Earth Worm Optimization for Home Energy Management System in Smart Grid

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Abstract. Smart grid based energy management system promises an efficient consumption of electricity. For optimized energy consumption, a bio inspired meta-heuristic algorithms: Earth Worm Algorithm (EWA) and Bacterial Foraging Algorithm (BFA) are presented in this paper. In this work, we targeted residential area. Our aim is to reduce the electricity cost and Peak to Average Ratio (PAR). We have used the Critical Peak Pricing (CPP) scheme for calculating electricity bill. Through simulations, we have compared the results of EWA, BFA and unscheduled appliances. After implementing our techniques, EWA based energy management controller gives more efficient results than BFA in term of cost, while for PAR reduction, BFA performs better than EWA.

Keywords: Smart grid · Meta heuristic techniques · EWA algorithm · BFA algorithm · Critical peak point · Home Energy Management System · PAR

1 Introduction

Energy management is one of the interesting area for scientific research. The demand of energy is increasing with the passage of time due to increased number of homes, industries and other commercial buildings. Increasing demand of anything requires a manageable production in order to facilitate the consumer with the best satisfaction. Similarly, the generation of energy also needs to be managed. For smart management of electricity distribution among consumers, Smart Grids (SGs) are introduced. The main functions of SG are energy controlling that it gather, distribution and act on information about the behavior of all participants including industries, homes and other buildings. Demand Side Management (DSM) facilitates more proficient and reliable grid tasks in SG. Moreover, SG increases the connectivity, coordination and automations between transmission and consumption of energy. Figure 1 represents the abstract architecture of SG framework. Energy Management Controller (EMC) is a device, through which we can adjust our appliances in home. EMC is connected via

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Wide Area Network (WAN) that communicates with the SG domain for electricity management. In Home Energy Management System (HEMS) all the components perform their task, i.e. Smart Meters (SM), EMC, appliances etc. Different pricing schemes are provided by the utility that are used for calculating the electricity bills in different scenarios like hourly base, daily base etc. The main focus of this paper is to reduce electricity cost and PAR for HEMS through the implementation of optimization techniques.

Rest of the paper is organized as follows: Sect. 2 contains the brief description of related work. Next, Sect. 3 explains our proposed solution. Simulation results are discussed in Sect. 4. Finally, the conclusion of our work is described in Sect. 5 by pointing out the future work.

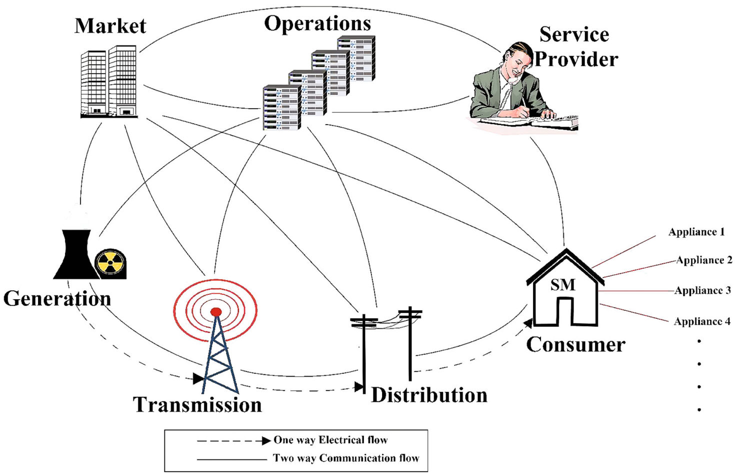

Fig. 1. Energy flow with smart grid

2 Related Work

From decades, number of research have been done globally on SG and energy management system. Different optimization techniques have a key role in scheduling of appliances in order to manage electricity consumption. Different researchers proposed different types of technique on energy management, i.e. heuristic algorithms based, dynamic programming algorithms, divide and conquer technique based etc. In this regard, few research papers are discussed below.

In [1], EMC general architecture for Home Area Network (HAN) is proposed. Demand Response (DR) is used in SG to indicate the electricity price in real time and to transform it to EMC. Through Real Time Pricing (RTP) scheme it is not possible to handle PAR balancing, therefore authors integrated RTP and Inclined Block Rate (IBR) pricing scheme to reduce PAR. Genetic Algorithm (GA) is used as optimization technique for scheduling the appliances. The main target is to reduce electricity cost and PAR. Authors successfully reduced electricity cost after implementing their technique. They also reduce the delay time of appliances' operation which means User Comfort (UC) has also taken under account. So, they proved that integrated technique (IBR and RTP) provides better results than alone RTP. According to paper, security issues are not addressed. Authors used five heuristic techniques in [2], and compared the results in order to achieve the optimal solution for HEMS. The mentioned techniques are GA, Binary Particle Swarm Optimization (BPSO), Bacterial Foraging Optimization Algorithm (BFOA), Wind-Driven Optimization (WDO) algorithm and their proposed Hybrid Genetic Wind-Driven (GWD) algorithm. Through statistical analysis, results depicted that Hybrid GWD reduces cost 10% by GA and 33% by WDO while rest of other results are far behind from their proposed technique. So, overall Hybrid GWD results are better in reducing bill as compared to GA, BPSO, BFOA and WDO. The limitations are that the priority based scheduling is not intelligently installed and did not compare with other techniques for better exploration.

In [3], authors have presented an EMC for avoiding the peak formation, the electricity bill reduction and maintaining the acceptable UC by formulating problem as Multiple Knapsack Problem (MKP). Authors also integrated Renewable Energy Resources (RES) in HEMS. They used two pricing schemes for bill calculation; Time Of Use (TOU) and IBR. In paper three heuristic algorithms GA, BPSO, and Ant Colony Optimization (ACO) are used to achieve the optimal solution for their designed model. The results show the validity of the proposed solution that it reduces the electricity bill and PAR. As there is a trade-off between cost reduction and UC, UC is compromised. New metaheuristic technique inspired by the nature of earthworm reproduction system is proposed in [4]. That reproduction is categorized into 2 types (Reproduction 1 and Reproduction 2). Reproduction 2 gives the optimized solution after applying 9 crossovers functions then they applied cauchy mutation for the extraction of most optimized value. Authors just designed the technique in the paper but did not apply on SG for its performance exploration. According to [5], DSM is introduced to handle the issue of energy demands plus to utilize the energy efficiently. Authors proposed the hybrid technique and compared their proposed technique with GA, BFA and unscheduled appliances. After simulation and practical implementation, they successfully achieved the goal they want by reducing electricity cost and maintained UC with the comparison of unscheduled appliances but, still limited to some extent as BFA shows better result in term of cost reduction.

In [6], authors focused on scheduling of load and power trading with RES. They have adopted dynamic programming scheme to schedule operation of appliances and game theoretic approach to interact between different users with excess energy generation. Users are encouraged to avoid reverse transferring of excess energy to utility using RES. After simulations load is scheduled, electricity cost is reduced and user with excess energy generation is able to sell the electricity to local users cheaper than energy provider. As a result there is a reduction in electricity payments and proposed system provides the gateway to earning revenues. Moreover, no security issue is mentioned regarding to protection of RES for trading the excess energy transmission.

The consumption of energy is managed in residential SG network according to [7]. Each house is configured by 2 types of demands, flexible and essential demands, the subcategory of flexible demands are delay-sensitive and delay-tolerant demands. Service of delay-sensitive demand is considered to be more important than delay-tolerant demands. Meanwhile, to decrease the waiting time of delay-tolerant demands, these demands need to be upgraded for high priority queue. A centralized algorithm based on dynamic programming is proposed by authors to optimize the solution. As an addition, a distributed algorithm is proposed for implementation and the neural network. Simulation results show that the usage of electricity in household is managed and for flexible demands operation delays are reduced as well. There is an issue regarding to inconsideration of parameters tuning.

Authors in [8], target the Peak Power Consumption (PPC) minimization. To address such issue, authors proposed the family plan approach that divides users into schedule groups. User's appliances are scheduled for PPC minimization through clustering scheme. Their aim is to achieve the reduction in payments, PPC and fuel cost. PPC is reduced by scheduling the jobs of each controllable family. They also balance the PAR and PPC by incorporating divide and conquer rule. User has to stay connected as a group member as mentioned in paper. Although their simulation work well however, limitations are still for research analysis that their system cannot handle interruptible jobs. In [9], user aware management approach is used that manages load by user preferences. Problem is trade-off between cost and UC. So, Game theoretic based energy optimization technique is used. It is different from other demand management systems, that it allows the user to prioritize the user preferences and savings. Load is distributed by means of game theoretic approach which has successfully reduced the electricity cost. Authors also analyze the performance of algorithm that approaches to 96% closer to optimal solution. As limitations, their proposed technique is not perfect in the presence of multiple energy resources.

Integer Linear Programming (ILP) technique is proposed in [10], for minimizing the peak load and scheduling the load in SG. Moreover, another aim is to schedule the power for power shift-able appliances and to optimize the operation time for time shift-able appliances. Authors are able to schedule both optimal operation time, optimal power and accomplished effective electricity consumption. Again, authors did not address the UC issue. Authors proposed a power scheduling strategy for the residential consumers in [11], to achieve a trade-off between the electricity cost and discomfort. Day ahead pricing signal is used in this paper. The result shows that the authors achieved low electricity price, reduction in PAR and achieved the limited user comfort because of the trade-off between cost and user comfort. As limitation for this paper authors did not provide incentive based DR load adjustments. As [12], elaborates that DR is essential for reducing electricity costs and loads. Authors focused on developing strategy for Heating, Ventilating and Air-Conditioning (HVAC) to respond to real time pricing for reduction of peak load. Proposed technique Dynamic Demand Response (DDR) changes the temperature's set point to control HVAC loads depending on electricity retail price after each 15 min then shift the loads of appliances partially. When DDR changed the set point of temperature, discomfort level decreases. Simulation showed DDR in residential HVAC systems can reduce peak load and electricity bill. Electricity cost for both hot and cold months are reduced to 31% and 29% respectively.

3 Proposed Solution

In residential areas, every home is considerably being equipped with SM that provide two-way communication between customer and utility, shown in Fig. 2. In our proposed system, we have categorized 13 appliances into 3 classifications; interruptible, non-interruptible and fixed appliances. We have scheduled the appliances according to [6]. Classified appliances are mentioned below in Table 1.

Table 1. Classification of appliances

Non-Interruptable	Interruptable	Fixed
Washing machine	Air conditioner	Light
Dish washer	Refrigerator	Fans
Cloth dryer	Water heater	Cloth iron
	Space heater	Microwave oven
		Toaster
		Coffee maker

Interruptible appliances are those, that can be turned off any time during operation. Non-interruptible appliances, that cannot be interrupted during operation time, while Fixed appliances are considered as non-manageable or non-modified appliances because they are regular appliances that cannot affect much on load scheduling issues. End users are allowed to customize the parameters of appliances according to their will by interacting with EMC to establish connection with utility. Moreover, end users are remained updated about the pricing scheme announced by the utility through DSM. The aim of utility is to educate users about the efficient energy consumption. Figure 2 elaborates the generic work flow of DSM for HEMS.

Peak and off peak hours are the time slots, where load of energy varies during the whole day. In this work we have assumed that 11 to 18 h are the slots for peak hours during the whole day. Hence, the parameters are initialized in advance by

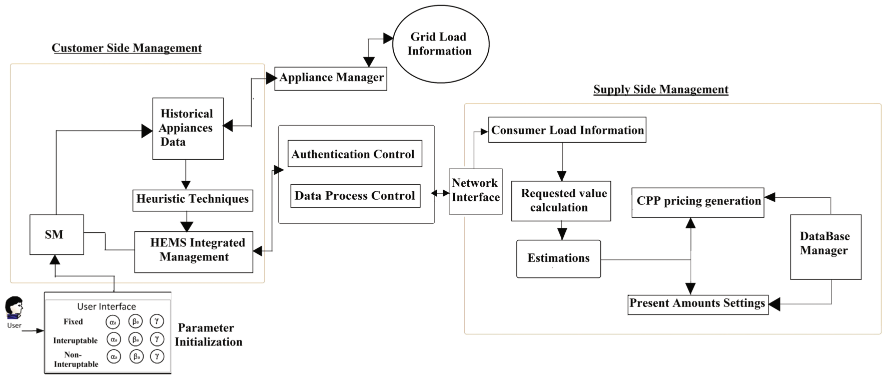

Fig. 2. DSM work flow

Table 2. Non-Interruptable appliances

Appliances	α	β	γ	Ω (kWH)
Washing machine	8	16	5	0.78
Dish washer	7	12	5	3.60
Cloth dryer	6	18	5	4.40

Table 3. Interruptable appliances

Appliances	α	β	Ω (kWH)
Air conditioner	6	24	1.44
Refrigerator	6	24	0.73
Water heater	6	24	4.45
Space heater	6	24	1.50

end user using DSM. Parameters for non-interruptible appliances are shown in Tables 2 and 3 for interruptable appliances and Table 4 represents the parameters for fixed appliances.

According to Table 2, α represents the starting time for the appliances, β represents ending time of appliances in hours. For specific appliance, γ represents the number of operational hours in which energy is utilized at any time slot between α and β, while Ω represents the load of specific appliance in kWH. Similarly, in Table 3 for interruptible appliances, α, β and Ω are same as described for Table 2 however, there is no constraint of operational hours in which appliances have to operate for limited hours between α and β. On the other hand in Table 4, parameters for fixed appliances are initialized in which appliances can be operated independently at any hour during a whole day.

We have used CPP scheme for electricity bill calculation. The main purpose to use this pricing scheme is that it provides the accurate information to cus-

Table 4. Fixed appliances

Appliances	Ω (kWH)
Lighting	0.6
Fans	0.75
Clothes iron	1.5
Microwave oven	1.18
Toaster	0.5
Coffee maker	0.8

tomer about the cost of electricity, so that customer can make decisions that how and when to use electricity. CPP pricing scheme awares the customer about the peak hours during the day. CPP rate offers lower prices during all other times. Therefore, the customer can have the opportunity of better assesement and thus reduces the overall energy costs. A bio-inspired meta-heuristic algorithm; EWA [4], is used for optimizing the electricity consumption. In EWA, there are two kinds of reproductions; Reproduction 1 and Reproduction 2. In nature, Reproduction 1 generates only 1 offspring either from male or female, while Reproduction 2 may generates more than one offspring at a time. Multiple crossover operators are used in order to improve the version of crossover head, addition to this Cauchy mutation is implemented to extract the best value after iterations. An abstract representation of natural behavior of earthworm is mentioned in Fig. 3.

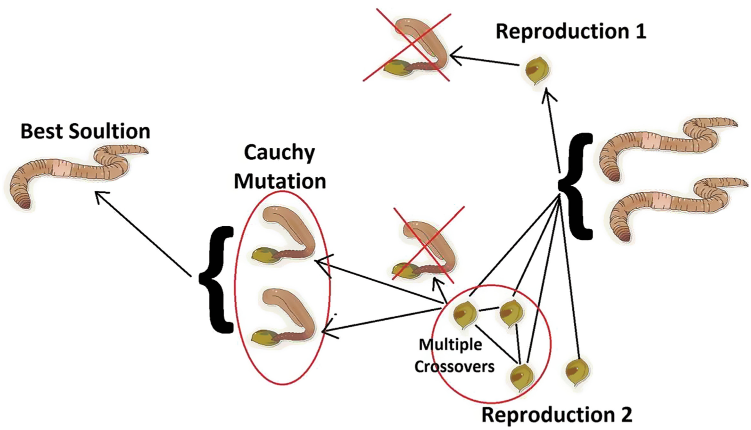

Fig. 3. Earth worm natural behaviour.

3.1 EWA Algorithm

The reproduction quality of earthworm performs multiple optimization steps, production steps of earthworm is optimized by the following scenarios:

- Every earthworm in population has the ability to regenerate its offspring in nature and ever individual earthworm has the capability of 2 reproductions.
- Every child of earthworm singular generated holds the entire genetic factor whose length is equivalent to parental earthworm.
- The earthworm singular with the fitness permits on straight next generation, and can not be altered by operators. This can be an assurance that population of earthworm can not fail in the increment in generations.

Steps of EWA algorithm are mentioned in Algorithm 1

Algorithm 1. EWA

procedure START
Initialization: Generates counter of t = 1; Set P as population of NP individual earthworm which is randomly distributed in search space; numbers of kept earthworm are set as $nKEW$, maximum generation $MaxGn$, α as similarity factor, proportional aspect β, constant $\gamma = 0.9$.
Evaluation of Fitness: each earthworm is evaluated individually according to its position
While till best solution is not achieved or t $< MaxGen$
All the earthworms in population are then sorted according to their fitness values
for i = 1 to NP (all earthworms) **do**
Generate offspring xi1 through Reproduction 1
Generate offspring through Reproduction 2
Do crossover
if i $< nKEW$ **then**
set the number of particular parents (N) and the produced off springs (M); Select the N parents using method i.e. roulette wheel selection; Generate the M offspring; Calculating x_{i2} according to offspring M generated
else
Randomly an individual earthworm as x_{i2}
end if
Update the location of earthworm **end for** i
for j = $nKEW$ + 1 to NP (earthworm individuals non-kept)
do Cauchy mutation
end for j
Calculate the population according to the newly restructured positions;
t = t + 1.
Step 4:
end while
Step 5:
Best solution is extracted
End.

Our next task is to compare EWA with BFA [5]. For BFA, we have used same appliances classification and parameters as mentioned in Tables 3, 4 and 5. Then we merged both techniques in order to depict the clear justifications. BFA is also a bio-inspired technique in which animals with poor foraging strategies are eliminated and replaced by healthy ones in nature. The main focus of this algorithm is to allow cells to randomly transmit towards the optimal solution by means of chemotaxis, swarming, reproduction and elimination-dispersal steps. Such behavior involve different steps as shown in Algorithm 2.

Algorithm 2. BFA

procedure START
Step 1:
Chemotaxis: number of chemotactic steps measures the length of bacteria's life time.
if favorable environment = *true*
bacteria = continue swimming
else
bacteria = direction changed
do *swarming*
bacterias attraction complete.
Step 2:
Reproduction: for optimized value
Calculate the reproduction of bacteria quality
then bacteria reproduce the generation
fitness value = *found*
creat next generation.
Step 3:
Elimination-dispersal: Cells are eliminated and new random samples are inserted for local search
reproduction created for chemotaxis
End.

4 Simulation Results

For simulations, we have evaluated the performance of different techniques in MATLAB. Scheduling of appliances are managed according to [6]. Different parameters of appliances can be defined through customers also. We have conducted the simulations on the basis of energy consumption, peak to average ratio, waiting time and electricity cost.

In Fig. 4, the numbers of hour are mentioned on the x-axis and load (kWhs) of electricity is given on y axis of graph. After simulations, the load is maintained for BFA scheduled appliances between 1 to 6 h. BFA shows almost the constant load of 2 kWh at 1 to 6. While EWA permits a little bit higher load between same time slots (1 to 6) that is almost 3 kWhs. On the other hand unscheduled appliances are showing the consumption of electricity slightly higher than BFA at 1 to 3 h but less than EWA during the time slots of 3 to 5 h. Load of BFA gradually increases during time slots of 6 to 8 with the variant resultant load of 6 to 17 kWHs. For EWA, in 6 to 10 h, load increases from 3 to 18 kWHs. On the other hand unscheduled appliances also depict the same behavior with different results having maximum load of 19 kWHs at 8 h. After 11 h, load of appliances starts decreasing for EWA and BFA while for unscheduled appliances, load decreases after 8 h. We can not totally neglect the consumption of electricity in peak hours however; we at least accomplished to optimize the consumption to some extent using BFA and EWA algorithms. In case of unscheduled appliances, we can clearly visualize that the consumption is not smart. In peak hours, load is higher at peak hours because no smart technique is used. We can see the effect of shifting the loads that in peak hours, unscheduled appliances are not efficient while our proposed scheme works well, another reason is that we have classified different appliances into three categories. Overall, the loads of appliances are same during 24 h but the consumption of energy is optimized in order to avoid higher electricity cost.

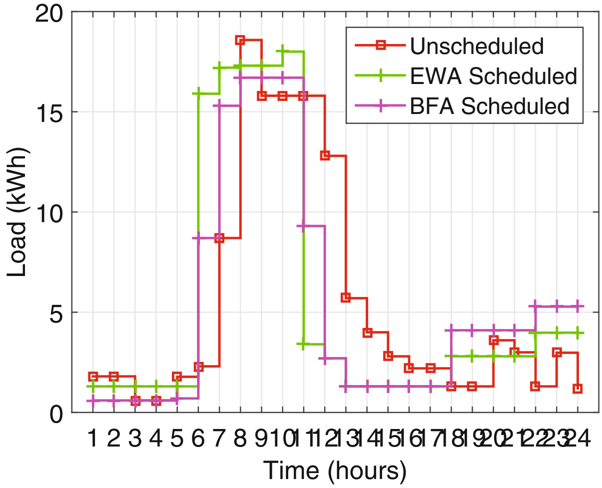

Fig. 4. Electricity load for 24 h.

As PAR is concerned, we have utilized our techniques for optimization. PAR is reduced which is beneficial to balance the power supply and demand. In case of PAR reduction we have given more priority to interruptible and non- interruptible appliances than fixed appliances. In Fig. 5, we can see that there is a difference regarding the PAR reduction, that EWA technique reduces PAR to almost 5% and BFA to 7% as compared to non scheduled appliances. So therefore, regarding to PAR reduction BFA performs better than EWA. For avoiding peak formation, we have used CPP pricing scheme that provides information to user about rates of electricity bills. Hence reduction in electricity bills are accomplished. Moreover, EWA algorithm's quality of multiple crossovers assists to achieve best solution for optimizing the problem. Unscheduled appliances show poor results because, they do not tackle the peak formation problems while our scheduled schemes are designed to avoid peak formation in any hour of the day because appliances are optimally distributed for 24 h.

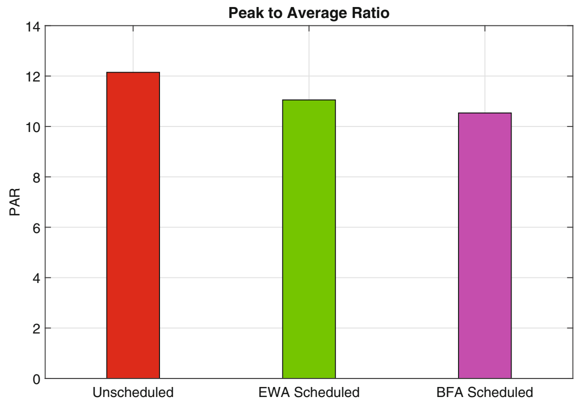

Fig. 5. Peak to average ratio.

Figure 6 elaborates that the result of scheduled appliances are optimal as compared to unscheduled appliances in term of electricity cost reduction. For 24 h, maximum electricity bill in case of unscheduled appliances are 1998 cents at peak hours between 11 to 12 h, while for BFA scheduled appliances we can see that during 11 to 12 h the maximum cost lies almost at 1200 cents and in case of EWA technique, the results are more efficient. During peak hours, the cost is reduced to 450 cents in same time slots (11 to 12). From simulation results, we can extract the information in chunks that, during 1 to 6 h both scheduled and unscheduled appliances have almost same electricity cost. When we slightly go further from 7 to 17 h we can see the drastic change that our proposed optimization technique EWA is forming very little peak in peak hours, i.e. 200 to 450 then 450 to 130 cents. On the other hand BFA shows slightly higher peak formation as compared to EWA but less then unscheduled. Such accomplishment was achieved due to the BFA parameters (reproduction and elimination) and EWA's two reproduction formations. Then total electricity bill reduction is mentioned in Fig. 7 to almost 45% for BFA and 55% for EWA, the fact is that we have delayed the operation of some appliances according to designed objective functions.

Waiting time of appliances in Fig. 8 directly affects the cost of electricity bill and User Comfort. Waiting time is increased because we have reduced the electricity cost by shifting the load of appliances from peak to off peak hours. According to Fig. 8 BFA is better than EWA in term of waiting time. Waiting

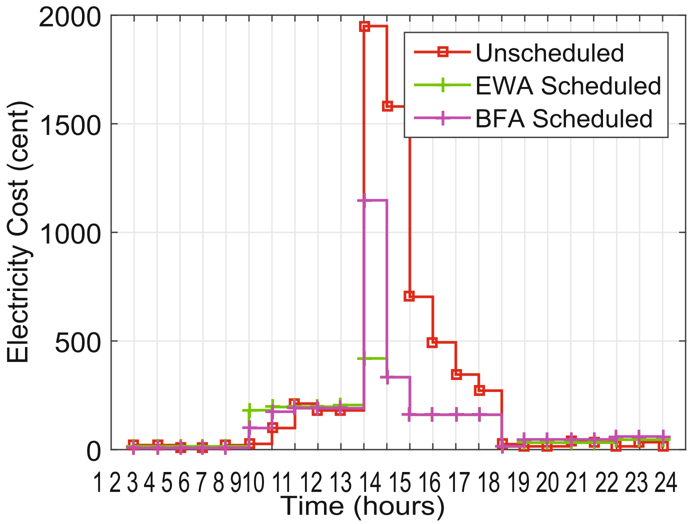

Fig. 6. Electricity cost.

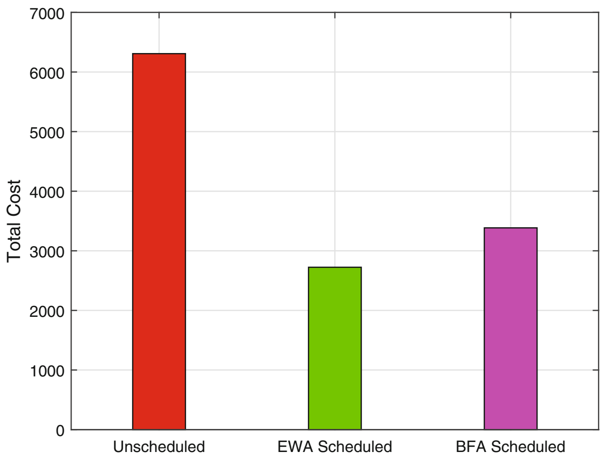

Fig. 7. Total electricity bill.

time factor has an important role for user satisfaction, increasing waiting time User Comfort also sacrifices. The relationship between Electricity cost and waiting time is inversely portion. So, in Fig. 8 simulation, waiting time for EWA has increased but bill decreased. EWA has sacrificed the user comfort and user has to wait for specific appliances to be operated.

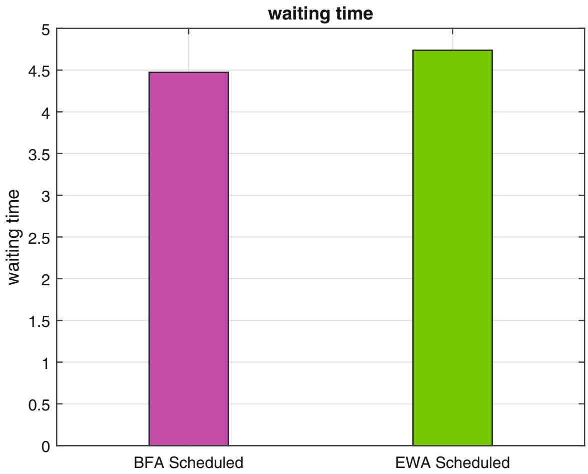

Fig. 8. Waiting time.

5 Conclusion

We have proposed the techniques for optimized electricity consumption in HEMS. Through simulations we have deduced the results that EWA performs better than BFA in term of cost and in term of PAR reduction BFA have a better results. Using CPP pricing scheme PAR reduction is achieved. We are able to accomplish the optimal results after shifting the load of appliances from peak hours to off peak hours. As there is a trade-off between cost reduction and UC, therefore in our work we have compromised the UC. In future we will focus on reducing the waiting time to meet the acceptable UC and concentrate on contribution of Renewable energy resources.

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