School of Engineering and Mathematical Sciences
CITY UNIVERSITY LONDON

# Development of an Intelligent Decision Supporting Home Energy Management System

By

Md. Moktadir Rahman

Student ID: 090045951

## MPhil Report

Supervisors

Dr. Lambros Ekonomou
&
Prof P Liatsis

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School of Engineering and Mathematical Science (SEMS)
City University London
Northampton Square, London
United Kingdom EC1V OHB
Tell: +44 (0)2070405060

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**DECLARATION**

I declare to allow the University Librarian to copy this thesis in whole or in part without further reference to me.

Md Moktadir Rahman

15/05/2015

# ABSTRACT

One of the main goals of Smart grid is to achieve Demand Response by increasing the end users' participation in decision-making and increasing the awareness that will help consumers to efficiently manage their energy consumption. However the existing demand response (DR) mechanism reduces power consumption based on predetermined policies of load priority (direct load control and pricing techniques) during the peak times without considering consumer comfort and environmental issues. Demand response has been achieved by forcefully shutdown the consumers' loads during peak hours which violate users' comfort life style. This is due to lacking of intelligent energy management system and smart automation tools at home level.

The main objective of this thesis paper is to develop a model based intelligent decision supporting Energy Management system which will understand the customer consumption behaviours while simultaneously reduce the energy consumptions. To achieve these, a Fuzzy Multi Criteria Decision Making (MCDM) based load controller has been developed to prioritize the consumers' preferences and to take decision on behalf of the consumers in order to best manage the use of their appliances. The Fuzzy Multi Criteria Decision Making (MCDM) methodology has been used because it can solve decision and planning problems involving multiple criteria.

Furthermore a comparative analysis for the power consumption and cost saving performance is carried out to show the benefit of using renewable energy sources along with the proposed fuzzy MCDM based load controller. Simulation results show that the proposed load controller successfully limits the power consumption during the peak hours and concurrently maximizes the savings of energy consumption cost without violating consumer comfort level.

*Index Terms* – Smart meter, Direct Load control, Mathlab – Simulink, Smart Grid, Energy savings, Fuzzy logic techniques.

# CHAPTER 1

## *INTRODUCTION*

A power grid has four segments: generation, transmission, distribution and demand. Demand side management systems are receiving a growing attention in the development of the future smart grid. Line losses are proportional to the current squared, so it is easily understandable that a grid is more energy-efficient with low demand, and therefore load reduction is an obvious way of improving a grid's energy efficiency. Flattening the demand curve is another way of making a grid more energy-efficient. To understand this, consider a load that draws a current of 2i for half of the day, but no current for the rest of the day, and thereby incurring a line loss that is proportional to $(2i)^2 \times .5$ day. Considering another load that draws a current of i throughout the day, and thereby incurring a line loss that is proportional to $i^2 \times 1$ day, the latter load which represents a flat demand incurs half line loss. Therefore, a flat demand curve is better for energy efficiency, and also better for infrastructure utilization.

**1.1 The structure of the report**

This research report has divided into six chapters. Chapter 1 describes about the existing Demand side management (DSM) techniques and classifications. The Demand side management (DSM) communication techniques using Advance meter infrastructure has also described in here. Chapter 2 contains main Research problems finding, Research Methodologies and Research objectives. In this chapter some key points of solving the current research problems have been proposed. Chapter 3 contains literature reviews. In chapter 4 describes the developed intelligent residential energy management model with the maximum and minimum energy cost functions. The AC modelling, Battery and Water heater modelling for the residential building has also included in this chapter. Chapter 5 contains simulations and case study. The development of Fuzzy Multi Criteria Decision Making (MCDM) load controller using Mathlab simulation software has described in this chapter. Also a case study has been carried out to compare different load management techniques' energy reduction and cost savings performances. Chapter 6 contains discussion and conclusion.

### 1.2 Definition of Demand side Management

The concept of Demand Side Management (DSM) in power systems [1] is to bring both supplier and consumer around a common platform to discuss for effective utilization of available electrical energy with minimum inconvenience and maximum profit. For effective use of DSM at consumer level the home electrical appliances need to inquire the instantaneous price and decide the efficient consumption of power without violating the consumer comfort. The power consumption in buildings represent a 30-40% of the final energy usage, which is mostly caused by: HVAC (Heating, ventilation and air conditioning), lighting and appliances with any connection to the power grid. Recent research shows that 20%–30% of building energy consumption can be saved through optimized operation and management without changing the structure and hardware configuration of the building energy supply system [2]. Smart appliances and pricing or a direct reduction of energy for a particular type of appliance can shave local area peaks and play a significant role in reducing utility costs [3].

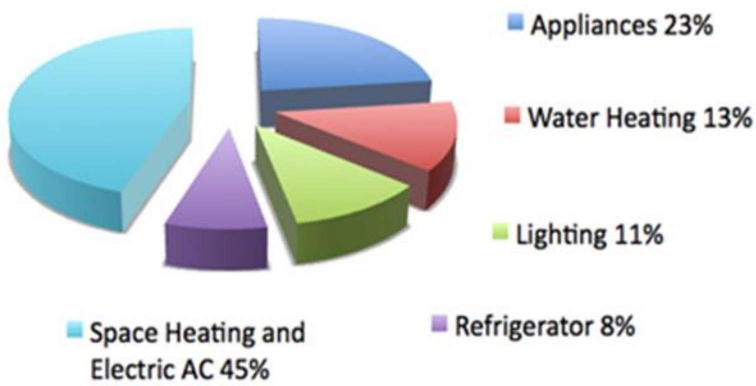



Figure 1.1 Approximate power consumption in a typical house [4].

45% of total energy is consumed by the HAVC systems (figure 1.1). Therefore it is very important to control the AC and heating system energy consumptions.

### 1.3Classification of Demand Response

Demand Side Management (DSM) is Called Demand Response (DR) in the deregulated power markets. Demand response programs can be roughly classified into two groups according to the party that initiates the demand reduction action:

- Price-based DR programs: These are the programs where the tariff fluctuates according to the real-time cost of electricity. Examples are critical peak pricing and time-of-use pricing. In critical peak pricing (dynamic peak pricing), customers are notified in advance of critical peak times – limited to several days per year – during which the tariffs will be much higher than average. In time-of-use pricing, the tariff varies with different time blocks of the day.
- Incentive-based DR programs: These are the programs where a utility rewards its customers for their participation. Examples include peak-time rebate and direct load control. A peak-time rebate program offers a credit or rebate to customers who reduce usage during critical peak hours. Direct load control is a program by which the program operator remotely shuts down or cycles its customers' appliances (e.g., electric water heaters) on short notice.

Price-based programs (TBP) can be divided into three categories:

1. Time-of-use program (TOU)

In TOU program, the price of electricity is calculated at least in peak, off-peak and base load, based on the energy cost in each period [5]. These tariffs could change in hours of a day, days of a week or in different seasons of a year (Figure 1.2).

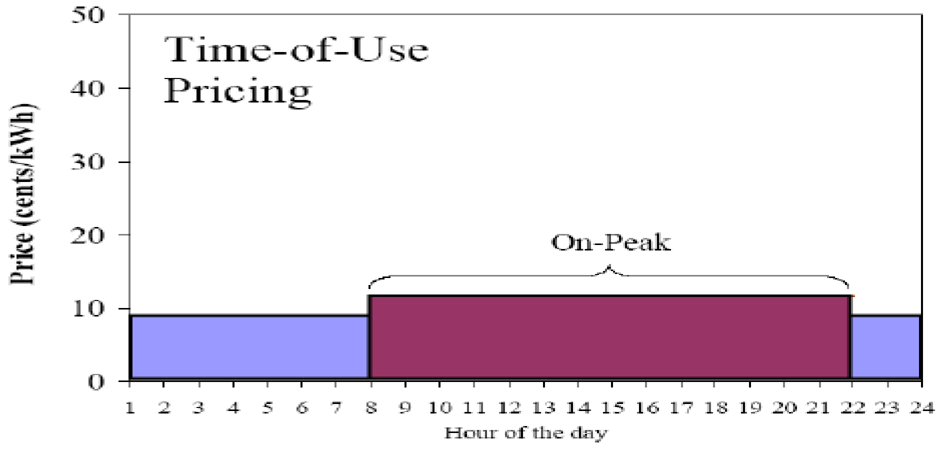



Figure 1.2 An illustration of TOU program [5].

2. Critical Peak Pricing program (CPP)

CPP is a combination of TOU and flat rate pricing programs (Figure 1.3). This program is based on the real time cost of energy in peak price periods, and has various methods in implementation.

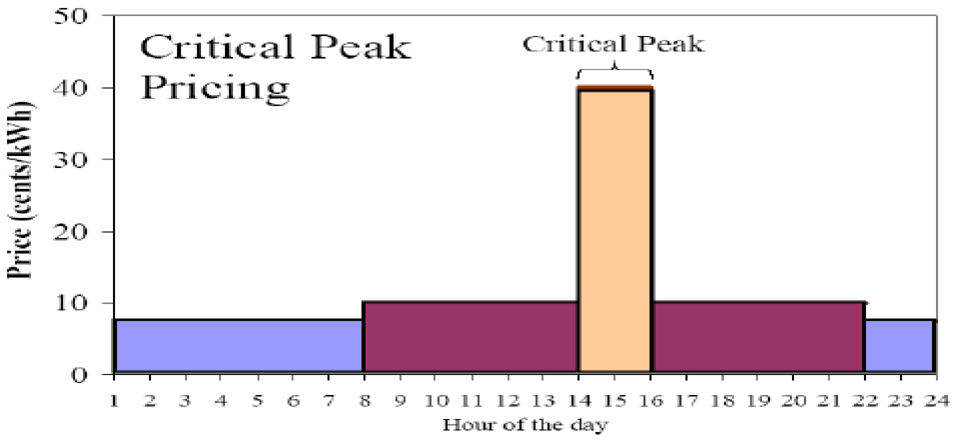



Figure 1.3 An illustration of critical peak pricing (CPP) program [5].

3. Real Time Pricing program (RTP)

In RTP program, electricity price is calculated based on hourly energy cost. RTP links hourly prices to hourly changes in the day-of (real-time) or Day-Ahead cost of power. RTP is implemented by two methods: one-part RTP and two-part RTP. The price is calculated in an hour or a fraction of an hour basis in the one-part RTP (Figure 1.4). In the two-part RTP a cap consumption is defined for the customers, in which the electricity price is different whenever the consumption is below or above the mentioned cap.

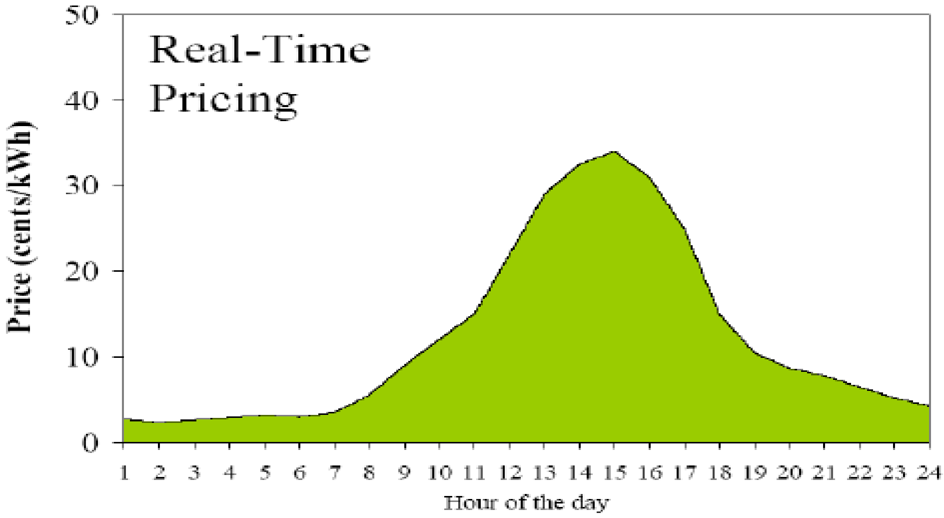



Figure 1.4 Real Time Pricing Program [5].

### 1.4 Demand side management using Advance meter infrastructure (AMI)

Advanced metering infrastructure (AMI) is an important component of Demand Side Management (DSM) which helps in realizing the interaction of consumers and power systems [6]. AMI is not a single technology, but rather an integration of many technologies (such as smart metering, home area networks, integrated communications, data management applications, and standardized software interfaces). The two-way communications, advanced sensors, and distributed computing make AMI possible to provide both consumers and system operators the information and means to make decision or choice leading to the improvement of the efficiency, reliability and safety of power delivery, and usage [7].

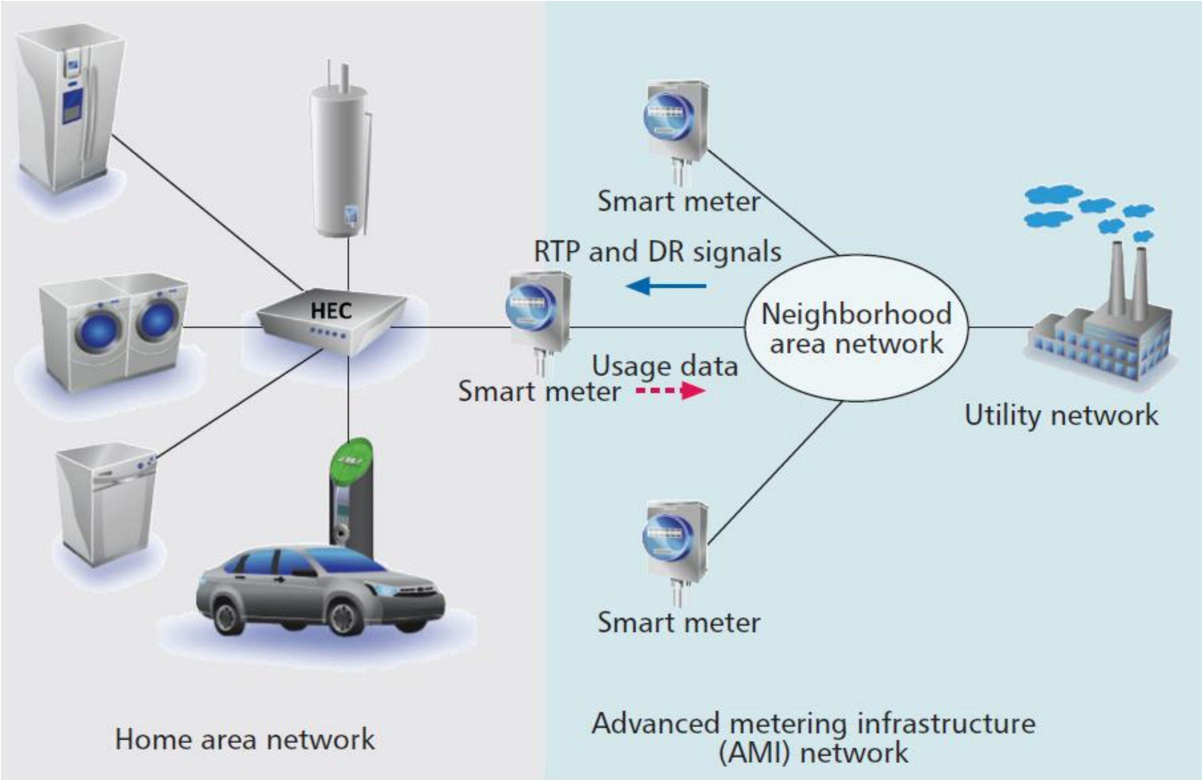



Figure 1.6 Demand side management using Advance meter infrastructure (AMI)[8]

This infrastructure includes home network systems (including communicating thermostats and other in-home controls), smart meters, and communication networks from the meters to local data concentrators.

### 1.5 Demand side Management technique

The DSM techniques are more useful and most effective in real time pricing environment. A large number of DSM techniques are available. The most popular are [9]:

a) Load priority techniques

b) End use equipment control

c) Peak Clipping Valley Filling

d) Differential Tariff

*a)* Load Priority Technique [LPT].

The loads are classified into interruptible and non-interruptible loads [10]. Non-interruptible loads are important loads and interruptible loads are non-vital loads. The success of LPT is totally dependent on the development of various load priorities for operation which will not disturb the production schedule and gives enough scope of reduction of load demand [11].

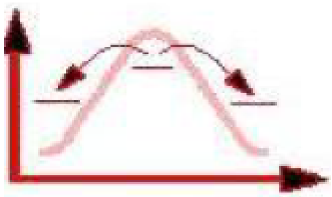


Figure 1.7 Load shifting [10]

*b) End Use Equipment Control:*

It deals with the control operation of various end use appliances for better utilization of available resources without effecting the production and supply [12]. This is one of the most active areas of DSM Technology development.

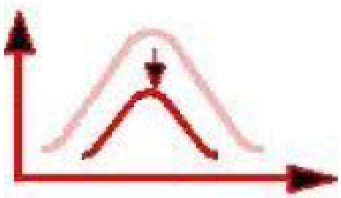


Figure 1.8 Conservation [10]

*c) Peak Clipping and Valley Filling:*

The consumers demand curve consists of peaks and valleys. Reduction of peak demand reduces the demand charges of the consumer. Peak clipping is achieved by direct control of equipment's which are responsible for the peaks. It helps in matching the available power with the demand without going for additional generation, thereby reducing capital charges, fuel charges and operation charges.

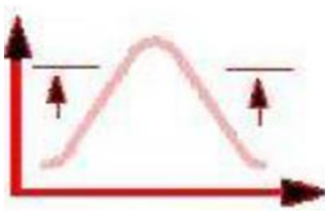


Figure 1.9 *Peak Clipping* [10]

The principle involved in valley filling is to build up load or consume power during light load periods of supply system [12]. This results in high efficiency and lower cost of operation because of improved load factor or energy efficiency of the system. This flattens the load curve more. In this way this technique helps in reducing the peaks and improving load factor.

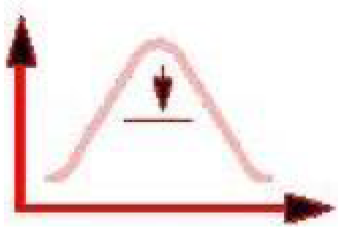


Figure 1.10 *Valley Filling* [10]

*d) Differential Tariff:*

Different tariffs are employed in order to flatten the load curve. As the variable load has some peaks and valleys, the supplier must install his equipment which will be capable of supplying the peak load of consumptions. However during valley period, the equipment will be underutilized thereby decreasing the energy efficiency of equipment [12]. Hence, the supplier will insist or will try by all their possible means to utilize the equipment to its rated capacity for the entire duration whenever it is in the commissioned state [13]. With this type of tariff, the consumer will try to consume more energy during valley periods by avoiding energy consumption during peak hours.

# CHAPTER 2

## IDENTIFICATION OF CURRENT PROBLEM

### 2.1 Problem formulation

The recent growing attention is focused on the luxurious means of comfort, the trend going on with electronic goods for maximum applications giving rise to heavy growth in the demand. The production of the energy is being same, giving rise to problems like heavy power cut in the peak hours. One of the options left is to utilize the available electrical power very effectively at customer side, i.e, at home level where each user is able to play his own active part in order to achieve Demand Response.

In this case home users can participate in demand response by reducing their energy consumption during the peak hours by assigning the priorities to the loads in the respective time. However lacking of intelligence in home energy management and smart automation tools have made more complex to schedule of multiple devices and manual device control is inefficient and unattractive to residents [14]. As an example during peak hour if a consumer wants to turn on AC while other electrical appliances are running, i.e. washing machine, dishwasher etc. The consumer has to pay more bills in order to carry on his/her preferred consumptions. To save energy bills and participate in demand response program the user has to turn off either AC or other appliances which actually violating the consumer preferences and comfort. In this scenario the user needs an intelligent decision supporting energy management system that captures the user's preference and behaviour and then assist them to reduce energy consumptions. Therefore, implementing of the intelligent residential energy management system can play important role in demand side management.

According to the Smart grid context the requirements of implementing DSM the design principles should be carried out as follows [11]:

1) Interacting between the grid and users should be involved in the system design, that is, the users can actively adjust their electricity consumption in response to the real-time price according to their own characteristic.

2) Design of the system should aim to change the way of using electricity and improve the energy efficiency so as to optimize the management of Demand Side.

3) The system should provide user comprehensive information on historical and time of use electricity in order to interact actively with user and then make decision rationally.

4) Intelligent DSM system should be helpful to solve a series of resource and environmental problems so as to realize the energy conservation and emission reduction, that is, to ease the pressure of increasing peak-valley difference, coal consumption, generation cost, generating hours and reliability, etc.

5) The system should be designed to meet various demands and respond to several factors.

### 2.2 Research Problems and proposed solutions:

The major challenge is to minimize the power consumption and cost of energy by optimizing the operation of several loads without violating customer's comfort. The uncertainty in the householders' preferences increases the uncertainty of appliance prioritization and the difficulty of determining consistency of preferences.

Existing demand response (DR) mechanism (i.e. direct load control and pricing technique) reduces power consumption according to predetermined policies of load priority during the peak times but does not consider consumer comfort, economic condition and environmental situation. Pricing techniques significantly reduce high power consumption during peak hours. However, a significant proportion of residential customers are non-responsive to price [15], and higher prices discriminate against lower income households. Also the household's demand response to price decreases as household income increases [16].

Most of the research has been done to achieve demand response with price efficiency and less progress has been made to achieve demand response (DR) effectiveness on the customer-side. However none of them has proposed any solution for following questions:

a) An Intelligent decision supporting energy management system which works on behalf of the customers when consumers are not well trained and too passive to change their consumptions behaviour during peak to off peak hours.

b) Direct load control is nowadays popular in controlling the demand response which utilities use to force the consumer to switch off the appliances or postpone their energy consumption during peak hours. However no alternative solutions have been made to understand the consumer comfort level while simultaneously reduce the consumptions of energy.

c) Most of researches have proved the benefit of renewable energy sources in controlling the demand response. However no approach has been proposed to encourage the customers increase the use of renewable sources and simultaneously shift their dependence on them.

To overcome this, home energy management system need to design such way that consumer can decide whether their energy consumption is cost effective or comfort life style. For the dynamic pricing system it is difficult for the customer to know if their consumptions decisions are effective and efficient and more often customers are too passive to participate in the DR program [17]. In this case the system needs to be more intelligent to make a decision on behalf of the customers to increase the reliability of the service. The home intelligent system need to capture the outside variables like price signals, environmental conditions, control signals such as direct load control, demand reduction from the DMS and available Renewable Energy Sources through Smart meter.

## 2.3 Research Objectives

The main objective is to develop an intelligent decision supporting home energy management model where three optimization parameters – comfort, cost and demand response will be satisfied.

**Steps:**

- Develop a Fuzzy Multi Criteria Decision Making (MCDM) load controller to optimize the operation of different home electrical appliances without violating the consumer comfort while minimizing the energy consumption.
- Develop mathematical models to optimize energy cost and saving according to the consumer consumption behaviours.
- Use Mathlab-Simulink to build Fuzzy Multi Criteria Decision Making (MCDM) load controller.

## 2.4 Research Methodology

The research methodology that was followed is concentrated in following steps:

- Performed fundamental studies to familiarize about the research area.
- Performed literature reviews to identify the current research problems.
- Proposed model based intelligent residential energy management system to overcome existing issues.
- Implement Mathlab-Simulink to develop Fuzzy Multi Criteria Decision Making (MCDM) load controller.

# CHAPTER 3

## LITERATURE REVIEW

Many researchers have done research on achieving demand response. Most of the researches have been done to achieve demand response by using smart pricing techniques and direct load control. Less progress has been made to achieve demand response (DR) considering consumer comfort life style.

Among different techniques considered for DSM (e.g., voluntary load management programs or direct load control), smart pricing is one of the most effective tools that can encourage users to consume wisely and more efficiently. Several pricing methods have already been proposed (e.g., flat pricing, peak load pricing, adaptive pricing.

Based on each user's preferences and energy consumption patterns a novel Vickrey Clarke Groves (VCG) mechanism has been used [18] each user is equipped with an energy consumption controller (ECC) as part of his smart meter. This proposed VCG mechanism improves the performance of the system by encouraging users to reduce their power consumption and shift their loads to off-peak hours. However, in this proposed VCG mechanism for DSM programs to encourage efficient energy consumption among users by load shifting and Pick load reducing however this mechanism hasn't described the possibility of the customers to join in energy biding program. This mechanism assumed customers as a price taker which means customers are only considered as a energy consumer not as a provider.

Hongming Yang and Yeping Zhang [6] proposed model indicates the importance of electricity price and the great impact of use-of-time price on the total quantity of power demand and curve shape of power load in demand side management. It showed that by increasing the capacity or energy price the total power demand, output value and power consumption of unit output value will decrease. If the electricity price increases 2.25 times, the maximum load reduces from the peak load to the valley load. This proposed model only described how the total consumption of the electricity will decrease by implementing higher electricity consumption prices but it didn't consider the consumer satisfaction as well as the efficient use of energy.

The paper presented in [19] utilizes system dynamics theory to establish the dynamic model of demand side management, which consists of internal and external structure among the power demand, the two-part electricity price, the output value of customers, technology development and economic situation based on computer simulation of many differential equations with feedback and time delays. By using this model, the policies of electricity price, such as the ratio of capacity and energy fees in the two-part electricity price, the r By using model, it can been seen that increasing the capacity or energy price, the total power demand, output value and power consumption of unit output value decrease, which indicates the importance of electricity price and the great impact of use-of-time price on the total quantity of power demand and curve shape of power load in demand side management. Ratio of peak and valley time price in the time-of-use electricity price are analysed and proposed. This analysis method can be extended to the demand management for the hyper-power industry and residential customer, etc.

Load controlling at customer side is very important for DSM. Many solutions have been investigated for the management and control of distributed loads [20]; however, two classes of approaches seem to be particularly suitable in the DSM context: the hierarchical and the clustered system architectures. In order to gather all the information needed to apply dynamic tariffs, final users have to be organized in a proper Measurement and control structures. The best system that matches the DSM requirement is a multilevel cluster structure. The proposed solution in [21] for demand side management and distributed load control is a multilevel cluster structure which is a multilevel system in where each level is formed by groups of homogeneous entities. The highest levels deploy the most important decisional infrastructure with software both for load control and energy metering, the lowest levels host measuring units, sensors and devices that send feedback to high level nodes. The advantage of such a structure is that it allows execution of multiple operations in parallel; hence it alleviates the workload of each node. However this proposed model has only considered the low voltage customer load shifting using with time-of-use tariffs.

Shuai Lu [22] has described a model with details household loads control technique using voltage and frequency deep.  This paper discusses these two control philosophies and compares their response performances in terms of delay time and predictability. Only AC system and water heater participate in Demand Response program and other house hold loads will not consider for this model.

Scheduling home appliances according to the peak and off peak hours can save electricity consumptions cost and protect grid network from voltage and frequency deep during peak hours. Quanyan Zhu and Zhu Han [23] have used the framework of dynamic games to model the distribution demand side management. At the lower level, for each player (such as one household), different appliances are scheduled for energy consumption. At the upper level, the dynamic game is used to capture the interaction among different players in their demand responses through the market price. Direct load control and demand management in response to market price has been considered. The decisions of household appliances by solving distributed optimization problems for each user or household. Here demand side management is controlled by market price while customers' satisfaction haven't considered. When users in a neighbourhood collaborate to determine the optimal energy allocation for each time slot, the system's demand curve can be flattened more effectively. This kind of scheme group load shifting (GLS). Kishore and Snyder [24] propose a distributed neighbourhood-level load scheduling protocol, where users in a neighbourhood contend for energy from a finite energy resource for every time slot. The protocol is heuristic and assumes the "energy management controllers" in a neighbourhood are one step away from each other, which is a severe limitation. Other issues include: packet collisions are not handled; no countermeasures against selfish controllers (e.g., controllers that do not wait for a random delay before requesting for energy). Distributed group load shifting (GLS) schemes have the advantage that users do not need to surrender control of their appliances to their utilities, but do expose the users to security and privacy risks.

Not only individual or group load controls and load consumption scheduling can help consumers to achieve Demand Response. Renewable energy generation integration at customer side plays a vital role in saving energy cost and manage grid efficiency. Customer's behaviour based home energy management system [25] model has presented by El Hassan. The proposed solution allows large number renewable energy resource integration and leads to global efficiency and demand side management optimization in smart grids. A new graphic user interface (GUI) based platform for developing, testing, and investigating the consumer-based DSM was presented. The functional algorithm helps to improve the efficiency of energy utilization by a factor of 16.4% resulting in significant annual savings for the consumer. But didn't describe if customers were unwilling to participate in direct load control.

Based on the presented work, it is demonstrated that the load profile, the load shifting and scheduling and power consumption are mainly dependent on the consumer's preferences and lifestyle behaviour. Current imposition of Demand Response program (direct load control) leads to the possibility of a comfort level violation or a high load compensation. Therefore a decision supporting system is needed which will allow user to consume electricity in cost effective and efficient way while participating in Demand Side Management (DSM). A Fuzzy logic controller is designed by Ravibabu [9] to reduce the gap between the demand and the supply of electrical energy loads in both peak hours and off peak hours aiming to properly utilize the available power for the vital loads and power wastage can be restricted. The combined application of DSM techniques and fuzzy logic gives rise to an intelligent system which acts as a demand limiter, which is more user friendly. The intelligent system helps in avoiding the non-vital loads during the peak hours. But how customer comfort level will affect in participating in Demand Reponses program hasn't clearly identified.

Xiandong Tan [26] proposed a general frame, software architecture, hardware platform and main function modules of DSM decision supporting system, and constructed a DSM decision supporting system of B/S structure according with J2EE architecture. In this proposed model Demand Side Management - decision supporting system consists of two layers, one is supporting layer and the application layer.

The paper showed in [27], an application of *Artificial Neural Network* techniques is done and *Demand Side Management* to industrial costumer. The results obtained provided a better load factor and reduction cost, due to *peak clipping*. *Load Priority Technique* is used. Furthermore, *Tariff differential* is proposed, encouraging to consume less during peaks hours and punishing those customers with more consumption in valley hours. Power consumption saving achieved without impact the customer's comfort.

# CHAPTER 4

## PROPOSED RESEARCH TECHNIQUES

### Development of Intelligent decision supporting home energy management system

The developed system is referred as Intelligent Decision support system (IDSS) because it will use consumers' comfort or preferences to control their energy consumptions and take intelligent decision on behalf of the consumers to meet various demands and respond to several factors. A Fuzzy Multi Criteria Decision Making (MCDM) tool has been used to quantify and evaluate consumers' comfort level according to peak and off hours in order to best manage the use of the appliances. The purpose of using Fuzzy Multi Criteria Decision Making (MCDM) system is because it can solve decision and planning problems involving multiple criteria. As an example, if someone wants to purchase a car, cost, comfort, safety, and fuel economy may be the main criteria to consider. The Fuzzy MCDM will consider different variables as inputs and calculate the outputs in according to the inputs change. In this proposed work the inputs for the Fuzzy MCDM load controller are Time (peak and off peak hours), consumer comfort level temperature, temperature deviation, forecast load and consumption time. The outputs from the Fuzzy MCDM load controller include: Allow load scheduling and Run loads.

### 4.1 Home appliances connection with IDSS

The Intelligent decision supporting system (IDSS) for home energy management connects with the utility system through Smart meter (Figure 4.1). All energy consumption devices (HVAC, lights etc.) links with smart appliances that are combining with embedded computing, sensing and communication technologies to enable energy consumption devices connect with IDSS. Intelligent decision support system (IDSS) could be combination of four technologies such as a web portal, an in-home display (IHD), a programmable communicating thermostat (PCT) which can automatically monitor and control the operation of all the connected smart appliances and notify residents about energy consumption and can learn and react with the customers' preferences. Command from Intelligent decision support system (IDSS) to smart appliances are simple on/off signals, or a demand response command to operate in energy saving mode. All the renewable energy sources like wind generator, PV system, CHP etc. Including batteries and total load consumptions information deliver to the IDSS. In-home display (IHD) will display the total consumptions, total production from renewable sources, Dynamic prices, device priority, current household power utilization, and a maximum power threshold for the home user. IDSS grasps the energy amount used in the electric appliances and calculates the amount of electricity consumed by customer on real time basis.

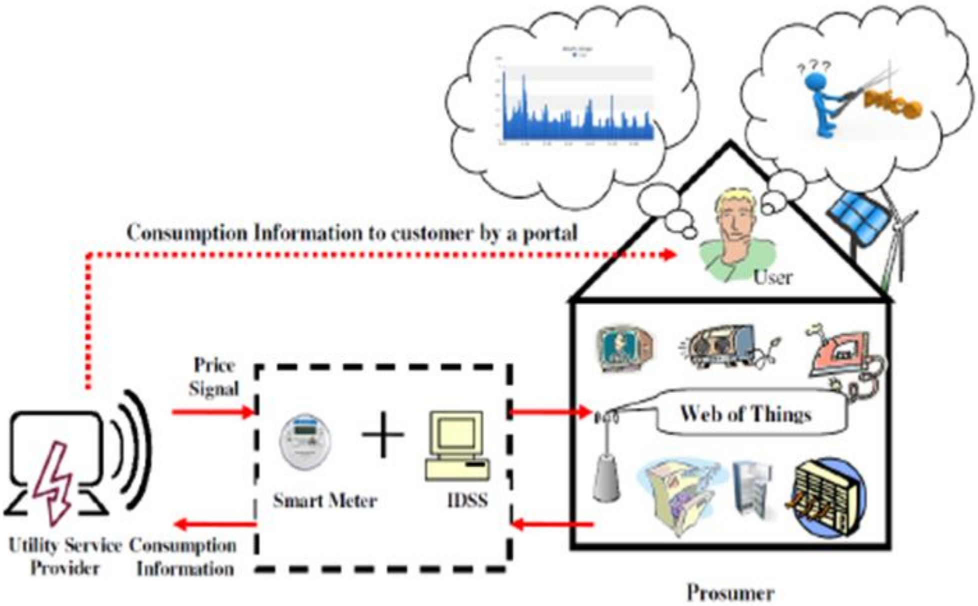



Figure 4.1 Overall data flow for IDSS in Smart Grid system

#### 4.2 Data collection in IDSS

The Intelligent Decision Supporting System (IDSS) as shown in figure.4.2 will the collect information about an environment and resident's situations such as a temperature, humidity, intensity of illumination, a resident's movement and the power consumption via a wireless network or a wired network (PLC or RS485) as shown in figure(4.3) . Zigbee is the best low-cost wireless technology for the home appliances communication with IDSS).

Utility company will display variable price including real time pricing (RTP), time of use pricing (TOU), day ahead pricing (DAP) and critical peak pricing (CPP) and electricity utilization information on home display (IHD). User can control their smart appliances remotely through HAN when they are out home (can use mobile phone to control smart appliances, configure home security system, adjust intelligent thermostat or edit a home entertainment program).

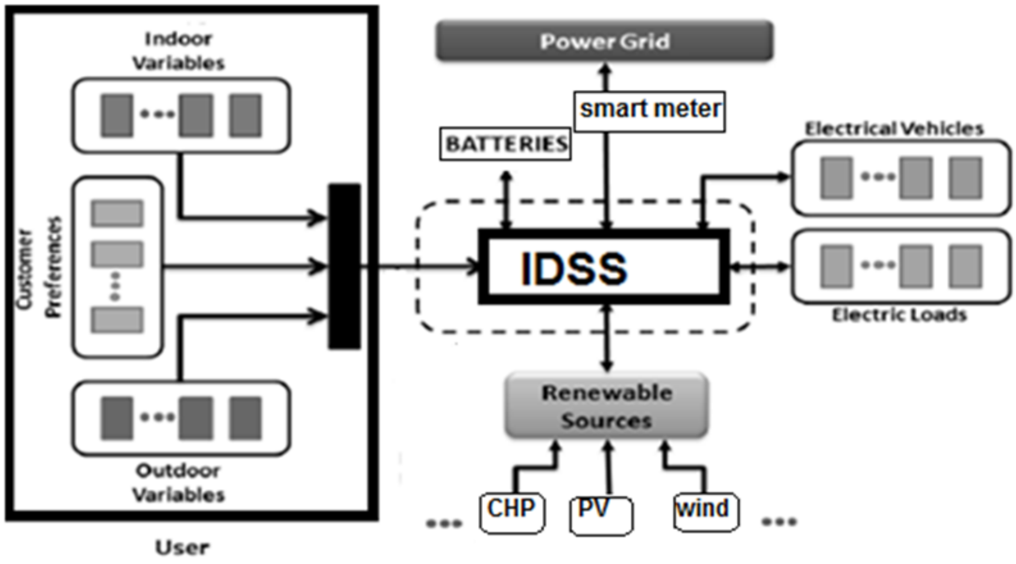



Figure 4.2 Structure of Home Energy Management System

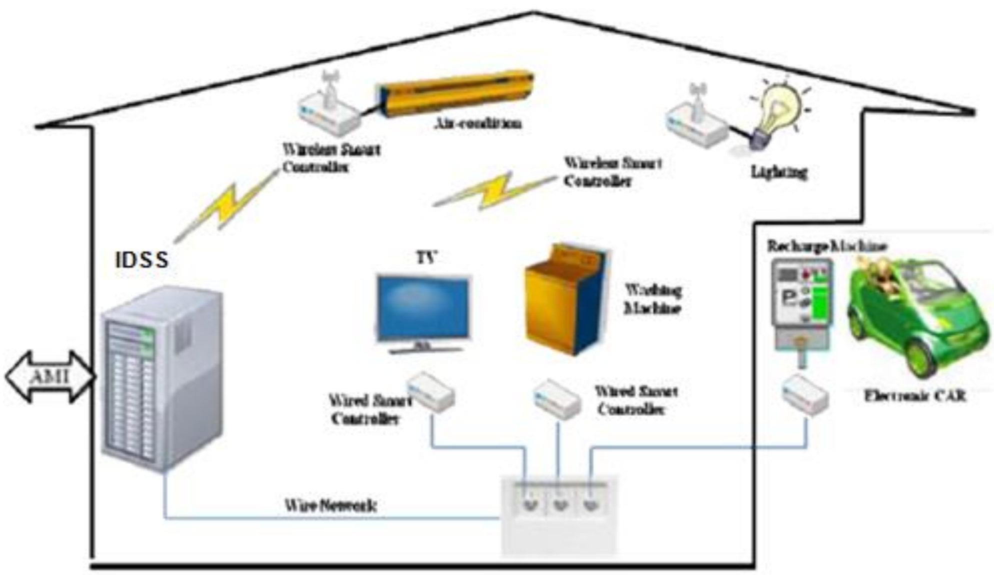



Figure 4.3 Home appliances connection with IDSS

### 4.3 Developed IDSS operation

The whole processes are divided into two main phases:

1. Data processing or collection model
2. Decision making model (Fuzzy Multi Criteria Decision Making tool)

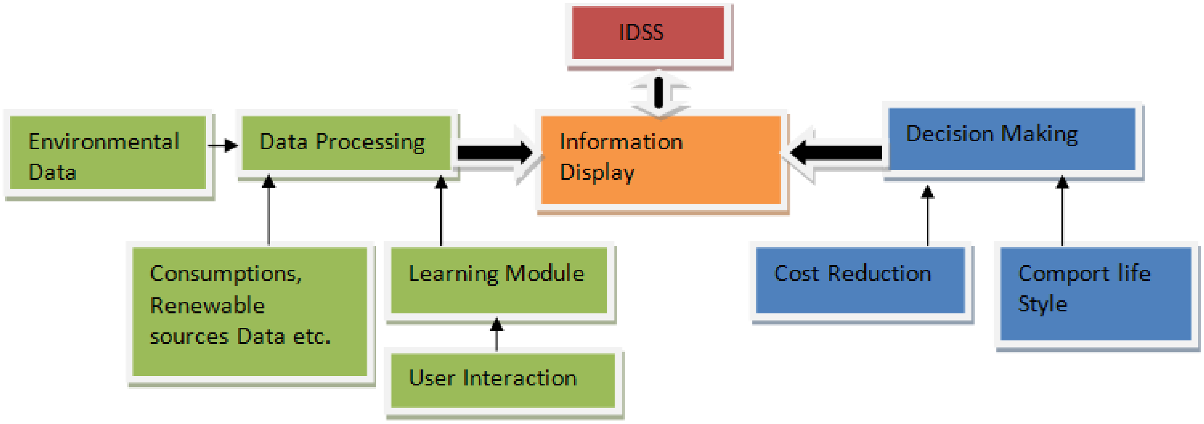



Figure 4.4 Proposed IDSS operation

*1. Data processing or collection model*

In data processing model IDSS will identify the different types of variables that need to be captured for studying the consumer's preferences such as price signals from the grid, environmental conditions, room temperature and available renewable sources and consumer consumption profile. IDSS will have a learning module which will learn the consumer's preferences and consumption profile based on the preliminary data and store these data for future use. Data processing system will collect all the information through smart meter and smart appliances. Electrical Equipment Statistics Amount and power of the electrical equipment are counted so as to update the information timely with in a time frame 15 minutes.

## 2. *Decision making model*

In this paper only decision making model has been developed which is Fuzzy Multi Criteria Decision Making methodology in according to the consumer comfort and cost saving objective. The Decision supporting system mainly follows two objectives:

a) Cost reduction and
b) Comfort life style.

The Data processing model will provide the all collected information including customer preferences, environmental condition, room temperature, grid prices and available renewable energy to the Decision making system. Then the *Decision* making system will evaluate the total consumptions according to the Cost reduction objective and Comfort life style. An example is when the system will receive any signals from Smart meter about load shedding or Direct Load control, and it will match with customer requirements. If customer chooses the cost reduction option and there are no priority loads then the *Decision* making system will participate in Direct Load Control (DLC) program to shift their demands through changing on and off circle based on the real time prices for saving energy cost. Here customers can adjust their consumption through setting the operating time of some of the home appliances as an example Washing machine, dishwasher etc. The home electricity applicants can be categorized into three types:

- Re-schedulable usage loads.
- Re-schedulable usage and service loads and,
- Non-reschedule usage and service loads.

If consumer chooses Comfort life style setting during the Peak hours the customers will be given the flexibility to set their own preferences by configuring various user-defined parameters. For example, when consumers prepare to use the A/C, variables such as the inside and outside temperatures or the level of humidity will influence their preferred A/C settings. The IDSS will show user the dynamic price for that current price and will calculate the total consumption for the AC. Figure 4.5 shows the operation techniques of IDSS for home energy management.

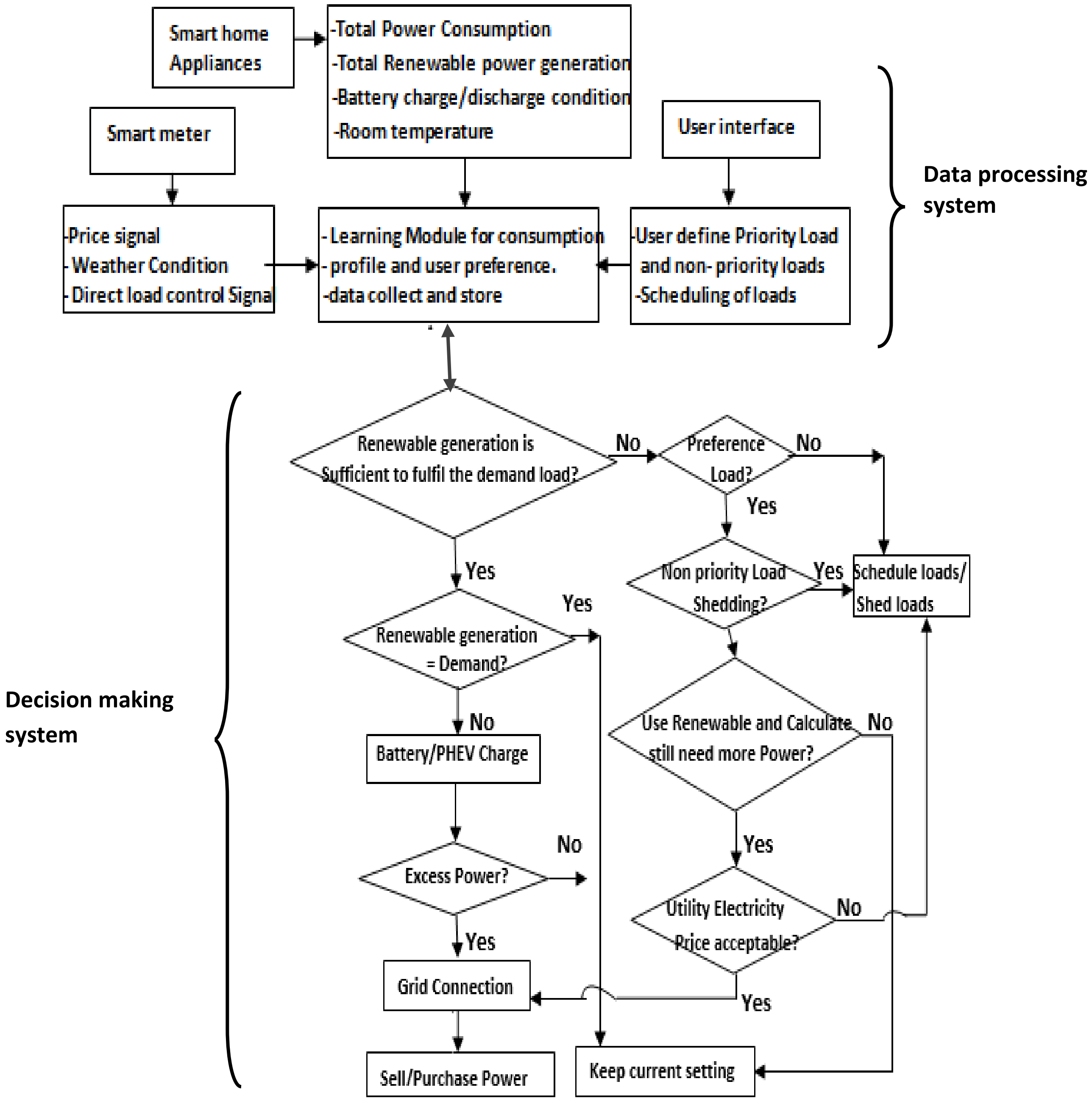



Figure 4.5: Intelligent decision support system (IDSS) model for home energy management.

***Model description:***

**Step 1:** The house will always consume the available renewable energy generator (such as wind turbine, PV, batteries etc.) first. If there is any surplus energy from the renewable resources, the batteries will be charged and the remaining energy will be sold back to the utility grid.

**Step 2:** If the total preferred consumption is higher than renewable energy generation and consumer has no priority loads, the IDSS system will shed few loads to level down the consumption with the generation.

**Step 3:** If the total preferred consumption is higher than renewable energy generation and consumer has priority loads, (such as AC, water heater, room heater etc.), the IDSS system will schedule the non-priority loads (such as washing machine, dishwasher, clothes dryer etc.) to off peak hours to reduce the energy consumptions, and if there is no deficiency of energy from renewable energy generators the IDSS system will run these priority loads.

**Step 4:** If the renewable energy generation is not enough to run the priority loads, the IHEM system calculates extra energy that need to be purchased from the grid and the total price for these consumptions. It will then inform the consumer whether to accept the consumption price or not. If the utility electricity rate is acceptable, utility power will be purchased to fulfil the total load demands of the house. If not the IDSS will shed few loads or schedule it according to the consumer settings.

### 4.4 Developed Model mathematical equations and explanation

#### 4.4.1 Scheduling loads elements

One of the most severe issues is that voltage magnitude at the proximity of distributor generator (DG) may rise above the statutory limits during maximum power output of DG and minimum power demands on the distribution networks. Once the voltage exceeds the statutory limit, then the distribution networks may not operate effectively and safely. The statutory limit for the voltage at busbars is $\pm 6\%$ of the nominal value.

This voltage rise effect can be explained by the following equation [1]:

$$\Delta V = \frac{PR+QX}{V} \qquad (1)$$

where,

ΔV = Magnitude of voltage rise,

p = Active power output of DG,

Q = Reactive power output of DG,

X = Reactance of the line connecting to DG,

R = Resistance of the line connecting to DG, and

V = Nominal voltage at the terminal of DG.

This equation shows that if the X/R ratio of an electrical network is relatively low, then any significant amount of power injected by DG will raise the voltage magnitude at proximity of DG. Since the typical X/R ratio of a distribution network is relatively low, therefore any significant power output of DG will result in voltage rise on the distribution network.

The proposed IDSS system will use this logic to schedule the electrical appliances to run. As an example when there is a voltage deviation (here voltage rise) at the bus where a household is connected, the IDSS will receive this information from Smart meter and then it will command the queued electrical appliances to start running (dish washer, water heater etc.). When the voltage magnitude drops below a threshold, V (i.e., 0.9 p.u.), the IDSS will provide a turn off signal.

### 4.4.2 Individual Load Modelling

In order to control each device autonomously, need an actuator for each device. An intelligent component is a power monitoring and controlling system that use a power socket. Power consumption by the AC is measured by units installed in the AC compressor. This monitors present power consumption, predicts future power consumption based on the monitored data and senses risk situations in each device plugged into the power socket.

*Lighting Control:*

Lighting is the second largest electricity consumer and can easily control by ZigBee-based wireless sensors, magnetic reed switches on doors, passive infrared motion sensors, and a Ambient light sensors can be used to check illumination is below 500 lux then activate additional lighting.

*A/C modelling:*

IDSS will control AC system automatically by the sending the turn on/off signal or change the AC temperature setting high/low according to the users, preference. For this, IDSS will collect the inside temperature (from room sensors) and outside temperatures (from smart meter) or the level of humidity which influence users for their preferred A/C settings.

A/C modelling is a critical task to accurately simulate the behaviour of a distribution system and evaluate the design of DR because:

(i) A/C unit consumes a large portion of reactive power in a single household, especially during starting period and

(ii) The switching action of an A/C usually has a significant impact on system transients in terms of frequency and voltage deviations. Such impact becomes even larger when subsystem has a large number of A/Cs. The A/C model includes house temperature dynamics and a motor load.

The heat transfer of a house can be modelled as [8]:

$$Q_A - U_A (T_A - T_O) - H_M (T_A - T_M) - C_A \frac{dTA}{dt} = 0 \qquad (2)$$

$$Q_M - H_M (T_M - T_A) - C_M \frac{dTA}{dt} = 0 \qquad (3)$$

where,

$\mathbf{Q_A}$ is the heating/cooling capacity of the air conditioner,

$\mathbf{U_A}$ is a conductance of the equivalent thermal envelope of the household through which heat is transferred from outside environment to the household,

$\mathbf{T_A}$ is the room air temperature and

$\mathbf{T_O}$ is the outdoor air temperature;

$\mathbf{T_M}$ is the temperature of the solid mass inside the household,

$\mathbf{H_M}$ is the interior mass surface conductance,

$\mathbf{C_M}$ represents the majority solid mass in the home,

Whereas, $\mathbf{C_A}$ is the mass of the air (much smaller than $\mathbf{C_M}$).

$\mathbf{T_A}$ will be collected in real time and user can set his desired room temperature setting. IDSS learning model will store this setting for the future use.

Let, User choose $\mathbf{T_{A\_set}}$ for the desired room temperature with a dead-band of $\mathbf{T_{A\_deadband}}$, for an A/C to cool down the house, the control logic is:

(a) If $\mathbf{T_A >= T_{A\_set} + T_{A\_deadband}}$, then turn on the A/C.

(b) If $\mathbf{T_A <= T_{A\_set} - T_{A\_deadband}}$, then turn off the A/C.

The A/C temperature setting ranges from 72 to 80 °F, the dead-band is set to5 °F.

*Water heater model*

The physical heat transfer balance is modelled as a first order differential equation [8]:

$$Q_{elec} - mC_p\,(T_w - T_{inlet}) + UA_{wh}\,(T_A - T_w) = C_w \frac{dTw}{dt} \qquad (4)$$

where,

$Q_{elec}$ is the heating capacity of the resistor in the water heater in BTU/min,

m is the hot water flow rate in lb/min,

$C_p$ is the thermal capacitance in BTU/(lb*°F),

$T_w$ is the water temperature, in degree F,

$T_{inlet}$ is the temperature of inlet water, in degree F,

$UA_{wh}$ represents the thermal conductance of the tank shell,

$T_A$ represents the room temperature, in °F,

$C_w$ is thermal capacitance, in BTU/°F.

This model equation can calculate the actual water temperature at any given time, which is used to control the switching action of the water heater.

For a desired temperature, $T_{set}$, a controller similar to the one for A/C unit can be designed as follows:

(a) If $T_w >= T_{w\ set} + T_{w\ deadband}$, then turn off the water heater.

(b) If $T_w <= T_{w\ set} - T_{w\ deadband}$, then turn on the water heater.

Typically, the temperature setting ranges from 110 to 130 °F. In this study, the dead-band of the water heater controller is set to 5 °F.

<u>Modelling of the battery system:</u>

The maximum energy storage capacity of the battery ($E_b$) is given by [10]:

$$E_b = A_b * V_b \qquad (5)$$

Where,

$A_b$ is the current-hour (given by A-H) rating of the battery,

$V_b$ (in Volts) is the maximum voltage of the battery at 100% State of Charge (*SOC*).

To maximize the life of battery, the State of Charge (*SOC*) should not drop below a specified discharge point. The energy available in the battery at the discharge point is defined as the battery energy discharge capacity ($E_{DC}$).

$$E_{DC} = SOC_{min} * E_b \qquad (6)$$

Where, $SOC_{min}$ is the discharge point percentage value.

It is assumed that during the highest cost rate time period of the day, the complete energy available from the renewable sources of energy and the energy storage battery is utilized by the appliances. After the utilization of the battery during high cost periods, the battery has to be recharged during the course of the day.

At any instance, the amount of energy that will be used to recharge the battery is given by x*(PVE + WTGE).

Where,

PVE is Photovoltaic power,

WTGE is Wind power energy.

*Battery charging limit:*

$E_b \geq E_{ba} + x^*(PVE + WTGE)$ (7)

After using the all the available renewable Energy (*PVE* + *WTGE*), If there is any surplus energy IDSS will charge the battery according to the above equation. When the sum of total energy used to recharge the battery $x^*(PVE + WTGE)$ and the prior energy available $E_{ba}$ in the battery is equal to the battery maximum capacity $E_b$, it will stop charging the battery and sell the rest of the energy to the Grid.

**4.5 Total Energy generation and cost for consumptions**

Total energy of the system and generation consumption:

At a given time, total energy production from Renewable source is given by:

$P_R = PVE + WTG\ E$ (8)

where,

PVE is is the total solar energy;

WTGE is the total wind energy at the time of calculation.

The total energy consumption for all the appliances in a household is given by:

$F(x) = E - \{(1 - x) * (PVE + WTG\ E)\}$

$= E + x * (PV\ E + W\ T\ G\ E) - (PVE + WTG\ E)$ (9)

where,

*E* is the total energy consumption by all the appliances,

The value of *x* is a percentage value

x*(PVE + WTGE) is  battery charging at the time of calculation.

Total Energy cost functions:

Total Energy consumptions optimization cost followed by:

*Minimum cost*

F = $\sum_{t=1}^{T}\{gp(t).Pg(t) - rp(t).PR(t)$ (10)

If, $Pg(t) \geq PR(t)$

Maximum cost

F = $\sum_{t=1}^{T}\{gp(t).Pg(t) - rp(t).PR(t)$ (11)

If, $Pg(t) > PR(t)$

here,

*F* is the total cost function,

$gp(t)$ is the grid price,

$Pg(t)$ is power consumption from grid,

$rp(t)$ is power delivered to grid price from renewable source,

$PR(t)$ is power produce from Renewable Energy and

T is the total time.

# CHAPTER 5

## SIMULATION AND CASE STUDY

### 5.1 Building Fuzzy Multi Criteria Decision Making (MCDM) Load controller

In recent years, fuzzy set theory has been regarded as a useful and systematic theory that is more applicable when dealing with uncertainty and vagueness in human originated information. Fuzzy Multi Criteria Decision Making (MCDM) Load controller is designed in such a way that, when the consumers increase their consumptions during peak hours, it identifies the nonpriority loads to switch off and shifts the consumptions to the off-peak hours. The power consumption during peak hours is limited by cutting some loads off and hence there will be proper utilization of supplied power to the high priority loads.

The controller also keeps load consumptions within a certain limit (in this example 2.5kW maximum) which means the load consumptions will not exceed the limit during the high peak hours. However, it will allow the consumer to exceed the limit only if the load consumption time is small (2 to 15 minutes). As an example if a consumer turns on coffee maker or toaster during the peak hours and consumption time is between 2 to 15 minutes, the fuzzy MCDM load controller will not take any action and will allow the load to operate in that period of time.

In this experiment household appliances are divided into four categories which are: Base loads, Priority loads, Schedulable loads or Non-priority loads and Short-time loads. Table I presents each category of load and their power consumption.

TABLE I. LOAD CATAGORIES AND POWER CONSUMPTION

| **1. Base loads** | **Consumptions (kW)** | **3.Schedulable loads** | **Consumptions (kW)** |
|---|---|---|---|
| Lights | 3*0.04 = 0.12 | Washing machine | 0.5 |
| Fans | 2*.08 = 0.16 | Dishwasher | 1 |
| TV | 0.15 | Clothes dryer | 2 |
| Computer | 0.17 | Water heater | 4.5 |
| Fridge | 0.5 | **4. Short-time loads** | **Consumptions (kW)** |
| **2. Priority loads** | **Consumptions (kW)** | Coffee maker | 1 |
| AC | 1.5 | Toaster | 1 |
| Room heater | 1.5 | Vacuum cleaner | 1 |
| - | - | Micro oven | 1 |

To design the fuzzy MCDM load controller the steps followed are:

1) Define input and output of the Fuzzy MCDM load controller.

2) Create Fuzzy membership functions.

3) Define Fuzzy rules.

4) Simulate in Fuzzy logic system.

*1) Define input and output of the Fuzzy MCDM load controller*

The load controller will have five inputs: Time, Comfort Level, Temperature Deviation, Forecast Loads and Consumption Time and two outputs: Allow Load Scheduling and Run Loads. Figure 5.1 shows the block diagram of the proposed fuzzy load controller which has 25 rules, five inputs and two output signal. Some of the fuzzy rules are given later in the paper.

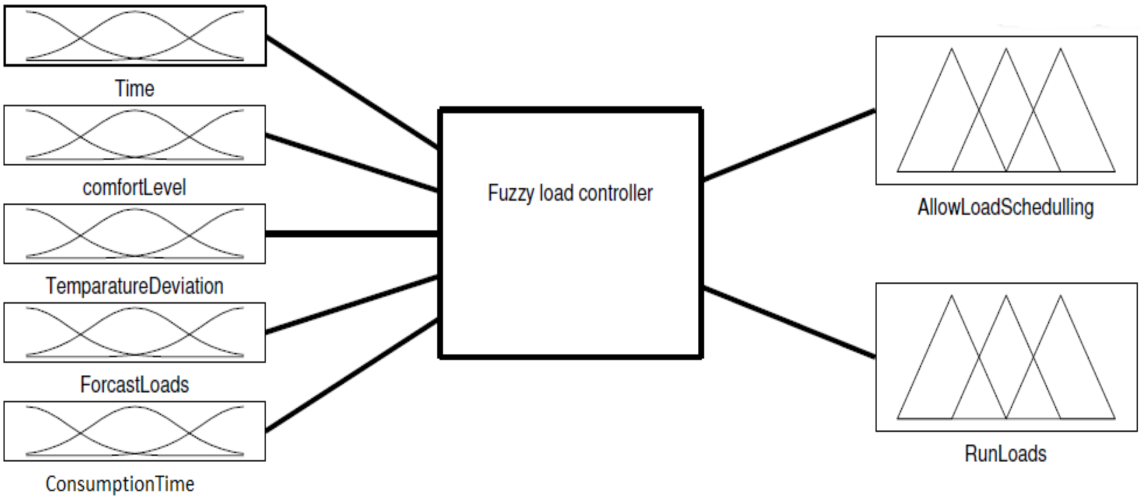



Figure 5.1: Input and Output of Fuzzy load controller.

The inputs and outputs of the above model shown in figure 5.1 are as follows:

**Input1- Time:** Data was sampled for a period of 24 hours. Peak-on, off-peak (moderate) and peak-off are included in membership function trapezoidal type.

**Input2- Comfort level:** The desired temperature level set by the consumers at which they feel comfort.

**Input3- Temperature deviation:** Room temperature deviation from consumer comfort level temperature.

**Input4 - Forecast load:** The total predicted loads consumption includes: existing running loads and new selected loads. For an example if existing running loads consumption is 2 kW and consumer decided to run Air conditioner (1.5 kW), the forecast load would be 3.5 kW.

**Input5 – Consumption time:** The power consumption duration (minutes) of individual load.

**Output1 – Allow load scheduling:** The amount of load in kW that will be shifted to off-peak hours.

**Output2 – Run load:** The total amount of load in kW that controller will allow operating in a particular period of time.

The controller takes the crisp or real input values, fuzzifies them and assigns a fuzzified control signal to provide control over the loads based on the rules assigned and membership functions. The control signal is then converted to two crisp signals through defuzzification process.

2) *Create Fuzzy Membership Functions*

Fuzzy membership functions are needed for all input and output variables in order to define linguistic rules that govern the relationships between them. The membership functions were found to be more suitable for the fuzzy load controller inputs “time” (trapezoidal). On the other hand, sharp membership functions were chosen for the “output variables”, “allow load scheduling” and “run load” because of the sharp constraints on those variables. All the input and output membership functions are shown in figures 5.2 to 5.8.

Figure 5.2 shows the membership functions for input variable “Time” which are divided into Offpeak (am), Peak (am), Offpeak (Moderate), Peak (pm) and Offpeak (pm) for a period of one day.

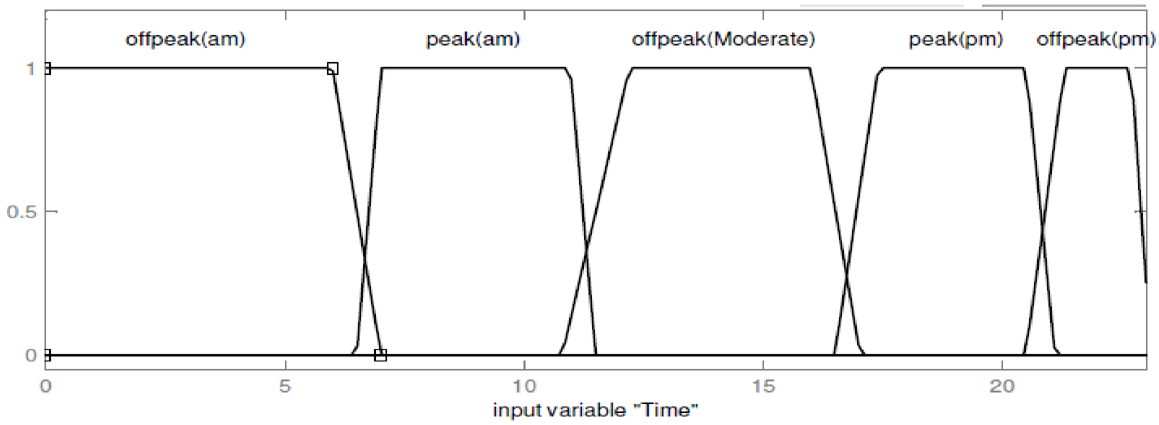



Figure 5.2 Fuzzy membership function of Time (input)

The input variable “Comfort level” is shown in figure 5.3 is divided into three membership functions: Cool and Average and Warm. Consumer can choose any three options as per their preference life style. The comfort ranges for the room temperature during occupied periods is 20 to 24 degree of Celsius.

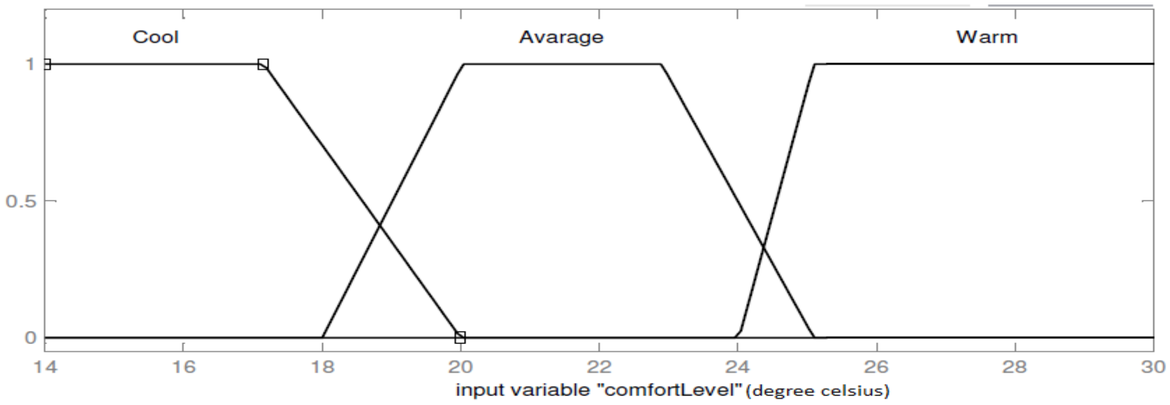



Figure 5.3 Fuzzy membership function of Comfort level (input).

The Temperature deviation membership function is shown in figure 5.4 will be used for controlling AC and Room heater according to the consumer comfort level temperature setting. Temperature deviation functions defines the deviation of the room temperature from the consumer preferred setting.

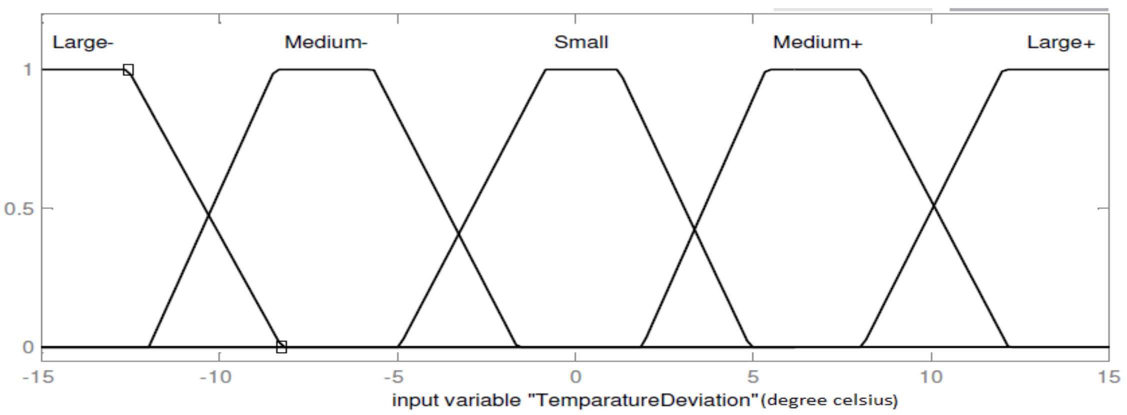



Figure 5.4 Fuzzy membership function of Temperature deviation (input).

Figure 5.5 shows the Fuzzy membership functions for input variable “ForcastLoads”. Fuzzy MCDM load controller turns on/off the appliances according to the kW demand of the forecast loads. The forecast is combined with current running loads and new selected loads. For an example if current running loads consumption is 2 kW and consumer decided to run Air conditioner (1.5 kW), the forecast load would be 3.5 kW.

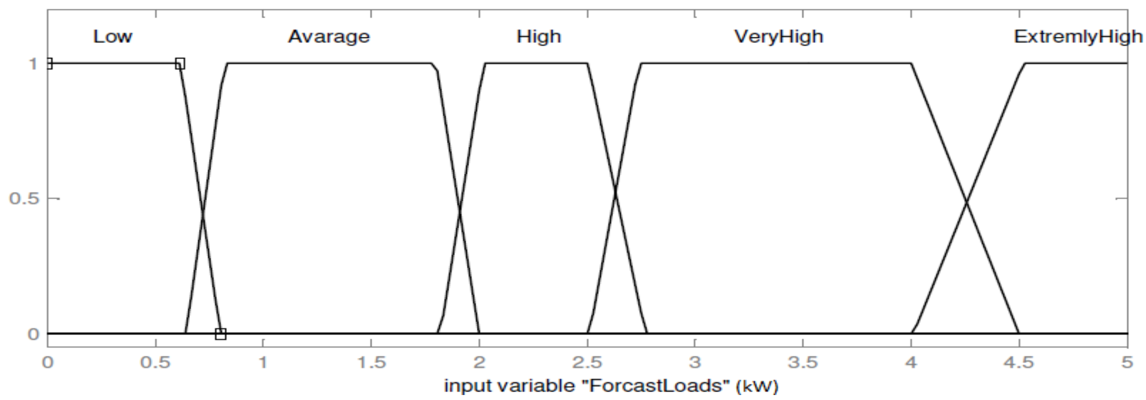



Figure 5.5 Fuzzy membership function of Forecast loads (input)

The Fuzzy load controller controls the appliances according to their defined consumption time settings. The load controller has a maximum 2.5 kW consumption limit during peak hours. It will not allow operating any appliance beyond 2.5 kW unless the duration of consumption is less than 16 minutes. For an example if a 1 kW coffee maker and a 1 kW of micro-oven operation time settings are less than 16 minutes and the current running load is 2 kW, the total forecast load will be 4 kW in that particular period of time. The fuzzy MCDM load controllers will allow consumer to operate the loads if the load consumptions time is less than 16 minutes. Figure 5.6 shows the membership function for the input variable "Consumption Time" in minutes.

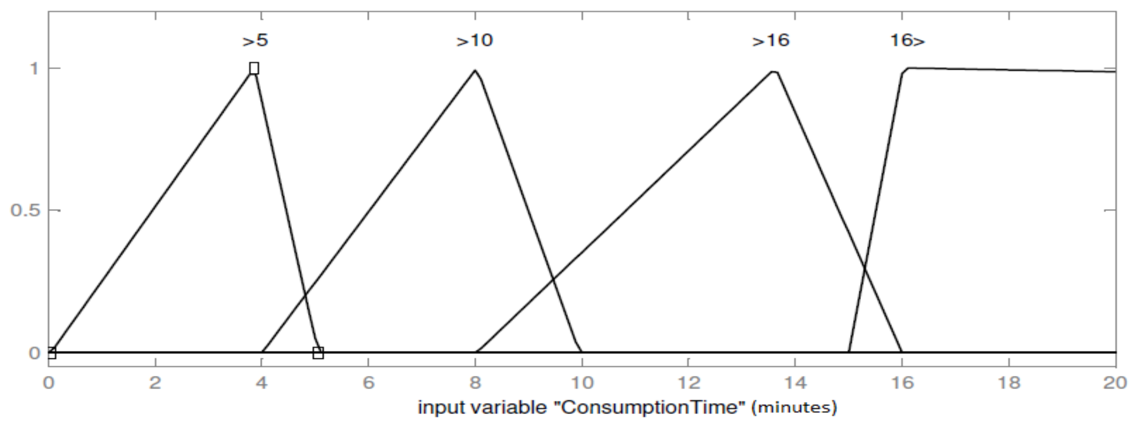



Figure 5.6 Fuzzy membership function for Consumption time (input).

Figure 5.7 shows the membership functions for the output variable "Allow Load Scheduling". The fuzzy load controller will schedule the loads to offpeak hours according to the forecast loads during peak hours. Here maximum 4.5 kW of loads can be scheduled to offpeak hours.

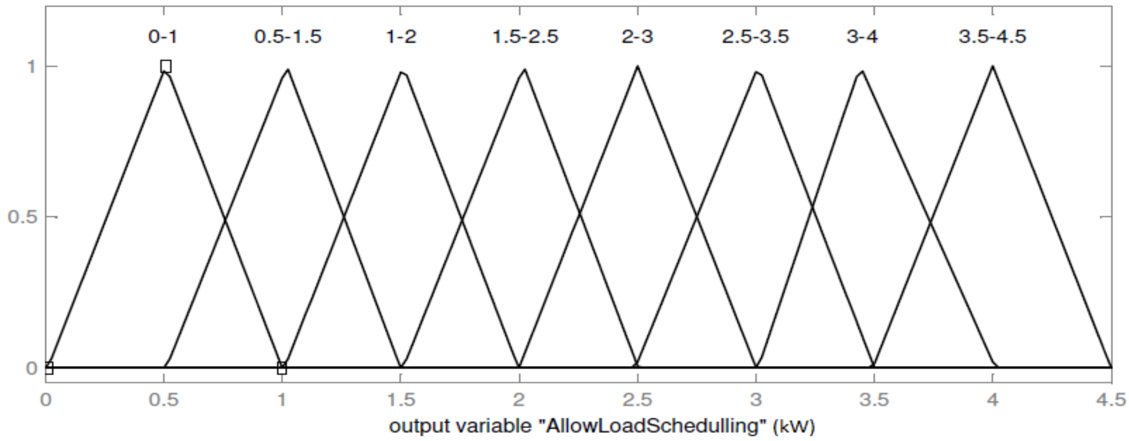



Figure 5.7 Fuzzy membership function of Allow load scheduling (output)

According to the forecast load consumption (kW), consumption duration (minutes), preferred room temperate setting (degree Celsius) and consumption time (peak/offpeak), the fuzzy MCDM load controller take decision which loads need to operate. The maximum consumption is allowed up to 5.5 KW with this load controller. Figure 5.8 shows the membership functions for the output variable “Run Loads” in kW.

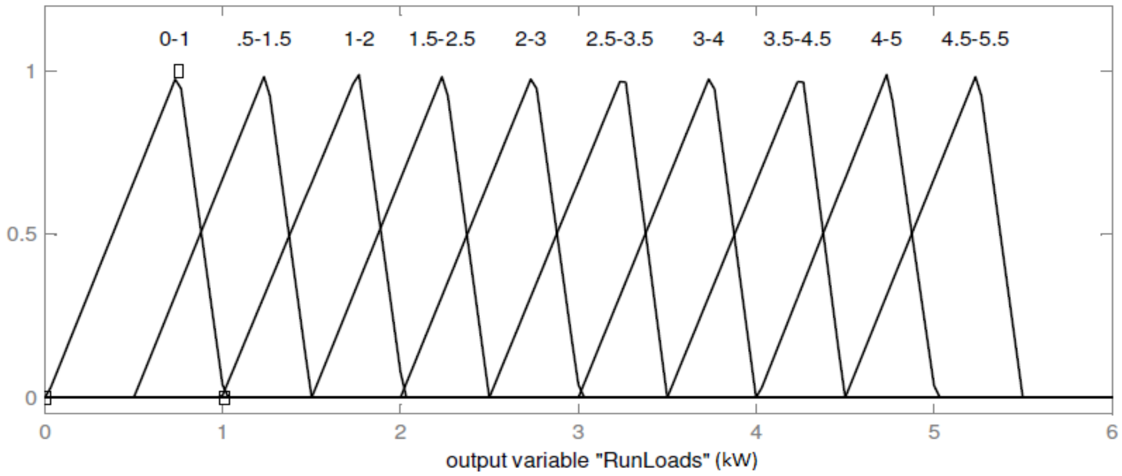



Figure 5.8 Fuzzy membership function of Run Load (output).

*3) Define Fuzzy Rules for the MCDM load controller*

Fuzzy rules form the vital part of the entire fuzzy *MCDM load controller system*. The number of rules framed depends on the number of membership functions considered in the input and output blocks. The more the rules the more precise is the *load controller* output.

Considering consumers' preferences and energy saving, constraints demand profile was obtained using 25 rules, 6 of them are listed below (rest of the rules can be found in Appendix).

***Rules:***

**1)** *If (Time is peak (pm)) and (comfortLevel is Cool, 14 to 18 degree) and (TemparatureDeviation is Large+) and (ForcastLoads is ExtremlyHigh, 4.5 kW>) and (ConsumptionTime is 16> minutes) then (AllowLoadSchedulling is 3 to 4 kW) (RunLoads is 1.5 to 2.5 kW).*

**2)** *If (Time is peak(am)) and (comfortLevel is Cool, 14 to 18 degree) and (TemparatureDeviation is Small) and (ForcastLoads is VeryHigh, 2.5 to 4.5 kW) and (ConsumptionTime is 16> minutes) then (AllowLoadSchedulling is 2.5 to 3.5 kW)(RunLoads is 0 to 1 kW).*

**3)** *If (Time is peak(am)) and (comfortLevel is Cool, 14 to 18 degree) and (TemparatureDeviation is Small) and (ForcastLoads is Avarage, 0.6 to 2 kW) and (ConsumptionTime is 16> minutes) then (AllowLoadSchedulling is 0 to 1 kW)(RunLoads is 0 to 1 kW).*

**4)** *If (Time is peak(pm)) and (comfortLevel is Avarage) and (TemparatureDeviation is Large-) and (ForcastLoads is VeryHigh, 2.5 to 4.5 kW) and (ConsumptionTime is 16> minutes) then (AllowLoadSchedulling is 1.5 to 2.5 kW)(RunLoads is 1.5 to 2.5 kW).*

**5)** *If (Time is offpeak(Moderate)) and (comfortLevel is Avarage) and (TemparatureDeviation is Large-) and (ForcastLoads is VeryHigh, 2.5 to 4.5 kW) and (ConsumptionTime is 16> minutes) then (AllowLoadSchedulling is 1 to 2 kW)(RunLoads is 1.5 to 2.5 kW).*

**6)** *If (Time is peak(am)) and (comfortLevel is Cool, 14 to 18 degree) and (TemparatureDeviation is Medium+) and (ForcastLoads is ExtremlyHigh, 4.5 kW>) and (ConsumptionTime is >10 minutes) then (AllowLoadSchedulling is 3to 4 kW)(RunLoads is 4to5 kW).*

*4) Simulate in Fuzzy logic system*

According to the fuzzy defined rules and the inputs specified by the consumers, the fuzzy MCDM load controller output results are shown in Table II. The load controller optimizes the loads that need to operate during peak hours in order to achieve consumer comfort level temperature and energy savings and shifts the nonpriority loads to off-peaks hours. In Figure 5.9 each column at the input side represents all the input variables with their selected values and other side shows the simulation results of the out variables. There are 6 rows which represented the 6 Fuzzy MCDM rules.

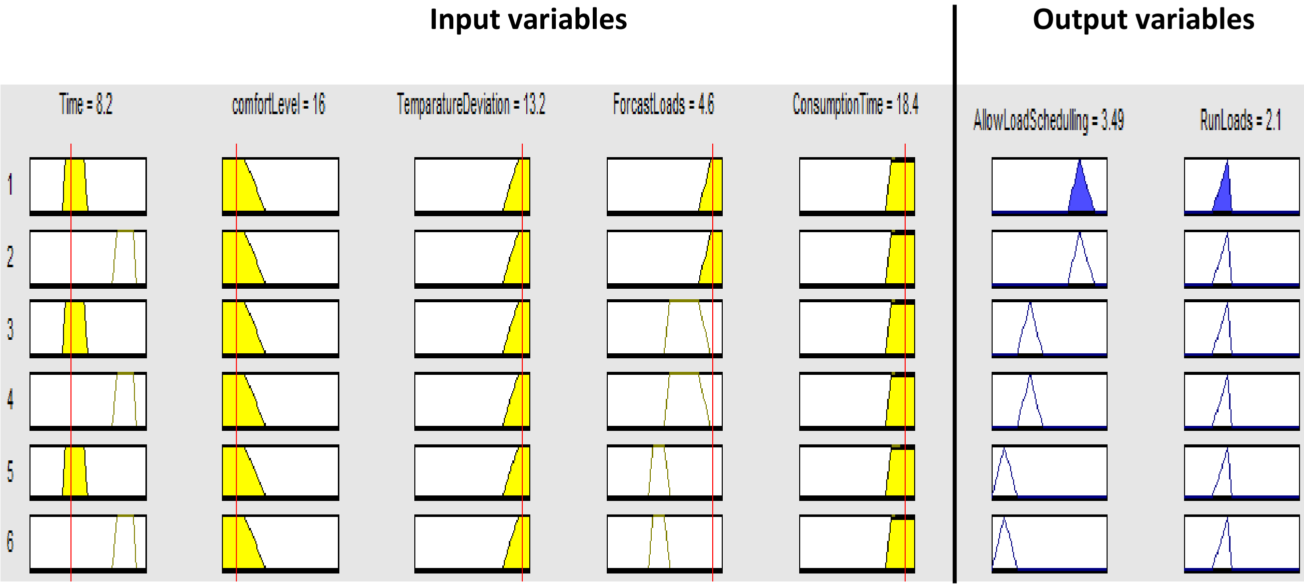


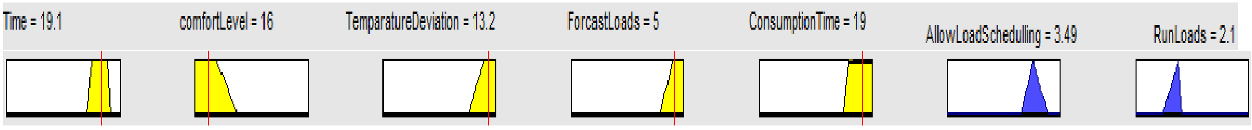

Figure 5.9 shows the simulation of fuzzy defined rules with input and output variables.

TABLE II FUZZY LOAD CONTROLLER RESULTS

| Rule no | Time | Comfort Level © | Temp deviation © | Forecast loads (KW) | Consumption time (mints) | AllowLoadScheduling (KW) | Run Loads (KW) |
|---|---|---|---|---|---|---|---|
| 1 | peak(am) | 16 | 13 | 5.5 | 16> | 3.5 | 2.1 |
| 2 | peak(pm) | 15 | 3 | 3.5 | 16> | 3 | 0.6 |
| 3 | peak(pm) | 17 | -2 | 1.1 | 16> | 0.5 | 0.6 |
| 4 | peak(am) | 22 | -12 | 3.6 | 16> | 2 | 2.1 |
| 5 | offpeak(am) | 21 | -10 | 3.5 | 16> | 1.5 | 2.1 |
| 6 | peak(pm) | 15 | 7 | 7.6 | >10 | 3.5 | 4.6 |

## 5.2 Simulation results analysis:

***1)** If (Time is peak (pm)) and (comfortLevel is Cool, 14 to 18 degree) and (TemparatureDeviation is Large+) and (ForcastLoads is ExtremlyHigh, 4.5 kW>) and (ConsumptionTime is 16> minutes) then (AllowLoadSchedulling is 3 to 4 kW) (RunLoads is 1.5 to 2.5 kW).*

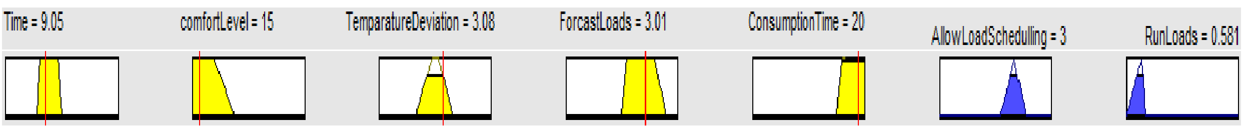



According to the first rule and the inputs specified by the consumer, the fuzzy MCDM load controller operated only 2.1 kW of loads during peak hours and scheduled 3.5 kW of loads to offpeak hours while the forecast load was more than 5.5 kW (including fixed loads). The fuzzy load controller operation according to the first rule is shown in Table III. It is observed that rule 1 imposed in fuzzy load controller, has achieved the consumer comfort temperature by allowing the AC to operate during peak hours and simultaneously reduced the load consumptions.

TABLE III LOAD OPTIMIZATION BY FUZZY RULE ($1^{st}$)

| Time | Forecast load (kW) | | Fixed load (kW) | | Loads run by Fuzzy controller (kW) | | Scheduled loads (kW) to offpeak hours | |
|---|---|---|---|---|---|---|---|---|
| Peak (pm) | AC (1) | 1.5 | Refrigerator(1) | 0.5 | AC (1) | 1.5 | Washing machine | 0.5 |
| | Washing machine | 0.5 | Others (light, fan, doorbell) | 0.1 | Fixed loads | 0.6 | Cloth dryer | 2.0 |
| | Cloth dryer | 2.0 | | | - | - | Dishwasher | 1.0 |
| | Dishwasher | 1.0 | - | - | - | - | | |
| | **Total** | **5.0** | **Total** | **0.60** | **Total** | **2.1** | **Total** | **3.5** |

***2)** If (Time is peak(am)) and (comfortLevel is Cool, 14 to 18 degree) and (TemparatureDeviation is Small) and (ForcastLoads is VeryHigh, 2.5 to 4.5 kW) and (ConsumptionTime is 16> minutes) then (AllowLoadSchedulling is 2.5 to 3.5 kW)(RunLoads is 0 to 1 kW).*



According to the second rule, when the load forecast was more than 3.5 kW (including fixed loads) during peak hours, the fuzzy controller operated only 0.6 kW of loads and scheduled 3.0 kW of loads to offpeak hours. Table IV shows the load operation by fuzzy load controller with rule 2.

TABLE IV LOAD OPTIMIZATION BY FUZZY RULE (2nd)

| Time | Forecast load (kW) | | Fixed load (kW) | | Loads run by Fuzzy controller (kW) | | Scheduled loads (kW) to offpeak hours | |
|---|---|---|---|---|---|---|---|---|
| **Peak (am)** | Cloth dryer | 2.0 | Refrigerator (1) | 0.5 | Fixed loads | 0.60 | Cloth dryer | 2.0 |
| | Dishwasher | 1.0 | Others (light, fan, doorbell) | 0.1 | - | - | Dishwasher | 1.0 |
| | **Total** | **3.0** | **Total** | **0.60** | **Total** | **0.60** | **Total** | **3.5** |

***3)*** *If (Time is peak(am)) and (comfortLevel is Cool, 14 to 18 degree) and (TemparatureDeviation is Small) and (ForcastLoads is Avarage, 0.6 to 2 kW) and (ConsumptionTime is 16> minutes) then (AllowLoadSchedulling is 0 to 1 kW)(RunLoads is 0 to 1 kW).*

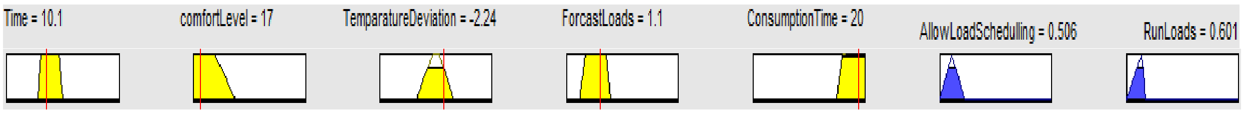



Table V shows the load operation by fuzzy controller according to the third rule. The forecast load was 1.1 kW including the fixed loads (0.6 kW) and load operated by the controller was 0.6 kW and scheduled 0.5 kW of washing machine to offpeak consumption.

TABLE V LOAD OPTIMIZATION BY FUZZY RULE (3rd)

| Time | Forecast load (kW) | | Fixed load (kW) | | Loads run by Fuzzy controller (kW) | | Scheduled loads (kW) to offpeak hours | |
|---|---|---|---|---|---|---|---|---|
| **Peak (am)** | Washing machine | 0.5 | Refrigerator (1) | 0.5 | Fixed loads | 0.60 | Washing machine | 0.5 |
| | - | - | Others (light, fan, doorbell) | 0.1 | - | - | - | - |
| | **Total** | **0.5** | **Total** | **0.60** | **Total** | **0.60** | **Total** | **0.5** |

*4) If (Time is peak(pm)) and (comfortLevel is Avarage) and (TemparatureDeviation is Large-) and (ForcastLoads is VeryHigh, 2.5 to 4.5 kW) and (ConsumptionTime is 16> minutes) then (AllowLoadSchedulling is 1.5 to 2.5 kW)(RunLoads is 1.5 to 2.5 kW).*

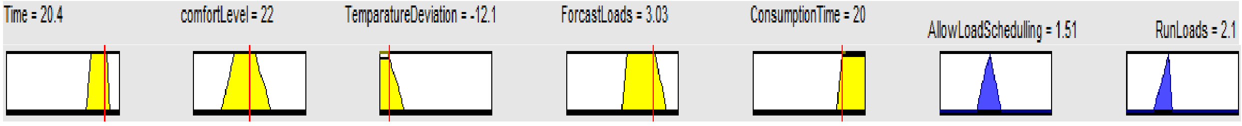



Table VI shows the load operation according to the forth fuzzy rule. Here forecast load demand is 3.6 kW including the fixed loads.

TABLE VI LOAD OPTIMIZATION BY FUZZY RULE (4th)

| Time | Forecast load (kW) | | Fixed load (kW) | | Loads run by Fuzzy controller (kW) | | Scheduled loads (kW) to offpeak hours | |
|---|---|---|---|---|---|---|---|---|
| **Peak (am)** | Washing machine | 0.5 | Refrigerator (1) | 0.5 | Fixed loads | 0.6 | Washing machine | 0.5 |
| | Room heater | 1.5 | Others (light, fan, doorbell) | 0.1 | Room heater | 1.5 | Dishwasher | 1.0 |
| | Dishwasher | 1.0 | - | - | - | - | - | - |
| | **Total** | **3.0** | **Total** | **0.60** | **Total** | **2.1** | **Total** | **1.5** |

*5) If (Time is offpeak(Moderate)) and (comfortLevel is Avarage) and (TemparatureDeviation is Large-) and (ForcastLoads is VeryHigh, 2.5 to 4.5 kW) and (ConsumptionTime is 16> minutes) then (AllowLoadSchedulling is 1 to 2 kW)(RunLoads is 1.5 to 2.5 kW).*

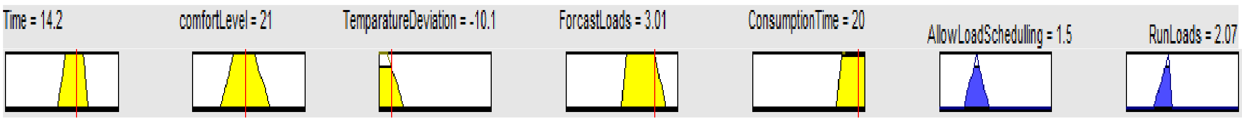



Table VII shows the load operation optimization by fuzzy load controller according to fifth fuzzy rule. Forecast load demand was 3.6 kW including the fixed loads. Fuzzy load controller operated the room heater during offpeak moderate hours in order to satisfy the consumer comfort temperature and shifted washing machine and dishwasher to offpeak hours.

TABLE VII LOAD OPTIMIZATION BY FUZZY RULE ($5^{th}$)

| Time | Forecast load (kW) | | Fixed load (kW) | | Loads run by Fuzzy controller (kW) | | Scheduled loads (kW) to offpeak hours | |
|---|---|---|---|---|---|---|---|---|
| ***Offpeak (Moderate)*** | Room heater | 1.5 | Refrigerator (1) | 0.5 | Fixed loads | 0.6 | Washing machine | 0.5 |
| | Washing machine | 0.5 | Others (light, fan,doorbell) | 0.1 | Room heater | 1.5 | Dishwasher | 1.0 |
| | Dishwasher | 1.0 | - | - | - | - | - | - |
| | **Total** | **3.0** | **Total** | **0.60** | **Total** | **2.1** | **Total** | **1.5** |

***6)*** *If (Time is peak(am)) and (comfortLevel is Cool, 14 to 18 degree) and (TemparatureDeviation is Medium+) and (ForcastLoads is ExtremlyHigh, 4.5 kW>) and (ConsumptionTime is >10 minutes) then (AllowLoadSchedulling is 3to 4 kW)(RunLoads is 4to5 kW).*

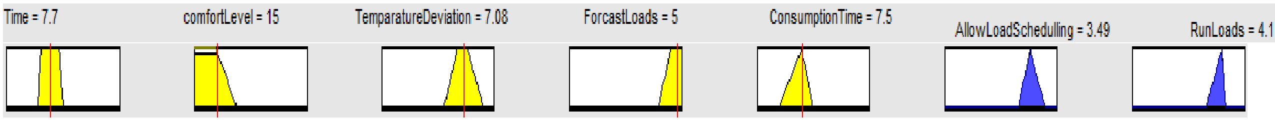



Table VIII shows the load operation by fuzzy load controller according to the sixth fuzzy rule. The forecast load was more than 5 kW (7.6 kW) including the fixed loads. The fuzzy load controller operated 4.1 kW of loads which actually exceeded the fuzzy load controller load operation limitation (2.5 kW). This is because of the load consumption duration was less than 8 minutes. According to the fuzzy sixth rule, fuzzy load controller will allow to operate more than 2.5 kW of loads if the load consumption time setting is less than 10 minutes.

TABLE VIII LOAD OPTIMIZATION BY FUZZY RULE (6th)

| Time | Forecast load (kW) | | Fixed load (kW) | | Loads run by Fuzzy controller (kW) | | Scheduled loads (kW) to offpeak hours | |
|---|---|---|---|---|---|---|---|---|
| Peak (am) | AC (1) | 1.5 | Refrigerator(1) | 0.5 | AC (1) | 1.5 | Washing machine | 0.5 |
| | Oven | 1.0 | Others (light, fan, doorbell) | 0.1 | Oven | 1.0 | Cloth dryer | 2.0 |
| | Coffee maker | 1.0 | - | - | Coffee maker | 1.0 | Dishwasher | 1.0 |
| | Washing machine | 0.5 | - | - | Fixed loads | 0.6 | - | - |
| | Cloth dryer | 2.0 | - | - | - | - | - | - |
| | Dishwasher | 1.0 | - | - | - | - | - | - |
| | **Total** | **7.0** | **Total** | **0.60** | **Total** | **4.1** | **Total** | **3.5** |

From the defined fuzzy rules and simulation results, it is observed that the intelligent fuzzy load controller achieved the consumer comfort (by turning on the AC or room heater) during peak hours and reduced the excessive load consumptions. It shifted the nonpriority loads (i.e. washing machine, dishwasher, clothe dryer, etc.) to the offpeak consumption and saved the high energy cost during peak hours. While maintaining the consumer comfort, the load controller always kept the load consumption below 2.5 kW during peak hours. Another intelligent approached of the fuzzy MCDM load controller: it allowed the consumer to exceed the predefined 2.5 kW demand limitation during peak hours when the load consumption duration setting was less than 10 minutes (showed in table VIII). This means, the fuzzy load controller only allows the consumer to operate oven, toaster, coffee makers and vacuum cleaner during peak hours if the consumption duration is less than 16 minutes. Therefore, the proposed fuzzy load controller not only prioritized the consumer preferences but also capable to take decision on behalf of the consumers in order to best manage the use of their appliances and met the main objective parameters- comfort, cost and demand response.

# CASE STUDY

A typical -two bed room house power consumption data in a summer time have been used for this experiment. Basic households appliances considered in this typical house are described in Table I. The house is fitted with photovoltaic (PV) panels and a battery system. The battery system will be charged by the photovoltaic (PV) power during the course of the day. It will be discharged during high cost periods when there is no photovoltaic power available. The specifications for the renewable sources of energy were set as follows:

- Two lithium-ion 100 A-H, 12 V batteries. The batteries have 80% deep discharge capacity and provide 2 discharge cycles per 24 hours and one bulk charge. There is a power loss of 20% through the battery charger/rectifier. Each battery provides 0.96 kW of power during 5 hours of discharge and charges by 0.288 kW of power during 5 hours of charge.

- 1.5 kW of PV system. This 1.5 kW system only produces just a touch over 1 kW of power at its peak. The PV system first charges the 2 batteries and rest of the energy contribute to the household appliances.

A daily consumption curve in typical summer day, battery charging/discharging and PV power generation curves are shown in figure 5.10. It shows that the two batteries are discharging from 1am to 5 am and 6 pm to 10 pm at 0.192 kW/hour of each, and both of them are charging from 11 am to 3 pm at 0.576 kW/hour. There are two critical peak demands that occurred during peak hours from 9 am to 11 am and 6 pm to 9 pm. The PV output was maximum during the midday.

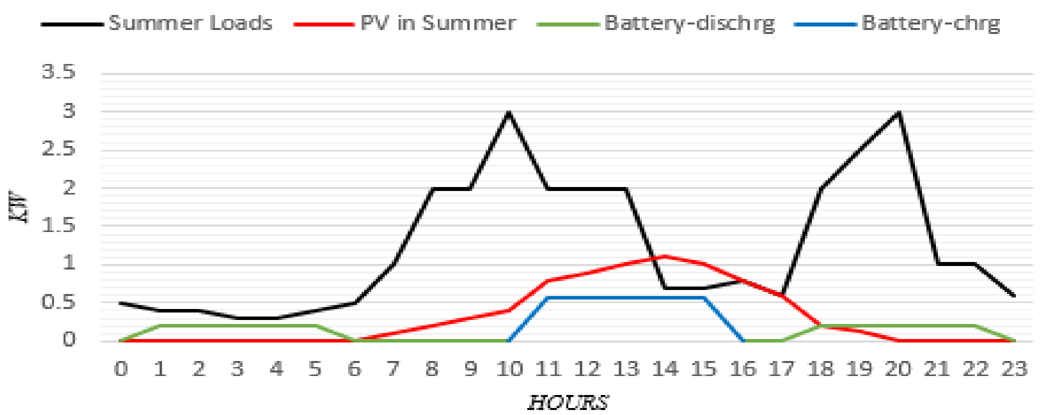



Figure 5.10 Daily consumptions curve

The load curves before and after the contribution of PV and battery storage systems are shown in figure 5.11. Load priority was performed with the fuzzy MCDM load controller and results are shown in Fig. 12. The load controller took advantage of the hours of the day when there were peak hours; it reduced the high consumption by predefined fuzzy rules and scheduled the nonpriority loads to their respective time. It is clear from figure 5.12 that the peaks of the load profile of the household was reduced significantly and shifted to low demand periods (see Table X in appendix for details information).

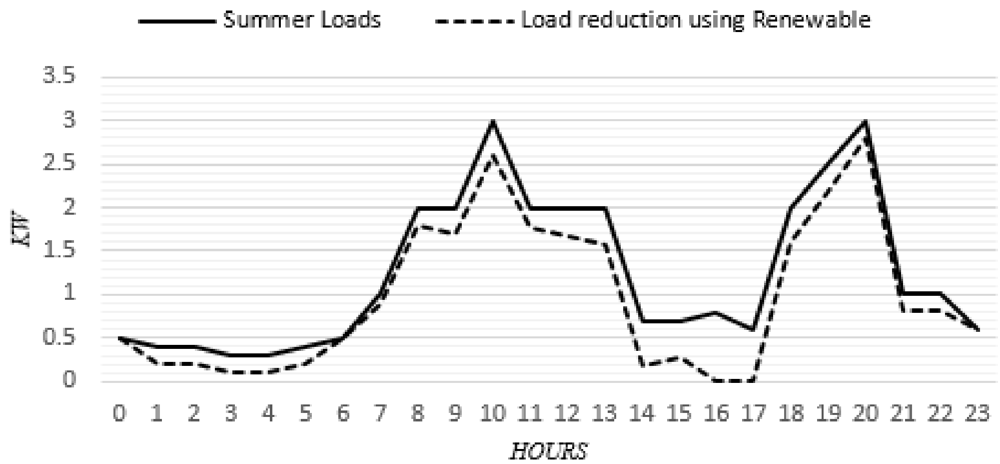



Figure 5.11  Load reduction using renewable energy

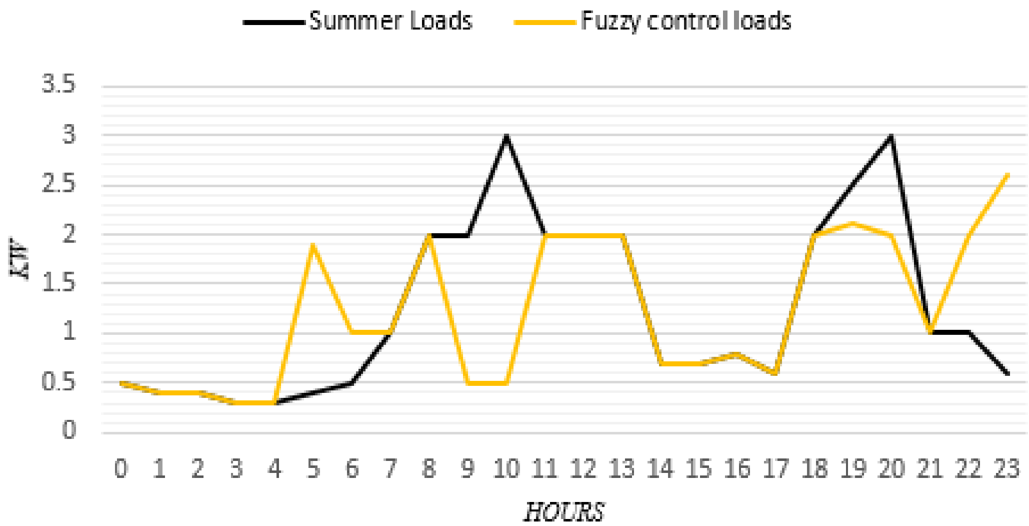



Figure 5.12  Results obtained with fuzzy load controller

Table IX and figure 5.13 present the comparative analysis of integration of different load control techniques to evaluate the power consumption performance. In this experiment direct load control (DLC) was used to switch off the air conditioner (1.5kW) when it operated during peak hours. Figure 5.13, shows that combined operation of renewable energy sources with fuzzy MCDM load controller presented better performance compared to direct load control (DLC), it provided adequate energy savings without compromising consumers comfort level. The different tariffs [28] for consumption of energy were used to analyse the total cost of energy consumption for the different load management criteria and results are summarized in Table IX (see Table XI in appendix for details information).

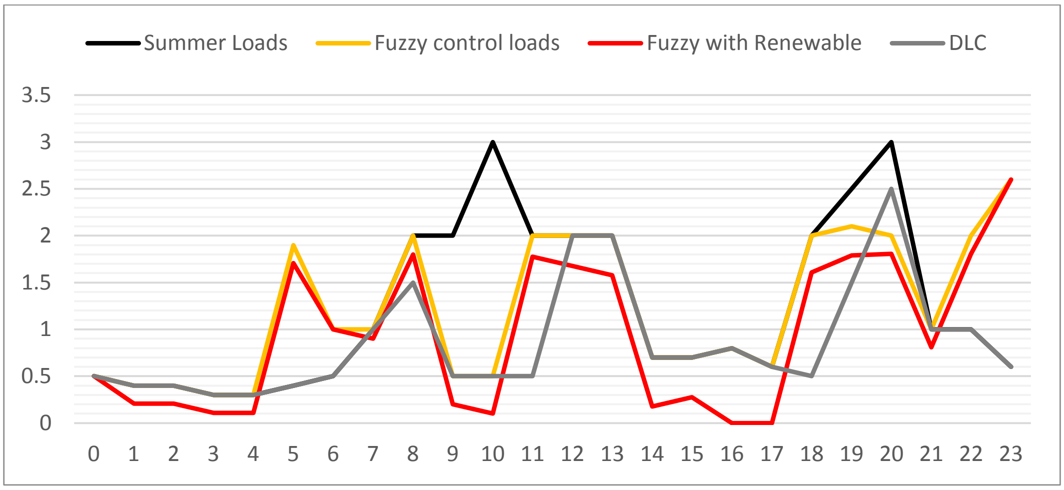



Figure 5.13 Comparison between different load controllers

TABLE I X Energy Consumption and Cost Comparison Analysis

| | Energy Cost($/kWh) | NML (kWh) | NML Cost ($) | DLC (kWh) | DLC Cost($) | LMR (kWh) | LMR Cost($) | LMF (kWh) | LMF Cost($) | LMFR (kWh) | LMFR Cost($) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Off-peak time** | 0.1514 | 4.4 | 0.67 | 4.4 | 0.67 | 3.248 | 0.49 | 9.4 | 1.42 | 8.248 | 1.25 |
| **Moderate time** | 0.2652 | 6.2 | 1.64 | 6.2 | 1.64 | 3.704 | 0.98 | 6.2 | 1.64 | 3.704 | 0.98 |
| **Peak time** | 0.4981 | 19.1 | 9.51 | 10.1 | 5.03 | 16.19 | 8.06 | 13.7 | 6.82 | 10.79 | 5.37 |
| **Total** | - | **29.7** | **11.82** | **20.7** | **7.34** | **23.1** | **9.53** | **29.3** | **9.89** | **22.74** | **7.60** |
| **% of energy saving/day** | - | - | - | **30.3** | - | **22.2** | - | **1.34** | - | **23.4** | - |
| **Cost saved/day** | - | - | - | - | **4.483** | - | **2.29** | - | **1.93** | - | **4.22** |

NML = non managed loads (kWh), DLC = direct load control (kWh), LMR = load management with renewable (kWh), LMF = load management with fuzzy (KWh), LMFR = load management with fuzzy logic and renewable (kWh).

The results presented in Table IX, shows the total load consumptions and cost of Energy during different time periods (peak, offpeak-moderate and offpeak hours) in a particular day obtained from different load management techniques (NML, DLC, LMR, LMF and LMFR). With NML (Non Managed Load) the total energy consumption and cost of consumption were 29.7 kWh and $11.82 per day. Whereas the cheapest consumption price ($ 7.34) was obtained with direct load control with minimum consumptions of 20.7 kWh. With the proposed fuzzy MCDM load controller (LMF) the energy consumption during the day was 29.3 kWh and energy cost was $9.89.

Direct load control (DLC) performed significant energy and cost reduction. The proposed fuzzy load controller (LMF) contributed small amount of energy reduction 1.34%, compare to direct load control which was 35.3%. The energy reduction was less compare to DLC because of the fuzzy load controller allowed the consumers to operate the air conditioner during peak hours to achieve their comfort and it shifted the nonpriority loads to offpeak consumptions. However with DLC the consumer comfort level and preferences were violated due to switch off of the air conditioner during peaks hours.

The results obtained with combined operation of Fuzzy load controller and Renewable sources (LMFR) shows the better management of load reductions (23.4%) with adequate cost savings ($4.22/day) compared to the load management with renewable sources (LMR) which were 22.1 kWh and $2.28 per day. Figure 5.14 shows the comparison of the energy cost per hour during the day between Non Management Load controller (NML), Load management with Fuzzy load controller and Renewable source (LMRF) and Direct Load Control (DLC). It shows that non-management load has highest energy cost per hour.

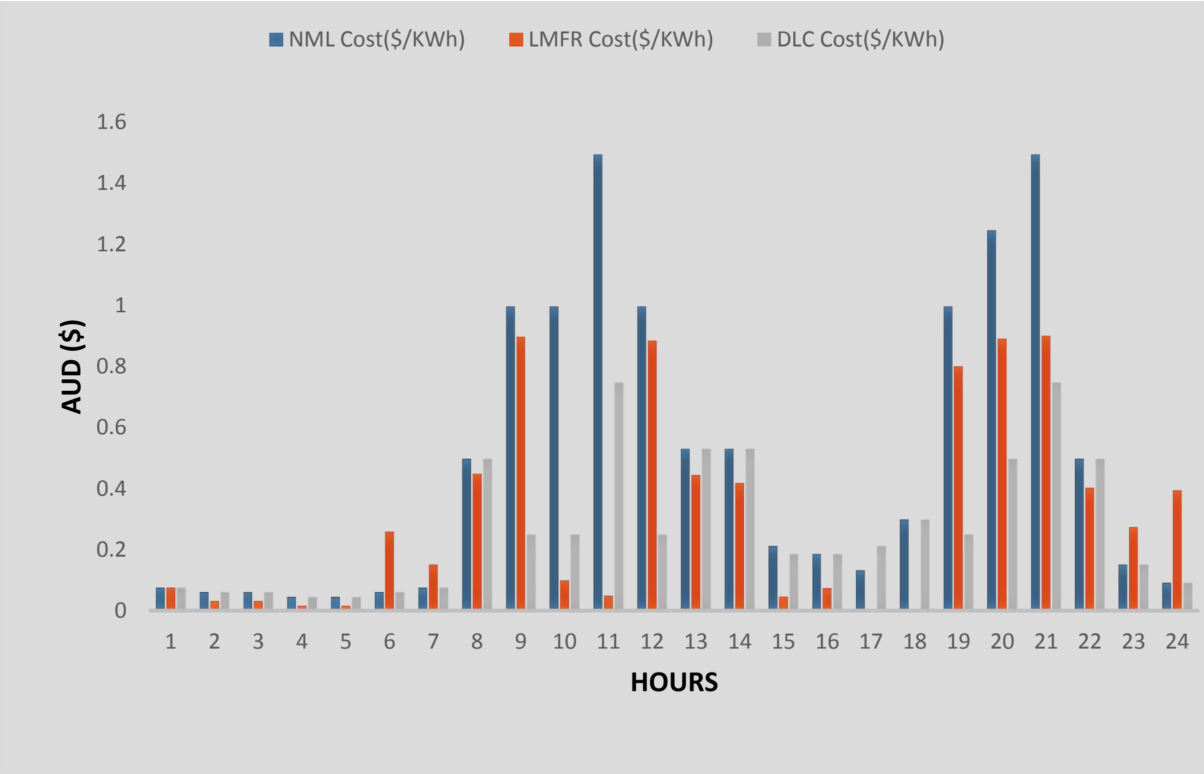



Figure 5.14 Energy cost comparison between Non-management Load (NML), Load management with Renewable and Fuzzy (LMRF) and Direct Load control (DLC).

# CHAPTER 6

## DISCUSSION AND *CONCLUSION*

The main aim of this thesis is to present a methodology to achieve Demand Side Management by using intelligent decision supporting residential energy management system. The developed fuzzy Multi Criteria Decision Making (MCDM) load controller for home energy management satisfied three optimization strategies – comfort, cost, and demand response. The load controller mitigates the excessive consumptions when the energy consumptions prices are very high without any adverse impact on consumers' comfort level. From the simulation results it can be seen that load management with intelligent fuzzy MCDM load controller 1.34% of energy reduction and $2 of energy cost saving is possible per day without affecting consumer comfort.

Energy reduction and cost saving are more intensive with the load management with fuzzy MCDM load control and renewable sources (LMFR) which reduced almost 18 times higher energy compared to load management with fuzzy MCDM load controller (LMF) alone. If the costs are compared, the fuzzy MCDM load control and renewable sources (LMFR) saved more than twice of the energy cost saved by the fuzzy MCDM load controller (LMF). Therefore, it can be concluded that load management with the fuzzy MCDM load control and renewable sources is the best choice.

# APPENDIX

**Fuzzy Rules:**

1. If (Time is peak(am)) and (comfortLevel is Cool) and (TemparatureDeviation is Large+) and (ForcastLoads is ExtremlyHigh) and (ConsumptionTime is 16>) then (AllowLoadSchedulling is 3-4)(RunLoads is 1.5-2.5).

2. If (Time is peak(pm)) and (comfortLevel is Cool) and (TemparatureDeviation is Large+) and (ForcastLoads is ExtremlyHigh) and (ConsumptionTime is 16>) then (AllowLoadSchedulling is 3-4)(RunLoads is 1.5-2.5).

3. If (Time is peak(am)) and (comfortLevel is Cool) and (TemparatureDeviation is Large+) and (ForcastLoads is VeryHigh) and (ConsumptionTime is 16>) then (AllowLoadSchedulling is 1-2)(RunLoads is 1.5-2.5).

4. If (Time is peak(pm)) and (comfortLevel is Cool) and (TemparatureDeviation is Large+) and (ForcastLoads is VeryHigh) and (ConsumptionTime is 16>) then (AllowLoadSchedulling is 1-2)(RunLoads is 1.5-2.5).

5. If (Time is peak(am)) and (comfortLevel is Cool) and (TemparatureDeviation is Large+) and (ForcastLoads is High) and (ConsumptionTime is 16>) then (AllowLoadSchedulling is 0-1)(RunLoads is 1.5-2.5).

6. If (Time is peak(pm)) and (comfortLevel is Cool) and (TemparatureDeviation is Large+) and (ForcastLoads is High) and (ConsumptionTime is 16>) then (AllowLoadSchedulling is 0-1)(RunLoads is 1.5-2.5).

7. If (Time is peak(am)) and (comfortLevel is Cool) and (TemparatureDeviation is Small) and (ForcastLoads is VeryHigh) and (ConsumptionTime is 16>) then (AllowLoadSchedulling is 2.5-3.5)(RunLoads is 0-1).

8. If (Time is peak(pm)) and (comfortLevel is Cool) and (TemparatureDeviation is Small) and (ForcastLoads is VeryHigh) and (ConsumptionTime is 16>) then (AllowLoadSchedulling is 2.5-3.5)(RunLoads is .5-1.5).

9. If (Time is peak(am)) and (comfortLevel is Cool) and (TemparatureDeviation is Small) and (ForcastLoads is Avarage) and (ConsumptionTime is 16>) then (AllowLoadSchedulling is 0-1)(RunLoads is 0-1).

10. If (Time is peak(pm)) and (comfortLevel is Cool) and (TemparatureDeviation is Small) and (ForcastLoads is Avarage) and (ConsumptionTime is 16>) then (AllowLoadSchedulling is 0-1)(RunLoads is 0-1).

11. If (Time is peak(am)) and (comfortLevel is Cool) and (TemparatureDeviation is Small) and (ForcastLoads is Low) and (ConsumptionTime is 16>) then (RunLoads is 0-1).

12. If (Time is offpeak(am)) and (comfortLevel is Cool) and (TemparatureDeviation is Large+) and (ForcastLoads is Avarage) and (ConsumptionTime is 16>) then (RunLoads is 3-4).

13. If (Time is offpeak(am)) and (comfortLevel is Cool) and (TemparatureDeviation is Small) and (ForcastLoads is Low) and (ConsumptionTime is 16>) then (RunLoads is 4-5).

14. If (Time is offpeak(Moderate)) and (comfortLevel is Cool) and (TemparatureDeviation is Large+) and (ForcastLoads is ExtremlyHigh) and (ConsumptionTime is 16>) then (AllowLoadSchedulling is 3-4)(RunLoads is 1.5-2.5).

15. If (Time is offpeak(Moderate)) and (comfortLevel is Cool) and (TemparatureDeviation is Large+) and (ForcastLoads is Avarage) and (ConsumptionTime is 16>) then (AllowLoadSchedulling is 1-2)(RunLoads is 1.5-2.5).

16. If (Time is offpeak(Moderate)) and (comfortLevel is Cool) and (TemparatureDeviation is Small) and (ForcastLoads is Low) and (ConsumptionTime is 16>) then (RunLoads is .5-1.5).

17. If (Time is peak(pm)) and (comfortLevel is Avarage) and (TemparatureDeviation is Large-) and (ForcastLoads is VeryHigh) and (ConsumptionTime is 16>) then (AllowLoadSchedulling is 1-2)(RunLoads is 1.5-2.5).

18. If (Time is peak(pm)) and (comfortLevel is Avarage) and (TemparatureDeviation is Large-) and (ForcastLoads is High) and (ConsumptionTime is 16>) then (RunLoads is 1.5-2.5).

19. If (Time is peak(pm)) and (comfortLevel is Avarage) and (TemparatureDeviation is Small) and (ForcastLoads is Low) and (ConsumptionTime is 16>) then (RunLoads is .5-1.5).

20. If (Time is offpeak(Moderate)) and (comfortLevel is Avarage) and (TemparatureDeviation is Large-) and (ForcastLoads is ExtremlyHigh) and (ConsumptionTime is 16>) then (AllowLoadSchedulling is 3.5-4.5)(RunLoads is 1.5-2.5).

21. If (Time is offpeak(Moderate)) and (comfortLevel is Avarage) and (TemparatureDeviation is Large-) and (ForcastLoads is VeryHigh) and (ConsumptionTime is 16>) then (AllowLoadSchedulling is 1-2)(RunLoads is 1.5-2.5).

22. If (Time is offpeak(Moderate)) and (comfortLevel is Avarage) and (TemparatureDeviation is Small) and (ForcastLoads is Low) and (ConsumptionTime is 16>) then (RunLoads is .5-1.5).

23. If (Time is peak(am)) and (comfortLevel is Warm) and (TemparatureDeviation is Medium-) and (ForcastLoads is ExtremlyHigh) and (ConsumptionTime is >5) then (AllowLoadSchedulling is 3-4)(RunLoads is 4.5-5.5).

24. If (Time is peak(am)) and (comfortLevel is Cool) and (TemparatureDeviation is Medium+) and (ForcastLoads is ExtremlyHigh) and (ConsumptionTime is >10) then (AllowLoadSchedulling is 3-4)(RunLoads is 3.5-4.5).

25. If (Time is peak(pm)) and (comfortLevel is Cool) and (TemparatureDeviation is Large+) and (ForcastLoads is ExtremlyHigh) and (ConsumptionTime is >16) then (AllowLoadSchedulling is 3-4)(RunLoads is 2.5-3.5).

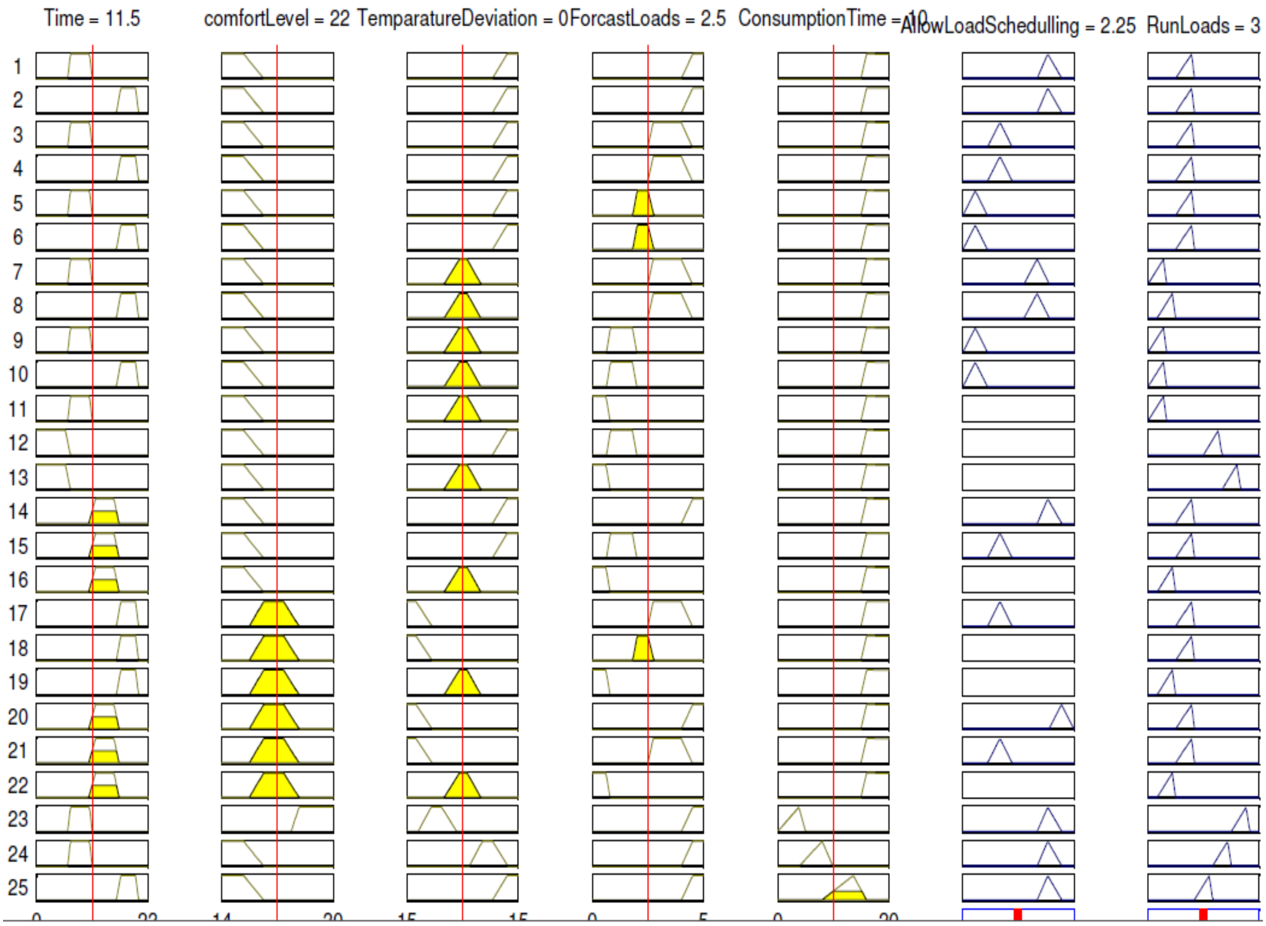



Figure 6.1 Fuzzy rules simulation with Mathlab

TABLE X 24 HOURS ENERGY CONSUMPTION AND GENERATION

| Day-hr | Summer Loads | PV in Summer | Battery-chg/dis | PV and Battery | Load reduction with Renewable | Fuzzy control loads | Fuzzy with Renewable | Load shifting using Fuzzy+R | DLC |
|---|---|---|---|---|---|---|---|---|---|
| 0 | 0.5 | 0 | 0 | 0 | 0.5 | 0.5 | 0.5 | 0 | 0.5 |
| 1 | 0.4 | 0 | 0.192 | 0.192 | 0.208 | 0.4 | 0.208 | 0.192 | 0.4 |
| 2 | 0.4 | 0 | 0.192 | 0.192 | 0.208 | 0.4 | 0.208 | 0.192 | 0.4 |
| 3 | 0.3 | 0 | 0.192 | 0.192 | 0.108 | 0.3 | 0.108 | 0.192 | 0.3 |
| 4 | 0.3 | 0 | 0.192 | 0.192 | 0.108 | 0.3 | 0.108 | 0.192 | 0.3 |
| 5 | 0.4 | 0 | 0.192 | 0.192 | 0.208 | 1.9 | 1.708 | -1.308 | 0.4 |
| 6 | 0.5 | 0 | 0 | 0 | 0.5 | 1 | 1 | -0.5 | 0.5 |
| 7 | 1 | 0.1 | 0 | 0.1 | 0.9 | 1 | 0.9 | 0.1 | 1 |
| 8 | 2 | 0.2 | 0 | 0.2 | 1.8 | 2 | 1.8 | 0.2 | 1.5 |
| 9 | 2 | 0.3 | 0 | 0.3 | 1.7 | 0.5 | 0.2 | 1.8 | 0.5 |
| 10 | 3 | 0.4 | 0 | 0.4 | 2.6 | 0.5 | 0.1 | 2.9 | 0.5 |
| 11 | 2 | 0.8 | 0.576 | 0.224 | 1.776 | 2 | 1.776 | 0.224 | 0.5 |
| 12 | 2 | 0.9 | 0.576 | 0.324 | 1.676 | 2 | 1.676 | 0.324 | 2 |
| 13 | 2 | 1 | 0.576 | 0.424 | 1.576 | 2 | 1.576 | 0.424 | 2 |
| 14 | 0.7 | 1.1 | 0.576 | 0.524 | 0.176 | 0.7 | 0.176 | 0.524 | 0.7 |
| 15 | 0.7 | 1 | 0.576 | 0.424 | 0.276 | 0.7 | 0.276 | 0.424 | 0.7 |
| 16 | 0.8 | 0.8 | 0 | 0.8 | 0 | 0.8 | 0 | 0.8 | 0.8 |
| 17 | 0.6 | 0.6 | 0 | 0.6 | 0 | 0.6 | 0 | 0.6 | 0.6 |
| 18 | 2 | 0.2 | 0.192 | 0.392 | 1.608 | 2 | 1.608 | 0.392 | 0.5 |
| 19 | 2.5 | 0.12 | 0.192 | 0.312 | 2.188 | 2.1 | 1.788 | 0.712 | 1.5 |
| 20 | 3 | 0 | 0.192 | 0.192 | 2.808 | 2 | 1.808 | 1.192 | 2.5 |
| 21 | 1 | 0 | 0.192 | 0.192 | 0.808 | 1 | 0.808 | 0.192 | 1 |
| 22 | 1 | 0 | 0.192 | 0.192 | 0.808 | 2 | 1.808 | -0.808 | 1 |
| 23 | 0.6 | 0 | 0 | 0 | 0.6 | 2.6 | 2.6 | -2 | 0.6 |
| Total | 29.7 | 7.52 | -0.96 | 6.56 | 23.14 | 29.3 | 22.74 | 6.96 | 20.7 |

From the Table X,

1st column represents the hours of the day,

2nd column shows the load consumption in a typical summer day (kW),

3rd column shows 1.5 kW PV system output during the day (kW),

4th column shows two 12 V, 100 AH batteries charging and discharging cycles (kW),

5th column shows combined generation of PV and batteries (kW),

6th column shows load reduction with renewable source = (summer load –combined output of PV and batteries) kW,

7th column shows Fuzzy load control loads = the fuzzy load controller shifted the high peak hours loadings to offpeak hours,

8th column shows load reduction with Fuzzy load controller and renewable sources = (summer load - fuzzy control load - PV and battery production) kW, 9th column shows load shifting with fuzzy load control and renewable sources which means the total amount of loads (kW) that are reduced with fuzzy load controller, PV and batteries,

10th column shows the remaining loads after Direct Load control. Here DLC used to switch off the 1.5 kW of air conditioner during peak hours.

TABLE XI ENERGY COST ANALYSIS WITH DIFFERENT LOAD CONTROLLERS

| Day-hr | Summer Loads | Cost(Cents/KW) | Cost(Cents/KW) | Fuzzy control loads | Cost(Cents/KW) | Fuzzy with Renewable | Cost(Cents/KW) | Load with Renewable | Cost(Cents/KW) | DLC | Cost(Cents/KW) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 0.5 | 15.1415 | 7.57075 | 0.5 | 7.57075 | 0.5 | 7.57075 | 0.5 | 7.57075 | 0.5 | 7.57075 |
| 1 | 0.4 | 15.1415 | 6.0566 | 0.4 | 6.0566 | 0.208 | 3.149432 | 0.208 | 3.149432 | 0.4 | 6.0566 |
| 2 | 0.4 | 15.1415 | 6.0566 | 0.4 | 6.0566 | 0.208 | 3.149432 | 0.208 | 3.149432 | 0.4 | 6.0566 |
| 3 | 0.3 | 15.1415 | 4.54245 | 0.3 | 4.54245 | 0.108 | 1.635282 | 0.108 | 1.635282 | 0.3 | 4.54245 |
| 4 | 0.3 | 15.1415 | 4.54245 | 0.3 | 4.54245 | 0.108 | 1.635282 | 0.108 | 1.635282 | 0.3 | 4.54245 |
| 5 | 0.4 | 15.1415 | 6.0566 | 1.9 | 28.76885 | 1.708 | 25.861682 | 0.208 | 3.149432 | 0.4 | 6.0566 |
| 6 | 0.5 | 15.1415 | 7.57075 | 1 | 15.1415 | 1 | 15.1415 | 0.5 | 7.57075 | 0.5 | 7.57075 |
| 7 | 1 | 49.8154 | 49.8154 | 1 | 49.8154 | 0.9 | 44.83386 | 0.9 | 44.83386 | 1 | 49.8154 |
| 8 | 2 | 49.8154 | 99.6308 | 2 | 99.6308 | 1.8 | 89.66772 | 1.8 | 89.66772 | 1.5 | 74.7231 |
| 9 | 2 | 49.8154 | 99.6308 | 0.5 | 24.9077 | 0.2 | 9.96308 | 1.7 | 84.68618 | 0.5 | 24.9077 |
| 10 | 3 | 49.8154 | 149.4462 | 0.5 | 24.9077 | 0.1 | 4.98154 | 2.6 | 129.52004 | 0.5 | 24.9077 |
| 11 | 2 | 49.8154 | 99.6308 | 2 | 99.6308 | 1.776 | 88.4721504 | 1.776 | 88.4721504 | 0.5 | 24.9077 |
| 12 | 2 | 26.525 | 53.05 | 2 | 53.05 | 1.676 | 44.4559 | 1.676 | 44.4559 | 2 | 53.05 |
| 13 | 2 | 26.525 | 53.05 | 2 | 53.05 | 1.576 | 41.8034 | 1.576 | 41.8034 | 2 | 53.05 |
| 14 | 0.8 | 26.525 | 21.22 | 0.7 | 18.5675 | 0.176 | 4.6684 | 0.176 | 4.6684 | 0.7 | 18.5675 |
| 15 | 0.7 | 26.525 | 18.5675 | 0.7 | 18.5675 | 0.276 | 7.3209 | 0.276 | 7.3209 | 0.7 | 18.5675 |
| 16 | 0.5 | 26.525 | 13.2625 | 0.8 | 21.22 | 0 | 0 | 0 | 0 | 0.8 | 21.22 |
| 17 | 0.6 | 49.8154 | 29.88924 | 0.6 | 29.88924 | 0 | 0 | 0 | 0 | 0.6 | 29.88924 |
| 18 | 2 | 49.8154 | 99.6308 | 2 | 99.6308 | 1.608 | 80.1031632 | 1.608 | 80.1031632 | 0.5 | 24.9077 |
| 19 | 2.5 | 49.8154 | 124.5385 | 2.1 | 104.61234 | 1.788 | 89.0699352 | 2.188 | 108.9960952 | 1.5 | 74.7231 |
| 20 | 3 | 49.8154 | 149.4462 | 2 | 99.6308 | 1.808 | 90.0662432 | 2.808 | 139.8816432 | 2.5 | 124.5385 |
| 21 | 1 | 49.8154 | 49.8154 | 1 | 49.8154 | 0.808 | 40.2508432 | 0.808 | 40.2508432 | 1 | 49.8154 |
| 22 | 1 | 15.1415 | 15.1415 | 2 | 30.283 | 1.808 | 27.375832 | 0.808 | 12.234332 | 1 | 15.1415 |
| 23 | 0.6 | 15.1415 | 9.0849 | 2.6 | 39.3679 | 2.6 | 39.3679 | 0.6 | 9.0849 | 0.6 | 9.0849 |
| Total | 29.5 | | 1177.24674 | 29.3 | 989.25608 | 22.74 | 760.5442272 | 23.14 | 953.8398872 | 20.7 | 734.21314 |

<u>From the Table XI,</u>

1st column represents the hours of the day,

2nd column shows the load consumption in a typical summer day (kW),

3rd column shows the peak and offpeak hours energy cost (cents/kW) determined by Synergy energy company in Australia,

4th column shows the hourly cost for the summer loads consumption (cents/kW), 5th column shows Fuzzy load control loads = the fuzzy load controller shifted the high peak hours loadings to offpeak hours ,

6th column shows the hourly cost for the loads consumption with fuzzy load controller,

7th column shows load reduction with Fuzzy load controller and renewable sources = (summer load - fuzzy control load - PV and battery production) kW,

8th column shows the hourly cost for the load consumptions with Fuzzy load controller and renewable sources (cents/kW),

9th column shows load reduction with renewable source = (summer load –combined output of PV and batteries) kW,

10th column shows the hourly cost for the load consumptions with renewable source s(cents/kW),

11th column shows the remaining loads after Direct Load control (kW).

12th column shows the hourly cost for the load consumptions with Direct Load control (cents/kW).

# *REFERENCES*


| | |
|---|---|
| [1] | M. E. Rudd, D. Popa. (). “*Steven’s brightness law, contrast gain control and edge integration in achromatic colour perception: A unified model*,” *J. Opt Soc. Amer.*, vol. 23, no. 9, 2007, pp. 2766–2782. |
| [2] | C. D. Courter. (2005). “*How bright is moonlight”*? Retrieved from : http://home.earthlink.net/~kitathome/LunarLight/moonlight/gallery/technique/moonbright.htm |
| [3] | D. Keane, R. Cruz, and M. J. Sullivan. “*Can dispatchable pricing options be used to delay distribution investments? Some empirical evidence*,” in *Proc. Load Management: Dynamic DSM Options for the Future, Electric Power Research Institute*, May, 1994 |
| [4] | *“How Much Power Do Your Appliances Use?”* (Accessed this document on March 20, 2014). *Retrieved from :* http://www.wholesalesolar.com/StartHere/HowtoSaveEnergy/PowerTable.html |
| [5] | "*Regulatory Commission Survey On Demand Response And Time Based Rate Programs/ Tariffs*"; (August 2006). *Retrieved from:* www. FERC. Gov. |
| [6] | H. Yang, Y. Zhang, X. Tong. *“System Dynamics Model for Demand Side Management”; 3rd International Conference 6n Electrical and Electronics Engineering, 2006, pp. 1-4.* |
| [7] | *“Ameren Illinois Real Time Prices*”; (document accessed on March 21, 2014). *Retrieved from:* https://www2.ameren.com/RetailEnergy/realtimeprices.aspx, accessed: 06-Feb-2011. |
| [8] | A. Iwayemi, P. Yi. *“Knowing When to Act: An Optimal Stopping Method for Smart Grid Demand Response”;* IEEE Journal & Magazine, October 2010. Vol.25, pp. 44 - 49. |
| [9] | P. Ravibabu, A. Praveen. *“An approach of DSM Techniques for Domestic Load Management using Fuzzy Logic*; IEEE International Conference on Fuzzy logic, 2009, pp. 1303-1307. |
| [10] | Technical Task Force of Load Management Sub-committee. “*LMITS-Load management innovative techniques*”; IEEE Trans. Power App. Syst. Vol.2 PAS-103, July 1984, pp. 1732-1738. |
| [11] | Dr.G.Thomas, P. Bellarmine. “*Load Management Techniques*”; Proceedings of the IEEE on Southeastcon, 2000, pp. 139-145. |
| [12] | W. Gellings, H. Chamberlin. “*Demand-Side Management: Concepts and Methods*” Text book published by The Fairmont Press, Victoria, Canada, January 1993. |
| [13] | P.Ravi Babu. “*DSM Techniques and Fuzzy Logic Application to an Air Conditioner- a case study*”, 8th WSEAS, Power Systems, Spain, Sept, 2008, pp. 291-298,. |
| [14] | O.A.Sianaki, O. Hussain, T. Dillon, A.R. Tabesh. ”Intelligent Decision Support System for Including Consumers’ Preferences in Residential Energy Consumption in Smart Grid”; Second International Conference on Computational Intelligence, Modelling and Simulation (CIMSiM), Sept, 2010, pp. 154 – 159. |
| [15] | Reiss PC, White MW. “Household electricity demand”, Stanford University Publication; 2002. |
| [16] | Simons, S.I. and I.H. Rowlands, “TOU rates and vulnerable households: electricity consumption behavior in a Canadian Case Study”. Department of Environment and Resource Studies 2007. |
| [17] | O. A. Sianaki, O. Hussain, T. Dillon and A. R .Tabesh, “Intelligent decision support system for including consumers' preferences in residential energy consumption in smart grid,” |

| | |
|---|---|
| | *2010 IEEE Second International Conference on Computational Intelligence, Modelling and Simulation,* pp. 154-159. |
| [18] | P. Samadi, H.Mohsenian. *"Advanced Demand Side Management for the Future Smart Grid Using Mechanism Design";* IEEE TRANSACTIONS ON SMART GRID, 2012, VOL. 3, NO. 3. Sept. 2012, pp. 1170-1180. |
| [19] | H. Yang, Y.Zhang, Xi.Tong. "*System Dynamics Model for Demand Side Management*"; 3rd International Conference on Electrical and Electronics Engineering, Sept. 2006 , pp. 1-4. |
| [20] | Y. Law, T. Alpcan. *"Demand response architectures and load management algorithms for energy-efficient power grids: a survey"*; 7th International Conference on Knowledge, Information and Creativity Support Systems, 2012, pp. 134- 141. |
| [21] | A. Capozza, B. Apice. *"Measurement and Control System Architecture for Electrical Energy Demand Side Management"; Power Tech, IEEE Russia. 2005, pp 1-7.* |
| [22] | Shuai Lu ; Samaan, N. *"Centralized and Decentralized Control for Demand Response"; IEEE, Jan. 2011, pp. 1-8.* |
| [23] | Q. Zhu, Z.Han and T. Basar. "A *Differential Game Approach to Distributed Demand Side Management in Smart Grid"; IEEE International Conference on Communications (ICC), June 2012, pp. 3345-3350.* |
| [24] | S. Kishore and L. Snyder. "*Control mechanisms for residential electricity demand in smart grids*"; IEEE International Conference on Smart Grid Communications, Oct. 2010, pp. 443–448. |
| [25] | D.El Hassan, Et. Tolba, M. Maaroufi. "*Demand side management algorithms and modeling in smart grids A customer's behavior based study*"; IEEE Renewable and Sustainable Energy Conference (IRSEC), March, 2013, pp. 531-536. |
| [26] | Xiandong Tan, Baoguo Shan and Zhaoguang Hu. "*Study on Demand Side Management Decision Supporting System*"; IEEE 3rd International Conference on Smart Grid, June, 2012, pp. 111-114. |
| [27] | P. Ravi Babu. "*Application of ANN and DSM Techniques for peak load Management a Case Study,", IEEE Region 8 International Conference on Computational Technologies in Electrical and Electronics Engineering*, 2008, pp. 169-174. |
| [28] | Synergy Electricity Smart Power (SM1) tariff. Retrieved from: https://www.synergy.net.au/at_home/smartpower_sm1_tariff.xhtml. |