I J C T A, 9(26) 2016, pp. 23-31

Investigating Various Cost Models for Residential Load Scheduling in Smart Grid

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ABSTRACT

Smart Grid has been evolved from the recent technological growth in electrical network. One of the major challenges in Smart Grid is to reduce fluctuations in electricity demand and thereby to keep the stability of the entire grid system. The residential demand side management plays the vital role for keeping balance between the electricity demand and supply in Smart Grid. In this paper, Adaptive Breeder Genetic algorithm is applied for reshaping the consumer's electricity demand, thereby to reduce the electricity payment (cost) for the consumers. The proposed algorithm concentrates on the tuning of the parameter settings adaptively. The performance of the Adaptive Breeder Genetic algorithm is compared with Simple Genetic algorithm in order to demonstrate the effectiveness of the proposed algorithm. The result shows that the proposed algorithm provides better solutions than Simple Genetic algorithm within reasonable computation time.

Keywords: Smart Home Scheduling, Genetic Algorithm, Electricity Cost Minimization

1. INTRODUCTION

Power industry has been the most essential resource for the economical growth of a nation. Further, it has been the driving source for the promotion of all industries. But still, the development of the electricity grid was not sufficient even in the developed countries. In this context, the society had attracted towards the 'Smart Grid'. As per the European Technology Platform, the European Commission, 2006 defines Smart Grid as follows: "A Smart Grid is an electricity network that can intelligently integrate the actions of all users connected to it – generators, consumers and those that do both in order to efficiently deliver sustainable, economic and secure electricity supplies" [1]. It can offer various benefits to the society namely enhancement in the energy usage levels, reduction of carbon footprint in the environment, amplifying the electricity production through proper utilization the electricity assets. The Smart Grid can be abstractly viewed as a composition of four layers namely, Grid Physical Infrastructure Layer (GPIL), Smart Data Processing Layer (SDPL), Communication Layer (CL) and Smart Energy Services Layer (SESL) which is shown in Figure 1. Each Layer in smart grid is responsible for obtaining respective objectives by performing the related events as shown in Figure 1. Each of these four layers in smart grid is still now at the evolving stage only. Hence, vast number of research works pertaining to smart grid has been carried out in recent years. One of the major challenges in Smart Grid is to handle the dynamic nature of electricity demand and supply. In order to satisfy the increasing electricity usage of consumers, the smart grid encourages the supplementary use of Distributed Energy Resources (DER) for electricity generation.

Due to the volatile nature of DER, high level of instability was induced in the energy supply of smart grid. Thus, the fluctuations presented in energy generation as well as in energy demand makes it very complex to keep balance between the electricity demand and supply in smart grid. As the smart grid promotes the consumers as 'Prosumers', it enables them to save, buy and to sell energy by means of reshaping their electricity consumption. The reshaping of electricity usage done by the consumers at the demand side is

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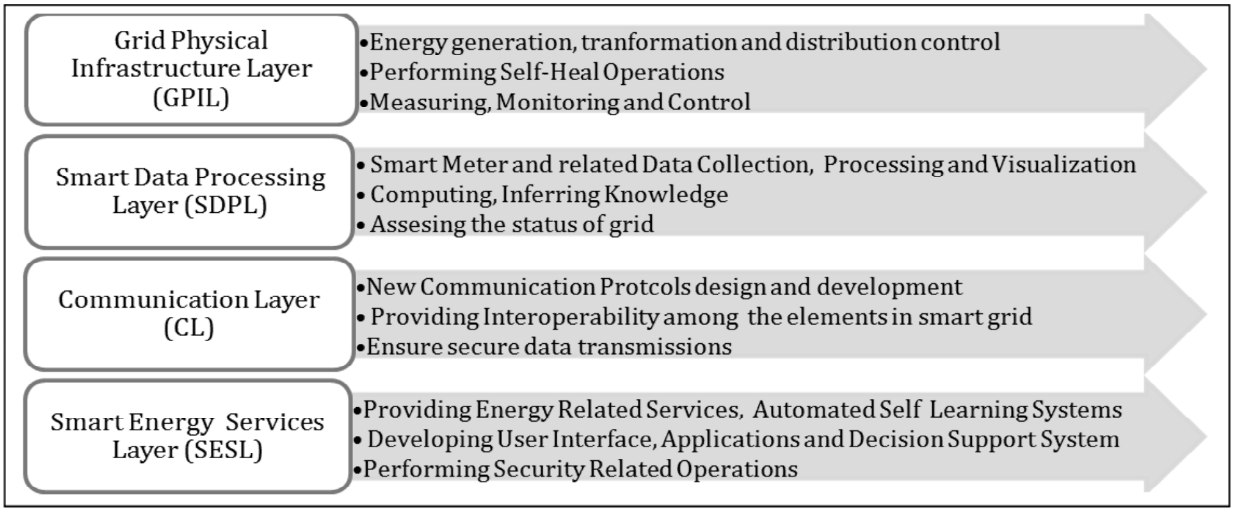

Figure 1: Smart Grid – Layered View

termed as "Demand Side Management" (DSM). Various strategies can be tagged under the DSM, where Demand Response (DR) programs are the most popular one. DR helps to improve the reliability of the power system by means of lowering the peak demand, capital cost investments and postpones the need for network updates [2]. The altering of residential electricity usage induced by the price based DR programs in smart home energy management system has been concentrated in this paper. There has been a rich research literature regarding the smart home energy management in the recent works [3-11].

2. RELATED WORKS

Chengshan Wang (*et al.*2013) had proposed the novel Traversal-and-Pruning (TP) algorithm for minimizing the electricity cost of smart home by controlling the thermostatically controlled household appliances [3]. The TP algorithm had concentrated only on the scheduling of Electrical Water Heater (EWH). The result of the TP algorithm is the schedule generated for controlling the ON/OFF state of the specific appliance, for the period of scheduling time window. Thillainathan Logenthiran (*et al* 2012) had proposed the heuristic evolutionary algorithm as the day ahead load shifting for addressing the problem [4]. Christopher and Lingfeng Wang [5] had discussed the benefits of prosumer based demand side management technique. They had calculated the time-of -use probabilities for realizing the electricity consumption pattern of the consumers. K. M. Tsui and S. C. Chan [6] had analyzed the convex programming and regularization technique for the household load management problem. They had converted the original mixed integer problem into a convex problem before solving the problem. Yusuf Ozturk (*et al* 2013) [7] had developed a decision support system which helps to predict the load profile of the consumers and then the scheduling for smart homes was carried out. Based on the load prediction, the utilities modify their electricity prices for the consumers. Pengwei Du and Ning Lu [8] had also concentrated on the single appliance scheduling, namely the EWH in the smart home. The authors had predicted the water usage and then applied the multi-loop algorithm to solve the appliance commitment problem. Xiao-Min Hu (*et al.* 2013) had proposed a multi objective Genetic Algorithm (GA) to address the optimization problem in smart grid by means of shifting the starting time of the controllable appliances [9]. Zhuang Zhao (*et al.* 2013) discussed about the architecture of smart home energy management system with a home network [10]. The authors had focused on the electricity cost minimization of the energy management system. The RTP combined with IBR cost model was proposed in their work. In order to provide the optimum schedules, the electricity demand is forecasted based on the past usage.

Rather than the works in the literature, this paper attempts to study and analyze the scheduling of residential energy usage in smart homes under various energy pricing models. Rest of this paper is structured as follows. In Section 3, the problem description was discussed and the methodology was elaborated in Section 4. Simulations and Results were evaluated in Section 5. Finally, the conclusion and future work was given in Section 6.

3. PROBLEM DESCRIPTION

A smart home consists of any number of electrical appliances. Among them, the operational time of some household appliances can be postponed whereas some are fixed. Based on the operational time of the household appliances, it is broadly classified into two groups namely, shiftable load and non-shiftable appliances. Further, depending upon the ability to interrupt the operation of shiftable appliances, they can be classified as preemptive and non-preemptive appliances. Since, the shiftable appliances offer the space for reshaping the residential electricity demand, scheduling in shiftable appliances is focused in this paper.

The Energy Management System (EMS) in a smart home has the ability to control and schedule smart home appliances connected in home area network. The EMS contains the smart meter which acts as the receiver of announced electricity prices in Smart Grid and as the sender of the electricity usage of consumers to Smart Grid.

The objective of consumer is to reduce the electricity cost whereas the objective of the electricity utilities is to reduce the peak loads in the consumers electricity demand. In order to reduce the electricity cost for the consumer, the different cost models can be used for inducing the consumers to reshape their electricity demand. In this paper, the Real Time Prime (RTP), Time-of-Use (TOU), and Inclining Block Rate (IBR) combined with RTP cost models are considered. In RTP model, the electricity price will vary every hour with the reflection of wholesale electricity. TOU divides the whole day as peak hour, mid-peak and off-peak hours and provides the different electricity price to consumers. Inclining Block Rate (IBR) combined with RTP, changes the electricity price every hour. It differs from RTP model by fixing the demand limit for each hour and increase the price if the total demand of user exceeds the limit.

Once the electricity demand of smart home and the electricity price information submitted to the EMS, the smart scheduler intelligently schedules the appliances. The smart scheduler needs an intelligent algorithm to generate the best schedule for reshaping the residential electricity demand. Hence, the main objective of this paper is to schedule the household appliances which reduces the electricity cost for a smart home under the given electricity information.

4. ADAPTIVE BREEDER GENETIC ALGORITHM FOR RESIDETIAL LOAD SCHEDULING

A. Review on Genetic Algorithm (GA)

Genetic algorithm belongs to the class of meta-heuristic algorithms, which was invented by John Holland in the 1960s and presented the GA with theoretical framework in his book “Adaption in Natural and Artificial Systems”. The algorithm was developed based on the inspiration from the human biological evolution. The concept behind the algorithm is the survival of the fittest. It has been found that an extensive amount of applications were utilizing GA for solving the optimization problems in many fields. There has been a lot of research works which were aimed to enhance in the simple genetic algorithm and hence presented numerous variants of the genetic algorithm. Although, some research works were successful in launching the various novelty in their work, the GA was often fail to overcome from the local optimum problem and affects from generic drift. Hence, this paper had tried to improvise the Simple Genetic (SG) algorithm by means of offering the adaptive breeder block in the simple genetic algorithm.

B. Adaptive Breeder Genetic Algorithm

As the name implies, the Adaptive Breeder block is in charge of supplies the adaptiveness of the proposed algorithm which is shown Figure 2. The motive for the introduction of adaptive breeder is to avoid trapping into the local optimum and to control the diversity among chromosomes. The Adaptive Breeder Genetic (ABG) algorithm achieves these two goals by the way of dynamically controlling the elitism and reproduction process with respect to the execution cycle of the algorithm. The functional block diagram of the ABG algorithm is depicted in Figure 2 and the job of the each functional is described as follows.

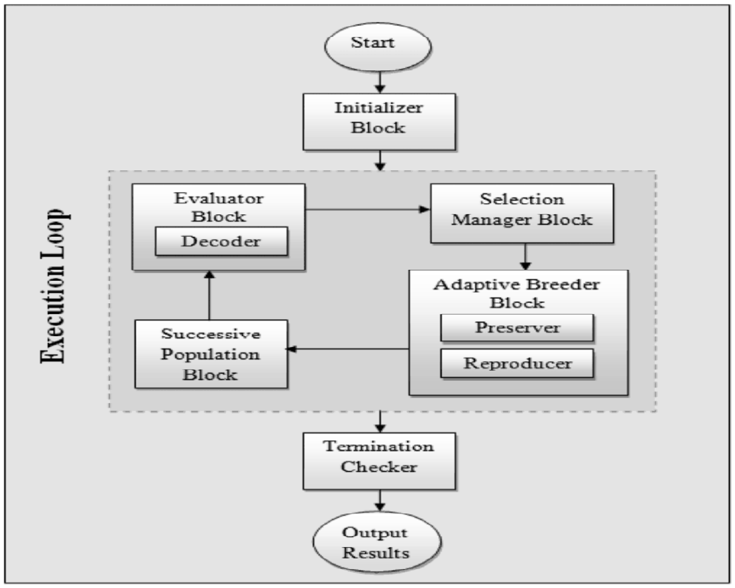

Figure 2: Functional Block Diagram of the AB-GA

- ***Initializer***: The GA starts functioning by generating the initial population of chromosomes. The initial population is created in such a way that it contains feasible solutions and provides genetic diversity. It is also responsible for providing the suitable function for the encoding of chromosomes. Moreover, it also does the initial parameter settings for the ABG algorithm.
- ***Evaluator***: The Evaluator block is accountable for finding the fitness of each chromosome in the current population. It inside contains the decoder segment which finds the objective value in the search space for the chromosome. The Evaluator block stores the objective values of the best chromosomes found so far in the execution loop.
- ***Selection Manager***: Based on the fitness, the Selection Manager chooses and places them into the mating pool. There are several strategies available for choosing the chromosomes from current population as parents into the mating pool. In this paper, the stochastic universal sampling selection is used as the selection mechanism, since it provides the least bias among the resultant chromosomes.
- ***Adaptive Breeder***: The Adaptive Breeder block plays the vital role, as it cleverly handles the reproduction process of the ABG algorithm. It controls the two operations namely the elite preservation and the chromosomes reproduction. The Preserver decides the number of best chromosomes to be preserved as elites in each iteration. Initially the elite percentage is nearly 40% of the population size and altered while execution. The Reproducer block performs the respective crossover and mutation operations with dependence on the chromosome representation and the constraints of the problem. This block uses the improvement in the objective value as the yardstick to detect the local optimum region and then adaptively controls the crossover and mutation operator to escape from it. The pictorial representation of the respective crossover operation is shown in Figure 3.
- ***Successive Population***: This block contains the current population of chromosomes by replacing the parent population with the new offspring population. The initial population is copied as the parent population at the start of the execution loop. Combined with this block, the three blocks

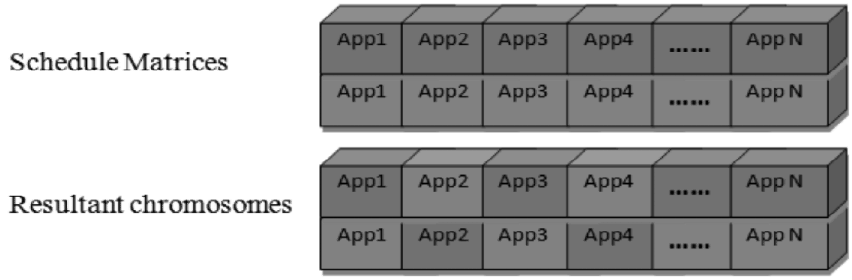

Figure 3: Pictorial Representation of Crossover Operator

namely, Evaluator, Selection Manager and Breeder all together constitutes the execution loop of the ABG algorithm.

- ***Termination checker***: In general, the stopping condition for the GA variants can be the number of generations reached or the computation time or the convergence towards the specified objective value. In this paper, the Termination checker block counts the number of generations and checks for the termination point in the algorithm execution. The respective pseudo-code of the ABG algorithm is given in the Figure 4.

```
The ABG Algorithm: Pseudo -code
Begin
    //Initialize Algorithm Parameters
     Set Population Size as PSIZE, Elite Size as ESIZE, No of Generations as
     MAX_GEN, Crossover Probability as CR_PB, Mutation Probability as MT_PB,
     Current Population as CUR_POP, Parent Population as PAR_POP, Offspring
     Population as OFF_POP, Mating Pool as MPOOL;
    //Initialize Problem Dependent Parameters
     Set Appliance Details as APP_INFO, Price Information as RATE;
    // Create Initial Population
     For i=1 to PSIZE
        Create and place the chromosome in the feasible search space randomly;
        Add it to CUR_POP;
     End
    //Begin Execution Loop
     For i=1 to MAX_GEN
       // Finding Fitness for each chromosome
          For j=1 to MAX_GEN
              Pick chromosome_j from CUR_POP;
              Calculate the fitness of chromosome_j;
          End
       // Apply the Elitism
                          ESIZE=((MAX_GEN-i)×PSIZE×0.4)/MAX_GEN ;
          Preserve the best chromosomes as per by the ESIZE;
       // Apply the Selection Scheme
          Assign sectors to each chromosome of the CUR_POP in the scale corresponds
           to their fitness;
          Loop
             Place the marker in the scale;
             Choose the respective chromosome from CUR_POP;
             Add it into MPOOL;
          Until the MPOOL is filled;
      // Apply the Crossover Operation
         Randomly choose the CR_PB between [0.4- 0.9];
         Check if stuck local in local optimum, then
             If CR_PB<0.9, then
                  Increase the CR_PB ;
             End
         End
```

```
                    For each pair of chromosomes from MPOOL
                         Cut the pair of chromosomes into appliances vise pieces;
                         Generate two offspring by randomly mergingthe pieces of these two chromosomes;
                         Add the two offspring into OFF_POP;
                    End
               // Apply the Mutation Operation
                    Randomly choose the MT_PB between [0.001- 0.1];
                    Check if stuck local in local optimum, then
                         If MT_PB<0.1, then
                                Increase the MT_PB ;
                         End
                    End
                    Apply the random shift mutation in the gene pool;
               // Generate Successive Population
                    Copy CUR_POP into PAR_POP;
                    Copy OFF_POP into CUR_POP;
          End
          Output the results;
   End
```

Figure 4: Pseudo-code of the ABG algorithm

5. EXPERIMENTAL STUDY

In this section, the ABG algorithm and SG algorithm were simulated and tested under the three various cost models. The Figure 5 shows the electricity prices taken under the three cost models.

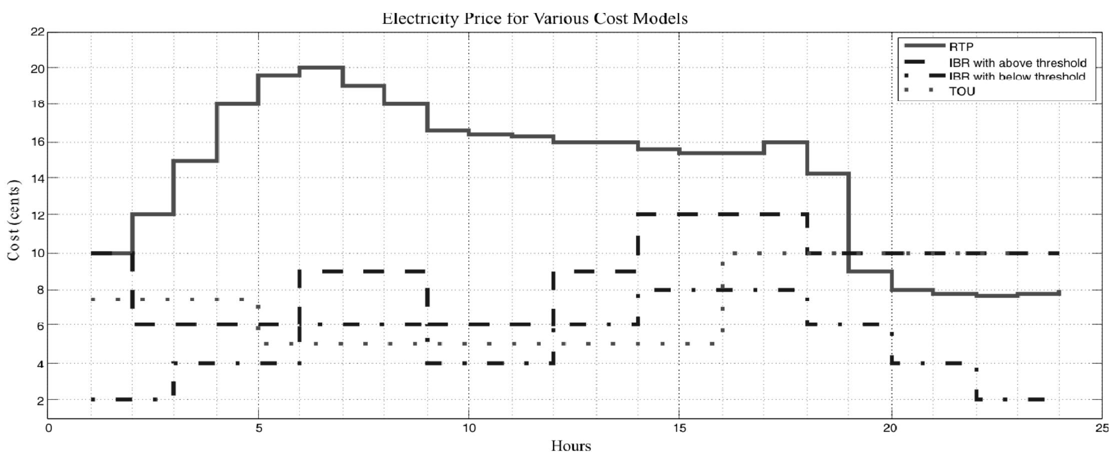

Figure 5: Electricity Price Under Three Different Cases

A smart home with 15 electrical appliances is taken into consideration for scheduling. The algorithm inputs are the scheduling time period, the number of appliances, power consumption profile for each appliance, operational time requirements and electricity price. The appliance information and the electricity price information are taken from the related works [5, 11]. The proposed approach used the day-ahead load shifting method. Finally, the parameter settings for simulating the algorithm are given the Table 1.

Table 1
Parameter Settings for ABG Algorithm

Parameter	*Value*
Population size	50
Iterations	50
Selection Scheme	Stochastic Universal Sampling
Crossover Probability	0.4-.9
Mutation Probability	0.001-.01

(a) Analysis on Cost Minimization

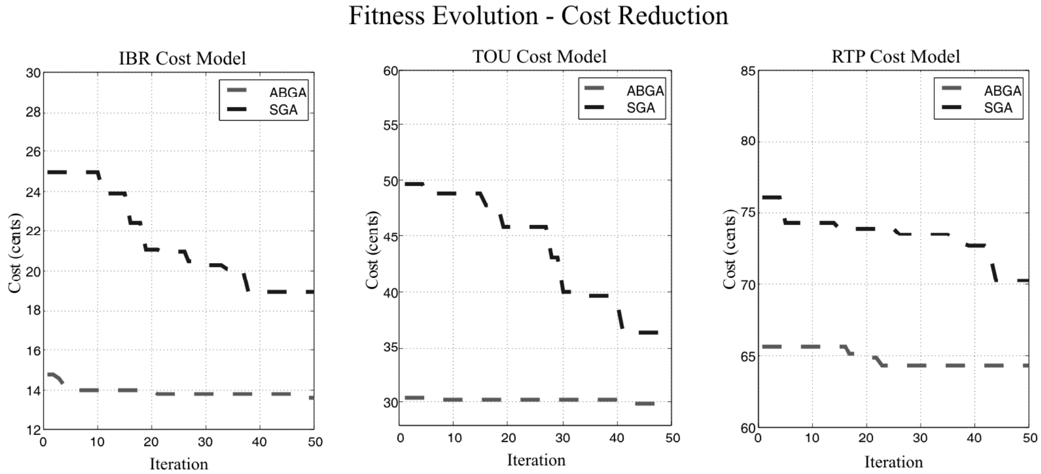

Figure 6: Fitness Evolution History

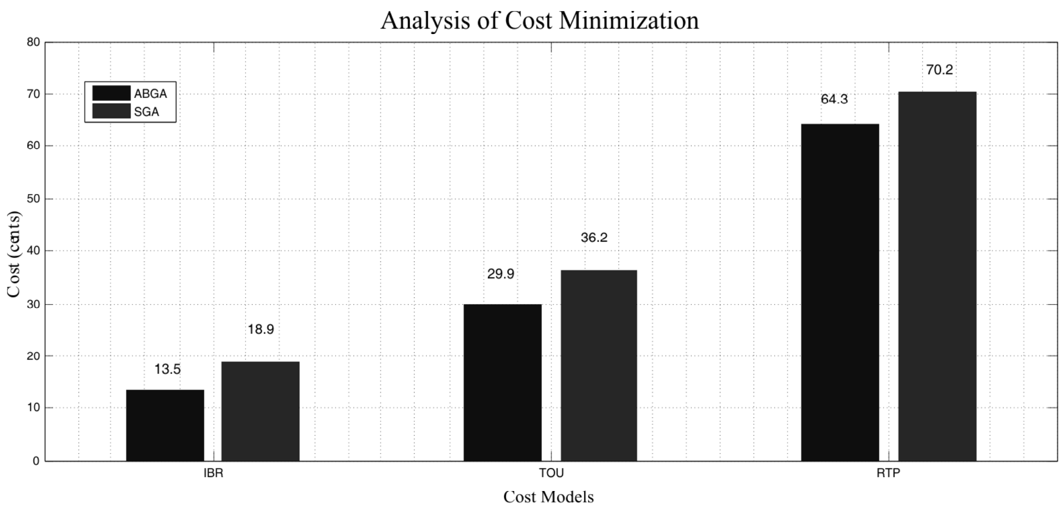

Figure 7: Analysis of Cost Reduction

The fitness evolution history of both the ABG and SG algorithms with three different cost models are shown in separate columns in Figure 6. From the three columns, it can be clearly understood that the ABG algorithm provides least cost than the SG algorithm. It is also observed that the IBR cost model provides the minimized cost for the consumers among three models. It can also be seen that the ABG had exhibit better convergence than the SG algorithm in their performance. The Figure 7 displays the final cost obtained by the two algorithms in each cost model. From the Figure 7, it can be evident that the ABG algorithm with IBR cost model provides significant cost reduction for the consumers.

(b) Impact on PAR Reduction

Even though the electricity cost minimization is the ultimate goal of this paper, the utilities are in need of reducing the peaks in the consumers load demand. Since the Peak-to-Average Ratio (PAR) value can be used as the metric for assessing the peak load in electricity demand, it was also analyzed in this paper. The Figure 8 shows the evolution of the PAR value reduction.

From the Figure 9, it can be illustrated that the IBR model had contributed more than the other two cost models, for the reasonable PAR reduction.

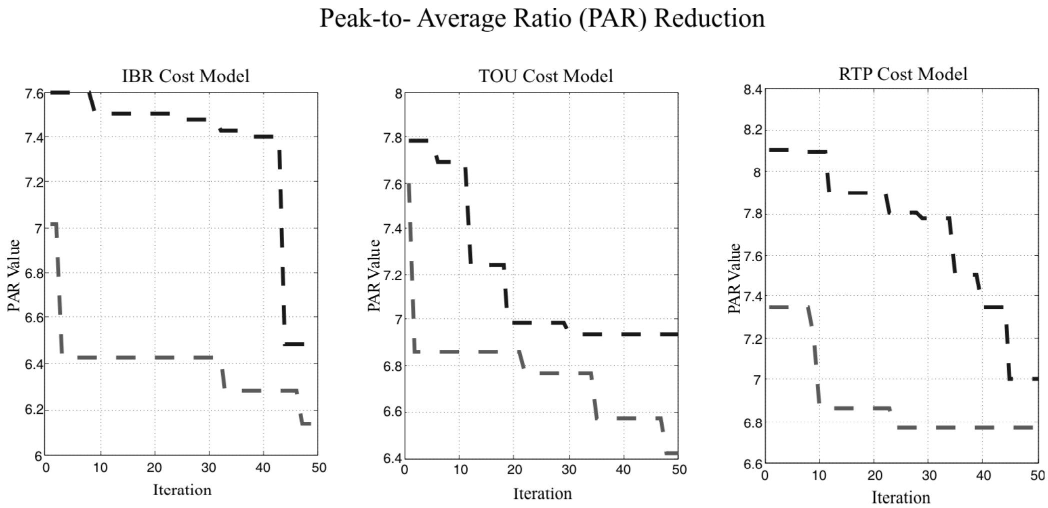

Figure 8: Reduction of Peak-to-Average Value

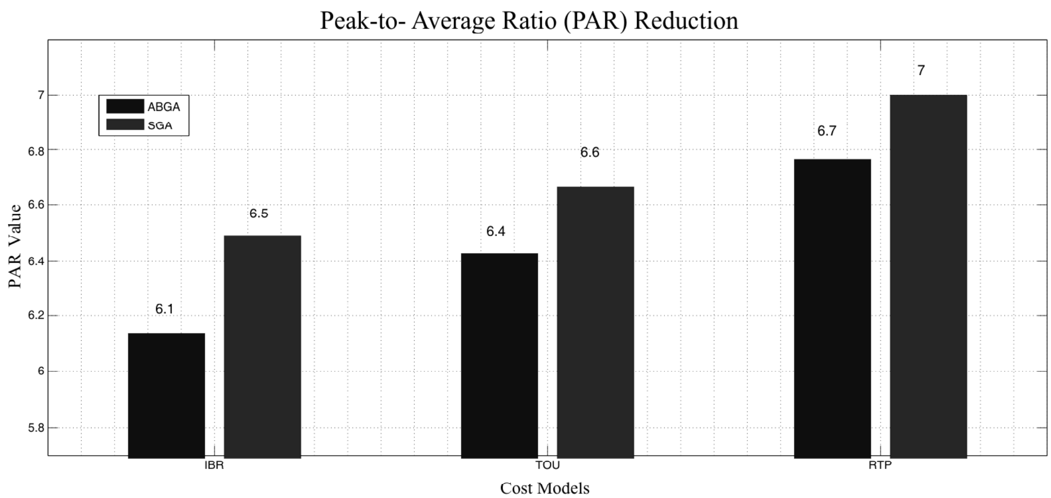

Figure 9: Analysis of Peak-to-Average Value

6. CONCLUSIONS

In this paper, the ABG algorithm is proposed and implemented for solving the residential load scheduling in smart grid. The proposed scheduling algorithm gives feasible schedules for the smart home. Further, the schedule generated by the algorithm satisfies the user specified comfort constraints. In order to reveal the usefulness of the proposed algorithm, it was compared with the SG algorithm. It can be realized that the proposed algorithm shows better performance in terms of electricity cost reduction for the smart home users. Furthermore, the proposed algorithm had tested with three different cost models namely, RTP, TOU and IBR combined with RTP. The demand limit entailed in IBR cost model provides added benefit to utilities as it also compresses the peak loads in the electricity demand. Hence, it is clearly observed that among the three different cost models taken in this paper, the IBR cost model provides more benefits to consumers as well as to electricity producers. Moreover, this work can be extent to accommodate the energy storage integrated with renewable energy resources for scheduling in smart homes.

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