# An Optimization Technique Based Electrical Appliance Scheduling For Smart Home Applications

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***ABSTRACT***

*The integration of information and communication technologies in traditional grid brings about a smart grid. Energy management plays a vital role in maintaining the sustainability and reliability of a smart grid which in turn helps to prevent blackouts. Energy management at consumers side is a complex task, it requires efficient scheduling of appliances with minimum delay to reduce peak-to-average ratio (PAR) and energy consumption cost. In this project, the classification of appliances is introduced based on their energy consumption pattern. An energy management controller is developed for demand side management. We have used fuzzy logic and heuristic optimization techniques for cost, energy consumption and PAR reduction. Fuzzy logic is used to control the throttleable and interruptible appliances. On the other hand, the heuristic optimization algorithms, is employed for scheduling of shiftable appliances. We have also proposed a hybrid optimization algorithm for the scheduling of home appliances, named as hybrid HFBA optimization algorithm. Simulation results show a significant reduction in energy consumption, cost and PAR*

## I. INTRODUCTION

Conventional sources of energy have been used for the production of electrical energy over the years. Electricity prices are soaring up due to the decline in the availability of these energy resources. Distributed Energy Resources (DER) are being installed to overcome these issues. DERs offer a distinct advantage of being able to be installed in domestic premises. DER along with an effective Home Energy Management System (HEMS) can help in minimizing the energy consumption from the grid and increase the renewable energy consumption, thereby reducing the energy cost.

Energy management (EM) is the process of monitoring, controlling and conserving the energy that is being consumed. This can be achieved by either managing the usage of loads or by managing the sources of generation. Both Load Management and Resource Management (RM) can be incorporated in the same system to achieve maximum efficiency. By monitoring energy, the user can control usage of various appliances. Better energy savings and efficient usage of resources are viable by when an appropriate HEMS is employed. Various algorithms like Back-Propagation Algorithm and Support Vector Machine were previously implemented for HEMS, but lags in accuracy and has been perceived slow. Genetic Algorithm has been used for implementation of HEMS and demand side management of loads.

## II - LITERATURE SURVEY

**Logenthiran, et. al.,** presents a demand side management strategy based on load shifting technique for demand side management of future smart grids with a large number of devices of several types. The day-ahead load shifting technique proposed in this paper is mathematically formulated as a minimization problem. A heuristic-based Evolutionary Algorithm (EA) that easily adapts heuristics in the problem was developed for solving this minimization problem. Itscarried out on a smart grid which contains a variety of loads in three service areas, one with residential customers, another with commercial customers, and the third one with industrial customers.

**Rostampour,** presents an energy management framework for building climate comfort (BCC) systems interconnected in a grid via aquifer thermal energy storage (ATES) systems in the presence of two types of uncertainty (private and common). ATES can be used either as a heat source (hot well) or sink (cold well) depending on the season. We consider the uncertain thermal energy demand of individual buildings as a private uncertainty source and the uncertain common resource pool (ATES) between neighbors as a common uncertainty source. We develop a large-scale stochastic hybrid dynamical model to predict the thermal energy imbalance in a network of interconnected BCC systems together with mutual interactions between their local ATES. We formulate a finite-horizon mixed-integer quadratic optimization problem with multiple chance constraints at each sampling time, which is in general a non-convex problem and difficult to solve. We then provide a computationally tractable framework by extending the so-called robust randomized approach and offering a less conservative solution for a problem with multiple chance constraints.

**Lingfeng, et. al., presents** Smart and energy-efficient buildings have recently become a trend for future building industry. The major challenge in the control system design for such a building is to minimize the power consumption without compromising the customers comfort. For this purpose, a hierarchical multiagent control system with an intelligent optimizer is proposed in this study. Four types of agents, which are switch agent, central coordinator-agent, local controller-agent, and load agent, cooperate with each other to achieve the overall control goals. Particle swarm optimization (PSO) is utilized to optimize the overall system and enhance the intelligence of the integrated building and microgrid system. A Graphical User Interface (GUI) based platform is designed for customers to input their preferences and monitor the results.

**Jingyu, et. al.,** propose a fuzzy logic controller was designed that considered daylight, movement information and lighting comfort. The digital DALI protocol was used to communicate the controller and LED luminaires. The simulation results demonstrated that lighting system without control can provide sufficient illumination. The lighting system provides wider controllability to make lighting environment operating at the most energy-saving state. The experimental results show that by using the designed controller, significant lighting energy can be saved. The office where the smart LED lighting system is installed can regulate lighting output automatically based on users' movements and allow users to choose their own lighting preferences.

## III - SYSTEM IMPLEMENTATION

### *A. DESCRIPTION*

In this project, the EMC is designed to control and manage the power consumption of automatic electrical appliances. The basic aim of this system is to reduce the energy consumption, monetary cost and PAR while keeping users' comfort as high as possible. Moreover, in our proposed system, the autonomous set points of HVAC system can be modified by user and our system also learns the changes which are made by end user. Moreover, for illumination, we have used user occupancy as an input variable and considered four types of appliances in this project: fixed, throttleable, interruptible and shiftable. The power consumption and operational cost are reduced by controlling the power consumption of throttleable appliances and by changing the ON/OFF status of the interruptible appliances while keeping user comfort within a specific range. For reduction of PAR and monetary cost, load of shiftable appliances is shifted from on-peak hours to off-peak hours. An upper limit for electricity load is also defined to avoid peaks in off-peak hours.

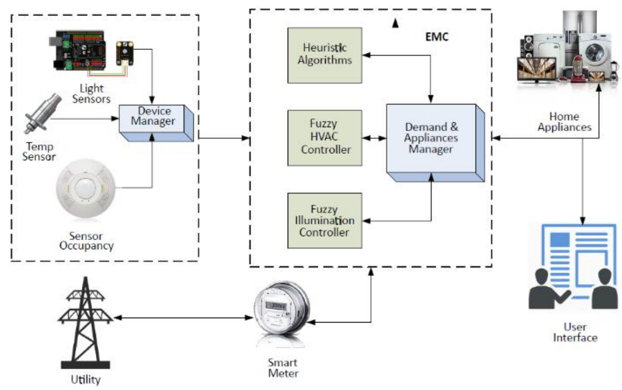



**Fig 1 System Model of Proposed EMC Controller**

The DSM system is shown in Figure 1. The basic components of our proposed DSM system are: sensors, EMC, appliances, smart meter and user interface. Sensors are used to observe environment and give input related to outdoor temperature, user's occupancy and light to the EMC for further action. The input by sensors includes data related to light status, temperature information and movement of a user. A smart meter interacts with the utility and EMC, and exchanges information related to the price and the demand of electricity. Appliances communicate with EMC and exchange information related to their status. An electricity consumer exchanges information with EMC about appliances, e.g., appliances to be scheduled, length of operational time (LOT), total allowable waiting time of each appliance and parameters relating to user's comfort. An EMC receives input from other components, performs scheduling using heuristic techniques. Furthermore, EMC adjusts set points of the HVAC system and illumination using fuzzy logic. Electrical appliances are categorized into four groups: fixed, throttleable, interruptible and shiftable appliances. This categorization is performed according to their power consumption pattern and their role in end user's comfort.

### *B. FUZZY LOGIC*

Fuzzy logic is a decision making model, it deals with the approximate values rather than exact values. In this paper, fuzzy logic is applied to adjust the set points of HVAC and illumination systems. These set points directly affect the user comfort. Fuzzy logic is easy to implement and does not require large amount of information. It can be used to acquire reliable results using small amount of information.

Fuzzy variables are used to generate these results. In fuzzy logic there are some input variables, set of rules and output variables. The input variables are fuzzified into membership functions (MFs), these MFs are basically fuzzy sets and the degree of membership of a value is defined as how much a value is closed to that set. An input value can belong to more than one sets at the same time. There are different types of MFs, in our system we have used triangular function because of its simplicity and good performance. In fuzzy logic, input and output variables are defined in simple human understandable language. Fuzzy rules are defined to specify the relationship of input variables and their effect on the values of output variables. Hence, fuzzy logic follows three basic steps: fuzzification of input values via fuzzifier, implementation of rules and defuzzification using defuzzifier.

### *a). Fixed Appliances*

These appliances are also known as regular appliances, because their LOT and power consumption pattern cannot be altered. We cannot schedule these appliances. Fixed appliances are turned on when required by the user. Table II contains the list of fixed appliances along with their power rating and LOT. These appliances do not play any useful role in DSM, but their load needs to be considered while managing other controllable appliances. We can calculate the energy consumption of fixed appliances as:

$$E_F(t) = \sum_{f \epsilon F} \wp_f \times \aleph_f(t) \qquad (1)$$

$$E_F = \sum_{t=1}^{120} E_F(t) \qquad (2)$$

$$\aleph_f(t) = \begin{cases} 1 & \text{if appliance is ON} \\ 0 & \text{otherwise} \end{cases}$$

Where EF (t) is energy consumed by fixed appliances at time interval ‘t’and F = ff1; f2; f3; :::; fMg. }f and @f (t) represent power rating and status of fth fixed appliance at time interval ‘t’ respectively. Moreover, total energy consumption of fixed appliances is represented by EF.

**TABLE I: Fixed Appliances**

| Appliances | LOT | Power rating | Appliances | LOT | Power rati |
|---|---|---|---|---|---|
| Computer1 | 20 | 0.4 | TV | 25 | 0.1 |
| Computer2 | 20 | 0.4 | Electric Iron | 2 | 1.5 |
| Cleaner | 2 | 1.5 | Hair Dryer | 1 | 1 |

### *b). Throttleable Appliances*

The LOT of these appliances is fixed and cannot be altered. However, their power consumption can be controlled within some specific range. HVAC systems come under the category of these appliances. In Canada and US approximately 64% to 74% of total residential energy is consumed by HVAC systems. So these systems play an important role in creating PAR during cold winter and hot summer. With the increase in population, the power demand of HVAC system is also increasing. In our paper, we have applied fuzzy logic to reduce the power consumption, while maintaining the comfort level of end-user between its comfort ranges defined by ASHRAE thermal comfort zone.

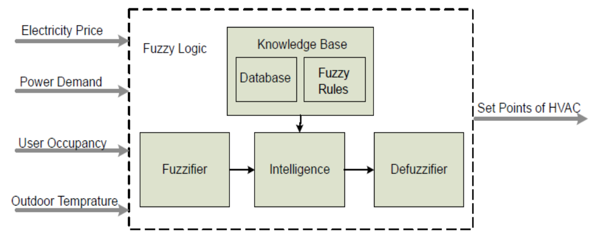



**Fig. 2: Fuzzy HVAC Controller**

### i) Inputs for Fuzzy HVAC Controller:

The input parameters of fuzzy HVAC controller are: electricity price, power demand, user occupancy and outdoor temperature. The output value of fuzzy controller is the adjusted set point value for HVAC system. Figure 3.2 presents the graphical illustration of fuzzy HVAC systems. It accepts crisp mathematical values as input, these crisp values are then converted into fuzzy sets by fuzzifier module. The intelligence module uses fuzzy rules present in knowledge base, and generates output fuzzy sets. These fuzzy sets are then converted back to crisp values by defuzzifier. The fuzzy rules are defined by system developer and vary from problem to problem.

### ii) Energy Consumption:

To estimate the energy consumption of our HVAC system, we need to know about the heat losses and the supply of energy during its operational time. The parameters of a home are given in Table IV.

**TABLE II: Home Parameters**

| Parameters | Values | Parameters | Values |
|---|---|---|---|
| Length | 6.2m | Width | 12.5m |
| Windows | 6 | Window Length | 1 |
| Window Thickness | 0.02m | Wall Thickness | 0.3m |
| Wall Thermal Coefficient | 0.038 | Window Thermal Coefficient | 0.78 |
| Altitude | 5.2m | Window Height | 1 |
| House Initial Tepm | 5°C | | |

The model of heat loss defined in, is presented as follows:

$$\left(\frac{\Delta Q}{\Delta t}\right)_{losses} = \frac{Temp_{in} - Temp_{out}}{q}, q = \frac{l}{\lambda.})$$

$$(\frac{\Delta Q}{\Delta t})_{heat} = (R_{heat} - Temp_{in}) \times A_m \times CP, A_m = d \times V$$

$$Temp_{in} = (\frac{\Delta Q}{\Delta t})_{heat} - (\frac{\Delta Q}{\Delta t})_{losses} \times \frac{1}{CP \times M_{air}} \quad (5)$$

$$E_{Tr}(t) = \sum_{tr \epsilon Tr} (\frac{\Delta Q}{\Delta t})_{heat,tr} \quad (6)$$

$$E_{Tr} = \sum_{t=1}^{120} E_{Tr}(t) \quad (7)$$

- Tempin: Indoor temperature of house.
- Tempout: Outdoor temperature of house.
- $\lambda$ = 0.0257 and l = Wall thickness.
- $R_{heat}$: Set point
- V: Volume of house.
- d: 1.21 (Air density)
- CP: 1.006 (Heat capacity)
- $M_{air}$: Mass of air assumed 1.

Where Equation 3 represents the heat losses and Equation 4 computes the required power by HVAC system to keep the room temperature on adjusted set point. However, Equation 5 computes the variation of indoor temperature that would be sensed by indoor temperature sensor in real scenario. Moreover, Equations 6 and 7 represent the computation of energy consumption of throttleable appliances at a specific time interval and their total energy consumption respectively.

### *c). Interruptible Appliances*

These appliances are fully controllable by EMC. In this paper, we consider the lightning bulbs as interruptible appliances. Approximately 20% to 40% of total energy is consumed by electric lights. Therefore, the optimized use of energy for lightning plays a vital role to reduce energy consumption, monetary cost and PAR. A fuzzy illumination controller is proposed to control the illumination level in a certain range, while keeping the comfort of user as high as possible. The comfortable lightning range for a home is between 150 (lux) to 250 (lux).

### i) Inputs for Fuzzy Illumination Controller:

The input parameters used for fuzzy illumination controller are: electricity price, user occupancy, outdoor light and indoor light. The output value of fuzzy controller is the adjusted set point for illumination. The graphical representation of proposed fuzzy illumination controller is given in Figure 3.3. The outdoor and indoor illumination play a very important role for the adjustment of indoor illumination set points. If the outdoor illumination is high, the system decreases the set points accordingly and it reduces the cost, PAR and power consumption. Indoor illumination indicates if there is a need to increase the set points of illumination.

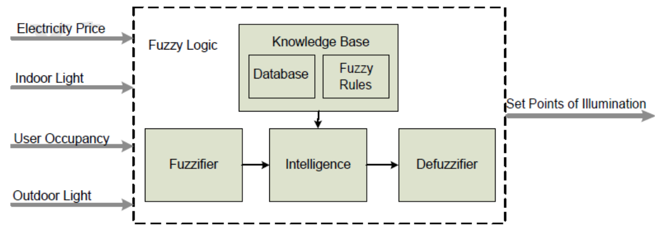



**Fig. 3: Fuzzy Illumination Controller**

### ii) Energy Consumption:

The set points of illumination are generated by fuzzy illumination controller. The next step is to calculate the required power to maintain illumination level on these set points. An energy consumption model is stated as follows:

$$EL = \frac{\phi \times CU \times LLF}{A} \quad (8)$$

$$E_I(t) = \frac{\phi}{LB} \quad (9)$$

$$E_I(t) = \frac{\phi}{LB} \quad (10)$$

$$E_I = \sum_{t=1}^{120} E_I(t) \quad (11)$$

- EL: Adjusted illumination set point by fuzzy illumination controller (lux).
- ϕ: Required illumination intensity to lit the house.
- CU = Coefficient of utility (its value depends on reflection of floor).
- A: Space area.
- LLF: Light Loss Factor.
- LB: Light emission of an electric bulb

Where Equation 8 is used to compute the illumination level in a room, Equation 9 is generated from Equation 8. Equation 9 is used to compute how much illumination is required from electric lights to maintain the illumination level, specified by fuzzy illumination controller for a house.

EI (t) contains the value of energy, consumed by interruptible appliances at time interval 't'. EI is the total energy consumption of interruptible appliances.

### *d). Shiftable Appliances*

These appliances are controllable and their operational pattern can be altered. EMC schedules these appliances to reduce the monetary cost and PAR. The user enters the required information about these appliances in user interface, it is then sent to EMC. There is no direct interaction between shiftable appliances, instead, they interact with EMC. An EMC sends them information related to their ON/OFF status.

This information is sent to each appliance separately. Power rating of each appliance is saved in EMC at the time of their integration with EMC. The information entered by user includes: LOT, start time, and end time of shiftable appliances. The interval from start time to end time of an appliance is called its schedule interval which can be mathematically represented as follows:

$$\alpha_s \leqslant \zeta_s \leqslant \beta_s \tag{12}$$

$$\zeta_s \geqslant LOT \tag{13}$$

Where, in Equation 12, $\alpha_s$ represents start time, $\beta_s$ represents the end time and $\zeta_s$ represents the schedule interval of shiftable appliance. Equation 13 shows that the schedule interval $\zeta_s$ of an appliance should be greater than or equal to the LOT of appliance. For example, if the start time of an appliance is 12th slot and its end time is 20th slot, its LOT should be less than or equal to eight as $\zeta_s$ is equal to eight. Moreover, when a user schedules an appliance more than once in a day (e.g. two times), scheduler take it as two separate devices of same type. Table VI shows the complete list of shiftable appliances along with their operational information. The scheduling of shiftable appliances is performed by using HFBA algorithm.

**i) Optimization Techniques:**

In an optimization problem, the values of input variables are optimized in such a way that the resultant profit is maximized or the cost is minimized. This problem seems like a black box, where input values of control parameters are entered and resultant output values are returned. These output values then specify that how much input values are close to the target solution. The black box contains a fitness function to evaluate the input values. Generally, in every optimization problem, we either minimize a function or maximize it f(x1, x2, x3...,xm). The optimization techniques used in this paper are discussed in the following subsections.

***A. HFBA:***

We have proposed our algorithm HFBA,

**Algorithm 1 HFBA**

1: Initialize all parameters
2: for i = 1:T
3: Initialize population using flower swarming steps
4: Convert values of population from continuous to binary
5: J evaluate fitness of population
6: for k = 1: Max-ite
7: Update frequency of BAT (slot)
8: Update velocity of BAT
9: Update position of BAT
10: Check pulse rate and update population
11: Update slot using global pollination
12: Evaluate finess and update best solution
13: end for
14: Subtract 1 from LOT of appliances if appliance is ON
15: Save the best solution for current hour
16: end for
17: Calculate cost
18: Calculate average waiting time
19: Calculate PAR

Fitness of each slot is evaluated after each iteration and best solution is selected as shown in Algorithm 1. In this algorithm, a population is generated using flower swarming step. Here, each flower represents a time slot. The cells of flower are appliances to be scheduled. Each slot has 24 cells, as we are going to schedule 24 appliance. Each cell has a value, which represents the status of appliance. The status of each appliance is either ON or OFF, where 1 shows the ON status and 0 shows OFF status of an appliance. There are some parameters which affect the performance of HFBA namely: population size, upper and lower bounds for swarming, number of iterations, values of frequency and velocity. These are called tuning parameters of an algorithm and values of these parameters are problem dependent. The control parameters of algorithm include: power rating, LOT, waiting time, start time and electricity price. The performance parameters are: monetary cost, user comfort and PAR. User comfort is determined through the average waiting time of appliances, more average waiting time means less user comfort.

**ii) Energy Consumption:**

The energy consumption of shiftable appliances can be computed as;

$$E_S(t) = \sum_{s \epsilon S} \wp_s \times \aleph_s(t) \tag{14}$$

$$E_S = \sum_{t=1}^{120} E_S(t) \tag{15}$$

$$\aleph_s(t) = \begin{cases} 1 & \text{if appliance is ON} \\ 0 & \text{otherwise} \end{cases}$$

Where ES(t) is the energy consumed by fixed appliances at time interval ‘t’and S = fs1; s2; s3; :::;

sMg. } $\wp_s$ and $\aleph_s(t)$ represent the power rating and the status of nth shiftable appliance at time interval ‘t’ respectively. Moreover, total energy consumption of shiftable appliances is represented by ES.

## IV - RESULTS & DISCUSSION

### *A. Fuzzy HVAC Controller*

Here, we have defined 72 fuzzy rules for our fuzzy HVAC controller. MFs of the inputandtheoutputvariablesaregiveninFigures4-10

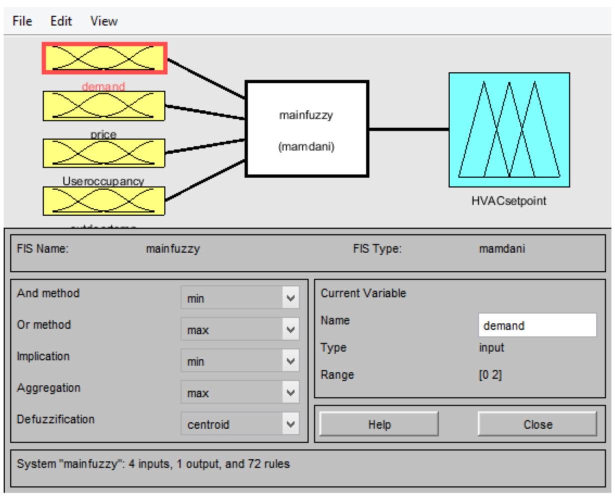



**Figure 4 Fuzzy HVAC controller**

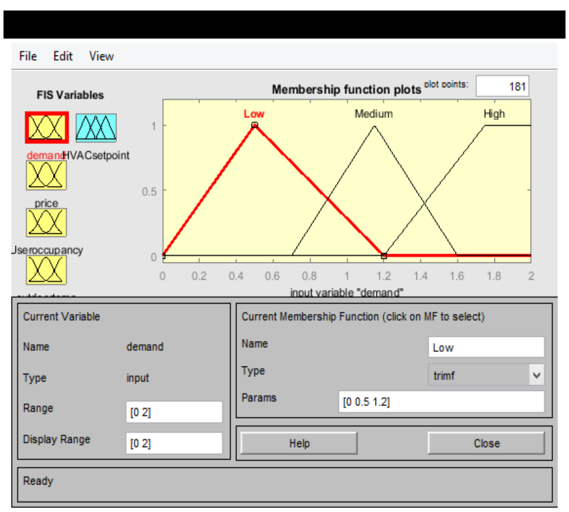



**Figure 5 Electric demand membership function**

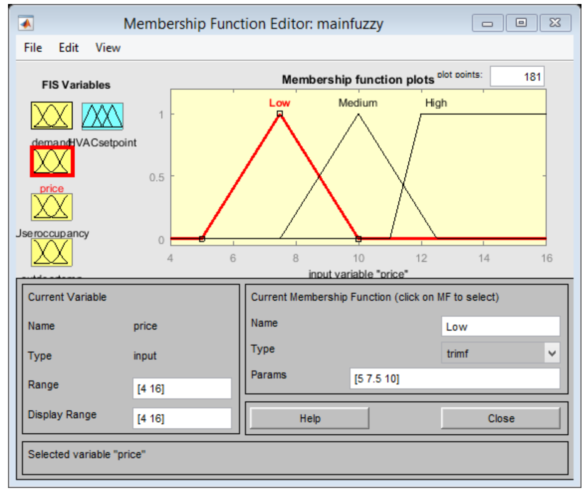



**Figure 6 Electricity Price membership function**

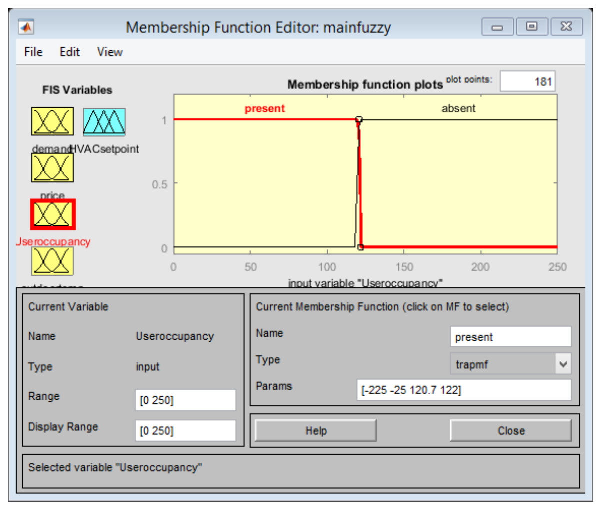



**Figure 7 User occupancy membership function**

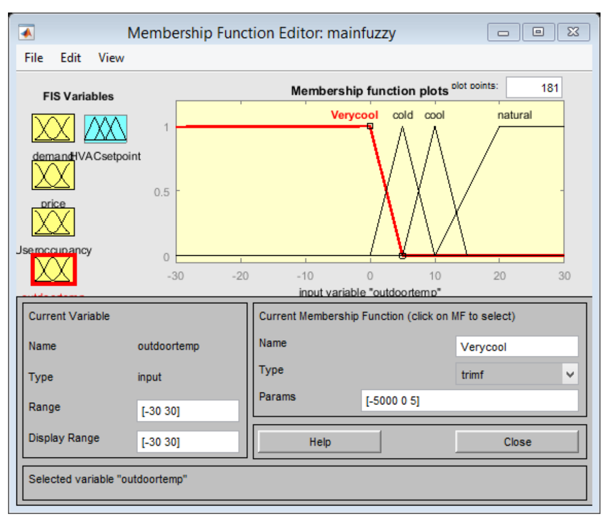



***Figure 8 Outdoor temperature membership function***

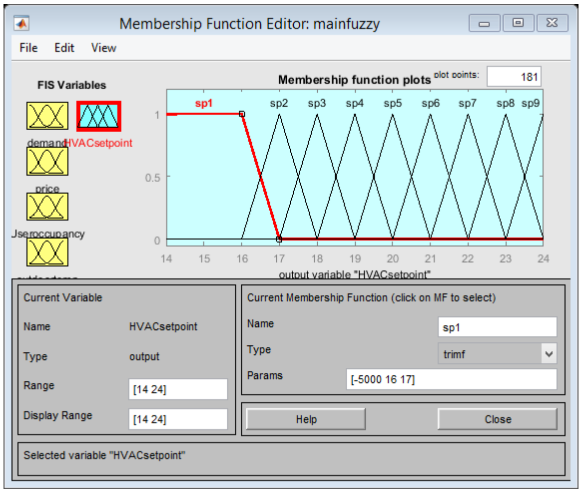



*Figure 9 Set point HVAC membership function*

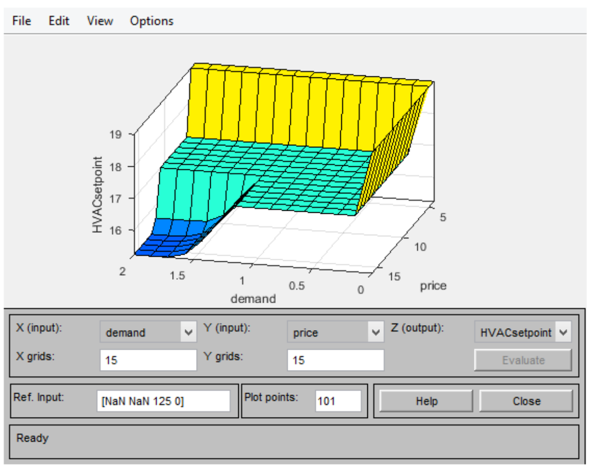



**Figure10 Fuzzy rules surf image**

Input values of price and demand are considered because in case of their high values fuzzy HVAC controller will lower the set points to reduce the energy consumption, cost and PAR. User occupancy is considered because in the absence of user, the set points are reduced without affecting its comfort. The outdoor temperature plays a very important role for the adjustment of indoor set points. If outdoor temperature is high, the system decreases the set points accordingly and it reduces cost, PAR and the power consumption.

### *B. Fuzzy illumination controller*

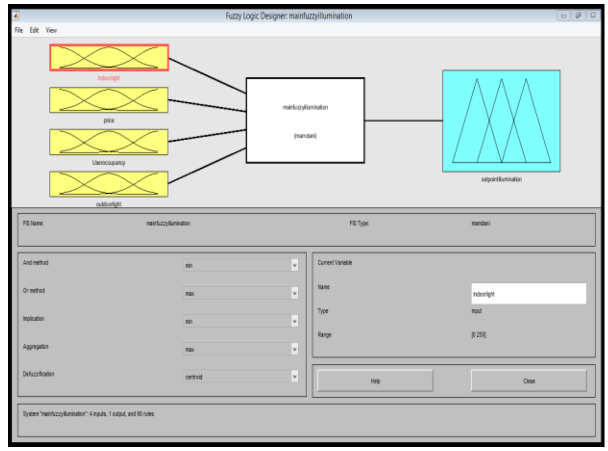


**Figure 1 fuzzy illumination controller**

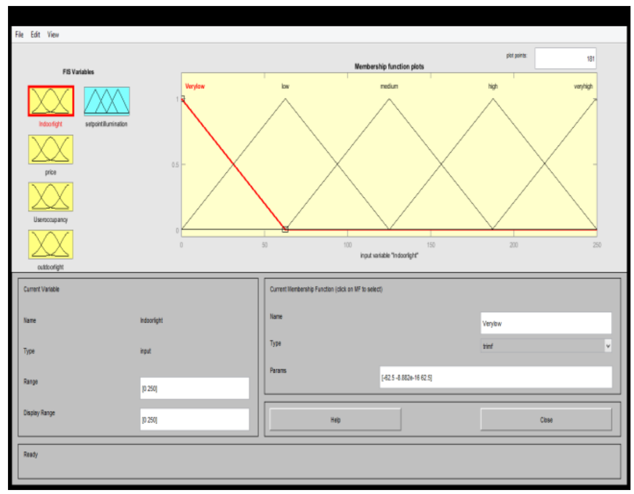


**Figure 2Indoor lighting membership function**

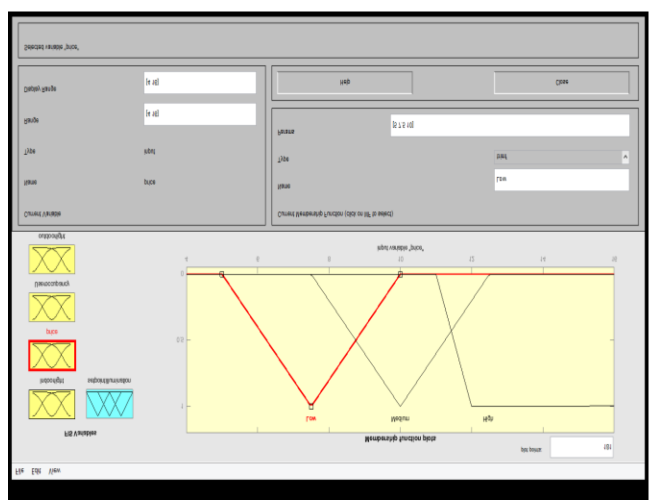


**Figure 3 Electricity price membership function**

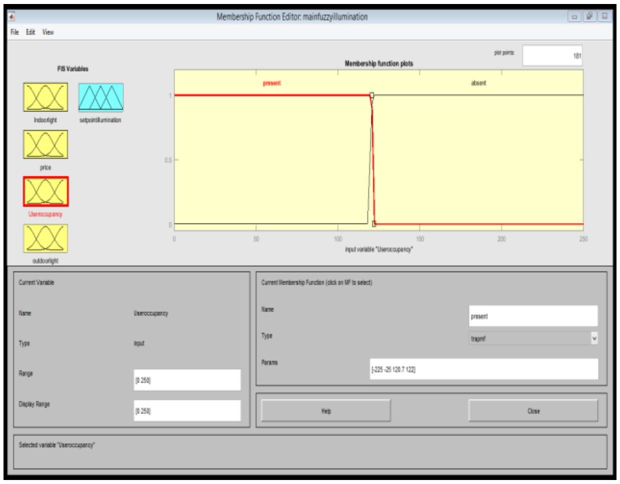


**Figure 4 user occupancy membership function**

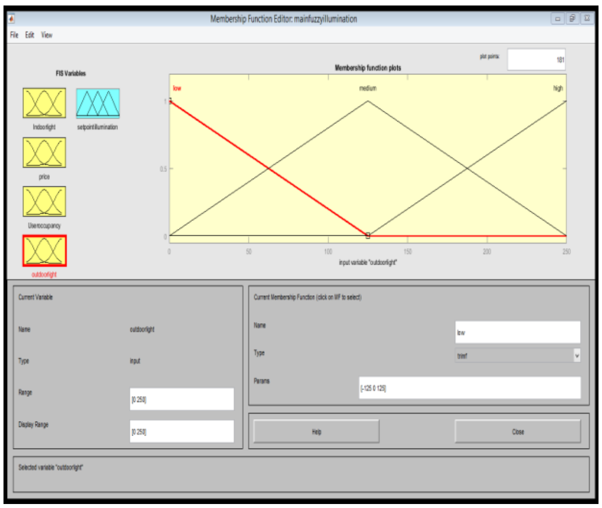


**Figure 5 outdoor membership function**

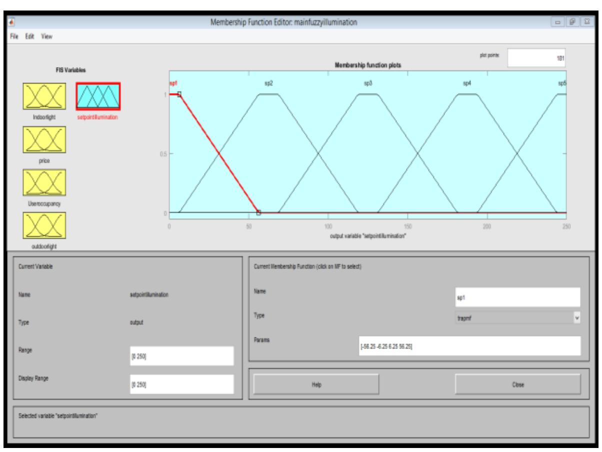


**Figure 6Setpoint illumination membership function**

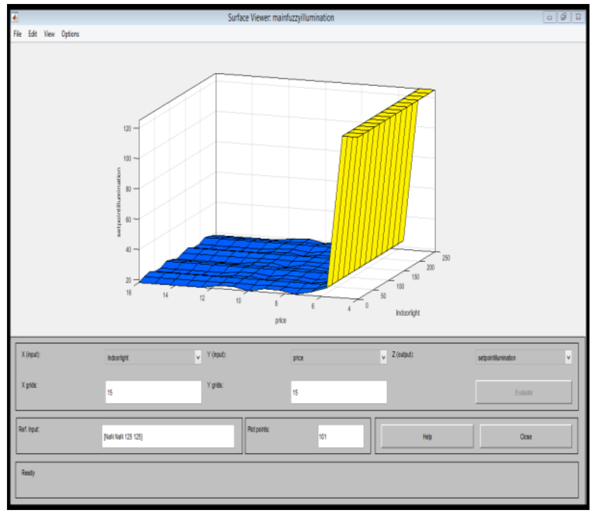


***Figure 77 surf image of illumination controller***

The fixed appliances and its power consumption is shown in the proposed system where in the simulation studies also the fixed electrical equipment are not involved with the energy management scheduling. The proposed work is calculating he total power consumption for the fixed appliances as 66W.

The Fuzzy controller for HVAC is shown in previous section and the response of the fuzzy controller is shown in the following figure where the input variables and the corresponding output value is displayed on command window. This controller is sending the HVAC set point power consumption as the output data which is based on four inputs.

```
Total Power consumption of Fixed appliances : 66 W

*********************************
FUZZY controller for HVAC systems
*********************************
Electricity Price (Rs.): 12
Electricity Demand (kWh): 1.50
User occuancy : 100
Outdoor temperature (°C): 25°C


**************************************
        Fuzzy contrller output
**************************************
HVAC Energy consumption : 18.65 kW-h
```

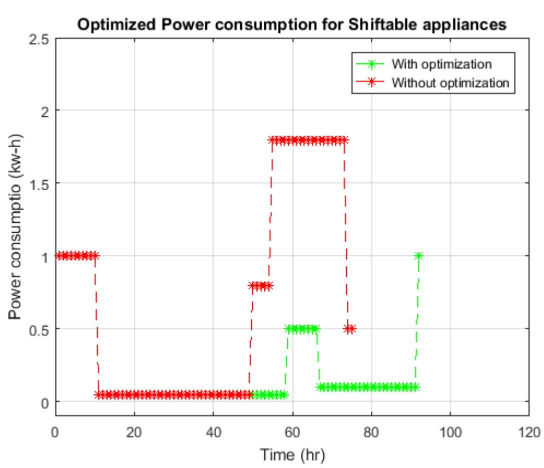
The fuzzy illumination controller system response is shown in the following figure and this controller is producing the set point illumination as output. The input variables may be given through sensor devices.

```
****************************************
 Fuzzy Illumination Controller systems
****************************************
Electricity Price (Rs.): 12
Indoor Light illumination(Lumen): 175
User occuancy : 120
Outdoor Light illumination(Lumen): 210
```

The HFBA optimization is implemented in this proposed work flow where the shiftable appliances can be scheduled based on power consumption. The top ten shiftable appliances are selected based on HFBA optimization algorithm. The response is shown in the following figure. Each appliances is listed along with their power rating.

```
****************************************
List of Optimized Shiftable appliances
****************************************
1. AC2 (1.00 k-W)
2. Humidifier1 (1.00 k-W)
3. Fan (1.00 k-W)
4. Cloth Dryer (0.05 k-W)
5. Pool Pump (0.05 k-W)
6. Electric Radiator1 (0.05 k-W)
7. Coffee Maker1 (0.80 k-W)
8. Coffee Maker2 (1.80 k-W)
9. Washing Machine (1.80 k-W)
10. Water filter (0.50 k-W)
```

The overall power consumption for the proposed optimization based work is shown in the following figure. Throughout the time scale the proposed system power consumption is plotted with green color marker. The power consumption without any optimization technique shows the different and undesired response which is plotted in red color marker.




## V. CONCLUSION

In this project, an EMC is presented to optimize the energy consumption and DSM. We have used three optimization techniques to schedule the operational pattern of shiftable appliances. The optimization technique include: HFBA algorithm. Results show the effectiveness of our system and optimization techniques. These techniques reduce the PAR and monetary cost up to a significant level as compared to the unscheduled load. Our proposed optimization technique out performs in two performance parameters: PAR and user comfort. According to the overall performance of optimization techniques, HFBA shows supremacy over BAT and FP algorithms in terms of predefined performance parameters. Moreover, fuzzy logic has been employed to reduce energy consumption and cost of HVAC and illumination system. It is evident from the results that we have successfully achieved our objectives and there is a significant reduction in the energy consumption, monetary cost and PAR.

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