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Cost Optimization in Home Energy Management System using Genetic Algorithm, Bat Algorithm and Hybrid Bat Genetic Algorithm

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***Abstract*—Home energy management systems are widely used to cope up with the increasing demand for energy. They help to reduce carbon pollutants generated by excessive burning of fuel and natural resources required for energy generation. They also save the budget needed for installing new power plants. Price based automatic demand response (DR) techniques incorporated in these systems shift appliances from high price hours to low price hours to reduce electricity bills and peak to average ratio (PAR). In this paper, electricity load of home is categorized into three types: base load, shift-able interruptible load and shift-able non-interruptible load. In literature many metaheuristic optimization techniques have been implemented for scheduling of appliances. In this work for the optimization of energy usage genetic algorithm (GA) and bat algorithm (BA) are implemented with time of use (TOU) pricing scheme to schedule appliances to reduce electricity bills, the peak to average ratio and appliance delay time. A new technique bat genetic algorithm (BGA) has been proposed. It is hybrid of GA and BA. It outperforms GA and BA in terms of cost reduction and peak to average ratio for single home scenario as well as multiple home scenario. Operation time internals (OTIs) 15 minutes, 30 minutes and 1 hour have been considered to check their effect on cost reduction, PAR and user comfort (UC).**

***Index Terms*—Home energy management, demand side management, genetic algorithm, bat algorithm, hybrid scheme**

I. Introduction

As the world is progressing humans are inventing new devices to make daily chores easy and time efficient. Electricity consumption is increasing rapidly as the use of electrical appliances is increasing in daily tasks. In order to deal with increasing demand of electricity more power plants are required. Installation of power plant demands big budget. Electricity generated from natural resources cause emission of carbon dioxide, which is affecting our climate in a hazardous way [9]. So, it is clear that to deal with the above stated problems we need to optimize the consumption of electricity and utilize electricity within the maximum generating capacity of working production units.

On the other hand, when multiple users start using appliances during particular hours than peaks are formed in those hours. To fulfill the requirement during peak hours extra generation units are put in the work, but carbon generated from those units is harmful, plus it increases the unit price in that hour. So, reducing demand peaks is in favor of both utilities and consumers. Home energy management system (HEMS) is used for optimization of energy consumption and scheduling of devices in such manner that energy consumption is reduced and peaks are not formed at any time of day. HEMS consist of demand side management (DSM) and DR. DSM is basically ability to control energy consumption profiles of users and tune it in such manner that it is beneficial both for utility and customer. In DSM different techniques are used such as load shifting, load curtailment, valley filling and peak clipping. HEMS implement different DR to shift loads other than base loads to off peak hours [10]. DR can be incentive based or price based. In incentive based DR customers are given some incentives if they are cooperative with utility and use electricity according to utility instructions. Price based DR include different pricing schemes such as TOU, real time pricing (RTP) or day ahead pricing (DAP) [6-9]. In case of price based DR electricity price for on peak hours is increased, in this way

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people are forced to use heavy power consumption appliances during off peak hours to avoid high bills.

HEMS aims at minimization of electricity cost, appliance delay, power consumption and PAR. Various optimization techniques such as GA, particle swarm optimization (PSO), evolutionary differential algorithm (ED), harmony search algorithm (HSA), ant colony optimization (ACO) and bacterial foraging algorithm (BFA) have been implemented in this domain to achieve these aims [6-8]. In this paper GA and BA are implemented with TOU pricing scheme to optimize the energy consumption and shift appliances from high price hours to low price hours. A new hybrid scheme BGA has been proposed. BGA achieves more reduction in cost and PAR as compared to GA and BA. UC is also considered in terms of waiting time. It is worth mentioning that nomenclature is given in table I.

This paper is organized as follows: Sections II and III present the related work and system model, respectively. Section IV gives the problem formulation and optimization algorithms GA, BA and BGA are discussed in section V. Section VI explains the results obtained by applying optimization algorithms and effects of considering different OTIs, followed by conclusion in section VII.

TABLE I: Nomenclature

Variable	Description
t	Time interval
p_n	On or off status of appliance n
PR_n	Power rating of appliance n
EP_t	Electricity cost at slot t
App	Total number of appliances for scheduling
TP^{sch}_{total}	Total cost after schedule
TP^{unsch}_{total}	Total cost before schedule
$Load^{sch}_{total}$	Total cost after schedule
$Load^{unsch}_{total}$	Total cost before schedule
F_i	Emission frequency of ith bat swarm
F_{min}	Minimum emission frequency value
F_{max}	Maximum emission frequency value
A^t_i	Loudness value of ith bat swarm at time t
α	Initial value of loudness
r^t_i	Pulse emission rate of ith bat swarm at time t
x^0_i	Initial value of pulse emission rate
x^t_i	location of ith bat at time t

II. Related Work

In the ever-changing field of technology, the demand of electricity for the residential and industrial areas is increasing day by day. The increase in demand leads to the problem of load management on the side of utility providers. Utility increases the price of electricity according to load demand. Customers do not want to pay high prices, so here HEMS comes into play to cater the scheduling of load and reducing the cost. It manages the load profiles of users to reduce cost and demand from the utility. Now a days HEMS has become a broad domain of research.

Techniques from different domains are implemented for appliance scheduling. In [1,11], machines learning technique artificial neural networks (ANN) have been implemented in the field of HEMS. In [1], authors propose a mechanism to develop optimal DR using ANN from the field of artificial intelligence. As compared to the previous results using this ANN cost reduces up to 4.6%. However, author did not consider the peak to average ratio (PAR). In paper [11] ANN with GA (ANN-GA) is implemented and system is trained to achieve 10%, 25% and 40% reduction in grid energy.

Authors has worked to reduce the chance of error while estimating the cost of electricity in DR [2].They used two schemes improved PSO and two-point estimation method in terms of error reduction. As previous studies mentioned that PSO has a low convergence rate that is why authors used improved PSO which is a gradient based PSO. It can be seen from the results that the chance of error in constrained DR is reduced and proposed system shows comparable results with reduced computational time. However, the authors have not considered any pricing technique to calculate the electricity cost. In [3], authors used modified PSO implementation at residential, industrial and commercial areas to resolve DSM problem. They used TOU pricing technique and achieved 9.65%, 7.24% and 18.72% cost reduction in commercial, residential and industrial areas of DSM respectively. Authors missed to consider the PAR that may lead to raise the chance of peak creation that will have effect on utility and user side as well.

In [4], authors use fuzzy logic technique for communication between different agents of smart home. They considered two scenarios of communication: one is communication in between appliances of single home and communication in between multiple homes. For the scheduling of load, they use a localize concept of energy sharing in between multiple homes according to their state of battery. A priority based approach is followed to turn on any appliance in smart home. Multiple agents in different homes can communicate and share the energy. They consider the bidirectional flow of energy.

Normally the running cost functions are not considered as power disruption to satisfy UC. Authors used TOU pricing technique with two scheduling algorithms for two different purposes. GA scheduling algorithm is used to optimize the running cost while heuristic approach is used for cost estimation. Results of both techniques are comparable with the difference of 8% to 10% [5].In [6], authors compared the performance of HSA, enhanced differential evolution (EDE), harmony search differential evolution (HSDE) scheduling algorithms. They also considered reusable energy resources in the system along with RTP pricing technique. Results are the evident of the fact that the usage of reusable energy resources has a great effect in terms of cost reduction. HSA performed better than other scheduling algorithms in both cases with and without reusable energy resources. However, the limitation arises that waiting time increases which minimizes the users comfort. There is always a trade off in between cost and UC which is measured as delay.

Authors in paper [7], used dynamic programming, GA,binary particle swarm optimization (BPSO) and a combined GAPSO in terms of load scheduling. Objectives of authors are minimization of cost and PAR as well as maximization of UC. They used two pricing techniques critical peak pricing (CPP) and DAP for calculation of cost and perform comparison in both cases. Simulation results show that the GAPSO algorithm gives best results, increases UC level and reduces PAR and cost upto 23.9% This paper has a limitation that they did not consider the consumption cost which is increasing. In [8], authors proposed enhanced differential teaching learning technique to reduce cost, discomfort and PAR. Authors compare results of proposed technique with some existing techniques used for scheduling namely GA, TLBO and EDE. RTP used to calculate the cost. Authors proposed an enhanced technique of TLBO which reduces cost upto 36.02%.

In [10, 12], TOU pricing scheme has been used. Authors use binary backtracking search algorithm (BBSA) and BPSO for scheduling. Energy consumption reduction achieved by BPSO is 20% while for BBSA it is 21.3% [9]. Multi user and load priority (MULP) algorithm has been used with different pricing schemes TOU, RTP with direct load control (DLC) and RTP with inclined block rate (IBR) and achieved 22%, 14.5% and 19% reduction in bill[10].

Improved HSA and GA has been implemented for scheduling of energy storage systems on the basic of priority in residential area. Improved HSA outperforms GA in terms of cost reduction [13]. In [14], an optimization scheme has been proposed by authors to schedule appliances. 13% cost reduction and delay time in appliances operation is achieved using proposed technique. In [16], authors made comparative analysis of GA, ACO and BPSO by implementing these schemes on energy management controllers to observe which scheme works best for achieving maximum electricity bill reduction, UC and peak reduction.

Multi-time scale optimization (MTSO) for HEMS is considered to reduce operational cost, time and user discomfort as well. EV, heating, ventilation, and air conditioning (HVAC) system and base appliances has been considered and it is ensured that the cost reduction in single-time scale and multiple time scale remains same. Cooperative particle swarm optimization (CPSO) is implemented with proposed MTSO algorithm and dynamic DAP scheme is used [19]. Concept of local HEMS and global HEMS have been introduced to divide computational load. A multi home problem has been discussed. Energy storage devices will be scheduled at global level while other appliances are scheduled at local level according to customer priority [20].Automatic DR for HEMS has been proposed using DAP. Advance integrated multidimensional modeling software (AIMMS) has been considered to solve the problem using AIMMS's outer approximation algorithm (AOA) [21]. HVAC and other loads have been scheduled using learning based HEMS. ANN and regression based techniques error has been compared and regression has been selected over ANN for scheduling purpose [22].

BA is proposed by Xin-She Yang in 2010 [17]. It is inspired by the ecological behavior of bats. It is used to solve optimization problems in many fields. Binary version of BA knows as binary BA has been proposed in [18]. Differential bat algorithm (DBA) has been proposed by Coelho [23] by combining DE and BA to reduce power consumption of HVAC system, it is observed that in mean index error is reduced by 43.3% by proposed hybrid technique. In another paper, battery energy storage is connected

TABLE II: SOTA table

Problem Addressed	Techniques	Pricing	Results	Limitations
Cost reduction [1]	ANN	DR	4.6 and decrement in cost	PAR not considered
Load Management on DSM [3]	Improved PSO	TOU	9.65%, 7.24%, 18.72%	PAR not Considered
Cost, PAR and waiting reduction with integration of RESs [6]	HSA, HSDE, EDE with RESs	RTP	Cost reduced	UC compromised
Load scheduling in terms of cost reduction with maximization of UC [7]	Dynamic Programming, GA, BPSO, GAPSO	CPP, DAP	23.9% reduction in cost in case of GAPSO	Consumption cost increased
Minimization of cost, discomfort and PAR [8]	GA, Teaching learning based optimization, EDE, EDTLA(proposed technique) Enhanced differential teaching learning algorithm	RTP	36.02% reduction in cost EDTLA, 14.70% GA, TLBO 33.82%, EDE 12.76%	Trade off in between electricity bill and delay
Energy consumption. reduction [9]	BPSO, BBSA	TOU	21.3% energy consumption reduction	PAR not considered
Energy consumption and cost reduction [10]	MULP	TOU, RTP with DLC, RTP with IBR	TOU 22%, RTP + DLC %14.5 and RTP +IBR %19	increase in bill reduction in summers UC not considered
Energy consumption optimization [11]	ANN-GA	TOU	10%, 25% and 40%,Reduction in grid energy	PAR not considered
Price Reduction, Minimization of peak load[12]	MIP	TOU	3.6% cost reduction	UC not under consideration
Cost reduction [13]	Improved HSA	TOU	4% more cost reduction than GA	UC ignored
Reduction in energy consumption and cost [14]	Priority based scheduling	DAP	2% cost reduction	Tradeoff b/w UC and PAR
Minimize cost and delay [15]	MOEA	TOU	13% cost reduction	PAR not considered
Energy consumption reduction [16]	GA, BPSO and ACO	TOU and IBR combined	48.79%, 40.43% and 28.26% resceptively	Tradeoff b/w UC and cost reduction
Multi-time scale optimization [19]	CPSO + MTSO	DAP	Percentage decrease is same for both STS and MTS	PAR not considered
Comparison of distributed and centralized distribution optimization [20]	MILP	TOU	Same for both LHEMS and DHEMS	PAR not considered
Cost reduction keeping UC under consideration [21]	AOA	DAP	68% cost reduction	Waiting time of appliances not considered
Learning based DR [22]	Regression	DAP	56.77% cost reduction	Industrial and commercial areas not considered
Meta Heuristic algorithms for cost reduction [23]	GA and BA	TOU	Cost reduction 70% BA, 65%	Tradeoff b/w UC and Cost reduction
Power consumption reduction [24]	DBA	DAP	43.3% error reduction	Multi objective system not considered

with micro grid to check the optimized size of battery to reduce cost reduction. BA is implemented for this purpose and results shows that 40% cost reduction is achieved by using 250kWh battery energy storage [24]. In this paper a hybrid technique BGA has been proposed and results are simulated to check its performance. TOU is considered as price signal and performance of new technique is compared with that of GA and BA.

III. System Model

DSM makes the working of smart grid (SG) effective and stable. DSM helps both user and utility by managing electricity usage by scheduling the appliances according to HEMS through energy management controller (EMC). Advance metering infrastructure (AMI) is configured in houses for two-way communication between utility and homes. Pricing scheme information is sent from utility to home and energy consumption information is sent

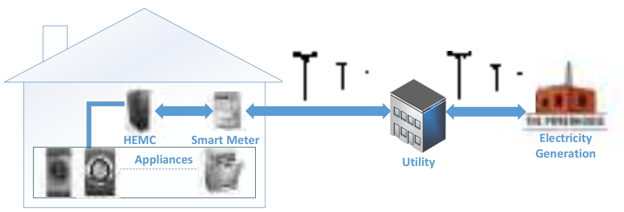


Fig. 1: Proposed system model

from home to utility through AMI. Decision of turning appliances on and off is made by the system keeping in regard the customer's priorities. In this research work, we are scheduling the appliances of a home. The length of operation time (LOT) and range of power ratings of appliances used for simulations are given in Table III. Moreover, three OTIs 15 minutes, 30 minutes and 1 hour has been considered in this work. Diagram of proposed system model is shown in fig 1.

A. Pricing Scheme

In this work we are considering TOU pricing scheme. In TOU pricing scheme, we divide day into three portions that are off peak hours (12am-6am, 7pm-11am), shoulder hours (7am-10am, 5pm-6pm) and on peak hours (11am-4pm). Electricity price for a portions remains constant throughout the season.

B. Load Categorization

Appliances load in a home can be divided into two categories manageable and non-manageable [12]. Mostly the scheduling is done for manageable load as it has high power consumption and operation time is predictable. Manageable load is further categorized as follow:

1) 1) Shift-able load: The appliances that can be delayed but cannot be interrupted during operation belong to this category e.g., cloth washing machines, cloth dryer etc.
2) 2) Shift-able load and Interruptible load: The appliances that can be delayed as well as interrupted during operation time belong to this category e.g., dishwasher, iron etc.
3) 3) Base load: The appliances that work for the whole day and cannot be scheduled e.g., refrigerator, air conditioners, central heating and cooling systems etc.

TABLE III: Appliance categories and power ratings

Appliance Category	Appliance Name	Energy Consumption range (KW/h)
Shift-able and non-Interruptible	Washing Machine Cloth Dryer	0.65-0.52 0.19-2.97
Base Load	Refrigerator AC	0.35-0.37 0.25-2.75
Shift-able and Interruptible	Oven Morning Dish Washer Oven Evening Vacuum Cleaner Iron Electric Vehicle	0.83-1.28 0.6-1.2 0.75-2.35 2.37-5 4-5 7.5-8.5

Appliances in non-manageable load category are TV, laptops, lights, fans, phones, coffee maker, computers etc. Their power consumption is very small as compared to the major load discussed above. Moreover, these appliances are interactive and have little scheduling flexibilities. Range of power ratings and working slots of appliances to be scheduled are shown in table III.

IV. Problem Formulation

The major objectives of this research work are reduction of consumers electricity bills by optimizing electricity usage and PAR reduction. This problem is mapped to multiple knapsack problem (MKP). In MKP problem there are multiple knapsacks and each object has a value and a weight associated with it. Sum of weights for all selected objects should not exceed knapsack capacity. Here, the problem is formulated as an optimization problem with base loads, shift-able non-interruptible loads and shift-able interruptible loads. Optimization function can be defined as:

$$minimize \sum_{t=1}^{T} \sum_{n=1}^{App} (P_n \times PR_n \times EP_t) \tag{1}$$

Such as:

$$1 \leq t \leq T \tag{2}$$

$$1 \leq n \leq App \tag{3}$$

$$p_n \in [0, 1] \tag{4}$$

$$TP_{total}^{sch} \leq TP_{total}^{unsch} \tag{5}$$

$$Load_{total}^{sch} = Load_{total}^{unsch} \tag{6}$$

$$Load \leq Threshold \tag{7}$$

Equation 1 shows cost minimization objective function. Equation 2 shows time slot variable t, its maximum value T depends upon the OTI size, such as for OTI of 1 hour, 30 minutes and 15 minutes T will be 24, 48 and 96 respectively. In our work we are considering ten appliances that are to be scheduled. Equation 4 shows that appliances can have either on or off status. Equation 5 shows total cost after schedule should be less than total cost before schedule. Condition that total energy consumption before and after scheduling should remain same in shown in equation 6. Equation 7 shows load at particular slot after thresholding should be less than the threshold. This threshold is set to controls PAR.

V. Optimization Algorithms

In this work heuristic algorithms GA, BA and BGA has been used for the optimization of our MKP. We cannot apply traditional optimization techniques due to the stochastic nature of our problem.

A. Genetic Algorithm

GA is inspired by the natural selection procedure of living organisms. In GA random population of chromosomes in generated and this population is converted to binary form. Each gene of chromosome represents the status of an appliance. Then two parent chromosomes are selected using roulette wheel method and crossover is done. Crossover is of multiple types, one point, multi point or uniform crossover. Probability for crossover is set to 0.9. High probability of crossover will lead to fast convergence. To introduce randomness in solution, space mutation procedure is performed with probability of 0.1. Pseudo code of GA is shown in algorithm 1.

Algorithm 1 GA

```
Initialize App, P, MaxIterP
Generate random population Xi(i = 1,2,...,n)
for 1:24 do
    Apply constraints
    Calculate fitness
    Set gBest as current hour schedule
    while ( doIter< MaxIter)
        Select parents
        for i=1:POP do
            if rand<0.9 then
                Crossover
            end if
            if rand>0.1 then
                Mutation
            end if
        end for
    end while
end for
```

B. Bat Algorithm

It is a swarm intelligence meta-heuristic algorithm. It is based on the echolocation capacity of bat that helps it to find prey and estimate the distance and location of prey. Efficiency and accuracy of the algorithm depends upon the exploration and exploitation rate. Exploration can be explained as exploring new areas for prey while exploitation is searching for prey in the present locality. Balance between exploration and exploitation is important. As due to more exploitation rate algorithm can get stuck in local minimum and lose diversity while high exploration may cause low convergence. Frequency is adjusted to control the speed of BA. Loudness and pulse emission rate controls the search in nearby locality. Equations for calculation of BA parameters are given below:

$$F_i = F_{min} + (F_{max} - F_{min}) \cdot \lambda \tag{8}$$

$$v_i^t = v_i^{t-1} + (x^* - x_i^{t-1}) \tag{9}$$

$$x_{(i)}^{t+1} = x_{(i)}^t + v_i^t \tag{10}$$

$$x_{(i,new)}^t = x_{(i,old)}^t + \varepsilon \cdot A_i^{(t-1)} \tag{11}$$

$$A_i^t = \alpha \cdot A_i^{(t-1)} \tag{12}$$

$$r_i^t = r_i^0 \cdot (1 - e^{(-\gamma t)}) \tag{13}$$

$$\lambda \in [0,1] \tag{14}$$

$$r \in [0,1] \tag{15}$$

$$\varepsilon \in [-1,1] \tag{16}$$

Algorithm 2 BA

```
Initialize parameters MaxIter, POP, x_i^t, v_i^t
Initialize parameters F_i^t, r_i^t, A_i^t
Generate random population Xi(i = 1,2,...,n)
for 1:24 do
    while ( doIter< MaxIter)
        for i=1:POP do
            Generate new solutions using equ. 8, 9 and 10
            if rand> r_i^t then
                Generate x_{i,new}^t using equ.11
                Update r_i^t, A_i^t using equ. 12 and 13
            end if
        end for
    end while
    Calculate fitness
    Set gbest as current hour schedule
end for
```

C. Bat Genetic Algorithm

It is a hybrid technique that has features of BA and GA combines. GA is phenomenal in case of global search. BA perform better than GA in terms of local search. BA has two main steps exploration and exploitation. Balance between exploration and exploitation is really important because if exploration reduces algorithm gets stuck in local minimum. This limitation is often faced by BA, to overcome this limitation a new algorithm BGA is proposed in this work. BGA performs mutation step of GA after formation of new solution using BA to increase the diversity of search space.

VI. Simulation Results and Discussion

Proposed scheme has been used for scheduling of appliances in single home and multiple homes.

Algorithm 3 BGA

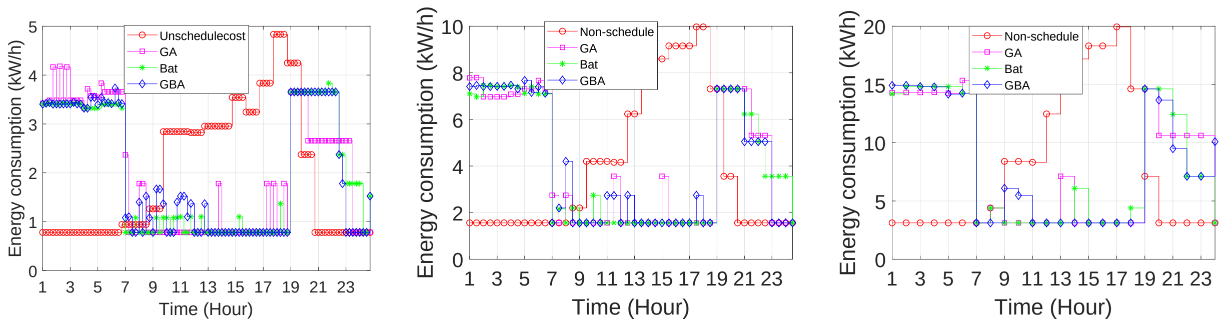
```
Initialize parameters MaxIter, POP, x_i^t, v_i^t
Initialize parameters F_i^t, r_i^t, A_i^t
Generate random populationXi(i = 1,2,...,n)
for 1:24 do
    while ( doIter< MaxIter)
        for i=1:POP do
            Generate new solution using equ. 8, 9 and 10 respectively
            if rand> r_i^t then
                Generate x_{i,new}^t using equ. 11
                Update r_i^t, A_i^t using equ. 12 and 13 respectively
            end if
        end for
        if rand<0.1 then
            Mutation
        end if
    end while
    Calculate fitness
    Set gbest as current hour schedule
end for
```

A. Single Home

For single home power rating of appliances is fixed. Home has ten appliances. Appliances are further categorized as: base appliances, shift-able interruptible appliances and shift-able non-interruptible appliances. TOU pricing scheme is used for scheduling of appliances. GA, BA and BGA has been used for scheduling the load of smart home. Results for three OTIs 15 minutes, 30 minutes and 1 hour are discussed in this section. Performance measures considered for this work are electricity cost, PAR and UC as waiting time. Objective is to reduce cost, appliance delay and PAR while maintaining same total load of a home before and after scheduling of appliances.

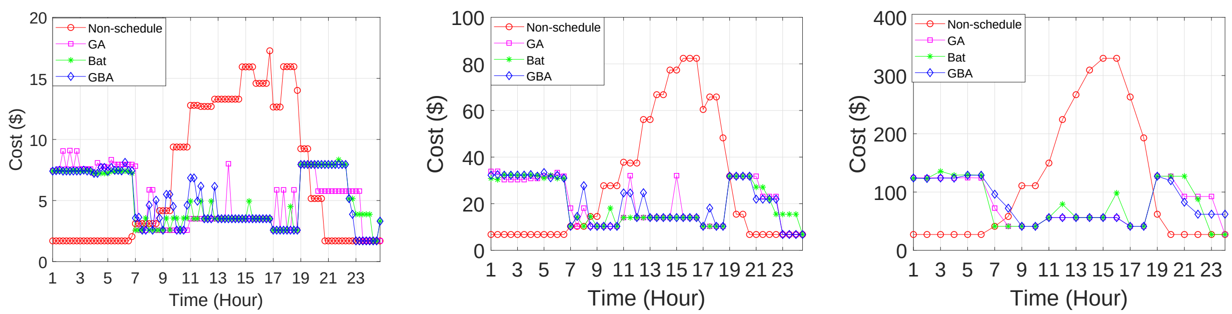
Fig 2 (a), (b) and (c) shows energy consumption for each time interval before and after scheduling for OTIs 15 minutes, 30 minutes and 1 hour respectively.Using any appliance during on peak hours will increase the electricity bills rapidly, so through scheduling a part of load has been shifted from on peak hours to off peak hours.

Cost per unit time for different OTIs is shown in fig 3. Cost for on peak hours is more as compared to off peak hours, even small energy consumption



(a) OTI 15 minutes (b) OTI 30 minutes (c) OTI 1 hour

Fig. 2: Energy consumption per unit time for all considered OTIs



(a) OTI 15 minutes (b) OTI 30 minutes (c) OTI 1 hour

Fig. 3: Cost per unit time all considered OTIs

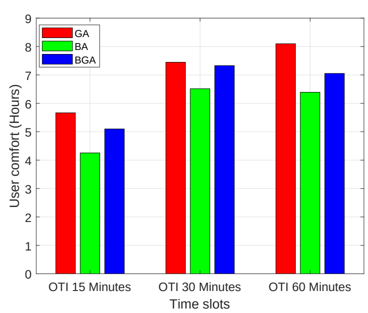


Fig. 4: User comfort for OTIs

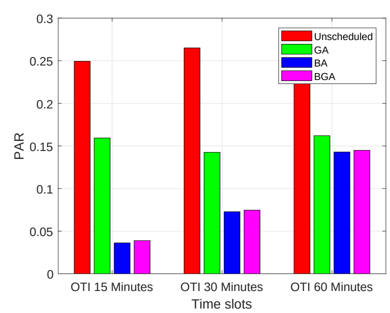


Fig. 5: PAR for OTIs

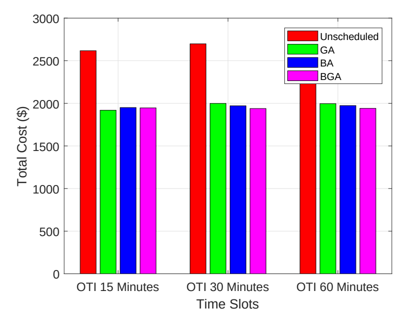
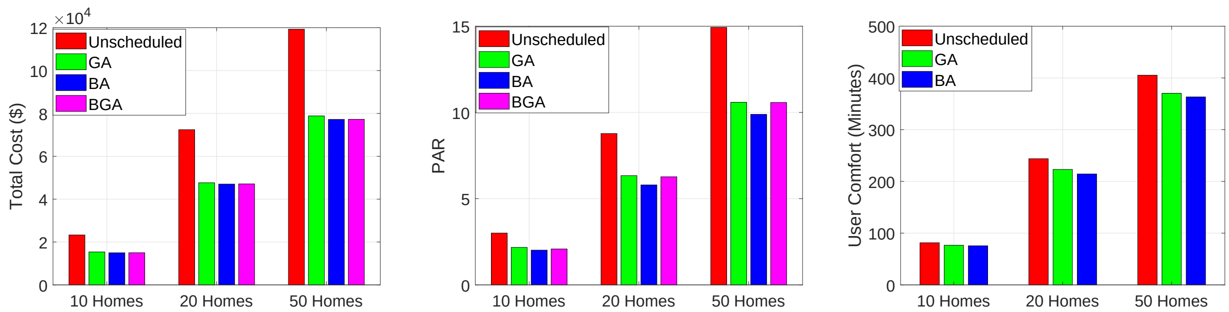


Fig. 6: Total cost for OTIs

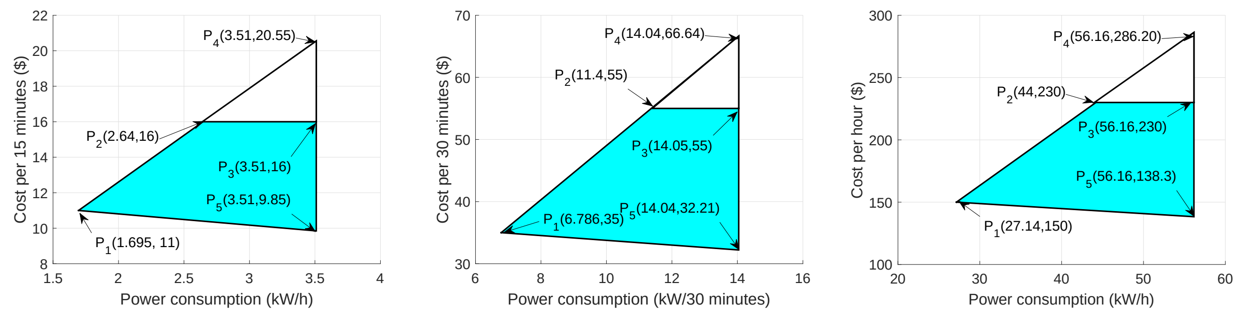
during off peak hours will lead to insignificant increase in cost. UC is measured as the delay in appliance operation time after scheduling. There is a trade-off between UC and cost reduction. If a person wants immense decrease in cost UC will be compromised. Fig 4 shows UC for OTIs 15 minutes, 30 minutes and 1 hour respectively. It is obvious from plots that UC increases as OTI decreases. The reason is scheduler has more options for scheduling the appliance as compared to longer OTIs. UC will be more disturbed by technique that gives more cost and PAR reduction as appliance operation time delay will be more.

In a unit time PAR is a ratio between the peak load and average load. Reducing PAR is important both for utilities and users. If PAR crosses a certain limit it can damage utility. Increased PAR increases customers electricity bill as well. PAR increases as the OTI increases because the probability of scheduling appliances at the same slot will increase



(a) Total Cost (b) PAR (c) UC

Fig. 7: Simulation results for multiple homes



(a) OTI 15 minutes (b) OTI 30 minutes (c) OTI 1 hour

Fig. 8: Feasible regions for all considered OTI

TABLE IV: Possible cases for OTIs

Cases	**OTI 15 Minutes**			**OTI 30 Minutes**			**OTI 1 Hour**		
	Load (kWh)	**EP**	**Cost ($)**	**Load (kWh)**	**EP**	**Cost ($)**	**Load (kWh)**	**EP**	**Cost ($)**
Min. load, Min. EP	0.78	2.1750	1.695	1.56	4.35	6.786	3.12	8.7	27.144
Min. load, Max. EP	0.78	4.5	3.51	1.56	9	14.04	3.12	18	56.16
Max. load, Min. EP	4.567	2.1750	9.85	7.405	4.35	32.2117	14.62	8.7	127.19
Max. load, Max. EP	4.567	4.5	20.55EP	7.405	9	66.645	14.62	18	263.16

for larger OTI. As shown in fig 5 PAR for OTIs 15 minutes, 30 minutes and 1 hour. PAR of GA is more than that of BA in all scenarios. PAR of BGA is less than that of GA and BA. Fig 6 shows bar graphs of total cost per day before and after scheduling for OTIs 15 minutes, 30 minutes and 1 hour. Objective of reduction in total cost has been achieved by GA, BA and BGA. Average cost reduction by GA is 24.90%, 27.46% and 25.41% for OTIs 15 minutes, 30 minutes and 1 hour respectively. Average cost reduction by BA is 25.95%, 28.59% and 28.93% for OTIs 15 minutes, 30 minutes and 1 hour respectively. Average cost reduction by GBA is 26.31% 29.23% and 29.14% for OTIs 15 minutes, 30 minutes and 1 hour respectively. For all OTIs BGA is giving more cost reduction than GA and BA. Energy consumption for small OTIs is more because sometimes the LOT of appliances is less than the OTI. Even if the LOT of an appliance is less than the unit length of OTI we apply it for one complete slot; appliance turns off after completing LOT and remaining time slot energy is wasted and user is charged for it.

B. Multiple Homes

Same number of appliances has been considered for all homes. Power rating of an appliance is different for different homes. Power rating of appliances lie in the ranges given in table III. Results are simulated at 10 homes, 30 homes and 50 homes. OTI of 1 hour has been considered. Total load before and after schedulling remains for multiple homes. Results of total cost reduction are shown in fig 7 (a). For different number of homes cost reduction is 33.3%, 34.4% and 35% for GA, BA and BGA respectively. It is evident from plot that cost reduction of BGA is slightly more than GA and BA. Fig 7 (b) shows that the PAR increases as the cost reduction increases. UC is maximized by BGA as compared to GA and BA as shown in fig 7 (c).

C. Feasible Region

Set of all possible values that satisfy optimization problem constraints is known as feasible region. For TOU pricing scheme signal range is (2.1750:4.5) for 15 minutes slots. Power consumption range for 15 minutes slot is (0.78:4.567). Table IV shows all the possible cases with respect to TOU scheme. Feasible region cost must be less than the maximum cost of unscheduled load \$16. Constraints for feasible region are given below:

C1: $9.85 \geq$ PH ≤ 16

C2: PH $\geq$ 558.3289

C3: $1.695 \geq$EH ≤ 3.51

C1 depicts the range of the hourly cost of scheduled load. C2 shows that daily scheduled load cost must be less than unscheduled load cost. C3 gives the range of scheduled energy consumption. Points P1, P2, P3 and P5 shows the feasible region obtained under given constraints in fig 8 (a).

For TOU pricing scheme signal range is (4.35:9) for 30 minutes slots. Power consumption range for 30 minutes slot is (1.56:7.405). Table IV shows all the possible cases with respect to TOU scheme. Feasible region cost must be less than the maximum cost of unscheduled load \$32.21. Constraints for feasible region are given below:

C1: $66.64 \geq$PH ≤ 32.21

C2: PH$\geq$ 1222.6

C3: $6.786 \geq$EH ≤ 14.04

C1 depicts the range of the hourly cost of scheduled load. C2 shows that daily scheduled load cost must be less than unscheduled load cost. C3 gives the range of scheduled energy consumption. Points P1, P2, P3 and P5 shows the feasible region obtained under given constraints in fig 8 (b).

For TOU pricing scheme signal range is (8.7:18) for one hour. Power consumption range for 15 minutes slot is (3.12:14.62). Table IV shows all the possible cases with respect to TOU scheme. Feasible region cost must be less than the maximum cost of unscheduled load \$16. Constraints for feasible region are given below:

C1: $138.3 \geq$PH ≤ 230

C2: PH $\geq$ 2862.4

C3: $27.14 \geq$EH≤ 56.16

C1 depicts the range of the hourly cost of scheduled load. C2 shows that daily scheduled load cost must be less than unscheduled load cost. C3 gives the range of scheduled energy consumption. Points P1, P2, P3 and P5 shows the feasible region obtained under given constraints in fig 8 (c).

D. Trade-off

There is a trade-off between UC, PAR and cost reduction. As an algorithm will give more cost reduction, it shifts most of appliances other than base appliances to off peak hours. Due to shifting of appliances to off peak hours waiting time of appliances increase that effect UC.

VII. Conclusion

In this paper simulations results has been observed for scheduling a home with ten appliances and multiple homes with ten appliances. OTIs of 15 minutes, 30 minutes and 1 hour have been implemented and their affect has been noted. When OTI is small cost reduction is more as some appliances have LOT less than OTI. If we have OTI of one hour then the appliance that has LOT less than one hour will be given one complete hour, in this way energy for remaining time of one-hour slot after completion of LOT will be wasted. PAR will decrease as OTI decreases because there are more slots to schedule the appliances and probability of scheduling more than one appliance at the same slot decreases. UC decreases as OTI deceases as the number of slots are more for scheduling. There is a trade-off between UC and cost reduction. Optimization schemes GA, BA and GBA are used for scheduling. Cost and PAR reduction for proposed technique GBA is more than GA and BA is most scenarios. As the cost is more reduced waiting time of appliances increases.

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