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Pigeon Inspired Optimization and Enhanced Differential Evolution using Time of Use Tariff in Smart Grid

Hafsa Arshad[1], Saadia Batool[1], Zunaira Amjad[1], Mudabbir Ali[1], Syeda Aimal[1] and Nadeem Javaid[1,*]

Abstract In this paper, a scheduler for Home Energy Management (HEM) is proposed using Pigeon Inspired Optimization (PIO) and Enhanced Differential Evolution (EDE). Performance of these two optimization algorithms is evaluated in this study. Performance is determined by the amount of energy consumed by the appliances in on-peak hours and off-peak hours. Time Of Use (TOU) tariff is used for bill calculation of the consumed energy. Evaluation is performed in terms of Peak to Average Ratio (PAR) and electricity cost. Simulation results show that PIO outperforms EDE in terms of cost, PAR reduction and waiting time.
Keywords: Smart grid, home energy management, time of use tariff, user comfort, pigeon inspired optimization, enhanced differential evolution.

1 Introduction

Electricity demand is increasing day by day as it has became the essential part of our daily life. Smart grids are introduced to utilize and deliver electricity efficiently and reliably to the consumers as traditional grids are not very effective. Smart grid shown in figure 1 is a system that includes physical power system and information system that links a variety of equipments and assets together to form a customer service platform [1]. Smart homes involve incorporating smartness into homes for comfort, healthcare, safety, security, and energy conservation [2, 3]. Smart homes are equipped with smart meters. There is a burden on utility in peak hours as so many people are using electricity in that particular time period. Hence, utility increases cost in that time slot. Consumers can manage their energy consumption and cost by optimally scheduling the appliances. Utility also has a great benefit from the modernized grid as peak loads are reduced, security in enhanced with lower opera-

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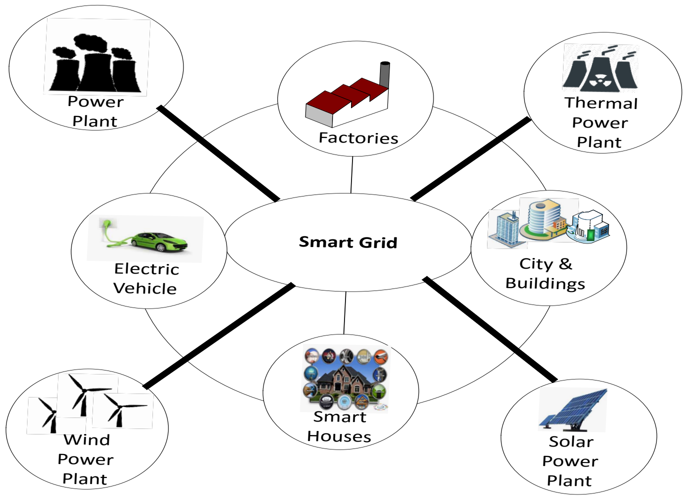

Fig. 1 Proposed System Model in a Smart Grid

tional costs. Our objective is to reduce electricity price, to maximize user comfort and to manage load, i.e., shifting on-peak hours to off-peak hours.

DSM is used by the electric utilities to enhance customer service. DSM refers to as controlling the amount of energy used at specific times to reduce system peak demand, utilize energy efficiently and balance the DR of the system. Along with balancing the supply and demand, minimizing peak power requirements is also important in DSM which include energy efficiency programs and smart metering, i.e., real-time pricing. RTP is one of the most important DR strategies where the prices announced by retailer change hourly over time to reflect variations in the market prices. Customers are notified of RTP prices before delivery time [4]. The prices in TOU are set well before the period and do not adjust to reflect actual conditions. The customers already know that how many costs they will pay for electricity during pre-set time periods. This allows customers to adjust their usage in response to the price signals and manage the overall energy costs by altering their usage at lower cost or by reducing complete usage.

In this paper, two optimization techniques; PIO and EDE, are used. These two techniques are used to find out the best optimal solution with maximum user comfort, minimum PAR and cost reduction. In PIO homing behavior of pigeons is considered whereas, in EDE trial vector strategy is followed to find out the best optimal solution. List of abbreviations is given in table 1.

The rest of the document is organised as follows. Section 2 contains brief description of related work. In section 3, the problem is stated. Section 4 describes the proposed model. Section 5 explains the simulations and results of the proposed system. In section 6, the document is concluded.

Table 1 List of Abbreviations

Abbreviations	Definition
PIO	Pigeon Inspired Optimization
EDE	Enhanced Differential Evolution
EMS	Energy Management Systems
HAN	Home Area Network
RTP	Real-Time Pricing
IBR	Inclined Block Rate
PAR	Peak to Average Ratio
DSM	Demand Side Management
ILP	Integer Linear Programming
GA	Genetic Algorithm
BPSO	Binary Particle Swarm Optimization Algorithm
BFOA	Bacterial Foraging Optimization Algorithm
WDO	Wind-Driven Optimization
GWD	Genetic Wind-Driven
RERs	Renewable Energy Resources
DERs	Distributed Energy Resources
ACO	Ant Colony Optimization
HEM	Home Energy Management
TOU	Time of use
ICTs	Information and Communication Infrastructures
OPEX	Operational Expenditure
GDSM	Generic Demand Side Management
WTA	Waiting Time of Appliances
DR	Demand Response

2 Related Work

Many of the scholars worked on the scheduling of the smart appliances. We categorize these contributions according to the issues faced in scheduling the appliances. The contributions of some of the researchers are as follows:

The authors in [1], introduced EMS in a HAN. The problem addressed by the authors is optimal power scheduling for home power usage. They use RTP tariff model along with IBR to avoid peak formation. The simulation results show that using RTP combined with IBR pricing model reduces cost and PAR more efficiently as compared to RTP alone. In order to schedule power consumption, authors propose a dynamic pricing approach along with game theoretic DSM framework in [2]. Proposed system is better in terms of cost, peak demand and convergence time however, total bill is increased a little. In article [11], the authors have highlighted the power scheduling issues for residential users in smart grid. Optimal scheduling strategies are obtained under three operational modes using day ahead pricing signal. Desired tradeoff between electricity payments and discomfort is achieved. However, PAR is not determined. Hence, by solving the problem of power scheduling, cost and PAR can be reduced as mentioned in [1, 2], and convergence time can also be decreased.

In [5], the authors have used the algorithms for scheduling the residential load. They have designed an energy management controller based on heuristic algorithm for residential area in a smart grid. Five of the heuristic algorithms are used, along with RTP pricing signal, for scheduling the domestic load which namely are GA, BPSO, BFOA, WDO and hybrid GWD algorithm. Samadi *et al* in [6], have proposed an algorithm for controlling load for DSM and adopted the approximate dynamic programming for scheduling of appliances. Simulations show that this algorithm lowers the energy cost. An ILP technique is proposed in [10], which is based on optimization mechanism for the home area load management. The aim of this proposed scheduling technique is to reduce the peak hourly load in order to achieve an optimal daily load schedule and to minimize combined power consumption. Simulation results show that a more balanced hourly load is achieved, when multiple households participate in scheduling. The authors in [13], introduce a concept of residential load scheduling framework on the basis of cost efficiency to enhance the economical efficiency of the residential electricity consumption. In the framework, the service fee and DERs are also considered and their influence on the cost efficiency is examined. The proposed algorithm results in better utilizing and saving the power. The cost efficiency criterion can be used in consumption with variable pricing scheme. The aim of [17], is to inaugurate a decentralized framework to organise DR of residential users in a smart grid. This framework is used to transform system load profile in order to minimize the payments of customers, and to keep their comfort and privacy. The results tell that the used approach provides great benefits without bothering for the cost and comfort of customers. In this paper, it is presumed that customers are supported by time changing prices and their response for energy minimization changes.

Liu *et al* in [7], proposed a demand queuing-based energy management scheme on residential area. The goal of authors was to minimize cost by managing demand. They propose adaptive dynamic programming in order to solve the optimization problem. Achievements of proposed scheme are that it is able to manage tradeoff between operational delay and energy consumption and minimization of energy cost. In [8], authors focus on the problem of excessive use of power. They took a survey and found out that the ICTs consume more power and emits greenhouse gases. The authors took survey on smart grid in order to find ways to reduce cost, efficient energy usage and to reduce emission of gasses. In [9], author presented a game theoretic demand side management in order to reduce PAR, energy cost and WTA. This is applied for multiple users with different power consumption. GA and RTP is used. Load shifting strategy is used instead of load reduction. The proposed model is bi-directional. Rahim *et al* have introduced an architecture for DSM in [11]. GA, BPSO and ACO are proposed to calculate the performance of HEM controller. The problem with which the authors are dealing is the multiple knapsack problem. Combined model of TOU tariff and IBR is used for energy pricing. This results in cost effective solution to increase maintainability of smart grid. The main achievements of this study are electricity bill reduction, PAR minimization and user comfort maximization. Appliances are classified according to their features and users preferences.

Hence, PAR minimization and user comfort maximization are the major goals along with energy cost minimization as mentioned in [7–10].

3 Problem Statement

The major objectives of this work are to maximize user comfort and reduce PAR along with cost minimization by optimizing power consumption patterns of the end users. The problem is stated as an optimization problem with time shiftable, power shiftable and fixed appliances. As in [5–9], user comfort is ignored. Hence, along with cost we are taking user comfort in consideration which is being tackled in this paper. In [17], comfort level of users is achieved on the cost of high electricity price as there is always a tradeoff between user comfort and cost.

4 Proposed Solution

Non-schedulable appliances have fixed power and time while schedulable appliances include power shiftable and time shiftable appliances. By assigning priorities to the appliances the scheduling problem can be solved. In scheduling problem, fixed appliances are given high priority and they are omitted from scheduling strategies. In terms of user comfort, the user has to wait for the appliances to turn on when the maximum load is shifted from on peak hours to off peak hours in order to reduce the electricity bills. Hence, appliances are assigned priorities to reduce the waiting time and maximize the user comfort. Along with waiting time, PAR reduction is also considered. PAR reduction is important in order to maintain balance between demand and supply. It can be defined as ratio of peak load to average load. Internal structure of one of the home including several appliances is shown in Figure 2. The system model includes a smart grid which supplies energy to the smart homes. Home is equipped with smart meter which records the energy consumption of electricity in specific intervals of time and communicates that information on daily basis back to the utility for monitoring and billing.

Table 2 shows the power consumption, length of operational time and working hours of the appliances. Pigeon inspired optimization and EDE is used along with TOU pricing signal to reduce the PAR, cost, and WTA.

4.1 PIO

PIO algorithm is a new bio-inspired swarm intelligence algorithm proposed by Duan *et al* in [14] inspired by the homing behaviours of pigeons. It is an optimization technique which uses two operators:

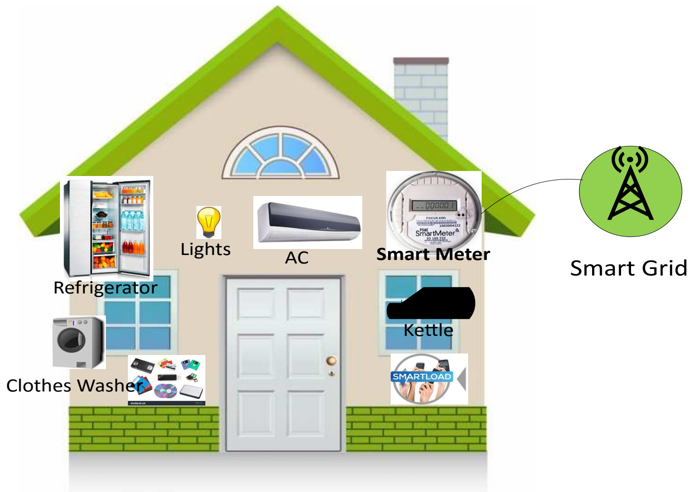

Fig. 2 An under consideration home's system model

Table 2 Proposed System Model's Parameters

Appliances	Working Hours	Power (kWh)	LOT(hours)
Clothes washer	6p.m. - 7a.m.	0.7	2
Lights	6a.m. - 11p.m.	0.5	14
A.C.	8a.m. - 8a.m.	1.4	15
Toaster	7a.m. - 10a.m.	1.146	3
Kettle	5a.m. - 9a.m., 5p.m. - 7p.m., 7p.m. - 8p.m.	1.2	3
Refrigerator	6a.m. - 6a.m.	0.2	17

(1) In map and compass operator, pigeons can sense the earth magnetic field by using magnetoreception to shape the map in their brains. To adjust the direction, pigeons use the altitude of the sun as compass. As pigeons fly to their destination, they rely less on sun and magnetic particles.
(2) In landmark operator, the pigeons will rely on neighbouring landmarks when they fly close to their destination. If they are familiar to the landmarks, they will fly straight to the destination. On the other hand, they will follow the pigeons who are familiar to the landmarks if they are far from the destination and unfamiliar to the landmarks. The working of PIO is shown in the algorithm 1. Some of the steps of this algorithm are taken from [15].

4.2 EDE

In EDE trial vector strategy is followed to improve the accuracy. Crossover and mutation takes place for finding the best optimal solution. Five trial vectors are

Algorithm 1: PIO

```
Parameters initialization
Set initial path Xi for each pigeon
Set Xp=Xi, Nc=1
Calculate fitness values of different pigeon individuals
Xg:=arg min [ f(Xp)]
for Nc=1 to Nc1maxdo do
    for i=1 to Np do while Xi is beyond the search range do do
        Calculate Xi
    end
end
Evaluate Xi, and update Xp and Xg
for Nc= Nc1max+1 to Nc2max do do
    while Xp is beyond the search range do do
        Rank all the available pigeon individuals according to their fitness values
        NP = NP/2
        Keep half of the individuals with better fitness value, and abandon the other half
        Xc=average value of the paths of the remaining pigeon individuals
        Calculate Xi
    end
    Evaluate Xi, and update Xp and Xg
end
Xg is output as the global optima of the fitness function f
```

formed. First three trial vectors are obtained by taking three different crossover rates. Fourth trial vector increases convergence speed while fifth increases diversity of search space. Mutant vector and target vector are created for finding the best optimal solution. Some of the algorithmic steps are taken from [16] in order to map the working of EDE shown in algorithm 2.

5 Simulations and Results

The simulations are performed in matlab in order to compare the electricity cost, PAR and power consumption. For simulation results, a home with 6 appliances is considered along with 24-hour time slot. The appliances are divided into two categories; schedulable appliances and non-schedulable appliances. This categorization is done for effective scheduling of appliances. Schedulable appliances are further divided into two categories: (i) Time shiftable appliances and (ii) Power shiftable appliances. EDE and PIO along with TOU pricing signal is used to reduce the PAR and electricity bills of the appliances.

Figure 3 represents the load of the appliances. Load is reduced during on-peak hours and shifted to the off-peak hours. Load for unscheduled appliances is 4.2kWh while that of PIO and EDE is 4kWh and 3.8kWh respectively. Hence, the load is

Algorithm 2: EDE

```
Initialize all parameters
Evaluate fitness of initial memory
Generate new solution using crossover and mutation
Initialize particle position to P_best
for i = 1:T do
    Evaluate fitness of initial memory
    Generate new solution using crossover and mutation
    Perform mutation
    for itr = 1:Max. iterations do
        Evaluate fitness
        Perform crossover
        Generate 1st trial vector using crossover rate 0.3
        if rand() ≤ 0.3 then
            u_j = v_j
        end
        if rand() > 0.3 then
            u_j = x_j
        end
        Generate 2nd trial vector using crossover rate 0.6
        if rand() ≤ 0.6 then
            u_j = v_j
        end
        if rand() > 0.6 then
            u_j = x_j
        end
        Generate 3rd trial vector using crossover rate 0.9
        if rand() ≤ 0.9 then
            u_j = v_j
        end
        if rand() > 0.9 then
            u_j = x_j
        end
        Generate 4rth trial vector
        Generate 5th trial vector
        Find the best vector among 5 trial vectors
        x_new ← besttrialvector
    end
    Perform selection using HSA selection procedure
    if f(x_new) < f(x_worst) then
        x_worst = x_new
    end
end
```

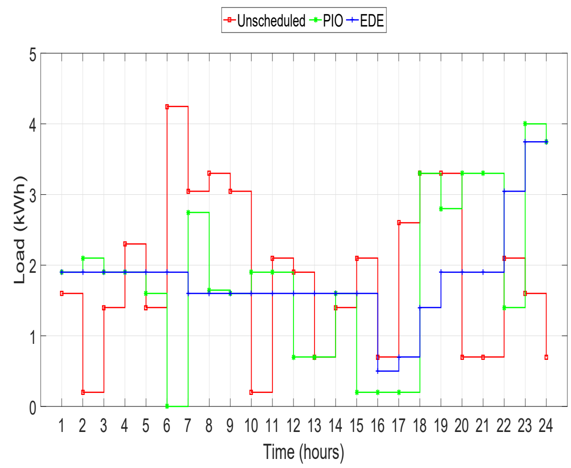

Fig. 3 Hourly Load in kiloWatt hours

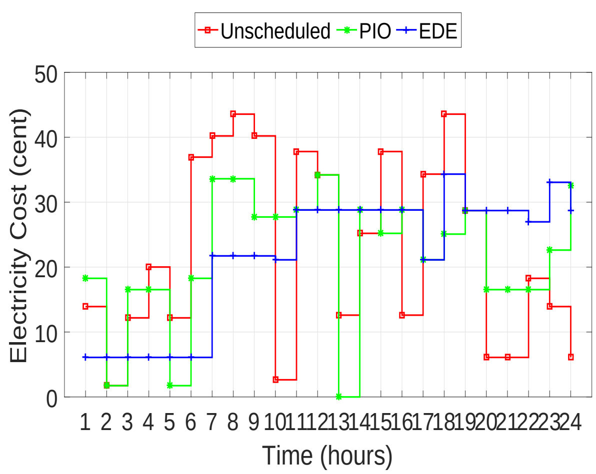

Fig. 4 Hourly Electricity Cost

decreased upto 10% in schedulable appliances as compared to non-schedulable appliances.

The cost of scheduled and non-scheduled appliances in shown in figure 4 and figure 5. From figure 4, it can be understood that hourly electricity cost of scheduled appliances is decreased per cent as compared to the non-scheduled appliances. This decrease in the cost is due to the selection of operational time of the appliances by the consumers themselves. The user may choose to adjust the operational time of the appliance to the time slots with less electricity price to lower the pay-

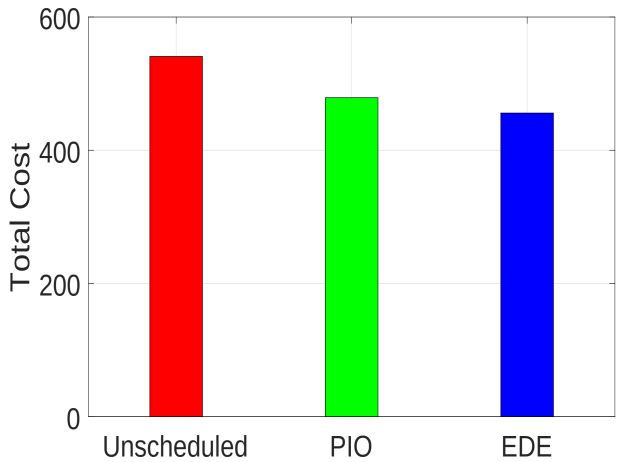

Fig. 5 Total Cost in Cents

ments. However, holding up the operation of the appliance will result in uneasiness. The maximum electricity cost of non-scheduled appliances is 44 cents while that of scheduled appliances is 34 cents in case of PIO while 33 cents in case of EDE. Hence, the cost of EDE and PIO is approximately 10% less than that of the non-scheduled appliances. This is because the cost of scheduled appliances is always less than that of non-scheduled appliances. Figure 5, demonstrates that the cost of non-scheduled appliances is 570 cents approximately while that of scheduled appliances is 490 cents and 450 cents in PIO and EDE, respectively. Hence, the customer has to pay approximately 10% more for achieving comfort. This is because there always exists a trade-off between the cost and the discomfort.

Figure 6, demonstrates that the PAR of scheduled appliances is less than that of the non-scheduled appliances. PAR reduces the formation of peaks and maintains balance between on-peak hours and off-peak hours. Hence, along with peak load, peak to average ratio is also reduced. In case of non-scheduled appliances, the PAR is 1.4 while in case of scheduled appliances it is reduced upto 0.75 approximately in PIO and EDE. Hence, PAR of scheduled appliances is 40% less than that of non-scheduled appliances. By shifting load in schedulable appliances peak formation can be avoided. However, in non-schedulable appliances peaks are formed as load is not balanced. Hence, PAR is reduced to a large extend in case of scheduled appliances. Thus, PAR of scheduled appliances is always less than that of non-scheduled appliances.

Figure 7, shows the user comfort which is calculated in terms of waiting time. There is a trade-off between discomfort and electricity cost. To reduce electricity bills, load should be shifted because of this user has to wait for an appliance to turn ON. If a user does not want to compromise their comfort, then it will result in high electricity cost and also peak down the on-peak hours which will burden the user.

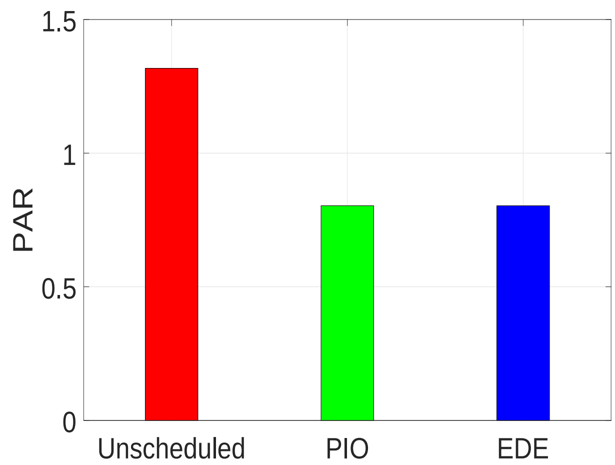

Fig. 6 Peak to Average Ratio

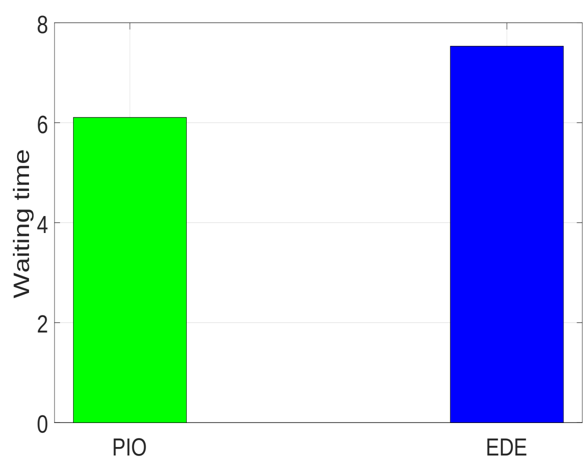

Fig. 7 User Comfort

Waiting time in case of PIO is 6.1 minutes and that of EDE is 7.8 minutes which clearly shows that waiting time of PIO is 20% less than that of EDE. This employs that users can achieve more comfort using PIO rather than EDE. Hence, the desired trade-off is achieved.

Figure 8, shows the TOU price signal. This pricing signal is used for the cost estimation in on peak and off peak hours of the day. Under TOU model, electricity prices are set at different prices during different day times. The electricity prices are lower when used in off-peak hours and most expensive when many customers

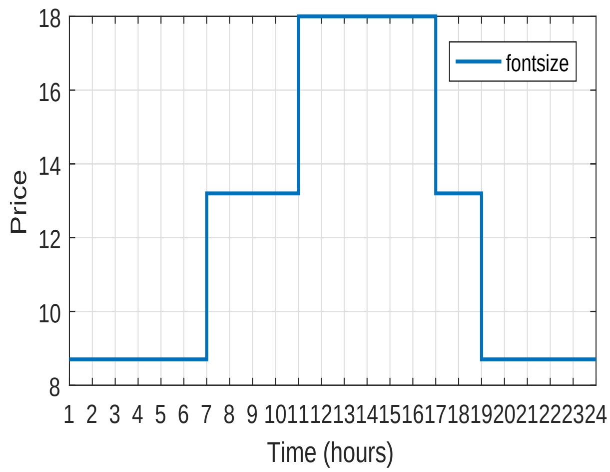

Fig. 8 TOU Pricing Signal

are using electricity simultaneously. Utilities may even develop the rates between on-peak and off-peak times of the day. The customers already know that how many costs they will pay for electricity during pre-set time periods. This pre-determination of the electricity cost allows customers to adjust their usage in response to the price signals and manage the overall energy costs by altering their usage at lower-cost or by reducing complete usage. Simulation results show that PIO outperforms EDE in terms of user comfort maximization among all the selected performance parameters.

6 Conclusion

In this paper, a scheduler for HEM is proposed using PIO and EDE. The performance of both of these optimization techniques is evaluated by determining the amount of energy consumed. TOU pricing signal is used for bill calculation of the consumed electricity. Evaluation is performed in terms of PAR, electricity cost and waiting time. From the simulation results, we conclude that waiting time of PIO is 20% less than that of EDE which clearly shows that users can achieve more comfort using PIO rather than EDE. PAR of PIO and EDE are 40% less than that of unscheduled appliances. Electricity cost of EDE and PIO is determined to be 10% less than unscheduled appliances. This is because of the fact that there is always a tradeoff between user comfort and cost. Load of PIO is 4kWh and that of EDE is 3.8kWh. Hence, it is clear that PIO outperforms EDE in user comfort maximization.

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