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Short Term Electrical Load Forecasting Using Fuzzy Logic

تنبؤات الأحمال الكهربائية قصيرة المدي بإستخدام المنطق الغامض

A Dissertation Submitted In Partial Fulfillment for the Requirements of the Degree of M.Sc. In Electrical Engineering (Microprocessor and Control)

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الآيـة

قَالَ تَعَالَىٰ:

﴿ قُل لَّوۡ كَانَ ٱلۡبَحۡرُ مِدَادٗا لِّكَلِمَٰتِ رَبِّي لَنَفِدَ ٱلۡبَحۡرُ قَبۡلَ أَن تَنفَدَ كَلِمَٰتُ

رَبِّي وَلَوۡ جِئۡنَا بِمِثۡلِهِۦ مَدَدٗا ١٠٩ ﴾

سورة الكهف الاية (109)

DEDICATION

To the fountain of patience and optimism and hope

Mother

To the big heart

Father

To those who have demonstrated to me what is most beautiful in life

Brothers

To the taste of the most beautiful moments with

Friends

To those who taught me how to find them and taught me as well how not loss them

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ABSTRACT

Load forecasting is an important component for power system energy management system. Precise load forecasting helps the electric utility to make unit commitment decisions, reduces spinning reserve capacity and schedule device maintenance plan properly. It also reduces the generation cost and increases reliability of power systems. In this work, a fuzzy logic approach for short term load forecasting is attempted. Time, temperature and similar previous day load are used as the independent variables for short term load forecasting. Based on the time, temperature and similar previous day load, fuzzy rule base are prepared using Mamdani implication, which are eventually used for the short term load forecasting. MATLAB SIMULINK software is used here in this work for system designing and simulation. For the short term load forecasting, load data from the specific area load control center is considered.

مستخلص

تنبؤ الاحمال هو عنصر هام للمنظومة الكهربائية لادارة الطاقة. دقة تنبؤ الحمل يساعد مؤسسات الكهرباء في إتخاذ القرارات وخفض الفقدات في القدرة الاحتياطية واستخدام خطة صيانة الاجهزة بشكل صحيح وفقا للجدول الزمني كما أنه يقلل من تكلفة التوليد وتزيد من موثوقية أنظمة الطاقة . كما أن عدم الدقة في هذه التنبوات يؤدي الي عواقب وخيمة في شكل معدلات عالية في الاستخدام . في هذه الدراسة ، استخدم المنطق الغامض للتنبؤ بالحمل على المدى القصير. حيث يتم استخدام الوقت ودرجة الحرارة والحمل المماثل لليوم السابق والمتغيرات المستقلة للتنبؤ على المدى القصير . وعلى أساس الوقت ودرجة الحرارة والحمل المماثل لليوم السابق , واستخدام قواعد اساسية يتم بنائها عن طريق تضمين مامداني والتي تستخدم في النهاية للتنبؤ بالاحمال . يستخدم برنامج SIMULINK MATLAB في هذه الدراسة من أجل تصميم ومحاكاة النظام. لتنبؤ الحمل على المدى القصير ويتم جلب البيانات من مركز الاحمال الخاص بالمنطقة المراد تنبؤ الاحمال لها .

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CHAPTER ONE

INTRODUCTION

1.1 General Concepts

Load forecasting is an important component for power system energy management system. Precise load forecasting helps the electric utility to make unit commitment decisions, reduce spinning reserve capacity and schedule device maintenance plan properly and it also reduces the generation cost and increases reliability of power systems.

The prime duty of any utility is to provide reliable power to customers. Customer load demand in electric distribution systems is subject to change because human activities follow daily, weekly, and monthly cycles.

1.2 Problem Statement

The estimation of future active loads at various load buses ahead of actual load occurrence is known as load forecasting. If it is done inappropriately, then the direct effect is on the planning for the future load, and the result is the difference of the load that will develop from the planning done for the same, and eventually the entire planning process is at risk.

As the utility supply and consumer demand is fluctuating and the change in weather conditions, energy prices increases by a factor of ten or more during peak load, load forecasting is vitally important for utilities.

In this study matlab program will be used for load forecast using fuzzy logic. Basically matlab program doesn't need good experience or complex mathematical analysis methods.

1.3 Objectives

The main objectives of this study are to:-

i. Design of fuzzy logic system for short term electric load forecasting.

ii. Design of Microsoft excels for short term electric load forecasting.

iii. Compared the result between the Microsoft excel and fuzzy load forecasting .

1.4 Methodology

i. Study of all previous related works.

ii. Use of fuzzy logic Mamdani implication in fuzzy inference.

iii. Use of MATLAB SIMULINK to simulate the proposed system.

1.5 Research Layout

This thesis consists of five chapters including chapter one. Chapter Tow present the literature review, introduction of load forecasting, and method load forecasting. Chapter Three concentrates on design of fuzzy logic load forecasting, short term load forecasting in Sudan network generation, fuzzification load forecast, fuzzy rule base and system simulation. Chapter Four contains the system design implantation and testing, analysis and discusses of results using Microsoft excel; finally Chapter Five gives the conclusion and recommendation of the research.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

In general forecasting methods can be divided into two broad categories: Parametric methods and artificial intelligence based methods. Based on analyzing qualitative relationships between the load and the factors affecting the load, the parametric methods formulate mathematical or statistical models of load. Then the parameters of the built model are estimated from historical data and the performance of the model is verified by analysis of forecast errors. Artificial intelligence based methods use artificial neural networks or fuzzy systems as load models. For both of the categories, several factors should be considered in short-term load forecasting, such as the time factor, weather data as well as possible customers' classes. The time factors influence the load hourly, daily and seasonally. Loads between weekdays and weekends, as well as holidays and non-holidays also show differences. Apparently the electric loads are dependent upon weather conditions significantly. Variations of dry-bulb temperature, dew point, wind speed, humidity, and cloud cover can change the load dynamics. This is especially true in residential areas. For those areas where the industry collects, temperature may not be an important variable any longer. It may be necessary to have information regarding operational decisions of plants taken into account as factors.

2.2 Load Forecasting

Load forecast accurate models for electric power load forecasting are essential to the operation and planning of a utility company. Load forecasting helps an electric utility to make important decisions including decisions on purchasing and generating electric power, load switching, and infrastructure development. Load forecasts are extremely important for energy suppliers, financial institutions, and other participants in electric energy generation, transmission, distribution, and markets.

Load forecasts can be divided into three categories: short-term forecasts which are usually from one hour to one week, medium forecasts which are usually from a week to a year, and long-term forecasts which are longer than a year. The forecasts for different time horizons are important for different operations within a utility company.

Load Forecasting depends not only on the load forecasting techniques, but also on the accuracy of forecasted weather scenario [1].

For the next year peak forecast, it is possible to provide the probability distribution of the load based on historical weather observations. It is also possible, according to the industry practice, to predict the so-called weather normalized load, which would take place for average annual peak weather conditions or worse than average peak weather conditions for a given area. Weather normalized load is the load calculated for the so-called normal weather conditions which are the average of the weather characteristics for the peak historical loads over a certain period of time. The duration of this period varies from one utility to another. Most companies take the last 25-30 years of data.

Load forecasting has always been important for planning and operational decision conducted by utility companies. However, with the deregulation of the energy industries, load forecasting is even more important. With supply and demand fluctuating and the changes of weather conditions and energy prices increasing by a factor of ten or more during peak situations, load forecasting is vitally important for utilities. Short-term load forecasting can help to estimate load flows and to make decisions that can prevent overloading. Timely implementations of such decisions lead to the improvement of network reliability and to the reduced occurrences of equipment failures and blackouts. Load forecasting is also important for contract evaluations and evaluations of various sophisticated financial products on energy pricing offered by the market.

In the deregulated economy, decisions on capital expenditures based on long-term forecasting are also more important than in a non-deregulated economy when rate increases could be justified by capital expenditure projects.

Most forecasting methods use statistical techniques or artificial intelligence algorithms such as regression, neural networks, fuzzy logic, and expert systems. Two of the methods, so-called end-use and econometric approach are broadly used for medium- and long-term forecasting. A variety of methods, which include the so-called similar day approach, various regression models, time series, neural networks, statistical learning algorithms, fuzzy logic, and expert systems, have been developed for short-term forecasting.

As we see, a large variety of mathematical methods and ideas have been used for load forecasting. The development and improvements of appropriate mathematical tools will lead to the development of more accurate load forecasting techniques. The accuracy of load forecasting depends not only on the load forecasting techniques, but also on the accuracy of forecasted weather scenarios.

2.2.1 Important factors for forecasts

For short-term load forecasting several factors should be considered, such as time , weather data, and possible customers' classes. The medium- and long-term forecasts take into account the historical load and weather data, the number of customers in different categories, the appliances in the area and their characteristics including age, the economic and demographic data and their forecasts, the appliance sales data, and other factors.

The time factors include the time of the year, the day of the week, and the hour of the day. There are important differences in load between weekdays and weekends. The load on different weekdays also can behave differently. For example, Mondays and Fridays being adjacent to weekends, may have structurally different loads than Tuesday through Thursday. This is particularly true during the summer time. Holidays are more difficult to forecast than non-holidays because of their relative infrequent occurrence [1].

Weather conditions influence the load. In fact, forecasted weather parameters are the most important factors in short-term load forecasts. Various weather variables could be considered for load forecasting. Temperature and humidity are the most commonly used load predictors. An electric load prediction survey published in [2].

Most electric utilities serve customers of different types such as residential, commercial, and industrial. The electric usage pattern is different for customers that belong to different classes but is somewhat alike for customers within each class. Therefore, most utilities distinguish load behavior on a class-by-class basis [1].

2.3 Methods of Load Forecasting

Over the last few decades a number of forecasting methods have been developed. Two of the methods, so-called end-use and econometric approach are broadly used for medium- and long-term forecasting. A variety of methods, which include the so-called similar day approach, various regression models, time series, neural networks, expert systems, fuzzy logic, and statistical learning algorithms, are used for short-term forecasting. The development, improvements, and investigation of the appropriate mathematical tools will lead to the development of more accurate load forecasting techniques.

Statistical approaches usually require a mathematical model that represents load as function of different factors such as time, weather, and customer class. The two important categories of such mathematical models are: additive models and multiplicative models. They differ in whether the forecast load is the sum (additive) of a number of components or the product (multiplicative) of a number of factors [3].

2.3.1 Medium- and long-term load forecasting methods

The end-use modeling, econometric modeling, and their combinations are the most often used methods for medium- and long-term load forecasting.

Descriptions of appliances used by customers, the sizes of the houses, the age of equipment, technology changes, customer behavior, and population dynamics are usually included in the statistical and simulation models based on the so-called end-use approach. In addition, economic factors such as per capita incomes, employment levels, and electricity prices are included in econometric models. These models are often used in combination with the end-use approach. Long-term forecasts include the forecasts on the population changes, economic development, industrial construction, and technology development.

- **End-use models**

The end-use approach directly estimates energy consumption by using extensive information on end use and end users, such as appliances, the customer use, their age, sizes of houses, and so on. Statistical information about customers along with dynamics of change is the basis for the forecast.

End-use models focus on the various uses of electricity in the residential, commercial, and industrial sector. These models are based on the principle that electricity demand is derived from customer’s demand for light, cooling, heating, refrigeration, etc. Thus end-use models explain energy demand as a function of the number of appliances in the market [4].

Ideally this approach is very accurate. However, it is sensitive to the amount and quality of end-use data. For example, in this method the distribution of equipment age is important for particular types of appliances. End-use forecast requires less historical data but more information about customers and their equipment.

- **Econometric models**

The econometric approach combines economic theory and statistical techniques for forecasting electricity demand. The approach estimates the relationships between energy consumption (dependent variables) and factors influencing consumption. The relationships are estimated by the least-squares method or time series methods.

One of the options in this framework is to aggregate the econometric approach, when consumption in different sectors (residential, comer coal, industrial, etc.) is calculated as a function of weather, economic and other variables, and then estimates are assembled using recent historical data. Integration of the econometric approach into the end-use approach introduces behavioral components into the end-use equations.

- **Statistical model-based learning**

The end-use and econometric methods require a large amount of information relevant to appliances, customers, economics, etc. Their application is complicated and requires human participation. In addition such information is often not available regarding particular customers and a utility keeps and supports a profile of an "average" customer or average customers for different type of customers. The problem arises if the utility wants to conduct next-year forecasts for sub-areas, which are often called load pockets. In order to simplify the medium-term forecasts, make them more accurate and avoid the use of the unavailable information. The focus of the study was the summer data. We compared several load models and came to the conclusion that the following multiplicative model is the most accurate

$$L\,(t) \;=\; F\,(d\,(t), h\,(t)) \;\cdot\; f\,(w(t)) \;+\; R(t) \qquad (2.1)$$

Where L(t) is the actual load at time t,

d (t) is the day of the week,

h (t) is the hour of the day,

f(d, h) is the daily and hourly component,

w(t) is the weather data that include the temperature and humidity,

f(w) is the weather factor, and R(t) is a random error.

In fact, w (t) is a vector that consists of the current and lagged weather variables. This reflects the fact that electric load depends not only on the current weather conditions but also on the weather during the previous hours and days. In particular, the well-known effect of the so-called heat waves is that the use of air conditioners increases when the hot weather continues for several days.

The described methods can be applied to both medium- and long term forecasting. However, the long-term forecasts should incorporate economic and population dynamic forecasts as input parameters [3].

2.3.2 Short-term load forecasting methods

Short-term load forecasting draws much attention. A variety of methods using statistical techniques or artificial intelligence algorithms, which include regression models, time series, neural networks, statistical learning algorithms, fuzzy logic, or expert systems, have been developed for short-term forecasting [1]. These methods all have been succeeded in short-term load forecasting problems. The success of a forecasting technique depends not only on the approach but also on the quality of input data which could contain proper patterns representing the system dynamics. In general, the load presents two distinct patterns: weekday and weekend load patterns. Weekday patterns include Tuesday through Friday and weekend patterns include Sunday through Monday. In addition, holiday patterns are different from non-holiday patterns.

A large variety of statistical and artificial intelligence techniques have been developed for short-term load forecasting.

- **Similar-day approach**

This approach is based on searching historical data for days within one, two, or three years with similar characteristics to the forecast day. Similar characteristics include weather, day of the week, and the date. The load of a similar day is considered as a forecast.

Instead of a single similar day load, the forecast can be a linear combination or regression procedure that can include several similar days. The trend coefficients can be used for similar days in the previous years.

- **Regression methods**

Regression is the one of most widely used statistical techniques. For electric load forecasting regression methods are usually used to model the relationship of load consumption and other factors such as weather, day type, and customer class. Engle et al [5]. Presented several regression models for the next day peak forecasting. Their models incorporate deterministic influences such as holidays, stochastic influences such as average loads, and exogenous influences such as weather describe other applications of regression models to loads forecasting [6].

- **Time series Time**

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

In particular, autoregressive moving average (ARMA), autoregressive integrated moving average (ARIMA), autoregressive moving average with exogenous variables (ARMAX), and autoregressive integrated moving average with exogenous variables (ARIMAX) are the most often used classical time series methods. ARMA models are usually used for stationary processes while ARIMA is an extension of autoregressive moving average (ARMA) to non stationary processes. ARMA and ARIMA use the time and load as the only input parameters. Since load generally depends on the weather and time of the day, ARIMAX is the most natural tool for load forecasting among the classical time series models. describe implementations of ARIMAX models for load forecasting. Used evolutionary programming (EP) approach to identify the ARMAX model parameters for one day to one week ahead hourly load demand forecast. Evolutionary programming is a method for simulating evolution and constitutes a stochastic optimization algorithm, proposed a fuzzy autoregressive moving average with exogenous input variables (FARMAX) for one day ahead hourly load forecasts [7].

- **Neural networks**

The uses of Artificial Neural Networks (ANNs or simply NNs) have been a widely studied electric load forecasting technique since.

Neural networks are essentially non-linear circuits that have the demonstrated capability to do non-linear curve fitting.

The outputs of an artificial neural network are some linear or nonlinear mathematical function of its inputs. The inputs may be the outputs of other network elements as well as actual network inputs. In practice network elements are arranged in a relatively small number of connected layers of elements between network inputs and outputs. Feedback paths are sometimes used.

In applying a neural network to electric load forecasting, one must select one of a number of architectures (e.g. Hopfield, back propagation, Boltzmann machine), the number and connectivity of layers and elements, use of bi-directional or unidirectional links, and the number format (e.g. binary or continuous) to be used by inputs and outputs, and internally.

The most popular artificial neural network architecture for electric load forecasting is back propagation. Back propagation neural networks use continuously valued functions and supervised learning. That is, under supervised learning, the actual numerical weights assigned to element inputs are determined by matching historical data (such as time and weather) to desired outputs (such as historical electric loads) in a pre-operational “training session”. Artificial neural networks with unsupervised learning do not require pre-operational training. developed an Artificial Neural Networks (ANN) based short-term load forecasting model for the Energy Control Center of the Greek Public Power Corporation. In the development they used a fully connected three-layer feed forward ANN and back propagation algorithm was used for training [8].

Input variables include historical hourly load data, temperature, and the day of the week. The model can forecast load profiles from one to seven days. Also Papal exopoulosetal. Developed and implemented a multi-layered feed forward Artificial Neural Networks(ANN) for short-term system load forecasting. In the model three types of variables are used as inputs to the neural network: season related inputs, weather related inputs, and historical loads. Artificial neural networks for short-term system load forecasting(ANNSTLF) is based on multiple ANN strategies that capture various trends in the data. In the development they used a multilayer perception trained with the error back propagation algorithm. ANNSTLF can consider the effect of temperature and relative humidity on the load. It also contains forecasters that can generate the hourly temperature and relative humidity forecasts needed by the system[9].

In the new generation, ANNSTLF includes two ANN forecasters, one predicts the base load and the other forecasts the change in load. The final forecast is computed by an adaptive combination of these forecasts.

The effects of humidity and wind speed are considered through a linear transformation of temperature. As reported in, ANNSTLF was being used by 35 utilities across the USA and Canada developed a three layer fully connected feed forward neural network and the back propagation algorithm was used as the training method.

ANN though considers the electricity price as one of the main characteristics of the system load. Many published studies use artificial neural networks in conjunction with other forecasting techniques (such as with regression trees, time series or fuzzy logic [10].

- **Expert systems**

Rule based forecasting makes use of rules, which are often heuristic in nature, to do accurate forecasting. Expert systems, incorporates rules and procedures used by human experts in the field of interest into software that is then able to automatically make forecasts without human assistance.

Expert system use began in the 1960's for such applications as geological prospecting and computer design. Expert systems work best when a human expert is available to work with software developers for a considerable amount of time in imparting the expert's knowledge to the expert system software. Also, an expert's knowledge must be appropriate for codification into software rules (i.e. the expert must be able to explain his/her decision process to programmers). An expert system may codify up to hundreds or thousands of production rules.

proposed a knowledge-based expert system for the short term load forecasting of the Taiwan power system. Operator's knowledge and the hourly observations of system load over the past five years were employed to establish eleven day types. Weather parameters were also considered. The developed algorithm performed better compared to the conventional Box-Jenkins method developed a site-independent technique for short-term load forecasting. Knowledge about the load and the factors affecting it are extracted and represented in a parameterized rule base. This rule base is complemented by a parameter database that varies from site to site. The technique was tested in several sites in the United States with low forecasting errors [11].

2.4 Fuzzy Logic

Fuzzy logic is a logic having many values, approximate reasoning and have a vague boundary. The variables in fuzzy logic system may have any value in between 0 and 1 and hence this type of logic system is able to address the values of the variables (called linguistic variables) those lie between completely truths and completely false. Each linguistic variable is described by a membership function which has a certain degree of membership at a particular instance.

The human knowledge is incorporated in fuzzy rules. The fuzzy inference system formulates suitable rules and based on these rules the decisions are made. This whole process of decision making is mainly the combination of concepts of fuzzy set theory, fuzzy IF-THEN rules and fuzzy reasoning. The fuzzy inference system makes use of the IF-THEN statements and with the help of connectors present (such as OR and AND), necessary decision rules are constructed.

The fuzzy rule base is the part responsible for storing all the rules of the system and hence it can also be called as the knowledge base of the fuzzy system. Fuzzy inference system is responsible for necessary decision making for producing a required output [3].

The fuzzy control systems are rule-based systems in which a set of fuzzy rules represent a control decision mechanism for adjusting the effects of certain system stimuli. The rule base reflects the human expert knowledge, expressed as linguistic variables, while the membership functions represent expert interpretation of those variables.

Fuzzy logic is a generalization of the usual Boolean logic used for digital circuit design. An input under Boolean logic takes on a truth value of “0” or “1”.

Under fuzzy logic an input has associated with it a certain qualitative ranges. For instance a transformer load may be “low”, “medium” and “high”. Fuzzy logic allows one to (logically) deduce outputs from fuzzy inputs. In this sense fuzzy logic is one of a number of techniques for mapping inputs to outputs (i.e. curve fitting).

Among the advantages of fuzzy logic are the absence of a need for a mathematical model mapping inputs to outputs and the absence of a need for precise (or even noise free) inputs. With such generic conditioning rules, properly designed fuzzy logic systems can be very robust when used for forecasting. Of course in many situations an exact output (e.g. the precise 12PM load) is needed. After the logical processing of fuzzy inputs, a “defuzzification” process can be used to produce such precise outputs describe applications of fuzzy logic to electric load forecasting [12].

2.4.1 Fuzzy sets

In classical, or crisp, sets the transition for an element in the universe between membership and non membership in a given set is abrupt and well-defined (said to be ‘‘crisp’’). For an element in a universe that contains fuzzy sets, this transition can be gradual. This transition among various degrees of membership can be thought of as conforming to the fact that the boundaries of the fuzzy sets are vague and ambiguous. Hence, membership of an element from the universe in this set is measured by a function that attempts to describe vagueness and ambiguity.

A fuzzy set, then, is a set containing elements that have varying degrees of membership in the set. This idea is in contrast with classical, or crisp, sets because members of a crisp set would not be members unless their membership was full, or complete, in that set (i.e., their membership is assigned a value of 1). Elements in a fuzzy set, because their membership need not be complete, can also be members of other fuzzy sets on the same universe.

Elements of a fuzzy set are mapped to a universe of membership values using a function-theoretic form [12].

2.4.2 Fuzzy set operations:

Define three fuzzy sets A~, B~, and C~ on the universe X. For a given element x of the universe, the following function-theoretic operations for the set-theoretic operations of union, intersection, and complement are defined for A~, B~, and C~ on X:

Union $\mu A \sim \cup B \sim (x) = \mu A \sim (x) \vee \mu B \sim (x)$ (2.2)

Intersection $\mu A \sim \cap B \sim (x) = \mu A \sim (x) \wedge \mu B \sim (x)$ (2.3)

Complement $\mu A \sim (x) = 1 - \mu A \sim (x)$ (2.4)

2.4.3 Membership function

Membership function since all information contained in a fuzzy set is described by its membership function; it is useful to develop a lexicon of terms to describe various special features of this function. For purposes of simplicity, the functions shown in the following figures will all be continuous, but the terms apply equally for both discrete and continuous fuzzy sets [12].

2.4.4 Fuzzification

Fuzzification is the process of making a crisp quantity fuzzy. We do this by simply recognizing that many of the quantities that we consider to be crisp and deterministic are actually not deterministic at all: They carry considerable uncertainty. If the form of uncertainty happens to arise because of imprecision, ambiguity, or vagueness, then the variable is probably fuzzy and can be represented by a membership function. In the real world, hardware such as a digital voltmeter generates crisp data, but these data are subject to experimental error.

Fuzzification is the process of converting crisp numerical values into the degrees of membership related to the corresponding fuzzy sets. A membership function (MF) will accept as its argument a crisp value and return the degree to which that value belongs to the fuzzy set the MF represent [12].

2.4.5 Defuzzification

Defuzzification as mentioned in the introduction, there may be situations where the output of a fuzzy process needs to be a single scalar quantity as opposed to a fuzzy set. Defuzzification is the conversion of a fuzzy quantity to a precise quantity, just as fuzzification is the conversion of a precise quantity to a fuzzy quantity. The output of a fuzzy process can be the logical union of two or more fuzzy membership functions defined on the universe of discourse of the output variable [13].

Methods of defuzzification:

One of the more common types of defuzzification technique is the maximum defuzzification techniques. These select the output with the highest membership function they include:

- First of maximum
- Middle of maximum
- Last of maximum
- Mean of maxima
- Random choice of maximum

2.4.6 Fuzzy rule base

The first inference method, due to mamdani and assilian, is the most common in practice and in the literature. To begin the general illustration of this idea, we consider a simple two-rule system where each rule comprises two antecedents and one consequent.

This is analogous to a dual-input and single-output fuzzy system. The graphical procedures illustrated here can be easily extended and will hold for fuzzy rule-bases (or fuzzy systems) with any number of antecedents (inputs) and consequents (outputs).

The mamdani method has several variations. There are different t-norms to use for the connectives of the antecedents, different aggregation operators for the rules, and numerous defuzzification methods that could be used [13].

In the field of artificial intelligence (machine intelligence) there are various ways to represent knowledge. Perhaps the most common way to represent human knowledge is to form it into natural language expressions of the type.

IF premise (antecedent), THEN conclusion (consequent).

CHAPTER THREE
FUZZY LOGIC DESIGN FOR LOAD FORCASTIING

3.1 Introduction

This section presents a formulation of a Fuzzy Logic System (FLS) that can be used to construct nonparametric models of nonlinear processes, given only input–output data. In order to effectively construct such models, in this section will discuss several design methods with different properties and features.

Designing a FLS can be viewed as approximating a function, or fitting a complex surface in a (probably) high dimensional space. Given a set of input–output pairs, the task of learning is essentially equivalent to determining a system that provides an optimal fit to the input–output pairs, with respect to a cost function. In addition, the system produced by the learning algorithm should be able to generalize to certain regions of the multidimensional space where no training data was given, i.e., it should be able to interpolate the given input–output data. Within the framework of approximation, and interpolation theory, it is common among many approximation/interpolation methods to generate the desired surface using a linear combination of basic functions (typically, nonlinear transformations of the input).

3.2 Short Term Load Forecasting In Sudan Network Generation

Short term load forecasting is basically is a load predicting system with a leading time of one hour to seven days, which is necessary for adequate scheduling and operation of power systems. For proper and profitable management in electrical utilities, short-term load forecasting has lot of importance.

High forecasting accuracy as well as speed is the two most vital requirements of short-term load forecasting and it is of utmost importance to analyze the load characteristics and identify the main factors affecting the load. In electricity markets, the traditional load affecting factors such as season, day type and weather, electricity price have a complicated relationship with system load.

3.3 Blocks Diagram And Flow Chart

The significance of this search is present short term load forecasting for a day ahead by taking into considerations time and weather parameters such as temperature. The classification of the load data is done using fuzzy set techniques.

Figure 3.1 shows the basic block diagram of the proposed work. The inputs to the fuzzy set based classifier i.e. hourly data of forecasted temperature and time are given to the fuzzy inference system through fuzzification block. The fuzzy inference block is the heart of the system as it processes the input data and gives output as the forecasted load. The inference system accomplishes the task of forecasting by the used of the fuzzy rule based prepared by the forecaster. The accuracy of the forecast depends on the experience of the forecaster, the rules prepared by the forecaster and the number of rules prepared. After, the inference system gives output; the defuzzification block converts the fuzzified output to the crisp output which can be further displayed on a graph known as the load curve.

Firstly, the historical data are examined and the maximum and the minimum range of different parameters are obtained. These ranges are used in the process of the Fuzzification of different parameters such as time and temperature. After the fuzzification is done, based on the different parameter of load forecasting rule are prepared. This rules are the heart of the fuzzy system, so utmost care should be taken to prepare these rules. Once, the rules are prepared forecast the load of the desired hour.

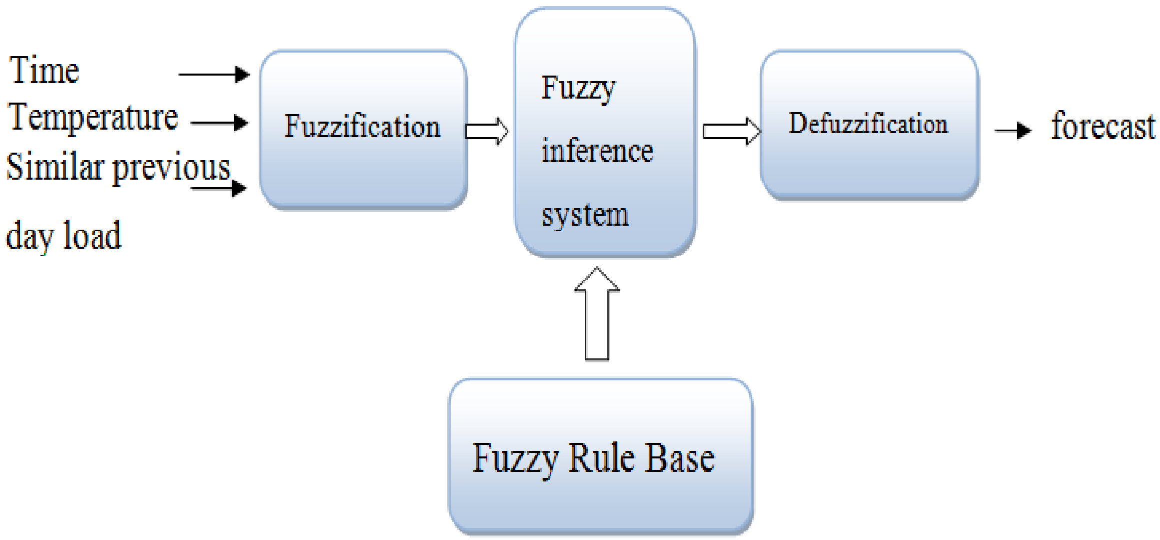

Figure 3.1: Fuzzy logic methodology for short term load forecasting.

Figure 3.2 shows the flow chat of STLF using fuzzy logic. The output obtained is compared with the actual load and the error in load forecasting is used to improve the rule base for future forecast. This improvement in rule of fuzzy logic increases the accuracy of the load forecasting.

3.3.1Fuzzy model: The data collection

There are two factors that are used to forecast next day electricity load which are temperature and load. Temperature is important because demand of load is depending on temperature of the day. Normally when temperature is high, the demand will also high. The hourly temperature and day temperature (℃) data obtained from the National Center for Control, Sudan. The hourly electricity load and day hourly electricity load demand in Sudan was provided by the National Center for Control in The Sudan

In this study, the load data from 3th and 4th Dec 2013 are used as date of previous date, 3th and 4th Dec 2014 as actual date and the forecast load value for the 3th and 4th Dec 2015 for identify the rule.. For testing purpose, we applied load data on June 2014 as date of previous date, June 2015 as actual date and the forecast load value for the June 2016.

Microsoft excel has been used to confirm the result .for its high ability in dealing with variable and forming equation that liked to these variable of the dependent variable and the independent variable .this prediction value always depend on the correlation factor between the dependent and independent variable .

So that if the correlation factor was zero, then every independent value can lead to the arithmetic mean via the (dependent value) .but if the correlation factor was between (0-1) the ability to predict the result increases more than the first case, that is when the correlation factor was zero and if the correlation equal 1 then the prediction from the values of the dependent and independent become conclusion and without any errors or mistakes.

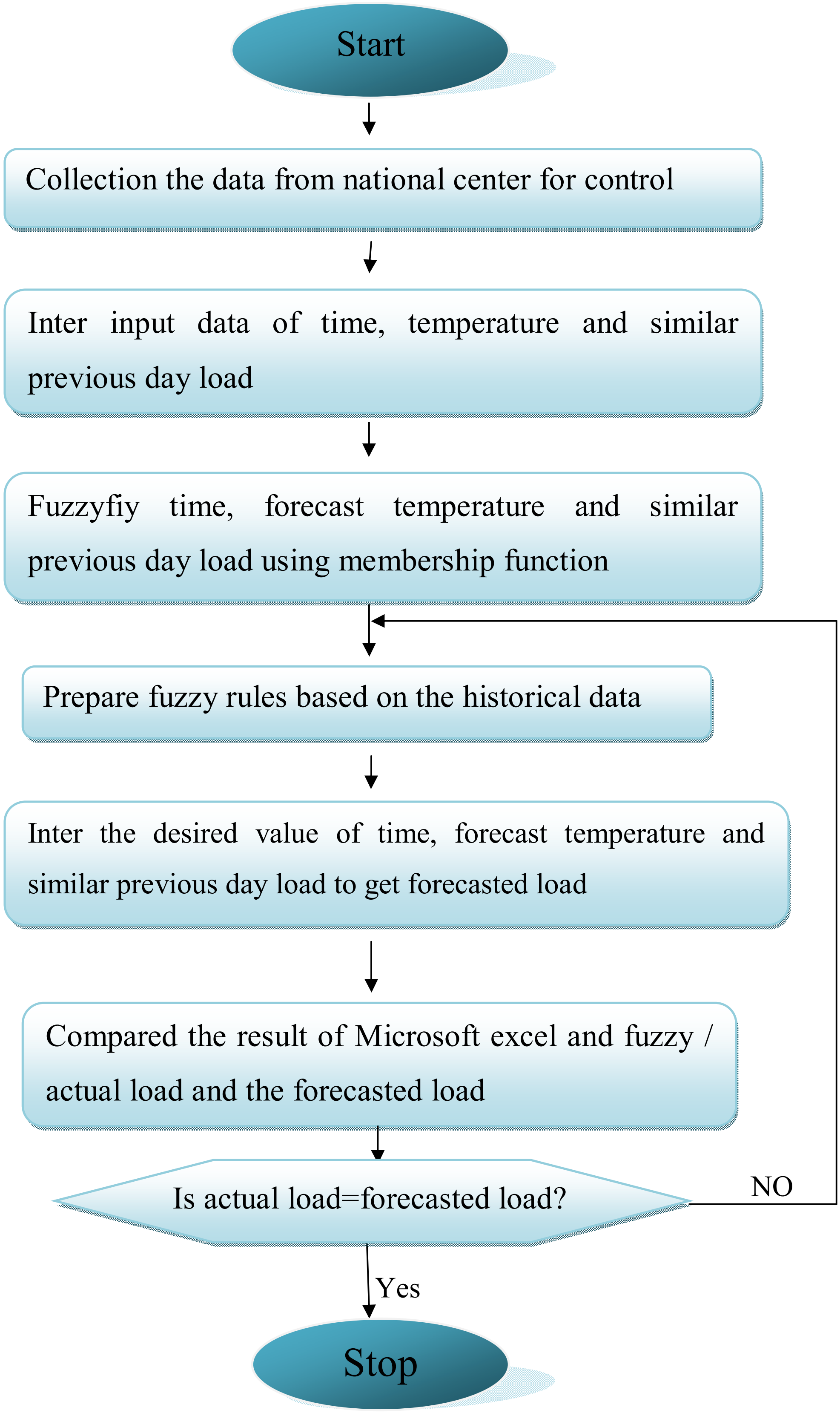

Figure 3.2: Flow chart of fuzzy logic methodology for Short term load forecasting.

3.4 Fuzzy Logic for Short Term Load Forecasting

One of the main characteristics of fuzzy model is the development of the rules. In this section, rules development which relates the fuzzy input and the required output are presented.

Figure 3.3 shows the whole structure of fuzzy logic system included input, reasoning rules and also the proposed output.

The inference rules relate the input to the output and every rule represents a fuzzy relation.

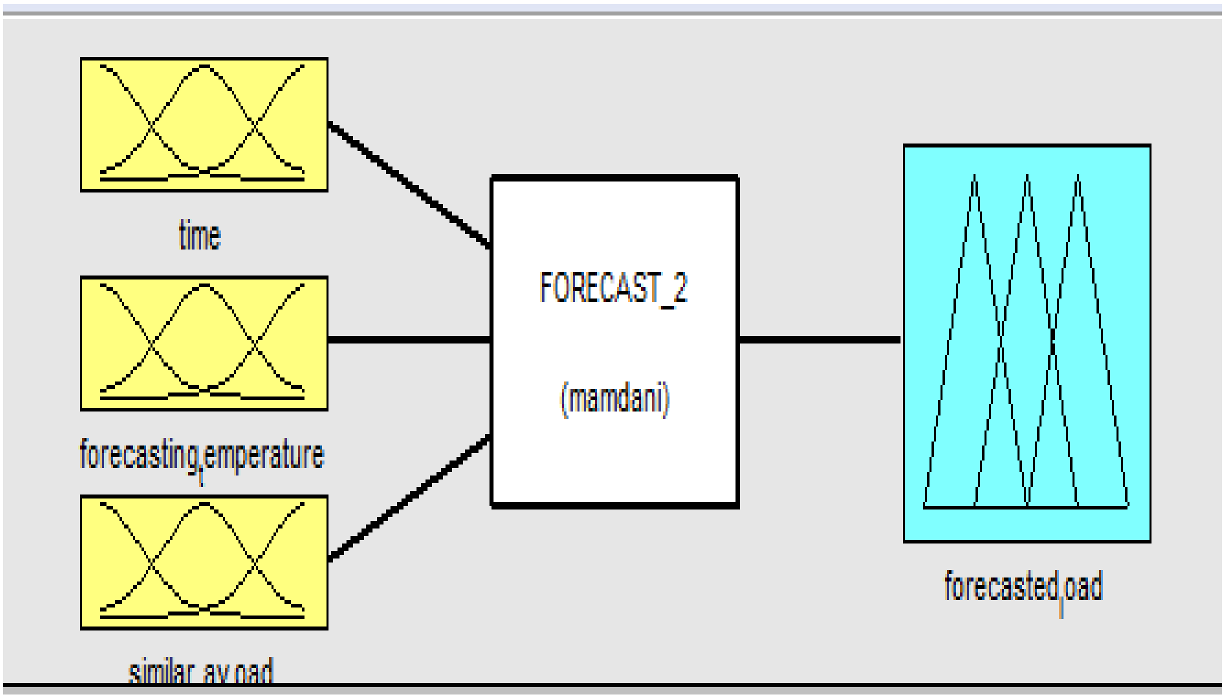

Figure 3.3: Fuzzy system structure.

4.3.1 Fuzzification load forecast

Fuzzification is used in order to express the fuzziness of data, in this study an arrangement is made of fuzzy subsets for different inputs and outputs in complete universe of discourse as membership functions. A triangular membership function is used for the inputs as well as the output.

The three inputs taken for short term load forecast (STLF) are time, temperature and previous similar day load, as shown in Figure 3.4. Time is divided into five triangular membership functions which are as follows:

- Dawn (DAWN)
- Morning (MORN)
- Noon (NOON)
- Evening (EVE)
- Night (NIGHT)

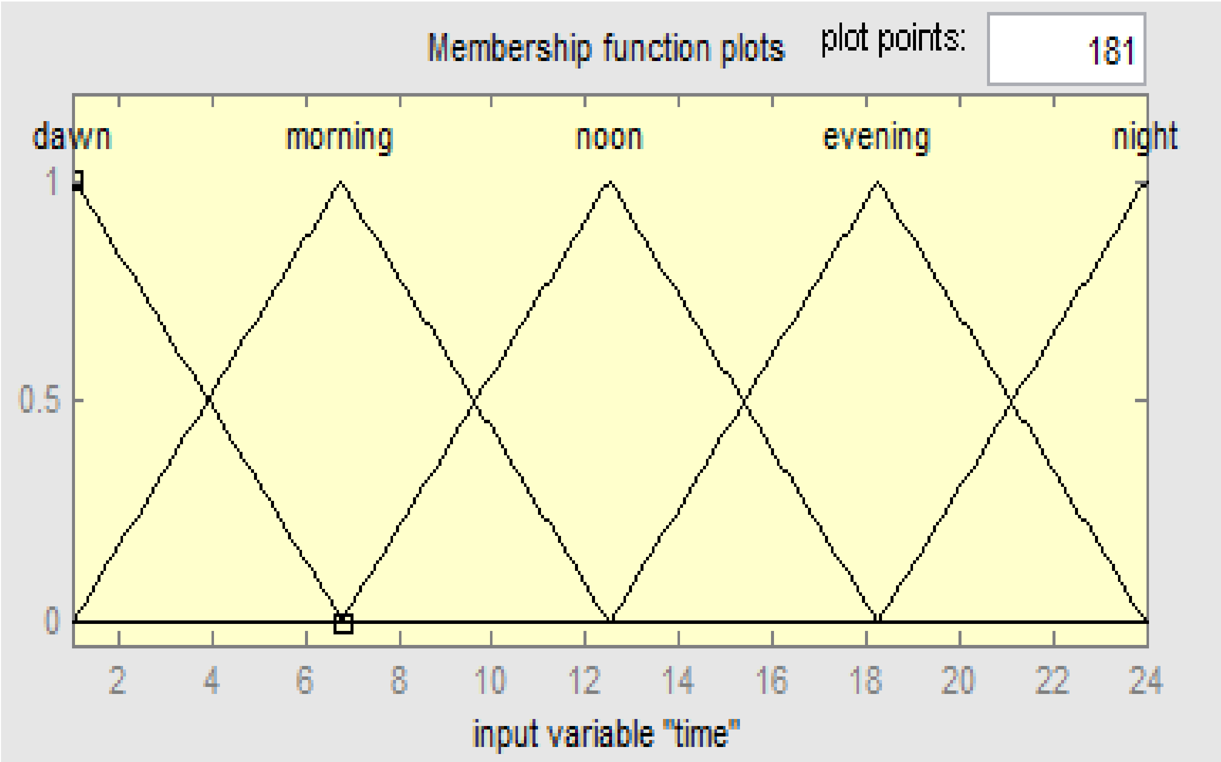

Figure 3.4: Triangular membership function for time.

Figure 3.5 shows temperature divided into five triangular membership functions which are as follows:

- Very cool (VC)
- Cool (C)
- Medium (M)
- Hot (H)
- Very hot (VH)

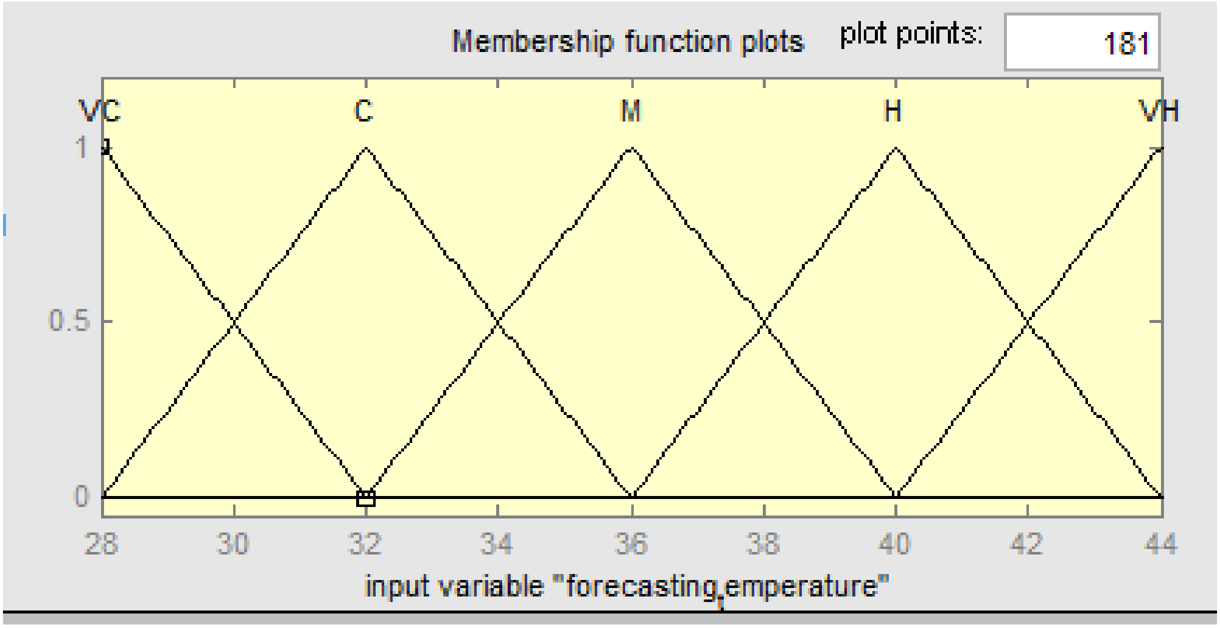

Figure 3.5: Triangular membership function for forecasted temperature.

Figure 3.6 shows similar pervious day load divided into five triangular membership functions which are as follows:

- Very low (VC)
- Low (C)
- Medium (M)
- High (H)
- Very high (VH)

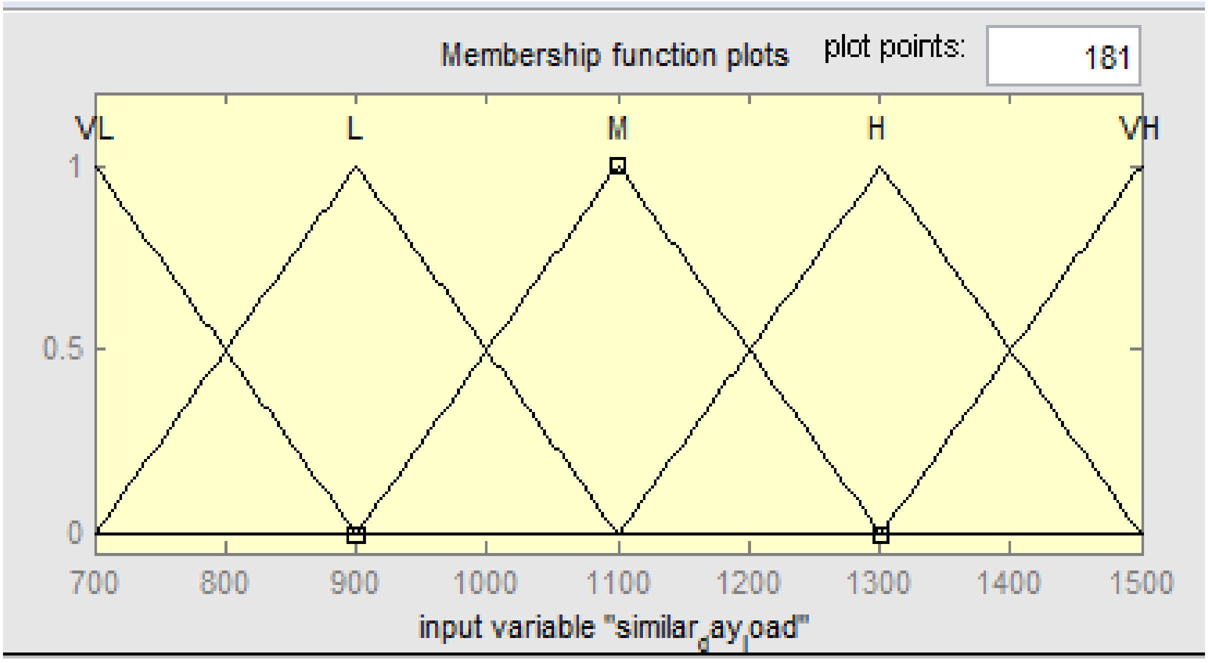

Figure 3.6: Triangular membership function for similar pervious day load.

Figure 3.7 shows forecasted load (output) divided into five triangular membership functions which are as follows:

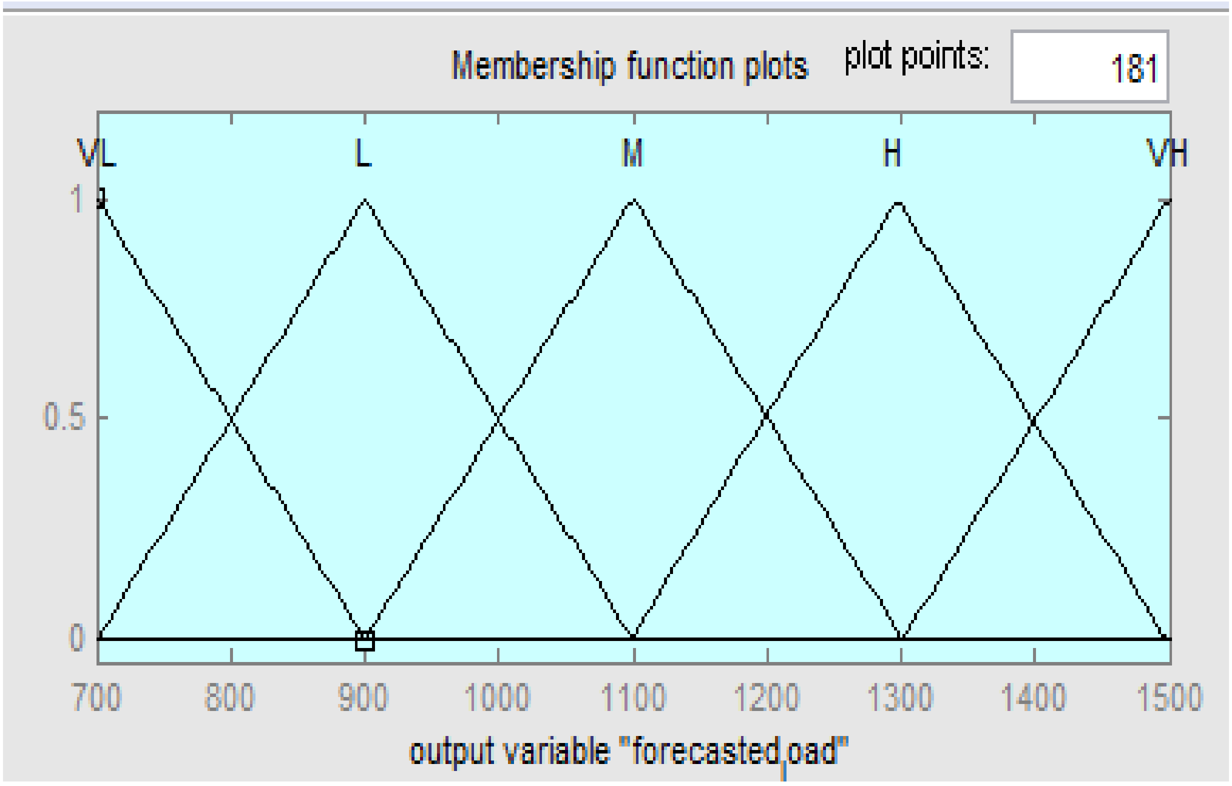

Figure 3.7: Triangular membership function for forecasted load.

3.4.2 Fuzzy Rule Base Load forecast

This part is the heart of the fuzzy system. The heuristic knowledge of the forecasted is stored in terms of "IF-THEN" rules. It sends information to fuzzy inference system, which evaluates the gained information to get the load forecasted output. In this study the 125 fuzzy rules are used. Some of the rules are as follows:

- If (time is dawn) and (forecasted-Temperature is VC) and (similar-day-load is VL) then (forecasted-load is VL) (1)
- If (time is dawn) and (forecasted-Temperature is VC) and (similar-day-load is L) then (forecasted-load is L) (1)
- If (time is dawn) and (forecasted-Temperature is VC) and (similar-day-load is M) then (forecasted-load is M) (1)
- If (time is dawn)and (forecasted-Temperature is VC) and (similar-day-load is H) then (forecasted-load is H) (1)

- If (time is dawn) and (forecasted-Temperature is VC) and (similar-day-load is VH) then (forecasted-load is VH) (1)

  .

  .

  .

  .

- If (time is night) and (forecasted-Temperature is H) and (similar-day-
  Load is VH) then (forecasted-load is VH) (1)
- If (time is night) and (forecasted-Temperature is V H) and (similar-day-load is VL) then (forecasted-load is VL) (1)
- If (time is night) and (forecasted-Temperature is VH) and (similar-day-load is L) then (forecasted-load is L) (1)
- If (time is night) and (forecasted-Temperature is VH) and (similar-day-load is M) then (forecasted-load is M) (1)
- If (time is night) and (forecasted-Temperature is VH) and (similar-day-load is H) then (forecasted-load is H) (1)
- If (time is night) and (forecasted-Temperature is VH) and (similar-day-load is VH) then (forecasted-load is VH) (1)

3.4.3 System Simulation

Figure 3.8 shows the simulation of fuzzy logic methodology short term load forecasting. MATLAB is used for the simulation purpose. As shown in the figure figure3.8 the input data's as well as actual load occurred are loaded. The input data are given to fuzzy logic controller block. In fuzzy logic controller block "FIS" of fuzzy inference system is loaded. Based on the rules prepared the fuzzy logic controller give forecasted output corresponding to the input data. the error is calculated along with the forecasting as shown in Figure 3.8.

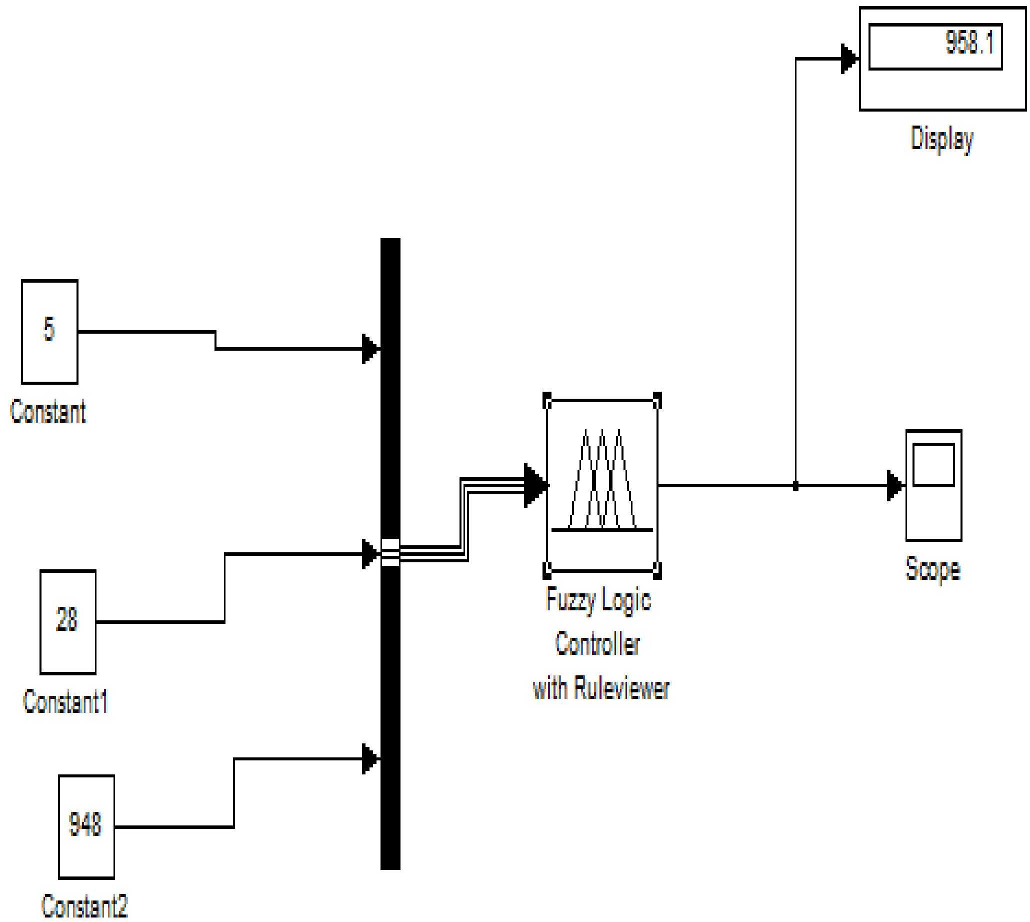

Figure 3.8: Simulink model of short term load forecasting.

The Figure 3.9 shows how the fuzzy system in MATLAB toolbox which works for the sample inputs.

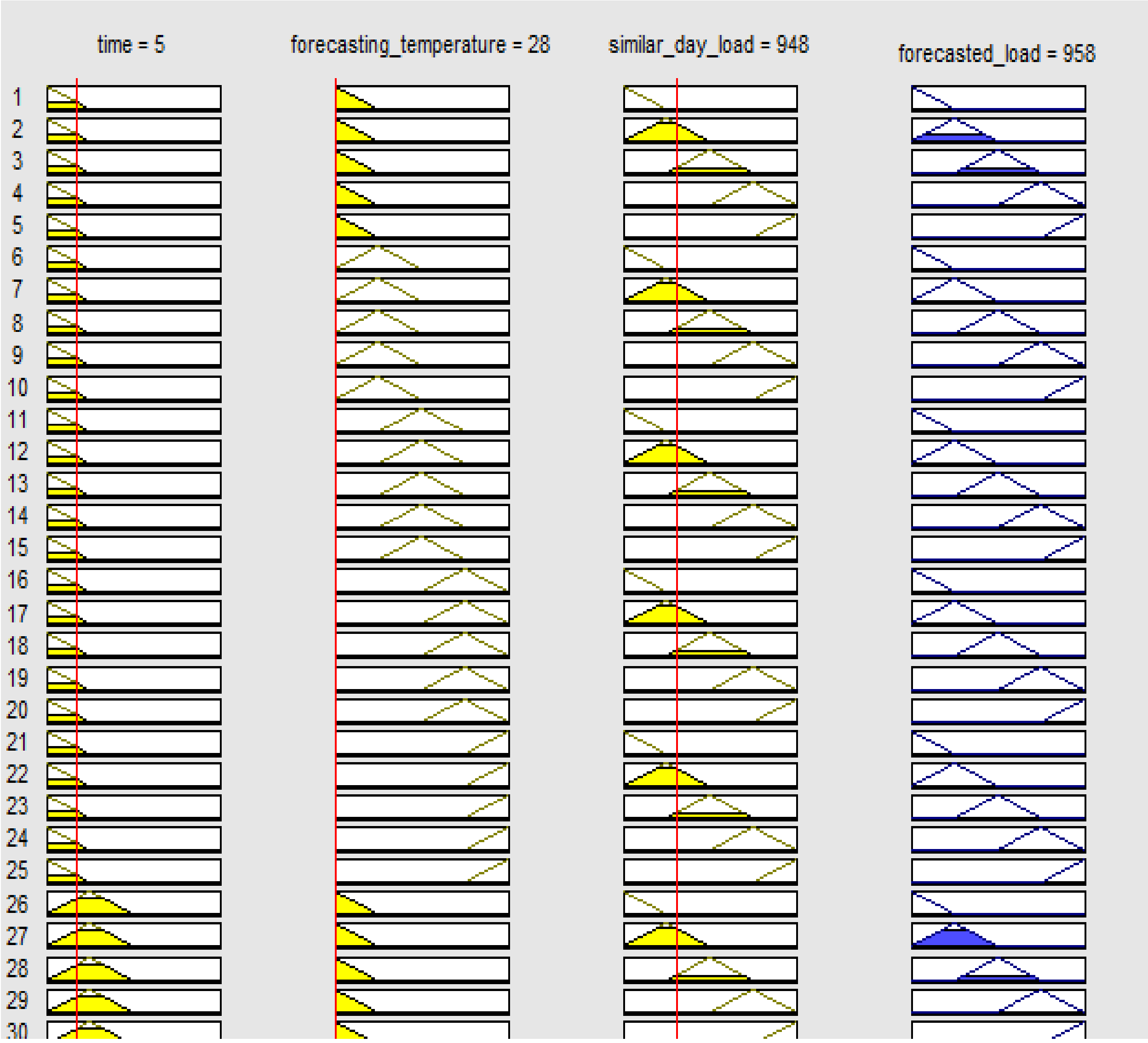

Figure 3.9 Defuzzified output for one sample data.

CHAPTER FOUR

RESULTS AND DISCUSSIONS

4.1 Results

Table 4.1 shows the actual load, forecasted load and also the percentage error in the forecasted load. The data of time, temperature and pervious similar day load are used as input data obtained from national center for control. The load forecast is done for the day 3rd of December 2015. The percentage error in forecast can be calculated as:

$$\%Error = \frac{\text{actual load} - \text{forecast load}}{\text{actual load}} \times 100 \tag{4.1}$$

Table 4.1: Hourly load forecast of 3rd December 2015.

Time (Hrs.)	Forecasted Temp. (C)	Pervious Similar Day Load (MW)	Actual(MW)	Excel forecast load(MW)	Fuzzy Forecasted Load (MW)	%Error	Error(Exel &Fuzzy)%
1	31	1024	956	1015	1020	-6.73	-0.53
2	30	1005	915	1024	1002	-9.48	2.12
3	30	971	917	1006	985.4	-7.49	2.01
4	29	962	896	972	977.5	-9.11	-0.60
5	28	963	900	962	969.3	-7.74	-0.73
6	28	977	940	963	981.8	-4.49	-1.93
7	27	1059	1011	977	1050	-3.91	-7.48
8	30	1070	1033	1058	1053	-1.95	0.52
9	32	1241	1137	1070	1228	-7.96	-14.77
10	34	1312	1203	1239	1299	-8.02	-4.86
11	36	1357	1217	1312	1307	-7.44	0.35
12	38	1390	1311	1357	1321	-0.76	2.64
13	39	1418	1340	1390	1335	0.40	3.95
14	40	1423	1342	1418	1338	0.31	5.66
15	41	1415	1379	1423	1332	3.4	6.40
16	40	1385	1321	1415	1317	0.32	6.94
17	39	1320	1293	1385	1299	-0.50	6.22
18	38	1280	1265	1321	1263	0.18	4.36
19	37	1478	1528	1280	1391	8.97	-8.66
20	36	1491	1519	1476	1411	7.08	4.41
21	35	1444	1527	1491	1342	12.14	10.00
22	34	1381	1399	1444	1317	5.89	8.81
23	34	1241	1295	1381	1222	5.67	11.54
24	32	1100	1145	1242	1100	3.91	11.47

The actual load, excel forecast load and fuzzy forecast load are present as shows is Figure 4.1

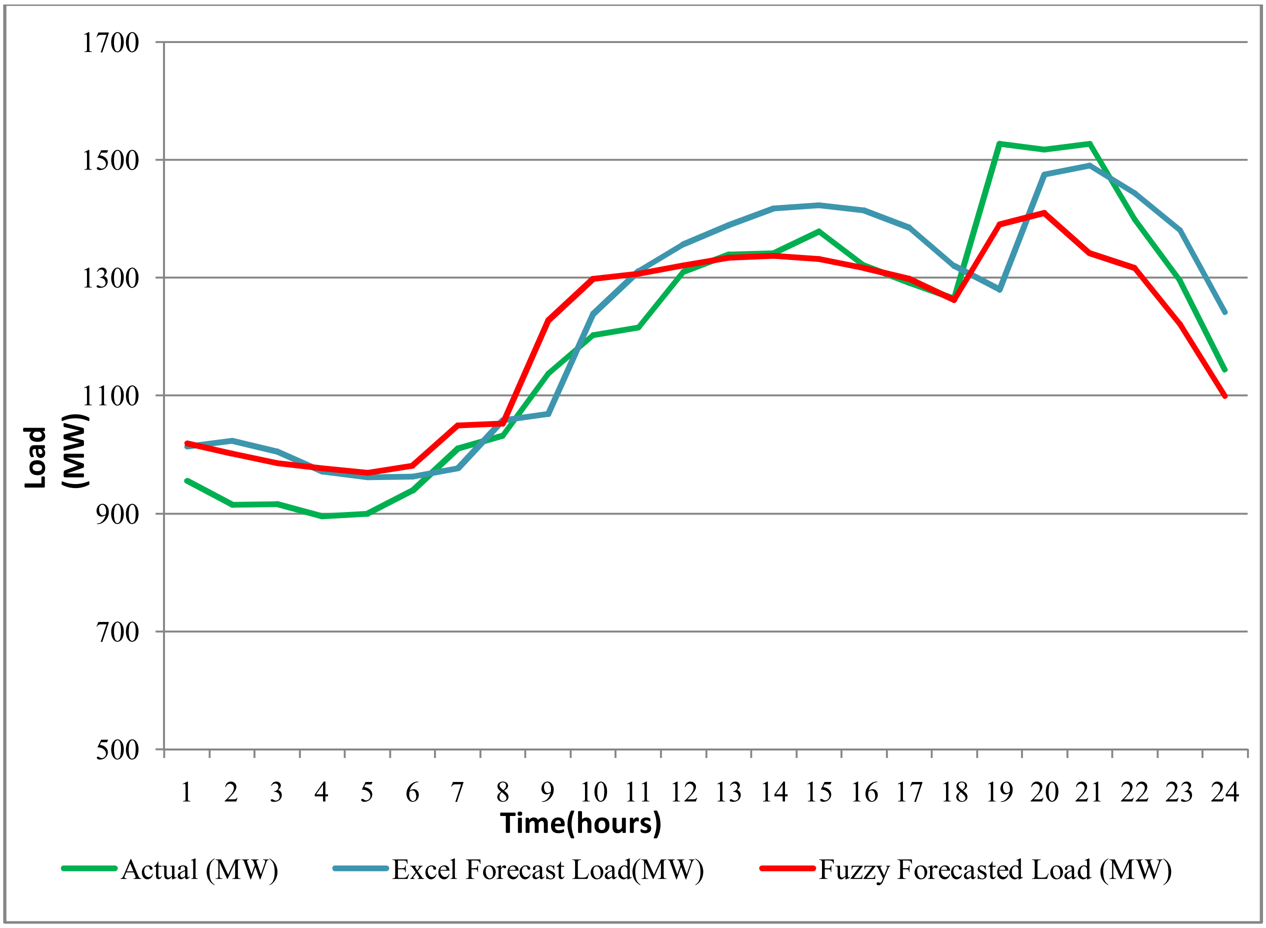

Figure 4.1: Load curve of 3th December 2015.

Table 4.2 shows the actual load, forecasted load and also the percentage error in the forecasted load. The data of time, temperature and pervious similar day load are used as input data obtained from national center for control. The load forecast is done for the day 4th December 2015.

Table 4.2: Hourly load forecast of 4th December 2015

Time (Hrs.)	Forecasted Temp. (℃)	Pervious Similar Day Load (MW)	Actual(MW)	Excel Forecasted Load(MW)	Fuzzy Forecasted Load (MW)	%Error	Error (Exel&Fuzzy)%
1	32	1028	1055	1010	1023	2.9	-1.28
2	31	993	1006	1027	995	1.0	3.17
3	31	961	970	993	970	-0.007	2.34
4	30	938	953	961	957	-0.44	0.39
5	28	945	962	938	955	0.67	-1.82
6	30	960	1014	945	978	3.59	-3.48
7	30	1036	1100	960	1020	7.23	-6.23
8	31	1062	1086	1035	1053	3.02	-1.73
9	33	1303	1244	1062	1298	-4.33	-22.22
10	35	1320	1338	1301	1300	2.80	0.05
11	37	1318	1354	1320	1299	4.06	1.56
12	39	1332	1374	1318	1301	5.28	1.26
13	40	1383	1393	1332	1316	5.56	1.20
14	41	1396	1445	1382	1322	8.50	4.35
15	42	1423	1439	1396	1330	7.59	4.70
16	41	1359	1363	1423	1308	4.01	8.07
17	40	1276	1337	1360	1265	5.36	6.98
18	39	1244	1305	1277	1235	5.39	3.29
19	38	1454	1484	1245	1348	9.17	-8.31
20	37	1487	1528	1452	1403	8.20	3.40
21	36	1461	1530	1487	1356	11.38	8.80
22	36	1394	1458	1461	1321	9.39	9.59
23	35	1239	1309	1395	1230	6.00	11.83
24	33	1128	1165	1240	1137	2.41	8.32

The actual load, excel forecast load and fuzzy forecast load are present as shows is Figure 4.2.

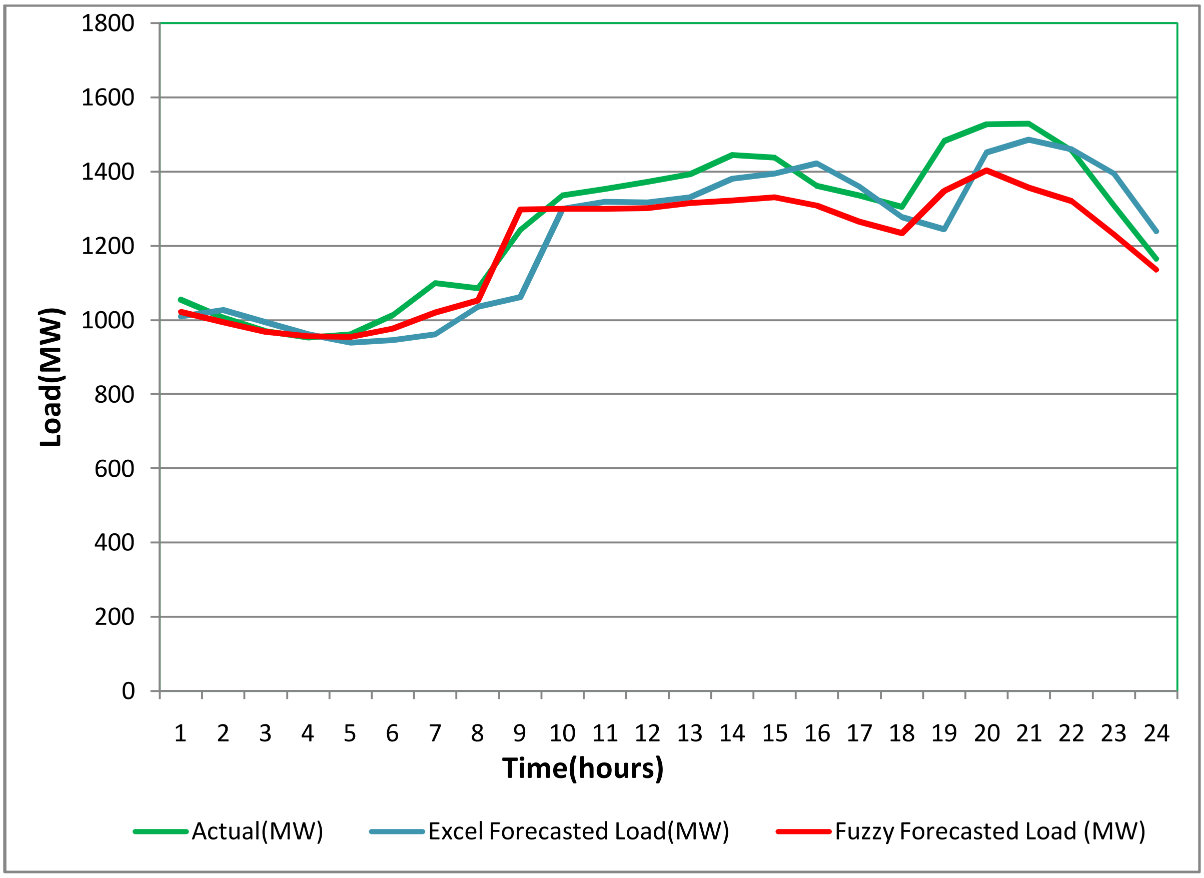

Figure 4.2: Load curve of 4th December 2015.

Table 4.3 show the monthly forecasting results of the fuzzy forecast load.

Table 4.3: day load forecast of month June 2016.

Time (day)	Forecasted Temp. (°C)	Pervious Similar Day Load (MW)	Actual(MW)	forecasted in excel(MW)	Fuzzy Forecasted Load (MW)	%Error
1	38	38417	41561	38193	38176	8.15
2	41	39890	42423	38415	40026	5.65
3	43	39666	43591	39875	39752	8.81
4	44	39803	43795	39668	39974	8.73
5	44	38956	38718	39802	38712	0.017
6	42	34390	40811	38965	35782	12.32
7	41	33482	44129	34435	34929	20.85
8	44	37779	45732	33491	37806	17.33
9	43	37760	45908	37736	37790	17.68
10	41	37772	43882	37760	37800	13.86
11	39	38436	42622	37772	38307	10.12
12	41	38695	39541	38430	38417	2.84
13	41	33875	42097	38693	35370	15.98
14	40	36077	44450	33923	36241	18.47
15	40	39040	44655	36056	38922	12.84
16	39	39016	43752	39010	38873	11.15
17	39	39146	43440	39016	39019	10.18
18	41	39846	47157	39145	40003	15.17
19	42	39480	42130	39839	36469	13.44
20	42	34877	44214	39483	35923	18.75
21	41	37330	46713	34924	37436	19.86
22	40	39257	46326	37306	39174	15.44
23	40	39834	46651	39237	39939	14.39
24	40	38893	46268	39828	38767	16.21
25	40	38842	44386	38903	38676	12.86
26	40	38185	44277	38843	38090	13.97
27	40	34535	43856	38191	35781	18.41
28	40	37824	46864	34572	37842	19.25
29	40	42897	47057	37791	42719	9.22
30	41	41802	49153	42846	41652	15.26

The actual load, previous similar day load, excel forecast load and fuzzy forecast load are present as shows is Figure 4.2.

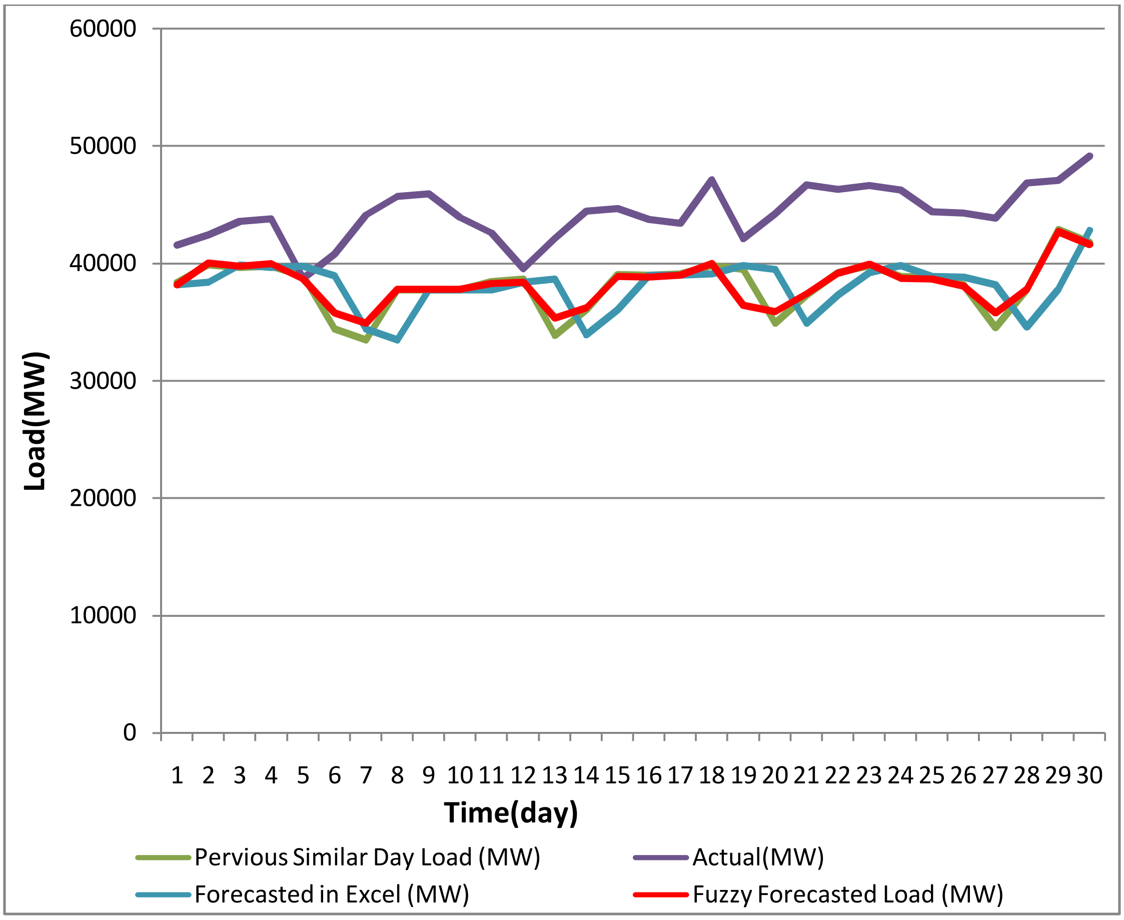

Figure 4.3: Load curve of month June 2016.

4.2 Discussion

The results obtained from the fuzzy logic are compared with the conventional method of short term load forecasting and it is found that there is an error is between +12.14% and-9.48 %. The load curve is plotted which is the comparison between the actual load and the fuzzy forecasted load. Figure 4.1 and Figure 4.2 shows the load curve plot for 3th Dec 2013 and 4th DEC 2013 respectively. From the curve it is observed that fuzzy forecasted load curve is very close to the actual load curve and excel load curve.

June shows the less error 0.017 % at day five. And the largest error is 20.85% record at day 7. In this year's it has been unexpected increase in actual load in average of 14% from the forecast load due to unnatural causes.

CHAPTER FIVE

CONCLUSIONS AND RECOMMENDATION

5.1 Conclusion

As electricity markets have deregulated over the last decade, accurate load forecasts have become a vital part of a utility's long, medium, and short-term generation and procurement planning. An inaccurate load forecast can has severe consequences for customers in the form of higher rates.

In this study fuzzy methodology for short term load forecasting is presented. It is concluded that using time, temperature and similar previous day load as the inputs and by formulating rule base of fuzzy logic using available data, load forecasting is done with an error margin of+12.14% and-9.48 %. Moreover, it is also concluded that fuzzy logic approach is very easy for the forecaster to understand as it works on simple "IF-THEN" statements. It also helps in unit commitment decisions, reduce spinning reserve capacity and schedule device maintenance.

5.2 Recommendation

- Use of Neural Network for short term load forecasting
- Use of Neural-Fuzzy System for Short Term Load Forecast
- Consideration of medium and long Term Load Forecast

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