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Demand Side Fuzzy Logic Based Management at Customer End Side

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ABSTRACT

Demand Side Management (DSM) technique encourages the consumers to adjust their energy usage patternto get optimized results for achieving the goal of minimizing theelectricity consumption cost. This mechanism provides benefitsto both side customer and utility in terms of bill cost reduction (for the customer) andensure grid stability (for the provider). To regulate the increasing energy demand extensiveresearch is being carried out for possible implementation of different DSM techniques.

In this thesis, an Energy Management System (EMS) **)** *atcustomer end side throughdesign of fuzzy logic based demand side management model is proposed for demand forecasting and load scheduling. The proposed system consistsof two fuzzy logic controllers, the 1st controller is applicable for the short term energy demand forecasting for the next day 24hours and the 2nd controller is used to schedule the home appliances based on the forecasted demand. The input variables for the forecasting controllers are previous demand, currentdemand, day type(work day or weekend) and time period of the day. Depending on these parameters it forecasts the next day demand which is considered as its output. Then this output (forecasted demand) will feed to the second fis (scheduler) controller to schedule the specified appliances.*

Finally the fuzzy logic based predictive controller is developed and implemented using appropriate membership function in order to forecast the next day's demand. And the result of

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this model shows that forecasted demand is highly affected by particular time period, previous demand, current demand and day type.The displayed result indicates that higher demand is occurred at peak hours and low demand at off-peak hours. Depend on the forecasted demand fuzzy logic based load scheduling controller is developed and implemented. The result of the scheduler shows at higher forecasted demand most of appliances are in off condition except continuously usable loads .And all home loads are in on condition at low and medium forecasted demand.From this we can conclude thateverybody can manage his power consumption by shifting their usage from peak hour to off peak hour by knowing the demand of energy for the next day with the help of the model.and the model appropriately schedules the home loads.

Keywords: *Fuzzy logic, demand side management, forecast, appliance schedule*

CHAPTER ONE

INTRODUCTION

1.1. Background

Electrical energy & distribution began at the time when Thomas Edison invented the direct current (DC) incandescent bulb. The DC generation was accompanied by an alternate current (AC), after the Nicola Tesla's introduction of electrical machines. This further upgraded to an electric energy distribution to a mass through the work of George Westinghouse that showed how electric energy could be transmitted from the source to the consumer. The work led to the current, large scale electrical power transmission and distribution system. The sources of energy are classified in to renewable and non renewable. The major sources of energy in developed countries range from solar to nuclear energy. According to the work in [1], the electric energy production of the globe from renewable energy source, excluding hydropower is around 4% of the total production. Nevertheless, nations turn their energy production to renewable energy sources due to the requirement of having economy of low carbon and sustainable society.

Nowaday, there is an increasing electricity demand and an increasing cost of the raw materials. It is necessary to do a better use of the electricity through proper management. Governments are passing laws to improve this management by means of Demand-Side Management (DSM). Demand-Side Management has been identified as one of the main strategies to be promoted in order to guarantee security of electrical energy supply in most countries [2].The major objective of DSM is to encourage customer to participate in schemes to reduce peak demand and shifting the load. However, there is no a commonly accepted definition for the term Demand-Side Management (DSM). In this paper, DSM is defined as the actions that influence the way consumers use electricity in order to achieve savings and higher efficiency in energy use based on their needs[3].

The combination of DSM with an automatic control of the household demand leads to a new concept called Active Demand Side Management (ADSM)[4,5]. ADSM allows modifying the demand profile in order to reduce the stress of the electrical system, maximize consumption when the resources are available and decrease congestion situations.The effectiveness of the

DSM ishighly depending on the quality of energy demand forecasting. So that load forecasting is prerequisite for demand side management. Forecasting for load demand prerequisite is the most imperative key for power system planning and power management. The ability of the generation, transmission and distribution capacities are strictly dependant on the precise energy and load forecasting for that system. Power system expansion planning starts with a forecast of anticipated future load requirements. Estimates of both demand and energy requirements are crucial to valuable system planning. The term forecast refers to projected load requirements determined using a systematic process of defining future loads in sufficient quantitative detail to permit important system expansion decisions to be made by the provider as well as appropriate scheduling by consumers.

The Energy Management System demands accurate load forecasting and short term Load Forecasting provides better and truthful results [6] because the prime duty of any utility is to provide reliable power to customers. Customer load demand in electric distribution systems is subject to change because human activities follow daily, weekly, and monthly cycles. The load demand is usually higher during the daytime and in evening, when industrial loads are high, lights are on, and lower in late evening and early morning when most of the population is asleep. Estimating the distribution system load expected at some time in the future is an important task in order to meet exactly any network load at whatever time it occurs. The estimation of future active loads at various load buses ahead of actual load occurrence is known as load forecasting. If itis done inappropriately, then the direct effect is on the planning for the future load and the result is the difference of the load that will develop from the planning done for the same, and eventually the entire planning process is at risk.

Therefore, load forecast plays a crucial role in all aspects of planning, operation, and control of an electric power system. It is an important task for operating a power system reliably and economically. So, the need and relevance of forecasting load for an electric utility has become an important issue in the recent past. It is not only important for distribution or power system planning but also for evaluating the cost effectiveness of investing in the new technology and the strategy for its propagation. However, in the deregulated market, loadforecasting is of utmost importance. As the utility supply and consumer demand is fluctuating and the energy prices increases by a factor of ten or more during peak load, load forecasting is vitally important for utilities as well as for the customer to give awareness about peak hour for them. Short-term load forecasting is a helping tool to estimate load flows and to anticipate for the overloading. Network reliability increases if the overloading effects areeliminated in time. Also, it reduces rates of equipment failures and blackouts.

Load forecasting is however not an easy task to perform. First, because the load on consumer side is complex and shows several levels of seasonality: the load at a given hour is dependent on the load at the previous hour as well as on the load at the same hour on the previous day, and also on the load at the same hour on the day with the same quantity in the previous week. Secondly, there are many important externally affecting variables that should be considered, particularly day type and time period [7].

There are large varieties of mathematical methods that are used for load forecasting, the development and improvements of suitable mathematical tools will lead to the development of more accurate load forecasting techniques. The accuracy of load forecasting depends on the load forecasting techniques used as well as on the accuracy of forecasted weather parameters such as temperature, humidity etc. As per the recent trends artificial intelligence methods are the most pronounced for the STLF. From different artificial intelligence methods, fuzzy logic and artificial neural network are the most used. Among the two methods fuzzy logic for STLF is gainingimportance nowadays, because of its some distinct advantages over ANN in that Fuzzy control strategies come from experience and experiments rather than from mathematical models and, therefore, linguistic implementations are much faster accomplished. Fuzzy control strategies involve a large number of inputs, most of which are relevant only for some special conditions. Such inputs are activated only when the related condition prevails. In this way, little additional computational overhead is required for adding extra rules. As a result, the rule base structure remains understandable, leading to efficient coding and system documentation.[8].

The general idea of demand side management is to design mechanism which decides the hourly demand that can persuade the consumers to change their usage patterns in order to lower the peak demand, with the expectation that the consumers will respond to it. Another objective of this mechanism is to eliminate fluctuations in the demand beyond a defined threshold. Thus every consumer are also very concerned about the demand in the coming hours, days which help them to schedule their appliances based on their priority which help them & the supplier to reduce their bill and continuous block out of the grid respectively.

1.2. Demand Side Management

There are basically two forms of action for energy management: supply side management, which involves the construction of new generating units and the control of demand using energy conservation policies, and demand side management (DSM), which involves the reduction of waste and the use of more efficient equipment [9]. Most researchers define DSM as a program or set of activities organized by the utility that affect the amount and timing of consumer use. DSM is a means to intervene in the use and the variety of modes of energy consumption [10–14]. One of the goals of DSM is to reduce the peak levels of energy demand throughout the day. The customer side demand management (DM) can be done in several ways but all the DM techniques are based on two aspects, reducing consumption and shifting consumption [15]. Scheduling the loads is also a popular method of DM where some of the loads are selected while others are shifted.

Authors K.E. Parameter et al. have defined DSM as planning, implementation, and monitoring of the utility activities that influence the customer's use of electricity in ways that changes the utility load shape [16], i.e., changes in the time pattern and magnitude of a utility's load. One type of demand side management is demand response, which focuses on price signals to handle peak demand. Peak demand can be handled by either using a price based system, where the electricity price fluctuates according to the load, or by using an incentive based system, where incentives are given to customers to reduce load at peak times [17].

Demand response is a key factor of DSM. The Federal Energy Regulatory Commission defines demand response (DR) as "Changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardize". In other words, demand response (DR) is the technique to manipulate customer's load during peak demand to the other time, when the demand is less. This helps in reducing the peak demand of the grid, and also in reduction of prices on the customer side. DR can be applied to both residential and industrial loads and includes three different concepts: energy consumption reduction, shifting consumption to periods of low (or high) demand, and efficient utilization of energy storage systems [18] Thus, a crucial issue in Smart Grids (SGs) is to manage DR in order to reduce peak electricity load, utilizing the existing infrastructure more efficiently and in a better planned manner [19].

1.3. Load Forecasting

The functionality of electrical grids depends on the load served for a particular service area. Load is an important aspect of the DR systems and the efficiency of utility companies depends on how effectively the electric load can be managed. Customer load depends on several factors such as temperature, heating/cooling of the property, hot water utilization, and lighting conditions. Thus, load forecasting is essential to perform DSM on the grid and on the distribution as well as at customer end.

There are three types of load forecasting (LF) - Short term LF used to predict load on an hourly basis, medium term LF used to predict load on a weekly to monthly basis and, long term LF to predict load up 50 year ahead[20]. Advanced data mining techniques such as multiple regression, exponential smoothing, time series analysis, and Kalman filtering are used to forecast loads [8].a short term to medium term LF is achieved using the electrical data of years 2010 to 2015 and employing the technique of regression based load forecasting proposed in [21–24].

1.4. Proposed Solution

In this paper the appliance scheduling integrating with demand forecasting is done by fuzzy logic system on mat labsimulink.Fuzzy logic or Fuzzy systems are logical systems for standardization and formalization of approximate reasoning. It is similar to human decision making with an ability to produce exact and accurate solutions from certain or even approximate information and data. The reasoning in fuzzy logic is similar to human reasoning. Fuzzy logic is the way like which human brain works, and we can use this technology in machines so that they can perform somewhat like humans. Fuzzy logic system has three general parts such as crisp input, fuzzification, defezification and lastly crisp output. from this Fuzzification provides superior expressive power, higher generality and an improved capability to model complex problems at low or moderate solution cost. Fuzzy logic allows a particular level of ambiguity throughout an analysis. Because this ambiguity can specify available information and minimize problem complexity, fuzzy logic is useful in many applications. For power systems, fuzzy logic is suitable for applications inmany areas where the available informationinvolves uncertainty.

Fuzzy logic provide the conversions from numerical to symbolic inputs, and back again for the out puts [25]. So that due to this all functions of fuzzy logic we are interested to use it in our system as controller for both forecasting and scheduling purpose.

Accurate short-term load forecasting, defined in the hours-to-days' time frame integrated with automatic appliance scheduling, can lead to an efficient and economic system operation. In this thesis, a bi functional controller which is used for short-term load forecasting and appliance scheduling model is developed that can forecast load for hours to days' time intervals and schedules the load based on the consumers interest.

A load profile is gathered from different customers by making interview for them about their energy usage behavior and then the controller is modeled. Load profiles are data points that reflect the variations of electrical loads with respect to time, and are generated by cumulative electrical energy consumption of any building. Typically, the load profile varies according to the customer type, and is different for domestic, industrial and agricultural sectors. Load consumption also depends on the temperature, non-working days or holidays and the time of day, which are discussed more in the methodology part. For an accurate load forecasting, an hourly load data is used in this thesis. As given by Nurettinetinkaya [25], an hourly load profile can be used to generate load forecasts for a weekly, a daily, and an hourly basis.

Here all the process of the system for the appliance scheduling integrating with demand forecasting is done by fuzzy logic system on mat lab. The overall active demand side management simulation is tested on mat lab Simulink. This will encourage customers to actively participate in demand side management to save their money as well as for reducing continuous blackout of the grid by maintaining constant balance between demand and supply, therebyreducing system operator load shedding interference and the customers save their many due to reduction in peak hour demand.If customers have information about changes in electricity price during a day they can choose optimal time for using their electrical appliances. They use it when price is lower, i.e. during off-peaks. It shapes load curve, reduces power peaks. But energy consumption remains the same.

The advantages of the proposedmethod are: (1) it is used automatically to control the home appliance based on their need. And, (2) heuristic rules can be integrated to the control strategies of human operators. Fuzzy control strategies applied here come from experience and measurements rather than from mathematical models and, therefore, linguistic implementations are much faster accomplished. Fuzzy control strategies involve a large number of inputs, most of which are relevant only for some special conditions. Such inputs are activated only when the related condition prevails. In this way, little additional computational overhead is required for adding extra rules. As a result, the rule base structure remains understandable, leading to efficient coding and system documentation.[26]

The project can be divided into four stages, each of which leads to the next stage and helps in the formulation of the overall system (controller) model.

- Data acquisition and analysis: In this project, electric consumption load data from customers are used for both forecasting and scheduling. This data is then combined with the day type, time period, current load and previous load data. Here this data is gathered from the customer by making interview.
- Data analysis: Load profile can be the time-dependent electric consumption data for a specific utility, region, village or a building (village in our case). An accurate load profile is needed to train the predictive model in order to perform predictions. After the data gathered its analysis is done with the help of excel software.
- Formulate a predictive model: For obtaining a short-term prediction, a predictive model is formulated, (as given in chapter 3) and is analyzed with the load profile. Fuzzy logic predictivemodel and scheduler is formulated in this project.
- Test the model: the model is tested by implementing the overall controller on mat lab Simulink.

1.5. Problem statement

Ethiopia, while working hard to maximize energy production and become regional energy hub, still its distribution and energy management system is traditional. This traditional system results in frequent power interruption, system damage and consumer dissatisfactions. On the other hand, due to lack of awareness about energy utilization scheme, consumers put unessasery burden on the system by demanding maximum energy at peak periods. This affects both the consumer and service provider in that the service provider should perform frequent maintenance on the system and the consumer will also pay more for their peak hour usage of the service. And ,also By its nature, power demand fluctuates highly, and often, there are situations where power demand becomes far more than the system can actually deliver. In this case the system operators have to take special measures to allocate power in those situations. These special measures, in most cases, are not fair because load shading decisions are made on bias basis.

In order to avoid the above mentioned problems demand side management at customer end side is the answer.Demand side managementat customer end side allows consumers to actively participate in their energy management process. It helps them to use the provided energy efficiently by shifting their usage from peak hour to off peak periods with the help of the proposed model which displays the next day's energy demand throughout the day depend on the forecasted power demand at specific time theconsumer can schedule their electricityusage for the next 24hour. Both forecasting and scheduling action are automatically performed by the proposed model. The model developed in this thesis is called as fuzzy logic based active energy demand management system, we call it active because the model performs two activities at a time that are forecasting and scheduling.The success of this project (DSM) is to provide consumers with a better energy service at a lower cost, reducing equipment faller and reducing the duration of blackouts.

1.6. Research Objective

1.6.1. General Objectives

The main objective of this work is to develop a fuzzy logic based demand side management at customer end side.

1.6.2 .Specific Objectives

- To do data acquisition for the selected area
- To develop fuzzy logic model for hourly demand forecasting
- To develop fuzzy logic model for appliance scheduling based on the forecasted value.
- To design overall demand side management model on matlabSimulink.

1.9. Methodology

This entire thesis work is divided in to four condensed steps. Data gathering and analysis are done in the 1st step. Depending on this data development and implementation of hourly load forecasting model is preceded. Then development and implementation of home appliances load scheduling model is followed. Finally the implemented model is interfaced in math lab simulink for testing the overall model.

To accomplish this work the materials and software used arequestioner and interview for data gathering, Microsoft excel for the load data analysis andStandard fuzzy logic controller from matlabsimulinkwasused in this thesis for the development and implementation of hourly demand forecaster as well as load scheduler using appropriate member ship function to define the input variables and output variables. The input parameters for the fuzzy logic controller are previous day load, current day load, day type and time period of the day. The output parameter of the fuzzy logic controller1 is the forecasted demand and this is used as input for the 2nd controller that used to schedule home loads which outputs the on/off condition of the loads. The entire block diagram of the work is as follows.

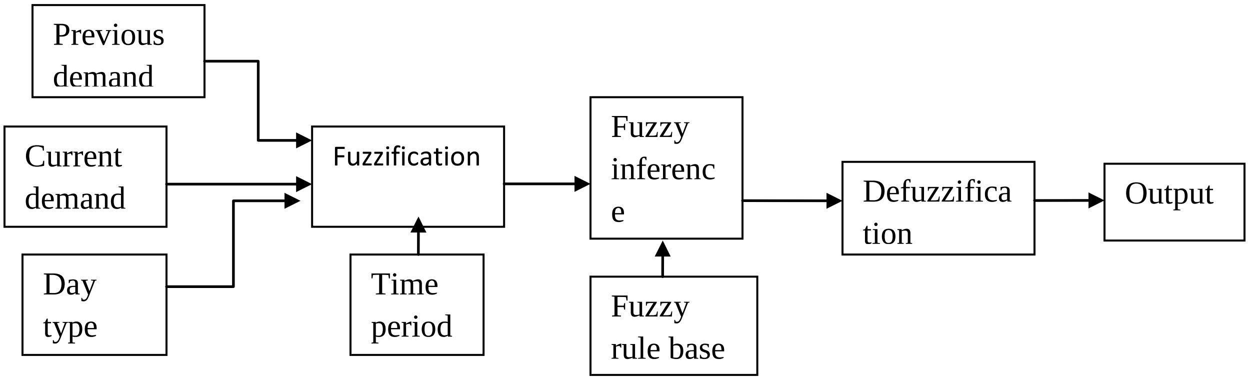

Figure 1.1 Shows block diagram of the fuzzy logic process for the proposed model

Linguistic Variables

Linguistic variables are the input or output variables of the system whosevalues are words or sentences from a natural language, instead of numericalvalues. A linguistic variable is generally decomposed into a set of linguisticterms.

Fuzzification

Fuzzification is the process of converting crisp numerical values into the degrees of membership related to the corresponding fuzzy sets. A MF will accept as its argument a crisp value and return the degree to which that value belongs to the fuzzy set the MF represents. Defuzzyfication is the inverse process of fuzzyfication.

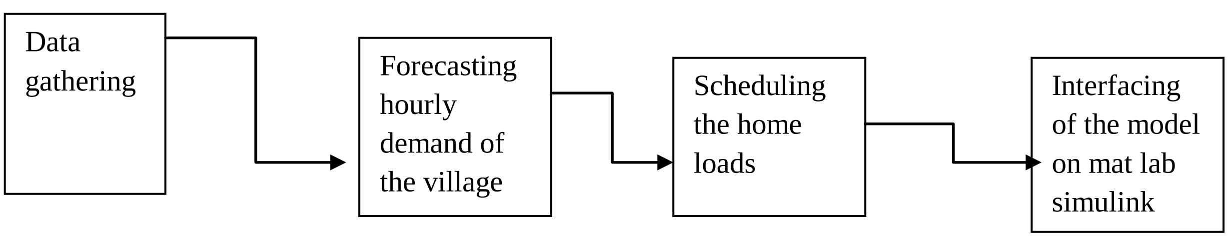

Figure1.2Shows the four condensed process of the entire work

Each and every component of fig1.1 and fig 1.2 arediscussed in chapter three in details. And also the overall algorism of the work is as follows: first the input dates current demand,previous demand, day type and time periods are given to the controller then based on the rule sated the controller forecasts the next day demand then depend on the forecasted demand the 2nd controller schedules the home loads.

CHAPTER TWO

2. LITERATURE REVIEW

2.1. Introduction

Numerous techniques for forecasting electric energy consumption and appliance scheduling have been proposed in thelast few decades. For operators, energy consumption (load) forecast is useful in effectivelymanaging power systems. Consumers can also benefit from the forecasted information inorder to yield maximum satisfaction. In addition to these economic reasons, load forecastinghas also been used for system security purposes. When deployed to handle system securityproblems, it provides expedient information for detecting vulnerabilities in advance.

In the past, computationally easier approaches like regression and interpolation, havebeen used, however, this methods may not give sufficiently accurate results. As advancesin technology and sophisticated tools are made, complex algorithmic approaches are introduced and more accuracy at the expense of heavy computational burden can be observed. Several algorithms have been proposed by several researchers to tackle electric energy consumption forecasting problem. Previous works can be grouped into three [27]:

Time Series Approach: In this approach, the trend for electric energy consumption is handled as a time series signal. Future consumption is usually predicted based on various time series analysis techniques. However, time series approach is characterized with prediction inaccuracies of prediction and numerical instability. This inaccurate results is due to the fact the approach does not utilize weather information. Studies have shown that there is a strong correlation between the behaviors of energy consumed and weather variables. Zhou R. *et al*. [28] proposed a data driven modeling method using time series analysis to predict energy consumed within a building. The model in [28] was applied on two commercial building and is limited to energy prediction within a building. Basu K. *et al*. [29] also used the time series approach to predict appliance usage in a building for justanhour.Simmhan Y. *et al*. [30] used an incremental time series clustering approach to predict energy consumption. This method in [30] was able to minimize the prediction error, however, very large number of data points were required. Autoregressive integrated moving average (ARIMA) is a vastly used time series approach. ARIMA model was used by Chen J. *et al*. [31] to predict energy consumption in Jiangsu province in China based on data collected from year 1985 to 2007. The model [31] was able to accurately predict the energy consumption; however it was limited to that environment. The Previous works on time series usually use computationally complex matrix-oriented adaptive algorithms which inmost scenarios, become unstable.

Functional Based Approach: Here, a functional relationship between a load dependent variable (usually weather) and the system load is modeled. Future load is then predicted by inserting the predicted weather information into the pre-defined functional relationship. Most regression methods usefunctional relationshipsbetween weather variables and up-to-date load demands. Linear representations are used as forecasting functions in conventional regression methods and this method finds an appropriate functional relationship between selected weather variables and load demand. Liu D. *et al*. [32] proposed a support vector regression with radial basis function to predict energy consumption in a building. The approach in [32] was only able to forecast the energy consumed due to lightingfohours.
In [34] a grey model, multiple regression model and a hybrid of both were used to forecast energy consumption in Zhejiang province of China. Yi W. et al. [33] proposed regression model to also forecast energy consumption. However these models were limited to a specific geographic area.

Soft Computing Based Approach: This is a more intelligent approach that is extensivelybeing used for demand side management. It includes techniques such as fuzzy logic, genetic algorithm and artificial neural networks (ANN) [35,36,37,38,39]. The ANNapproach is based on examining the relationship that exists between input and outputvariables. ANN approach was used in [38] to forecast regional load in Taiwan. Empirical data was used to effectively develop an ANN model which was able to predict theregional peak load. Catalao J. P. S. ˜ *et al*. [39]used the ANN approach to forecast shortterm electricity prices. Levenberg-Marquardt’s algorithm was used to train data and theresulting model [39] was able to accurately forecast electricity prices. However, it wasonly able to predict electricity prices for about 168 hours. Pinto T. *et al*. [40] also worked on developing an ANN model to forecast electricitymarket prices with a special feature of dynamism. This model [40] performs well whena small set of data is trained; however, it is likely to perform poorly with large number ofdata due to the computational complexities involved. Load data from year 2006 to 2009were gathered and used to develop an ANN model for short-term load forecast in [41]. In[42], ANN Hybrid with Invasive Weed Optimization (IWO) was employed to forecastthe electricity prices in the Australian Market. The hybrid model [43] showed goodperformance, however, the focus was on predicting electricity prices in Australia. Mostof the ANN models developed in existing work considered some specific geographicarea [38, 43].

Two types of approaches for appliance scheduling have often been discussed in literaturei.e. mathematical and heuristic. In [44] authors proposed a scheduling scheme that is based on Integer Linear Programming (ILP) which is a mathematical optimization technique. It is a centralized technique which returns optimalsolution but it is computationally expensive. To reduce the overall cost and PAR along with the consideration of user comfort.In [45] author proposed ILP for solving optimizationproblem. While considering user comfort, appliance shouldonly experience minimum delay during load shifting. Thisscheme is computationally good but does not consider theprice flexibility because only three pricing peaks are considered so user is obliged to operate appliances in high peak hoursif delayed criteria are not met.

Intelligent control reduce system complexity, several approximations to the mathematical model of the system can be made. However, in practice, it is not possible to construct a mathematical model using traditional methods, which characterizes the system completely and accurately in terms of its non-linear behavior and other physical phenomena. These limitations of conventional model-based control mechanisms for flexible robot arm systems have stimulated the development of intelligent control mechanisms incorporating adaptive controls, neural networks and fuzzy logic[48]. Thus, an investigation into the development of an intelligent control mechanism using fuzzy is intended in this research work .

Intelligent Control Approaches

The basic difference between the intelligent control and traditional control is that the control strategy in intelligent control does not demand any precise model of the system. Therefore, intelligent control approaches are getting more attention from research community in applying them to systems, which are complex, nonlinear and uncertain [49].Fuzzy sets theory can handle real life uncertainties and therefore ideal for nonlinear, time varying and hysteretic system control. The membership functions are distributed according to the possible values of each variable after fuzzification [50, 51].

The rule base creates the transformation that links each input fuzzy sets with the appropriate output fuzzy sets using the suitable fuzzy logic operations. Figure 3.3 explains the structure of FLC. Mamdani inference engine and rule base makes the best decision for each situation. After application of a centroid defuzzification, the controller gives a possible output to the valves. four inputs (I/p) and one output (O/p) for the forecasting part and vice versa for the scheduler part are used for fuzzy logic controller in this work. Fuzzy Logic Controllers have been widely applied to both consumer products and industrial process controls. In particular, fuzzy logic controller is very effective techniques for complicated and imprecise processes for which either no mathematical model exists or the mathematical model is severely nonlinear, because FLC's can easily approximate a human expert's control behaviors that work fine in such ill-defined environments [52].

This work proposes a bi functional model which functioned to forecast and to schedule the home appliances without affecting customer comfort. The model was applied to forecast weekly working day, weekly off day (holyday) and hourly demandof particular day and based on this forecasted load it is applied to schedule home appliances and this model is developed by using fuzzy logic controller which is better than the conventional controlling methods as we see from the literature above.

Fuzzy logic methods are the alternative to the conventional methods of load forecasting. In that it is an appropriate method especially when it is difficult to get a mathematical relationship between historical data. The design method to capture the nonlinear relationships between inputs (previous day‘s load, current day load, day type and time period) and outputs (predicted load) is very complex in terms of its mathematical representation, and it does not offer the user an intuitive understanding. Using fuzzy logic, this mathematical relationship can be reduced to a logic table, such as a set of IF-THEN statements (e.g. IF Day is Weekend and Time period ispeak hour THEN Load is very high) and that gives the user more confidence to use the model.

In the proposed system, load information, day type and time period are converted into 'fuzzy' information. A fuzzy rule base is developed to produce 'fuzzy ‘forecasts and defuzzification is performed to generate a point estimate for system load. This methodology has yielded accurate results comparable to other more complex statistical models, [55], [58].In this area, the time period ,day type ,previous load data and electricity demand diversity(number of customer) across the entire area is a key issue that influences the forecasting accuracy. In general the load will fluctuate more based on the number of customer at a certain time of that area (peakhour). In day times the load is different from the night times, also in the week days and the normal days, the seasons will highly effect the load variations.In this study, a short term load forecasting method using fuzzy logic has been developed. A part of complete and generalized software by means of Fuzzy Logic has been attempt to put into survival to forecast electrical load for domestic as well as commercial areas such as industries, institute or residential colonies etc.

Short-term load forecasting is a helping tool to estimate load flows and to anticipate for the overloading. Network reliability increases if the overloading effects are eliminated in time. Also, it reduces rates of equipment failures and blackouts. The forecasted output of the fuzzy system is the input for the next controller or scheduler. Our proposed model modifies the previous works by adding scheduler to the forecaster in order to schedule automatically the home appliances by taking the forecasted demand as input.

2.2. Overview of Demand Side Management

Proposed and defined by Gellings in [59], Demand Side Management (DSM)) is the planning and implementation of those electric utility activities designed to influence the customer usage of electricity in ways that will produce desired changes in the utilities load shape. It is generally most convenient for utilities [59] to look at DSM in terms of broad load shaping objectives. The load shape is the daily and seasonal electricity demand by time of-day, day-of-week, and season. A study based on the significance of DSM application to smart grid based big data sources is done by Keyan Liu et al. in [60]. Authors in [61] propose a game theory based approach to achieve demand side management in smart grids. According to [62], game theory is a mathematical tool that analyzes potentially arising conflict of interest among independent and rational agents and seeks to maximize their ownbenefit when they strategically interact with each other. In other words, the use of game theory can optimize the load profile by manipulating the peak and valley loads uniformly over the day. A significant amount of research is being done in formulating a decentralized approach to achieve DSM in micro-grids. Authors in [63] propose an IoT based approach to perform DSM in grids, even this practice is good but it is applicable only for grid label. There are several authors done related work with this title summarized in table 2.1 bellow.

Table 2.1 summery of related work

Authors	Approach	Contribution	Limitation
Chen J. *et al*.	Autoregressive integrated moving average (ARIMA)	accurately predict the energy consumption	• computationally complex • limited to that environment
Pinto T. *et al*.	ANN	forecast electricitymarket prices	perform poorly with large number ofdata
. Catalao J. P. S. ˜ *et al*.	ANN approach	forecast shortterm electricity prices	It wasonly able to predict electricity prices for about 168 hours.
Lee, S. H., and Wilkins, C. L.	Integer Linear Programming (ILP)	the scheduling scheme gives optimal solution	computationally expensive
Hsu, Y. Y., and Su, C. C.	proposed ILP for solving optimization problem	reduce the overall cost and along with the consideration of user comfort	computationally good but does not consider the price flexibility

2.3. Summary of literature review

The basic difference between the intelligent control and traditional control is that the control strategy in intelligent control does not demand any precise model of the system. Therefore, intelligent control approaches are getting more attention from research community in applying them to systems, which are complex, nonlinear and uncertain [55].Fuzzy sets theory can handle real life uncertainties and therefore ideal for nonlinear and time varying system control. The membership functions are distributed according to the possible values of each variable after fuzzification [56, 57].

The rule base creates the transformation that links each input fuzzy sets with the appropriate output fuzzy sets using the suitable fuzzy logic operations. Figure 3.2 explains the structure of FLC. Mamdani inference engine and rule base makes the best decision for each situation. After application of a centroid defuzzification, the controller gives a possible output to the valves. Four inputs (I/p) and one output (O/p) for the forecasting part and viceversa for the scheduler part are used for fuzzy logic controller in this work. Fuzzy Logic Controllers have been widely applied to both consumer products and industrial process controls. In particular, fuzzy logic controller is very effective techniques for complicated and imprecise processes for which either no mathematical model exists or the mathematical model is severely nonlinear, because FLC's can easily approximate a human expert's control behaviors that work fine in such ill-defined environments [58].

So that as we see from the above literature all researches done regarding demand side management are either through forecasting or through scheduling loads are at grid level and utility level . And most of them uses traditional way of management and even they use intelligentmethods they are only practiced at grid and utility level. Specially in our country Ethiopia demand side management at customer end side is not practiced, not only this the proposed system is different from other in that it consists abi functional controller means that it integrates both predictor controller and scheduler at the same time. and all the previously done projects aims to give functionality for the grid or utility without considering customer comfort ,that means there is no participation of customers in demand side management. But the proposed system make customers to fully participate in demand side management by controlling their electricity usage without any intervention in order to reduce their bill. Then indirectly the utility also benefited from this system in that equipment familiarity, total block out and continuous power interruption due to over loading is decreased automatically when customers use this controller.

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CHAPTER THREE

SYSTEM DESCRIPTION AND DEMAND FORECASTING WITH LOAD SCHEDULINGUSING FUZZY LOGIC APROACH

3.1. System Description

In this thesis a design of demand side management model which integrates bothelectricity demand forecasting & appliance scheduling is being proposed. The proposed system is used to help in optimizing electricity consumption and reducing peak load consumption as aresult it reduces billing cost for the costumer and consequent power interruption which results in equipment damage for the utility.The proposed system has been modeled using MATLAB TOOLBOX. Two fuzzy logic approaches were attempted to design the Model. Both approaches were based on madman's inference System for the forecasting part and the scheduling part. Theoverall proposed system consists of ten different parts: data acquisition, previous maximum demand calculation ,current maximum demand calculation, available power, time period, day type,fuzzy logic controller1,fuzzy logic controler2, on/off condition of appliances such as stove, mitad, fridge, washing machine, grinding machine as illustrated in Fig.3.3.The work presented here is divided into four steps:

I. Collection of data and data analysis (data acquisition)
II. Hourly demand forecasting using fuzzy logic approach with appropriate membership functions for input and output load data.
III. Load scheduling using fuzzy logic approach with appropriate membership functions for input and output load data.
IV. Design of the overall active demand side management model on mat lab Simulink.

3.2. Data acquisition

Data acquisition is the first step in demand side management at customer end. The load data are obtained from interview conducted for 200 peoples randomly about their energy usage, type of appliances they used and time of usage in the day. In tuludimtu condominium eleven thousand (11000) peoples are living by using different home appliances such as stove, blender, electric mitad, lamp, TV, mobile, laptop, frig, grinding machine, washing machine ,shaver, coffee machine etc. in their daily life activities. As the information obtained from the quaternaries, for the costumers in the condominium approximately 9000peoples uses stove, laptop & TV, Around 4000peoples use electric mitad, frig, coffee machine, blender ,toaster & fan, Around 102 people uses Electric Washing machine, hair drier &19 peoples uses shaver. Daily electricity consumption of the village is vary with day type (work day, holly day or weekend), time period of the day that means the consumption of energy during day time is not the same with night time and the maximum energy usage of the site is 98.8Mwh and minimum of 6.8Mwh dailyenergy consumption of the village so that the demand fluctuates b/n this value. Daily electricity consumption of the village is shown as follows with table and graph.

Table3.1:**Shows the demand table for the for house one in 5/4/2010 EC**

Time24h	Appliance								
Monday	mitad(W)	washer(w)	lamp(w)	Coffee grinding machine(w)	refregretoe(w)	juicer(w)	stove(w)	TV(w)	total demand
11pm:00-1:00am	3500	0	100	0	3000	0	2500	500	9600
1:00-3:00am	0	0	0	0	3000	0	0	500	3500
3:00-5:00am	0	0	0	0	3000	0	0	0	3000
5:00-7:00am	0	0	0	0	3000	200	2500	500	6200
7:00-9:00am	0	0	0	320	3000	200	0	0	4420
9:00-11:00am	0	0	0	0	3000	0	0	0	3000
11:00am-1:00pm	0	0	100	320	3000	0	2500	500	6420
1:00-3:00pm	0	0	100	320	3000	0	2500	500	6420
3:00-5:00pm	0	0	100	0	3000	0	0	500	3600
5:00-7:00pm	0	0	100	0	3000	0	0	0	3100

Table3.2Shows the demand table for the for house one in 6/4/2010 EC

Time24h	Appliance								
Tuesday	mitad(W)	washer(w)	lamp(w)	Coffee grinding machine(w)	refregretoer(w)	juicer(w)	stove(w)	TV(w)	total demand
11:00-1:00am	0	0	100	0	3000	0	2500	500	6100
1:00-3:00am	0	0	0	0	3000	0	0	500	3500
3:00-5:00am	0	0	0	0	3000	0	0	0	3000
5:00-7:00am	3500	0	0	0	3000	200	2500	0	9200
7:00-9:00am	0	0	0	320	3000	200	0	0	3520
9:00-11:00am	0	0	0	0	3000	0	0	0	3000
11:00am-1:00pm	0	0	100	320	3000	0	2500	500	6420
1:00-3:00pm	0	0	100	0	3000	0	2500	500	6100
3:00-5:00pm	0	0	100	0	3000	0	0	500	3600
5:00-7:00pm	0	0	100	0	3000	0	0	0	3100

Table3.3The demand table for house one in 7/4/2010 EC

Time24h	Appliance								
Wednesday	mitad(W)	washer(w)	lamp(w)	Coffee grinding machine(w)	refregretoe(w)	juicer(w)	stove(w)	TV(w)	total demand
11:00pm-1:00am	3500	4000	100	0	3000	0	2500	500	13600
1:00-3:00am	0	0	0	0	3000	0	0	500	3500
3:00-5:00am	0	0	0	0	3000	0	0	0	3000
5:00-7:00am	0	0	0	0	3000	0	2500	0	5500
7:00-9:00am	0	0	0	320	3000	200	0	0	3520
9:00-11:00am	0	0	0	0	3000	0	0	0	3000
11:00am-1:00pm	0	0	100	320	3000	0	2500	500	6420
1:00-3:00pm	0	0	100	320	3000	0	2500	500	6420
3:00-5:00pm	0	0	100	0	3000	0	0	500	3600
5:00-7:00pm	0	0	100	0	3000	0	0	0	3100

Table3.4 Shows the demand table for house one in 8/4/2010 EC

Time24h	Appliance								
Thursday	mitad(W)	washer(w)	lamp(w)	Coffee grinding machine(w)	refregretoe(w)	juicer(w)	stove(w)	TV(w)	total demand
11:00pm-1:00am	0	0	100	320	3000	0	2500	0	5920
1:00-3:00am	0	4000	0	0	3000	0	2500	500	7000
3:00-5:00am	0	0	0	0	3000	0	0	0	3000
5:00-7:00am	0	0	0	0	3000	0	2500	500	3000
7:00-9:00am	0	0	0	320	3000	200	0	0	3520
9:00-11:00am	3500	0	0	0	3000	0	0	0	6500
11:00am-1:00pm	0	0	100	320	3000	0	2500	500	3320
1:00-3:00pm	0	0	100	320	3000	0	2500	500	6420
3:00-5:00pm	0	0	100	0	3000	0	0	500	3600
5:00-7:00pm	0	0	100	320	3000	0	0	500	3920

Table3.5Shows the demand table for house one in 9/4/2010 EC

Time in24h	Appliance								
Friday	mitad(W)	washer(w)	lamp(w)	Coffee grinding machine(w)	refregretoe(w)	juicer(w)	stove(w)	TV(w)	total demand
11:00pm-1:00am	3500	0	100	0	3000	0	2500	500	6600
1:00-3:00am	0	0	0	0	3000	0	0	500	3500
3:00-5:00am	0	0	0	0	3000	0	0	0	3000
5:00-7:00am	0	0	0	0	3000	200	2500	500	6200
7:00-9:00am	0	0	0	320	3000	200	0	0	3520
9:00-11:00am	0	0	0	0	3000	0	0	0	3000
11:00am-1:00pm	0	0	100	320	3000	0	2500	500	6420
1:00-3:00pm	0	0	100	320	3000	0	2500	500	6420
3:00-5:00pm	0	0	100	0	3000	0	0	500	3600
5:00-7:00pm	0	0	100	0	3000	0	0	0	3100

Table3.6: Shows the demand table for house one in 10/4/2010 EC

Time in24h	Appliance								
Saturday	mitad(W)	washer(w)	lamp(w)	Coffee grinding machine(w)	refregretoe(w)	juicer (w)	stove(w)	TV(w)	total demand
11:00pm-1:00am	0	0	100	320	3000	0	2500	0	5920
1:00-3:00am	0	0	0	0	3000	0	2500	500	6000
3:00-5:00am	0	0	0	0	3000	0	0	500	3500
5:00-7:00am	0	0	0	0	3000	200	2500	500	3200
7:00-9:00am	0	0	0	320	3000	200	0	0	520
9:00-11:00am	0	0	0	0	3000	200	0	0	3200
11:00am-1:00pm	0	0	100	320	3000	0	2500	0	5920
1:00-3:00pm	0	0	100	320	3000	0	2500	500	6420
3:00-5:00pm	0	0	100	0	3000	0	0	500	3600
5:00-7:00pm	0	0	100	0	3000	0	0	0	3000

Table3.7: Shows the demand table for house one in 11/4/2010 EC

Time in24h	Appliance								
Sunday	mitad(W)	washer(w)	lamp(w)	Coffee grinding machine(w)	refregretoe(w)	Juicer(w)	stove(w)	TV(w)	total demand
11:00pm-1:00am	3500	0	100	0	3000	0	2500	500	6600
1:00-3:00am	0	0	0	0	3000	0	0	500	500
3:00-5:00am	0	4000	0	0	3000	0	0	0	7000
5:00-7:00am	0	0	0	320	3000	200	2500	500	3520
7:00-9:00am	0	0	0	320	3000	200	2500	500	3520
9:00-11:00am	0	0	0	0	3000	200	0	500	700
11:00am-1:00pm	0	0	100	320	3000	0	2500	500	6420
1:00-3:00pm	0	0	100	320	3000	0	2500	500	6420
3:00-5:00pm	0	0	100	0	3000	0	0	500	600
5:00-7:00pm	0	0	100	0	3000	0	0	0	100

Table 3.8: Shows Daily energy consumption of the village

Time 24h	Monday (mwh)	Tuesday (mwh)	Wednesday (mwh)	Thursday (rmwh)	Friday (mwh)	Saturday (mwh)	Sunday (mwh)
1:00am	60.25408	60.76407	60.26407	60.27407	60.27407	63.27407	63.27417
2:00am	60.25408	60.76407	60.26407	60.27407	60.27407	63.27407	63.37507
3:00am	55.57204	55.40273	55.49773	55.4877	55.4877	58.4877	58.4867
4:00am	55.57204	55.50273	55.49773	55.4977	55.4977	58.4977	58.4997
5:00am	40.29839	40..41339	40.28239	40.28329	40.28329	42.28329	42.27329
6:00am	40.29837	40.41239	40.28239	40.28239	40.28239	42.28239	42.29239
7:00am	49.5673	49.4593	49.5843	50.12123	50.12123	52.12123	52.13123
8:00am	49.5673	49.4593	49.5843	49.5834	49.5834	50.5834	50.5834
9:00am	33.12642	33.14142	33.16642	33.16462	33.16462	35.16462	35.17462
10:00am	33.12642	33.14142	33.15642	33.15642	33.15642	35.15642	35.25642
11:00am	42.45933	42.73733	42.76733	42.76733	42.76733	44.76733	44.76733
12:00pm	43.45933	48.73733	42.76733	42.76812	42.76812	44.76812	44.76812
13:00pm	88.31139	88.62539	88.14669	88.15123	88.15123	89.25123	89.25123
14:00pm	88.31139	88.62439	88.14669	88.14669	88.14669	90.14669	90.14669
15:00pm	89.69478	89.05278	89.70278	89.70278	89.70278	89.70278	89.70278
16:pm	89.69478	89.05278	89.70278	89.70188	89.70278	99.71278	99.71278
17:00pm	35.8108	35.9844	35.3354	35.3455	35.3354	35.3354	35.3354
18:00pm	34.8108	34.9844	34.3354	34.3364	34.3354	34.3354	34.3354
19:00pm	10.21256	10.47256	10.94056	10.94057	10.94056	10.94056	10.94056
20:00pm	6.21256	6.47256	6.94056	6.94086	6.94056	6.94056	6.94056
21:00pm	26.78779	26.76789	26.49293	26.48293	26.49293	26.49293	26.49293
22:00pm	26.76779	26.76779	26.49293	26.49793	26.49293	26.49293	26.49293
23:00pm	46.84908	46.37094	46.39094	46.39195	46.39094	46.39194	46.49094
24:00am	43.84908	43.37084	46.49094	46.49084	46.49194	46.49054	46.49194

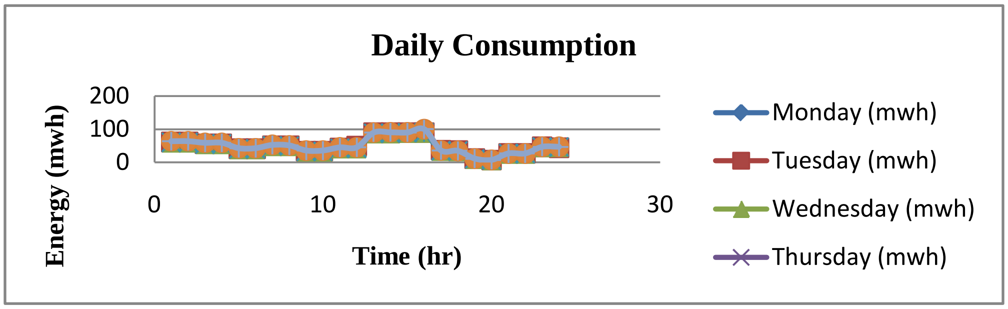


Figure 3.1Shows Daily energy demand curveof the village

All this data's are used as input for the fuzzy logics model. The analysis of the data is done on excel software as shown in appendix and this data are used as input for the fuzzy controller.

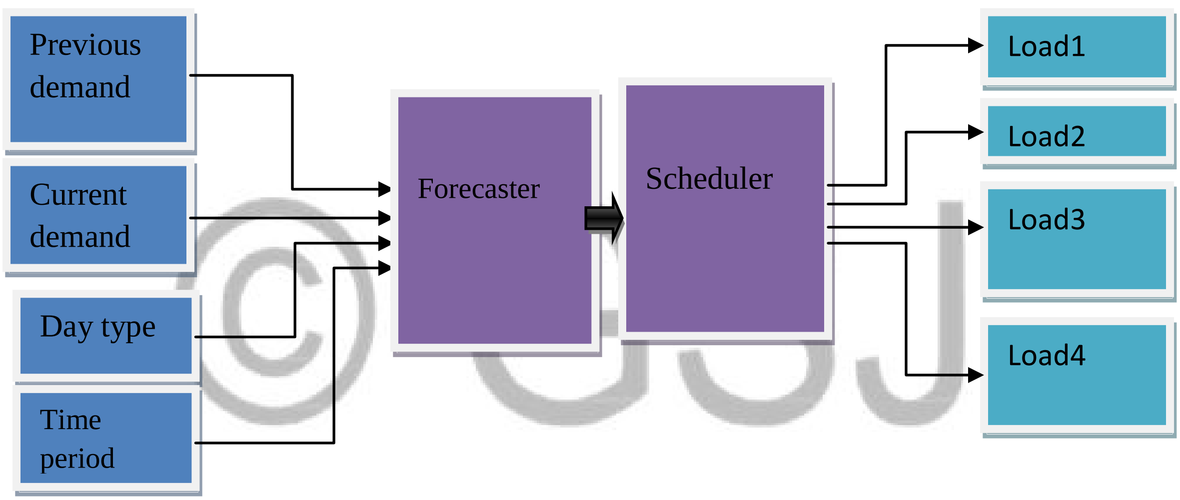


Figure 3.2: Shows Block diagram of the proposed system

Current and previous demand calculation

Based on the connected load at the data acquisition part daily demand is computed by excel which adds all the connected loads in order to camper the available power from utility and the demand of the village .This leads to jug at what time peak hour ,off peak ,normal time is occurs.

Time periods

From the observation of the data set, it can be seen that a load of a particular time (for example 10am-11am) of a day depend upon certain factors. They are, the time periods, forecasted maximum load of Current load, the day (whether it is Weekend or weekday), and historical load (previous load). So that time period of the day influences the forecasted demand. The hours of the day grouped in to four periods: Peak hour, Average peak, Normal & Off peak. Thisparameter is needed because the demand is highly affected by this parameter that is consumption in the day time and night time is different.

Day type

From the observation of the data set, it can be seen that a load of a particular time (for example 10am-11am) of a day depend upon certain factors such asthe day (whether it is Weekend or work day) at work day or every day the demand is almost the same but at weekend or holly days the demand is very high because all peoples are in home and thy uses energy.

Forecaster

Here forecaster is fuzzy logic Controller used to forecast the next days demand of the village. Depend on the input parameters the forecaster which is fuzzy logic controller 1 forecasts the next day demand withappropriate membership function as discussed in the next section detail.

Scheduler

This controller uses the output of the 1st controller as input to perform its scheduling task the detail of this also presented in the next section.

3.3. Hourly demand forecasting using fuzzy logic controller using appropriate membership functions for input and output load data

In the design of fuzzy logic (FL) [51] systems, the Mamdani model [52][53] has its strong points In its closeness to Zadeh's method of fuzzy reasoning and for its human-like representation of the response policy. Being close to Zadeh's definition of FL, it allows a natural extension to the fuzzy domain of the familiar crisp modus ponenslogicalinferencing rule. As opposed to Takagi's and Sugeno'smodel [53] [54], Mamdani's expresses the output using fuzzy terms Instead of mathematical combinations of the input variables.Mamdani's fuzzy inference method is the most commonly seen fuzzy methodology. Mamdani's method was among the first control systems built using fuzzy set theory. It was proposed in 1975 by Ibrahim Mamdani[53] as an attempt to control a steam engine and boiler combination by synthesizing a set of linguistic control rules obtained from experienced human operators. Mamdani's effort was based on LotfiZadeh's 1973 paper on fuzzy algorithms for complex systems and decision processes [54].

The process of fuzzy logic is explained as Firstly, a crisp set of input data are gathered and converted to a fuzzy set using fuzzy linguistic variables, fuzzy linguistic terms and membership functions. This step is known as fuzzification. Afterwards, an inference is made based on a set of rules. Lastly, the resulting fuzzy output is mapped to a crisp output using the membership functions, in the defuzzification step. Fuzzification is the process of decomposing a system input and/or output into one or more fuzzy sets. Many types of curves can be used, but triangular or trapezoidal shaped membership functions are the most common because they are easier to represent in embedded controllers.

Fig 3.3 shows a system of fuzzy sets for an input with trapezoidalmembership functions. Each fuzzy set spans a region of input (or output) value graphed with the membership. Any particular input is interpreted from this fuzzy set and a degree of membership is interpreted. The membership functions should overlap to allow smooth mapping of the system. The process of fuzzification allows the system inputs and outputs to be expressed in linguistic terms so that rules can be applied in a simple manner to express a complex system. The design of fuzzy logic controller generally follows the following procedures.

1. Define the linguistic variables and terms (initialization)

2. Construct the membership functions (initialization)

3. Construct the rule base (initialization)

4. Convert crisp input data to fuzzy value using the membership functions (fuzzification)

5. Evaluate the rules in the rule base (inference)

6. Combine the results of each rule (inference)

7. Convert the output data to non-fuzzy values (defuzzification)

To start the building of fuzzy interface system the untitled fuzzy interface system editor was opened, with one input labeled input1, and one output labeled output1. When input variable and output variable were added using the add variables input option and output option from Edit menu. To change the variable names, the input and the output boxes were selected, the name field were selected, and the name field was edited from input/output to belonging symptoms name.

The fuzzy logic control system modeled in Mat lab is being illustrated in Fig.3.3. In this figure, the input variables are defined as previous demand, current demand, available power, day type and time periods for the 1st fuzzy system and the output of this controller is forecasted demand which is used as input for the 2nd controller used to schedule the home appliances. The 1st fuzzy Inference System is called the forecast and schedule for the 2nd FIS using Mamdani method. Lastly, the output variable forecasted demand from the 1st controller and on/off condition of home appliances from the second controller is shown. The following procedures are taken in order to answer Q1 and to meet specific objective 2

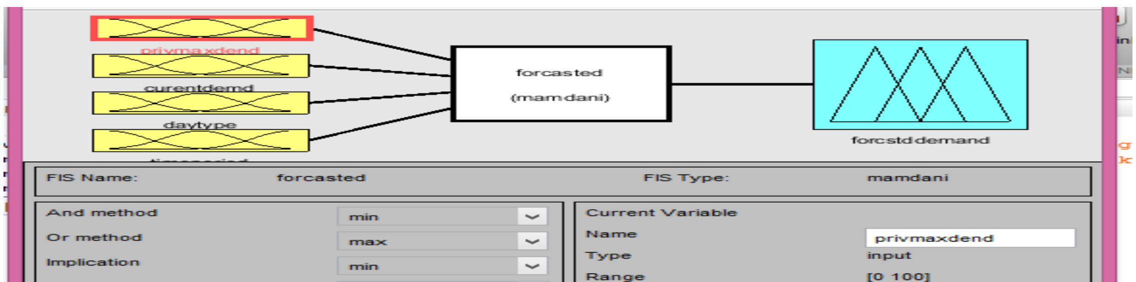


Figure 3.3: Fuzzy logic designer for demand forecasting

3.3.1. Defining membership function

After the FIS editor is opened the next step is to define the membership functions .in fuzzy logic model Membership functions are used in the fuzzification and defuzzification stepsof a FLS, to map the non-fuzzy input values to fuzzy linguistic terms and viceversa.Membership function editor is used to define the shapes of all the membership functions associated with each variable[13]. The process of specifying the membership functions is as follows:

- The input or output variables were selected to open the Membership Function Editor
- In the Membership Function Editor, the range can be decided to separate the data into different levels, which is displayed in Display Range field.
- While deciding the range, overlapping should be considered to avoid missing of the data.
- To rename the Membership Function for the input and output variables and to specify their parameters the curve named mf were selected and the followingfields in the Current Membership Function area was specified:

- The appropriate membership functions shapes and their parameters in a fuzzy system are determined. Fuzziness in a fuzzy set is determined by its membership function.
- Membership functions may have different shapes like triangular, trapezoidal, Gaussian, etc. The only condition a MF must really satisfy is that it must vary between 0 and 1.

The Name field was specified with the name of Membership Function, like weekend, workday, high, very high, medium, low, very low, sufficient ,insufficient etc. The type field was specified with the type of Membership Function, like Trapmf. The Parameter field was specified with the specific range for each Membership Function.

3.3.1.1. Defining membership function for input variable previous demand

For defining membership functions of current demand and previous demand Available power for the village is needed to specify the ranges. Here for Tuludimtu condominium the allowed energy is 77000kwh which is 7kwh per house and my objective is to control this distributed energy by considering this power as constant. This parameter is added to this system because it is what I want to control. And also I have defined all the membership functions based on this available power. In that if the total demands of the village exceeds the available power at that time I have assigned peak hour, high or very high demand, if the available power much the demand, at that time I assigned normal time, medium demand etc. If available power exceeds the demand this time is assigned as off peak, low or very low demand.Based on the connected load at the data acquisition part daily maximum demand is computed in order to camper the available power from utility and the demand of the village .this leads to jug at what time peak hour ,off peak ,normal time is occurs. The previous demand value is one of the input variable has five categories as illustrated in Fig.3.4. The membership functions are denoted by v.low, low, medium, high& v. high respectively with trapezoidal mf as shown in appendex1.

Table3.9 Shows Membership function value for input variable current and previous day demand and output variable forecasted demand value

Membership Function name	Type	Parameter
v.low	Trapmf	[0 0 20 20]
low	Trapmf	[10 25 30 40]
Medium	Trapmf	[30 40 50 60]
High	Trapmf	[55 62 80 89]
v.high	Trapmf	[88 90 100 100]

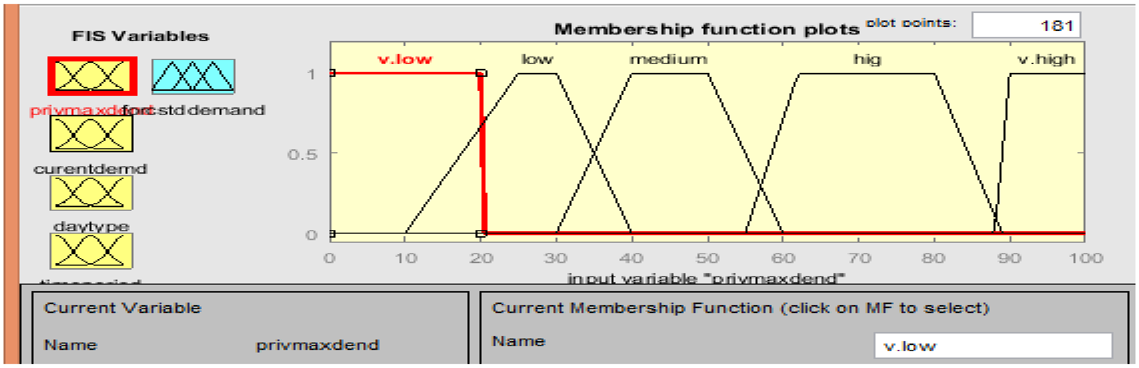


Figure 3.4: The input variable "previous demand" membership function

3.3.1.2. Defining membership function for input variable Current demand

The current demand value is one of the input variable membership functions and it has five categories as illustrated in figure.3.5.The membership functions are denoted by v.low,low,medium,high&v. high.

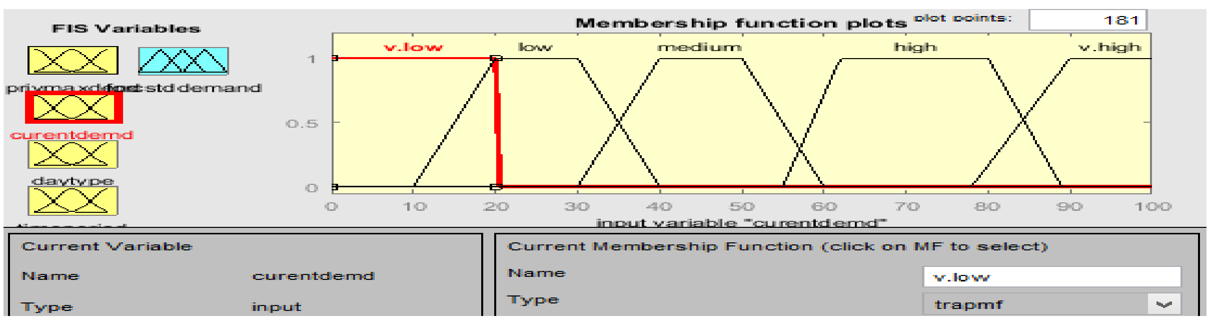


Figure 3.5: The input variable "current demand" membership function

The algorism, range and type of membership function of fig3.4and fig3.5 are presented in appendex1.

3.3.1.3Defining membership function for input variable Day type with 2MF

Day type is one of the input variables for the controller forecastand it have two membership functions definedas follows. From the observation of the data set, it can be seen that a load of a particular time (for example 10am-11am) of a day depend upon certain factors such as the day (whether it is Weekend or work day) at work day or every day the demand is almost the same but at weekend or holly days the demand is very high because all peoples are in home and thy uses energy. The day type is one of the input variable membership functions and it has two categories as illustrated in Fig.3.6. The membership functions are denoted by work day &weekend (holly days), which has ranges work day =assigned ranges from 1st -5th day, weekends=the last two days (5th -7th days) with trap mf.

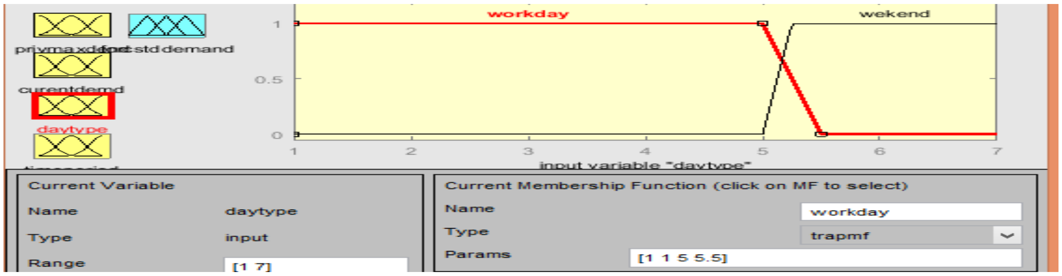


Figure 3.6: The input variable "day type" membership function

Table 3.10Membership function value for input variable day type

Membership Function name	Type	Parameter
'workday	Trapmf	[1 1 5 5.5]
Weekend	Trapmf	[5 5.25 7 7]

3.3.1Defining membership function for input variable time period with 4MF

From the observation of the data set, it can be seen that a load of a particular time (for example 10am-11am) of a day depend upon certain factors. They are, the time periods, forecasted maximum load of the day, the day (whether it is Weekend or work day), and historical load. So that time period of the day influences the forecasted demand. The hours of the day grouped in to four periods: Peak hour, Average peak, Normal & Off peak. This parameter is needed because the demand is highly affected by this parameter that is consumption in the day time and night time is different. The time period is one of the input variable membership functions and it has four categoriesas illustrated in Fig.3.7.The membership functions are denoted as average peak,normal, peak ,off peak &sufficient, which has rangesaveragepeak =assigned ranges from (0-3h,5-7h) ,normal (3-5h,7-12h) ,peak=(12-16h),off peak(16-24h)with trap mf.

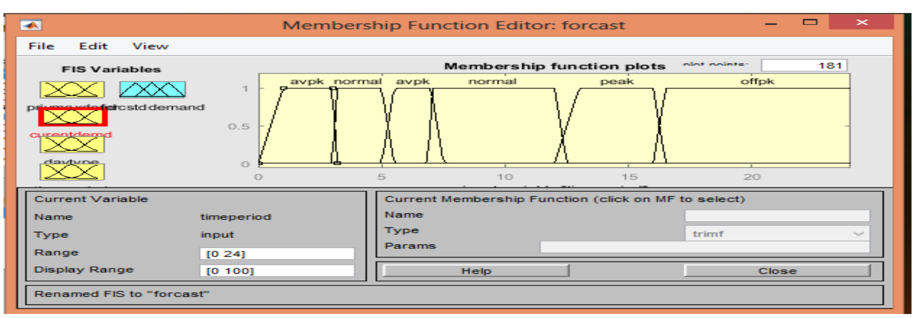


Figure 3.7: The input variable "time period" membership function

Table 3.11Membership function value for input variable time period

Membership Function name	Type	Parameter
Average peak hour	Trapmf	[0 1 3 3.2]
Normal	Trapmf	[3 3.2 5 5.5]
Average peak hour	Trapmf	[5 5.5 7 7.5]
normal hour	Trapmf	[6.9 7 12 12.5]
peak hour	Trapmf	[12 13 16 16.5]
Off peak hour	Trapmf	,[16 16.5 24 24]

3.3.2. Output variable membership functions

The forecasted demand value is one of the output variable membership functions and it has five categories as illustrated in Fig.3.8. The membership functions are denoted by v.low, low,medium,high&very high.

Table 3.12 Shows membership function value for output variable forecasted demand

Membership Function name	Type	Parameter
v.low	Trapmf	[0 0 20 20]
Low	Trapmf	[10 22 30 40]
Medium	Trapmf	[30 35 50 60]
High	Trapmf	[55 60 80 89]
v.high	Trapmf	[78 90 100 100]

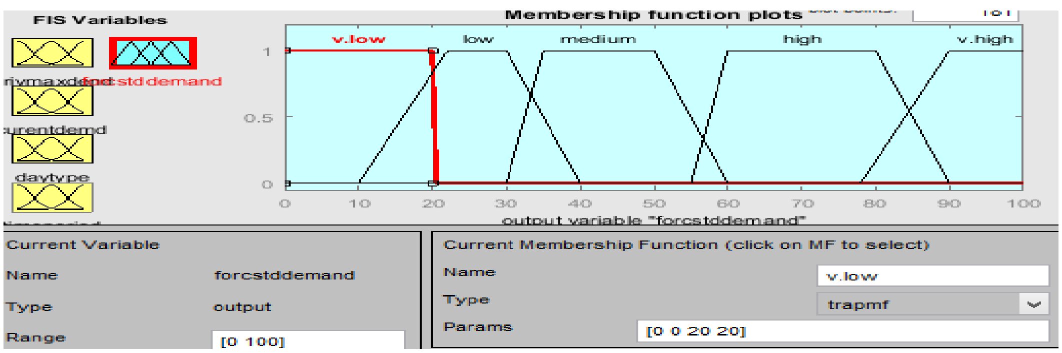


Figure 3.8: The output variable forecasted demand membership function

3.3.3. Rule base definition

Once the input and output variables and MF are defined, we have to design the rule-base (or decision matrix of the fuzzy knowledge-base) composed of expert IF antecedents THEN conclusions rules. These rules transform the input variables to an output that will tell us the forecasted demand of particular day at particular time (this output variable,also have to be defined with MF). Depending on the number of MF for the input and output variables, we will be able to define more or less potential rules. This is illustrated in fig.3.9.

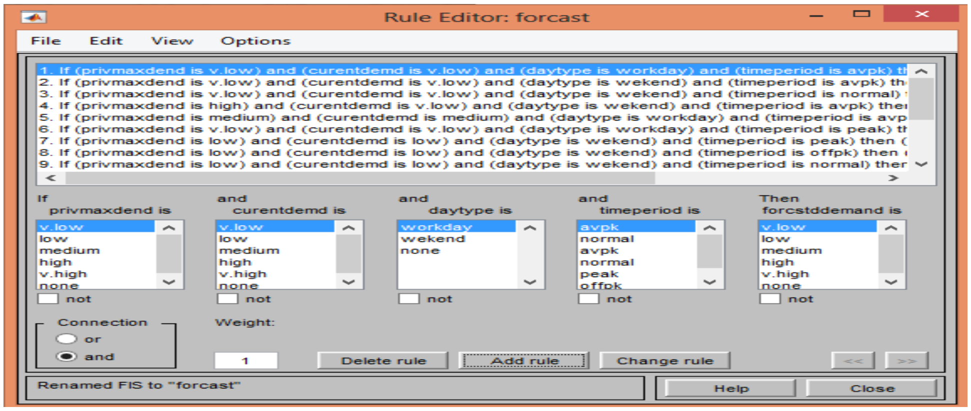


Figure 3.9: Rule viewer for the fis forecast

Some of the rules are as follows:

- If (privious demand is verry low,curent demand is verry low,day type is working day and time period is average peak)then forcasted demand is very low.
- If (privious demand is very low,curent demand is verry low,day type is working day and time period is peak)then forcasted demand is high
- If (privious demand is low,curent demand is low,day type is wekend day and time period is average peak)then forcasted demand is medium.etc.

3.4. Development and implementation of fuzzy logic controller for appliance scheduling

To start the building of fuzzy interface system the untitled fuzzy interface system editor was opened, with one input labeled input1, and one output labeled output1. When input variable and output variable were added using the add variables input option and output option from Edit menu. To change the variable names, the input and the output boxes were selected, the name field was selected, and the name field was edited from input/output to belonging symptoms name. The fuzzy logic control system modeled in Mat lab is being illustrated in Fig3.9. In this figure, the input variables are defined as the output of the forecasting part. The following tasks are followed in order to meet the 3rd specific objective as well as to answer Q2

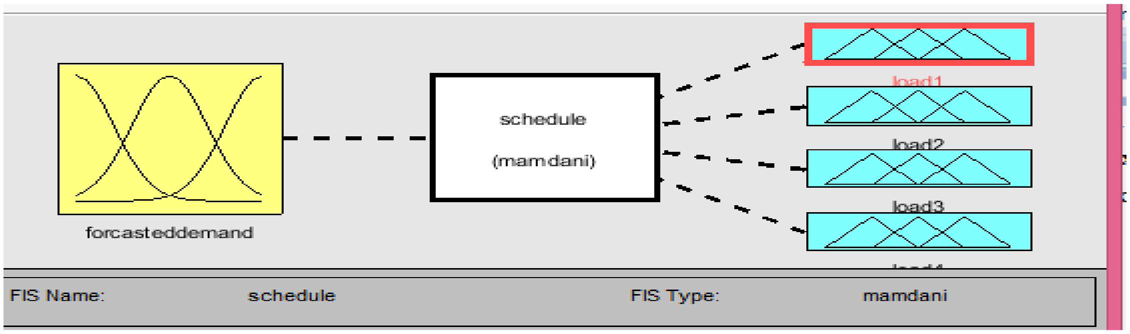


Figure 3.10: Fis designer for schedule

3.4.1. Defining membership function for input variable forecasted demand

The input variable for the second fis(controller) is forecasted demand with5MF

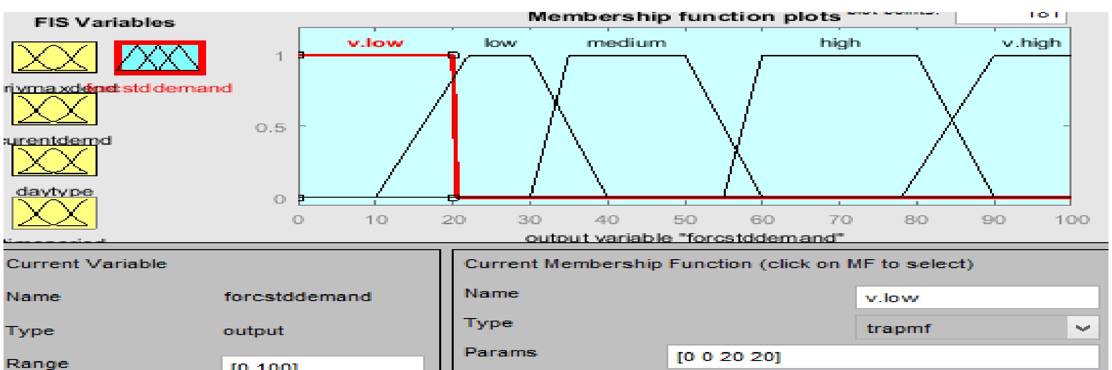


Figure 3.11: The input variable forecasted demand membership function

Table 3.13: Membership function value for input variable forecasted demand value

Membership Function name	Type	Parameter
V.low	Trapmf	[0 0 20 20]
Low	Trapmf	[10 22 30 40]
Medium	Trapmf	[30 40 50 60]
high	Trapmf	[52.5 60 80 88]
v.high	Trapmf	[77 88 100 100]

3.4.2. Definingmembership functions for the output variables of the scheduler

Once the input parameter for the scheduler is defined on the forecasting part we are proceedingto defining of the output variables. The on/off condition of the home loads classified as non shiftableloads that are used continuously and shift able loads.load1, load2 and load3 are the shiftableload outputs and load4 is the fourth output of the scheduler that is continuously usable loads on/off statusThe membership functions are denoted by on and off which hasdifferent rangesdepend on their load rating with trapezoidal mf.The home appliances rating used in the study area has maximum rating of 4000(4KW)watt such as electric heater and minimum of 1watt watch as shown in appendix 4

3.4.2.1. Defining membership functions for the output variable load1 for the scheduler

The membership function for the output variable load1 is defined as follows depend on the load rating. There are two membership functions named as on and off with trapezoidal MF

Table 3.14 Membership function value for output variables on/off condition of load1

Membership Function name	Type	Parameter
On	Trapmf	[1 1.074 2.875 2.95]
Off	Trapmf	[2.5 3.4 3.625 4]

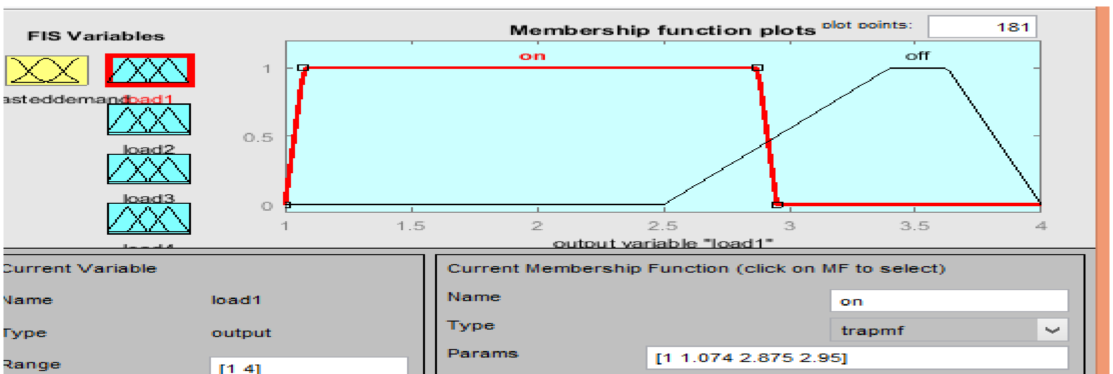


Figure 3.12: The output variable on/off condition of load1 membership function

3.4.2.2.Defining membership functions for the output variable load2 for the scheduler

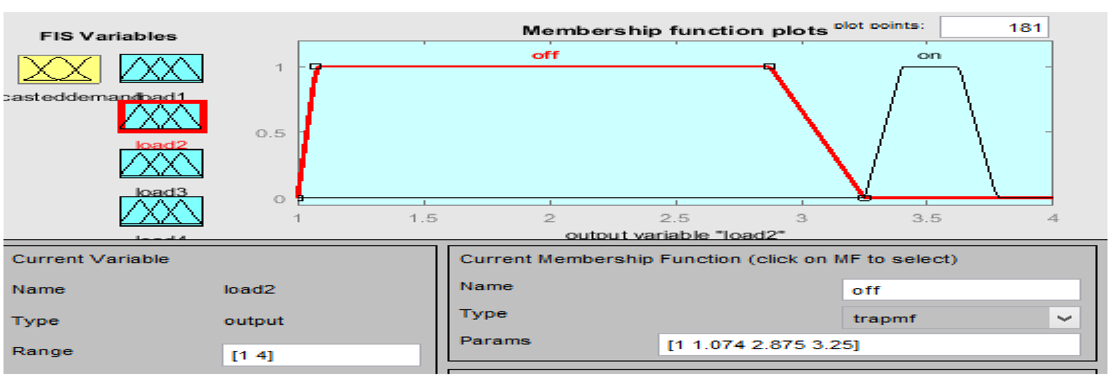


Figure 3.13: Shows the membership function of output variable load2

Table 3.15Membership function value for output variables on/off condition of load2

Membership Function name	Type	Parameter
On	Trapmf	[3.25 3.4 3.625 3.775]
Off	Trapmf	[1 1.074 2.875 3.25]

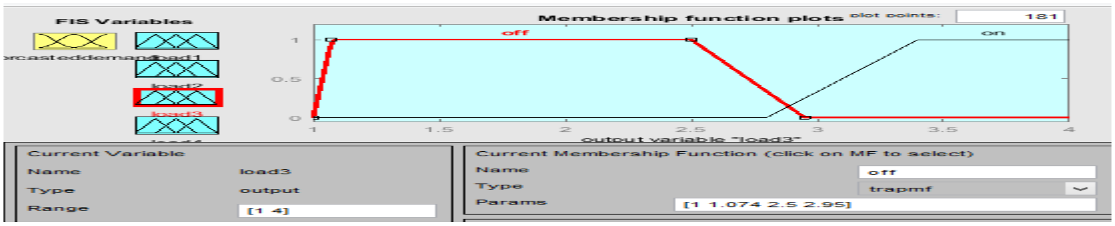


Figure 3.14: The output variable on/off condition of load3membership function

Table 3.16 Membership function value for output variables on/off condition of load3

Membership Function name	Type	Parameter
On	Trapmf	[2.8 3.4 4 4]
Off	Trapmf	[1 1.074 2.5 2.95]

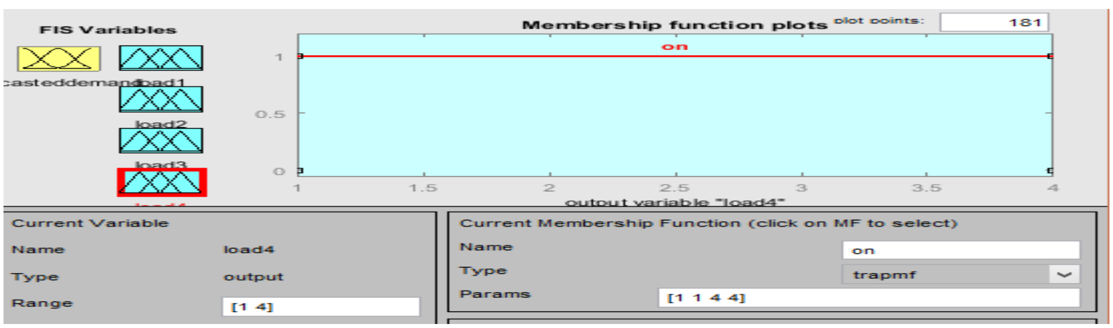


Figure 3.15: Membership function of the output variable load4

Table 3.17Membership function value for output variables load4

Membership Function name	Type	Parameter
On	Trapmf	[1 1 4 4]

3.4.3. Rule base definition

Once the input and output variables and MF are defined, we have to design the rule-base (or decision matrix of the fuzzy knowledge-base) composed of expert IF <antecedents> THEN <conclusions> rules. These rules transform the inputvariables to an output that will tell us the on off condition of particular appliances at particular time (this outputvariable, also have to be defined with MF). Depending on the number of MF for the input and output variables, we will be ableto define more or less potential rules.

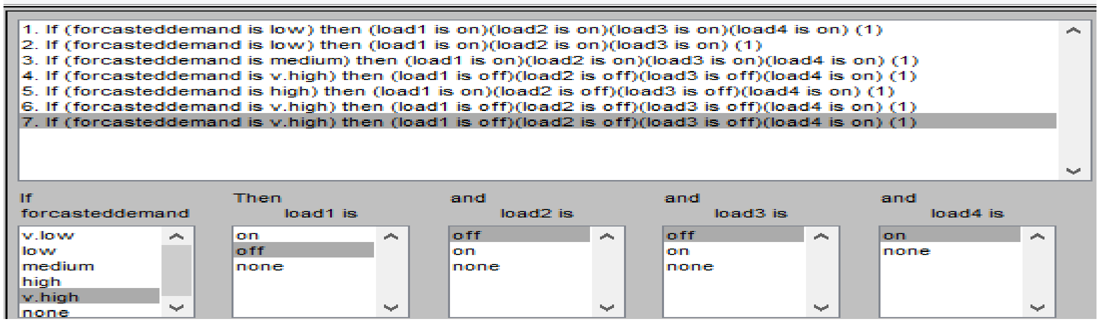


Figure 3.16: Rule viewer for the scheduler

After defining the membership functions then the development of if then fuzzy rule is proceeded. As follows:

- If forecasted demand is very low then (load1 is on, load2 is on, load3 is on andload4is on).
- If forecasted demand is low then (load1is on, load2 is on, load3 is on and load4 is on).
- If forecasted demand is medium then (load1is on, load2 is on, load3 is on and load4 is on).
- If forecasted demand is veryhigh then (load1is off, load2 is off, load3 is off and load4 is on).
- If forecasted demand is high then (load1is on, load2 is off, load3 is off and load4 is on).

The evaluations of the fuzzy rules and the combination of the results of theindividual rules are performed using fuzzy set operations. After evaluating the result of each rule, these results should be combined to obtain a final result; this process is called inference which will be discussed detailin the next chapter.

The linguistic fuzzy variables very low, low, medium, high ,very high, peak ,off peak ,normal ,weekend, work day compares the four fuzzy sets; Current demand, previous demand, day type and time period The first input has five fuzzy variables and second input has five fuzzy variables ,the 3rd has 2 variables and4th input has four fuzzy variables, as shown in Figure above and used to develop Linguistic Rules. The products of these rules are then aligned to determine the demand of the next day and to schedule the appliances for that day.

Linguistic variables are the input or output variables of the system whosevalues are words or sentences from a natural language, instead of numericalvalues. A linguistic variable is generally decomposed into a set of linguisticterms.

Fuzzification is the process of converting crisp numerical values into the degrees of membership related to the corresponding fuzzy sets. A MF will accept as its argument a crisp value and return the degree to which that value belongs to the fuzzy set the MF represents. In order to express the fuzziness of data, this paper makes an arrangement of fuzzy subsets for different inputs and outputs in complete universe of discourse as membership functions. The relationship between several inputs and output may be nonlinear but linear membership functions have been used for simplicity. A trapezoidal &triangular membership functions are used for the inputs as well as the output. The four inputs taken for STLF are Time period, previous load, current load and day type. As shown in figure of membership function above the inputs are divided into different trapezoidal membership functions which are as follows:

For time (Peak hour, Average peak, Normal time, Off Peak Time), for day type(work day and weekend), for previous load and current load (v.high,high,medium,low&v.low),for forecasted load (v.high,high,medium,low&v.low)

Fuzzy set theory can handle real life uncertainties and therefore ideal for nonlinear, time varying and hysteretic system control. The membership functions are distributed according to the possible values of each variable after fuzzification [7, 8]. There is no mathematical model exists for all parameters. Therefore, fuzzy logic technique is most suitable for modeling. Fuzzy logic controller behaves like human brain so it’s better doing with this controller.

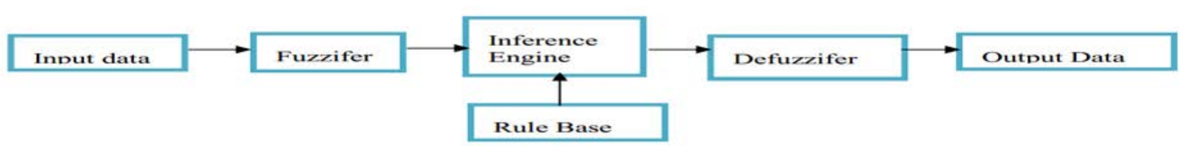


Figure 3.17: Fuzzy logic controller structure

According to the data acquisition from individual houses we calculate the hourly demand of current day and previous day. Then based on available powerthe membership function are defined, day type &time periods including this calculated demand are feed to the fuzzy system. The fuzzy system could forecast the demand at any time and this forecasted demand is fed to the 2^{nd} fuzzy system which used to control the on/off scheduling of appliances based on the specified rules on the customer's perspective. Mamdani inference algorithm will employ as fuzzy control model for this closed-loop control system [5]. Fuzzy controller will design by MATLAB fuzzy logic toolbox. The control system will simulate by Simulink

CHAPTER FOUR

4. RESULTS AND DISCUSSION

4.1. Result and discussion of the Simulation Work

This section discusses the results related to forecasted energy rule viewer, surface viewer, rule and surface view for appliance scheduling. Lastly overall simulation result for the proposed model by interchanging the input parameters.Regularload will be served without anyscheduleand this load does not participate in Demand side management however energy consumption data of this type will be add to total energy demand.

4.2. Hourly demand forecasting rule viewer:

As illustrated in Fig.4.1, the values of 43.2(previous demand is medium), 42.3(thecurent demand is medium) ,day type 6 (weekend) and time period 12(normal) have beenapplied to the input variables of previous demand, current demand, day type and time periode respectively. The corresponding crisp output of the fuzzy logic on the forecasted demand is43.9 MW(medium).

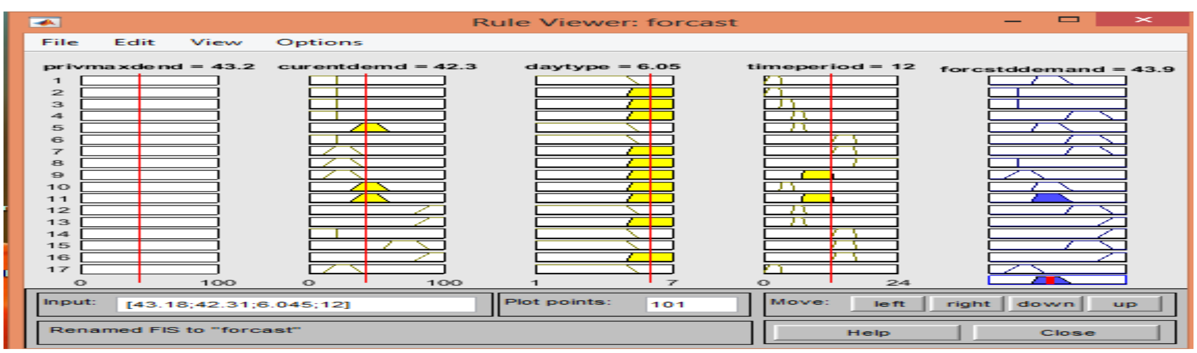


Figure 4.1. Rule view of fuzzy logic based demand forecasting

Figure 4.2 Indicates that when input variables (previous demand=55.3,current demand=60.8,day type is work day(5)and time period =13(peak hour) then the output forecasted demand=72.5(high)).

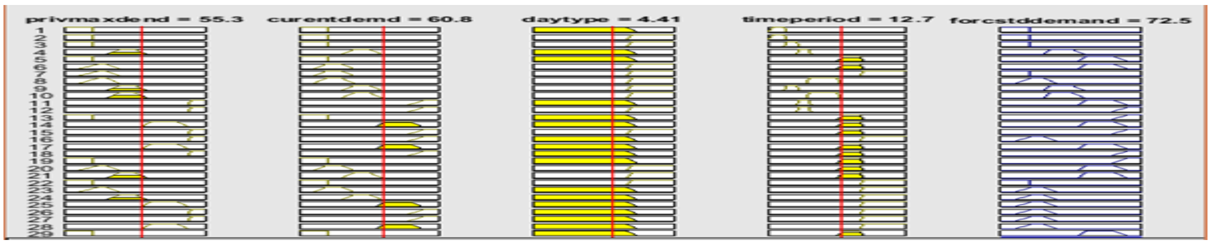


Figure 4.2. Rule view of fuzzy logic based demand forecasting

Figure 4.3Indicates that when input variables (previous demand=49.2, current demand=51.3,day type is work day(5)and time period =12(normal hour) then the output forecasted demand=50(medium

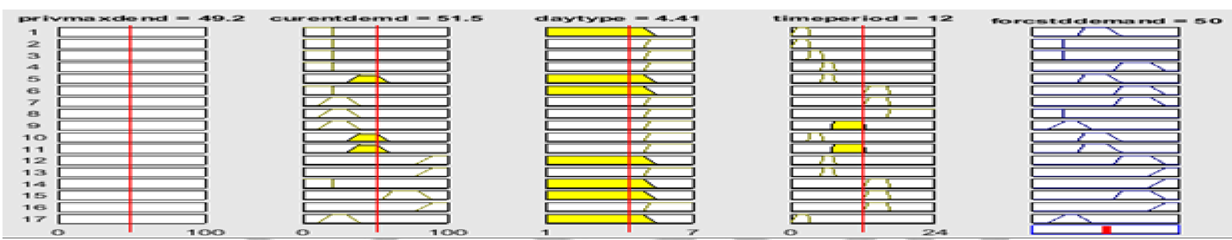


Figure4.3. Rule view of fuzzy logic based demand forecasting

Fig 4.4 Indicates that when input variables (previous demand=99.2(very high),current demand=91(very high),day type is work day(4)and time period =23(off peak) then the output forecasted demand 25.4(low)).this indicates that time period highly affects the forecasted demand.

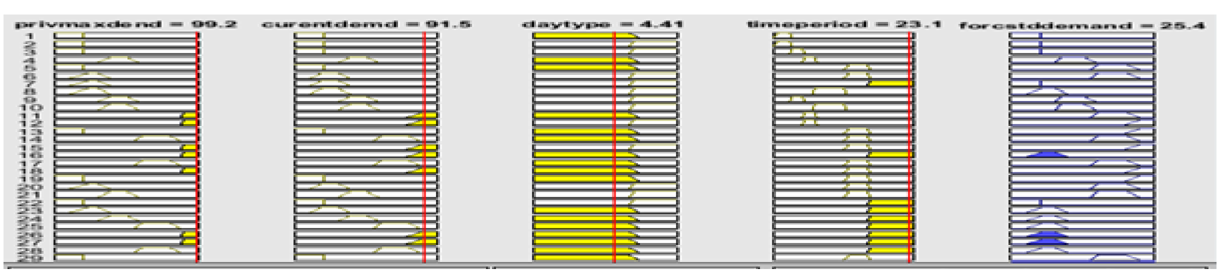


Figure4.4Rule view of fuzzy logic based demand forecasting

Figure 4.5 Indicates that when input variables (previous demand=87.1,current demand=82.3,day type is work day(5)and time period =13(peak hour) then the output forecasted demand=90.3(high)).here also the effect of time period is high.

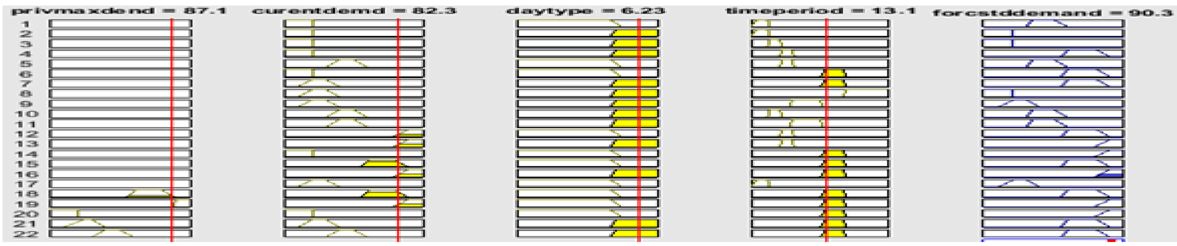


Figure4.5Rule view of fuzzy logic based demand forecasting

4.3. Surface view of the designed rule forecast

As we discussed in chapter3, we have four input parameters. By combining two of these four input parameters alternatively, we can obtain four different surface plot of forecasted demand. Based on the fuzzy rule, a surface plot of forecasted demand fuzzy prediction can be obtained, as shown in Fig.4.6. It shows that the forecasted demand have direct relation with both current demand and previous demand.From this fig x axis represents current demand y axis represents previous demand (input)and z axis represents the output value forecasted demand.

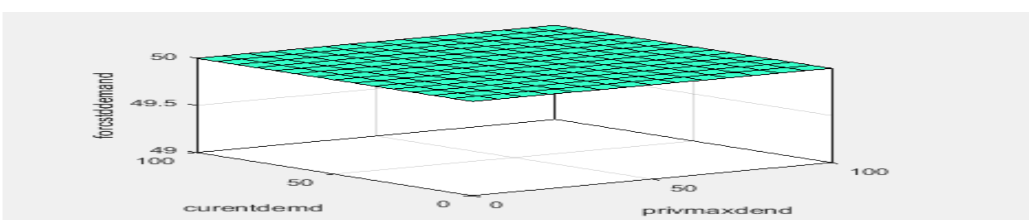


Figure 4.6Surface view of fuzzy based demand forecasting

Figure 4.6 shows surface view simulation with respect to current load and previous load.When we combine current demand with time period a surface plot of forecasted demand fuzzy prediction can be obtained, as shown in Fig.4.7.It shows that the forecasted demand increased with the decreasing of time period.and.In thisfigure forecasted demand is highly increased in peak hour that is between 12 pm to 16 pm.

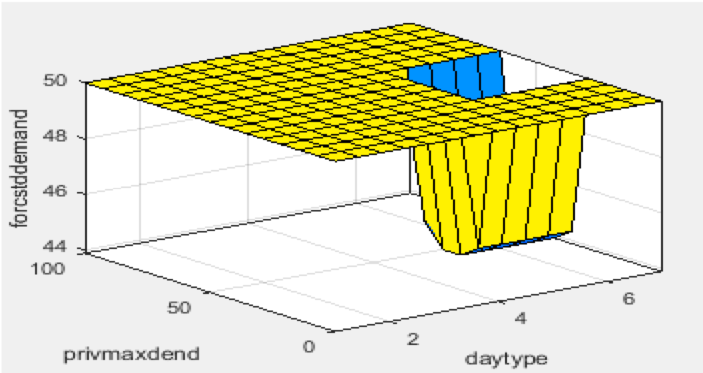


Figure4.7: Surface view of fuzzy based demand side management

Based on the fuzzy rule a surface plot of forecasted demand fuzzy predictioncan be obtained, as shown in Fig.4.8. It shows that the forecasted demand ishighly affected by time period .. In this figure the forecasted demand is highlyincreased between time period of 12 and 16pm .This result is obtained by combining time period previous demand.

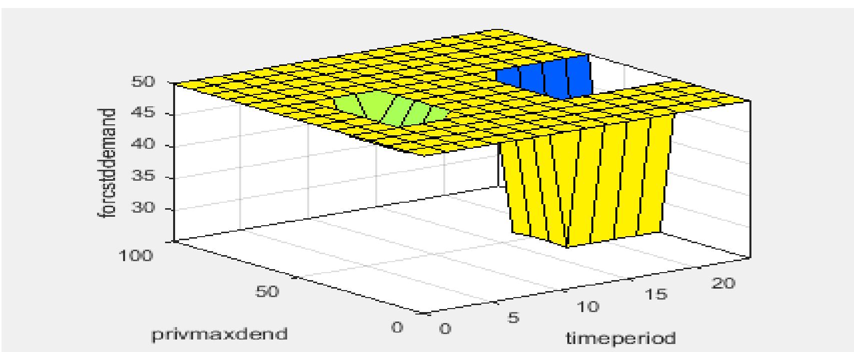


Figure 4.8surface view simulation with respect to time period and previous load.

When we combine day type with time period a surface plot of forecasted demand fuzzy prediction can be obtained, as shown in Fig.4.9.It shows that the forecasted demand increased with the decreasing of time period..In this figure forecasted demand is highly increased in peak hour that is between 12 pm to 16 pm. And it also affected by day type in that at holly day and weekends the forecasted demand high that is <=70 MW.

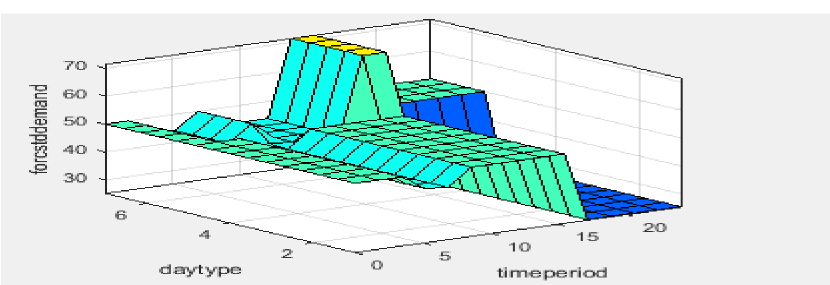


Figure4.9 Surface view simulation with respect to time period and current load

4.4. Surface and rule viewer forAppliance scheduling

From the following figure it is shown that the on/off time of loads is decrease with an increase of the forecasted demand. From the following figure we observe that most of high power intensive loads are in on condition when forecasted demand is low ,v.low and medium or the time is in off peak and most of them are off when the demand is high and v.highor the time is peak hour. In other word when we forecast the demand with respect to combining differentinputs the following rule viewer and surface views are obtained.

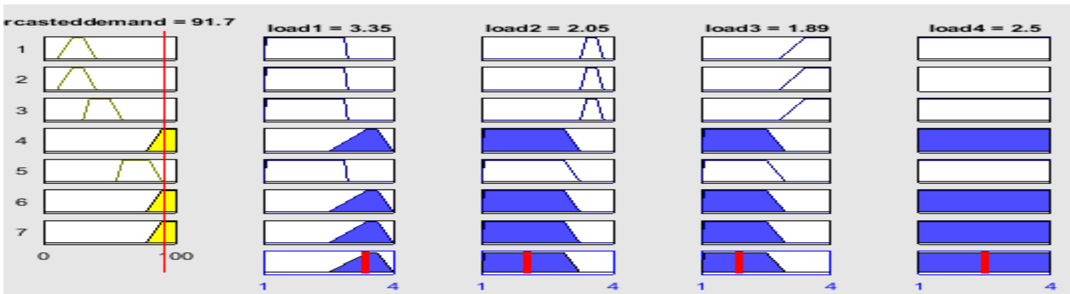


Figure 4.10Rule view of fuzzy logic based load scheduling

Fig 4.10 indicates at forecasted demand=91(v.high) then all loads are in off condition except load4 which is continuously usable load. Depend on the rule we sated Load1 to be on its load should be<=3kw and >=3 to be off,Load2 to be on its load should be>=3 <4 and <=3 to be off ,Load3 to be on its load should be>=2.8<=4 and <=3 to be off and Load4 is on for all conditions.

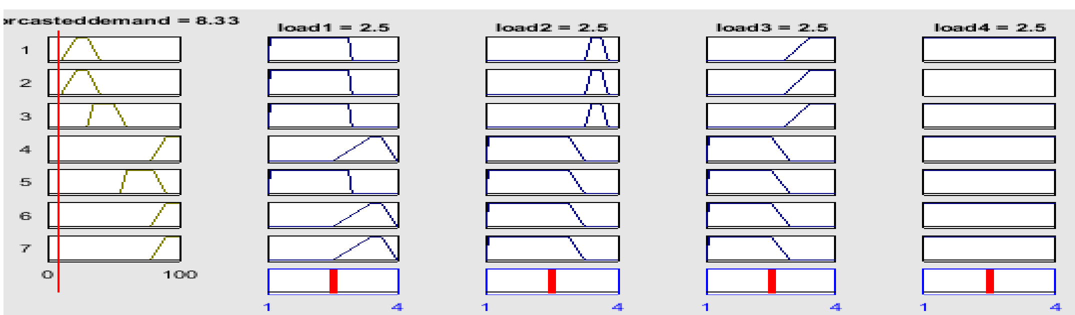


Figure4.11Rule view of fuzzy logic based load scheduling

Figure 4.11indicates at forecasted demand=8.3(v.low) then all loads can be in on condtion..

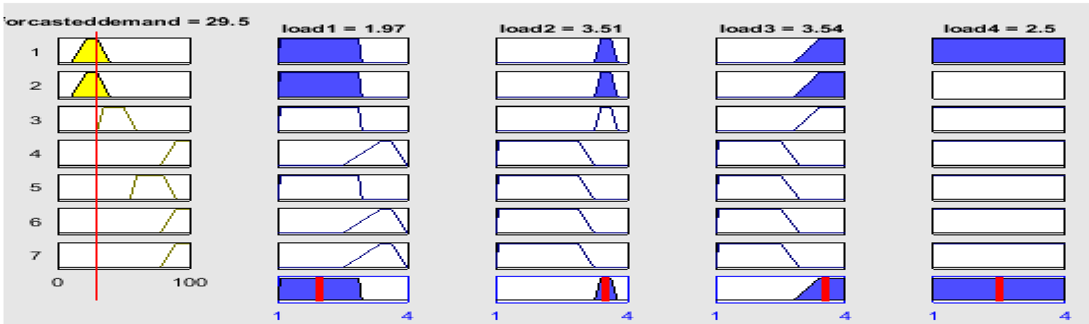


Figure4.12Rule view of fuzzy logic based load scheduling

Figure 4.12indicates at forecasted demand=29(low) then all loads are in on condition.That is load1 on, load2on, load3 on and load4 is on.

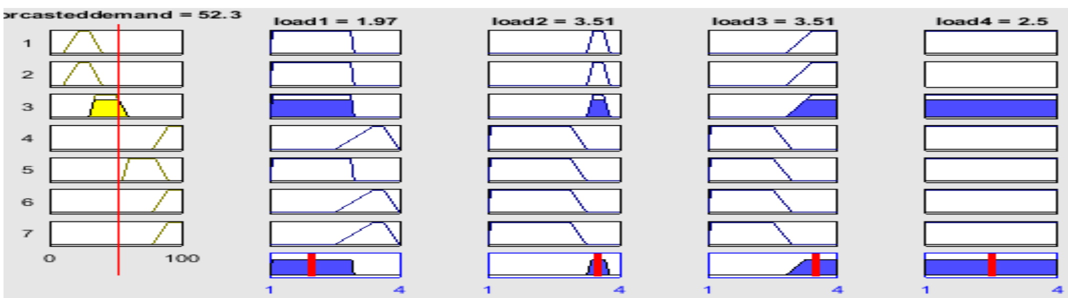


Figure4.13. Rule view of fuzzy logic based load scheduling

Figure 4.13 indicates at forecasted demand=52(medium) then in this case all loads load1,load2,load3 and load4 are in on condition depend on the rule we sated. .

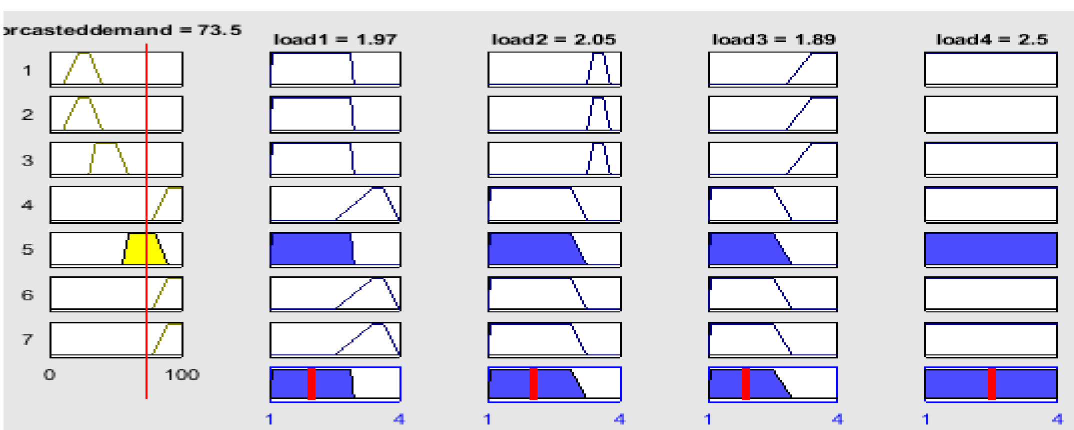


Figure4.14Rule view of fuzzy logic based load scheduling

Figure 4.14 indicates at forecasted demand=73.(high) in this case load1=1.9 which is on and load4are in on and load2 =2.05 which is off and load3 =1.89 which is off are in off condition depend on the rule sated.

4.5.Surface view of appliances scheduling

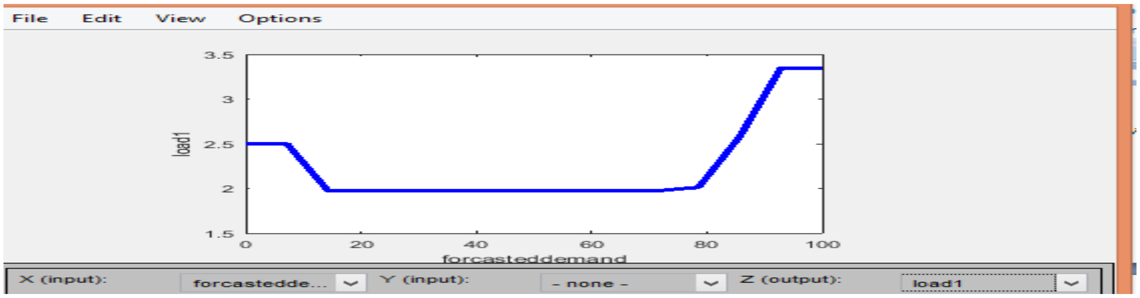


Figure 4.15. Surface view of fuzzy based load scheduling

Figure 4.15 shows surface view simulation with respect toforecasted demand. When we combine forecasted demand with load1 a surface plot of load scheduling fuzzy prediction can be obtained, as shown in Fig.4.15.It shows that the   load1 is on for all v.low,low,mediumand high forecasted demand value that is o to 80 MW.And off for the forecasted demand v.high that is >=80 MW..

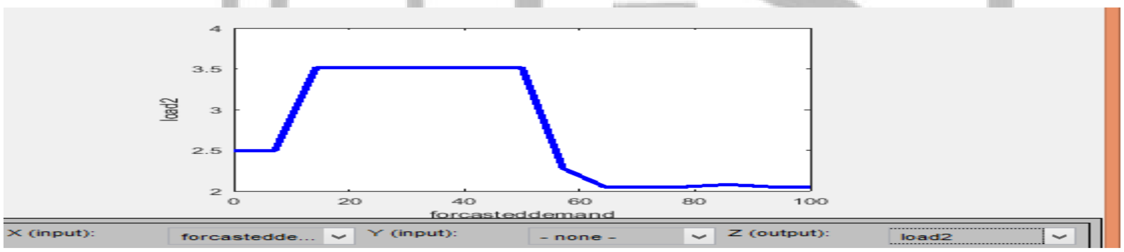


Figure4.16. Surface view of fuzzy based load scheduling

Figure 4.16 shows surface view simulation with respect to forecasted demand.When we combine forecasted demand with load2a surface plot of load scheduling fuzzy prediction can be obtained, as shown in Fig.4.16.It shows that the   load2 is on for all v.low,low and medium forecasted demand value that is o to 59 MW.And off for the forecasted demand high and v.high that is >=60 MW.

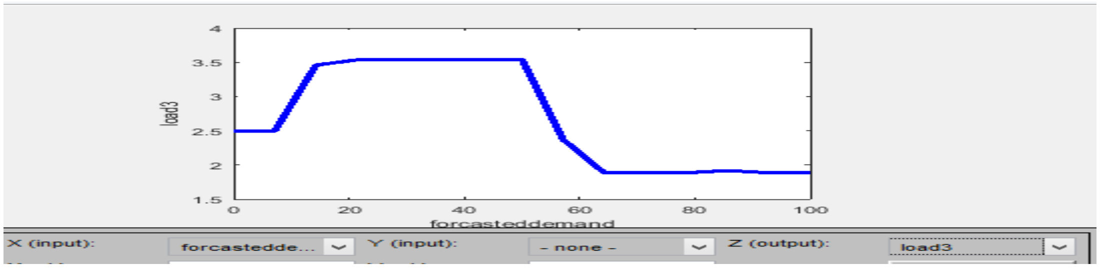


Figure 4.17. Surface view of fuzzy based load scheduling

Figure 4.17 shows surface view simulation with respect to forecasted demand. When we combine forecasted demand with load3a surface plot of load scheduling fuzzy prediction can be obtained, as shown in Fig.4.17.It shows that the load3 is on for all v.low,low and medium forecasted demand value that is o to 59 MW.And off for the forecasted demand high and v.high that is >=60 MW.

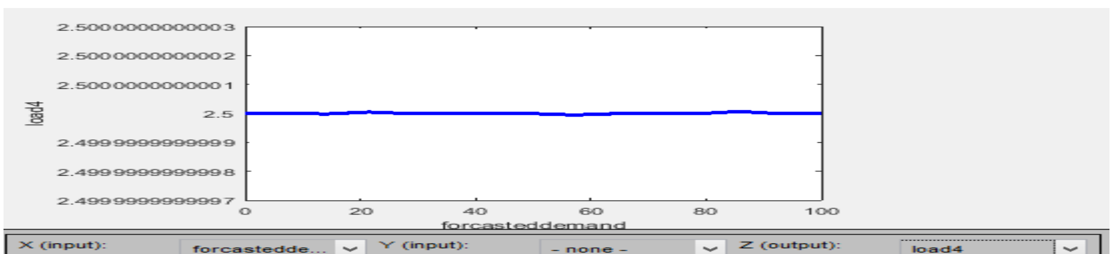


Figure 4.18. Surface view of fuzzy based load scheduling

Figure 4.18 shows surface view simulation with respect to forecasted demand. When we combine forecasted demand with load4a surface plot of load scheduling fuzzy prediction can be obtained, as shown in Fig.4.18.It shows that the load4 is on for all v.low,low , medium, high and v.highforecasted demand value that is 0 to 100MW.And no off condition for all value of the forecasted demand .

4.6. Simulink block diagram implementation and outputs of the proposed model

now we will consider and analyze the fuzzy logic controllersystem by applying all the four input variables that is previous demand, current demand ,day type and time period. We will show the following analysis based on the different values of the mentionedinputs as follows.

The following figure (fig 4.19) shows the simulation of fuzzy logic methodology for short term load forecasting integrated with automatic appliance scheduling. MATLAB is used for the testing of the proposed model. As shown in the figure (fig 4.19)The input data are given to fuzzy logic controller block. In fuzzy logic controller block ".fis" of fuzzy inference system is loaded. Based on the rules prepared the fuzzy logic controller give forecasted output corresponding to the input data. Then depending on the forecasteddemand the2ndcontroller schedules the loads. Thus, final schedule of home load is obtained from the overall simulation of the proposed model as follows.

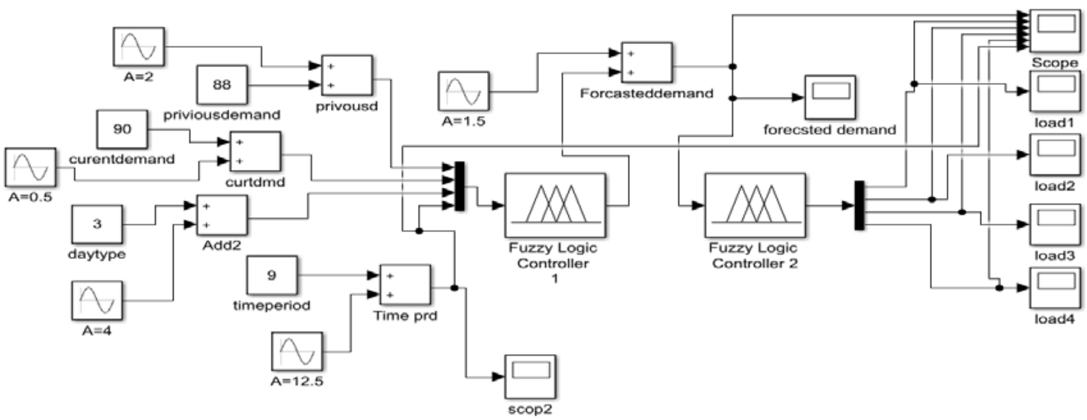
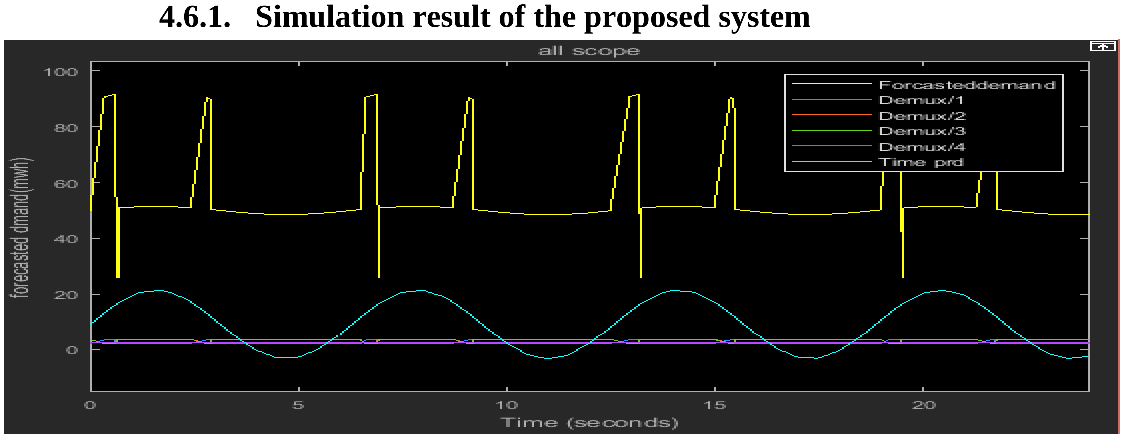


Figure4.19. Matlabsimulink diagram of demand side management

Figure4.19 shows overall Simulink block diagram of active demand side management with input variables, previous demand=88 (with amplitude 2 this amplitude is taken based on the data acquisition previous demand at that particular time fluctuates between 88&90 so that I take it averagely),current demand=90,day type=2(work day)with amplitude =4 which indicates that we have seven days then day type fluctuates between minimum of 1and maximum of 7 then we take average 4,time period=9 with amplitude 12.5 here amplitude is also average of time period of a day). Then the output of this block diagram is as shown in the next sub topics.

4.6.1. Simulation result of the proposed system



45

Figure4.20. Shows Matlabsimulink output of fuzzy logic based load scheduling for overall output display of the model in fig. 4.19

In figure 4.20 (demux1 is load1, demux2 is load2 ,dimux3 is load3 and demux4 is load4).This figure displays the forecasteddemand which is the output of the first controller which fluctuates between 90 and 25.And theon off condition of appliances depending on the forecasted demand is displayed as Demux(1,2,3&4). As shown in the fig4.20 all appliances are scheduled that means at lower demand all appliances are in on condition and at higher demand most of them are in off condition except load4 as shown bellow.

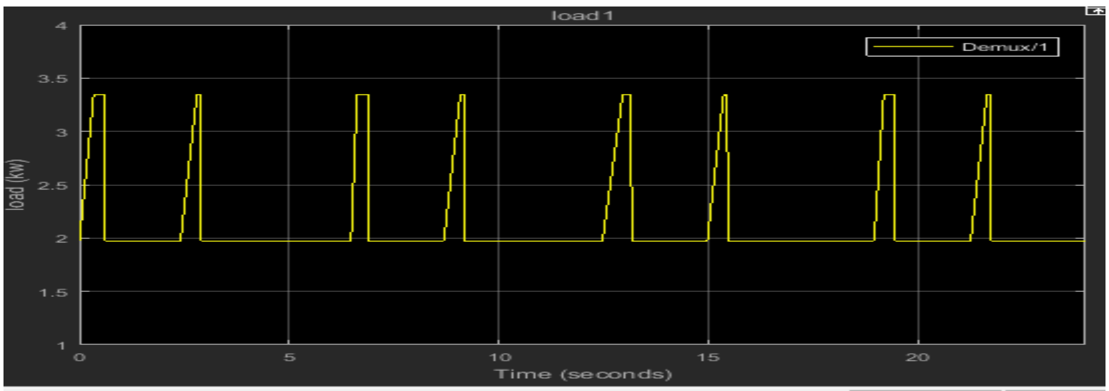


Figure4.21. Matlabsimulink output of fuzzy logic based load scheduling for load1

This result displays that the on off condition of load1 varies depend on the forecasted demand value and its power rating. The y axis of graph represents the load value this is due to the rule sated in the controller in that the on condition of the load1 ranges from 1 to 3and off condition ranges as 2.5 to 4.And the x axis of the graph indicates the sampling time that is the simulation time, here throughout the simulation it takes different time periods which fluctuates between maximum of 24 and minimum of 1 in houras shown in fig(4.25).

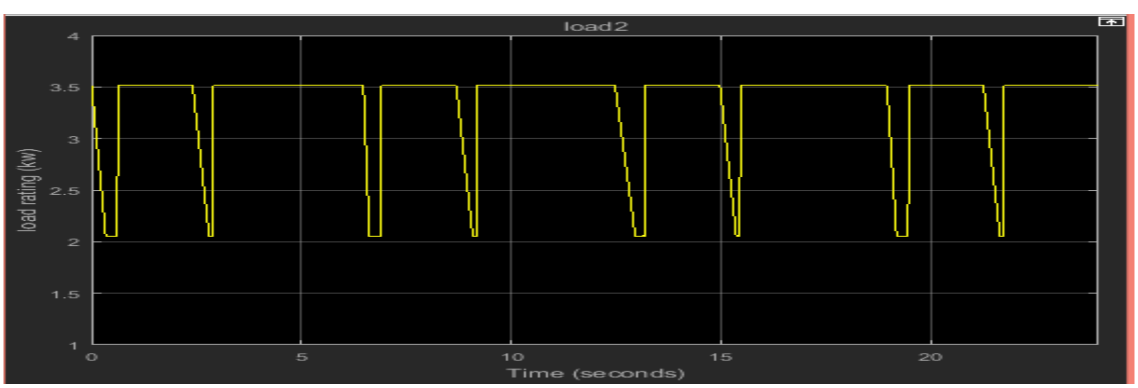


Figure4.22. Matlabsimulink output of fuzzy logic based load scheduling for load2

This result displays that the on off condition ofload2 varies depend on the forecasted demand value.from this display we can observe that load2 is off at higher forecasted demand and on at lower demand.The y axis of graph represents the load rating value due to the rule sated in the controller .In that the on condition of load2 ranges from 3.25to 3.75and off condition ranges as 1 to 3.25.And the x axis of the graph indicates the sampling time that is the simulation time, here throughout the simulation it takes different time periods which fluctuates between maximum of 24 and minimum of 1 in houras shown in fig(4.11). Hence load2 is high power incentive equipment which is not recommended to use it at peak hour so we can save energy or reduce peak demand.

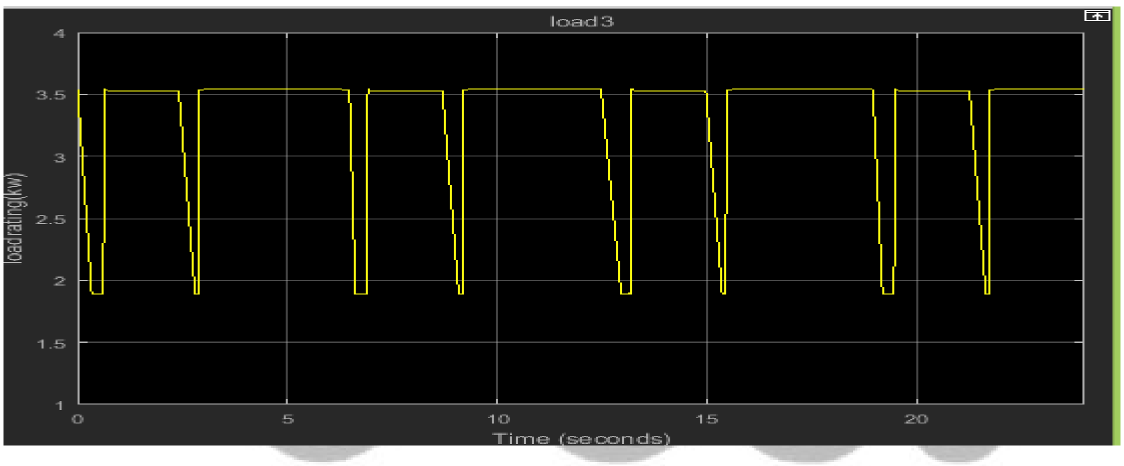


Figure4.23. Matlabsimulink output of fuzzy logic based load scheduling for load3

Figure 4.23displays that the on off condition of load3varies depend on the forecasted demand value. From this display we can observe that this load is off at higher forecasted demand and on at lower demand.The y axis of graph represents load rating (kw) this is due to the rule sated in the controller in that the on condition of load3 ranges from 2.8 to 4 and off condition ranges as1 to 3.And the x axis of the graph indicates the sampling time that is the simulation time, here throughout the simulation it takes different time periods which fluctuates between maximum of 24 and minimum of 1 in houras shown in fig(4.25).

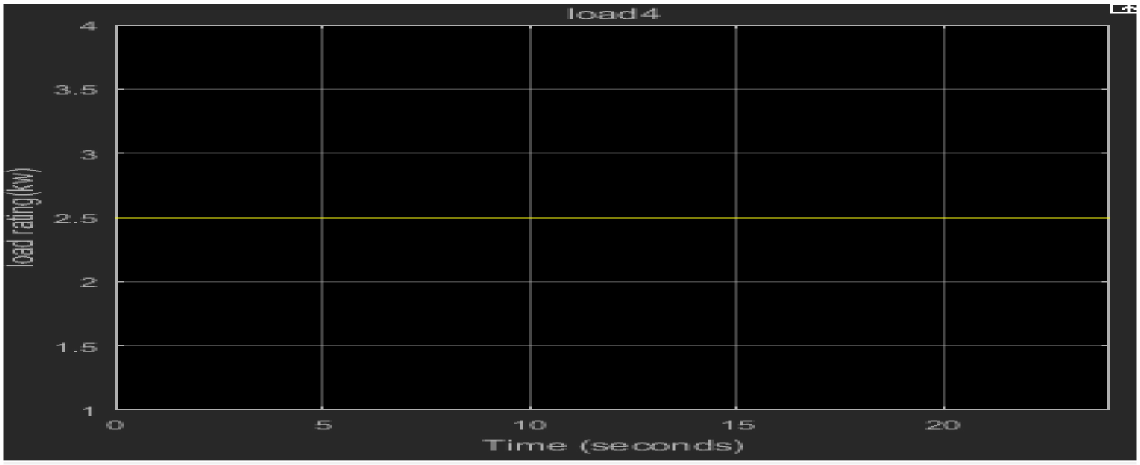


Figure4.24. Matlabsimulink output of fuzzy logic based load scheduling for load4

From this fig we observe that the on off condition of load4 didn't depend on the forecasted demand value.From this display one can conclude that this loads arecontinously usable that means no need of interruption for them.The y axis of graph represents the load rating value.And the x axis of the graph indicates the sampling time that is the simulation time, here throughout the simulation it takes different time periods which fluctuates between maximum of 24 and minimum of 1 in hour as shown in fig(4.25).

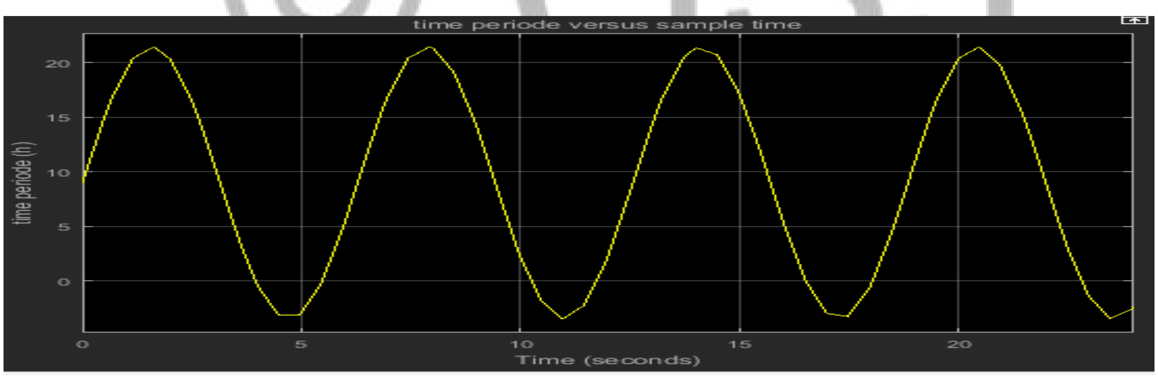


Figure 4.25. Matlabsimulink output of fuzzy logic based load scheduling for time period

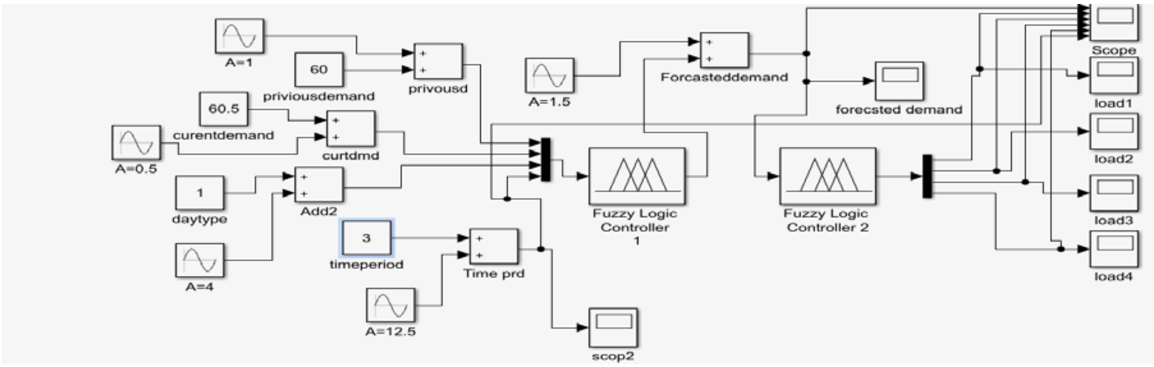


Figure4.26. Matlabsimulink diagram of demand side management

Figure 426 illustrate overall Simulink block diagram of active demand side management(with input variables, previous demand=60 (with amplitude 2 this amplitude is taken based on the data acquisition previous demand at that particular time fluctuates between 60&61 so that the amplitude is taken based on this),current demand=60,here also the demand is fluctuated between 60 and 61 due to this the amplitude is taken as 0.5.day type=1(work day)with amplitude =4 which indicates that we have seven days then day type fluctuates between minimum of 1and maximum of 7 then we take average 4,time period=3 with amplitude 12.5 here amplitude is also average of time period of a day)then the output of this block diagram is as shownbelow.

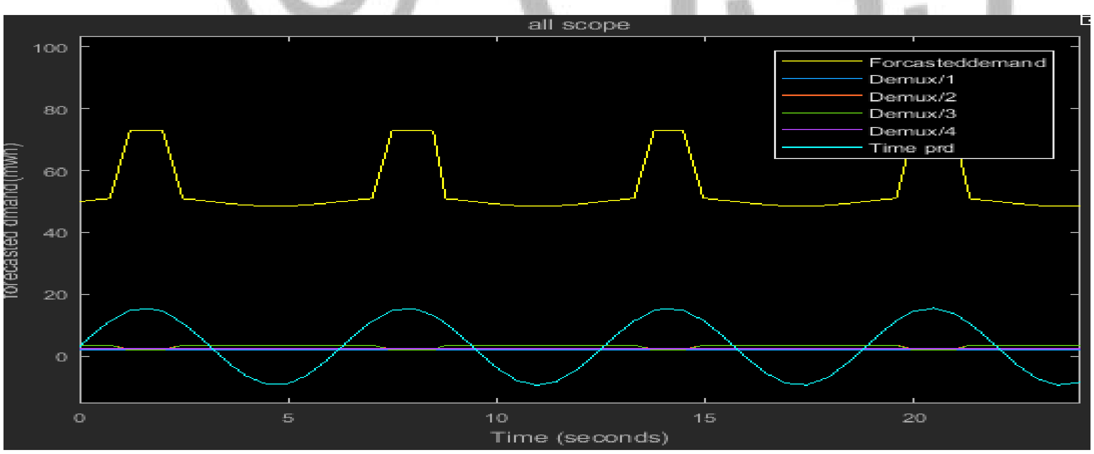


Figure4.27. Matlabsimulink output of fuzzy logic based load scheduling for forecasted demand, time period and on off condition of home loads

In figure 4.27 (demux1 is load1, demux2 is load2, dimux3 is load3 and demux4 load4).This figure displays the forecasteddemand which is the output of the first controller which fluctuates between 75 and 50.And the on off condition of appliances depending on the forecasted demand is displayed as Demux (1,2,3&4) As shown in the fig4.27 all appliances are scheduled that means at lower demand all appliances are in on condition and at higher demand most of them are in off condition as shown bellow except load4.

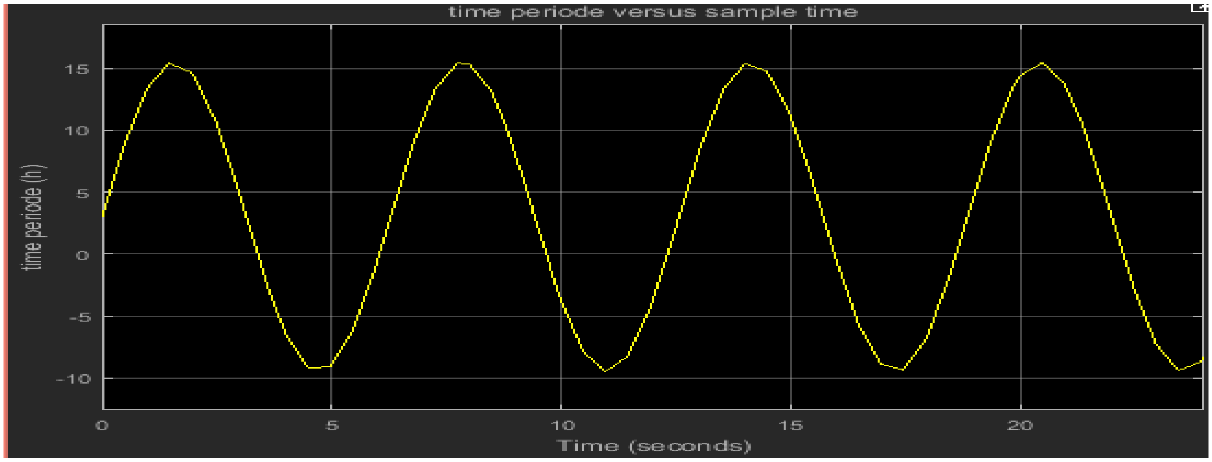


Figure4.28. Ma lab simulink output of fuzzy logic based load scheduling for time period

This fig shows that at time period 15 the forecasted demand is high that is around75 becouse this time is peak hour and when we come to time period 9(-) the forecasted demand becomes medium because this time is normal time .then the on off condition display of appliances (Demux1,Demux2,Demux3 and DEMUX4) is proceeded based on this forecasted demand as follows.

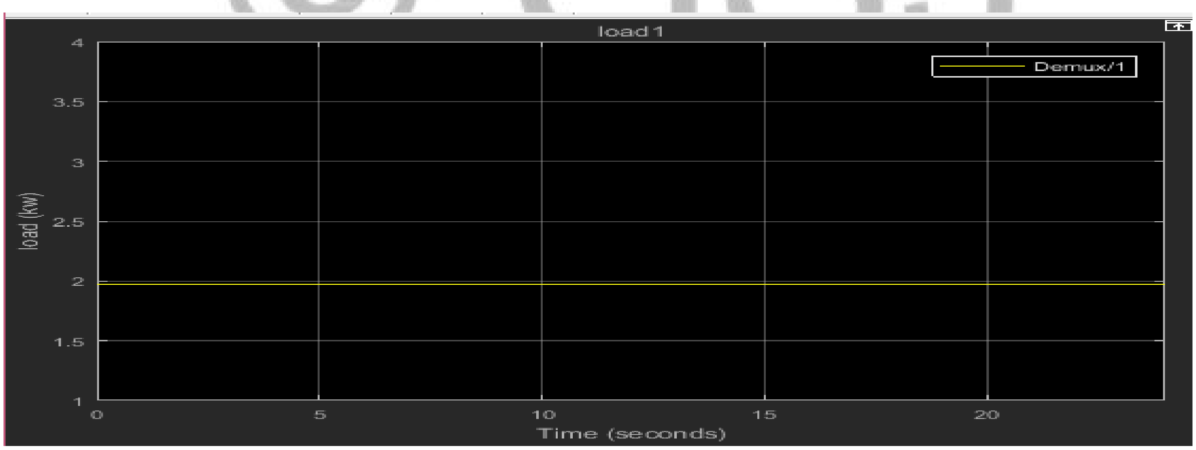


Figure 4.29. Matlabsimulink output of fuzzy logic based load scheduling for load1

This result displays that the on off condition of sload1 is decided depend on the forecasted demand value.From this we observe thatload1 can be in on condition for both medium and high demand.The y axis of graph represents the load rating value. This is due to the rule sated in the controller in that the on condition of load1ranges from 1 to 3and off condition ranges as 2.5 to 4.And the x axis of the graph indicates the sampling time that is the simulation time, here throughout the simulation it takes different time periods which fluctuates between maximum of 24 and minimum of 1 in hour as shown in thetime period graph.

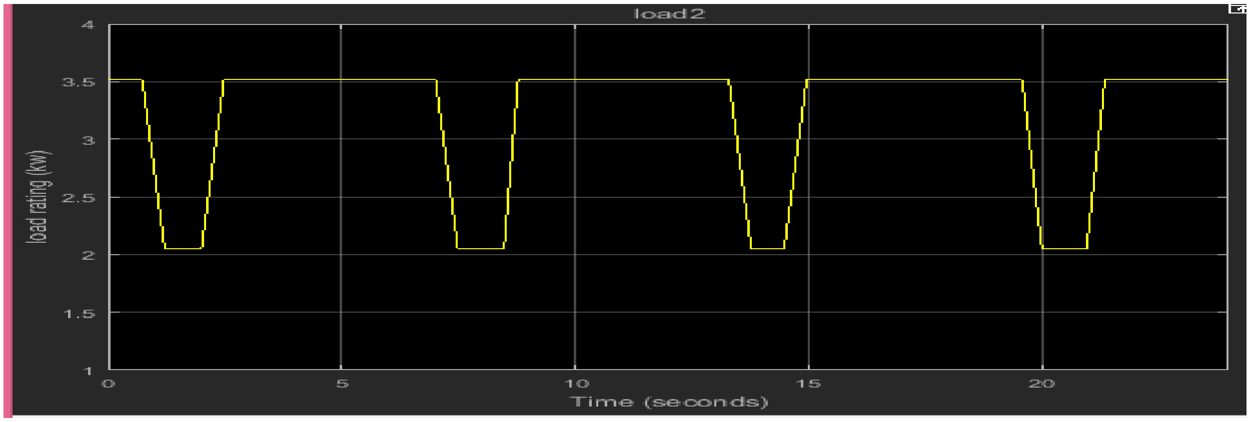


Figure 4.30. Matlabsimulink output of fuzzy logic based load scheduling for load2

Fig 4.30displays that the on off condition of load2is decided depend on the forecasted demand value. From this we observe that load2can be in on condition forlow,v.low andmedium and off at high and higher demand. The y axis of graph represents the membership function value this is due to the rule sated in the controller in that the on condition of the appliance condition of appliance ranges from 3.25 to 4and off condition ranges as 1 to 3.25.And the x axis of the graph indicates the sampling time that is the simulation time, here throughout the simulation it takes different time periods which fluctuates between maximum of 24 and minimum of 1 in hour as shown in the time period graph.

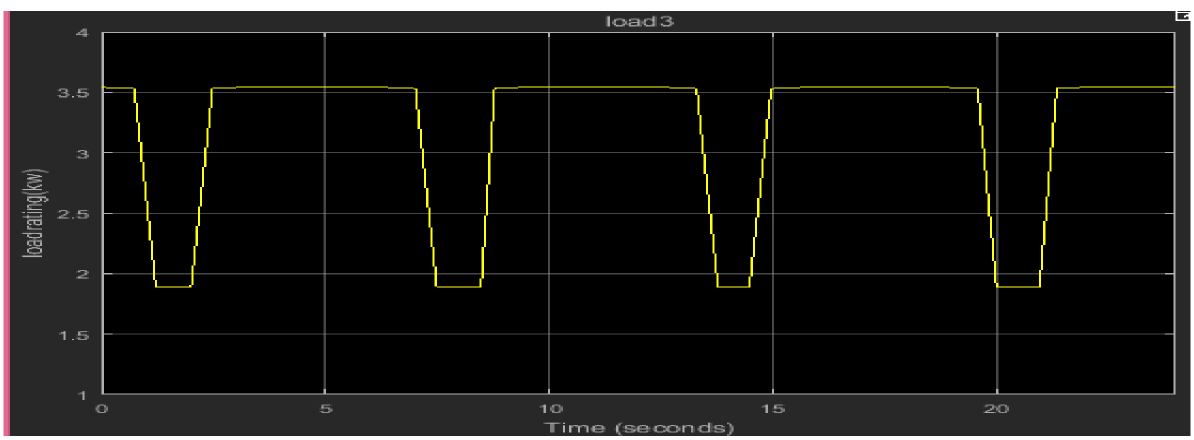


Figure4.31.Matlabsimulink output of fuzzy logic based load scheduling for load3**.**

This result shows that the on off condition of load3is decided depend on the forecasted demand value. From this we observe that load3 can be in off condition for both v.high and high demand.The y axis of graph represents the load rating value.This is due to the rule sated in the controller in that the on condition of the appliance ranges from 2.8 to 4 and off condition ranges as1 to 3.And the x axis of the graph indicates the sampling time that is the simulation time, here throughout the simulation it takes different time periods which fluctuates between maximum of 24 and minimum of 1 in hour as shown in the time period graph.

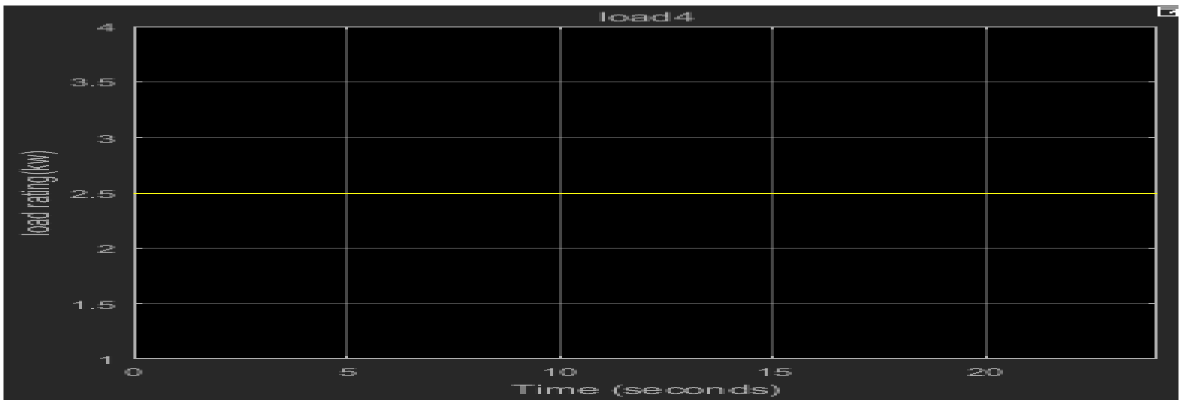


Figure 4.32.Matlabsimulink output of fuzzy logic based load scheduling for load4.

This result displays that the on off condition of load4 doesn't depend on the forecasted demand value. From this we observe that load4 can be in on condition for all demand. The y axis of graph represents the load rating ..And the x axis of the graph indicates the sampling time that is the simulation time, here throughout the simulation it takes different time periods which fluctuates between maximum of 24 and minimum of 1 in hour as shown in the time period graph.

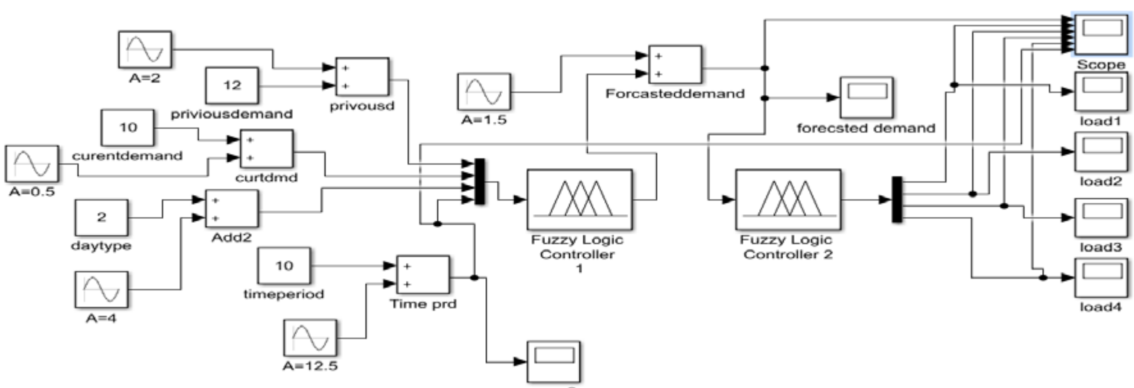


Figure4.33.Matlab simulink diagram of demand side management

Figure 4.33 shows Overall Simulink block diagram of active demand side management(with input variables, previous demand=10 (with amplitude 2 this amplitude is taken based on the data acquisition previous demand at that particular time fluctuates between 10&12 so that I take it averagely),current demand=12,day type=3(work day)with amplitude =4 which indicates that we have seven days then day type fluctuates between minimum of 1 and maximum of 7 then we take average 4,time period=9 with amplitude 12.5 here amplitude is also average of time period of a day)then the output of this block diagram is as shown bellow.

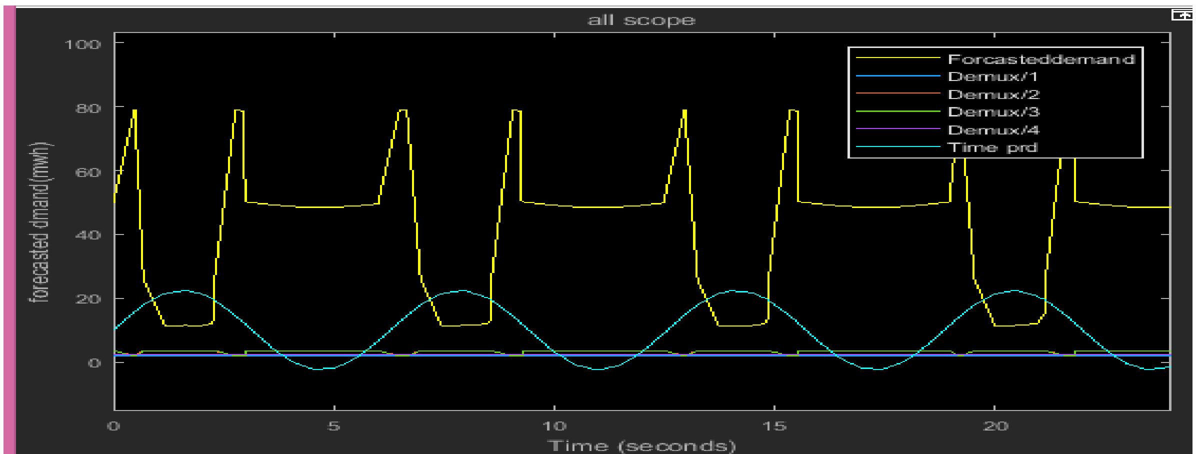


Figure 4.34Matlabsimulink output of fuzzy logic based load scheduling for forecasted demand, time period and on off condition of home loads

In figure 4.34(demux1 isload1,demux2 isload2, dimux3 isload3,demux4 is load4This displays the forecasteddemand which is the output of the first controller which fluctuates between 80 and 10 and depending on the forecasted demand all appliances are scheduled that means at lower demand appliances are in on condition and at higher demand most of them are in off condition except load4 as shown bellow.

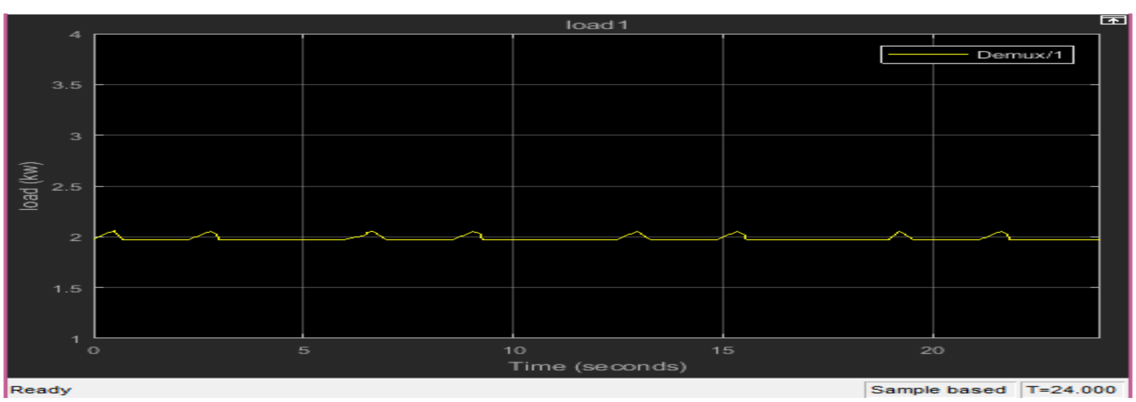


Figure4.35Matlabsimulink output of fuzzy logic based load scheduling for load1

This result displays that the on off condition of load1 is decided depend on the forecasted demand value. From this we observe that load1can be in on condition for both medium , high &low demand. The y axis of graph represents load rating value.And the x axis of the graph indicates the sampling time that is the simulation time, here throughout thesimulation it takes different time periods which fluctuates between maximum of 24 and minimum of 1 in hour as shown in the time period graph.

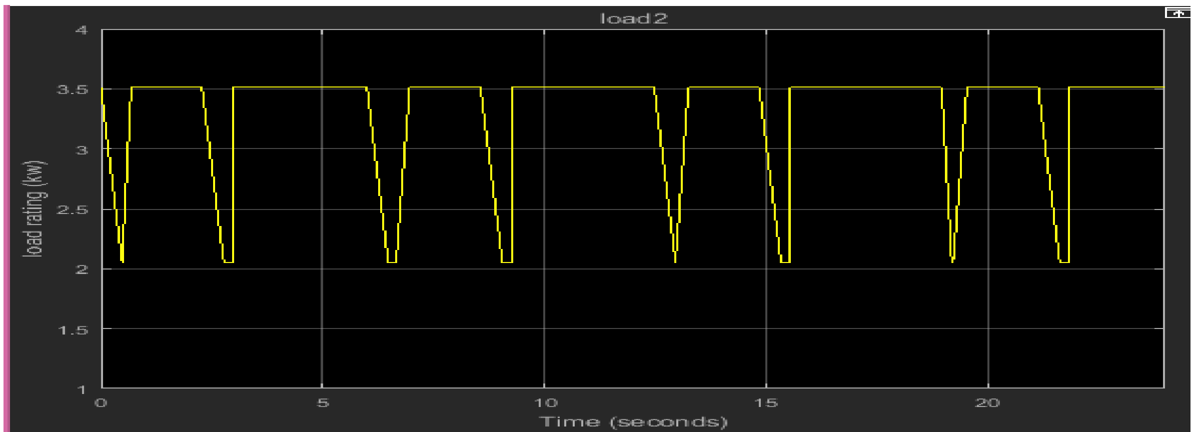


Figure 4.36Matlabsimulink output of fuzzy logic based load scheduling for load2

This result displays that the on off condition of load2is decided depend on the forecasted demand value.From this we observe that load2can be in on condition for low,v.low and medium and off at high and higher demandThe y axis of graph represents the load rating value.And the x axis of the graph indicates the sampling time that is the simulation time, here throughout the simulation it takes different time periods which fluctuates between maximum of 24 and minimum of 1 in hour as shown in the time period graph.

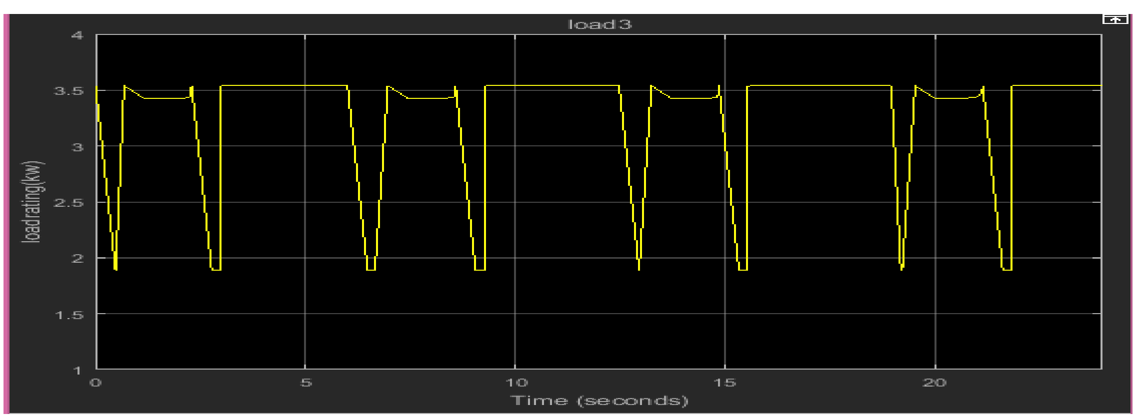


Figure 4.37Matlab simulink output of fuzzy logic based load scheduling for load3

This result displays that the on off condition of load3 is decided depend on the forecasted demand value. From this we observe thatload3can be in on condition for both medium, v.lowand low demand but off at high demand. The y axis of graph represents the load rating value. And the x axis of the graph indicates the sampling time that is the simulation time, here throughout the simulation it takes different time periods which fluctuates between maximum of 24 and minimum of 1 in hour as shown in the time period graph.

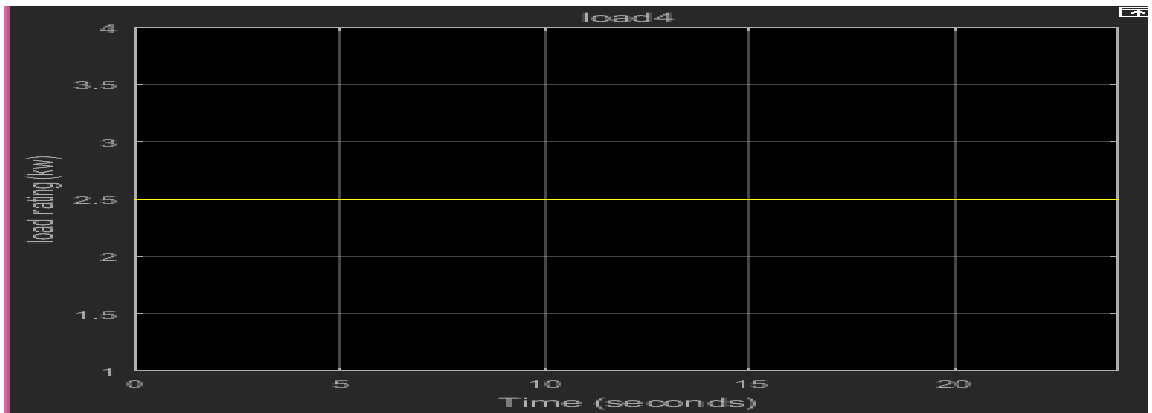


Figure 4.38Matlabsimulink output of fuzzy logic based load scheduling for load4

This result displays that the on off condition of load4 doesn’tdepend on the forecasted demand value. From this we observe that load4 can be in on condition for all value of demand. The y axis of thegraph represents the load rating value. And the x axis of the graph indicates the sampling time that is the simulation time, here throughout the simulation it takes different time periods which fluctuates between maximum of 24 and minimum of 1 in hour as shown in the time period graph.

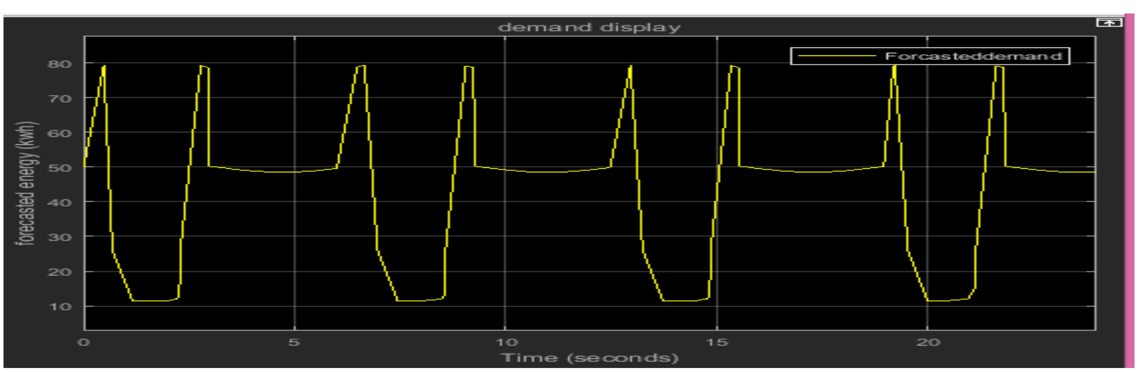


Figure 4.39Matlabsimulink output of fuzzy logic based load scheduling for forecasted demand graph

This fig shows that at time period 16 the forecasted demand is high that is around80because this time is peak hour and when we come to time period 21 the forecasted demand becomes low because this time is off peak time .then the on off condition display of loads (Demux1,Demux2,Demux3 and DEMUX4) is proceeded based on this forecasted demand as discussed above.

5. CONCLUSION AND RECOMMENDATION

5.1. CONCLUSION

This project aims at developing a short term load forecasting integrated with appliance scheduling model for demand side management at customer end side forthe study area. In general the following tasks are done in order to achieve the objective of this thesis.

- As a part of this work, an hourly load profile is gathered, which is the backbone of the predictive model.
- The forecasting model is developed and implemented using fuzzy logic controller with appropriate membership function to forecast the daily energy demand of the village.
- The scheduling model is developed and implemented based on the forecasted demand using fuzzy logic controller with appropriate membership function to schedules the home loads such as load1(medium power intensive appliances),load2(high power intensive loads),load3 (very high power intensive loads) and load 4(are non shift able loads or continuously usable loads).
- The implemented model can help the utilitycompanies to better manage their operations, reduce grid failure occurrences and damage of equipment's.
- Ithelps more the end use customers to control their loads without any intervention and reduce theirutility bills by avoiding using the power equipment's at peak hours with the help of the proposed model. As a result peak demand reduction is addressed.

However, this model has a limitation. The suggested model is not able to consider any sudden load change. If the load requirement changes abruptly for few hours only due to any unpredictable reason, this model will not be able to follow the change, this means that it will not be able to forecast the load for that particular time.

5.2. RECOMMENDATION

This project aims to provide the short-term load forecasting data to the end use customer as well as automatic load control on the bases of their interest, to assist in their DSM participation. Hence the load data's used here are directly from the customer end. An advanced version of the project can process real-time data from millions of smart metering systems and formulate individual load forecasting models for each residential unit and automatic load adjustment can be achieved for every individual if the loadcan be predicted accurately. So that changing the old metering system to smartest one is proceeded that means any one can use this data as input for doing project in smart metering because as we see from literatures smart meter is bi directional that means customers and providers can communicate each other which has relation with this work in that the customers can use real data for current and previous demand instead of using forecasted demand for the next time. This research can also be extended for utility level and grid level.In order to control the total distributed energy of the country it is better to develop and implement the controller for the country level

The limitation of this work is that by now it is designed only for the study area but other researcher cando with this model at utility level and grid level by modifying the parameters and rules on the existing system.

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