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Demand side management using meta-heuristic techniques and ToU in smart grid

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Abstract In this paper, we perform performance evaluation of home energy management system (HEMS) for demand side management (DSM) in smart grid. In this work, smart home is equipped with HEMS, smart meter, and smart appliances for two-way communication between utility and consumer. HEMS performs scheduling of smart appliances based on meta-heuristic techniques to balance load for whole day to avoid peak creation in any hour. Smart meter performs electricity cost calculation for consumed energy based on time of use (ToU) pricing signal provided by utility. Our focus is to efficiently handle user demand, reduction in peak-to-average ratio (PAR) and electricity cost minimization. The implemented meta-heuristic techniques in this work are: Enhanced differential evolution (EDE), harmony search algorithm (HSA), bacterial foraging algorithm (BFA), and genetic algorithm (GA). The simulation results show the performance of HEMS based on optimization techniques using ToU.

1 Introduction

Smart grid is bi-directional communication between user and utility by installing smart meter and HEMS for DSM. This bi-directional communication is useful for energy optimization, load balancing, electricity cost reduction and minimizing PAR [2], [3], [4]. Load balancing is basically efficient management of energy consumption by balancing load in on-peak hours and off-peak hours [13], [14]. User tries to minimize electricity cost by shifting load from on-peak hour to off-peak hours. In addition, this load shifting creates peak in any other hour which ultimately affects PAR. Thus, load balancing is an efficient way to avoid PAR for complete operational

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time of smart appliances. However, utility wants reduction in PAR for efficient supply of energy to fulfil user demand in any hour. In terms of user comfort, there is always tradeoff between electricity cost and waiting time [4]. While, performing load balancing through HEMS by optimization techniques, this ultimately affects user defined scheduled operational time of smart appliances.

Smart meter takes utility pricing schemes and appliances schedule as input. Consequently, smart meter performs electricity cost calculation based on energy consumption by smart appliances schedule provided by HEMS. Smart meter helps in reducing electricity cost by providing calculations to HEMS and utility [2], [3], [4].

HEMS is also known as scheduler in smart grid environment. HEMS is responsible for two-way communication between smart meter and user demand. HEMS helps in giving efficient demand response (DR) which is also known as DSM [2]. HEMS performs scheduling of smart appliances to balance load for operational time according to user demand. This scheduling helps in reducing PAR in any hour to minimize electricity cost.

Demand response model consists of aggregator, which is responsible for communication between house hold appliances for their scheduling and running time for predefined time duration [1]. DSM became successful for multiple homes with contribution of generators, retailers, large users and aggregator. Demand from multiple user including smart home, smart business, and industrial area is controlled by control center. Power is generated from wind turbine, conventional, hydroelectric, nuclear, and solar panels [2].

In [3], the grid power system with renewable energy resources is modeled to generate extra energy. The system consists of batteries, multiple users, smart appliances, and energy providers work efficiently under power generation from renewable resources. In this paper [4], a system model is proposed to examine system performance, energy and power consumption calculations, performance parameter optimization and energy management. The system consists of smart meter, HEMS controller, and appliances. Local area network (LAN) is used to share appliances control. Appliances are categorized in schedulable (flexible) and real time devices (less flexible).

DSM in smart grid based on regularization, bi-directional framework, and newton method is applied in this paper [5]. The regularization helps to improve interrupts in appliance scheduling and minimizing PAR by reducing duration. Bi-directional framework helps in bidirectional communication among agents and HEMS. The newton method helps in fast convergence and this increase user comfort in terms of waiting time. The HEMS system model in smart grid is shown in fig 1.

In this paper, section 2 reflects the related work in smart grid. Section 3 illustrates system model of this research work. In addition, meta-heuristic techniques including HSA, EDE, BFA, and GA are highlighted in section 4. Moreover, simulation results and discussions are presented in section 5. Finally, complete work is concluded in section 6.

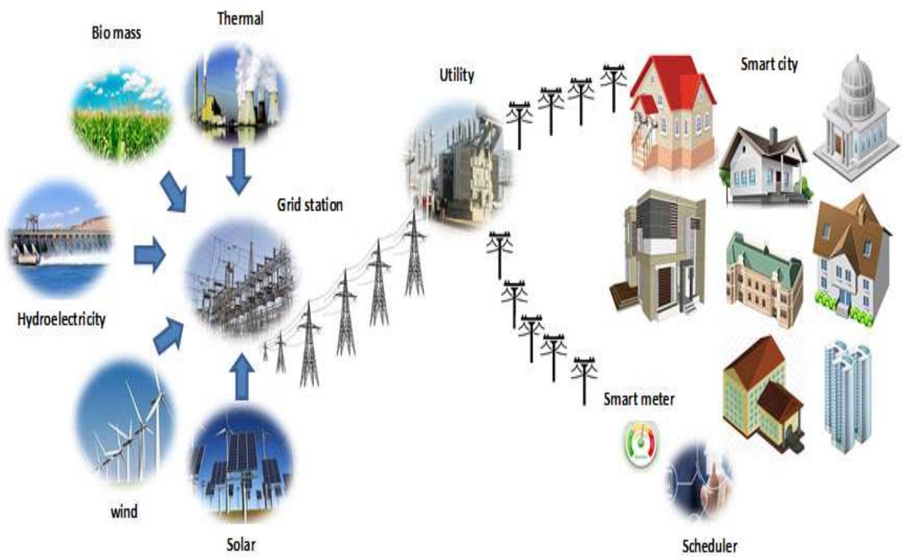

Fig. 1 Home Energy Management System in Smart Grid

2 Related Work

In this section, the previous work done in smart grid is described. Energy optimization is focus in smart grid to control energy consumption. Energy maximization, load balancing, controlling power consumption, using renewable energy sources, and minimizing PAR is achieved by different work in smart grid.

In [6], authors focused on load scheduling and energy consumption using renewable energy resources. Appliances are categorized as interruptible and fixed appliances. In this proposed system, each user can sell excessive power generated by renewable energy sources. To model the connection between user and generated by renewable energy resources, a game theoretical approach adopted by authors. The proposed system has reduced energy consumption from power grid, and minimized electricity cost. Load balancing and PAR problems are addressed by generating power from renewable energy resources. However, cost of renewable energy resources is neglected in this proposed system.

In this paper [7], the authors proposed a decentralized system to establish a connection between demand response and user. The proposed system is used to manage load to avoid peak in on-peak hours. Balancing load in on-peak hour cause reduction in electricity cost. However, the waiting time of user in increased. In this proposed system, when the HLM does not find acceptable load profile then complete load shifted to peak hours. Convergence is very slow and it required many iterations to finally receive balanced load profile.

Efficient cost reduction for residential load scheduling in smart grid is proposed in [8]. The proposed load scheduling algorithm works for cost reduction in DSM system. Day ahead bidding and RTP mechanisms are used in this proposed scheduler. The distributed energy resources (DERs) are used in proposed load scheduling algorithms; this cause high computational cost and increase user waiting time. The service charges are also considered for better results in cost efficiency. The cost of implementing DERs is neglected in this proposed system.

In [9], the proposed DSM technique deals with the load management in residential area for single and multiple homes. The authors focused on maximizing user comfort, minimizing electricity cost and PAR. The proposed system is a hybrid technique of genetic algorithm and wind driven algorithms. In this proposed system, the scheduler shift load from on-peak hours to off-peak hours for interruptible appliances to reduce energy consumption in peak hour. User comfort in terms of waiting time of appliances is neglected in proposed hybrid technique during load balancing.

Energy consumption scheduling mechanism by load balancing for residential area in smart grid is proposed in [10]. In this proposed technique, author achieved balanced load for each hour using proposed scheduling mechanism. The proposed system schedule appliances to minimize energy consumption in on peak hour, maximizing user comfort by scheduling power and operational time. Load balancing achieves minimum power consumption, electricity cost and PAR in peak hours.

In [11], the authors focused on reducing electricity cost and PAR by scheduling power usage in smart homes. The authors proposed energy management system (EMS) and scheduling method for proposed EMS. In this proposed system, authors combined RTP and inclining block rate (IBR) pricing schemes. Hybrid pricing signals performed better to achieve reduction in electricity cost and PAR. The authors focused on optimizing power consumption, however proposed system implemented by strong assumptions of same power consumption in each hour.

In this paper [12], the authors proposed a system to schedule appliances in smart homes. The focus of the work is to minimize electricity cost by load balancing in peak hour for interruptible appliances. Ahead of time pricing signal is used in this proposed model. User comfort is compromised in terms of waiting time to run required appliance. The proposed system is based on wireless connection between smart meter, smart appliances, and system model. However, unavailability of internet cause rise in PAR and load unbalancing cause maximizing electricity cost.

3 System Model

The proposed system model is composed of 12 appliances for single smart home in smart grid. However, the authors in [9], have used same appliances classification and power ratings for multiple homes using RTP pricing signal. Appliances are categorized as: shift able and non-shift able appliances as shown in fig.2. In our system model, we have used ToU pricing signals for electricity cost calculation. The scheduler performs appliance scheduling for 24 hours according to TOU pricing signal as

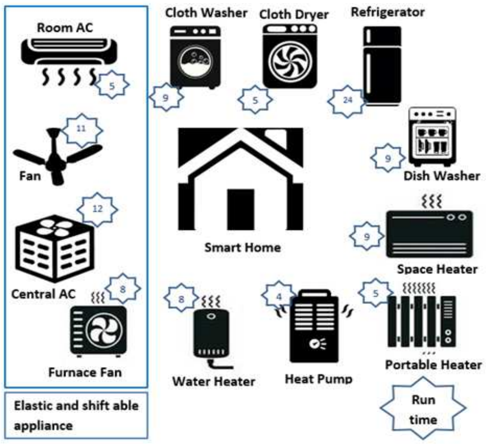

Fig. 2 System Model

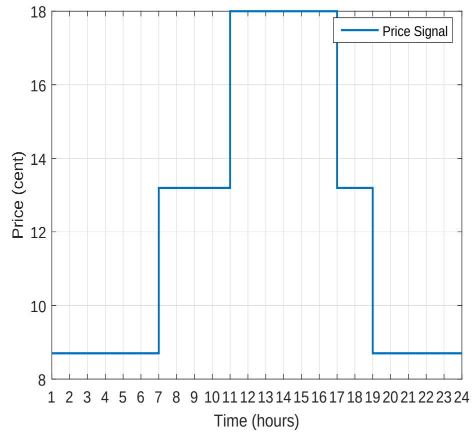

Fig. 3 TOU Pricing signal

shown in fig. 3. The scheduler performs load balancing in on-peak hours and off-peak hours to minimize PAR in any hour. Smart meter is installed in smart home for bi-directional communication between utility and HEMS. Appliances classification, life time and power ratings are shown in table 1. We have used equation 1 to calculate electricity cost for 24 hours, equation 2 is used to calculate load and as shown in equation 3 PAR is calculated using this equation. These equations are used by the authors in [13] for electricity cost, load, and PAR calculations.

$$\text{Electricity-Cost} = \sum_{hour=1}^{24} E_{Rate}^{hour} \times P_{Rate}^{App} \quad (1)$$

$$\text{Load} = P_{Rate}^{App} \times App \quad (2)$$

$$\text{PAR} = \frac{\max(\text{load}^2)}{\hat{a}(\text{load}^2)} \quad (3)$$

4 Meta-heuristic Techniques

In this section, meta-heuristic techniques have been discussed to perform appliances scheduling by HEMS for DSM. 12 appliances of single home are scheduled using these techniques for HEMS performance evaluation.

Table 1 Appliances and Power Ratings

Appliance Categories	Appliance Name	Power Rating (kwh)	Life Time (hours)	Deferrable Load
Elastic and shift able appliances	Space Heater	1	9	Yes
	Space Heater	1	9	
	Heat Pump	0.11	4	
	Portable Heater	1.00	5	
	Water Heater	4.50	8	
	Clothes Washer	0.51	9	
	Clothes Dryer	5.00	5	
	Dishwasher	1.20	11	
	First-Refrigerator	0.50	24	
Fixed load appliances	Fan	0.5	11	No
	Furnace Fan	0.38	8	
	Central AC	2.80	12	
	Room AC	0.90	5	

4.1 EDE

It consists of multiple efficient features over other optimization techniques. In EDE, main steps are: mutation, crossover, and selection phase. Initially, random population is generated using upper and lower bounds for random function. In mutation phase, randomly three target vectors are selected from initially created memory. One mutant vector is formed by taking difference to any two previously selected target vector and adding the results in third target vector as shown in equation 4 given below.

$$V_{j,i,G+1} = x_{best,G} + F(x_{r1,G}) + F(x_{r2,G} - x_{r3,G}) \tag{4}$$

In crossover phase, a random value is generated and compared with crossover rates. However, these crossover rates are predefined in EDE. If the random number is less than crossover rate then information is taken from selected mutant vector. Meanwhile, if random value is greater than the crossover rate then target vector becomes trial vector of this optimization technique. In EDE, it generates 5 trial vectors based on 5 distinct crossover rates as shown in equation 5 to equation 9. After getting five trial vectors, fitness of these five trial vectors is calculated and the vector having minimum value is selected for final trial vector.

$$U1_{j,i,G+1} = \begin{cases} V_{j,i,G+1}, & if(\text{randb(j)}) \leq 0.3 = \text{Irand} \\ x_{j,i,G}, & if(\text{randb(j)}) > 0.3 \neq \text{Irand} \end{cases} \tag{5}$$

$$U2_{j,i,G+1} = \begin{cases} V_{j,i,G+1}, & if(\text{randb(j)}) \leq 0.6 = \text{Irand} \\ x_{j,i,G}, & if(\text{randb(j)}) > 0.6 \neq \text{Irand} \end{cases} \tag{6}$$

$$U3_{j,i,G+1} = \begin{cases} V_{j,i,G+1}, & if(\text{randb(j)}) \leq 0.9 = \text{Irand} \\ x_{j,i,G}, & if(\text{randb(j)}) > 0.9 \neq \text{Irand} \end{cases} \tag{7}$$

$$U4_{j,i,G+1} = (\text{randb(j)}) \times x_{j,i,G} \tag{8}$$

$$U5_{j,i,G+1} = (\text{randb(j)}).v_{j,i,G} + (1 - (\text{randb(j)})) \times x_{j,i,G} \tag{9}$$

In selection phase, the selected trial vector is compared with target vector and the vector having minimum fitness value is selected for next generation. The authors in [14] have used equation 5 to equation 9 for EDE algorithm 1. EDE Parameters and Values are shown in table 3.

4.2 HSA

The steps involved in this evolutionary algorithm are: random initial population, harmony improvising process, memory consideration, and pitch adjustment for new generation. Initially, harmony memory is created randomly using random function by specifying upper and lower number range. After completing first step of initial random memory creation using equation 10, harmony improvising process gets started. HSA Parameters and Values are shown in table 4.

$$x_{i,j} = lj + rand() \times (U_j - l_j) \tag{10}$$

In harmony improvising step, generation of new harmony is based on harmony memory consideration rate (HMCR) and pitch adjustment ratio. In this step, a random number is generated and compared with HMCR. If the generated value is less than HMCR then the existing harmony memory contributes in selecting new harmony. If the randomly generated number is greater than HMCR then a new random value is generated to create new harmony using equation 11 as given below.

$$V_{i,j} = \begin{cases} x_{randb(j)}, if(\text{rand()}) < HMCR, \\ l_j + (\text{rand()}) \times (U_j - l_j), else \end{cases} \tag{11}$$

The harmony selected in memory consideration process further go through the process of pitch adjustment ratio. In this step, a random number is generated and if it is less than pitch adjustment ratio then the existing harmony memory contributes in selecting new harmony. If the randomly generated number is greater than pitch adjustment ratio then a new random value is generated to create new harmony using equation 12.

$$V_{i,j} = \begin{cases} V_{i,j} \pm (\text{rand()}) \times bw_j, (\text{rand()}) < PAR, \\ V_{i,j}, else \end{cases} \tag{12}$$

After getting a final new vector, compare it with worst harmony value in existing harmony memory. If new results are better than worst, replace it in previous worst harmony value in existing harmony memory. HSA complete steps are shown in algo-

Table 2 EDE Parameters and Values

Parameter	Value
Population Size	30
Number of appliances	12
Maximum pitch adjustment rate	0.9
Minimum pitch adjustment rate	0.4
Harmony memory consideration rate	0.9
Maximum bandwidth	1.0
Minimum bandwidth	0.0001
Maximum iteration	100
Lower limit	0.1
Upper limit	0.9
Stopping Criteria	Max. iteration

Table 3 HSA Parameters and Values

Parameter	Value
Population Size	30
Number of appliances	12
Number of target vectors	3
Number of mutant vector	1
Number of crossover rates equations	5
Number of trail vectors	5
Maximum iteration	100
Lower limit	0.1
Upper limit	0.9
Stopping Criteria	Max. iteration

rithm 2. Detail description of all symbols, parameters used in equations, algorithms are shown in table 5 and 6, respectively.

4.3 BFA

Among nature inspired optimization techniques, BFA is most commonly used optimization technique. BFA technique is based on real bacteria foraging process. In this optimization algorithm, stochastically and collectively it allows the cell to swarm for optimal solution. The steps involve in BFA are: chemotaxis step, reproduction and elimination-dispersal. In chemotaxis step, it is life duration of the bacteria based on number of chemotactic steps. In reproduction cell, it is basically selection phase of this algorithm. In this step, bacteria cells performed well over their life duration are selected for next generation. Elimination dispersal step is based on fitness function in which previous expired cells are discarded and new population is inserted.

4.4 GA

To find optimal solutions, GA is the most popular optimization technique. The concept behind genetic algorithm is alike chromosomes. The main steps involve in GA are: selection, crossover, and mutation. In selection phase, initially population is generated randomly which is basically representation of chromosomes. Then for selection process this generated population is broken down. Crossover phase is then performed on selected chromosomes from selection phase. In mutation phase, bits are changed randomly and finally a chromosome is selected based on fitness function. GA is relatively better algorithm for optimal solution [4], [9]. While, probabilistic nature of GA does not guarantee optimality. GA performs best for larger population, while BFA performs best for small population [13]. Execution time of GA is less as compare to other meta-heuristic techniques [14].

Algorithm 1 HSA

Input:(HMS, $NVAR$, $HMCR$, $PAmin$, $PAmax$, $BWmin$, $BWmax$, $maxItr$, Xl, Xu)

```
for Hour = 1 → 24 do
    if hour < 24 then
        Select electricity cost of next hour
    else
        Select electricity cost of current hour
    end if
    for j = 1 → maxItr do
        Pitch adjustment
        for p = 1 → NVAR do
            Bandwidth adjustment
        end for
        for I = 1 → NVAR do
            if rand(1) < HMCR then
                Select new harmony from existing
                if rand(1) < PA then
                    V[í, ĵ] + rand()
                else
                    V[í, ĵ] − rand()
                end if
            else
                Randomly select new harmony
            end if
        end for
    end for
    if new < HM(worst) then
        HM(worst) = new
    else
        HM(worst) = HM(worst)
    end if
end for
```

5 Simulation Results and Discussions

In this section, the simulation results show performance comparison of implemented meta-heuristic techniques. Moreover, meta-heuristic techniques do not guarantee optimal solutions [9]. In addition, computational time and optimal solutions are important parameters in research. The implementation of meta-heuristic techniques is based on random initial population generation process. Therefore, the confidence interval is calculated based 10 times average to evaluate performance of HEMS. Fig 3 elucidates the pricing rate for 24 hour. TOU is commonly used tariffs for electric-

Algorithm 2 EDE

Input:(pop_size, NA, $maxItr$, Xl, Xu)

```
B1 = rendperm(pop_size)
Randomly select 3 target vectors T, T1, T2, T3
Mutant_vectorM = T1 + 0.5 * (T2 - T3)
for m = 1 → maxItr do
    for n = 1 → NA do
        if rand(1) >= 0.3 then
            t1 = T else
            t1 = M
        end if
    end for
    for n = 1 → NA do
        if rand(1) >= 0.6 then
            t2 = T else
            t2 = M
        end if
    end for
    for n = 1 → NA do
        if rand(1) >= 0.9 then
            t3 = T else
            t3 = M
        end if
    end for
    for n = 1 → NA do
        if rand(1) * targetvector then
            t4 = Telse
            t4 = M
        end if
    end for
    for n = 1 → NA do
        if rand(1) * Mutant_vector + 1rand(1) * targetvector then
            t5 = Telse
            t5 = M
        end if
    end for
    F1 = eletricitycost * t1
    F2 = eletricitycost * t2
    F3 = eletricitycost * t3
    F4 = eletricitycost * t4
    F5 = eletricitycost * t5
    New trial vector = min [F1, F2, F3, F4, F5]
    if Newtrialvector > T1 then
        New target vector = New trial vector
    else
        New target vector = T1
    end if
end for
```

Table 4 Detail Description of Symbols

Symbols	Description
E^{hour}_{Rate}	Electric Rate per Hour
P^{App}_{Rate}	Power Rate of an Appliance
A_{pp}	Appliance
$V_{j,i,G+1}$	Mutant Vector
$x_{best,G}$	Best target vector
$x_{r1,G}$	First target vector
$x_{r2,G}$	Second target vector
$x_{r3,G}$	Third target vector
$x_{j,i,G}$	Target vector
$U1_{j,i,G+1}$	First trial vector
$U2_{j,i,G+1}$	Second trial vector
$U3_{j,i,G+1}$	Third trial vector
$U4_{j,i,G+1}$	Fourth trial vector
$U5_{j,i,G+1}$	Fifth trial vector
$x_{i,j}$	Initial harmony memory
$rand()$	Built in function for random value generation
l_j	Lower limit of rand function
U_j	Upper limit of rand function
$v_{i,j}$	New harmony memory
bw_j	Bandwidth

Table 5 Detail Description of Parameters

Parameters	Description
HMS	Population size HSA
NVAR	Number of appliances in EDE
HMCR	Harmony memory consideration rate
PAmax	Pitch adjustment maximum value
PAmin	Pitch adjustment minimum value
BWmin	Bandwidth minimum value
BWmax	Bandwidth maximum value
maxItr	Maximum iteration
Xu	Random function upper limit
Xl	Random function lower limit
Popsize	Population size EDE
NA	Number of appliance in EDE
F1	Fitness value 1st trail vector
F2	Fitness value 2nd trail vector
F3	Fitness value 3rd trail vector
F4	Fitness value 4th trail vector
F5	Fitness value 5th trail vector
t1	1st trial vector
t2	2nd trial vector
t3	3rd trial vector
t4	4th trial vector
t5	5th trial vector
HM(worst)	worst value from harmony memory

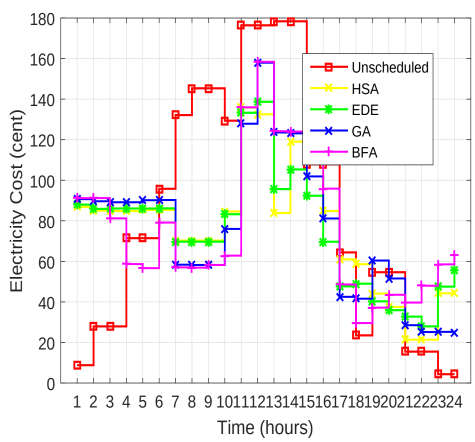

Fig. 4 Electricity Cost

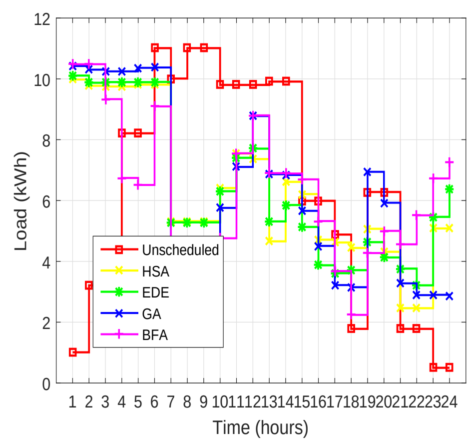

Fig. 5 Per hour Load Demand

ity pricing which varies in all countries. Fig 4 clearly demonstrates electricity cost consumed for 12 appliances during 24 hours. The electricity cost is high in on-peak hours from 11th hour to 17th hour for unscheduled load. Electricity cost for sched-

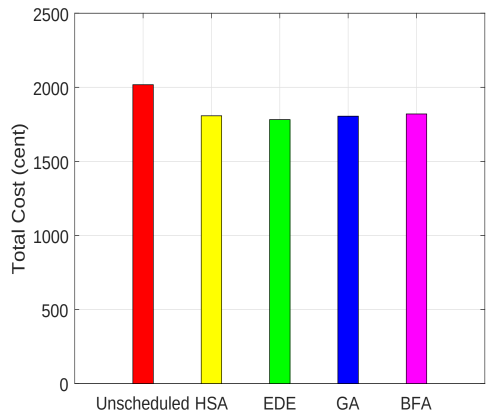

Fig. 6 Total Cost

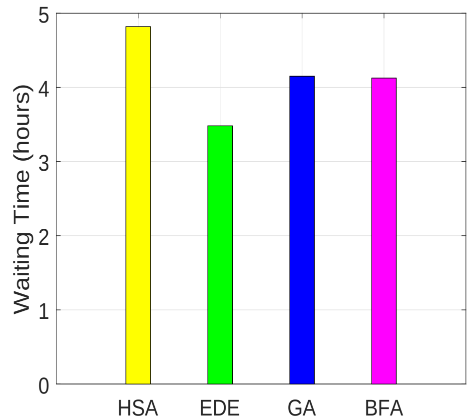

Fig. 7 Waiting Time

uled algorithms is less then unscheduled because load is balanced by scheduling techniques.

The load is completely distributed in off-peak hours and on-peak hours; it cause electricity cost within range of 40 - 60 cents for off-peak hours. HSA algorithms performs selection of fitness value less than worse; it enables the scheme to fully distribute load in 24 hours. EDE algorithm compares electricity cost for two hours including current and next hour; this helps to schedule high power consumption appliances accordingly to reduce electricity cost. Load balancing cause balanced energy consumption and reduction in electricity cost.

Fig 5 represents the load balancing through optimization techniques. Load is balanced for 24 hours in on-peak hours to off-peak hours. To minimize the cost, most of the schedulers shift load toward off-peak hours which cause maximization in PAR. Load unbalancing through schedulers can lead the smart cities to starvation. However, in our simulation results, it is clear that load is balanced in 24 hours.

Fig 6 shows total cost consumed during 24 hours. The total cost for unscheduled is higher than scheduled algorithms. The behaviour of EDE is better among all optimization techniques. Moreover, cost of BFA is highest among all implemented techniques. Total cost for all implemented optimization techniques vary from 1500 cents to 1700 cents. However, there is not a significant difference in total cost consumption. However, these scheduling techniques help in reduction of total cost consumed in 24 hours as compare to unscheduled case.

Fig 7 illustrates the total waiting time in appliances operational time for unscheduled and scheduled algorithms. The EDE optimization algorithm performs best in terms of less waiting time of appliances through scheduling criteria. However, waiting time for BFA is highest among all scheduled algorithms. Thus, total waiting time is reduced as compare to unscheduled scenario. Moreover, user comfort in terms of waiting time is compromised in implemented algorithm. These implemented

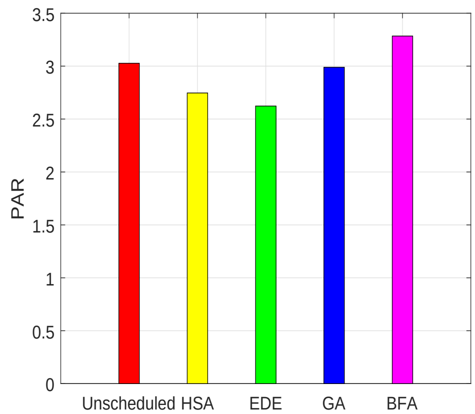

Fig. 8 PAR

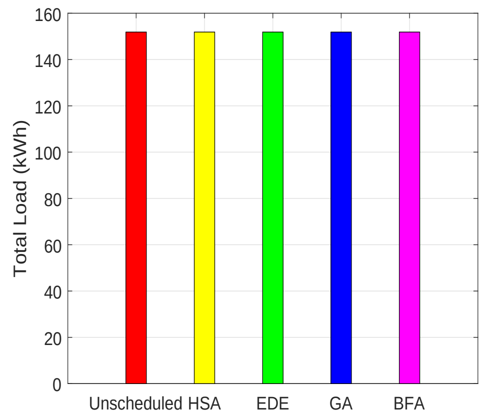

Fig. 9 Total Load

schemes perform efficient where the user concern is to minimize electricity cost and power consumption in on-peak hours.

Fig 8 clarify simulation result for PAR of implemented scheduled techniques with comparison of unscheduled case. The result shows that the PAR is highest for BFA. Moreover, HSA performs best among scheduling techniques. Appliance having high power rate consumes high electricity cost in peak hours in unscheduled scenario. In scheduled process, it balance load to avoid peak in any hours. Therefore, this effect user comfort in terms of waiting time. However, total load for all optimization techniques remains same as illuminated in fig 9. Total load is operational time of all smart appliances which is to be completed for whole day. However, these scheduling techniques help in reduction of total cost in 24 hours. Therefore, total load for all implemented scheduled algorithms and unscheduled are same. Moreover, the number of appliances for both are same and their power consumption required for complete day remains same for all techniques. Load is balanced in all scheduled techniques.

6 Conclusion

Efficient energy consumption, PAR reduction and load balancing for DSM is focus in smart grid to prevent starvation. In this paper, performance comparison of meta-heuristic algorithms is evaluated in terms of cost minimization and PAR reduction. Efficient energy consumption is achieved through scheduler, which helps in scheduling smart appliances within smart home. Smart grid helps in reducing electricity cost by load balancing. The objectives of study are achieved in terms of minimizing power consumption in peak hours to reduce electricity bills. Secondly, balancing load in on-peak hours and off-peak hours to minimize PAR. The utility comfort is achieved in terms of controlling energy consumption in on-peak hours. However, user comfort in term of waiting time of appliances. However, there is trade-off between electricity cost reduction and increase in waiting time.

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