FUZZY BASED SHORT TERM LOAD FORECASTING AND ITS VALIDATION

A Research report is submitted in partial fulfillment of the requirements for the award of Degree of Bachelor of Science in Electrical and Electronic Engineering

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DECLARATION

We hereby declare that this research "**Fuzzy Based Short Term Load Forecasting and its Validation**" represents our own work which has been done in the laboratories of the Department of Electrical and Electronic Engineering under the Faculty of Engineering of Daffodil International University in partial fulfillment of the requirements for the degree of Bachelor of Science in Electrical and Electronic Engineering, and has not been previously included in a thesis or dissertation submitted to this or any other institution for a degree, diploma or other qualifications. we have attempted to identify all the risks related to this research that may arise in conducting this research, obtained the relevant ethical and/or safety approval (where applicable), and acknowledged my obligations and the rights of the participants.

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APPROVAL

The thesis entitled **"Fuzzy Based Short Term Load Forecasting and its Validation"** submitted by **Shohanur Rahman (191-33-5058) & Shyhan Islam Rahat (191-33-5115)** has been done under my supervision and accepted as satisfactory in partial fulfillment of the requirements for the degree of **Bachelor of Science in Electrical and Electronic Engineering** in **January, 2023.**

Signed

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Dedicated

To

Our Parents

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ABSTRACT

A fuzzy based Short-term load forecasting (STLF) in strength gadget operations is the theme of this Paper. Precise load forecasting is necessary for lowering technology fee and base load potential as it presents load forecast generation scheduling and unit dedication decisions. In this particular piece of analysis, the inputs that are utilized by the fuzzy interfacing system are the month - to - month averages in both 'Time' and 'Temperature' & monthly 'Historical Load data' and the output is referred to as the 'forecasted load'. A set of six triangle membership functions have been created from the input variable 'Time'. The membership functions are Mid night, Morning,For-Noon,Afternoon,Evening,Fornight.Another input variable 'Temperature' has been divided into three triangular membership function. They are Low, Medium & High also we have another input is 'Historical load data' which is divided into three membership function & these membership function are Low Load,High Load, Very High Load. Real-world implementation studies of forecast load distribution in a one-story building,Kaliganj, Jehnaidah. Real consumption of April, October and December (month) load is compared to the fuzzy predicted load values. The expected and actual loads are quite similar & average MAPE of three months is 15.87%. Increasing the membership functions' number as well as taking the specific location temperatures all these contribute to reducing the percentage of error.

Keywords: Fuzzy interfacing system, Fuzzy logic, Membership function, Triangle membership function, Defuzzification. MAPE

CHAPTER 1
INTODUCTION

1.1 Introduction

Load forecast is a significant part of the power system. Load forecast is the same as necessary on the generation side & distribution side. The future load is predicted in advance so that the power system is efficient & cost-effective. In general, Time Series Models or Regression Models characterize traditional models for load forecasting. Future loads are extrapolated in Time Series Models using the previous load instead as a guideline. These models are frequently augmented with "transfer functions" to fully capture the customer's response to changing weather patterns and other often intangible factors. A significant drawback of these instances is the computation strategy's intricacy and the enormous data required to assemble a complete forecasting system. Regression Models include the dual central modeling approach utilized to predict short-term load. The database divides smaller segments, whereby a regression model will build for each element, such as a season or a day of the week. While these benchmarks exist practical because the gauged parameter values are readily inter-printable (e.g., amount of megawatt change per unit temperature change), they still demand a consequential database, conceivably enclosing bygone chronological data [1]. Another method was applied in short-term load forecasting & the application is ARTIFICIAL NEURAL NETWORK (ANN). The executed forecasting system serves reliably and with adequate accuracy. It is leisurely to employ since all functions of organizing data and retraining neural networks are done Automatically. The achieved precision relies on the time leader of the forecast and the season. For the 20, 30, casts, the mean absolute percentage error (MAPE) lies in a range of 0.4-1 .1% [2]. The main concession of ANN is its proficiency in yanking the affinity between input variables and output by learning from the functional input-output readings [1]. Fuzzy logic models have been offered as an alternative and, individually, an applicable forecasting method when the chronological data are not actual numerals but linguistic significances. It has been well demonstrated that fuzzy logic models may be integrated into expert systems or neural network models, thus completing the use of both user expertise and numerical data. It has been well established that fuzzy logic models may be combined into expert systems or neural network models, thus using both user expertise and numerical data. [1]

1.2 Problem statement

Despite being intended to represent the nonlinear correlations between inputs (historical load, historic and forecasted temperature) and outputs (historical load forecast), the mathematical complexity does not provide the user with an intuitive understanding. It is possible that the user would develop trust in the model and use it to produce, or aid in producing, the system predictions if these mathematical relationships could be simplified to a logic table, such as a series of IF-THEN expressions (e.g., if time is Evening, if temperature is high, then load demand is high). Essentially, the building blocks of a fuzzy logic model are a collection of logical assertions. These claims could be made based only on the knowledge of experts or, as the STLF problem shows, with the help of experts and a set of historical observations.

1.3 Objective

To accomplish this, the researchers here transform time series data on both load and climate into "fuzzy" data. For more precise predictions, a defuzzification procedure is undertaken to obtain a point estimate for system load once a fuzzy rule basis has been built to produce "fuzzy" forecasts. This approach has been used successfully elsewhere, producing results on par with those of more intricate statistical models.The This hopes to develop into the validity and performance of Fuzzy Interfacing System for short-term load forecasting. This research provides the early findings of an inquiry into the validity of fuzzy logic methodologies for short-term load forecasting.

1.4 Methodology

Load forecasting reduces utility risk by predicting the utility's future consumption of commodities it transmits or delivers. Methods include price elasticity, weather and demand response/load analysis, and predictive modeling for renewable power. Fuzzy logic is an approach to computing that measures the amount to which something is true, as opposed to relying on the binary distinction between true and false. As seen in Figure 1, the fuzzy logic process of the inputs, the controller (also known as the fuzzy inference engine), the rule base, and the defuzzification stage. During the input stage, the forecaster will select the number of inputs for electrical load forecasting. These inputs may include load data, time, or exogenous variables such as the weather. During the input stage, when they are fuzzified, the information is changed into fuzzy sets. There are no discrete components or values in fuzzy sets. The most significant component of the system, the fuzzy inference engine or controller, takes input both the fuzzification output and the fuzzy rule base. The fuzzy controller performs operations to the inputs in order to create an output. The controller set the rules developed by the electrical load forecaster predicated on the classification of the input data. The forecaster is responsible for inventing the rule base for the fuzzy inference system, and the system's accuracy is proportional to the rules. The greater the number of regulations, the higher the system's level of precision. In this type of application, the defuzzification block converts the processed fuzzy set into a clear output, which can then be shown on a graph as either the anticipated load or the load curve. The actual load, the current time, and the current temperature are all input to the fuzzy system that produces the short-term electrical load forecast. The basic fuzzy logic model for the load forecast is shown in Figure 1.1 as a block diagram. This model begins with the fuzzification of the input data preceding continuing to the fuzzy inference system with rules. Later, the defuzzification stage before the output display [3]

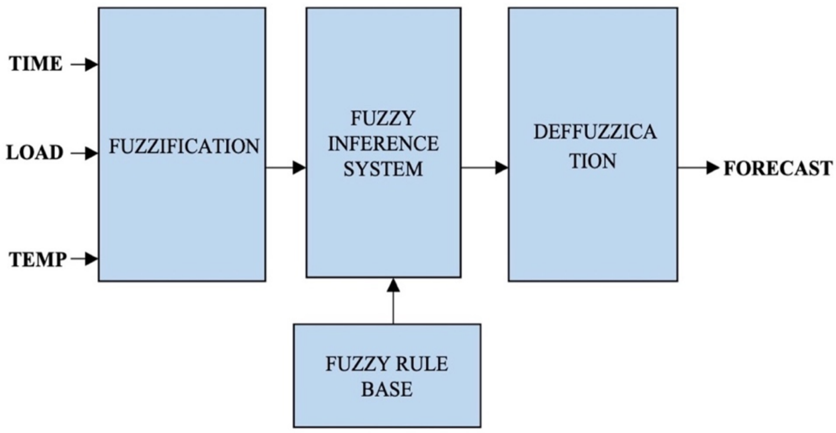

Fig.1. 1 Block diagram of fuzzy interfacing system

1.5 Implementation

In this study, we aim to estimate the monthly electrical consumption of a consumer in the 8th Maliut Union, Kaliganj Thana, and Jhenaidah Zila. We randomly chosen the months of April, October, and December for this experiment. This experiment focuses on the load in April, October, December of 2022. The inputs for the April, October and December 2022 loads are time, temperature, and historical load; the output is the forecasted load. The prior load consumption data for a three-year period (2019–2021) was provided by the consumer and was coupled with the minimum and maximum loads for the month of April, October and December which are listed in Resources. Temperature data is collected from a website (link1) listed in the References and Resources section. The collected temperatures are averaged with the month of April, October, December minimum and maximum temperatures. There is a significant temperature variation between Kaliganj Thana and Jhenaidah Zila due to the rural location and great distance between the two locations. Due to the precise meteorological information of the experimental region, it is important to measure the temperature in Zhenaidah Zila. Each of the six segments of time consists of four hours. Leaving aside the temperature variation, the actual and predicted loads are practically identical. Because load consumption is a distribution sector of the power system, the significant percentage of error can be attributable to the difference in temperature, the unseasonable event, or a family program.

1.6 Organization

Chapter 1, addresses the historical context of fuzzy logic implementation, which is comparable to the various short-term load forecasting methodologies. This chapter also discusses the application of fuzzy logic and error calculation. In addition, the input membership function is discussed. Fuzzification, the fuzzy interface system (which includes the fuzzy rule base), and defuzzification are the three stages of the fuzzy interface system. Chapter 2, examines the elements that influence short-term load forecasting, the technique for short-term load forecasting, the fuzzy logic approach to short-term load forecasting, and the fuzzy logic membership function, all of which are linked to the study that we have been doing. In addition to that, it includes evaluations of how our work stacks up against similar research. The 3rd chapter contributes to the growth of fuzzy logic control boxes. The diagram below depicts the configuration of a fuzzy control box. In the tables, input and output are classified as triangular membership functions. In order to drive the fuzzy interface using input data in order to estimate future load. In Chapter 4, the output or forecasted load is discussed. This research produced the rule view and the surface view. The tools, schedules, and goals we've set for ourselves in terms of our research are all laid out in Chapter Five. In the final chapter (Chapter 6), we'll go over some suggestions for moving forward and polishing those newly acquired abilities and experiences.

CHAPTER 2
LITERATURE REVIEW

2.1 Introduction

This section on load forecasting was examined by six different authors before being included in this chapter. Forecasting load requires a variety of approaches and takes into account a wide range of variables. This related body of work concentrates on estimating short-term load using a variety of techniques, such as time regression, artificial neural networks, and fuzzy logic, among others.

2.2 Related Works

AUTHORS [4] represents that the primary goal of load forecasting is to foresee potential shifts in consumption patterns. Predictions and simulations of the load's behavior can be made with high accuracy if a number of factors are considered. This study aims to analyze the effects of these variables so as to highlight their role in strategy and execution. Understanding the factors that influence load forecasting patterns is crucial for closing the gap between electrical energy demand and supply, which in turn can boost profit margins. The purpose of the load forecast is to predict the level of demand in the future. These factors are essential in developing the load forecasting model. Numerous factors, such as weather, air temperature, wind speed, calendar seasonal information, economic events, and geographical information, can influence forecasts. Short-term electric load forecasting errors can be attributed primarily to daily human activities and weather parameters. Thus, time, weather, and customer type all play a role in a short-term load forecast. Past load consumption values, weather data, the number of customers in different classes, the number of appliances sold in a particular field, and econometric and demographic data are often thought to be functions of medium- and long-term forecasts. AUTHORS [5]In this research, the two components that make up the load forecasting system are broken down into their respective categories. This article takes a look at the elements that might affect energy use as well as the methods that can be used to anticipate energy usage. It has been observed that a number of different factors have a significant influence on the amount of energy that is used and that the accuracy of the forecasts is directly proportional to the amount of information that is readily accessible. The approaches that are utilized may have an effect on the level of complexity as well as the trustworthiness of a method's projections. Load forecasting for the long term (LTLF) is completely independent of the time frame in which the forecast is made. Short-term load forecasting (STLF), intermediate-term load forecasting (ITLF), and long-term load forecasting were the categories that researchers used to categorize load forecasting (MTLF). It says that various forms of load forecasting need a variety of input parameters, methodologies, and applications, all of which are distinct from one another. In the harsh economic climate that exists today, it is very essential for energy utility firms to use a strategy that can reliably estimate their electric load. In this piece, we took a retrospective look at the factors and strategies that are considered when developing load projections. The statistics pertaining to the weather, such as temperature, humidity, cloud cover, and total rainfall amounts; the characteristics pertaining to the economy, such as customers' income, location, and population; and the load consumption pattern for a certain amount of time are all summarized here. These variables, since they have an effect on load consumption, need to have some kind of connection to it. AUTHORS [3]When there is a mismatch between the production of utility-scale power and the demand for it, there is often a waste of resources and energy that has to be reduced. The utility business may more accurately anticipate future energy consumption with the assistance of short-term load forecasting. The anticipated demand for electricity is used to make forward-looking plans for how it will be generated, transmitted, used, and distributed, which is essential to the economics and dependability of the power system. In order to test the fuzzy models' accuracy and efficacy for load forecasting, both the trapezoidal and the triangular membership function (MF) were used as the basis for the fuzzy models. The mean absolute percentage error (MAPE) was minimal, and the mean forecast was accurate. The results of the forecasted load revealed that both models are excellent for short-term load forecasting; however, the trapezoidal MF exhibited higher performance than the triangular MF did. The mean forecast error (MFE) and mean absolute deviation (MAD) figures came from the results of the forecasted load. A short-term prediction of the power requirements is presented in this research utilizing the fuzzy logic methodology. We looked at two different fuzzy MF systems, the trapezoidal MF and the triangular MF, to see which one was more effective and accurate in short-term load forecasting. The model that was designed.The performance of the model was tested using data representing normal loads, and a variety of error analysis methods were used in order to determine how accurate the model was. The findings of the error analysis demonstrated that the fuzzy model was appropriate for use in short-term load forecasting, and that the trapezoidal MF offered superior performance when compared to the triangular MF. The use of fuzzy logic in this work for the purpose of making short-term load projections for the next day and two MFs, a model was developed. Research was done on MFs that had both triangular and trapezoidal forms. The error analysis performed by comparing the actual load to the anticipated load demonstrates that fuzzy logic is acceptable for estimating the short-term load of power transmission stations. AUTHORS [2] Methods that are based on artificial intelligence make use of artificial neural networks. Models of loads applicable to the twenty-first century The most significant benefit of using neural.The capacity of networks to pick a suitable model by teaming up the aforementioned relationships directly from historical data and without the need for further data is one of their strengths. "Short-term load forecasting" refers to the process of forecasting hourly-integrated loads for the next one day to one What lies ahead. This kind of forecasting is often carried out (STLF). These hourly predictions are used by energy management systems (EMS) in order to develop operating plans for power plants, to arrange designated energy trails and actions, and to identify potential problems. The use of artificial neural networks to estimate load dynamics is presented in this article as an innovative method for forecasting extremely short-term loads. This changes the job that neural networks are responsible for from predicting real loads to forecasting relative increases in load, which ultimately results in improved accuracy. In addition to the conventional forecasts of hourly-integrated loads for the next few days, the instantaneous-load projections for the next several dozen minutes are also necessary in order to run the power system in a reliable and cost-effective manner. In order to accurately predict an integrated load, artificial neural networks have been effectively used. In order to get the most out of them for instantaneous-load forecasting with time leads ranging from several to several dozen minutes, a new strategy for approaching their design has to be adopted. Neural networks should put their attention on simulating the dynamics of load rather than coping with real loads. Because of this, the accuracy and dependability of the results will improve. AUTHORS [1] Predicting electric loads with a lead time of minutes, hours, days, or weeks in advance is the objective of the short-term load forecasting (STLF) technique. In this study, the findings of a preliminary examination into the viability of using a fuzzy logic model for short-term load forecasting are presented and discussed. The historical load data and weather data are both turned into "fuzzy" information for the purpose of this study. In order to construct "fuzzy" predictions, a fuzzy rule foundation has to be established, and then defuzzification must take place before a point estimate can be generated for the system. load. This technique has, in various contexts, been shown to provide reliable findings that are on par with those of other, more complicated statistical models. This should motivate the exploration of whether or if a fuzzy logic model can accurately predict short-term load levels, as well as how well it performs. In this study, we discuss the findings of an extensive exploratory inquiry on the application of a fuzzy logic model to the STLF issue. There have been a lot of discussions about the different design aspects, and for this specific collection of application data, the implications of sets on the performance of the model have been looked into. demonstrated. The suggested model has proven capable of generating projections that have a MAPE that is consistently lower than 2.3% on a regular basis. There may be a very good solution to the implementation and usage problems that have consistently limited the adoption of short-term load forecasting models. The flexibility of the proposed approach, which offers a logical set of rules that is readily adaptable and understandable by an operator, may be a very good solution to these problems. These problems have been a limiting factor in the adoption of short-term load forecasting models. AUTHORS [6] The authors use a fuzzy interface system that is implemented using gaussian-type membership functions in order to produce an accurate forecast of the load. This allows the authors to create an accurate prediction of the load. In the context of the operations of power systems, the focus of this article is short-term load forecasting, which is also frequently referred to as STLF. It offers load projections, which may be used for generation scheduling and unit commitment choices, in addition to providing exact load information. If one is interested in lowering the costs of producing and ramping up reserve capacity, then forecasting is an essential step to take. A fuzzy logic framework is one potential solution that has been proposed for the issue of short-term load forecasting, which is sometimes referred to by its acronym, STLF. In the process of running power systems, short-term load forecasting is an extremely important factor to consider. In general, forecasting is evaluated based on two primary considerations: 1) The process of forecasting takes priority over the long-term planning of both in generation and transmission, and 2) the process of forecasting will result in the most efficient design of distribution network infrastructure. The suggested STLF approach, when applied to actual distribution power networks, demonstrates that load forecasting with fuzzy implementation is both faster and more accurate than the traditional forecasting methods, which deal with rigid data and have a longer processing time. This is proved by the fact that conventional forecasting methods have a longer processing time and deal with rigid data. This stands in contrast to the fact that conventional approaches of forecasting need a prolonged time horizon for the processing. [6]

2.3 Compare and Contrast

As part of this research endeavor, we build fuzzy logic in MATLAB in order to make a monthly load prediction based on consumer activity. Chapter 3 contains a description of the functions that are specific to the membership. The use of fuzzy logic results in a more accurate forecast of the load and an hour-to-hour prediction of peak demand which is more accurate. The associated works concentrate on the hourly demands made by both the generation and distribution sides. The forecasting of short-term loads on a month-by-month basis is discussed in Chapters 3 and 4. The time is calculated once every twenty-four hours with the help of six triangular membership functions, and the temperature is calculated once every month with the assistance of three membership functions. In this experiment or case study, the monthly load that was expected or predicted is extremely comparable to the load that was really measured.

2.4 Summary

The purpose of the load forecast is to predict the level of demand in the future. Various factors, such as weather, air temperature, wind speed, calendar seasonal information, economic events, and geographical information, can influence forecasts. The accuracy of the forecasts is directly proportional to the amount of information that is readily accessible. In this piece, we took a retrospective look at the factors and strategies that are considered when developing load projections. We looked at two different fuzzy models, the trapezoidal MF and triangular MF, to see which one was more effective and accurate in short-term load forecasting. Fuzzy logic is acceptable for estimating the short-term load of power transmission stations. The most significant benefit of using neural. networks are their capacity to pick a suitable model by teaming up. relationships directly from historical data and without. need for further data. In this study, the findings of a preliminary examination into the viability of using a fuzzy logic model for short-term load forecasting are presented. The suggested model has proven capable of generating projections that have a MAPE that is consistently lower than 2.3% on a regular basis. A fuzzy logic framework is one potential solution that has been proposed for the issue of short-term load forecasting. When applied to actual distribution power networks, fuzzy implementation is faster and more accurate than the traditional forecasting methods, which deal with rigid data and have a longer processing time.

CHAPTER 3
FUZZY LOGIC IMPLEMENTATION

3.1 Introduction

When it comes to short-term, mid-term, and long-term load forecasting, fuzzy logic is an exceptionally common and trustworthy method. There are several different types of membership functions available, such as triangle membership function, trapezoidal membership function, and gaussian membership function. The triangular membership function is simple and easy to implement. It is recommended to use the Gaussian membership function since it produces more accurate results. Triangular MF has a more complicated implementation, yet it exceeds Gaussian MF in terms of performance. Triangular MFS is used in this study to forecast the load forApril, October and December 2022.

3.2 Fuzzy Logic Implementation

In this research, we implement a Mamdani fuzzy interference system (FIS) to predict month-wise consumer load. Utilizing Time,month wise average temperature (April19-April21),(Oct19-Oct21) and (Dec19-21), and historical load data(Oct19-Oct21), (April19-April21) and (Dec19-21) as inputs, the result is predicted load. Every input and output is organized into one of several membership function types. Matlab is applied to create a Mamdani fuzzy interfacing system with a triangular membership function using a set of rules that forecast the load of three inputs and outputs. Input 'Times' are arranged into six triangular membership functions (MN, MG, FN, AN, EV, FT), and input temperatures (LT, MT, HT) and previous historical loads (LL, HL, VH) are categorized into three membership functions respectively. Triangular Membership function of '**Times Data**' are given below Tables & Figs.

3.2.1 TIME (APRIL, OCTOBETR, DECEMBER)

Time	Notation	Range
Midnight	MN	1-4
Morning	MG	4-8
Forenoon	FN	8-12
Afternoon	AN	12-16

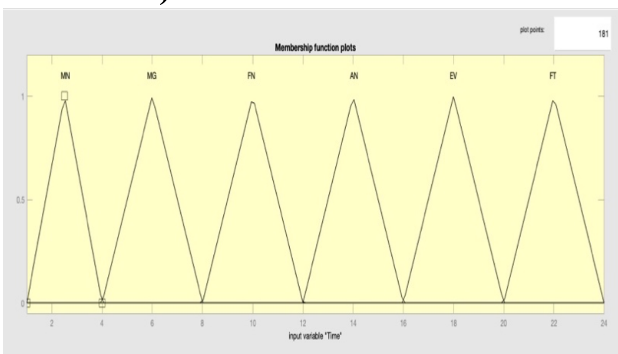

Fig.3.2.1. 1 Membership function of Time Range (April)

Evening	EV	16-20
Fore night	FT	20-24

Table.3.2.1. 1 Time Range (April)

Time	Notation	Range
Midnight	MN	1-4
Morning	MG	4-8
Forenoon	FN	8-12
Afternoon	AN	12-16
Evening	EV	16-20
Fore night	FT	20-24

Table.3.2.1. 2 Time Range(Oct)

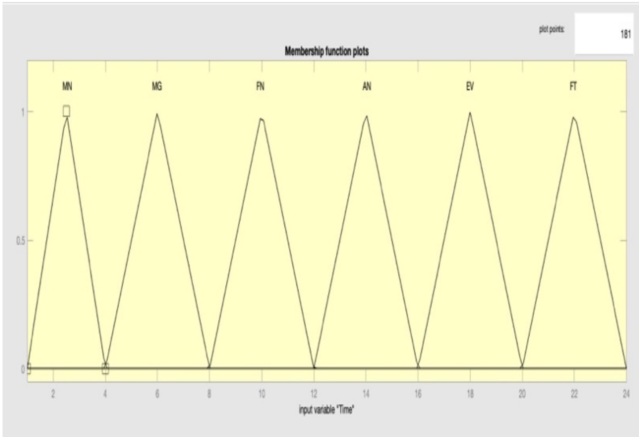

Fig.3.2.1. 2 Membership function of Time Range (October))

Time	Notation	Range
Midnight	MN	1-4
Morning	MG	4-8
Forenoon	FN	8-12
Afternoon	AN	12-16
Evening	EV	16-20
Fore night	FT	20-24

Table.3.2.1. 3 Time range (Dec)

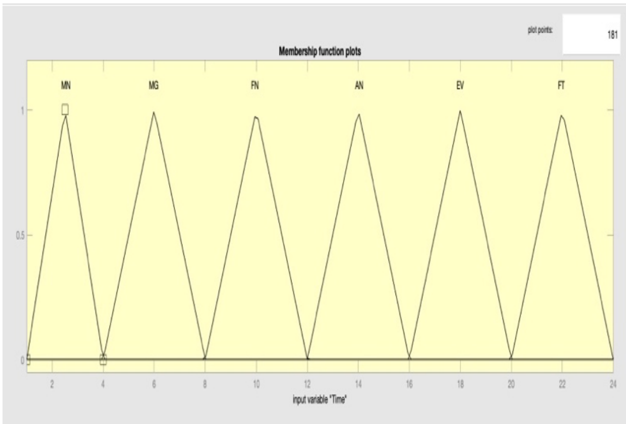

Fig.3.2.1. 3 Membership function of Time Range (December)

3.2.2 Historical Load (APRIL, OCTOBETR, DECEMBER)

Similarly, Another Input '**Historical Load Data**' for April(19-21),October(19–21) and December(19-21) with minimum and maximum values, is used, and the membership functions are given below Table and Fig.

Historical Load	Notation	Range
Low	LL	110-120
High	HL	120-130
Very High	VL	130-145

Table.3.2.2. 1 Load Range(April)

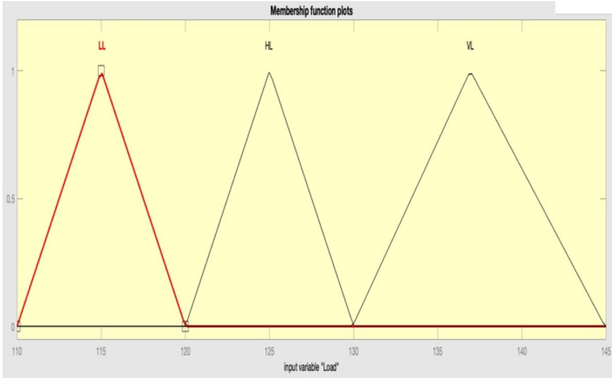

Fig.3.2.2. 1 Membership function of Load Range(April)

Historical Load	Notation	Range
Low	LL	105-115
High	HL	115-130
Very High	VL	130-140

Table.3.2.2. 2 Load Range(Oct)

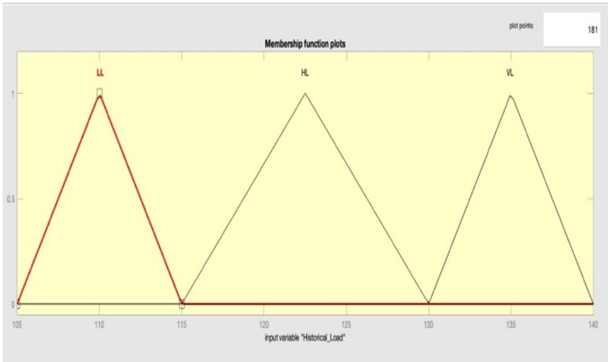

Fig.3.2.2. 2 Membership function of Load Range(Oct)

Historical Load	Notation	Range
Low	LL	50-60
High	HL	61-80
Very High	VL	81-100

Table.3.2.2. 3 Load Range (Dec)

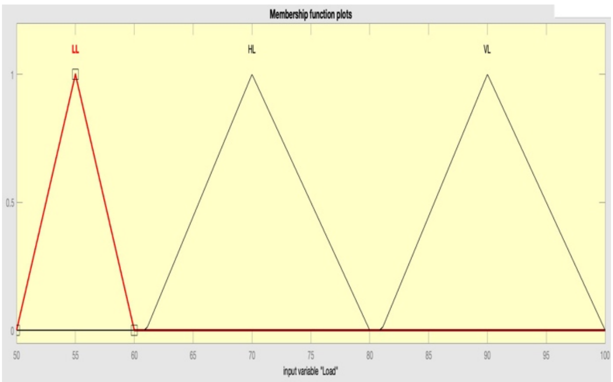

Fig.3.2.2. 3 Membership function of Load Range (December)

3.2.3 Temperature

The third input is termed "**Temperature Data** for April(19-21),October(19-21),and December(19-21) with average minimum and maximum temperatures and membership functions shown in Tables & Figs.

Temperature in Degree	Notation	Range
Low	LT	25-28
Medium	MT	28-30
High	HT	30-34

Table.3.2.3. 1 Temperature range (April)

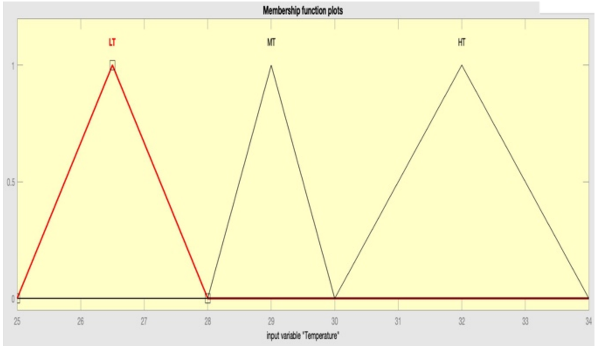

Fig.3.2.3 . 1 Membership function of Temperature Range (April)

Temperature in Degree	Notation	Range
Low	LT	26-28
Medium	MT	28-30
High	HT	30-32

Table.3.2.3. 2 Temperature Range(Oct)

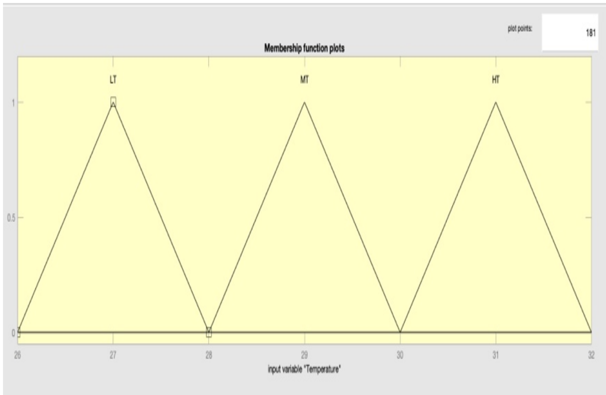

Fig.3.2.3 . 2 Membership function of Temperature Range (Oct)

Temperature in Degree	Notation	Range
Low	LT	17-20
Medium	MT	20-23
High	HT	23-26

Table.3.2.3. 3 Temperature Range(Dec)

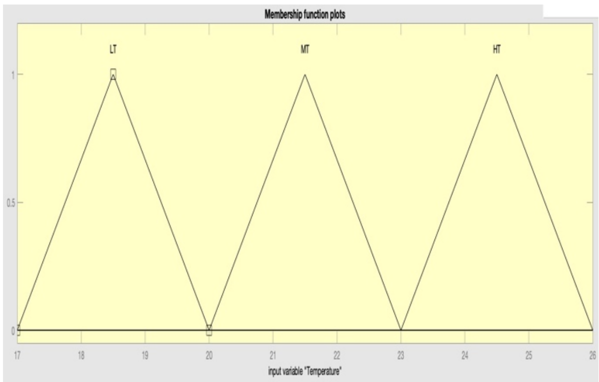

Fig.3.2.3 . 3 Membership function of Temperature Range (Dec)

The application of fuzzy rules requires the classification of the 'Forecasted Load/Output' into three membership functions: LL, HL, and VL. As per working procedure, the forecasted month's load is April2022,October 2022 and December 2022.The forecasted range for load and membership function are given below Table & Fig.

3.2.4 Forecast Load or Output

Forecast Load	Notation	Range
Low	LL	110-120
High	HL	120-130
Very High	VL	130-150

Table.3.2.4. 1 Output load Range(April)

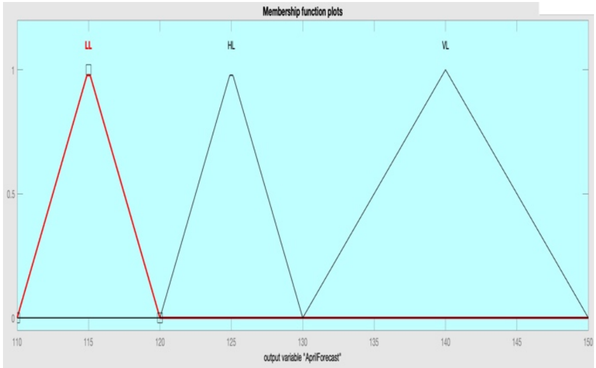

Fig.3.2.4. 1 Membership function of Output Range(April)

Forecast Load	Notation	Range
Low	LL	100-130
High	HL	115-150
Very High	VL	140-180

Table.3.2.4. 2 Output load Range(Oct)

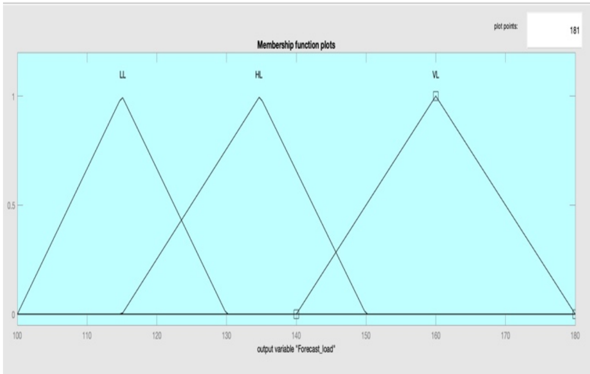

Fig.3.2.4. 2 Membership function of Output Range(Oct)

Forecast Load	Notation	Range
Low	LL	50-60
High	HL	60-80
Very High	VL	80-100

Table.3.2.4. 3 Output load Range(Dec)

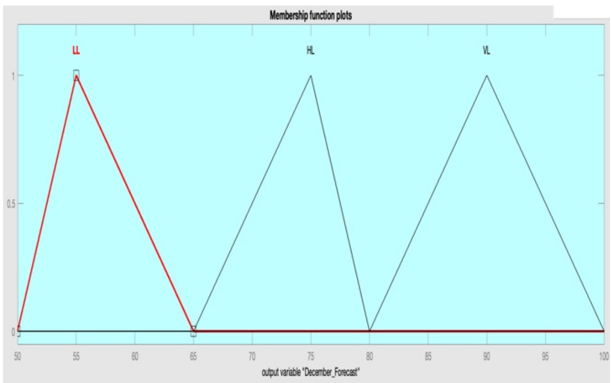

Fig.3.2.4. 3 Membership function of Output Range(Dec)

Mamdani and Sugeno are the two types of fuzzy interface systems. The most important distinction between Mamdani and Sugeno FIS is how crisp output is generated from fuzzy input. Sugeno FIS utilizes a weighted average to produce the crisp output, while Mamdani use the Center of Gravity approach for defuzzification. Any inference system with a linear or constant output may be modeled using a Sugeno-type system. The output membership functions (MF) are expected to be fuzzy sets according to the Mamdani system. Therefore, Mamdani FIS is more beneficial and simpler to deploy. The following image depicts Fig. 3.5 of the Mamdani interfacing system. To evaluate the predicted load, a set of rules, dubbed the "fuzzy rule base" shown in Fig. 1.1, must be maintained. The fuzzy rule is the driving force behind the fuzzy interface system. The rule is based on the modified membership functions of the input and output variables. The fuzzy rule basis established a forecasting logic. Make use of logical conjunctions like AND, OR, and NOT to arrive at a numeric result.

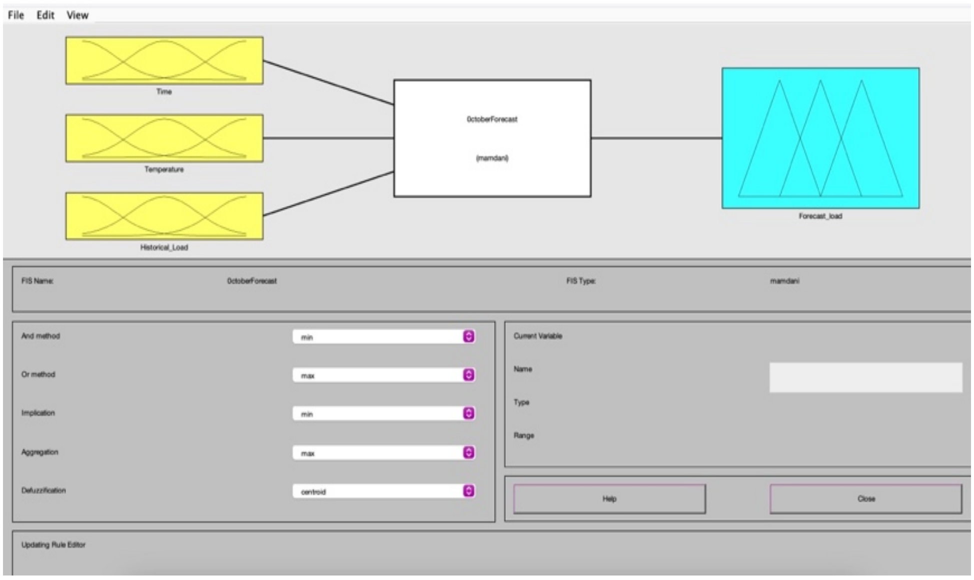

Fig.3.2.4. 4 Mamdani Fuzzy Interfacing System

3.3 Fuzzy Rules Implementation

Convert the linguistic variable in a fuzzy interface system to machine language. Trying to implement a logical circuit complete with a truth table in order to provide the computer the capability to calculate the output or forecast the load The fuzzy rule is completely controlled by the number of inputs and outputs' membership function. expanding not only the number of membership duties, but also the number of regulations that are put into operation inside the FIS. This Mamdani fuzzy interface system has been enhanced using ten rules to forecast the monthly demand & the truth table are given in below Tables & figs. Rules of three months are,

TIME	LOAD	TEMPERATURE	FORECAST LOAD
IF Time is MN	AND Load is LL	AND Temperature is LT	Then Forecast Load is LL
IF Time is MG	AND Load is HL	AND Temperature is LT	Then Forecast Load is HL
IF Time is MG	AND Load is HL	AND Temperature is MT	Then Forecast Load is HL

IF Time is FN	AND Load is HL	AND Temperature is MT	Then Forecast Load is LL
IF Time is FN	AND Load is HL	AND Temperature is HT	Then Forecast Load is HL
IF Time is AN	AND Load is HL	AND Temperature is HT	Then Forecast Load is HL
IF Time is AN	AND Load is VL	AND Temperature is HT	Then Forecast Load is VL
IF Time is EVE	AND Load is VL	AND Temperature is HT	Then Forecast Load is VL
IF Time is EVE	AND Load is VL	AND Temperature is MT	Then Forecast Load is VL
IF Time is FT	AND Load is HL	AND Temperature is LT	Then Forecast Load is HL

Table.3.3. 1 Fuzzy Rule (April)

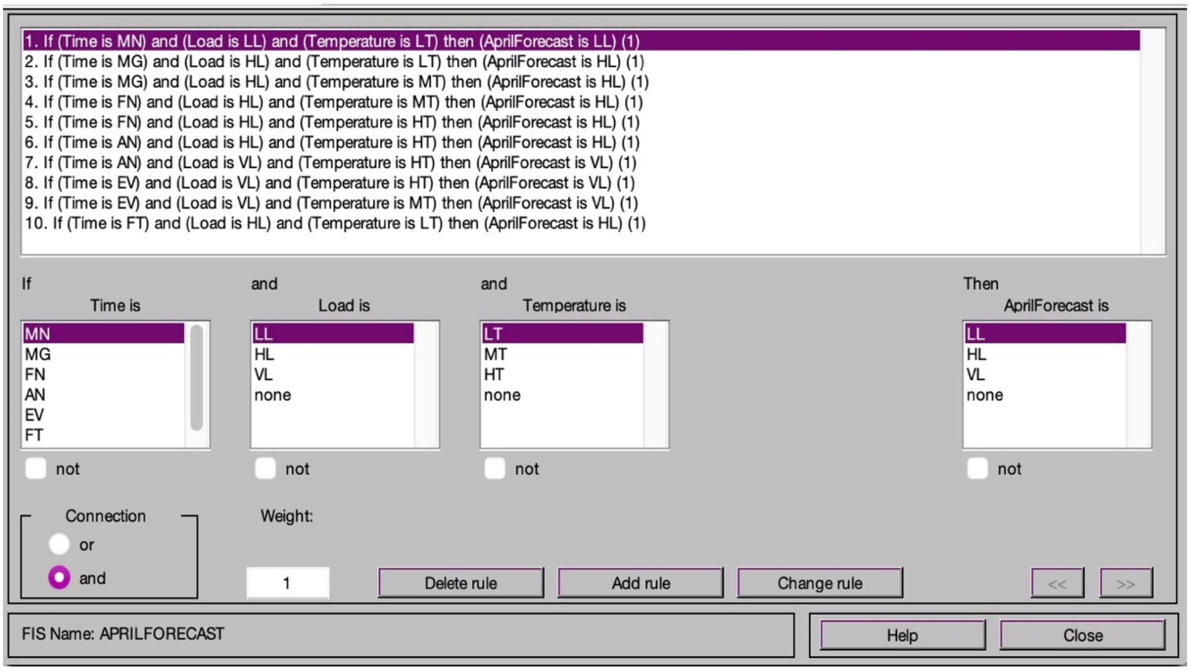

Fig.3.3. 1 Fuzzy Rule (April)

TIME	LOAD	TEMPERATURE	FORECAST LOAD
IF Time is MN	AND Load is LL	AND Temperature is LT	Then Forecast Load is LL
IF Time is MG	AND Load is HL	AND Temperature is LT	Then Forecast Load is HL
IF Time is MG	AND Load is HL	AND Temperature is MT	Then Forecast Load is HL
IF Time is FN	AND Load is LL	AND Temperature is MT	Then Forecast Load is LL
IF Time is FN	AND Load is HL	AND Temperature is HT	Then Forecast Load is HL
IF Time is AN	AND Load is HL	AND Temperature is HT	Then Forecast Load is HL
IF Time is EVE	AND Load is VL	AND Temperature is HT	Then Forecast Load is VL
IF Time is EVE	AND Load is HL	AND Temperature is MT	Then Forecast Load is VL
IF Time is FT	AND Load is HL	AND Temperature is MT	Then Forecast Load is HL
IF Time is FT	AND Load is LL	AND Temperature is LT	Then Forecast Load is LL

Table.3.3. 2 Fuzzy Rule (October)

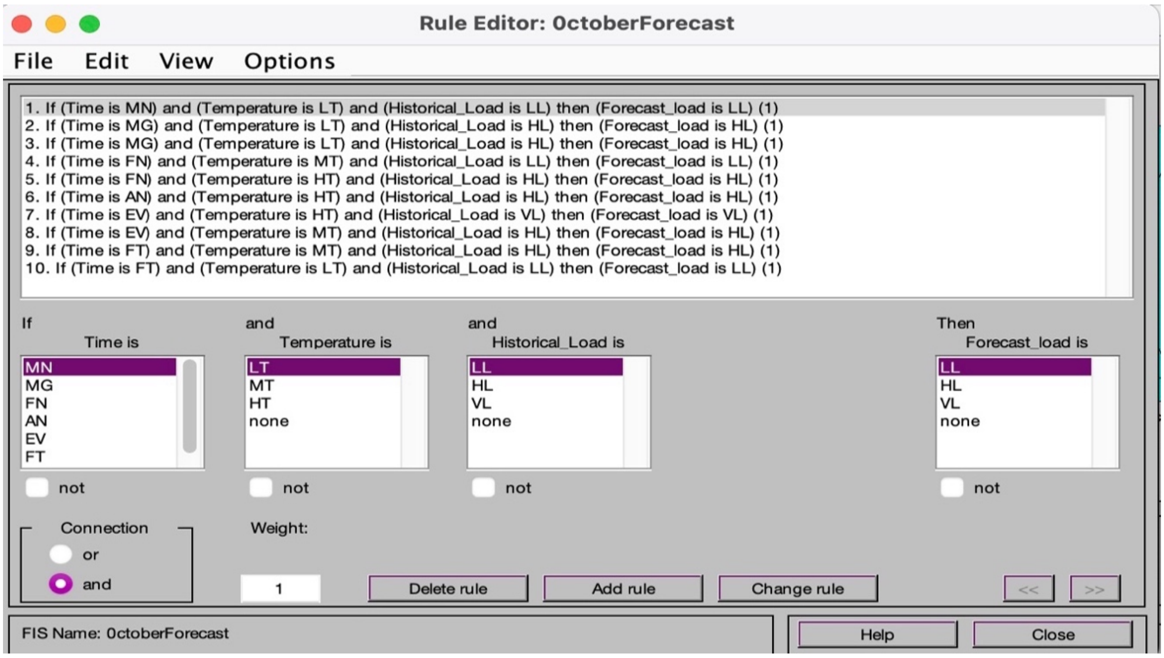

Fig.3.3. 2 Fuzzy Rule (October)

TIME	LOAD	TEMPERATURE	FORECAST LOAD
IF Time is MN	AND Load is LL	AND Temperature is LT	Then Forecast Load is LL
IF Time is MG	AND Load is HL	AND Temperature is LT	Then Forecast Load is HL
IF Time is MG	AND Load is HL	AND Temperature is MT	Then Forecast Load is HL
IF Time is FN	AND Load is LL	AND Temperature is MT	Then Forecast Load is LL
IF Time is FN	AND Load is HL	AND Temperature is HT	Then Forecast Load is LL
IF Time is AN	AND Load is LL	AND Temperature is MT	Then Forecast Load is LL
IF Time is EVE	AND Load is HL	AND Temperature is LT	Then Forecast Load is HL
IF Time is FT	AND Load is LL	AND Temperature is LT	Then Forecast Load is LL
IF Time is FT	AND Load is HL	AND Temperature is LT	Then Forecast Load is HL

Table.3.3. 3 Fuzzy Rule (December)

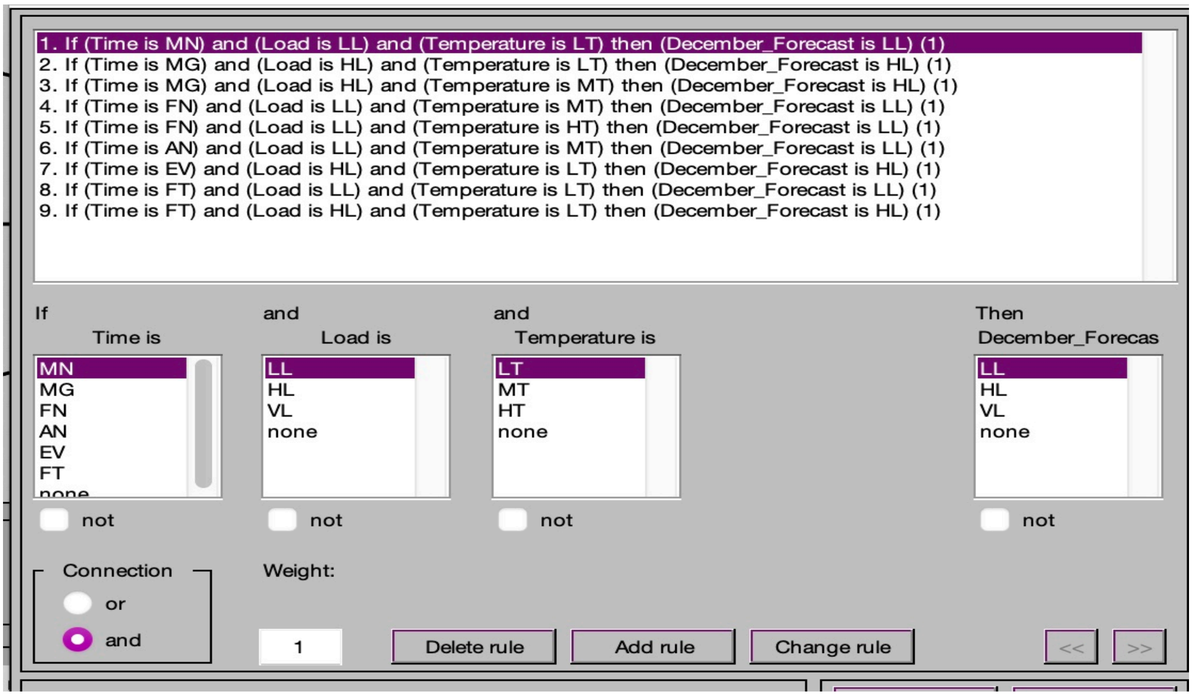

Fig.3.3. 3 Fuzzy Rule (December)

As shown in Figures and Tables the fuzzy rules editor allows for the creation of fuzzy rules. It is based on the combination of the membership functions of the inputs and the outputs. The fuzzy rule is flexible enough to allow for some alterations.

3.4 Summary

Triangular MFS is used in this study to forecast the load for April, October and December 2022. Each input and output are organized into one of several membership function types. MATLAB is applied to create a Mamdani fuzzy interfacing system with a triangular membership function. It is recommended to use the Gaussian membership function since it produces more accurate results. The application of fuzzy rules requires the classification of the 'Forecasted Load/Output' into three membership functions: LL, HL, and VL. Another input is termed "Temperature Data for April (19-21), October (19-21) and December (19-21) with average minimum and maximum temperatures and membership functions shown in Tables and figures.

CHAPTER-4
RESULT AND DISCUSSION

4.1 Result

This study focuses on determining the relationship between monthly load and time, temperature, and the load that occurred the month before. The fuzzy rule technique makes use of a triangle membership function in order to produce a description that is as accurate as it is possible to be of the input–output link of the actual circumstance. Comparison of the actual load to the projected load, which was not significantly different from the actual load, was used to determine the conclusion. Along with the current time, current temperature, and predicted load, the surface view of a 3D graph chart is referred to as the output. From the perspective of the rule, we also take into account the time, temperature, and load-based projections. In the Rules view, you can also see the daily load, which currently shows that it is evening and that the expected demand is high. The surface view and the rule perspective are both presented in figures represents the Time to Load view Graph. The monthly average load forecast is represented by the time to load graph.

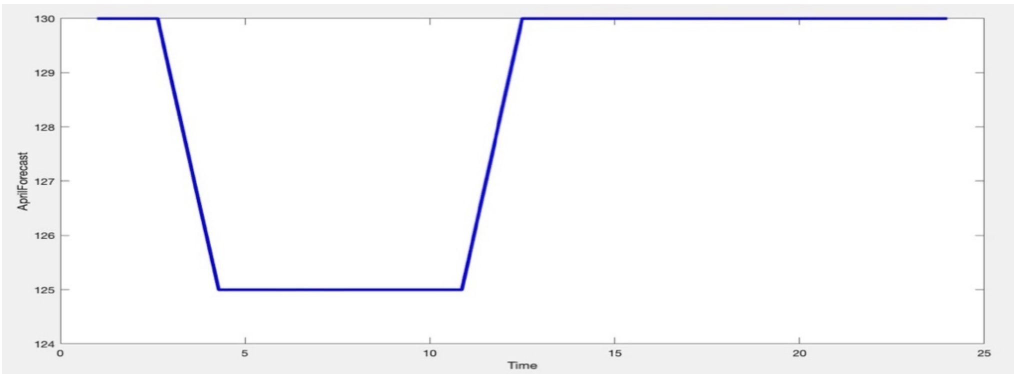

Fig.4.1. 1 Time to Load View (April-22)

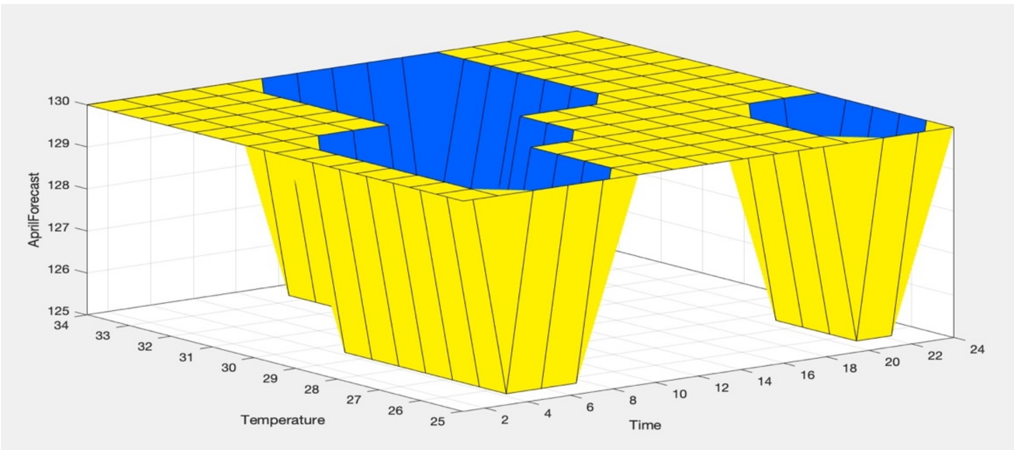

Fig.4.1. 2 Surface View of April-2022 Forecast Load

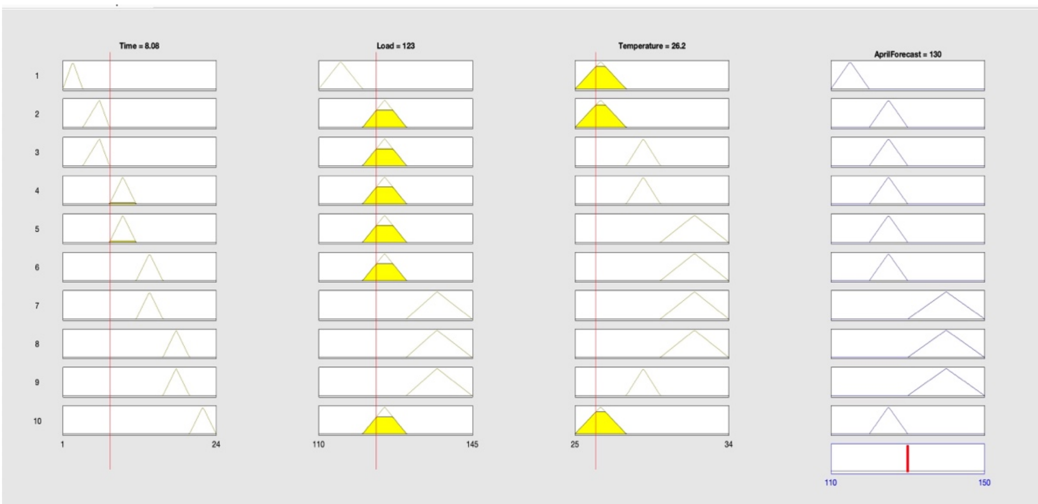

Fig.4.1. 3 Rules View Morning Peak Load Forecast(April-22)

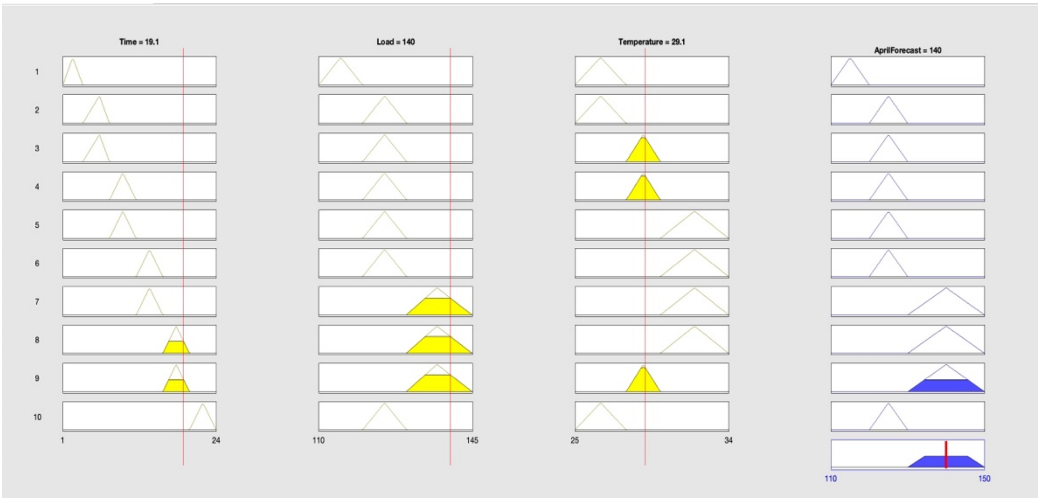

Fig.4.1. 4 Rules View Evening Peak Load Forecast(April-22)

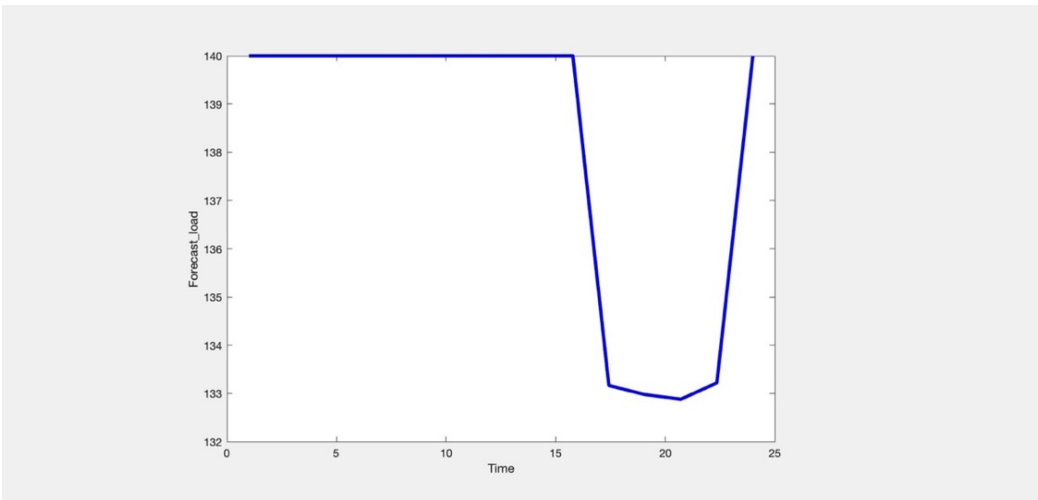

Fig.4.1. 5 Time to Load View (October-22)

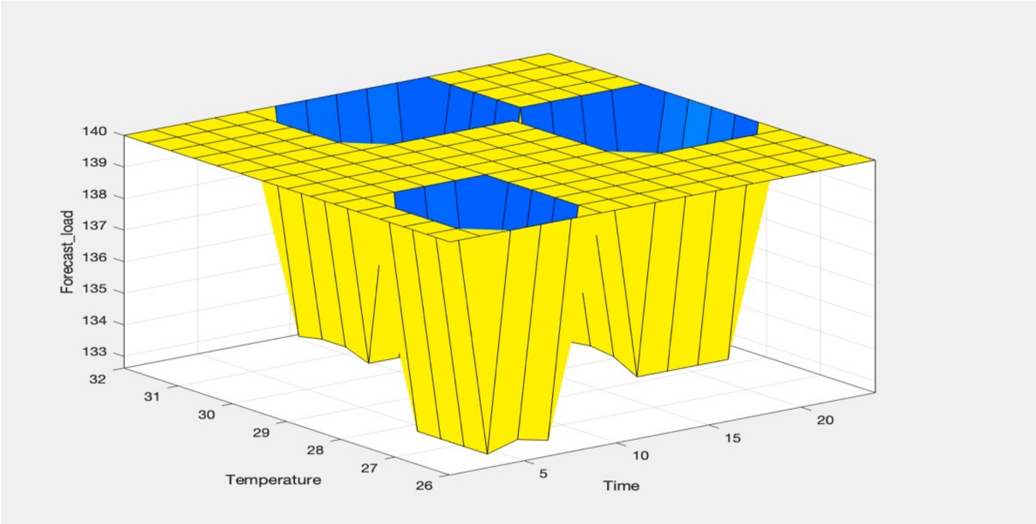

Fig.4.1. 6 Surface View of October-2022 Forecast Load

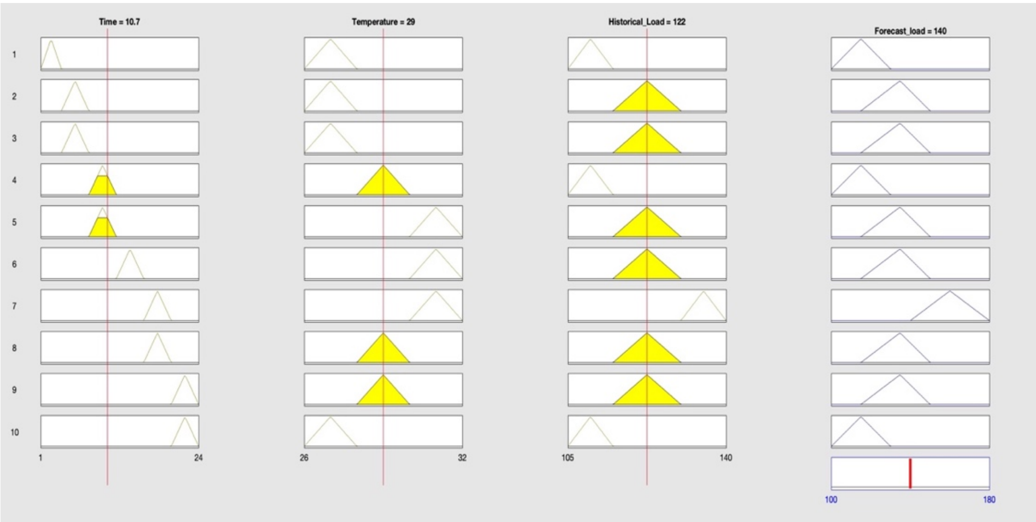

Fig.4.1. 7 Rules View Morning Peak Load Forecast(October-22)

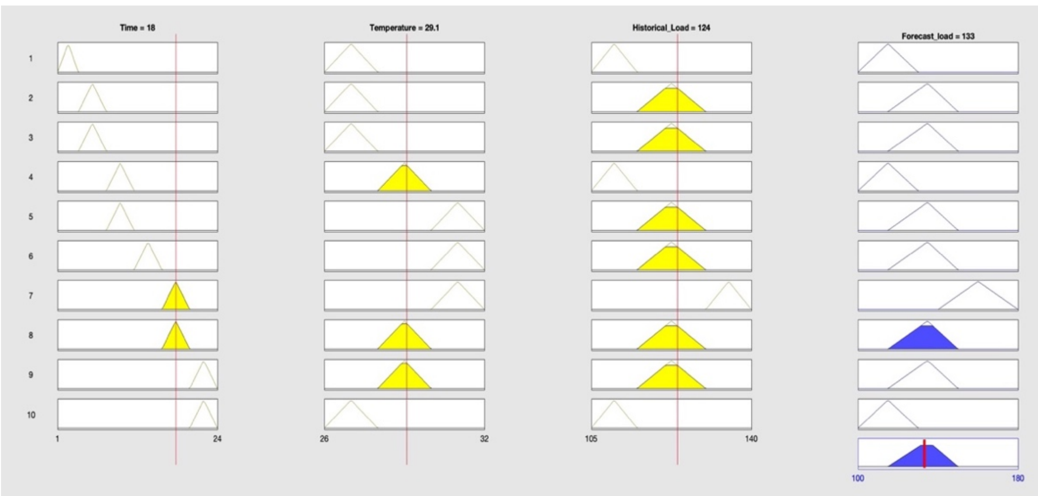

Fig.4.1. 8 Rules View Evening Peak Load Forecast(October-22)

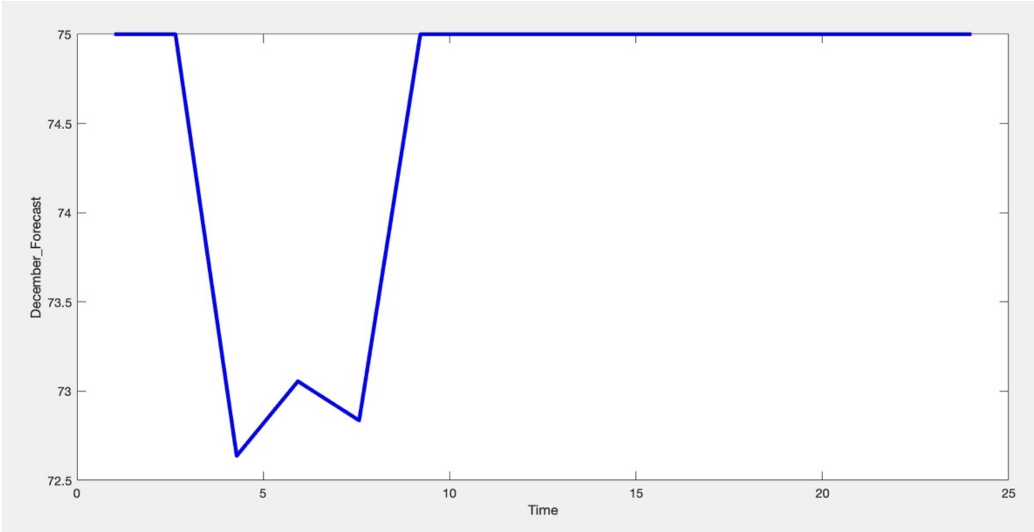

Fig.4.1. 9 Time to Load View (Decmber-22)

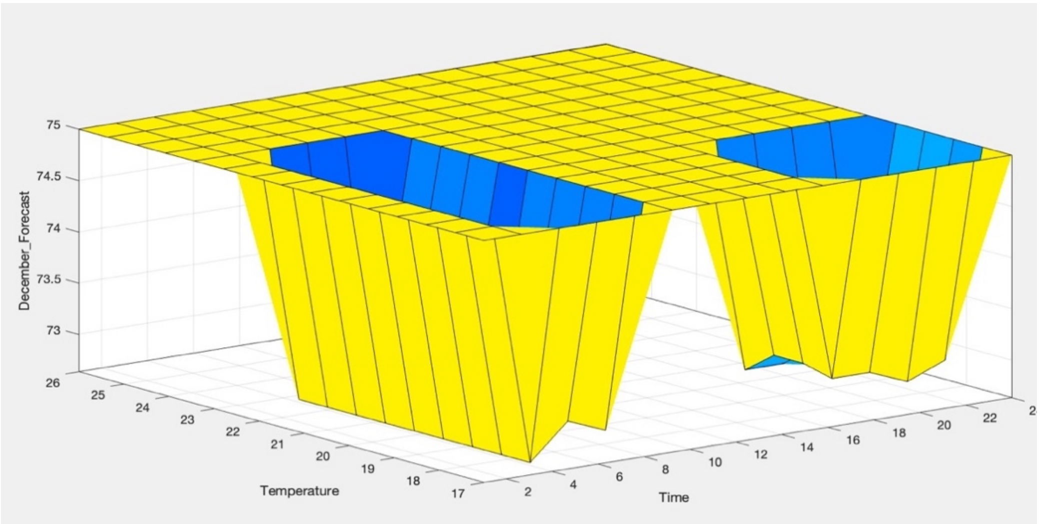

Fig.4.1. 10 Surface View of December-2022 Forecast Load

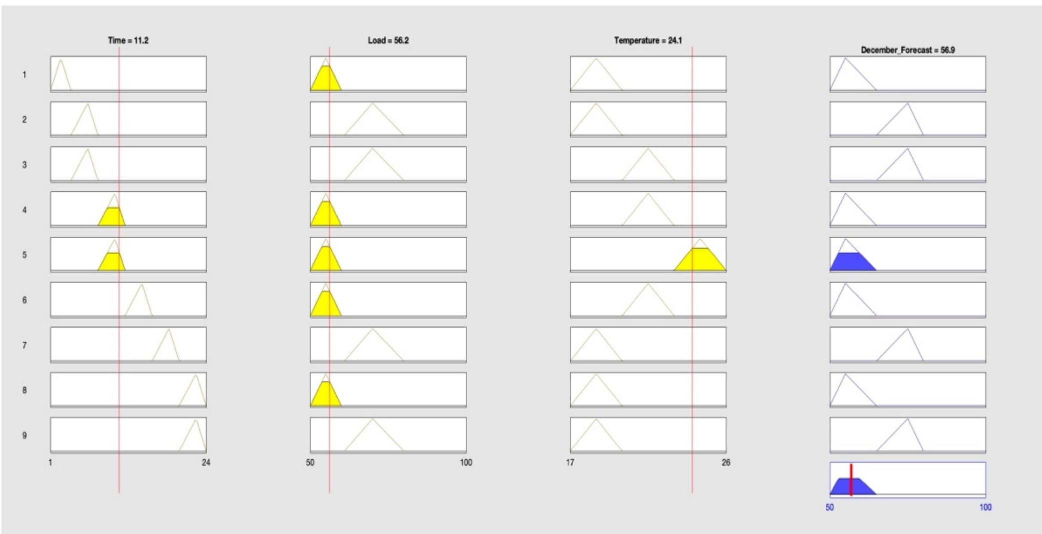

Fig.4.1. 11 Rules View Morning Peak Load Forecast (December-22)

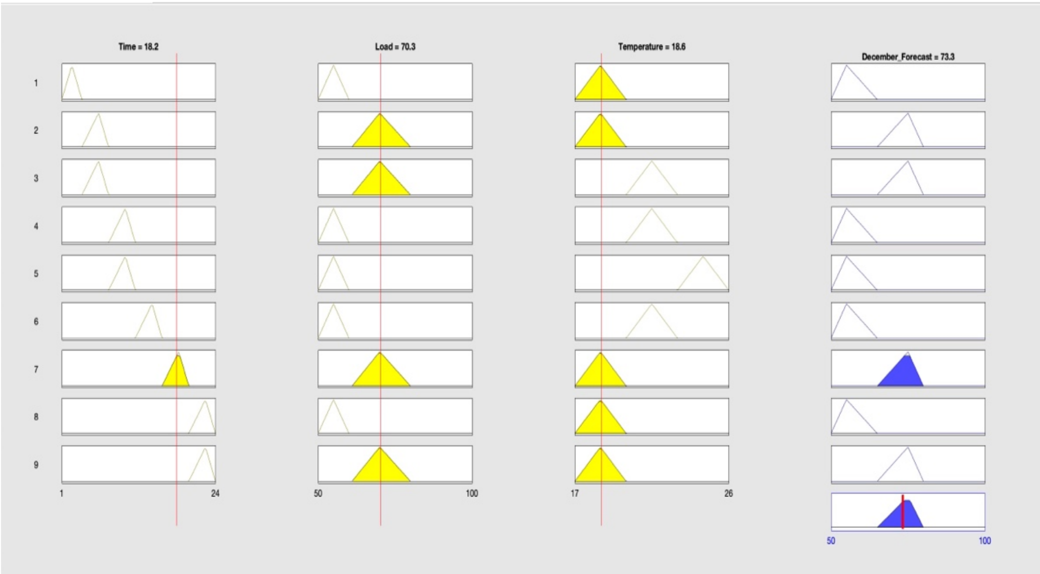

Fig.4.1. 12 Rules View Evening Peak Load Forecast (December-22)

The peak demands are represented in figures. The rule approach can predict peak demand if we take the morning and midnight to be the peak hours of the day. Below are the peak demand projections for the morning and fore night hours. This declaration informs us completely that the research concerns the monthly load forecast. Various error computation types, such as APE, MPE, and MAD, which are discussed in Chapter 1, are favored in fuzzy logic. The proportion of error is calculated by comparing the actual load to the predicted load.

$$\text{MAPE \%(April)} = \left(\frac{Actual\ Load - Forecasted\ Load}{Actual\ Load}\right)\times 100$$

$$= \left(\frac{120-130}{120}\right)\times 100$$

$$= 8.33\%$$

$$\text{MAPE \%(October)} = \left(\frac{Actual\ Load - Forecasted\ Load}{Actual\ Load}\right)\times 100$$

$$= \left(\frac{160-140}{140}\right)\times 100$$

$$= 14.28\%$$

$$\text{MAPE \%(December)} = \left(\frac{Actual\ Load - Forecasted\ Load}{Actual\ Load}\right)\times 100$$

$$= \left(\frac{60-75}{60}\right)\times 100$$

$$= 25\%$$

Average MAPE of three months is 15.87%. Where MAPE is Mean Absolute Percentage Error and Loads are measured in KWh.

4.2 Discussion

The purpose of this study is to forecast the1 April, October, December- 2022 load. In the fuzzy interface system, to predict the forecast load, time, temperature, and previous data with a specified membership function are taken as input, and the forecast load is output. The actual loads and the forecast loads are quite similar. The forecasted load is April-130 KWh (Actual-120KWh), October-140 KWh, and the actual load is 160 KWh and finally December forecasted load is 75kwh (Actual-60KWh). According to the error percentage mentioned in the 4.1 result, using accurate temperatures for the experimented area can help reduce errors. Already, this experiment is based on the distribution side of a single consumer. Because the consumer load is not constant, it varies according to the consumer. A consumer's load can be affected by a sudden occurrence. Also, the consumer load must be increased day by day. Additionally, by increasing the number of membership functions, the MAPE error can be reduced. Fuzzy short-term load forecasting is extremely useful. Increasing the number of inputs, such as the monthly average rainfall, can help reduce forecast error.

CHAPTER-5
RESEARCH MANAGEMENT

5.1 Task, Schedule and milestones

In this experiment, we exerted much effort to achieve our objective, the force-cast load. Our supervisor instructed us to accomplish our ideal objective. In this experiment, we predicted the load using fuzzy logic. We obtained temperature and previous load data from our residence for this purpose. For the implementation of fuzzy logic, the time, temperature, and prior load are supplied to generate a load forecast.

5.2 Resources

The consumer provided month-by-month load data for 2019 through 2021, and the load curves for those three years are depicted in Figs.

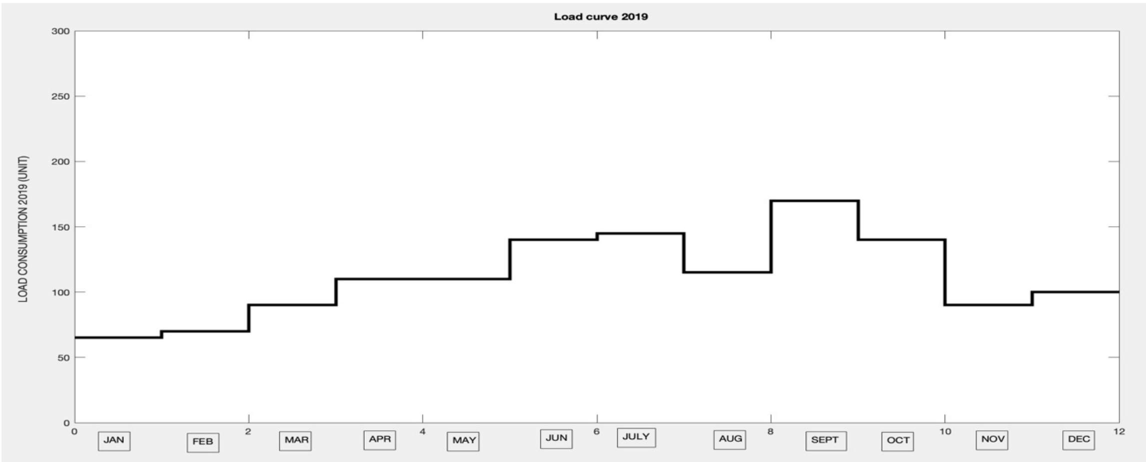

Fig.5.2. 1 Load curve of 2019

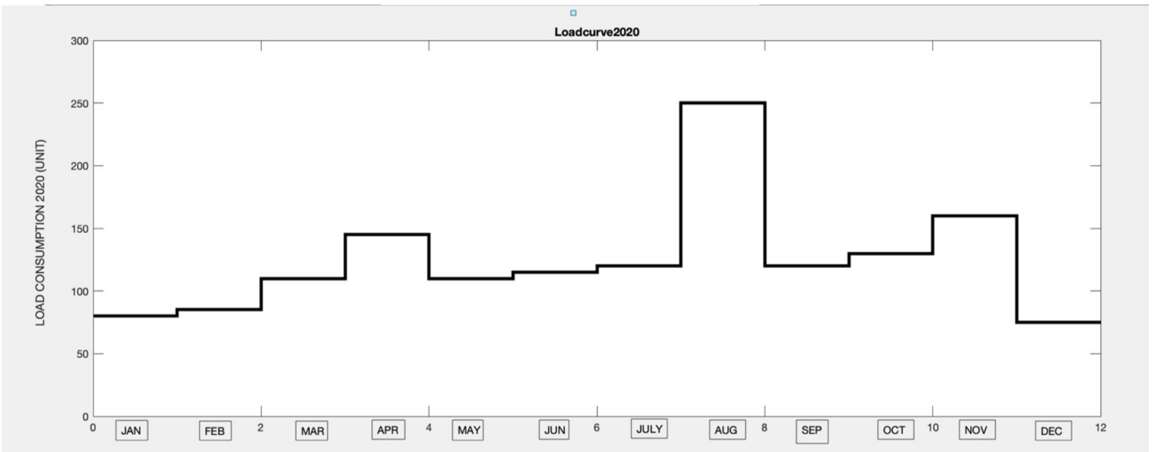

Fig.5.2. 2 Load curve of 2020

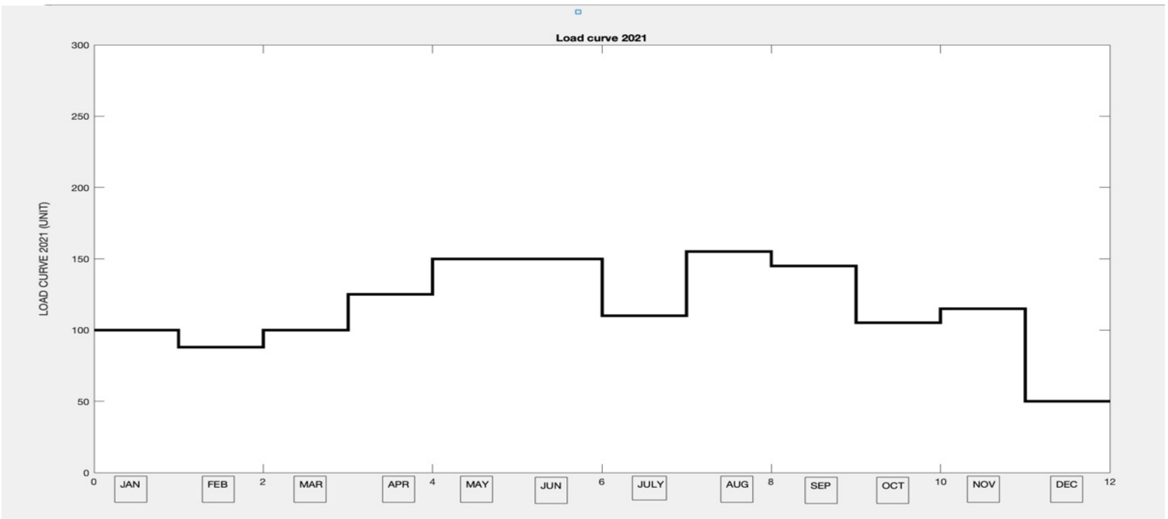

Fig.5.2. 3 Load curve of 2021

The temperature is averaged with monthly maximum temperature ang minimum temperature. The temperature collected from a website link 1 [7]

(https://bd.freemeteo.com/weather/jhenaidah-sardar-uz/history/monthly-history/?gid=7701326&station=9660&month=12&year=2019&language=english&country=bangladesh)

the located weather is Jhenaida Sadar upozila,Jhenaidah.

5.3 Lesson Learned

This exercise teaches us how to gather resources and construct a fuzzy interface. The membership function's implementation and the day's peak demand are discussed. Explore fuzzy methods for short-term load prediction as well.

CHAPTER-6
CONCLUTIONS

6.1 Conclusions

The particular section of the research in question the fuzzy rule technique makes use of a triangular membership function in order to produce a description of the scenario that is as precise as it is possible given the information that is at hand in order to do so, the fuzzy rule approach uses a membership function. The output of a 3D graph chart is termed the surface view (4.1 and 4.1.1), and the graph that shows the monthly average load forecast is called the time to load graph. Both of these terms relate to the same thing. This approach is able to provide an accurate estimate of peak demand provided that we consider demand to be at its maximum level both in the morning and at midnight. This particular piece of research focuses on the issue of short-term load forecasting, which is sometimes abbreviated as STLF (short for short-term load forecasting) (short-term load forecasting). In it, a possible solution to the problem is proposed in the form of a fuzzy logic framework, which requires the employment of a triangle membership function. This solution has the ability to resolve the issue. Because it deals with the load of the customer on an individual level, the traditional technique of addressing the load of the consumer in this scenario is not as precise as the fuzzy-based approach to load forecasting.

6.2 New Skills and Experiences Learned

MATLAB and Fuzzy logic were both new to us and we learnt how to use them. which refers to a method of processing variables that processes the same variable in such a way that it may handle numerous truth values that are equally plausible. how to construct the fuzzy logic function and predict the load that will be placed on the system. We learn about several fuzzy interface systems and membership functions, create a customized membership function, and implement a deriving fuzzy rule to forecast the outcome.

6.3 Future Recommendations

The load that is caused by the consumer is not constant; rather, it changes depending on the consumer. Increasing the number of inputs that are used, such as the monthly average rainfall, can assist lower the amount of inaccuracy that occurs in the prediction.

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[7] https://bd.freemeteo.com/weather/jhenaidah-sardar-uz/history/monthly-history/?gid=7701326&station=9660&month=12&year=2019&language=english&country=bangladesh