Residential Demand Side Management in Smart Grid Using Meta-Heuristic Techniques

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Abstract. The rise of energy demand is an alarming situation for mankind as it can lead towards a crisis. This problem can be easily tackled by assimilating Demand Side Management (DSM) with traditional grid by means of bi-directional communication between utility companies and consumers. This study evaluates the performance of Home Energy Management System (HEMS) using meta-heuristic optimization techniques: Genetic Algorithm (GA) and Crow Search Algorithm (CSA). The appliances are classified in three sets on the basis of their electrical energy consumption pattern. Moreover, the Real Time Pricing (RTP) scheme is used for power bill control. The core aims of this paper are to minimize electrical energy cost and consumption by scheduling of appliances, decline in peak to average ratio, while getting the best out of user comfort. Besides, simulation results illustrate that there is a trade-off between waiting time and electricity cost. The outcomes also indicate that CSA perform better as compared to GA in relation to cost.

Keywords: Demand response · Home energy management · Optimization · Smart grid · User comfort

1 Introduction

In the modern day world and with growing technology, electricity has become the basic necessity of all individuals. Moreover, the demand of electrical energy is also greater than before with the progress of population. It can result in distress as providing electricity to such masses has become a challenging problem in the current world. Besides, the customary power system is insufficient to tackle issues of power grid like consistency, immovability, and sturdiness [1]. As a consequence, a different setup is desired that is capable enough to tackle the challenges. In this regard, the novel technology of smart grid has been introduced in the literature which excels in the exciting features like communication expertise, computational facilities, control schemes and different measuring devices

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with present grid. Furthermore, smart grid qualifies bidirectional course of information concerning utility and consumers as presented in Fig. 1. In addition, smart grid has blessed the users to now become prosumers. The modern users are proficient enough to retail their produced electrical energy to the utility companies. It has been observed that utility is attracted in revenue percentage increase with the decline in Peak to Average Ratio (PAR).

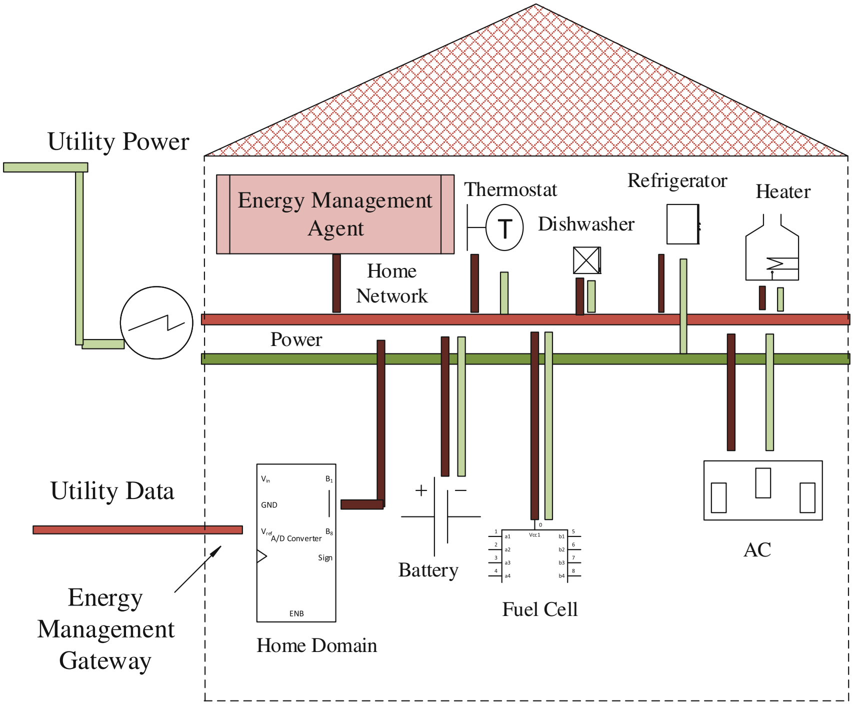

Fig. 1. Smart grid

Demand Side Management (DSM) is considered one of the significant features of a smart grid. DSM is regarded as the preeminent elucidation in order to sustain equilibrium between demand and supply. Moreover, administration of load and Demand Response (DR) is core utilities of DSM. On the subject of load administration, it is beneficial in lessening of peak power plants, effective consumption of power and decline in electricity cost of the smart grid in terms of dependability and tractability [2]. Nonetheless, DR is an approachable accomplishment in use by dint of a consumer, contrary to dynamic pricing schemes. The extremely instable nature of the load may perhaps creep up the reliability of the grid in a trice. Consequently, DR [3] is supposed to be significant in order to handle the qualms such as it is responsible for litheness at comparatively low tariffs. Generally, DR is alienated in two classifications: incentive DR program and price DR program.

The association of supply and demand are further precisely imitated by dynamic pricing schemes rather than flat rate pricing schemes. Time of Use (ToU), Inclined Block Rate (IBR), Critical Peak Pricing (CPP), Day Ahead Pricing (DAP), Real Time Pricing (RTP) and others are some of the dynamic estimating prices. These tariffs reassure the consumers to transfer high power load to off-peak hours as it will reduce the PAR and cost. RTP is deliberated as an utmost proficient pricing scheme for power fairs [4] and offers buyers statistics about the real price of electrical energy at any specified time.

The paper discusses Home Energy Management System (HEMS) in order to diminish the PAR by shifting of peak load from on-peak hours to off-peak hours to moderate the cost. One of the motivation for this study is all-encompassing usage of electrical energy in local and residential region. According to a recent survey, 21% of entire energy is being expended by domestic erections [5] which is accumulative each year promptly. The study has been a hot debate topic in literature from recent years as consumption of energy and its efficient management has become a goal for scholars. The paper presents the literature review and depicts the mechanism of smart grid optimization in Sect. 2. Consequent to this, Sect. 3 highlights the associated problem concerning the on-peak hours and its significances on the grid and user and Sect. 4 integrates the proposed elucidation of emphasizing complications with a complete depiction of formerly used methodologies GA and CSA. Moreover, the outcomes are demonstrated and substantiated on the base of simulation in Sect. 5. Section 6 accomplishes the study with future work.

2 Related Work

The accumulative need for electrical energy in the grid and the request to handle the electrical energy consumption efficiently has been premeditated in a number of mechanisms in the literature. A lot of methodologies have been recommended and executed in order to cope with power consumption and lessen the cost. This paper presents some significant papers that address this specific issue associated with this work.

2.1 Hybrid Techniques

The authors in [6,7] achieved the instability of the load during on-peak and off-peak hours. Besides, the goals of reduction of PAR, lessened cost plus increased User Comfort (UC) were also succeeded using hybrid techniques. The methods of Hybrid Genetic Wind Driven (HGWD), knapsack and multi-knapsack problem, Wind Driven Optimization (WDO), Binary Particle Swarm Optimization (BPSO) Bacterial Foraging Optimization Algorithm (BFOA) and Genetic Algorithm (GA) were used as proposed techniques in these papers.

An optimum load scheduling was the main objective between the appliance and cost effectiveness in [8] by means of BPSO with the pricing signal of ToU. In this scenario, the users were characterized on the basis of setting up the specified criteria of the appliances. Furthermore, conventional consumers were devoid of HEMS and assumed to be carefree of utility cost. Conversely, smart users were supposed to be well acknowledged with the HEMS design while the smart prosumers yield some energy from Renewable Energy Sources (RES) other than consumption. In this paper, HEMS was specified as the mark and reduction of cost was done. Nonetheless, UC and RES were found middle ground.

A Realistic Scheduling Mechanism (RSM) was proposed by [9] to condense user distress of a customer in the pricing scheme. This was attained by categorization of the appliances which had highest priorities and further lower ones. The classification recommended was activity dependent appliance, occupancy dependent and independent appliances and the set of rules significantly to their working intervals.

2.2 Dynamic Programming Techniques

Power transaction as well as scheduling of load with the incorporation of RES was achieved by [10] by means of Dynamic Programming (DP). A load control procedure for DSM was proposed for this scenario and DP was used to set up the functioning time of various categories of appliances. Besides, game hypothetical methodology was used to model the superfluous power generation which assists the user to sell their extra generated electrical power. Moreover, they could further offer it to domestic consumers at a subordinate value as compared to the buying price enforced by the electric company. That possibly will buoy up the usage of RES and thus consumers can consume the surplus power locally, which reduces the reverse power flow problem. Though, the original installation cost of RES was not considered.

2.3 Evolutionary Techniques

The aim of reduction in cost and taking full advantage of UC was accomplished by [11,12] by means of GA. They also scheduled appliances in different categories. In this regard, authors anticipated an instantaneous HEMS using scheduler, which used a GA in the company of RTP with IBR to control the uncertainty of classification or power failure. The projected pricing scheme arrangement accomplished better results and gratified all profits for both domestic and utility corporations. On the contrary, a relative examination of GA, BPSO and Ant Colony Optimization (ACO) techniques also took into account. Moreover, the outline of scheduling scheme with GA and other concerns of RES and Battery Storage System (BSS) was motivated as well. This particular objective was intended to decrease the electricity bill charges and get the most out of the UC. It was observed that RES reduced the load on the utility and offered the prospect for end users to accumulate their formed electricity for further usage when needed. In this scenario, BSS was not an operational idea for the real world as it has high installation and conservation charges.

2.4 Linear and Fractional Programming Techniques

The scheduling of appliances on different time slots and power rates was done by [13]. Load scheduling was accomplished in DSM for 24 h using the integer linear programming technique. Besides, branch and bound method put into practice so that UC can be scheduled. The anticipated solution can be functional in the domestic environment and local area. The scheduling of appliances was done by HEMS in built-up environment. Moreover, the proposed mechanism progresses the performance of the power grid by decreasing the PAR. Conversely, the UC and RES were not deliberated.

The authors in [14], mostly laid emphasis on electricity consumption. The Distributed Energy Resources (DER) were combined with smart house that delivered the substantial influence on the cost efficiency. The consumer can enhance the consumption scheduling and a new load scheduling algorithm was also developed to enhance the cost efficiency by using the innovative fractional programming tool. The DER were also combined with algorithm design and optimization was achieved. The cost efficiency was enhanced by optimal scheduling ever since the indicator of previous consumption behavior was delivered. Nonetheless, cost minimization was not measured by simulation.

2.5 Other Techniques

The authors in [15] put forward the concept of a weighted graph. The system could distinguish the requirement of energy for users that is much closer to the optimal need. The performance of the anticipated structure was assessed by way of different performance metrics which took account of peak-demand, demand variation, energy cost and the utility of the customers. Moreover, the simulations illustrated that the dynamic scheduling scheme, i.e., Dynamic Demand Scheduling (D2S), conceded enhanced performance in contradiction of the existing ones.

The regionalized structure was proposed by [16] in which the DR mechanisms for the inhabited operators were focused in order to minimize electrical energy bills and maximize the UC. In this context, customers Smart Meters (SM) integrated Home Load Management (HLM) modules to interchange the load allied data. Fast convergence rate and optimal arrangement were accomplished deprived of giving in waiting time as well as cost. The projected methodology congregated after scarce instants self-sufficiency of given size. The power effectiveness of smart grid and Smart Home Security (SHS) was discussed by [17]. It was a case study that designated the petition of electrical energy in the countryside of Colombia. The compromise was observed between the demand of electricity limit and UC.

3 Proposed System Model

The DSM facilitates more proficient and consistent grid processes in a smart grid. The two central utilities of DSM take account of demand side control activities and energy management for end consumers. Likewise, the DSM reassures the customers to put away a maximum of their energy requirements for the period of off-peak hours. Moreover, the smart meters consents bi-directional communication between utility companies and the purchaser as shown in Fig. 4. The users are capable to notify the utility on the subject of their power consumption configuration by means of smart meters. A number of optimization methods have been put into practice in this decade to elucidate the optimization problem in smart grid. In this paper, a single home is taken as an experimental model with six pieces of equipment. In this regard, the appliances are categorized into three sets: set A, set B and set C as illustrated in Fig. 2. The set A comprises of the interruptible appliances which consist of lights only. The appliances in this set can be turned on all through the day and any time. Besides, the set B encompasses base appliances like refrigerator and AC. The set C of appliances includes non-interruptible equipment's such as toaster, kettle and cloth washer.

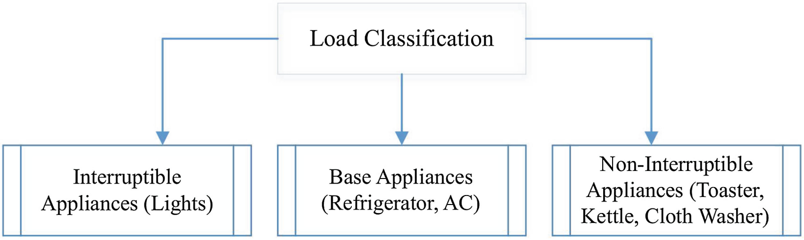

Fig. 2. Load classification

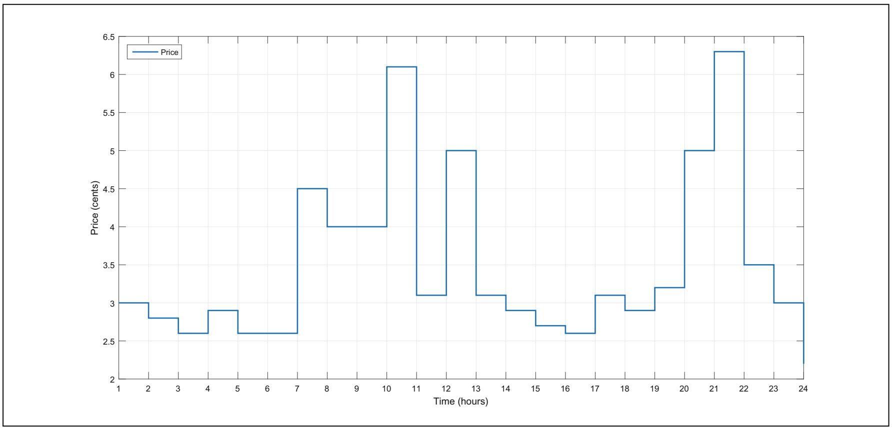

Fig. 3. RTP signal

The RTP pricing scheme is used for calculation of the electrical energy bill in this paper as shown in Fig. 3. In addition, the power consumption of every machine is assessed in kilo Watt hour (kWh). The categorization and power consumption of each appliance is specified in Table 1. The main aim of this research is the decline of PAR and reduce the consumption of power in order to lessen the rate of energy. Furthermore, the paper lay emphasis on the decline of total cost with reduction of peak load. The total cost, load and PAR are premeditated in Eqs. 1, 2 and 3 respectively.

$$TotalCost = \sum_{h=1}^{24} t_i (E|_1^h * \int_1^6 P) \tag{1}$$

$$TotalLoad = \int_1^6 P * A(\forall appliances \in A) \tag{2}$$

$$PAR = \lim_{x \to \infty} Avg(TotalLoad)^{-1} * \max(TotalLoad) \tag{3}$$

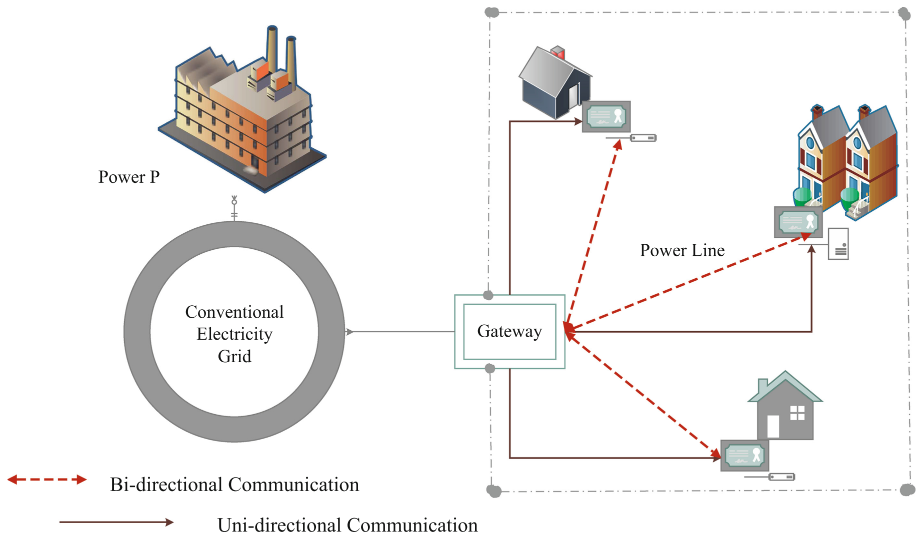

Fig. 4. Autonomous DSM in smart grid

4 Proposed Methodology

Lots of optimization methods have been premeditated in literature to tackle the smart grid associated complications. Likewise, numerous methodologies of artificial intelligence have been used to improve a capable system to find the solution near to optimal. GA is supposed to be the common approach among others as it is accustomed to find the paramount optimal elucidation from the group of specified chromosomes. The Crow Search Algorithm (CSA) is a population centered method which indicates that crow stock their leftover foodstuff in smacking places and recover it when the sustenance is desired. The paper scrutinizes the GA and CSA and evaluates which of the technique performs efficiently and gives better optimal results in the classification.

4.1 Genetic Algorithm

The Genetic Algorithm is an accepted selection procedure which is centered on the human heredities. It uses the unsystematic search heuristic methodology to resolve the constrained and unconstrained optimization complications. Generally, the practices surveyed in GA follow the standard "survival of the fittest" specified by Charles Darwin [18]. Moreover, GA is mostly appropriate for intricate non-linear models where the position of the inclusive most favorable solution is a challenging task. Nevertheless, GA does not assure optimality even though when it influences the solution owed to the prospect nature for expansion of result.

Table 1. Classification of appliances

Group	Appliances	Power rating (kWh)	Daily usage (Hours)
Interruptible base load	Lights	0.5	10
Base load item	Refrigerator	0.2	14
	AC	1.4	12
Non-interruptible base load	Toaster	1.14	1
	Kettle	1.2	3
	Cloth washer	0.7	2

The instigation of GA starts with the chromosomes populace and latterly new population is carefully chosen on the base of suitability value. The key segments of GA take in the following [19]: selection, crossover and mutation. In selection procedure, the fitness significance is assigned by calculating the procedure with genomes. The finer one is acknowledged by their fitness significance. Subsequently, two individuals are nominated from the selection procedure in crossover method. The selected one is in the form of bits, which then go through phases of crossover. However, the crossed bits are supposed to be the enhanced elucidation instead of the optimal solution. Furthermore, the ration of the new individuals will have more or less of their bits flicked or turnover with an approximately low prospect in mutation phase.

Algorithm 1. Genetic Algorithm

Initialize all parameters (α_a,β_a,τ_a)
Set bounds
for all the appliances **do**
  Generate an initial random population
  while $itr<maxItr$ **do**
    itr=itr+1
    calculate fitness function of each individual
    select individual according to fitness function
    choose pair for crossover according to roulette
    perform crossover with prospect P_c
    perform mutation with prospect P_m
  end while
end for

4.2 Crow Search Algorithm

The CSA is a population based meta-heuristic algorithm [20]. The major ideologies of CSA include some aspects which include: crows live in the group, crows commit to memory the location of their hiding spaces, crows follow each other for purposes of pilfering and crows defend their accumulations from being stolen by a possibility. The strengthening and modification in CSA is mostly measured by the constraint of Awareness Probability (AP). CSA has a tendency to demeanor the hunt on a limited area where a recent good way out is instituted by reduction of the AP value. Contrariwise, the prospect of examining the locality of recent good results declines and CSA lean towards the search space on an inclusive measure (randomization) by the escalation of the AP. Consequently, the usage of large values of AP upsurges divergence [21]. In the initialization of the problem, the decision variables are demarcated. Successively, the adaptable parameters of CSA like flock size (n), maximum iterations (maxiter), length of flight (fl) and the AP are esteemed. The flock size is then randomly located in a N-dimensional search space as shown in Eq. 4.

$$Crows = \begin{pmatrix} C_{1^1} & C_{2^1} & \cdots & C_{N^1} \\ C_{1^2} & C_{2^2} & \cdots & C_{N^2} \\ \vdots & \vdots & \ddots & \vdots \\ C_{1^n} & C_{2^n} & \cdots & C_{N^n} \end{pmatrix} \tag{4}$$

Here every crow signifies a viable clarification of the problem respectively. The memory for each crow is primed as depicted in Eq. 5. The memory for each crow is primed.

$$Memory = \begin{pmatrix} M_{1^1} & M_{2^1} & \cdots & M_{N^1} \\ M_{1^2} & M_{2^2} & \cdots & M_{N^2} \\ \vdots & \vdots & \ddots & \vdots \\ M_{1^n} & M_{2^n} & \cdots & M_{N^n} \end{pmatrix} \tag{5}$$

Algorithm 2. Crow Search Algorithm

Randomly initialize the position of flock of N crows (α_a,β_a,τ_a)
Evaluate the position of the crow
Initialize the memory of each crow
while $itr \leq iter^{max}$ **do**
  for $i = 1 \rightarrow N$ **do**
    randomly get the crow j to follow i
    Define awareness probability
    if $r^j \geq AP^{j,iter}$ **then**
      $x^{i,iter_1} = x^{i_iter} + rix(m^{j,iter} - x^{i,iter})$
    else
      $x^{i,iter} = arandompositionofsearchspace$
    end if
  end for
  Check the feasibility of new position
  Evaluate the new position of the crows
  Update the memory of crows
end while

The superiority of location is calculated for each crow by dint of introducing the values of decision variable hooked on the objective function. Then new population is generated and the feasibility of new positions is checked for each crow. Moreover, the fitness function of new positions is evaluated and memory is updated until the termination criteria is reached.

5 Results and Discussion

This section provides a brief description of simulation results. The experimentations and simulations were conducted in MATLAB in order to calculate the performance of the GA and CSA. The algorithms were assessed on the basis of electrical energy cost, power consumption, PAR and waiting time. The RTP tariff scheme is used for energy bill calculation as shown in Fig. 3 and discussed in Sect. 3.

The Fig. 5 expresses the variance of the entire cost among unscheduled and scheduled patterns. It can be evidently noticed that CSA succeeds having minimum cost as compared to GA. Besides, the Fig. 6 exemplifies the power cost for each hour for the GA and CSA. The consequences indicate that price compensated for the duration of on-peak hours is truncated in contradiction to unscheduled load since load for the period of on-peak hour has been budged to off-peak times. Moreover, 75% and 85% maximum load during on-peak hours is abridged in CSA and GA respectively. It is clear that CSA disturbed the load optimally and beats the GA scheduling by 5% approximately.

In addition, the waiting time is premeditated in terms of user comfort. There exists a trade-off concerning power cost and waiting time. The paper describes the waiting time as the period when a customer time lags for an appliance to turn ON. Similarly, off-peak hour or low price hour should be favored by end users to decrease power bills. Conversely, if luxury is chosen, then the customers will not delay for their processes to be executed. Thus, consumers have to find the middle ground for cost. The Fig. 7 presents user comfort of the consumer for techniques of CSA and GA. The records display the inverse association between cost and waiting time in cooperation.

The decrement of PAR supports to maintain the steadiness of the grid and it progresses the capability and adeptness of the grid as well. The performance of CSA and GA is illustrated in Fig. 8 for PAR. It can be noticed that the PAR of CSA is approximately 9% lower contrary to GA. Furthermore, the PAR of CSA and GA both are less as compared to unscheduled one. Nonetheless, the Fig. 9 shows the total load. The Fig. 10 signifies the consumption of power for each

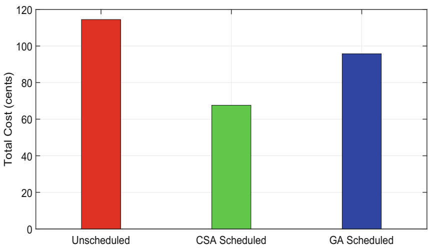

Fig. 5. Total cost

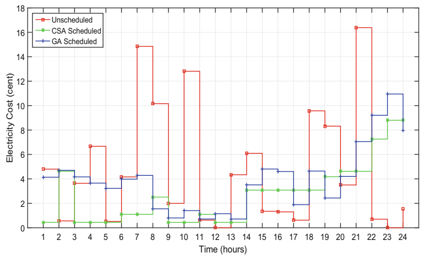

Fig. 6. Electricity cost per hour

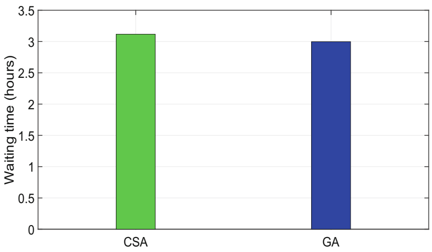

Fig. 7. Average waiting time

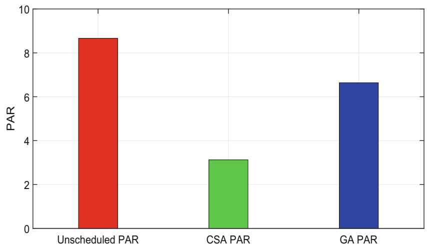

Fig. 8. Peak to average ratio

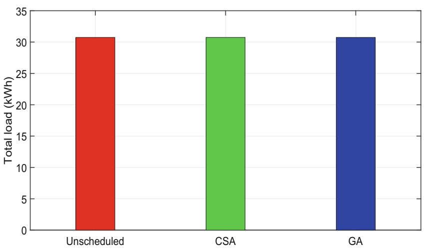

Fig. 9. Total load

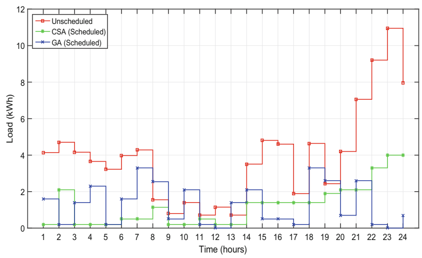

Fig. 10. Hourly energy consumption

hour afore and prior to scheduling. Moreover, the inclusive power consumption in scheduling case is fairly optimum and comparatively low.

6 Conclusion and Future Work

The paper estimates the challenge of domestic load management for different categories of appliances. In this regard, the piece of equipment's was arranged on the basis of their energy consumption pattern. Moreover, the performance of the meta-heuristic algorithms was calculated on the basis of cost decline, energy consumption, user comfort and PAR reduction. Besides, there was a trade-off between waiting time (UC) and electricity cost as illustrated from simulations. CSA demonstrated the efficiency in terms of cost as compared to GA with RTP pricing scheme. Likewise, the concentrated power consumption was abridged as well during on-peak hours in contradiction to unscheduled one. The load was also well-adjusted as per mandate and shifted towards off-peak hours shorn of generating the ultimate load. For the future, the integration of RES will be considered in smart grid for further decline in cost.

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