An Intelligent Approach of Achieving Demand Response by Fuzzy Logic based Domestic Load Management

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***Abstract*—Demand response is an important demand-side resource that allows consumers to consume less electricity when the system is under stress. Existing demand response mechanism reduces power consumption by forcefully shutting down the consumers' loads or punishing the consumers with high consumption prices during high peak hours without considering their comfort level. This paper presents a methodology to design a model for domestic load management based on fuzzy logic techniques where three optimization parameters – comfort, cost and demand response are taken into account. 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 a fuzzy logic based load controller. Simulation results show that the proposed controller successfully limits the power consumption during the peak hours and concurrently maximizes the savings of energy consumption cost without violating consumers' comfort level.**

***Index Terms*-- Consumer comfort level; Demand Response (DR); Direct Load Control (DLC); Energy savings; Fuzzy logic techniques.**

I. INTRODUCTION

Demand response (DR) is an electric market mechanism by which consumers can reduce consumption in response to energy price fluctuations, demand charges or a direct request to reduce demand when the power grid reaches critical levels. It is estimated that a 5% lowering of demand would result in a 50% price reduction during the peak hours [1]. The power consumption in buildings represent a 30-40% of the final energy usage, which is caused by: HVAC (heating, ventilation and air conditioning), lighting and appliances with any connection to the power grid. Recent research shows that load management at home level using computational intelligent techniques provide a reduction of power consumption by around 10 - 30% [2].

Direct load control (DLC) 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. While reducing peak demands, utilities will also need to keep customers satisfied with their performance and services. Within a deregulated electricity market, customer satisfaction is crucial. Thus, in such a business environment, any attempt to reduce the peak load of the system requires the full support of customer. Any control scheme should consider an adequate representation of the customers' specifications and preferences. If a particular customer's comfort is not kept in mind during the implementation of a control strategy, his or her tolerance level will decrease. Effectively, the customer's willingness to participate in any peak reduction plan also decreases. The major challenge is to minimize the power consumption by optimizing the operation of several loads without impacting the customer's comfort.

II. RELATED WORK

A Vickrey Clarke Groves (VCG) mechanism [3] has been used to control the consumers' energy consumptions in where each home is equipped with an energy consumption controller (ECC) as part of the smart meter. The 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. This mechanism assumes customers as price takers which means customers are only considered as energy consumers not as providers. Shuai Lu [4] has described a model with detailed household load control technique using voltage and frequency dip. This paper discusses these two control philosophies and compares their response performances in terms of delay time and predictability. Only air conditioner system and water heater participated in demand response program and other house hold loads have not been considered for this model. A fuzzy logic controller is designed by Ravibabu [5] to reduce the gap between the demand and the supply of electrical energy loads in both peaks hours and off peak hours aiming to properly utilize the available power for the vital loads and power wastage can be restricted. However, by limiting the demand, the impact on the customer comfort level has not been considered.

Increasing the energy price can significantly limit the total power consumptions. The proposed model [6] indicates the importance of electricity price and the great impact of time-of-use price on the total quantity of power demand reduction. Quanyan Zhu and Zhu Han [7] have used the framework of dynamic games to schedule different home electrical appliances. Direct load control and demand management in response to market price have been considered to reduce the energy consumptions. It showed that by increasing the energy price the power consumption will decrease however consumer satisfaction has not been considered as well as the efficient use of energy.

Some authors have shown papers that achieved a power consumption saving without impacting the customer's comfort [8], [9]. The study proposed in [10] presents the design of two levels of a multi-agent controller, central and local coordinators are mentioned. Particle Swarm Optimization (PSO) method is used to optimize energy efficiency and consumer´s comfort. Another proposed work in [11], achieved demand response by utilizing dynamic notion price to develop intelligent decision-making model at home level for increasing the efficiency of energy consumption and adapt consumers' preferences.

III. Solution Methodology

Lacking of intelligence in home energy management have made more complex to schedule of multiple devices and manual device control is inefficient and unattractive to the residents [11]. The home energy management need to be smart enough to integrate different sources of renewable energy and optimize the best use of available power to the appliances for optimal consumptions. In this paper we present an intelligent home energy model as shown in Fig. 1, which identifies the different types of variables that need to be captured for fuzzy logic load controller. Those variables are grid price signals, outdoor temperature, room temperature, available renewable energy and total consumptions which will be collected through smart meter and smart home sensors in certain period of time. It has a learning module which learns the consumer's consumption behaviours and stores these data for future use. The Intelligent Home Energy Management (IHEM) model in Fig. 1, utilizes four steps as depicted here:

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 IHEM 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 IHEM 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 IHEM 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 IHEM will shed few loads or schedule it according to the consumer settings.

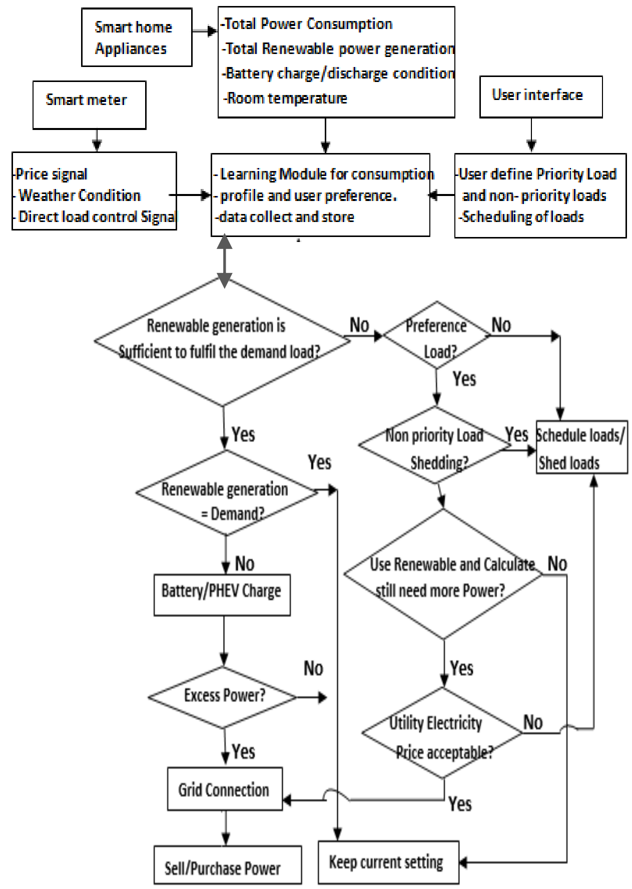

Figure 1. Intelligent Home Energy Management model

IV. Using Fuzzy Logic Based Load Management Techniques

Fuzzy logic based 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. In this case the power consumption during the peak hours is limited by cutting some loads off and hence there will be proper utilisation of supplied power to the high priority loads.

The controller also keeps energy consumption within a certain limit (in this example 2.5kWh maximum) which means consumption 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 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 load controller and to meet the consumers' constrains the steps followed are:

1) Fuzzy logic controller.
2) Fuzzy membership functions.
3) Fuzzy rules.

A. *Fuzzy Logic Load Controller*

The fuzzy system will have five inputs: Time, Comfort Level, Temperature Deviation, Forecast Loads and Consumption Time and two outputs: Allow Load Scheduling and Run Loads. Fig. 2 shows the block diagram of the proposed fuzzy load controller which has 230 rules, five inputs and two output signal. Some of the fuzzy rules are given later in the paper.

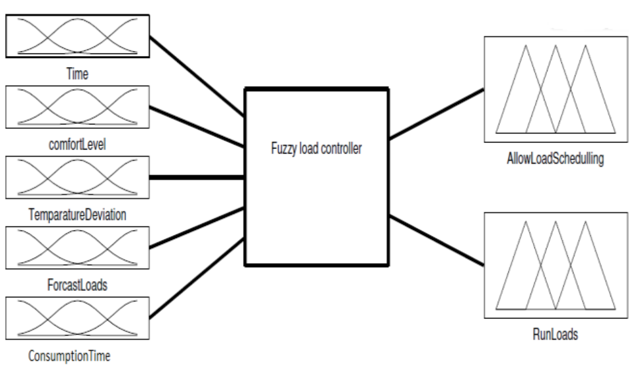

Figure 2. Input and Output block diagram

The inputs and outputs of the above model shown in Fig. 2, 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 including existing running loads and new selected loads. As 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 the controller will allow operating in that 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.

B. *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 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 3 to 9.

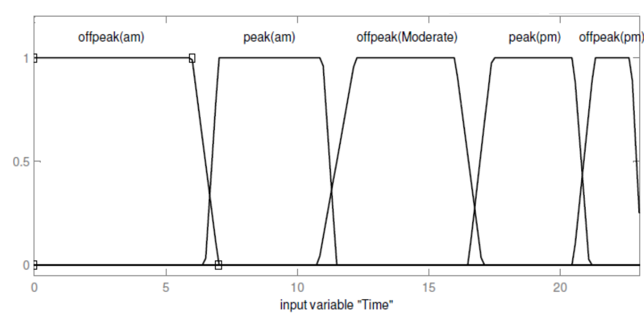

Figure 3. Fuzzy membership function of Time (input)

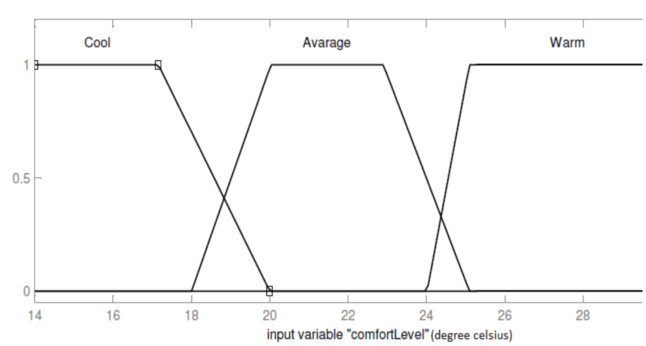

Figure 4. Fuzzy membership function of Compfort level (input)

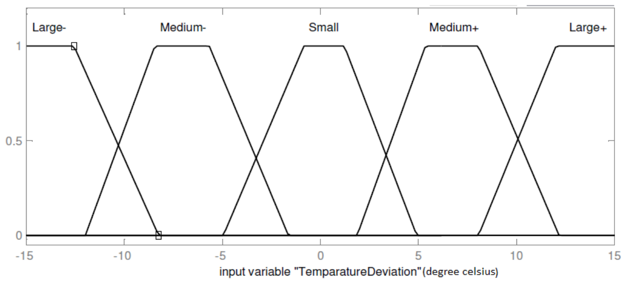

Figure 5. Fuzzy membership function of Temperature deviation (input)

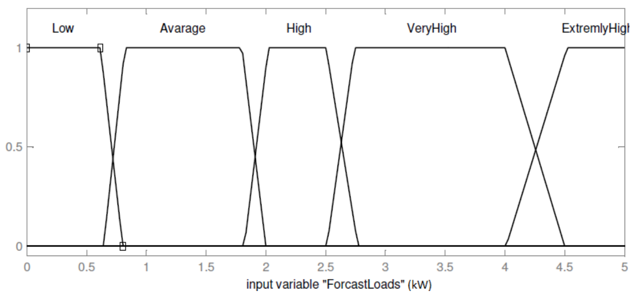

Figure 6. Fuzzy membership function of Forecast loads (input)

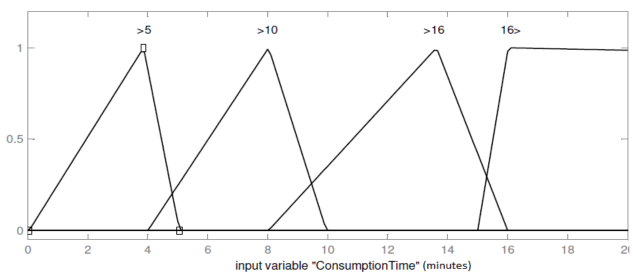

Figure 7. Fuzzy membership function of Consumption time (input)

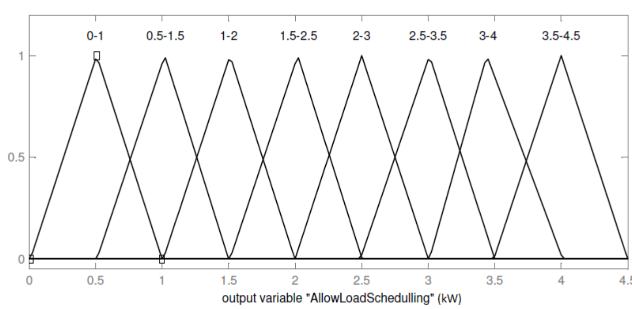

Figure 8. Fuzzy membership function of Allow load scheduling (output)

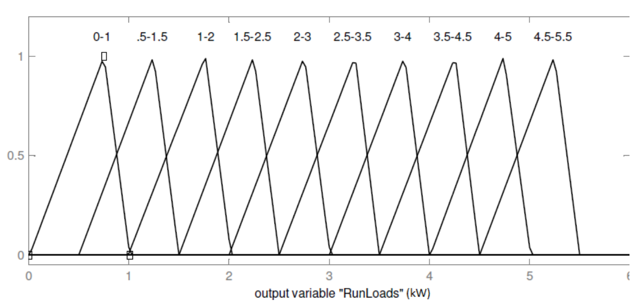

Figure 9. Fuzzy membership function of Run Load (output)

C. Fuzzy Rules

Fuzzy rules form the vital part of the entire fuzzy logic.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 output. Considering consumers' preferences and constraints demand profile was obtained using 230 rules, few of which are listed below.

D. Rules

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

2) 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 to 3.5)(RunLoads is 0 to 1).

3) 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 to 1)(RunLoads is 0 to 1).

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

5) 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 to 2)(RunLoads is 1.5 to 2.5).

6) If (Time is peak(am)) and (comfortLevel is Cool) and (TemparatureDeviation is Medium+) and (ForcastLoads is ExtremlyHigh) and (ConsumptionTime is >10) then (AllowLoadSchedulling is 3to 4)(RunLoads is 4to5).

E. Results

According to the defined rules and the inputs specified by the consumers, the fuzzy load controller results are shown in Table II. The controller optimizes the loads that need to run during peak hours to achieve consumer comfort level temperature and shifts the rest of the loads to off-peaks hours.

TABLE II. FUZZY LOAD CONTROLLER RESULTS

Input					Output	
Time	*Comfort Level C*	*Temp deviation C*	*Forecast loads (KW)*	*Consume time (mints)*	*Allow Load Scheduling (KW)*	*Run Loads (KW)*
peak(pm)	16	13	5.5	16>	3.5	2.1
peak(am)	15	3	3.5	16>	3	0.6
peak(am)	17	-2	1.5	16>	0.5	0.6
peak(pm)	22	-12	3.6	16>	2	2.1
offpeak	21	-10	3.5	16>	1.5	2.1
peak(am)	15	7	7.5	>10	3.5	4.6
Offpeak (am)	17	1	0.5	16>	0	4.52

V. Case Study

A typical -two bed room house power consumption data in a summer time has been used for this experiment. Basic households appliances are considered in this typical house as 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. The batteries 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.
- 1.5kW of PV system. This 1.5 kW system is 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 contributes to the household appliances.

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

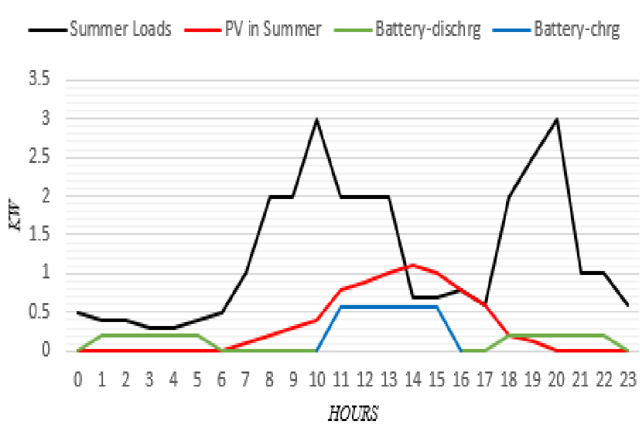

Figure 10. Daily consumptions curve

The load curves before and after the contribution of PV and battery storage systems are shown in Fig. 11. Load priority is performed with a fuzzy load controller and results are shown in Fig. 12. The fuzzy load controller takes advantage of the hours of the day when there are peaks hours, it reduces the consumption by predefined rules and schedules the nonpriority loads to their respective time. It is clear from Fig. 12, that the peaks of the load profile of the household have been reduced significantly and shifted to low demand periods.

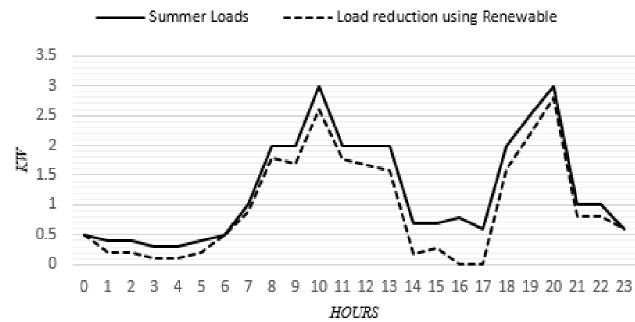

Figure 11. Load reduction using renewable energy

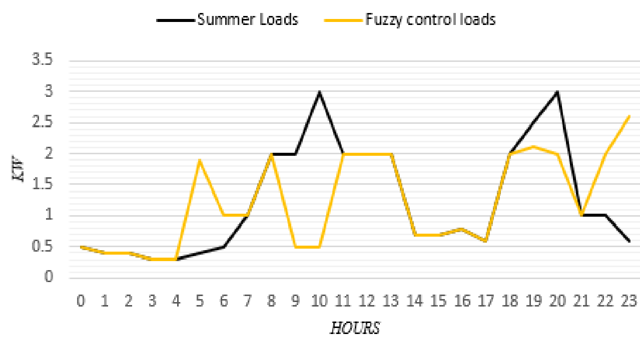

Figure 12. Results obtained with fuzzy load controller

Table III, together with Fig. 13, presents the comparative analysis of integration of different load control techniques to evaluate the power consumption performance. In this experiment direct load control (DLC) is set to switch off the air conditioner (1.5kW) when it operates during peak hours. Fig. 13, shows that utilization of renewable sources of energy with fuzzy load control technique presents a better performance compared to DLC, since it provides adequate energy savings without compromising consumers comfort level. The different tariffs [12] for consumption of energy have been used to analyse the total cost of energy consumption for the different load management criteria and results are summarized in Table III.

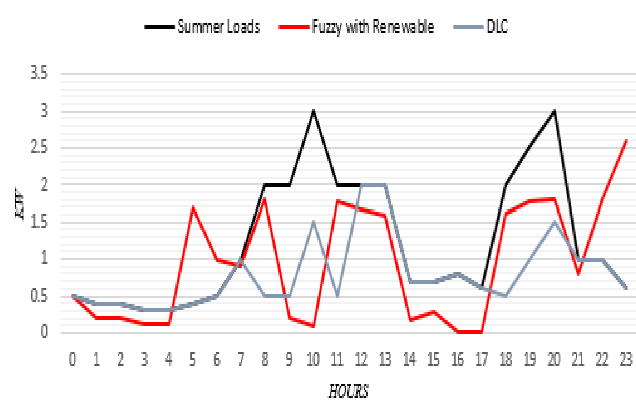

Figure 13. Comparison between different load controllers

TABLE III. ENERGY CONSUMPTION AND COST COMPARISON ANALYSIS

	Energy Cost (Cents/kWh)	NML (kWh)	NML Cost ($)	DLC (kWh)	DLC Cost($)	LMR (kWh)	LMR Cost($)	LMF (kWh)	LMF Cost($)	LMFR (kWh)	LMFR Cost($)
Off-peak time	15.1415	4.4	0.67	4.4	0.67	3.248	0.49	9.4	1.42	8.248	1.25
Moderate time	26.525	6.2	1.64	8.6	2.28	3.704	0.98	6.2	1.64	3.704	0.98
Peak time	49.8154	19.1	9.51	6.2	3.08	16.19	8.06	14	6.82	10.79	5.37
Total	-	**29.7**	**11.82**	**19.2**	**6.03**	**23.1**	**9.53**	**29**	**9.89**	**22.74**	**7.60**
% energy of saving	-	-	-	**35.3**	-	**22.2**	-	**2.35**	-	**23.4**	-
Cost saved/day	-	-	-	-	**5.79**	-	**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 III, shows that during different time periods in that particular day the total energy consumption and cost of consumption were obtained with non managed loads (NML) which are 29.7 kWh and $11.82. Whereas the cheapest consumption price ($ 6.03) was obtained with direct load control with minimum consumptions of 19.2 kWh. Direct load control performed significant energy and cost reduction. However the consumer comfort level and preferences were violated due to switch off of the air conditioner during peaks hours. The proposed load management based on fuzzy logic (LMF) contributed small amount of energy reduction 2.35%, compare to direct load control which was 35.3%. Conversely with the fuzzy load controller consumers were allowed to operate their air conditioner during peak hours to reach their comfort level temperature and simultaneously reduced their consumptions cost. The simulation results obtained with Load Management with Fuzzy and Renewable sources (LMFR) shows the better management of load reductions with adequate cost savings and simultaneously achieved consumers' satisfaction.

VI. CONCLUSION

The proposed fuzzy logic based 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 the load management with fuzzy and renewable sources (LMFR) saves almost ten times the energy when compared with load management with fuzzy logic (LMF) alone. If the costs are compared LMFR saves more than twice of the cost saved by LMF. Therefore, it can be concluded that load management with fuzzy logic and renewable sources is the best choice.

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