Demand Side Management Using Hybrid Genetic Algorithm and Pigeon Inspired Optimization Techniques

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Demand Side Management Using Hybrid Genetic Algorithm and Pigeon Inspired Optimization Techniques

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***Abstract*—In this paper, our goal is to minimize the electricity cost, electricity consumption at minimum user discomfort while considering the peak electricity consumption. Electricity consumption may not be the same in residential, commercial and industrial areas. It may vary from each and every area. It is a challenging task to maintain the balance between the conflicting objectives: electricity consumption and user comfort. To meet the rising electricity demand in residential area, schedule-able devices can be equally distributed to the available time slots on the basis of average power consumption. The main objective is to minimize the electricity usage during the electricity peak hours by distributing the electricity load during the off-peak hours. In this regard, Genetic Algorithm (GA), Pigeon Inspired Optimization (PIO) and our proposed hybridization of GA and PIO (HGP) in Demand Side Management(DSM) are applied for residential load management to optimize the fitness function. GA, PIO and HGP are evaluated on the basis of real time pricing scheme (RTP) for single home with three different operational time interval (OTI) and for multiple homes with a single OTI. Simulations results shows that GA, PIO and HGP are able to minimize electricity bill and electricity consumption while minimizing the user discomfort. The performance of HGP is better than GA, PIO with respect to PAR, electricity load and electricity cost for both single home and multiple homes scenario. The feasible region between electricity cost and electricity consumption is also represented. Moreover, the desired trade-off between electricity cost and user comfort is also achieved in both techniques.**

***Index Terms*—demand side management; pigeon inspired optimization; genetic algorithm; smart grid;**

I. Introduction

In recent decades, it is being observed that energy demand is increased immensely. In China and USA, residential area is considered to be the highest sector where energy is consumed, as a result huge amount of greenhouse gas (GHG) is emitted [17]. The traditional grid has the capability to deliver the electric power from power generation utility to the consumer. This one-way communication is not of handling several parameters of electrical network. In China, residential area is responsible for most of the power consumption and greenhouse emissions. In Arabian countries, 40 % of electricity is consumed in residential area [5]. Bulk generation and transmission infrastructure is needed to be installed, to fulfill the increase in demand in residential area. In respond to the high power demand, electricity price also been increased. To remove the deficiencies of the traditional grid, smart grid (SG) is emerged to fulfill the high energy demand efficiently.

Smart grid plays an important role to overcome the challenges of traditional grid. Smart grid has following three components: smart meter, smart appliances and energy management controller. Energy management is to handle and overcome capacity bounds, environmental issues, maintenance, operations. There are two categories of energy management: supply side management (SSM) and demand side management (DSM). The SSM is responsible for generating, managing and delivering the energy to the consumers. The DSM is responsible for managing the energy on the consumer end. Demand response programs are designed by DSM that are used in load shifting mechanism in case of variable prices on different prices on different OTI. Rasheed et al. in [2] used demand and response (DR) technique to minimize the cost and PAR while achieving maximum user comfort. Electricity load shifting from on-peak to off-peak hours significantly reduces the electricity cost but user comfort is compromised

because operation of appliances is delayed [6]. In [11], electricity load shifting is done by using distributed algorithm developed by the authors. Residential load scheduling quandary is proposed utilizing game theory approach. The convergence rate of Nash equilibrium is also expedited by the authors by applying the newton method. Simulation results show that PAR is minimized while minimizing the user discomfort.

Several aspects such as electricity cost, user comfort, electricity load and operational issues has to be considered in order to achieve coordination between utility and consumer. User comfort is the important component that must be considered while reducing the electricity bill. Lots of efforts has been done in the literature to handle and overcome these challenges. In [8], authors used GA to minimize electricity load in residential, commercial and industrial sector. The authors done the comparison of the performance of GA with other Evolutionary algorithms. The results shows that 21.9 % of electricity load reduced during on-peak hours. Sahar et al. in [14] presents a new hybrid approach in which they done hybridization of GA, BPSO and ant colony optimization (ACO) techniques for cost minimization, PAR reduction while considering user comfort on TOU pricing scheme. In [9], authors proposed a model for handling residential power consumption within user budget. The authors used genetic algorithm to solve the optimization quandary where the goal is to increase user comfort while minimizing electricity cost. Mahmood et al. in [20], presents Realistic scheduling algorithm (RSM), that maximizes the appliance usage at low cost. Simulation results shows that it maximize appliance usage while minimizing the electricity cost.

The main goal of this work is to an effective mechanism to handle the consumer power consumption and power demand. We applied GA,PIO and HGP on 14 appliances in a single home and for three different OTIs: 20 minutes, 30 minutes and 60 minutes. Moreover, we also applied GA, PIO and HGP on 10 homes, 30 homes, 50 homes with 30 minutes OTI and different power rating. GA,PIO and HGP are evaluated on the basis of real time pricing scheme (RTP). Simulations results shows that GA,PIO and HGP are able to minimize electricity bill and electricity consumption while minimizing the user discomfort. The feasible region between electricity cost and electricity consumption is also represented. Moreover, the desired trade-off between electricity cost and user comfort is also achieve in both techniques.

II. Related work

Zhou et al. [1], discussed the contemporary tendencies among HEMS. They present a general overview on the challenges that occurs while applying HEMS and the impact of appliance scheduling on the factors such as, electricity load and user comfort. However, the impact of integration of RESs and ESSs on electricity cost is not discussed. Calvillo et al. [3], discussed the importance of appliance scheduling in HEMS. They present a general review on the challenges that occurs during the implementation of HEMS and the impact of appliance scheduling on PAR. However, user comfort is not considered in appliance scheduling. Beaudin and Zareipour [4], discussed the importance of load scheduling in residential area. They discussed all the major factors that may effect the electricity cost, PAR, and electricity load. However they did not considered user comfort and the impact of user comfort on other mentioned factors.

In [5], a new hybrid scheme, GAPSO, that is based on binary particle swarm algorithm(BPSO) and genetic algorithm(GA) is used that is evaluated on day ahead price for single and multiple days. The proposed hybrid scheme minimizes the electricity bill and user discomfort. In [6], a new hybrid scheme, TLGO, that is based on teacher learning based optimization and genetic algorithm(GA) is used that is evaluated on day ahead price for single and multiple days.The proposed hybrid scheme minimizes the electricity cost at minimum user discomfort or waiting time. The performance of heuristics techniques is compared with linear programming (LP) in term of peak electricity consumption, PAR, electricity bill and user discomfort. Unlike TLBO and GA, TLGO minimizes both cost and user discomfort without effecting peak electricity consumption and PAR. In [7], OHEMS is proposed that facilitate renewable energy resources and energy storage system. The results of the proposed scheme and the heuristic algorithms shows that combining RSS and RES reduces PAR and electricity bill by 21.55% and 19.94%.

In [8], authors used GA to minimize electricity load in residential, commercial and industrial sector. The authors done the comparison of the performance of GA with other Evolutionary algorithms. The results shows that 21.9% of electricity load reduced during on-peak hours. In [9], authors proposed a model for handling residential power consumption within user budget. To solve the optimization quandary, the authors used genetic algorithm where the goal is to increase user satisfaction while minimizing electricity bill. Rasheed et

TABLE I Strength and limitations of State of the art work

Technique(s)	**Objective(s)**	**Findings**	**Remarks**
GA and BPSO [5]	Minimize electricity bill and user discomfort in single and multiple homes	Performance of proposed algorithm is compared with evolutionary algorithms	PAR is ignored
TLGO [6]	Minimize electricity bill and user discomfort	Performance of proposed algorithm is compared with LP	Electricity consumption is ignored
OEHMS [7]	Minimize electricity bill and PAR	Performance of proposed algorithm is compared with heuristic techniques	User comfort is not considered
GA [8]	Minimize electricity load in residential, industrial and commercial area	Algorithm is compared with evolutionary algorithms on the basis of performance	PAR is effected
GA, BPSO, ACO [14]	Minimize electricity cost and PAR	Algorithm is compared with evolutionary algorithms on the basis of performance	User comfort is effected
GA [9]	Minimize electricity bill while maximizing user satisfaction	Manage the load in user defined budget	PAR is ignored
Fractional Programming [10]	Minimize electricity bill	A novel concept of cost efficiency is proposed	PAR is effected
Distributed algorithm [11]	Minimize PAR and user discomfort	PAR is minimized by using distributed algorithm	Electricity cost is not considered
MILP [12]	Minimize electricity bill and carbon emmission	Electricity bill is minimized through MILP	PAR is effected
ILP [13]	Minimize electricity cost and PAR reduction	Electricity cost and PAR are reduced significantly	User comfort and ESS not considered

al. in [2] used demand and response (DR) technique to minimize the cost and PAR while achieving maximum user comfort. Electricity load shifting from on-peak to off-peak hours significantly reduces the electricity cost but user comfort is compromised because operation of appliances is delayed [6].

Chen et al. in [10], presented the residential load scheduling model with RTP. To achieve an optimal solution for electricity load scheduling, the authors presented the concept of electricity cost efficiency. The authors used fractional programming for the optimal solution. Simulation results shows that consumers electricity cost is reduced. In [11], electricity load shifting is done by using distributed algorithm developed by the authors. Residential load scheduling quandary is proposed utilizing game theory approach. The convergence rate of Nash equilibrium is also expedited by the authors by applying the newton method. Simulation results show that PAR is minimized while minimizing the user discomfort. Mahmood et al. in [20], presents Realistic scheduling algorithm (RSM), that maximizes the appliance usage at low cost. Simulation results shows that it maximize appliance usage while minimizing the electricity cost.

In [12], authors considered 30 homes, where each home has 12 appliances. The multi-objective optimization problem is solved using MILP. Carbon emissions reduction and consumers electricity bill are achieved. Shiftable appliances are not considered which plays a major role in cost minimization. The authors in [13], proposed an integer linear programming (ILP) algorithm predicated HEMS with builtin RES to shift the shiftable electricity load from electricity rush hours to off-peak hours. User comfort and ESS integration is not considered by the authors.The authors in [16], used a decentralized framework to minimize the cost in residential areas in smart grid by shifting the load from on-peak to off-peak hours. In [8], authors used GA to minimize electricity load in residential, commercial and industrial sector. The authors done the comparison of the performance of GA with other Evolutionary algorithms. The results shows that 21.9 % of electricity

load reduced during on-peak hours.

III. Problem statement

Optimization of energy is the one of the difficult challenge in smart grid because consumer energy demand and electricity prices are not fixed. In [12], authors considered 30 homes, where each home has 12 appliances. The multi-objective optimization problem is solved using MILP. Carbon emissions reduction and Consumers' electricity bill are achieved. Shiftable appliances are not considered which plays a major role in cost minimization.

In this paper, single home, 10 homes, 30 homes and 50 homes with 14 different appliances are considered. Three types of appliances are considered: schedule-able, non-schedule-able and uninterruptable. Our goal is to minimize the electricity cost, electricity load while minimizing the user discomfort. We applied GA, PIO, HGP to achieve our goals. The problem can be stated as: Given are (a) appliances start and end time (b) length of operational time (c) RTP signal (d) Time interval (e) Total power demand of each appliance. To be determined are (a) power consumption pattern To find the optimal solution with minimum electricity cost, electricity load and user discomfort, RTP is applied. We evaluated our model on three different time interval values: 20 minutes, 30 minutes and 60 minutes. The four parameter on the basis of which our model is evaluated are: electricity cost, peak-to-average ration (PAR), waiting time (user discomfort) and electricity consumption.

IV. System model

In this paper, a single home with 14 different appliances is considered. Appliances are categorized into three categories: scheduleable, non-scheduleable and uninterruptable. Moreover, 20 minutes OTI, 30 minutes OTI and 60 minutes OTI time slots are considered in the proposed model. All the appliances have different length of operation time and energy consumption. All appliances completes their allocated length of operation time. Nonscheduleable and uninterruptable appliances could not be shifted once they start operation. The proposed system model is shown in Fig. 1.

V. Proposed methodology

Problem that is stated in section III is solved using GA,PIO and HGP. In the literature, several mathematical techniques such as LP, MILP and ILP are used to handle electricity consumption problem. The computational complexity of mathematical techniques is very high. We applied population based techniques to address the electricity consumption problem. We applied GA, PIO and our proposed HGP techniques and compared them with previous researchers results.

A. GA

GA is inspired by the genetic process of living organisms. GA has the ability to search for best solution in minimum time. GA is able to handle complex problems with minimum computational effort [15]. The initial process of GA is to generate random population that updates on every iteration. The status of appliances is represented by chromosomes and number of hours for scheduling are represented by length of chromosomes. Fitness of each chromosome is evaluated based on the fitness function. The elitism process is performed so that chromosomes with high fitness value can be used in next iterations. Two parent chromosomes are selected after the elitism process is completed. Crossover is applied to the selected two parent chromosomes and a child/offspring, that contains the properties of both the parents, is added to the existing population. In mutation process the bits of the selected chromosomes are inverted by mutation operator to reduce the possibility of repetition of selected chromosomes in the population. The crossover rate is usually higher than the mutation rate to get the best possible solution. The mutation rate is used to maintain randomness to avoid repetition of same chromosomes. When the crossover and mutation process is done then fitness of current population is compared with the previous one until the termination criteria is achieved. The chromosome with highest fitness value is selected when the whole process is terminated.

B. PIO

PIO is derived from homing pigeons and it is proposed by Duan and Qiao [18]. It have two majors operators: map and compass operator and landmark operator. Initially the population is randomly generated. To find the best optimal solution, fitness function is used. All the population is sorted according to the fitness and half of the population is discarded using the landmark operator.

C. HGP

Hybridization means to combine two or more techniques [21]. GA,PIO and HGP are combined to form a hybrid approach, HGP algorithm. All the steps of GA performed in a same way as discussed earlier but the

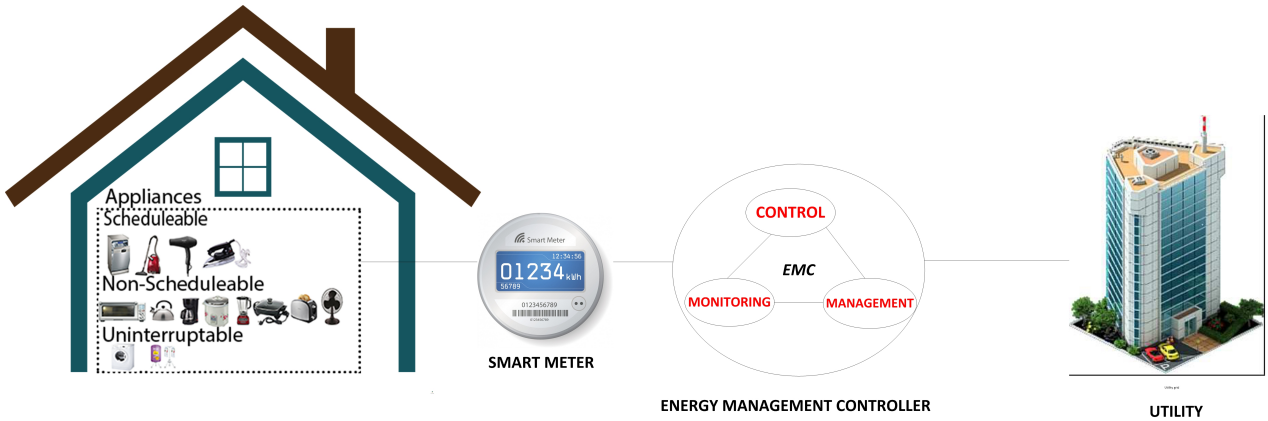


Fig. 1. System Model

TABLE II Classification of Appliances

Groups	Appliances	Power rating (kWh)	LOT
Non Schedule-able appliances	Oven	1.3	3 hour
	Fan	0.20	15 hour
	Kettle	2.0	3 hour
	Toaster	0.9	1 hour
	Rice Cooker	0.85	2 hour
	Blender	0.3	2 hour
	Frying Pan	1.1	3 hour
	Coffee Maker	0.8	4 hour
Non interrupt-able appliances	Washing Machine	0.5	3 hour
	Cloth Dryer	1.2	3 hour
Schedule-able appliances	Dish Washer	0.7	4 hour
	Iron	1.0	3 hour
	Vacuum Cleaner	0.4	4 hour
	Hair Dryer	1.5	2 hour

elimination and dispersal step of GA in which crossover and mutation is performed is replaced by the map and compass operator step of PIO.

VI. Simulation Results and Discussion

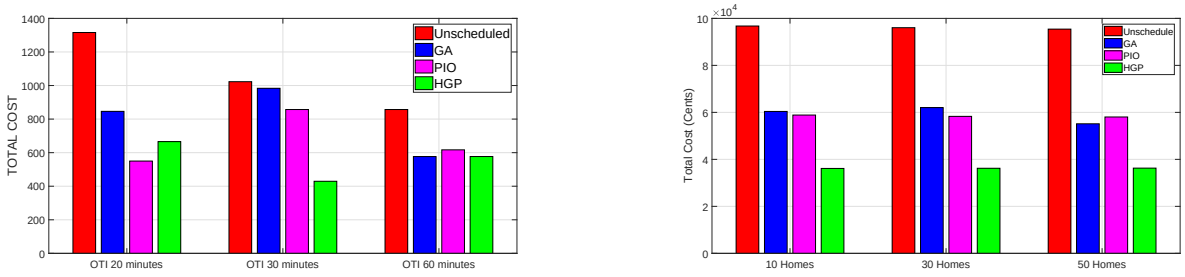
In this section we evaluated the performance of GA, PIO techniques and our proposed hybrid meta-heuristic technique HGP. We evaluated the following Techniques on the basis of four performance parameters: Electricity cost, PAR, Energy consumption and user comfort. We are considering a single home, consists of 14 appliances using the RTP price scheme and three different OTI of 20 minute, 30 minute and 60 minute. We also considered 10 homes, 30 homes and 50 homes scenario with 30 minute OTI and different power ratings. The classification of appliances is shown in Table II.

A. Eelectricity Cost

Total cost for single home and multiple homes is shown in Fig. 2. In single home scenario, GA reduces 4.54%, 2.94%, 20.54% of the total cost in case of 20 minutes OTI, 30 minutes OTI, 60 minutes OTI repectively. PIO reduces 20.54%, 27.94%, 20.94% of the total cost in case of 20 minutes OTI, 30 minutes OTI, 60 minutes OTI repectively. HGP reduces 30.72%, 40.94%, 24.24% of the total cost in case of 20 minutes OTI, 30 minutes OTI, 60 minutes OTI repectively. In multiple homes scenario, the cost is less than the unscheduled cost in all each case.

B. PAR

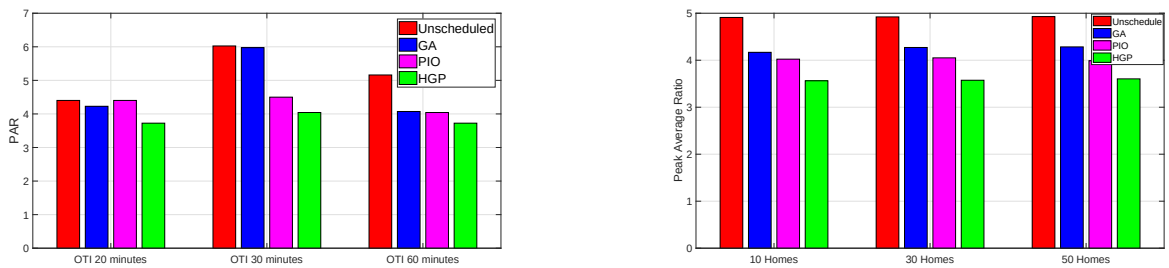
We applied GA, PIO and HGP on single home with three different OTIs and on 10 homes, 30 homes and 50 homes with 30 minutes OTI. It is clear from Fig. 3 that our techniques are working fine with respect to PAR ratio because in all cases the PAR after scheduling is less than the PAR in unscheduled, it means that our algorithms are scheduling the appliances and controlling the peak so that load is shifted evenly between the time slots.



(a) Total cost for a single home

(b) Total cost for multiple homes

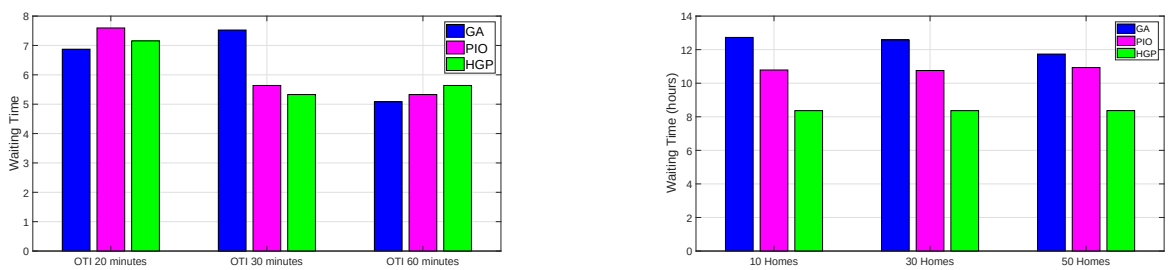
Fig. 2. Overall cost for single and multiple homes



(a) PAR for a single home

(b) PAR for multiple homes

Fig. 3. PAR for single and multiple homes



(a) Average waiting time for a single home

(b) Average waiting time for multiple homes

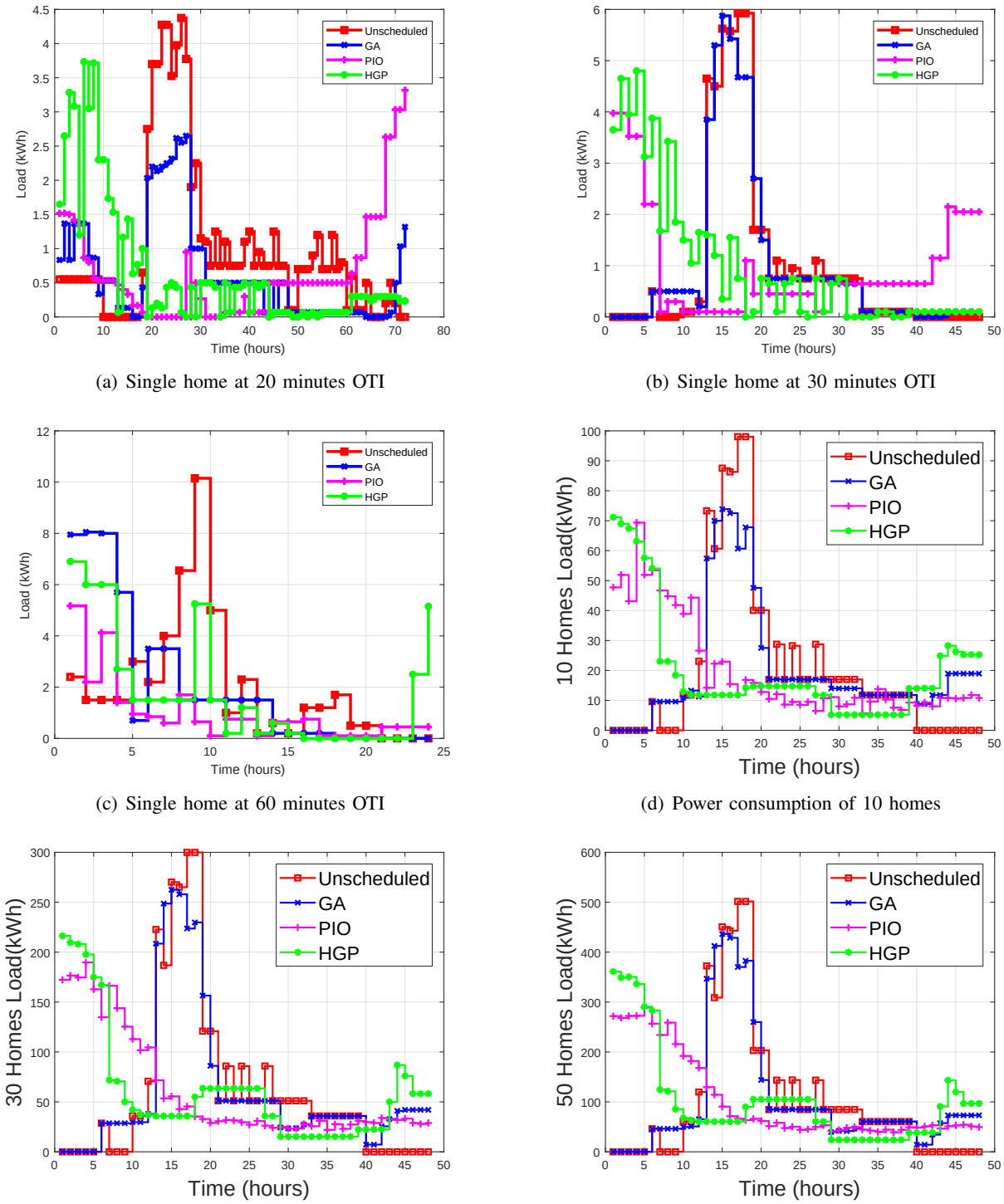
Fig. 4. Average waiting time for single and multiple homes

C. User Comfort

We applied GA, PIO and HGP on single home with three different OTIs and on 10 homes, 30 homes and 50 homes with 30 minutes OTI. It is clear from Fig. 4 that algorithm is working fine with respect to waiting time because in all cases the waiting time is just the schedule-able appliances and the non-schedule-able and uninterruptable appliances does not have any waiting time it means that user comfort is increased. There is a trade-off between user comfort and waiting time. In case of schedule-able appliance the waiting time will decrease the user comfort but in case of non-schedule-able and uninterruptable as there is no waiting time so user will not have to wait, as a result user comfort increases.

D. Electricity Consumption

We applied GA, PIO and HGP on single home having 14 appliances and multiple homes scenario. In single home scenario, we applied these algorithms for three different OTI to schedule the appliances from electricity peak hours to off-peak hours. In multiple homes scenario, we applied these algorithms for 30 minute OTI to schedule the appliances from electricity peak hours to off-peak hours. It is clear from Fig. 5 that GA, PIO and HGP are able to reduce the peaks



(a) Single home at 20 minutes OTI

(b) Single home at 30 minutes OTI

(c) Single home at 60 minutes OTI

(d) Power consumption of 10 homes

(e) Power consumption of 30 homes

(f) Power consumption of 50 homes

Fig. 5. Power consumption of single and multiple homes

Algorithm 1 Genetic Algorithm

```
Input: set of appliances A_i;
Initialization: PH_s, OPH_s, t = 0, avg_g a=0, H, PB = 0, 1;
for i=1 to T do
    for j=1 to H do
        Generate initial population
        for j=1 to P do
            Calculate fitness function
            Select best solution in population P
            Check status of A_i;

            if t == PH_s; then
                wait until OPH_s;
                Check the remaining t of all A_i
        end for
        Generate new population
        Crossover (Θ_i);
        Mutation (Θ_i);
    end for
end for
```

of load. Electricity load peaks have direct impact on PAR. It is clear from Fig. 5 and Fig. 3, when the peak electricity load is high then the PAR is high and vice versa.

E. Performance Trade-off

Performance trade-off is achieved between the electricity cost and the user discomfort. As shown in Fig. 2 and Fig. 4 when the total cost is high then the waiting time is low and when the total cost is low then the waiting time is high. It is clear from Fig. 5 that GA, PIO and HGP are able to reduce the peaks of load. Electricity load peaks have direct impact on PAR. It is clear from Fig. 5 and Fig. 3, when the peak electricity load is high then the PAR is high and when the peak electricity load is low then the PAR is low.

F. Feasible Region

Feasible region is a region that contains all the possible solutions based on our fitness function [19]. Our primary goal is to reduce electricity cost and PAR. Electricity cost depends on the electricity price and electricity consumption.We can do load shifting by shifting the load from on-peak hours where the electricity price is high to the off-peak hours in which the electricity price is low.We have to focus on following four parameters while reducing the electricity cost:

Algorithm 2 PIO Algorithm

```
Input: maximum iterations
Initialization: pigeonnum, D, map and compass factor, T1, T2, X_g
Specify LOT of appliances and power ratings
Randomly initialized the population
set initial path X_i and velocity V for each appliance
set X_p=X_i
calculate the fitness of individual appliances
find the optimal solution
map and compass operator
for i=1:T1 do
    for i=1:pigeonnum do

        while X_i is beyond the search range do
            calculate X_i and V_i
        end
    end
    for i=1:D do

        while X_p is beyond the search range do
            sort all the appliances according to their fitness values
            pigeonnum=pigeonnum/2
            keep half of the appliances with better fitness value and discard the other half
            X_c= average of the remaining appliances
            calculate X_i
        end
    end
        Output: X_g is output as the global optima of fitness function
end
```

- Minimum Load,minimum price
- Minimum Load,maximum price
- Maximum Load,minimum price
- Maximum Load,minimum price

The blue shaded region in Fig. 6 is the feasible region for 20 minutes, 30 minute and 60 minute OTI respectively.

VII. Conclusion and Future Work

In this paper, GA,PIO and our proposed HGP are applied on single home having 14 appliances and multiple homes scenario. In single home scenario, we

OTI	Cases	Load (kWh)	Price (dollars)	Cost (dollars)
20-minutes	Min.load, Min. price	0.462	8.1000	3.7422
	Min.load, Max. price	0.462	27.3500	12.6357
	Max.load, Min. price	3.0167	8.1000	24.4353
	Max.load,Max. price	3.0167	27.3500	82.5067
30-minutes	Min.load, Min. price	0.762	8.1000	6.1722
	Min.load, Max. price	0.762	27.3500	20.8407
	Max.load, Min. price	5.925	8.1000	47.9925
	Max.load,Max. price	5.925	27.3500	162.0488
60-minutes	Min.load, Min. price	0.462	8.1000	3.7422
	Min.load, Max. price	0.462	27.3500	12.6357
	Max.load, Min. price	10.150	8.1000	82.2150
	Max.load,Max. price	10.150	27.3500	277.6025

TABLE III Possible feasible regions for a single home

OTI	Cases	Load (kWh)	Price (dollars)	Cost (dollars)
10-homes	Min.load, Min. price	40.7620	8.1000	330.1722
	Min.load, Max. price	40.7620	27.3500	1115
	Max.load, Min. price	500.956	8.1000	4058
	Max.load,Max. price	500.956	27.3500	13701
30-homes	Min.load, Min. price	40.762	8.1000	330.1722
	Min.load, Max. price	40.762	27.3500	1115
	Max.load, Min. price	300.0690	8.1000	2431
	Max.load,Max. price	300.0690	27.3500	8207
50-homes	Min.load, Min. price	15.762	8.1000	127.6722
	Min.load, Max. price	15.762	27.3500	431.0907
	Max.load, Min. price	101.2070	8.1000	820
	Max.load,Max. price	101.2070	27.3500	2768

TABLE IV Possible feasible regions for a multiple homes

Algorithm 3 HGP Algorithm

```
Input: set of appliances A_i;
Initialization: PH_s, OPH_s, t = 0, avgga=0, H, PB = 0, 1;
for i=1 to T do
    for j=1 to H do
        Generate initial population
        for j=1 to P do
            Calculate fitness function
            Select best solution in population P
            Check status of A_i;

            if t == PH_s; then
                wait until OPH_s;
                Check the remaining t of all A_i
        end for
        Generate new population
        map and compass operator
    end for
end for
```

applied these algorithms for three different OTI to schedule the appliances from electricity peak hours to off-peak hours. In multiple homes scenario, we applied these algorithms for 30 minute OTI to schedule the appliances from electricity peak hours to off-peak hours. GA,PIO and HGP are evaluated on the basis of real time pricing scheme (RTP). Simulations results shows that GA,PIO and HGP are able to minimize electricity bill and electricity consumption while minimizing the user discomfort. The feasible region between electricity cost and electricity consumption is also represented. Moreover, the desired trade-off between electricity cost and user comfort is also achieved in existing and proposed techniques. The performance of HGP is better than GA, PIO with respect to PAR,electricity load and electricity cost for both single home and multiple homes scenario.

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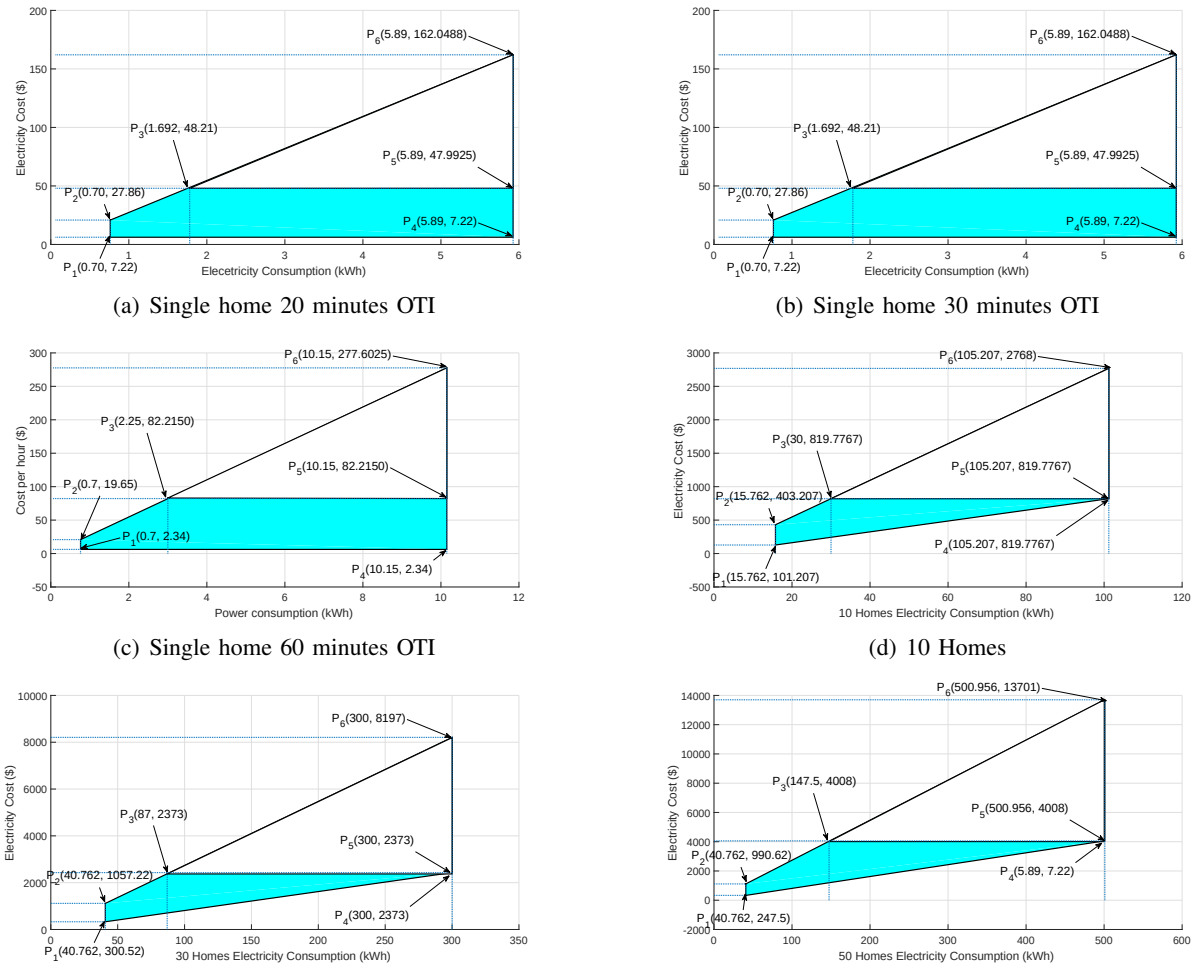

(a) Single home 20 minutes OTI

(b) Single home 30 minutes OTI

(c) Single home 60 minutes OTI

(d) 10 Homes

(e) 30 Homes

(f) 50 Homes

Fig. 6. Feasible Region for single and multiple homes

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