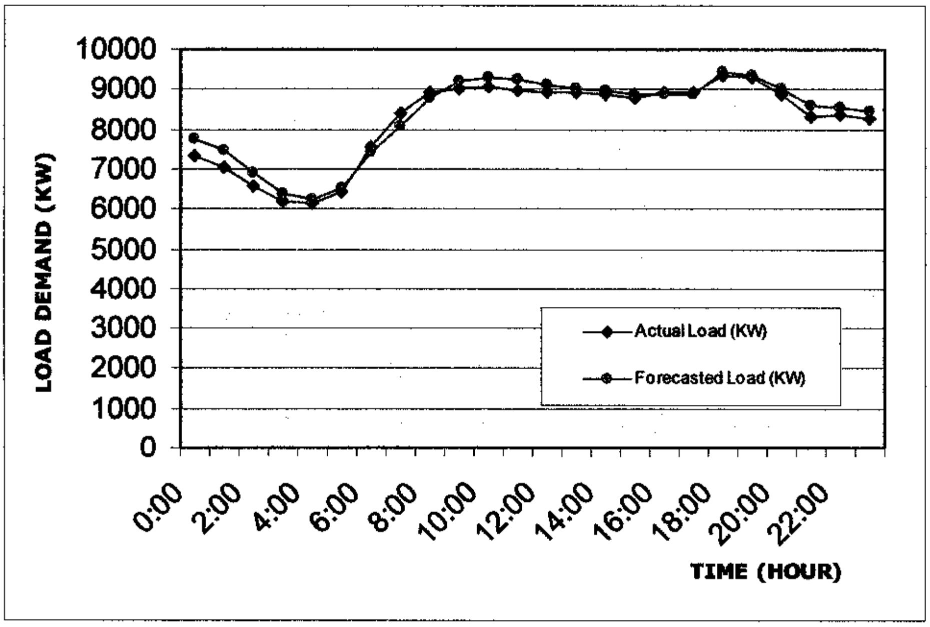

FIGURE 21: Forecasted and Actual Load for Monday 10th October 2005

4.5 DISCUSSION

To illustrate the performance of the system, Table 16 shows the summarize for each forecasting results for the UTP and New South Wales, Australia model in the Mean Absolute Percentage Error (MAPE).

4.5.1 UTP Forecast Model

TABLE 3: Average Forecasting Error for UTP Forecast

Forecast Date	Mean Absolute Percentage Error, MAPE (%)
Monday 10 October, 2005	2.63
Tuesday 11 October,2005	2.36
Wednesday 12 October, 2005	3.04
Thursday 13 October, 2005	4.91
Friday 14 October, 2005	4.90

Table 16 shows the forecasting result for weekdays starting from 10th October 2005 to 14th October 2005. Based on the above table, the MAPE for each day is below 4%. However, the highest absolute error obtained by this model is 10.17% and the lowest is 0.03%. The variation between each absolute errors shows that the forecast results depends on variation of the historical data. It is based on the range of minimum and maximum value of each output's MBF that using 2previous month of historical data as reference.

4.4.1 New South Wales, Australia Forecast Model

Table 17 shows the performance of each seasonal model. The minimum MAPE error is 1.70% and the highest is 6.03%. Summer forecast model has the highest error due to the variation of load profile during the season.

TABLE 4: Average Forecasting Error for New South Wales, Australia Forecast

	Mean Average Absolute Errors, MAPE (%)			
	Summer 14 – 18 Feb 05	**Autumn 02 – 06 May 05**	**Winter 08 – 12 Aug 05**	**Spring 10 – 14 Oct 05**
Monday	2.14	2.55	2.63	2.16
Tuesday	4.96	1.94	4.56	2.05
Wednesday	6.03	1.76	4.39	1.83
Thursday	5.58	1.89	3.55	1.70
Friday	2.26	2.08	1.68	2.75

CHAPTER 5
CONCLUSION AND RECOMMENDATIONS

5.1 CONCLUSION

Fuzzy Logic technique for short term load forecasting has been proposed and discussed in this thesis. The performance is evaluated through a simulation. The project shows that it is feasible to design a simple and satisfactory model using FuzzyTECH software that simplifies the implementation of Fuzzy Logic model.

In the case of UTP forecast model, the forecast results are compared between two techniques, Fuzzy Logic and Neural Network in order to demonstrate the accuracy of proposed model. The results of Neural Network forecasting are obtained from the previous research conducted by the student. The compared results are shown in Table 18, starting from Monday 10 October 2005 until Friday October 14 2005. Both methods are using the same historical data of 1 year basis.

TABLE 18: Comparison of Forecasting Results

Forecast Date	MAPE (%)	
	Fuzzy Logic	**Neural Network [7]**
Monday, October 10, 2005	2.63	3.08
Tuesday, October 11, 2005	2.36	3.77
Wednesday, October 12, 2005	3.04	4.6
Thursday, October 13, 2005	4.91	5.5
Friday, October 14, 2005	4.90	5.73

From table it is observed that fuzzy-based STLF is having much lower percentage of absolute error than Neural Network. Hence, the Fuzzy Logic technique is more effective compared to Neural Network. The advantage of the Fuzzy Logic model is that is only requires minimum acquired data to build the model. However, for Neural Network, it is recommended to acquire data of at least 3 years of historical data in order to forecast load with higher accuracy. Hence, it is concluded that for STLF, the fuzzy logic provides a better solution when it has minimal historical load data.

Meanwhile, for the seasonal models of New South Wales, Australia load profile, the average error for each model is 1.70% to 6.03%. An important reason is that the variation of historical load profile that makes the forecast a bit complicated. Based on the historical load data, summer and winter can be considered as Peak demand seasons while spring and autumn is considered as off-peak demand seasons. We can say that the meteorological condition such as wind speed, temperature, seasons, and weather affects the variation of load demand. Cold and hot weather are both increase the usage of electrical load of customers in residential and industry, High temperature also can decrease the efficiency of some industry utilities and hence increase their electric demand.

5.2 RECOMMENDATIONS

The forecast models still need to be improved improvement in order to reduce errors until reach the acceptable accuracy level. The meteorological variables such as weather temperature, humidity is required in order to achieve high precision of STLF model. The developed model is only applied to forecast during normal weekdays. However, further research can be done so that it can perform forecasts during semester break, public holiday with high accuracy.

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APPENDICES

APPENDIX A

SPREADSHEET RULE EDITOR FOR UTP MODEL

TABLE 6: Spreadsheet Rule Editor for RB1

IF		THEN							
MAX_LD_PVS_DAY	MIN_LD_PVS_DAY	DoS	LF0400	DoS	LF0800	DoS	LF1400	DoS	LF2000
low	low	1.00	low	1.00	low	1.00	low	1.00	low
medium	low	1.00	low	1.00	medium	1.00	medium	1.00	low
high	low	1.00	medium	1.00	high	1.00	high	1.00	medium
low	medium	1.00	medium	1.00	low	1.00	low	1.00	low
medium	medium	1.00	medium	1.00	medium	1.00	medium	1.00	medium
high	medium	1.00	medium	1.00	high	1.00	high	1.00	high
low	high	1.00	medium	1.00	low	1.00	low	1.00	medium
medium	high	1.00	high	1.00	medium	1.00	medium	1.00	high
high	high	1.00	high	1.00	high	1.00	high	1.00	high

TABLE 7: Spreadsheet Rule Editor for RB2

IF	THEN							
LF0400	**DoS**	**LF0000**	**DoS**	**LF0100**	**DoS**	**LF0200**	**DoS**	**LF0300**
very_low	1.00	very_low	1.00	low	1.00	low	1.00	very_low
low	1.00	low	1.00	low	1.00	low	1.00	low
medium	1.00	medium	1.00	medium	1.00	medium	1.00	medium
high	1.00	high	1.00	high	1.00	high	1.00	high
very_high	1.00	very_high	1.00	high	1.00	high	1.00	very_high

TABLE 8: Spreadsheet Rule Editor for RB3

IF		THEN						
LF0400	LF0800	DoS	LF0500	DoS	LF0600	DoS	LF0700
very_low	very_low	1.00	very_low	1.00	very_low	1.00	very_low
low	very_low	1.00	very_low	1.00	very_low	1.00	very_low
medium	very_low	1.00	low	1.00	low	1.00	low
high	very_low	1.00	low	1.00	low	1.00	low
very_high	very_low	1.00	medium	1.00	medium	1.00	medium
very_low	low	1.00	very_low	1.00	very_low	1.00	very_low
low	low	1.00	low	1.00	low	1.00	low
medium	low	1.00	low	1.00	low	1.00	low
high	low	1.00	medium	1.00	medium	1.00	medium
very_high	low	1.00	high	1.00	high	1.00	high
very_low	medium	1.00	low	1.00	low	1.00	low
low	medium	1.00	low	1.00	low	1.00	low
medium	medium	1.00	medium	1.00	medium	1.00	medium
high	medium	1.00	high	1.00	high	1.00	high
very_high	medium	1.00	high	1.00	high	1.00	high
very_low	high	1.00	low	1.00	low	1.00	low
low	high	1.00	medium	1.00	medium	1.00	medium
medium	high	1.00	high	1.00	high	1.00	high
high	high	1.00	high	1.00	high	1.00	high
very_high	high	1.00	very_high	1.00	very_high	1.00	very_high
very_low	very_high	1.00	medium	1.00	medium	1.00	medium
low	very_high	1.00	high	1.00	high	1.00	high
medium	very_high	1.00	high	1.00	high	1.00	high
high	very_high	1.00	very_high	1.00	very_high	1.00	very_high
very_high	very_high	1.00	very_high	1.00	very_high	1.00	very_high

TABLE 9: Spreadsheet Rule Editor for RB4

IF		THEN									
LF0800	LF1400	DoS	LF0900	DoS	LF1000	DoS	LF1100	DoS	LF1200	DoS	LF1300
very_low	very_low	1.00	very_low	1.00	very_low	1.00	low	1.00	low	1.00	very_low
low	very_low	1.00	low	1.00	low	1.00	low	1.00	low	1.00	low
medium	very_low	1.00	low	1.00	low	1.00	low	1.00	low	1.00	low
high	very_low	1.00	medium	1.00	medium	1.00	medium	1.00	medium	1.00	medium
very_high	very_low	1.00	high	1.00	high	1.00	medium	1.00	medium	1.00	high
very_low	low	1.00	very_low	1.00	very_low	1.00	low	1.00	low	1.00	very_low
low	low	1.00	low	1.00	low	1.00	low	1.00	low	1.00	low
medium	low	1.00	medium	1.00	medium	1.00	medium	1.00	medium	1.00	medium
high	low	1.00	medium	1.00	medium	1.00	medium	1.00	medium	1.00	medium
very_high	low	1.00	high	1.00	high	1.00	medium	1.00	medium	1.00	high
very_low	medium	1.00	low	1.00	low	1.00	low	1.00	low	1.00	low
low	medium	1.00	low	1.00	low	1.00	medium	1.00	medium	1.00	low

IF		THEN									
medium	medium	1.00	medium	1.00	medium	1.00	medium	1.00	medium	1.00	medium
high	medium	1.00	high	1.00	high	1.00	medium	1.00	medium	1.00	high
very_high	medium	1.00	high	1.00	high	1.00	high	1.00	high	1.00	high
very_low	high	1.00	low	1.00	low	1.00	medium	1.00	medium	1.00	low
low	high	1.00	medium	1.00	medium	1.00	medium	1.00	medium	1.00	medium
medium	high	1.00	medium	1.00	medium	1.00	medium	1.00	medium	1.00	medium
high	high	1.00	high	1.00	high	1.00	high	1.00	high	1.00	high
very_high	high	1.00	very_high	1.00	very_high	1.00	high	1.00	high	1.00	very_high
very_low	very_high	1.00	low	1.00	low	1.00	medium	1.00	medium	1.00	low
low	very_high	1.00	medium	1.00	medium	1.00	medium	1.00	medium	1.00	medium
medium	very_high	1.00	high	1.00	high	1.00	high	1.00	high	1.00	high
high	very_high	1.00	high	1.00	high	1.00	high	1.00	high	1.00	high
very_high	very_high	1.00	very_high	1.00	very_high	1.00	high	1.00	high	1.00	very_high

TABLE 10: Spreadsheet Rule Editor for RB5

IF		THEN									
LF1400	**LF2000**	**DoS**	**LF1500**	**DoS**	**LF1600**	**DoS**	**LF1700**	**DoS**	**LF1800**	**DoS**	**LF1900**
very_low	very_low	1.00	very_low	1.00	very_low	1.00	very_low	1.00	low	1.00	very_low
low	very_low	1.00	low	1.00	very_low	1.00	low	1.00	low	1.00	very_low
medium	very_low	1.00	low	1.00	low	1.00	low	1.00	low	1.00	low
high	very_low	1.00	medium	1.00	low	1.00	medium	1.00	medium	1.00	low
very_high	very_low	1.00	high	1.00	medium	1.00	high	1.00	medium	1.00	low
very_low	low	1.00	very_low	1.00	very_low	1.00	very_low	1.00	low	1.00	low
low	low	1.00	low	1.00	low	1.00	low	1.00	low	1.00	low
medium	low	1.00	medium	1.00	low	1.00	medium	1.00	medium	1.00	low
high	low	1.00	medium	1.00	medium	1.00	medium	1.00	medium	1.00	medium
very_high	low	1.00	high	1.00	high	1.00	high	1.00	medium	1.00	medium
very_low	medium	1.00	low	1.00	low	1.00	low	1.00	low	1.00	low
low	medium	1.00	low	1.00	low	1.00	low	1.00	medium	1.00	medium
medium	medium	1.00	medium	1.00	medium	1.00	medium	1.00	medium	1.00	medium
high	medium	1.00	high	1.00	high	1.00	high	1.00	medium	1.00	medium
very_high	medium	1.00	high	1.00	high	1.00	high	1.00	high	1.00	high
very_low	high	1.00	low	1.00	low	1.00	low	1.00	medium	1.00	medium
low	high	1.00	medium	1.00	medium	1.00	medium	1.00	medium	1.00	medium
medium	high	1.00	medium	1.00	high	1.00	medium	1.00	medium	1.00	high
high	high	1.00	high	1.00	high	1.00	high	1.00	high	1.00	high
very_high	high	1.00	very_high	1.00	very_high	1.00	very_high	1.00	high	1.00	high
very_low	very_high	1.00	low	1.00	medium	1.00	low	1.00	medium	1.00	high
low	very_high	1.00	medium	1.00	high	1.00	medium	1.00	medium	1.00	high
medium	very_high	1.00	high	1.00	high	1.00	high	1.00	high	1.00	high
high	very_high	1.00	high	1.00	very_high	1.00	high	1.00	high	1.00	very_high
very_high	very_high	1.00	very_high	1.00	very_high	1.00	very_high	1.00	high	1.00	very_high

TABLE 11: Spreadsheet Rule Editor for RB6

IF		THEN					
LF2000	load_0000_LT	DoS	LF2100	DoS	LF2200	DoS	LF2300
very_low	very_low	1.00	very_low	1.00	low	1.00	very_low
low	very_low	1.00	low	1.00	low	1.00	very_low
medium	very_low	1.00	low	1.00	low	1.00	low
high	very_low	1.00	medium	1.00	medium	1.00	low
very_high	very_low	1.00	high	1.00	medium	1.00	low
very_low	low	1.00	very_low	1.00	low	1.00	low
low	low	1.00	low	1.00	low	1.00	low
medium	low	1.00	medium	1.00	medium	1.00	low
high	low	1.00	medium	1.00	medium	1.00	medium
very_high	low	1.00	high	1.00	medium	1.00	medium
very_low	medium	1.00	low	1.00	low	1.00	low
low	medium	1.00	low	1.00	medium	1.00	medium
medium	medium	1.00	medium	1.00	medium	1.00	medium
high	medium	1.00	high	1.00	medium	1.00	medium
very_high	medium	1.00	high	1.00	high	1.00	high
very_low	high	1.00	low	1.00	medium	1.00	medium
low	high	1.00	medium	1.00	medium	1.00	medium
medium	high	1.00	medium	1.00	medium	1.00	high
high	high	1.00	high	1.00	high	1.00	high
very_high	high	1.00	very_high	1.00	high	1.00	high
very_low	very_high	1.00	low	1.00	medium	1.00	high
low	very_high	1.00	medium	1.00	medium	1.00	high
medium	very_high	1.00	high	1.00	high	1.00	high
high	very_high	1.00	high	1.00	high	1.00	very_high
very_high	very_high	1.00	very_high	1.00	high	1.00	very_high

APPENDIX B

MEMBERSHIP FUNCTION FOR INPUT & OUTPUT VARIABLES FOR UTP MODEL

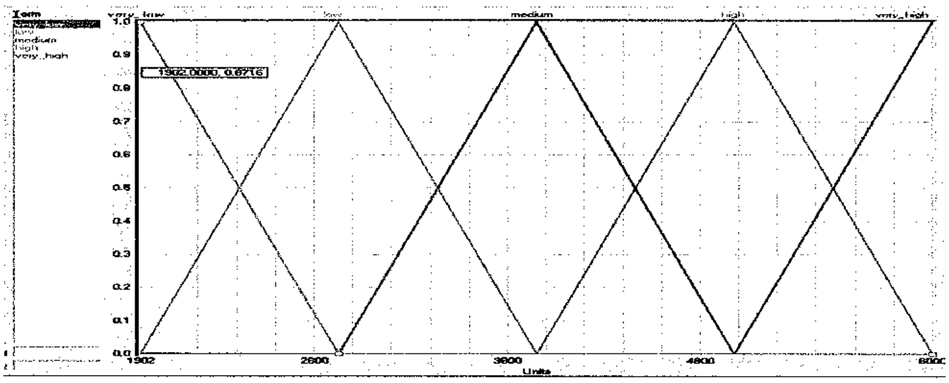

FIGURE 22: MBF for maximum load demand (previous day)

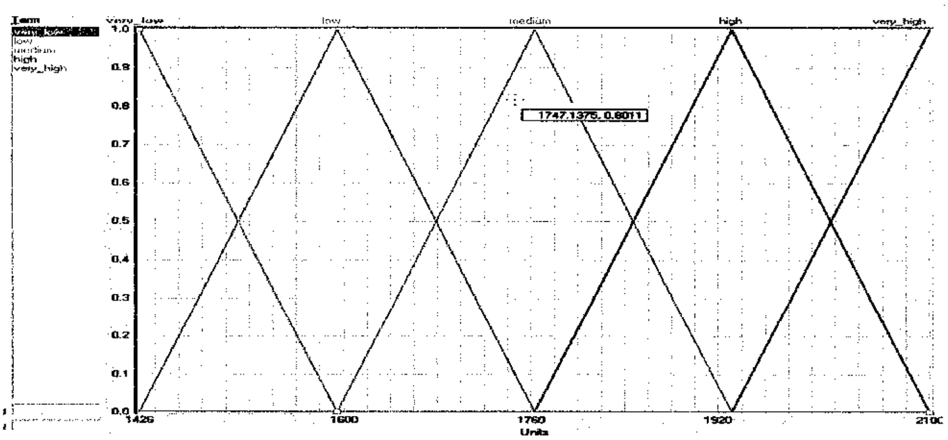

FIGURE 23: MBF for minimum load demand (previous day)

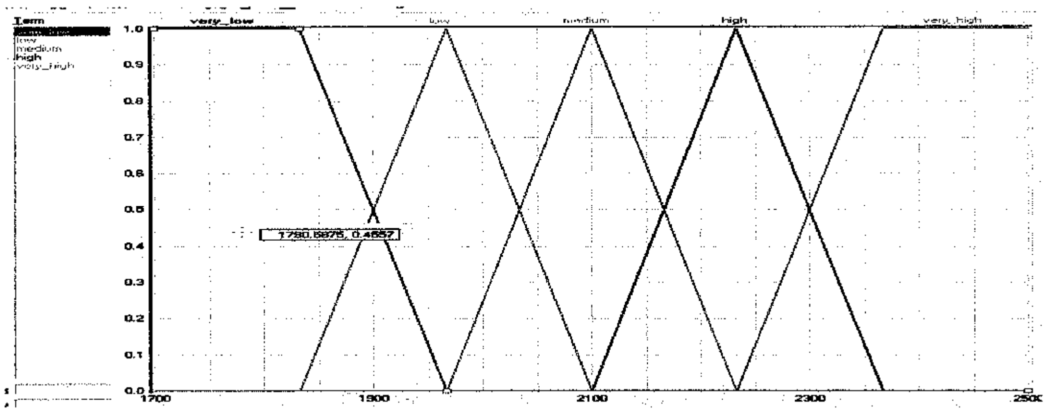

FIGURE 24: MBF for load demand at 0000 (6 days earlier)

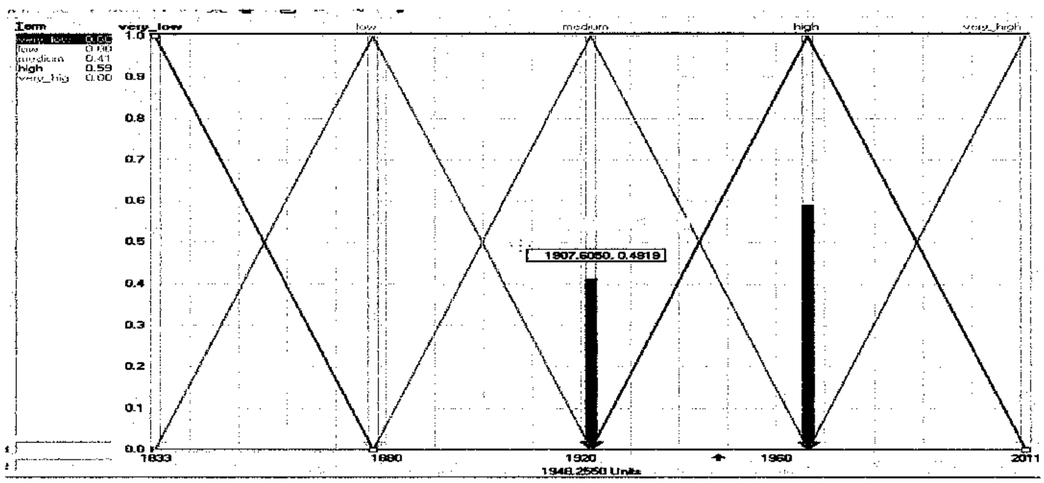

FIGURE 25: MBF for load forecast at 0400

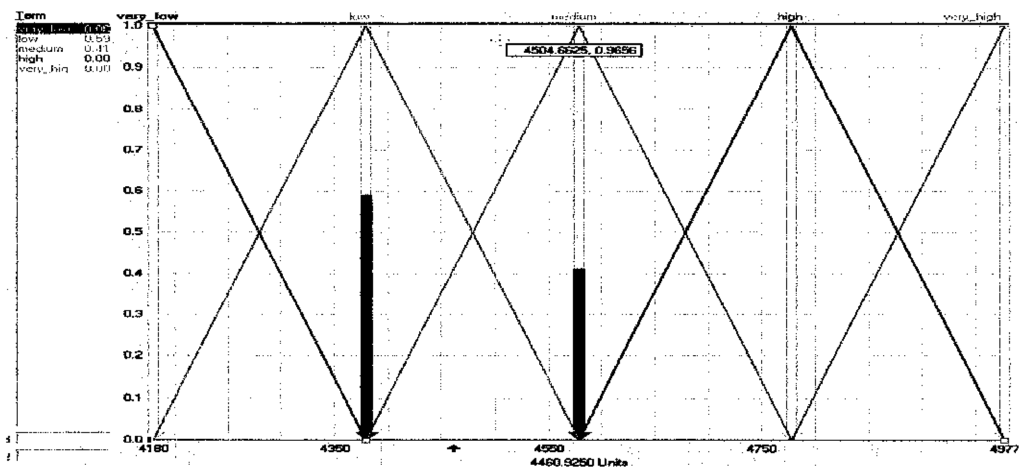

FIGURE 26: MBF for load forecast at 0800

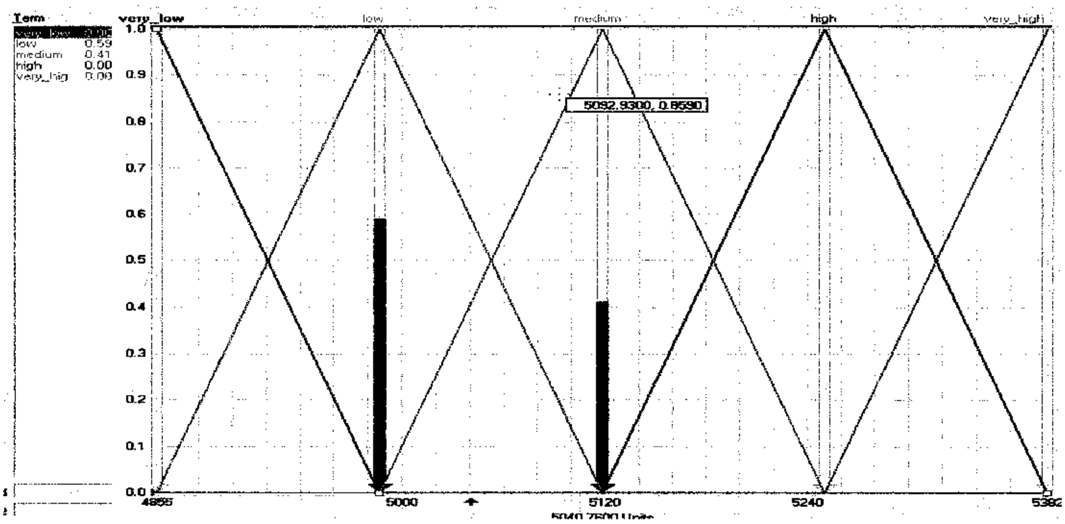

FIGURE 27: MBF for load forecast at 1400

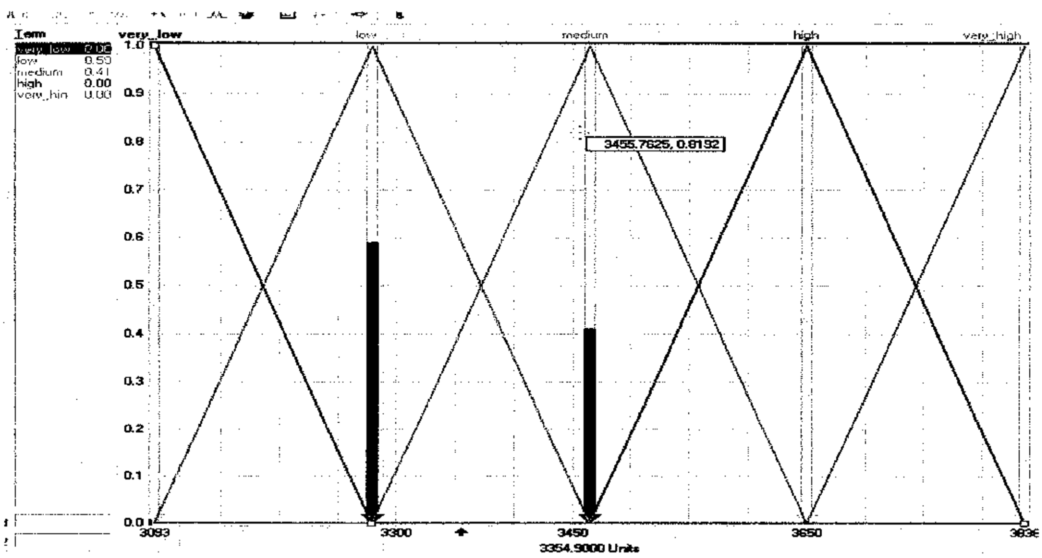

FIGURE 28: MBF for load forecast at 2000