DEPARTMENT OF ELECTRICAL AND COMPUTER ENGINEERING

AHMADU BELLO UNIVERSITY, ZARIA

EFFECT OF TRIANGULAR AND GAUSSIAN MEMBERSHIP FUNCTIONS IN FUZZY TIME SERIES FORECASTING:

A CASE STUDY OF ELECTRIC LOAD FORECASTING

By

ZUBAIR NANA HAUWA

MARCH, 2012

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BY

ZUBAIR NANA HAUWA

A Thesis submitted to the Department of Electrical and Computer Engineering, Ahmadu Bello University Zaria in partial fulfillment of the requirements for the award of Master of Science (M.Sc) Degree in Electrical Engineering.

DECLARATION

I hereby declare that the work in this thesis titled 'Effect of Triangular and Gaussian membership functions in fuzzy time series forecasting: a case study of electric load forecasting' was performed by me in the department of electrical engineering under the supervision of Dr. M.B. Mu'azu and Dr. D.D.Dajab.

The information derived from the literature has been duly acknowledged in the text and a list of references provided. No part of this work has been presented for another degree or diploma at any institution.

ZUBAIR, NANA. HAUWA		March, 2012
Name of student	Signature	Date

CERTIFICATION

This thesis titled "EFFECT OF TRIANGULAR AND GAUSSIAN MEMBERSHIP FUNCTIONS IN FUZZY TIME SERIES FORECASTING: A CASE STUDY OF ELECTRIC LOAD FORECASTING " by Zubair, Nana. Hauwa meets the regulations governing the award of the degree of Master of Science of the Ahmadu Bello University, Zaria and is approved for its contribution to knowledge and literary presentation.

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DEDICATION

I dedicate this work to my family, for their good nature forbearance with the process and for their pride in this accomplishment.

ACKNOWLEDGEMENT

Praise be to Almighty Allah for His kindness, mercies, and for seeing me through this study successfully. I would like to thank all the people who have helped and inspired me during my Masters Degree program.

First and foremost I offer my sincere gratitude to my supervisor, Dr M. B Muazu,, for his guidance and support during my thesis and study at Ahmadu Bello University. His perpetual energy and enthusiasm in research had motivated all his students, including me. In addition, he was always accessible and willing to help his students with their research. As a result, research life became smooth and rewarding for me. I attribute the level of my Masters degree to his encouragement and effort.

I was delighted to interact with Dr.D.D.Dajab by attending his classes and having him as my minor Supervisor, gratitude goes to him for his advice and support. My sincere appreciation goes to Engr. Suleiman Garba w ho offered much advice and insight throughout my work on the effect of Triangular and Gaussian membership functions in fuzzy time series forecasting.

Special thanks also goes to Dr. J.Y. Oricha, Engr Jibril, Dr.B. Jimoh and all distinguished lecturers of the department.

To my friend of more than a decade Sariyya Awwal , course mates , Kolade and Mall Yahaya who were all there for me throughout the period of my study,I say thank you so much, what will I have done without you guys.

My deepest gratitude goes to my family for their unflagging love and support throughout my life; this dissertation is simply impossible without them. I am indebted to my father, Alh Ismaila

Zubair, for his care and love. As a typical father in an African family, he worked industriously to support the family and spare no effort to provide the best possible environment for me to grow up and attend school. I cannot ask for more from my mother, Haj Maryam D.Shalshika, as she is simply perfect. I feel proud of my sister, Zulaihatu, for her talents. She had been a role model for me to follow unconsciously when I was a teenager and has always been one of my best counselors. To my dear sister Dr. Zainab who happens to also be my best friend I want to say thank you for your support and love. I want to also appreciate my uncle and his wife Col and Mrs. Shalangwa, and Col Abdulkareem.K for their kindness and generosity. May Almighty Allah grant you all aljannat Firdausi (Amin)

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TABLE OF CONTENTS

LIST OF TABLES

PAGE

LIST OF FIGURES

PAGE

LIST OF SYMBOLS AND ABBREVATION

C	constant
R	Correlation Factor
e	Euler's number.
A	Fuzzy Set
F(t)	Fuzzy Time Set
GMF	Gaussian Membership Function
gauss2mf	Gaussian two-sided membership function
µ	Membership Function
w	Model Basis
MBF	Membership Function
MSE	Mean Square Error
D1& D2	Positive integers
PHCN	Power Holding Company of Nigeria
RMSE	Root Mean Square Error
$R^w(t)$	Relationship Matrix
FTS	Time Series
TMF	Triangular Membership Function
C_i	variation,
σ.	Variance

ABSTRACT

Fuzzy Time Series (FTS) plays a great role in fuzzification of data, which is based on certain membership functions. In this thesis, a 24 weeks load demand data from PHCN was used and fuzzified based on the Gaussian Membership Functions, after that all fuzzified data are defuzzified to get normal form. The results obtained using the GMF (Gaussian Membership Functions) is compared with that of the TMF (Triangular Membership Function), from which the comparison basis was based on, qualitative performance indicator and statistical error. The RMSE Values obtained using the GMF and the TMF are 66.5 and 17.1 respectively, while their correlation factor R is 0.98 for TMF and 0.86 for GMF. From the analysis carried out the TMF generated the least RMSE and hence, is more suitable in forecasting for electric load.

CHAPTER ONE

INTRODUCTION

1.1 BACKGROUND

Load forecasting is of vital importance in the electricity industry, especially in a deregulated economy like that of Nigeria. It has many application including energy purchasing and generation, load switching, contract evaluation, and infrastructural development. A large variety of mathematical models have been developed and applied in carrying out load forecasting. In this work, the Fuzzy Time Series (FTS) approach is used for the load forecasting.

There is a planned Government policy towards unbundling the utility (Power Holding Company of Nigeria (PHCN)) company with the objective of improving efficiency of electricity generation, transmission, and distribution. This emphasizes proper and effective planning, management and operations of the network. The operation and planning of a power utility company requires an adequate model for electric power load forecasting.

Load forecasting plays a key role in helping an electricity utility to make important decisions on power, load switching, voltage control, network reconfiguration, and infrastructure development. It is extremely important for an optimal management of generation and distribution of electric energy to have as precise as possible the load profile prediction.

According to Abbasovand Mamedova (2003), time series represents a consecutive series of observations taken over equal time intervals. The application of Fuzzy Logic and fuzzy sets to time series analysis gave rise to Fuzzy Time Series. The method to be applied here is the method initially used by Abbasovand mamedova (2003), in forecasting population in

Azerbaijan but adopted by Adeola (2008) and Muazu (2009) in load forecasting. The emphasis of their works was on determining an optimal interval length and model basis.

AIM AND OBJECTIVES

The aim is to carryout comparative investigation on the effect of triangular and gaussian membership functions in fuzzy time series (FTS) forecasting.

The objectives are specifically listed as follows:

i. Defining the universe of discourse and interval lengths for the observations;
ii. Partitioning the universe based on the interval length;
iii. Defining the fuzzy set for the observation;
iv. Fuzzification of the observations using the appropriate membership function;
v. Establishing the fuzzy relationships;
vi. Performing the forecast;
vii. Defuzzification of the forecast result
viii. Qualitative and quantitative performance analysis

This study, therefore, is aimed at investigating the effect of triangular and gaussian Membership Functions on electric load forecasting, building upon the work of Adeola (2008) and Muazu *et al* (2009).

1.2 SIGNIFICANCE OF STUDY

In carrying out Fuzzy Time Series (FTS) forecasting, some critical issues include determination of the interval length and appropriate membership function amongst others. This research will address the implication of Membership Function in Fuzzy Time Series Forecasting. In Adeola

(2008) and Muazu *et al* (2009), investigated load forecasting using the Fuzzy Time Series (FTS) forecasting technique adopted by Abbasov and Mamdova (2003) and an optimal interval length of five (5) and model basis of six (6) were determined. It was also observed in their work that odd number interval lengths performed better than even number interval lengths. The fuzzification method based on the triangular membership function was used. It then becomes pertinent to determine the effect of membership functions used for the fuzzification on the forecasting result.

1.3 STATEMENT OF PROBLEM

- It is pertinent to determine the effect of triangular and gaussian Membership Functions in Fuzzy Time Series Forecasting. This couple with Optimal Interval length in FTS data analysis offers serious problem in forecasting.
- This Research will address the implication associated with Membership Functions in FTS Forecasting. The Gaussian membership function will be used in the fuzzification process and the optimal interval length and model basis obtained by Adeola (2008), Abbasov and Mamedova (2009). The essence then will be to compare and contrast between the effect of the triangular and Gaussian membership functions (qualitatively and quantitatively) on the forecasting result.

The following methodology as used by Adeola (2008),Muazu *et al* (2009) and Abbasov (2003) is also adopted:

i. Partitioning the data into training data (18-weeks) and validation data (6 weeks);

ii. Defining the universal set U containing the interval between least and greatest variation of load;

iii. Dividing the Universal set U into several interval lengths (5) containing variation values corresponding to different loads consumed;

iv. Determining the respective value of linguistic variable or the Fuzzy set (t) i.e. the qualitative description of variation values of total load as a linguistic variable;

v. Fuzzifying the input data or the conversion of numerical crisp values into fuzzy values. In this case, the Gaussian membership function will be used;

vi. Selecting the parameter w>1(model basis) (6) corresponding to the time period prior to the concerned week;

vii. Calculating the fuzzy matrix $p^w(T)$ and forecasting of the expected load for the preceding week;

viii. Defuzzifying the obtained result or conversion of fuzzy values into quantitative (crisp) values; and

Tabulating and comparing the results obtained using the Gaussian membership function and those obtained using the triangular membership function.

1.4 PROJECT OUTLINE

The thesis is divided into five chapters: Chapter One introduces the research work where the objectives of the research are defined and the methodology applied is explained. The reviews of literature of similar research work, with the theoretical background are contained in Chapter

Two. Chapter Three discusses the methodology in achieving the thesis aims, while Chapter Four deals with the analysis of the results obtained. Chapter Five contains limitations, conclusion and recommendation. References are provided at the end of the work.

CHAPTER TWO

LITERATURE REVIEW AND THEORETICAL BACKGROUND

2.1 LITERATURE REVIEW

2.1.1 INTRODUCTION

A great deal of work has been carried out in forecasting including statistical and data driven approaches. This chapter aims at reviewing previous works carried out in relevant and related areas

2.2 REVIEW OF PAST WORKS IN THIS AREA

Abbasov and Mamedova (2003) presented an approach to forecasting using the Fuzzy Time Series (FTS) technique for population growth in Azerbaijan. In the work, an interval length of five (5) and model basis of seven (7) were used even though no empirical basis was given for the choice of the interval length.

Muazu*et al* (2009) and Adeola (2008), based upon the technique proposed by Abbasov and Mamedova (2003) carried out a load demand forecast in order to determine the effect of varying the interval length and model basis. They concluded that the model basis of six (6) produced the best forecast results. It was also determined that odd number interval lengths performed better than even number interval lengths.

Song and Chissom (1993), used Fuzzy Time Series in forecasting enrollment of a University, they concluded that this approach was better than the Linear Regression Method in forecasting the university enrollment.

Xiaoyu *et al* (1999), used time series prediction based on fuzzy principles in their research in which a new modified approach was presented to predict chaotic time series. This method introduced a new concept-reliability factor which takes the randomness nature of the system into account.

Choudhury *et al* (1999), used a rule base to construct a Personnel Selection System (PSS) using Fuzzy Expert methodology.

Zuoyong *and* Zhempie (1998), proposed a method of classification of weather forecasts by applying fuzzy grade statistics. The rainfall in a certain region could be forecasted as one of three grades. The range of rainfall was chosen depending on the historical data, the membership functions of the fuzzy sets were also designed.

Feng and Guang (1993), described the model of fuzzy self-regression. The main steps were the making of the form of self-related sequence number according to the observed number, the calculation of self-related coefficient and the ascertaining of the forecasting model of fuzzy self-regression.

Sugeno and Tanaka (1991), proposed a successive identification method of a fuzzy model. The structure and initial parameters were determined to identify a model called 'initial model', which was identified by the offline fuzzy modeling method using some pairs of input-output data.

Mandal *et al* (2008), carried out work on the Role of Membership functions in Prediction of Shoot Length of Mustard Plant. In the Work, modeling of Fuzzy Time Series Prediction with different membership function was carried out and based on residual analysis (Absolute Residual, Maximum of Absolute Residual, Mean Absolute Residual, Mean of Mean Absolute

Residual, Median of Absolute Residual and Standard Deviation),it was determined that they had an effect on the prediction.

The emphases on these models have been on the establishment of Fuzzy relationships among observations. It is common for these models to include the following steps:

i. Defining the universe of discourse and interval lengths for the observations;
ii. Partitioning the universe based on the interval length;
iii. Defining the fuzzy set for the observation;
iv. Fuzzification of the observations using the appropriate membership function;
v. Establishing the fuzzy relationships;
vi. Performing the forecast;
vii. Defuzzification of the forecast result
viii. Qualitative and quantitative performance analysis

Article I. 2.3 FUZZY SET THEORY AND FORECASTING

Fuzzy sets theory can be defined as a mathematical formulation that enables the elimination of indefiniteness and deal with incomplete, inaccurate information of both qualitative and quantitative nature. The fuzzy set theory, advanced by Zadeh (1965), one of the well known representative of modern applied mathematics, excluded any definite description of the task and doing this offers such a solution scheme to the problem such that subjective reasoning and evaluation plays a principal role. Thus, anyone, encountering indefinite, incomplete information or data, can form some conclusion, by passing through reasoning all these realities.

The use of fuzzy verbal notation in every day speech such as, much, more, little, small, many, a number of, etc, enables one to give a qualitative description of the problems which must be tackled, taking into account of its indefinite nature as well as obtain explanation of the factors that cannot be described qualitatively.

The advent of fuzzy logic made it possible to tackle a great number of problems with fuzzy input data. One of them is the forecasting problem. Many of the structural elements of forecasting (input data and interdependence between its components, interval evaluation of indicators and their interdependence, expert evaluation and judgment etc) are either of a fuzzy nature or by being in Fuzzy relationship; condition the fuzzy description of the problem. The application of fuzzy logic to the handling of forecasting problem was undertaken by researchers in which the mathematical model of time series was described in a fuzzy form for handling the problems with fuzzy input data. This approach was developed later by other scientists to resolve analogous problem.

The consumer energy consumption feature, functioning under indefinite, uncertain circumstances, conditions the fuzziness of input data or loads the task unto fuzzy environment. Therefore, from both theoretical and practical stand point, handling the concerned problem based on Fuzzy time series will be more expedient.

2.3.1 FUZZY TIME SERIES

Time series represents a consecutive series of observation that is conducted by equal time intervals and lies at the root of exploring real processes in economics, meteorology and natural sciences etc Adeola (2008), Muazu *et al* (2009).

The analysis of time series observation consists of the followings:

1) Constructing the mathematical model of time series observation of real processes;

2) Model identification or selection of quantitative evaluation/ estimation method for assessing model parameters in order to test the extent to which the model is adequate to reflect the real process;

3) The conversion of identification model into time series through the statistical evaluation of model parameters.

Formally, time series can be defined as a discrete function x (t) whose argument and function values are dependent on discrete time moments as well as argument values, function values at different time intervals. It is assumed that the time interval 0≤t≤T of process x(t) is observed, that is to say, the parameter t varies along the time interval [0, T] (set R) or assumes any integer belonging to this interval. For every fixed time moment t=s, the value of the function, beginning from this moment, is generally determined by the values of the function arguments at all the time moments ranging from t=0 to t=s-1, and value of function at all the time moments ranging from t=0 to t=s-2.

Let us assume that U= {u1, u2…...un} is a universal time set. The fuzzy set A of universal set U is defined as follows:

$$A = \left\{ \left(\frac{\mu A(u1)}{u1}, \frac{\mu A(u2)}{u2} \dots\dots\dots \frac{\mu A(un)}{un} \right) \right\} \qquad (2.1)$$

$$A = \left\{ \left(\frac{\mu A(ui)}{ui} \right) \right\}, ui[0,n] \qquad (2.2)$$

Where: $\mu A(ui)$-membershipfunction.

Let us assume that Y(t) (t=0,1,2…),which is a subset of set R of real numbers, is simultaneously a universal set on which is defined a fuzzy set $\mu i(t), (t = 1,2, \dots\dots)$,that is to say, the membership function is time-dependent. Let us define a set F (t) is a set of fuzzy sets F (t)

$=\{\mu i(t), t = 1,2 \ldots\ldots\}$. Then F (t) is a fuzzy time series defined on a universal set $Y(t)$(t= $1,2,3 \ldots\ldots$)

2.3.2 FUZZY LOGIC OPERATORS

The basic operator: intersection (AND), Union (OR) and Complement (NOT) also exit for Fuzzy Set but defined differently as follows:

AND: The intersection of A and B;

μ (A∩B) = Min {μ (A), μ (B)};

OR: The union of A and B;

μ (AUB) = Max {μ (A), μ (B)}; and

NOT: The complement of a Fuzzy Set is defined as:

μ (A′) = 1 - μ (A).

Where μ = Membership Function. This is defined over the range of input and output variable values and linguistically describes the Universal of Discourse.

2.4 MEMBERSHIP FUNCTION

A membership function (MBF) is a curve that defines how each point in the input space is mapped to a membership value (or degree of membership) between 0 and 1. The input space is sometimes referred to as the universe of discourse.

2.4.1 MEMBERSHIP FUNCTIONS IN THE FUZZY LOGIC

The only condition a membership function must really satisfy is that it must vary between 0 and 1. The function itself can be an arbitrary curve whose shape can be defined as a function that is suitable from the point of view of simplicity, convenience, speed, and efficiency.

A fuzzy set is an extension of a classical set. If X is the universe of discourse and its elements are denoted by x, then a fuzzy set A in X is defined as a set of ordered pairs.

A(x) is called the membership function (or MBF) of x in A. The membership function maps each element of X to a membership value between 0 and 1.There are typically about eleven (11) fuzzy logic membership function types. These eleven functions are, in turn, built from several basic functions: piecewise linear functions, the Gaussian distribution function, the sigmoid curve, and quadratic and cubic polynomial curves.

The simplest membership functions are formed using straight lines. Of these, the simplest is the triangular srmembership function (as in Fig. 2.1), and it has the function name trimf. It is basically a collection of three points forming a triangle. The trapezoidal membership function (as in Fig. 2.2), trapmf, has a flat top and is really just a truncated triangle curve. These straight-line membership functions have the advantage of simplicity.

1) The **Triangle** membership function with straight lines as shown in Fig 2.1 can formally be defined as follows:

$$A(u:\alpha,\beta,\gamma) = \begin{cases} 0 & u < \alpha \\ \frac{u-\alpha}{\beta-\alpha} & \alpha <= u <= \beta \\ \frac{\alpha-u}{\beta-\alpha} & \beta <= u <= \gamma \\ 0 & u > \gamma \end{cases}$$

(2.3)

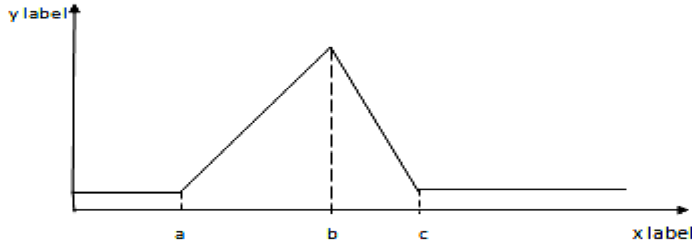

Fig 2.1 Triangular MBF

2) **Trapezoidal** Membership Function as shown in Fig 2.2 is defined as:

$$f(x,a,b,c,d) = \begin{cases} 0 \ whenx > d \\ \frac{x-a}{b-a} whena <= x <= b \\ 1 \ whenb <= x <= c \\ \frac{d-x}{d-c} whenc <= x <= d \\ 0 \end{cases}$$ (2

.4)

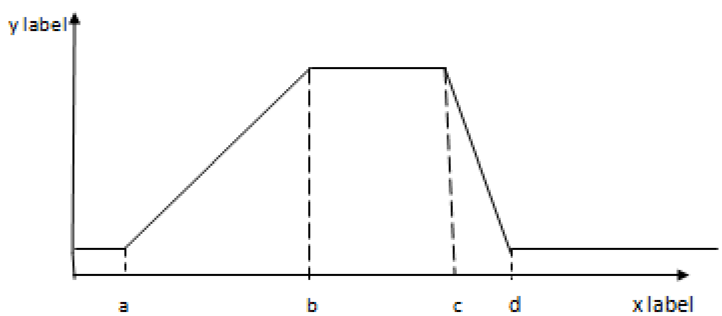

Fig 2.2 Trapezoidal MBF

Other commonly used membership functions (MBFs) include the Gaussian

(Fig. 2.3) and the Bell type (Fig. 2.4).

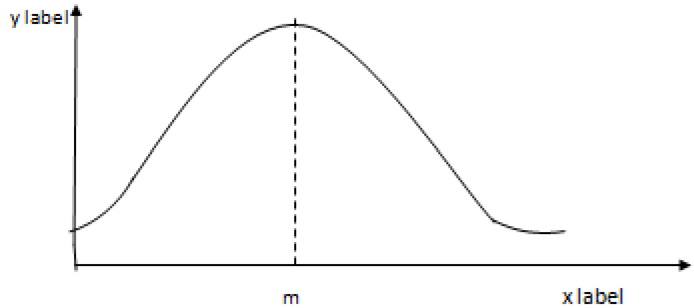

Fig 2.3 Gaussian MBF

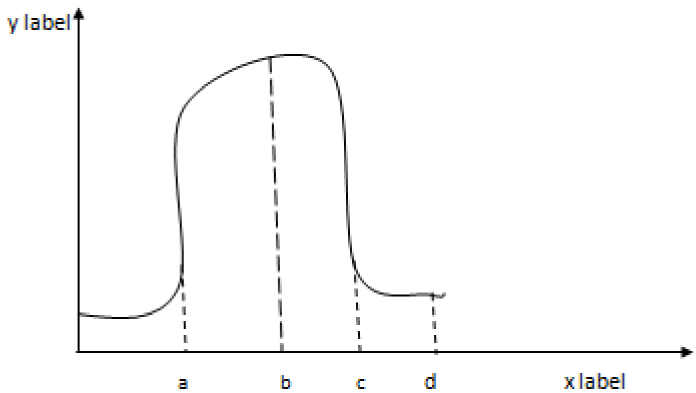

Fig 2.4 Generalized Bell MBF

2.4.2 MEMBERSHIP FUNCTIONS FOR FUZZIFICATION

In probability theory, the **normal** (or **Gaussian**) **distribution**, is a continuous probability distribution that is often used as a first approximation to describe real-valued random variables that tend to cluster around a single mean value. The graph of the associated probability density function is "bell"-shaped, and is known as the *Gaussian function* or *bell curve or Gaussian-Bell* [ ].

A) A Gaussian membership function is defined by

$$G(u; m, \sigma) = e^{[-\{\frac{u-m}{\sqrt{2}\sigma}\}^2\}]}$$ (2.5)

Where the parameters m and σ control the center and width of the membership function and

e ≈ 2.718281828 (Euler's number).

The normal distribution is considered the most "basic" continuous probability distribution due to Sits role in the central limit theorem. Specifically, by the central limit theorem, under certain conditions the sum of a number of random variables with finite means and variances approaches a normal distribution as the number of variables increases. For this reason, the normal distribution is commonly encountered in practice, and is used throughout statistics, natural sciences, and social sciences as a simple model for complex phenomena. For example, the observational error in an experiment is usually assumed to follow a normal distribution, and the propagation of uncertainty is computed using this assumption.

Normally-distributed variable has a symmetric distribution about its mean. Quantities that grow exponentially, such as prices, incomes or populations, are often skewed to the right, and hence may be better described by other distributions, such as the log-normal distribution or Pareto distribution.

B) The generalized **Bell** Function depends on the three parameters a, b and c as given by

$$f(x; a, b, c) = \frac{1}{1+|\frac{x-c}{a}|^{2b}}$$ (2.6)

The *generalized bell* membership function is specified by three parameters and has the function name gbellmf. The bell membership function has one more parameter than the Gaussian membership function. Because of their smoothness and concise notation, Gaussian and bell membership functions are popular methods for specifying fuzzy sets. Both of these curves have the advantage of being smooth and nonzero at all points.

C) The **Triangle** membership function with straight lines can formally be defined as follows: It has a triangular curve which is a function of a vector, x, and depends on three scalar parameters a, b, and c, as given by

$$f(x; a, b, c) = \begin{cases} 0 & x \le a \\ \frac{x-a}{b-a} & a \le x \le b \\ \frac{c-x}{c-b} & b \le x \le c \\ 0 & c \le x \end{cases} \qquad (2.7)$$

Or more compactly by:

$$f(x; a, b, c, d) = max\left[min\left(\frac{x-a}{b-a}, \frac{c-x}{c-b}\right), o\right]$$

The parameters a and c set the left and right "feet," or base points, of the triangle, and the parameter b sets the location of the triangle peak.

2.5 PERFORMANCE MEASURES

Quantitative and qualitative techniques are adopted for the forecast verification that is in determining the quality of the forecast. These techniques will compare the relationship between a forecast and corresponding observations using the previous MBF in the fuzzification techniques.

The qualitative technique involves the use of plots for a visual comparison. Quantitative techniques are statistical in nature and involve determining the RMSE and the correlation factor. The correlation factor is a measure of how well trends in the forecasted values follow trends in the actual data and is a number between 0 and 1

CHAPTER THREE

FORECASTING METHODOLOGY

3.1 INTRODUCTION

This chapter will explain the method used in carrying out this work. However, in carrying out the project. The under listed were done:

i) Review of the technique and results obtained by Adeola (2008) and Muazu *et al* (2009).The fuzzification method used in this case is based on the triangular MBF.

ii) Load Forecasting using the same data and optimal interval length as obtained by Adeola (2008) and Muazu *et al* (2009) but using a fuzzification method based on the Gaussian MBF.

iii) Comparison of results obtained in ii) with those of i) using qualitative and quantitative performance measures.

Article II. 3.2 FORECASTING ANALYSIS.

In view of the above, the Gaussian Membership Function Formula would be applied to the energy consumption data obtained from PHCN on a weekly basis by Adeola (2008) and Muazu *et al* (2009). The complete data set used in developing the Fuzzy Time Series (FTS) forecast model is 24 Weeks load data. The first eighteen (18) weeks is used as the training set while the remaining six (6) weeks data is used as the validation data. The analysis for the forecast is illustrated in the following steps:

STEP 1: Table 3.1 gives the dynamics of the total consumed energy over a period of 18 weeks (input data for retrospective forecast) and variation in the total consumed energy between every next and previous week. Variation for the current week is understood to be the difference between the energy consumed in the current week and that consumed in the previous week. For example, variation for week 17 is equal to the difference between load of week 17 and that of week 16

i.e. 2080 – 2131.0 = -51.

To define a universal set U, a range U on which the historical data are and upon which the fuzzy sets will be defined. Usually, when defining U, the minimum variation value for the load consumed V_{min} and the maximum variation for the load consumed V_{max} of known historical data are first of all found, the smallest and greatest variation values must be formed over the period (Week 1, to week 18). To ensure the smoothness of boundaries of the interval, adequate values D_1 and D_2 (positive Values) are selected based on Abbasov and Mamedova (2003). The universal set U can be defined as:

$$U: U= [V_{min}-D_1, V_{max}+D_2] \quad (3.1)$$

Where V_{min} =-219.4 is the smallest variation (week 2), V_{max}=107.4 is the greatest variation (week 4) and D_1 and D_2 are taken to be 0.6 and 2.6- Abbasov (2003) respectively Adeola (2008) and Muazu *et al* (2009). The universal set U is thus:

$$U = [-219.4 – 0.6, 107.4+2.6]$$

$$U = [-220, 110]$$

Table 3.1: Dynamics of Load Data for 18 weeks

Week	Energy consumed in MW	Variation in MW
1	2357.1	
2	2137.7	-219.4
3	2114.4	-23.3
4	2221.7	107.3
5	2323.6	101.9
6	2284.1	-39.5
7	2301	16.9
8	2210	-91
9	2220.6	10.6
10	2247.3	26.7
11	2155.1	-92.2
12	2249.6	94.5
13	2191.4	-58.2
14	2273.7	82.3
15	2127.3	-146.4
16	2131	3.7
17	2080	-51
18	2146	66

STEP 2: Partitioning U into several equal length intervals. [Adeola (2008) and Muazu *et al* (2009) determined that the interval length of five (5) gave the optimal forecasting. In view of this the universal set is partitioned into five equal length intervals as follows:

U_1 = [-220, -154]

U_2 = [-154, -88]

U_3 = [-88, -22]

U_4 = [-22, 44]

U_5 = [44, 110]

In order to account for the fact that forecasting with Fuzzy time series exhibits the least average error Abbasov and Mamedova (2003), it is necessary to find the middle points of the intervals e.g. the midpoint of U_1 is

$$c_m^1 = \frac{(-220)+(-154)}{2} = -187$$

(3.2)

And

$c^2{}_m$ = -121

$c^3{}_m$ = -55

$c^4{}_m$ = 11

$c^5{}_m$ = 77

STEP 3: Define fuzzy sets on U, by determining some linguistic variables. In this case "the variation in total load energy consumption" is a linguistic variable that assumes the following linguistic values:

A_1 = Significant Decrease in load consumption;

A_2 = Moderate Decision in load consumption;

A_3 = Minimal change in load consumption;

A_4 = Moderate increase in load consumption; and

A_5 = Significant increase in load consumption.

For example, the linguistics value “significant decrease in load consumption” is given by the variable < [-220, -154], A_1>, where A_1 is the Fuzzy set defined on the domain [-220, 110] of the universal set U.

The Fuzzy sets, A_1 ……., A_5 are defined on U by the following relationship, based on the Gaussian Membership Function:

$$e - \frac{0.5\, C(c_{i} - u_{i})^2}{\sigma^2}$$

(3.3)

Where c_i and ui are the centre and width of the i^{th} fuzzy set A_i, respectively.

ci= variation, u_i is the centre point of the corresponding interval; C is a constant and variance σ. There is no known empirical method of determining this constant (C) but according to Abbasov and Mamedova (2003), it must be chosen in such a way that it ensures the conversion of definite quantitative value into fuzzy values or belonging to the interval $A_i = (\mu_{Ai}(u_i/u_i), u_i \in u\ \mu_{Ai}(u_i) \in [0,1]$. A value of C = 0.06 is chosen for this work Adeola (2008) and Muazu *et al* (2009)

In two dimensions, the Gaussian function is the distribution function for uncorrelated variates x and y; having a bivariate normal distribution and equal standard deviation

$\sigma = \sigma x = \sigma y$ (3.4)

Full Width at Half Maximum (FWHM) for the Gaussian function is found to be Dug .H.H(2005)

FWHMσ=2.355σ(3.5)

And from Zadeh (1965)

σ=|di|/ (√2 x m)

Where di is the largest distance between the i[th]data center and other data centerss (di=-66) while m is the number of data centers (m = 5).

Hence

FWHMσ= 2.355 x |-66|/ (√2 x 5) and σ=49

Consequently,

$A_1 = 1/U_1 + 0.404/U_2 + 0.03/U_3 + 2.8E\text{-}04/U_4 + 4.97E\text{-}07/U_5$ (3.6)

$A_2 = 0.404/U_1 + 1/U_2 + 0.404/U_3 + 0.03/U_3 + 02.8E\text{-}04/U_5$ (3.7)

$A_3 = 0.03/U_1 + 0.404/U_2 + 1/U_3 + 0.404/U_4 + 0.03/U_5$ (3.8)

$A_4 = 2.8E\text{-}04/U_1 + 0.03/U_2 + 0.404/U_2 + 1/U_4 + 0.404/U_5$ (3.9)

$A_5= 4.97E\text{-}07/U_1 + 2.8E\text{-}04/U_2 + 0.03/U_3 + 0.404/U_4 +1/U_5$ (3.10)

The Gaussian membership functions of fuzzy set A_1 depicting the values of the linguistic values of the variation of load consumption are shown in Fig. .1

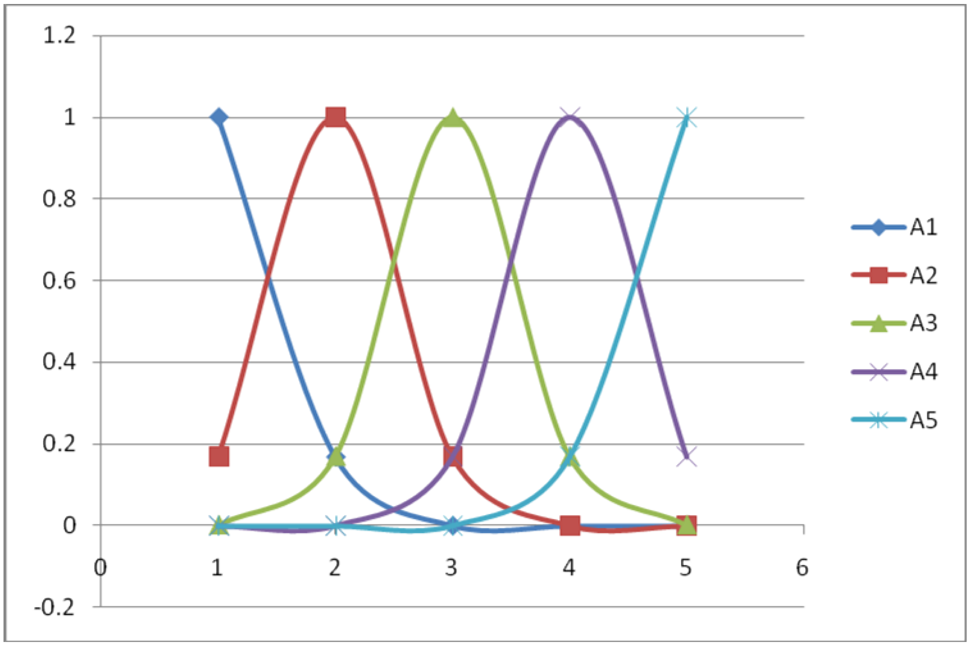

Fig 3.1 Gaussian Membership function (MBF) of set of Fuzzy interval

STEP 4: Fuzzify the input data that is, converting numerical values into Fuzzy values. This is also achieved using equation (3.3). This time, if $B_n \in y_i$ is a variation for the i^{th} week, then membership function for μ (μ_i) is calculated by means of equation (3.3). By holding valid the equality $y = B_n$, that is, to say by separating the interval, to which belongs the considered variation from the universal set U. The result is shown in

Table 3.2 Variation and Fuzzification of Variations with Interval Length of 5

Week	Load consumption in (MW)	Variation	Constant	U1	U2	U3	U4	U5
1	2357.1		0.06					
2	2137.7	-219.4	0.06	0.987	0.886	0.713	0.515	0.334
3	2114.4	-23.3	0.06	0.715	0.888	0.988	0.985	0.882
4	2221.7	107.3	0.06	0.339	0.521	0.720	0.891	0.989
5	2323.6	101.9	0.06	0.352	0.538	0.735	0.902	0.992
6	2284.1	-39.5	0.06	0.762	0.920	0.997	0.969	0.844

7	2301	16.9	0.06	0.595	0.789	0.937	1.000	0.956
8	2210	-91	0.06	0.891	0.989	0.984	0.878	0.703
9	2220.6	10.6	0.06	0.614	0.805	0.948	1.000	0.946
10	2247.3	26.7	0.06	0.565	0.761	0.920	0.997	0.969
11	2155.1	-92.2	0.06	0.894	0.990	0.983	0.875	0.699
12	2249.6	94.5	0.06	0.372	0.560	0.756	0.917	0.996
13	2191.4	-58.2	0.06	0.813	0.952	1.000	0.942	0.796
14	2273.7	82.3	0.06	0.404	0.597	0.790	0.938	1.000
15	2127.3	-146.4	0.06	0.980	0.992	0.901	0.734	0.536
16	2131	3.7	0.06	0.635	0.823	0.958	0.999	0.935
17	2080	-51	0.06	0.794	0.941	1.000	0.953	0.815
18	2146	66	0.06	0.449	0.646	0.833	0.963	0.998

STEP 5: Select the Parameter (w > 1) corresponding to the time period prior to the concerned week is used in the calculation of the relationship matrix. Based on the choice of W (the model basis) or the past weeks, a Fuzzy relationship matrix $R^w(t)$ is calculated by means of which is given a forecast. The relationship matrix $R^w(t)$ is then determined from the expression.

$$\mathbf{R^w(t) = 0^w(t)\ ^o\ C^w(t)} \qquad (3.11)$$

Where 0^w (t) is the operation matrix (i x j), $C^w(t)$ is the criterion matrix (i x j) and '^{o}' is the Min (n) operators. (Where i is the number of rows, which conforms to the sequence of week t – 2, t – 3 . . . , t – w and j is the number of columns conforming to the number of variation intervals (a row matrix corresponding to fuzzy variation in load consumption for the week t – 1).The choice of w is very critical to fuzzy series analysis and as such a sensitivity analysis is carried out for the Fuzzy Time Series (FTS) model with varying values of w in order to determine which one gives the least forecasting error. In Adeola (2008) and Muazu *et al* (2009), the sensitivity analysis of the model basis was carried out and it was concluded that a model basis of six (w=6) gave the least error. As an example, for week 19, a 5 x 5 operation matrix will be formed

0^6 (week 19) =

Fuzzy variation for week 13
Fuzzy variation for week 14
Fuzzy variation for week 15
Fuzzy variation for week 16
Fuzzy variation for week 17

0^6 (week 19) =

0.813	0.952	1.000	0.942	0.796
0.404	0.597	0.790	0.938	1.000
0.980	0.992	0.901	0.734	0.536
0.635	0.832	0.958	0.999	0.935
0.794	0.941	1.000	0.953	0.815

A 1 x 5 criterion matrix will be formed as follows:

C^6 (week 19) = |Fuzzy variation for week 18|

C^6 (week 19) = |0.449 0.646 0.833 0.963 0.998|

The relationship matrix, R^w (t) is then determined from equation (3.11)

resulting in:

$$R^w \text{ (week 19)} = \begin{vmatrix} R_{11} & R_{12} & R_{13} & R_{14} & R_{15} \\ R_{21} & R_{22} & R_{23} & R_{24} & R_{25} \\ R_{31} & R_{32} & R_{33} & R_{34} & R_{35} \\ R_{41} & R_{42} & R_{43} & R_{44} & R_{45} \\ R_{51} & R_{52} & R_{53} & R_{54} & R_{55} \end{vmatrix}$$

$$R^w \text{ (week 19)} = \begin{vmatrix} 0.449 & 0.646 & 0.833 & 0.942 & 0.796 \\ 0.404 & 0.597 & 0.790 & 0.938 & 0.998 \\ 0.449 & 0.646 & 0.833 & 0.734 & 0.796 \\ 0.449 & 0.646 & 0.833 & 0.963 & 0.796 \\ 0.449 & 0.646 & 0.833 & 0.953 & 0.796 \end{vmatrix}$$

The final fuzzified predicted variation $F^w(t)$ is given as:

$$\begin{vmatrix} \text{Max } (R_{11} \; R_{12} \; R_{13} \; R_{14} \; R_{15}) \\ \text{Max } (R_{21} \; R_{22} \; R_{23} \; R_{24} \; R_{25}) \end{vmatrix}$$

F^6 (week 19) = Max (R_{31} R_{32} R_{33} R_{34} R_{35})

Max (R_{41} R_{42} R_{43} R_{44} R_{45})

Max (R_{51} R_{52} R_{53} R_{54} R_{55})

F^6 (week 19) = |0.449 0.646 0.833 0.963 0.998 |

STEP 6: Defuzzify the obtained result, that is, conversion into quantitative values. In order to achieve this, Abbasov and Mamedov (2003), proposed the following:

$$V(t) = \frac{\sum_{i=1}^{5} \mu_t(U_i).U_m^i}{\sum_{i=1}^{5} U_t(U_i)} \qquad (3.12)$$

Where V(t) is the expected variation for the forecast week t, $\mu_t(U_i)$ is the calculated membership function (MBF) for the forecast week t and U^i_m the middle points of the interval (the size of the interval is 5).

Therefore, for week 19,

$$V\text{ (week 19)} = \frac{0.449*-187+0.646*-121+0.833*-55+0.963*11+0.998*77}{0.449+0.646+0.833+0.963+0.998}$$

$$V\text{ (week 19)} = \frac{-120.5}{3.88} = -31.05$$

This means that there will be a moderate decrease in load consumption from the value

(V(week 19)) for the load consumption in week 18. Therefore,

R(week 19) = R(week 18) + V(week 19) = 2146 – 31 = 2115.

Similarly, the load consumption value for week 20 is determined. The same approach is used to determine the forecasted load consumption for other weeks as shown in Table 3.3. After the defuzzification, the forecasted load consumption for week 19 to week 24 was obtained and compared with the actual load as shown in Table 3.3

Table 3.3Load consumption forecasts for week 19 to week 24

Week	Actual Load consumption in MW	Load consumption forecasts in MW
19	2119.9	2115.
20	2061.9	2064.8
21	1997.6	2010.8
22	1989	1956
23	1968.7	1901
24	1989.4	1846

CHAPTER FOUR

RESULTS AND ANALYSIS

4.1 INTRODUCTION

Load consumption over a certain period (six weeks) has been predicted. The training data, for the time interval [week 1, week 18] were selected as an experimental base.

The essence of this investigation consists of the following

i. The dynamics of the total load consumption for the examined period is considered to be unknown;
ii. With the aid of the model developed and used by Abbasov and Mamedova (2003),Muazu *et al* (2009) and Adeola (2008), the total load consumption forecasting for other weeks from week 19 to week 24,was carried out based on the changes in the consumption for the previous weeks;

The analysis of the result using statistical method (Root Mean Square Error (RMSE)) between the actual and forecasted load consumption is used as the performance function of the forecast model. The Root Mean Square Error (RMSE) is determined from

RMSE= $\sqrt{MSE}$

(4.1)

Where

MSE= $\dfrac{\sum_{t=1}^{n}\left(Actual\_load - forecasts\_load\right)^2}{n}$

(4.2)

In addition to this, the Pearson's correlation factor R between the actual load and the load forecasts has been determined. The simple linear correlation coefficient R is a number between -1and +1 that tells how well a linear equation describes the relationship between two variables (X and Y). R is designated as positive if Y increases as X increases and negative if Y decreases as X increases. An R of zero indicates an absence of relationship between the two variables. As R tends towards 1 the relationship gets better.

Table 4.1 shows the comparison of the results obtained using the Gaussian membership function and those obtained using the triangular membership functions. The comparison shows that the triangular method gave a better forecast result judging from their RMSE and R.

Table 4.1 Comparison of Load Forecastsusing Gaussian and Triangular MBF.

Week	Actual Load consumption in MW	Load consumption Forecasts in MW using Gaussian MF	Load consumption Forecasts in MW using Abbasov/Triangular Method
19	2119.9	2115	2127.5
20	2061.9	2064.8	2079.9
21	1997.6	2010.8	2030.9
22	1989	1956	1976.1
23	1968.7	1901	1960.6
24	1989.4	1846	1994
	MSE	4407.1	307.86
	RMSE	66.5	17.1
	R	0.86	0.98

Forecasts plots are qualitative indicators of the performance of a model as it allows for virtual comparison of the actual and predicted values.

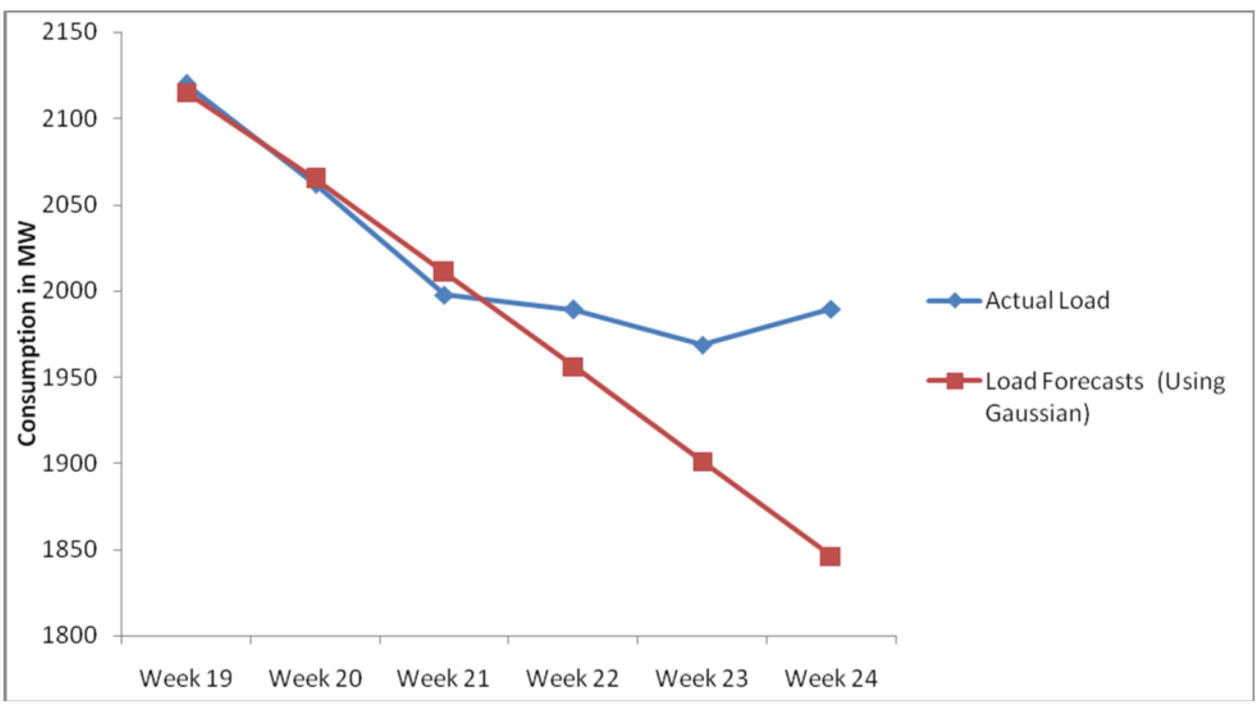

Fig. 4.1 Plot of Actual and Load Consumption Forecasts using Gaussian MBF

(The GMF follows the actual load from weeks 19 -21, before it starts deviating from weeks 22 this is because of the exponential function of the Gaussian Formula)

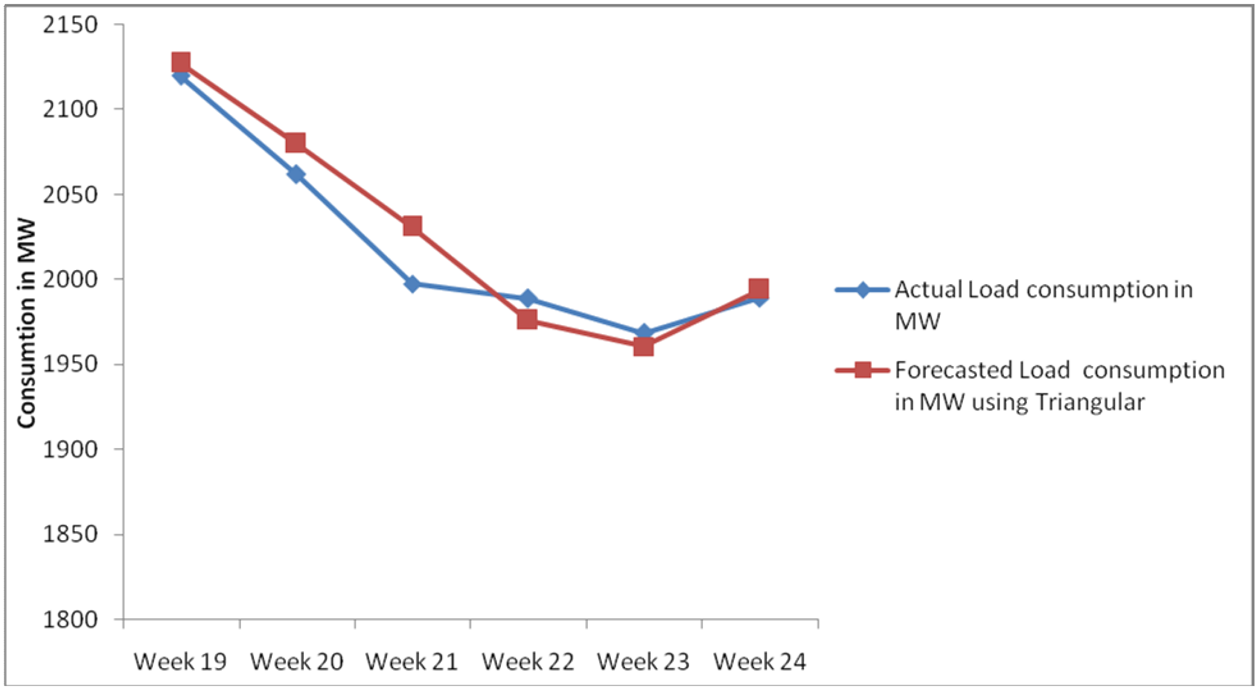

Fig. 4.2 Plot of Actual and Load Consumption Forecasts using Triangular MBF

(The TMF follows the trend of the actual plot; this is because of the simplicity nature of the TMFFormula)

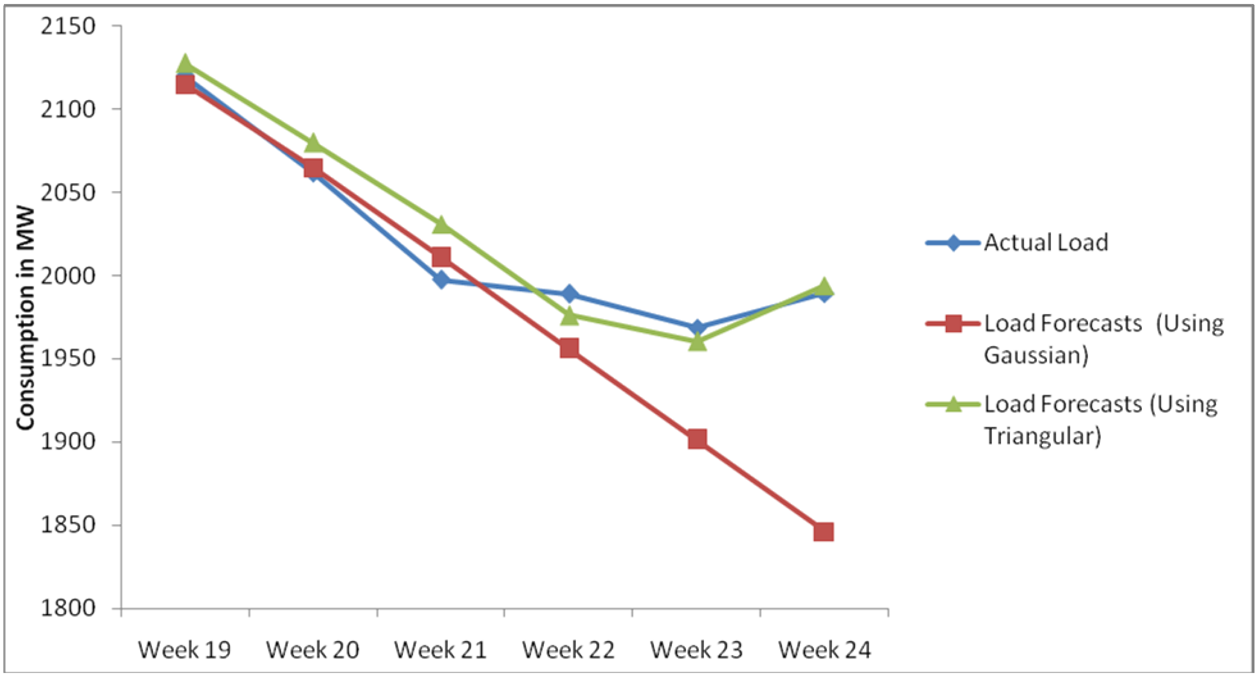

Fig.4.3 Comparison plot of actual consumption with load consumption forecasts using GMF and TMF

4.2 SIGNIFICANCE OF RESULT

The comparative analysis of the actual load, the load forecasts and the consequent RMSE and R, shown in Fig 4.3 and Table 4.1 established the need to properly determine an appropriate membership function to be applied in the fuzzification process of the Fuzzy Time Series (FTS) forecasting technique. This will enhance the quality of the forecast result.

From both qualitative performance indicator and the statistical error evaluation carried out for this work, it can be concluded that the triangular method gave a better result when viewed from the RMSE value and the correlation factor.

CHAPTER FIVE

Section 2.01 CONCLUSION AND RECOMMENDATION

5.1 SUMMARY

This work was aimed at comparing the triangular MBF method used by Adeola (2008) and Muazu *et al* (2009) with Gaussian MBF on electric load consumption forecasting using Fuzzy Time Series (FTS) method. Electricity is an important factor in the economic growth and well being of any economy; any method that can enhance forecasting the load demand or load consumption pattern becomes very important.

Fuzzy Time Series (FTS) has enormous advantages over traditional statistical models in that human knowledge can be applied from the start till the end of the forecasting procedure Abbasov and Mamedova (2003).

The key factors to be considered in applying the method adopted by Abbasov and Mamedova (2003) include determining an optimal interval length, model basis and an appropriate membership. In Adeola (2008) and Muazu *et al* (2009), the optimal interval length and model basis were determined for the load forecast using the triangular membership function for the fuzzification process. This work then is based on determining the effect of using a different membership function on the forecasting result.

5.2 LIMITATIONS

Fuzzy Time Series (FTS) forecasting method is a data driven technique. This means that the quality of data is very important to the working of this technique, which essentially means that the quality of the output is highly dependent on the quality of the input data. If certain error may exist in the actual data, that error data will enter into the model and as a result the prediction will not be accurate. In carrying out this work, therefore one of the main constraints is ascertaining the quality of the data used.

Another limitation is the possible high computational requirement of the Fuzzy Time Series technique. The max-min composition operations will take a large amount of computation time when the fuzzy relationship matrix $\mathbf{R^{w}(t)}$ is very big.

5.3 CONCLUSION

Fuzzy Time Series (FTS) forecasting has been applied in this work to carry out load forecast based on the technique adopted by Abbasov and Mamedova (2003), Adeola (2008) and Muazu *et al* (2009.In Adeola (2008) and muazu *et al* (2009) an optimal interval length of five (5) was determined to produce the best forecast result in addition to a model basis of six (6). The triangular membership function was used for the fuzzification process.

In this work, the effect of the membership function on the forecast result is determined by applying the Gaussian membership function in the fuzzification process using the obtained optimal interval length and model basis and comparing the forecast result. The selection of a particular membership function depends on the nature of data value to be used. If the selected membership function is not proper, the input fuzzy data will be wrong and as a result the output fuzzy data (the data outputted from a mathematical model) will also be wrong and the defuzzified output data will be improper and error might be high. It is very important that a mechanism be adopted to determine the appropriate membership functions to be used before forecasting is carried out.

Verification is the process of determining the quality of forecasts. Various procedures exist but all involves measurement of the relationship between a forecast and corresponding observations. Statistical performance functions of Root Mean Square Error (**RMSE**) and the Correlation Factor (**R**) are used to measure the performance of the different membership functions (as summarized in Table(4.1). In addition to these, forecast plots were used as qualitative performance functions. The value of Root Mean Square Error (**RMSE**) obtained using Gaussian membership function and triangular membership function is **66.5** and **17.1** respectively. The correlation factor **R** is **0.98** for triangular and **0.86** for Gaussian Membership Function respectively. These are measurements of the standard error and how well the validation value of the model used trends in the actual data of the forecast. It can therefore be concluded that triangular method gave a better result in this case, judging from the qualitative and quantitative performance functions.

5.4 SUGGESTIONS FOR FURTHER WORK

The following are suggested as possible ways of improving this work:

1) Extending the comparison to other membership functions like the trapezoidal (trapmf), Gaussian two-sided membership function (gauss2mf), etc to see their own effect on the forecast result.
2) Employing emerging pre-processing techniques such as Trapezoidal Function Approach (TFA), Minimum Entropy Probability Approach (MEPA), Cummulative Probability Distribution Approach (CPDA) to further enhance the fuzzification process.

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APPENDIX A

COMPLETE TRAINING DATA (24 WEEKS)

Weeks	Energy consumption in MW	Variation in MW
1	2357.1	
2	2137.7	-2194
3	2114.4	-23.3
4	2221.7	107.3
5	2323.6	101.9
6	2284.1	-39.5
7	2301	16.9
8	2210	-91
9	2220.6	10.6
10	2247.3	26.7
11	2155.1	-92.2
12	2249.6	94.5
13	2191.4	-58.2
14	2273.7	82.3
15	2127.3	-146.4
16	2131	3.7
17	2080	-51
18	2146	66
19	2119.9	-31
20	2061.9	-50.2
21	1997.6	-54
22	1989	-54.8
23	1968.7	-55
24	1989.4	-55