Load Scheduling Optimization Using Heuristic Techniques and Combined Price Signal

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Abstract. In this paper, a comparative analysis of two heuristic algorithms, i.e., enhanced differential evolution (EDE) and tabu search (TS) with unschedule load approach for its optimality is proposed. This paper aims to achieve minimum electricity bill and maximum peak to average ratio (PAR) reduction while considering the factor of user satisfaction. In order to achieve our aim, an objective function of electricity cost reduction is made based upon the scheduling strategies. A combined model of pricing schemes, i.e., time of use (ToU) and critical peak pricing (CPP) is used to calculate electricity bill and to tackle the instability. We implemented a state of art user-defined taxonomy of appliances in our paper to deal with the user comfort appropriately in a residential area. Simulation results shows that our proposed strategy works better to encourage the users for intelligent power consumption.

Keywords: Smart grid · Demand side management · Time of use tariff · Critical peak pricing · Home energy management

1 Introduction

Nowadays, the scope of smart grid (SG) as an efficient power network is increasing day by day. It adopts the demand side management (DSM), which provides energy management for reducing load, created by peak formations. In order to increase effectiveness, SG smartly distributes the power by monitoring advanced technologies and modified methodologies with reliable communication. Everyday the load waves highlight the high electricity demand of user. For the purpose of optimal scheduling of this load, the utility takes information about 24-hours schedule from the user. Due to this, it effectively increase user demand management. In this regard, different optimal and beneficial options are also provided to the users by utility to consume power efficiently.

Meanwhile, in a working system of DSM within SG shown in Fig. 1, the daily load is managed between off-peak hours (OPHs) and on-peak hours (PHs) via load shifting. However, if there is an excessive demand from the user-side,

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load is managed via distributed energy resources (DERs) [2]. The ability of self-healing in SG let it notify automatically when there is any error or failure during transmission. Applications of SG are not only limited to the efficient transmission, but it also provides better options of integration with renewable energy sources (RESs), hydraulic power generation, photo-voltaic etc. These types of integrated infrastructures successfully lead towards load shaving, load distribution and load reduction, however, the cost of mounting these is very high.

The desire for the efficient implementation of such system reflects benefits related to consumer satisfaction, maximum cost reduction, minimum PAR and a great revolution in a power sector. This thing also tackles the security issues and maintains a proper two way communication within the network topology. So, the extension of the useful life of smart grid depends on the way of keeping it.

While undertaking the state of art analysis, it is observed that there are so many techniques of DSM that are dealing with the optimization strategies. Such strategies hold the uncertainties while taking into account the reduction of electricity bills, minimization of PAR and integration of natural resources. For achieving these objectives, user satisfaction is completely ignored, e.g., in [1], Zhang, Di. *et al* used mixed integer linear programming (MILP) to cut the carbon footprint extensively and to make the cost reduction high. Along with the ε-constraint method, the appliances were scheduled under three different pricing mechanisms, i.e., real time pricing (RTP), CPP with peak demand charge and CPP with demand charge whereas the authors in [3] used binary particle swarm optimization (BPSO) to manage the load scheduling and reduction in electricity cost while ignoring the users waiting time aspect. In this paper, the authors addressed the maximum demand from the user and performed load shifting to minimize the demand and electricity cost. Similarly, in [4], deficiency lies in aspect of inconsideration of user satisfaction and PAR reduction. As, integer linear programming (ILP) is used to minimize the load on PHs. So, regarding its practical consideration, the authors divided the appliances with flexible power and flexible time in order to demonstrate the effectiveness of scheduling. In this paper, the authors worked upon increasing efficiency of the utility while limiting the factor of user satisfaction.

A decentralized framework in area of SG is presented in [5], to manage the load profiles of multiple consumers without affecting their preferences. The authors introduced pre-announced tariffs and load profiles, but if any issue occurs, the feedback is sent from the consumers to let the utility provide respective solutions. The load profiles of consumers modified on each iteration but limit the high demand of minimum cost and user satisfaction with inconsideration of PAR. In [6], to enhance the efficiency of electricity consumption, Ma, J. *et al* presented a concept of cost-efficiency. Different household appliances settings within the scope of multiple homes were applied to schedule the load and consumption of electricity. For its implementation, the authors used fractional programming (FP). This particular implementation is limited for DSM day-ahead bidding process. The integration of DERs along with cost-effective process was achieved to increase the performance of proposed framework and cost reduction while ignoring the user satisfaction factor.

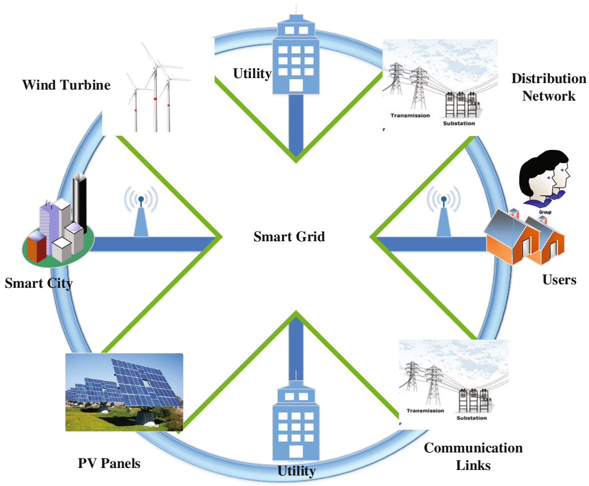

Fig. 1. SG communication architecture

Therefore, to tackle the aforementioned objectives, we have proposed a scheduler for home energy management system (HEMS). In this paper, a heuristic optimization approach is followed. Two of the optimization techniques, i.e., EDE and TS are implemented while taking into account the user satisfaction. Section 2 of this paper comprise of brief related work, Sect. 3 contains system model, Sect. 4 deals with the simulation results and Sect. 5 describes conclusion.

2 Literature Review and Motivation

In this section, we discussed the state of art analysis of techniques which have been used to resolve the scheduling issues as well as to attain the purpose of cost minimization.

In [2,5], and [11], hybrid pricing schemes are used to avoid the instability of the system. The combination of RTP and inclined block rate (IBR) in [5], and [11] enhanced the efficiency for both consumer-side and utility-side. In above mentioned three papers the combination of pricing schemes proved to be more reliable as compared to their separate performance. As, in [2], RTP is used with the combination of ToU tariff to avoid the data loss and peak formations which occurs due to using RTP single-handedly. Moreover, using RTP alone the electrical appliances work when the prices are low and causes excessive load on the grid.

In [1], authors achieved the trade-off between the electricity payments and user comfort. A model was designed using a mathematical function called Taguchi loss function to find discomfort cost. The power scheduling strategies were proposed under three operational modes while taking in account the day ahead price signals. The main deficiency in this study is inconsideration of the

PAR reduction. In [2], there is also an achievement of trade-off between delay time and cost reduction while reducing the PAR at optimal level. Zhang, Di. *et al* [3], also achieved the trade-off between the factors of CO2 emission and electricity cost while ignoring the consideration of PAR reduction. In [4], trade-off between payments and comfort is achieved but the excessive computational period, limits the confirmation for the optimal solution. Moreover, RTP used in this paper causes data loss and uncomfortable environment between suppliers and buyers. In [5], trade-off between delay time and bill reduction is achieved. An architecture of energy management system including home gateways, smart meters and RESs is proposed. In this paper, the increased PAR reduction is also achieved due to using the combination of RTP with IBR pricing mechanisms. [8], proposed a mathematical framework in order to achieve dual reduction, i.e., electricity cost reduction and power consumption reduction. The trade-off between user satisfaction and payments is also mentioned in this paper. In [6], authors addressed the problem of high electricity cost and user comfort. In order to resolve this issue, a multiple knapsack problem is introduced while considering the wind driven optimization (WDO) algorithm. The main focus in its implementation was the integration of knapsack problem with the optimization technique, i.e., K-WDO. In this study authors aim to lower the amount of bills, however, used standalone price signal, which most of the times creates uncertainty.Similarly, Khan, M.A. *et al* in [7], presented a general system framework to minimize the electricity cost and to achieve consumers satisfaction. For this purpose, GA is used while taking into account RTP pricing. They focused on minimizing PAR and cost with consideration of user comfort but the deficiency occurs where standalone pricing scheme is followed. [4], worked upon achievement of above mentioned objectives and claimed about the problem of high user demand and high electricity bills. Ha, L.D *et al* introduced an automated home energy system while focusing on tabu search (TS) algorithm in [9]. Similarly, in [10], and [12], authors used TS to optimize scheduling related tasks. The forthcoming section contains the proposed system in order to present the use of taxonomy of appliances taken from the base paper [2], of this research.

3 Proposed System

In our proposed system, we implemented two heuristic techniques, i.e. enhanced differential evolution (EDE) and tabu search (TS). To enable the calculation of electricity bill without creating instability of the system, a combined model of price signal CPP and ToU is used. We performed simulations in MATLAB to get the results in minimum computational time. Our proposed system is limited for the residential area. Moreover, the implementation is based upon the single home which consists of smart meters (SM) plugged inside the home. An electronic management controller (EMC) display is also connected with SM for the purpose of user involvement. There is a bi-directional relationship between utility and smart home shown in Fig. 2, in order to present the communication link between them. The energy reaches to our home from the smart grid through

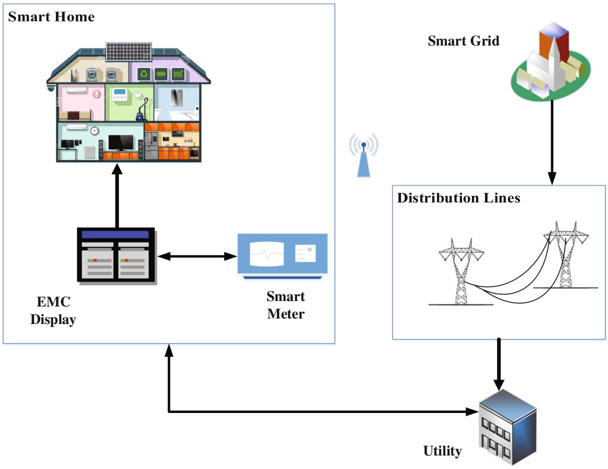

Fig. 2. Energy management system

distribution lines and utility. The schedular designed for this paper is based on the time slots of 24 complete hours of one day. The appliances distribution are shown in Tables 1, 2 and 3. Pseudo codes for TS and EDE are given in Algorithms 1 and 2.

In this paper, we categorized appliances to ease the way of scheduling understanding. The main division of appliances consists of three categories, i.e., (i) category A comprises of daily use items, (ii) category B of shiftable items and (iii) category C of interruptible appliances. Our simulations are implemented on 13 appliances, with length of operation time (LOT) in hours, power rating in kilo watt hours and time slots α to β, are given. α represent the starting running time of appliance and β represent the ending running time of appliances. The detail of assumed categorization include explanation given below.

Category A consists of the appliances, which can be operated at any time interval of the day. The running time of this type of appliances cannot be updated

Table 1. Category A: burstload daily appliances

Daily appliances	PowerRating (kWh)	LOT	α to β
Lights	0.6	12	[02:00–24:00]
Fan	0.75	16	[01:00–24:00]
Iron	1.5	6	[14:00–23:00]
Oven	0.18	7	[06:00–22:00]
Toaster	0.5	2	[06:00–10:00]
Coffee-Maker	0.8	2	[06:00–22:00]

Table 2. Category B: burstload shiftable appliances

Shiftable appliances	PowerRating (kWh)	LOT	α *to* β
Washing machine	0.78	5	[08:00–16:00]
Dryer	4.40	4	[06:00–18:00]
Dish washer	3.6	3	[07:00–12:00]

Table 3. Category C: interruptible appliances

Interruptible appliances	PowerRating (kWh)	LOT	α *to* β
Air condition	1.44	15	[06:00–24:00]
Refrigerator	0.73	14	[06:00–24:00]
Water heater	1.5	6	[06:00–24:00]
Space heater	1.50	12	[06:00–24:00]

Algorithm 1. TS

Initialize all parameter
x'=best solution among trails
S(x) sample of neighborhood $S(x)\epsilon N(x)$
Current solution $x'\epsilon X$
Set tabu list TL=150
Set aspiration criteria =0
Set iteration counter = 0
Randomly generate initial solution
Randomly generate trail solutions $S(x)\epsilon N(x)$ and sort them in ascending order to obtain SS(X)
Let x' be the best trail solution in SS(X)
    if$x' > x$
        $X'' = x$
        else
        X"=x'
    end **while** k<= number of iterations
        For i=1:TL
                Perform tabu search
                If $X'' > X'$
Update X" in tabu list
Else X" not present in tabu list
update X" in aspiration criteria
end **end** **end**
        If stopping criteria is satisfied
perform termination
else k=k+1
end

Algorithm 2. EDE

```
Initialize all parameter  pop size, D, MaxItr, xl, xu, f, vi
Initialize population
for j = 1:MaxItr
  for j = 1:D
    while  termination criteria not satisfied
      perform mutation
      for  each vector Xi randomly
        select three vectors
        Xr1,  Xr2,  Xr3
        r11,  r21,  r31
      end  for  mutant vector
        Vi = Xr1 + f(Xr2 − Xr3)
      end  if (G <= 100) then
        for i=1:D
          if randb<=CR1 do
           Y11=Xr1
          end  if
           randb<=CR2 do
           Y21=Xr21
          end  if
            randb<=CR3 do
           Y31=Xr31
          end  if
           randb*xj
           randb*vj+(1-randb(j)*xj)<- X51
          end  end
      if
        f(u) is better than f(xi) then
        replace xi with u
          end  if
        set G=g+1
          end while
```

as they run according to the user's habit, e.g., Toaster, Fan, Television, Oven, Lights, Iron,etc. The details are mentioned in Table 1.

The category B consists of the appliances which can be shifted to any other hour of the day w.r.t user's demand. While shifting their running time, load profile cannot be change as LOT is pre-announced from user-side. Such type of appliances includes: Dryer, Washing Machine, etc which are shown in Table 2. According to user demand, AC, Refrigerator, Water Heater etc. are the appliances with interruptible interval even during the running position. Such appliances belong to category C as shown in Table 3. The major contribution in our simulation result is the combined use of price signal CPP and ToU, which increases the reliability of communication between utility and customer. The graph of combined ToU and CPP price signal is shown in the Fig. 3 below. In order to perform simulation experiments, 13 appliances from [2] of a single home

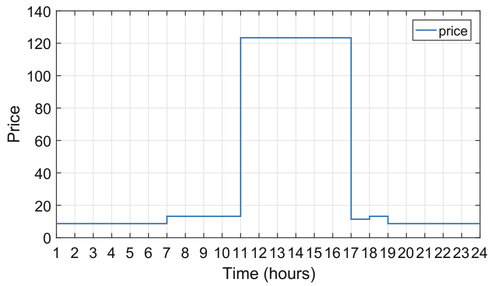

Fig. 3. Combined ToU and CPP

are considered. Its scope is limited to the residential users. After explaining the categorization criteria, simulation results will be discussed in the former section to analyze the performance of our optimization techniques.

4 Simulation Results and Discussion

In this section, the overall performance of our system model is discussed. The results show that how the variations are meeting our objective function related to minimizing cost and maximizing user comfort. According to Fig. 4, there is a flow of load shedding which can be easily observed. The unscheduled load is creating peak where the prices are high while our optimization techniques are transferring load to OPHs. EDE reduces the load more efficiently during the high price hours of the day than TS. The waved like distribution of load among the 24-hours is shown in the graph captioned as load demand of one day. The total load shown in this graph is distributed among 24-hours per day. In Fig. 5, the unscheduled cost during the hours (11–17) is creating the peak because of the CPP tariff as its values are high during this time interval of the day. Figure 3 show the peak in the middle of the graph that represent the high price. According to Fig. 6, the total cost of TS is 4825 cents which is 41.42% better in comparison to the unscheduled cost and 14.26% to the EDE. Here, the trade-off between the delay time and electricity cost reduction occurs because when delay time increases, the cost decreases and vice versa. The electricity cost before scheduling of control parameters is much more, i.e., 8238 cents per day which eventually decreased to 6000 cents per day in case of EDE while 4825 cents per day in case of TS. The percentage increase and decrease is a calculated affect of parameters with respect to unscheduled parameter.

The PAR reduction is shown in Fig. 7, according to it, TS reduces the peak ratio more than that of EDE. The unscheduled PAR is approximately equal to 2.17 which is reduced to 1.97 in case of EDE and 1.87 in case of TS. When we analyze Fig. 8, the delay time is 2 h and 24 min in case of EDE, which is less in comparison with the delay time caused by TS. As, the TS delay time is 3 h and 34 min approximately. It shows that EDE is achieving more reliable waiting time

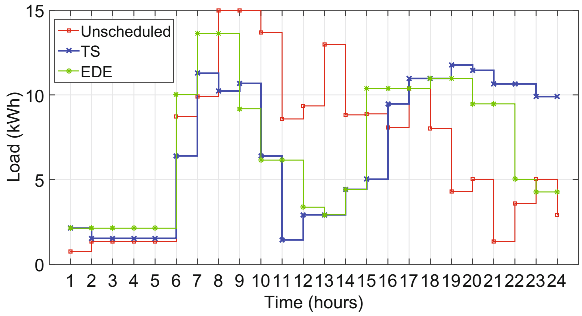

Fig. 4. Load demand of one day

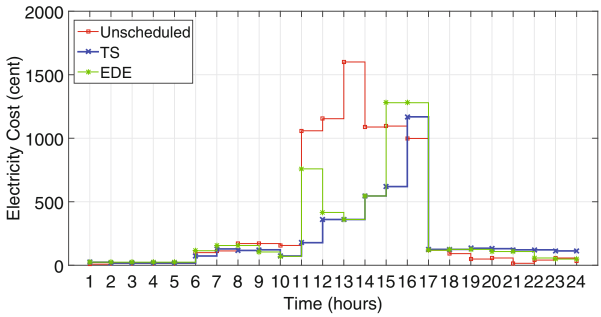

Fig. 5. Electricity cost of one day

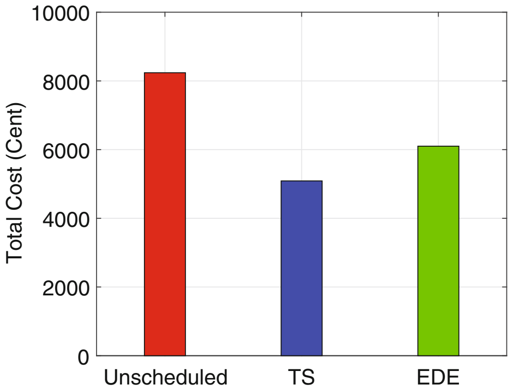

Fig. 6. Cost

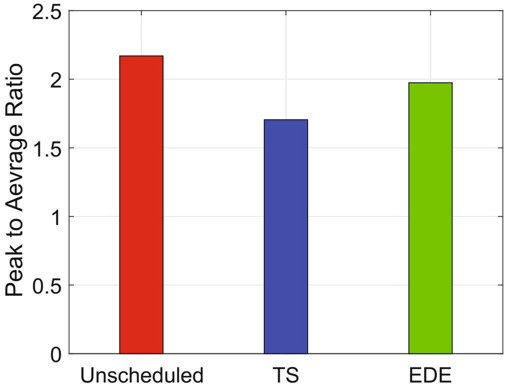

Fig. 7. PAR reduction

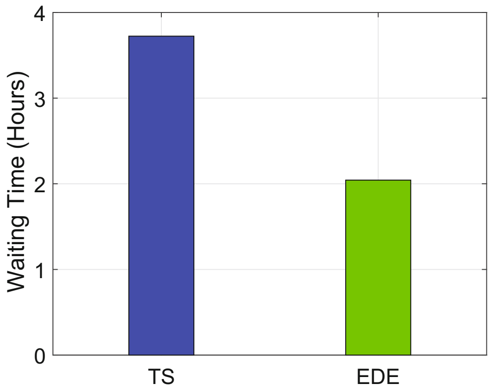

Fig. 8. User comfort

as compared to that of TS. In our paper, we have successfully achieved our aim of minimizing electricity cost as well as maximizing user's satisfaction and PAR reduction. However, there is a trade-off between these two objectives. In order to reduce electricity bills, somehow user has to compromise on his comfort, on the other side, to achieve high relaxation for using appliances freely, one has to pay high value for it.

5 Conclusion

DSM is considered to be very suitable for both utility-side and consumer-side. The simulations are performed in order to evaluate the system. Our results are based on the performance of heuristic techniques. The trade-off is also attained between user comfort and electricity bill reduction. Another trade-off that we have observed is between PAR and total reduced cost. In our study, we used combined pricing tariff in order to deal with the instability of system. As, CPP tariff generates the high cost value and increases cost rapidly in some particular hours of day, so combination with RTP proved the stability and reliability.

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