Received December 25, 2017, accepted February 6, 2018, date of publication February 13, 2018, date of current version July 12, 2018.

*Digital Object Identifier 10.1109/ACCESS.2018.2805849*

# Energy Efficient Smart Buildings Using Coordination Among Appliances Generating Large Data

**MUHAMMAD HASSAN RAHIM[1], ADIA KHALID[1], NADEEM JAVAID[1], (Senior Member, IEEE), MUSAED ALHUSSEIN[2], KHURSHEED AURANGZEB[2], AND ZAHOOR ALI KHAN[3], (Senior Member, IEEE)**

[1]COMSATS Institute of Information Technology, Islamabad 44000, Pakistan
[2]College of Computer and Information Sciences, King Saud University, Riyadh 11543, Saudi Arabia
[3]CIS, Higher Colleges of Technology at Fujairah, Fujairah 4114, United Arab Emirates

Corresponding author: Nadeem Javaid (nadeemjavaidqau@gmail.com)

The authors extend their appreciation to the Deanship of Scientific Research at King Saud University for funding this work through research group NO (RG-1438-034).

**ABSTRACT** Internet of Things based smart grids (SGs) represent a vision of future power systems which helps to provide electricity in a smart and user friendly way. Demand side management is one of the most important component of a SG which allows energy consumers to change their electricity consumption patterns to reduce the electricity consumption cost. In this paper, we propose a home energy management system which helps to achieve our desired objectives: reduced electricity consumption cost, peak to average ratio and maximize user comfort. For this purpose, we have proposed a scheduling technique which is a hybrid of already existing optimization techniques: bacteria foraging algorithm and harmony search algorithm and is named as hybrid bacterial harmony (HBH) algorithm. Being producer of electricity units to the consumers, a utility establishes an incentive based pricing tariff; we, on top of it have employed seasonal time of use tariff which allows consumers to take decisions regarding their consumption patterns. Moreover, we introduce the concept of coordination among smart appliances using dynamic programming (DP) approach. The coordination among appliances is achieved by the help of the large data generated from the appliances of multiple homes with the joint work of heuristic techniques and DP. The resultant coordination not only reduces the electricity cost but also increases the user comfort. At last, we evaluate the performance of our proposed energy management system using our proposed optimization technique HBH. To comparatively evaluate the performance of our proposed technique, we compare it with already existing techniques. Simulation results validate that the proposed technique effectively accomplish the desired objectives while considering the consumer comfort.

**INDEX TERMS** Smart grids, coordination, game theory, dynamic programming, big data.

## I. INTRODUCTION

Numerous challenges are being faced by the electric power industry. The reliability of existing power grid is one of the challenges of power system which is affected by the increase in power demand, a limited amount of natural resources, and aging infrastructure. To satisfy peak load demands, utilities turns on generators running on fossil fuels and natural gases which ultimately cause environmental issues as these generators are a great source of emitting harmful gasses. Therefore, a need of more reliable, sustainable, and an efficient power grid system has emerged. In order to make power grids more reliable, sustainable, and robust, an intelligent and revolutionary SG infrastructure is established. This revolutionized infrastructure is established by integrating two way communication technology such as advanced metering infrastructure, smart meters and smart appliances in already existing power system. Various methods; such as distributed energy, smart pricing and demand response (DR) are introduced to facilitate this continuously evolving infrastructure. It is observed that more than 65% of the reduction in the electricity consumption is achieved by residential sector and small commercial building [1]. Home energy management (HEM) system plays a vital role to enhance the efficiency of SG.

Demand side management (DSM) and DR are the two major components of SG. DSM strategies are adopted by many utility companies. In order to motivate consumers to efficiently use electricity, monetary incentives are also provided to the consumers so that they voluntarily use electricity in an optimal way and avoid electricity wastage. This strategy provides a balance between supply and demand.

DR programs are highly amenable and offer numerous benefits to the consumers [2]. It persuades consumers to modify their electricity usage pattern by shifting their heavy load from on-peak to off-peak hours in response to varying energy price. This facilitates in reducing the aggregated electricity consumption cost and PAR by efficiently managing power consumption pattern from which both consumers and utility get benefits.

Numerous energy pricing tariffs are established and are in use around the globe such as real-time pricing (RTP), critical peak pricing scheme (CPP), day ahead pricing (DAP), ToU, inclined block rate (IBR), etc. Energy consumption minimization, minimization of green house gas emissions, efficient load management to reduce PAR and consumer comfort are some of the major problems in the residential sector of SGs.

Electricity consumption cost reduction, optimal management of gross load, making the grid more sustainable, and PAR reduction are some of the common objectives of SG. Different heuristic algorithms and DSM strategies are proposed to achieve these objectives in the past. Researchers use linear programming (LP), mixed integer linear programming, mixed integer nonlinear programming (MINLP), etc., in order to minimize electricity cost and optimally schedule household appliances to manage the load.

In this paper, we propose a HEM system on the basis of two heuristic algorithms; BFA, HSA. In addition, HBH is also proposed. These three heuristic approaches are used for the comparative evaluation of the system on the basis of performance parameters: electricity consumption cost reduction and PAR. Consumer comfort in term of waiting time is also calculated. A concept of coordination among appliances is also introduced based on the knapsack problem. DP approach is used to solve the knapsack problem to get an optimal schedule of appliances. Seasonal ToU energy pricing tariffs are used to calculate energy consumption cost and PAR reduction. For simulations, two cases are considered (single home and multiple homes). In case of single home control parameters are kept same for all three algorithms. However, due to varying seasons and different need of the consumers, appliances and their power ratings may vary accordingly. In case of multiple homes, appliance classes remain same as in single home case, however, power rating (PR) and length of operation time (LoT) of each appliance vary randomly for each home.

The general idea behind this work is to cope with the challenges of SG while considering the consumers' participation and comfort. The major focus of our proposed algorithm is to manage the load in order to minimize the electricity cost and PAR. It also helps to make system flexible and robust. The main contributions of this paper are:

1) A new hybrid algorithm (HBH) is proposed which effectively exploits the search space to produce optimal results.
2) Concept of coordination among appliances is introduced.
3) We have analysed the effect of seasons (Summer and Winter) on performance parameters (electricity cost, PAR and consumer comfort) by tuning the control parameters of HBH.

The rest of the paper is organized as follow: Section II presents an overview of current literature work. Problem description is given in Section III. In Section IV, proposed system model is discussed. In Section V, proposed scheme is described. Feasible regions are discussed in Section VI. In Section VII, simulation and results are discussed. Section VIII, concludes the paper.

## NOMENCLATURE OF THE INDEX TERMS

| | |
|---|---|
| $N_e$ | Number of elimination dispersal steps. |
| $N_r$ | Number of reproduction steps. |
| $N_c$ | Number of chemotaxis. |
| $N_p$ | Number of populations. |
| $N_s$ | Number of swim steps. |
| $C_i$ | Step size. |
| $\Delta$ | Vector in random direction. |
| $x_{iL}$ | Lower bound of decision variable. |
| $x_{iU}$ | Upper bound of decision variable. |
| $x_i^{new}$ | Decision variable. |

## II. STATE OF THE ART LITERATURE REVIEW

In recent years, extensive research is going on in SG domain. To cope with the challenges of this domain such as electricity load management, minimization of energy consumption cost, PAR reduction, and maximization of consumer comfort, many heuristic techniques are used to find optimal solutions for scheduling problems. Consequently, making it more reliable, stable and efficient. In this regard, some of the papers are discussed in this section.

A novel energy management system (EMS) for DR is proposed in [1] for residential and small commercial buildings. They formulate a fully automated EMS's for rescheduling problem as a reinforcement learning problem, as this formulation does not require explicit modeling of the consumers dissatisfaction on job rescheduling. This enables the EMS to self-initiate jobs and allows the consumer to initiate more flexible requests.

A mixed integer nonlinear optimization model is proposed on the basis of ToU pricing tariff in [2]. Residential DR is analyzed by home appliances scheduling to minimize electricity cost. Consumers achieve more than 25% cost saving just by shifting their energy consumption in response to changing price. These relative incentives attract consumers to participate in DR programs. Electricity consumption cost minimization and efficient management of load consumption in on-peak hours is achieved.

Sherazi and Jadid proposed a HEM system with distributed energy resources along with thermal and Electrical appliance scheduling (HEMDAS) [3]. They use dynamic pricing scheme to schedule the controllable appliances in off-peak hours and avoid on-peak hours in order to minimize electricity consumption cost. The energy management problem is modeled as MINLP using dynamic pricing scheme. 24 h time horizon is divided into 48 slots, 30 mins each. Thermal resources are used during peak hours; consequently, minimizing the electricity consumption cost during on-peak hours and off-peak hours up to 22.2% and 11.7%, respectively.

Rahim *et al.* [4] evaluate the performance of HEM controller, based on three heuristic algorithms; genetic algorithm (GA), binary particle swarm optimization (BPSO) and ant colony optimization (ACO). They also propose a generic architecture for DSM, to integrate residential area domain with smart area domain. Problem formulation is done by using multiple knapsack problem (MKP). ToU with IBR pricing tariffs are used to evaluate the energy consumption cost and PAR. Results validate successful achievement of objectives; electricity consumption cost minimization and user comfort maximization. Trade-off between the electricity consumption cost and consumer comfort is there.

Mesari and Krajcar in [5], focus on the proper integration of renewable energy sources (RES) in a home. Electric vehicles (EVs) can give stability to micro grid and decrease grid dependency. In order to reach maximum amount of the RES, mixed integer programming (MIP) is designed to optimally schedule the appliances and energy storage system (ESS).

In [6], a model is proposed based on ToU pricing signal to manage and control appliances for multiple consumers in a home. An algorithm is proposed which manages and schedules the appliances based on the preference of multiple consumers. Two scenarios are implemented based on multiple consumers and their priorities to evaluate the performance parameters. Results show reduction in electricity consumption cost and PAR by efficiently managing energy consumption pattern.

Azar and Jacobsen in [7], proposed a local power scheduling algorithm to schedule appliance power request accordingly. Single objective optimization (SOO) and multi objective optimization (MOO) are also implemented in this research article having some trade-offs. Peak demand threshold (PDT) is imposed to shift appliances, they analyze the behaviour based on changing thresholds. Distributed system operators ensure that total power consumption always remains below PDT. DR system is developed to maximize consumers participation in order to optimize overall network performance. Appliances are categorized based on their shiftable and interruptable characteristics. $0-1$ knapsack problem is used to formulate the scheduling problem. They achieve significant reduction in aggregated consumption cost, $CO_2$ emissions and maximizing consumers satisfaction level.

Authors proposed an efficient scheduling method for home power usage and also introduced a general architecture of EMS in a home area network (HAN) in [8]. They adopt combined RTP and IBR pricing tariffs to automatically schedule all appliances in an optimal way. This adaptation results in minimal load and keeps PAR under control. In order to obtain an optimal solution, GA is incorporated to solve optimization problem due to its wide acceptance in solving non-linear problems. Additionally, the PAR is controlled efficiently to make the entire electricity system more stable.

In [9], an optimized HEM (OHEM) system is proposed, which incorporates the RES and ESS into the residential sector. They formulate constrained optimization problem as MKP and solve it by implementing heuristic algorithms: GA, BPSO, WDO, BFO and also proposed hybrid GA-PSO (HGPO) algorithms. HGPO based HEMS outperformed all other scheduling algorithms and achieved 40.05% and 41.07% reduction in electricity consumption cost and PAR, respectively. Integration of RES and ESS also minimize the electricity bill and PAR by 19.94% and 21.55%, respectively. Reduction in PAR enhances the power system stability and also ensures the stable and reliable grid operation. On the other hand, consumer comfort is not considered and also their is no coordination between renewable and sustainable energy resources.

Various scheduling algorithms for residential DR under RTP pricing environment along with RES are proposed in [10]. Authors categorized appliances and consumers on the basis of energy demand and consumer preferences. Electricity cost minimization problem is formulated as an optimization problem and solved by using optimal stopping rule (OSR) based algorithms. Appliances follow first come first serve (FCFS) scheduling scheme in the absences of EMC. FCFS scheme achieves 65.92% cost saving, however, violates the load constraint. Modified FCFS (MFCFS) scheduling algorithm is proposed to overcome aforementioned problem, it achieved 42.58% reduction in cost. Priority enable early deadline first (PEEDF) scheduling algorithm is proposed for consumer comfort maximization. This scheme achieves 48.28% cost reduction. They also implement total capacity constraint Q, for grid stability. Moreover, renewable energy is utilized during high peak hours. However, installation cost and investment benefits of RES are not analyzed.

Ma *et al.* [11], proposed a flexible power scheduling strategy to achieve a desired trade-off between the electricity consumption cost and consumer discomfort. They formulated power scheduling as an optimization problem and by solving optimization problem an optimal scheduling strategy is obtained. Two types of consumer appliances are considered in this article. In the first type, appliance's operations can be delayed and in second type, power levels of appliance operation can be reduced. Results validate that the scheduling strategy efficiently achieved an equilibrium between the electricity bill reduction and consumer discomfort. However, computational complexity of this scheme is very high.

Marzband *et al.* in [12], presented a multi-layer ant colony optimization (EMS-MACO) for energy management system. The main focus of this article is to figure out the optimum micro-source operation to minimize electricity production cost. Technical and economic time dependent constraints are also analyzed. Performance of MACO is compared with modified conventional EMS (MCEMS) and particle swarm optimization (PSO) based EMS. Results verify that the system performance is improved by applying MACO. Reduction in energy cost is achieved in comparison with MCEMS and PSO; 20% and 5%, respectively. Furthermore, the plug and play capability in real time applications is also investigated.

Improved PSO (IPSO) based HEMS under ToU with IBR environment is proposed to solve the cost minimization problem in [13], results show that IPSO algorithm brings the consumer load curve near to the objective curve. Electricity price and objective curve have an inverse relationship. Power system stability is achieved by reducing the PAR. However, the consumer comfort is scarified by rejecting the load demand request in peak hours.

Hong *et al.* [14] proposed an approach for load allocation problem. Allocation of electricity resources are done on the basis of demand, priority, fairness and price. Higher-priority appliances operate without interruption even in high price and low price hours, than the energy resources are given to remaining appliances. They also integrate ESSs to store energy during low-price hours. The algorithm proposed in this article has ability to reduce peak demand and maximize system efficiency.

Adika and Wang *et al.* [17] proposed an intelligent energy management framework to implement both energy storage and appliance scheduling schemes. Consumers can achieve electricity cost minimization by shifting their load to the off-peak hours. They purchase power during the off-peak hours when electricity prices are low and use batteries to fulfill their demand during high peak hour. Electricity storage also lowers the peak to average ratio of the grid and is therefore beneficial to electricity suppliers too. However, for efficient cost saving constant monitoring is required, uncoordinated charging and discharging of batteries could compromise the grid's stability.

Jovanovic *et al.* [18] proposed a model for the scheduling problem focusing on consumers satisfaction levels. MIP is used for defining a MOO problem. The Pareto front is mapped on problem instances based on the real-world household usage data and real-world electricity prices, in order to analyze the relation between two objectives. Authors divide households into five groups; family with children (FWC) and without children (FNC), multiple pensioners (MP), single pensioner (SP) and single non-pensioner (SNP). Energy consumption of each household and each individual appliance is monitored for every 10 *mins*. Trade-off between the production cost and consumer comfort is observed. In order to minimize the consumption cost, consumers have to compromise their satisfaction level.

Roh and Lee [19] study an electricity load scheduling problem in a residence. They classify various appliances into five sets on the basis of energy consumption and operation characteristics, and derive a mathematical models for them. They proposed an electricity load scheduling algorithm, it controls the operation time and energy consumption level of each appliance. The optimization problem is formulated as a MINLP problem and solved it by using the generalized Benders decomposition approach. This algorithm gives the optimal electricity load scheduling of various appliances with different energy consumption and operational characteristics.

Samadi *et al.* [20] adopt approximate DP approach to schedule the operation of different types of appliances. A game theoretic approach is adopted to model the interaction between users with excess generation. The excess generation locally reduces the load on utility and enhance the stability of the system. Simulation results show that the proposed algorithm reduces the electricity bill of the users and also encourages the user to efficiently utilize the RESs.

Logenthiran [21] proposed a day-ahead load shifting technique and mathematically formulated it as a minimization problem. A heuristic-based Evolutionary Algorithm (EA) is developed for solving this minimization problem for all three areas (industrial, commercial and residential). Results illustrate that the proposed DSM strategy achieves substantial cost savings and reduce the peak load demand of the SG. However, consumer satisfaction level is compromised in this research work.

An efficient heuristic approach is proposed in [22] to schedule smart home appliances in residential area. This algorithm follow greedy strategy to schedule consumer appliances under variable pricing model. The start time of appliances are optimized to achieve economic cost benefits while satisfying operational and peak power constraints. Results show that electricity cost obtained from heuristic algorithm is within 5% range of the optimal cost of the exact algorithm.

It is observed from the literature analysis that most of the researchers target two or more contradictory multi-objective problems. A trade-off always exists, if they are able to manage electricity bill and PAR. In that case, they have to compromise the comfort of the end users. Whereas, some of the researchers have considered the consumer comfort along with the electricity consumption cost by compromising the utility stability in off-peak hours.

The state of the art literature review has been summarized in table.1.

## III. PROBLEM DESCRIPTION

Minimization of energy consumption cost, PAR reduction and maximization of consumers satisfaction levels are some of the major challenging tasks in SG. However, consumers satisfaction is compromised in order to reduce the electricity consumption cost and PAR. To cope with the aforementioned problems, numerous strategies are proposed in past years. In [8], an efficient scheduling method for home power usage and a general architecture of EMS in a HAN is proposed. GA is used to solve optimization problem due to its wide acceptance in solving non-linear problems. Combined RTP and IBR price tariffs are used to automatically schedule all appliances in an optimal way. They achieve optimal results in minimizing electricity consumption cost and PAR. However, there is no mechanism in their scheduling method to facilitate consumers preferences. Ma *et al.* [11] formulate

**TABLE 1.** Summarized state of the art literature review.

| Techniques | Objectives | Achievements | Shortcomings/Limitations |
|---|---|---|---|
| Reinforcement Learning [1] | PAR reduction and optimization of appliances LoT | Avoid peak formation and electric bill minimization | Consumer comfort and RES are not considered |
| MINLP model under ToU [2] | Electric cost saving and minimization in consumers inconvenience level | By shifting load to off peak-hours according to ToU tariff, more than 25% cost saving is achieved, weighting factors give consumers choice either to participate in program or not | Integration of RES and ESS are not considered |
| HEMDAS [3] | Favorable trade-off between cost minimization and comfort level of consumers | HVAC model considered both cost minimization and consumer comfort level, also proposed a model electric bill minimization for both CEAs and CTAs | Proposed system increased system complexity and computational time |
| GA, BPSO, ACO with ToU pricing tariff [4] | Reduce electricity bill and PAR. Increased grid stainability. | GA based EMC prove best among other scheduling algorithms | Ignore consumer comfort. |
| MULP [6] | Reduction in electricity bill and total power consumption | Significant reduction in electric bill is achieved by reducing the total power consumption | Consumer comfort is not addressed |
| GA, BPSO, WDO, BFO and Hybrid GA-PSO [9] | Reduction in electricity consumption cost and PAR | HGPO based HEM achieved 40.05% and 41.07% reduction in cost and PAR. Moreover, 21.55% and 19.94% reduction in PAR and cost is achieved by integration of RES and ESS in HEM | Coordination between renewable and sustainable energy resources is not addressed. |
| FCFS, MFCFS and PEEDF [10] | Minimize electricity bill and appliance waiting cost. Maximize grid stability | Cost saving is achieved by 65.92%, 42.58% and 48.2% from FCFS, MFCFS, and PEEDF, respectively. Integrate RES as backup during high peak hours | Installation cost and investment benefit of RES are not analyzed. |
| IPSO [13] | Reduce PAR and electricity bill, increase grid stability | Reduction in PAR is achieved by rejecting extra demand in peak-hours | Consumer comfort is effected due to demand request rejection in peak-hours |
| GA [17] | PAR reduction and electricity bill reduction | Prevent peak formation by dividing appliances into clusters | Consumer comfort is ignored and RES is not integrated |
| EA [21] | Reduction in electricity bill and carbon emission | Day ahead load shifting technique achieve substantial cost saving and also minimize peak load demand | Compromised consumer satisfaction level. |

power scheduling as an optimization problem. Two types of appliances are considered: i) delay tolerant appliances, ii) appliances that can be operated with reduced power levels. They efficiently achieved a balance between the energy consumption cost and consumers discomfort. However, this strategy has very high computational time and complexity. EMS-MACO is presented in [12], to figure out an optimum micro-source operation to minimize electricity production cost. They also analyzed technical and economical time-dependent constraints. Performance of MACO is compared with modified conventional EMS (MCEMS) and PSO based EMS. The performance of the system is improved by applying MACO. The proposed system achieved reduction in energy consumption cost, in comparison with MCEMS and PSO. However, consumers satisfaction level is not considered. Authors proposed a load allocation approach in [14]. This approach allocate electricity resources on the basis of demand, priority, fairness and price. Appliances having higher priorities operate without interruption even in high price hours. Energy resources are then allocated to as many appliances as possible in low price hours. Integration of ESSs is also considered to store energy during low-price hours. However, the maintenance and installation costs of ESS are not considered.

Though, in literature, many popular techniques are available such as GA, BFA, HSA, PSO, etc., to solve the optimization problems. However, in this article, we propose a hybrid of two well known optimization techniques (BFA and HSA). BFA possesses effective local search abilities with inherent limitations in its global search procedure [15]. Whereas, HSA has a simple searching process and robust global searching abilities [16]. Both techniques have some limitations. To cope with these limitations, HBH is proposed. It achieves the local search by using chemotactic operator of BFA and search globally by using HSA operators. This maintains a balance between exploration and exploitation and provides the optimal results.

HEMSs proposed in [8], [11], and [12] deal with the single home, whereas, [4], [23], and [24] deal with multiple homes with in a residential area. However, [4], [23], and [24] did not discuss the situation when data get bigger (Big Data) due to increasing number of homes and appliances. This continuous increase in volume induces lot of challenges in data processing. The main purpose of scheduling in Big Data processing is to plan and complete the process in proficient way [25]. Different scheduling methods in paper [1]– [24] are preferred for resource allocation. However, dealing with Big Data is a challenging task.

## IV. PROPOSED SYSTEM MODEL

In our proposed work, basic objectives are the minimization of electricity consumption cost and PAR, while considering consumer's comfort. Pictorial representation of proposed system model is represented in Fig.1. A residential area, a generation unit and the transmission line is shown in Figure. In the residential area, a IoT based smart home is considered with

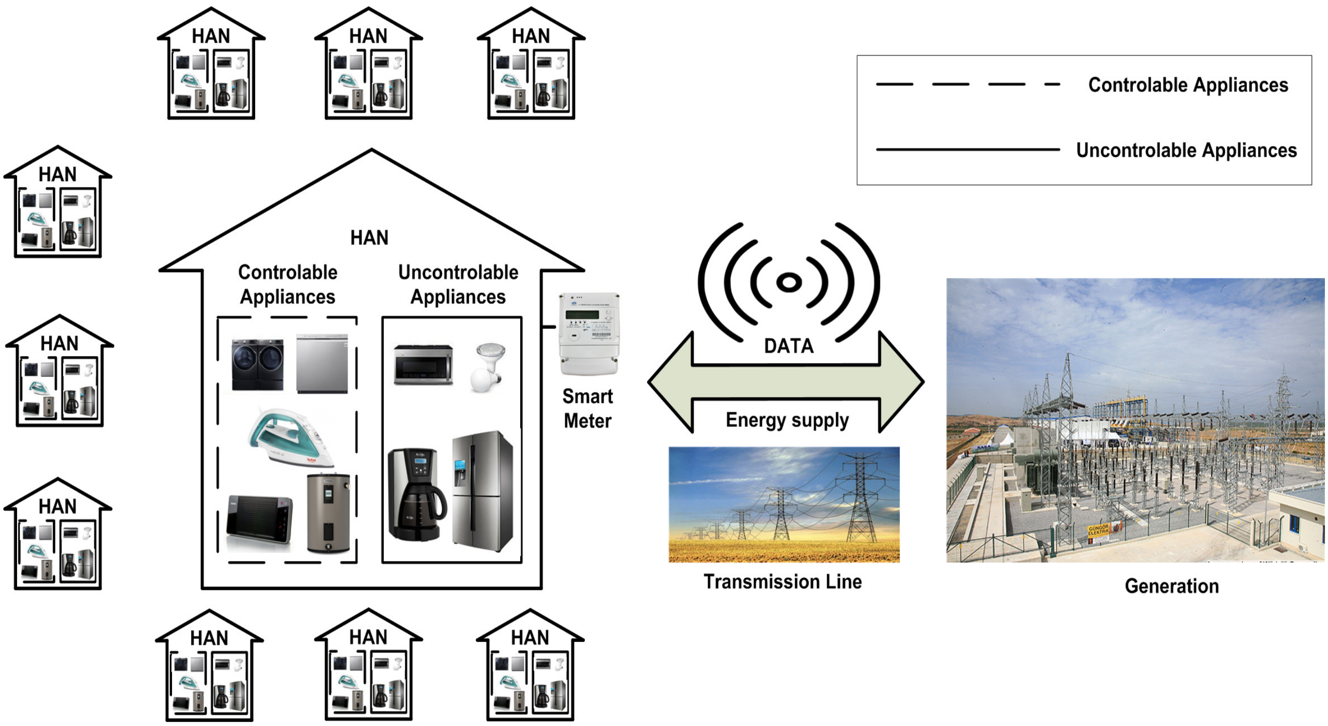



**FIGURE 1.** Proposed system model.

$n$ number of appliances. Appliances' PRs and LoTs are taken from the consumers, and stored in centralize unit. The HAN is used to provide the communication among the appliances, smart meter and EMC. EMC in embedded with a scheduler that schedule appliances according to user LoTs. The Zigbee, Zwave and wifi are widely adopted in HAN to provide cost effective communication. Further, we implement the coordination among the appliances with in smart buildings, while incorporating the real-time demand by making the system flexible.

In our proposed system, appliances are scheduled by using metaheuristic techniques BFA, HSA and HBH algorithms. The purpose of scheduling is to minimize the electricity consumption cost for consumers. The total time horizon is 24 h, each time-slot is of 1 h.

In this proposed solution, system flexibility depends upon the sudden changes in user demand. Where, on user demand EMC switches OFF an appliance, and then coordination among appliances is established to allocate that empty slot to priority appliance(s) at run-time. In this scenario, in order to incorporate the coordination at run-time, problem is formulated as knapsack problem. Where empty slot is considered as the knapsack capacity limit. This give consumers authority over schedular, they can assign priorities to the set of appliances according to their needs. This enables the consumer to switch appliances at run-time according to their preference. The scheduler generates a new schedule for appliances including consumer preferred appliances, without affecting the load profile of other appliances whenever an interrupt is generated in schedule. The length of operation of these preferred appliances are in minutes and do not need a complete 1 h time slot. When a consumer generates an interrupt, the schedular halts all scheduling operations and checks for running interruptable appliances in that particular time slot where interrupt is generated. Immediately, after finding a running interruptable appliance, operations of that particular interruptable appliance are stopped as this appliance is no longer needed. The schedular calculate the remaining time in that particular time slot and allocate the remaining time to the preferred appliances. This helps in effectively managing the load in order to maximize consumer's satisfaction level. DP is used to tackle this complex knapsack based scheduling problem, as it is highly suitable in handling decision making problems.

In this paper, we have proposed the system model for single home as well as for multiple homes. It is worth mentioned that dealing with IoT based multiple homes is a challenging task. Specially, when system manages Big Data in real time environment. The success of such system depends on the efficient coordination between the different entities (users, smart homes, smart appliances, etc.). Dealing with all entities is a challenging task, however, in this proposed system we implement the coordination among the appliances as an example scenario with in smart buildings. Scheduling Big Data is a problematic task due to large search space and it takes a long time to search out optimal solution. Though there are no specific algorithms which can help in finding optimal solution in polynomial time for aforementioned problem. Although it is preferable to find suboptimal solution, however, this approach is preferable in short time period. While dealing with the Big Data, meta-heuristic optimization techniques proved to be optimal one [26].

### A. SCENARIOS

Lets assume that in Summer season, $[A_1, A_2...A_n]$ is a set of priority appliances and $[a_1, a_2...a_m]$ is a set of interruptable appliances. A consumer generates an interrupt to switch on a priority appliance, schedular check for running interruptable appliances in that particular hour and stop its working and allocate the remaining time slot to the emergency appliances. As knapsack problem is incorporated for coordination, the remaining time after an interrupt is generated is considered as knapsack capacity, working time of appliance is considered as weight and the electricity consumption cost is considered as value of knapsack problem. In this research, Winter season is also considered, coordination among the appliances and schedular is achieved in similar way as explained earlier. Note that, consumers appliance preference and their PR are different in Summer and Winter seasons. For relative performance analysis, number of appliances to be scheduled, their power rating and length of operation are kept same for all three aforementioned algorithms in Summer and Winter seasons, respectively.

Major focus of this scheme is to efficiently manage energy consumption throughout a day in order to achieve desired objectives of electricity consumption cost minimization and PAR reduction. DSM manages energy consumption and controls demand side activities for the end consumers. It persuades consumers to shift their load from on-peak hours and promote them to use energy during off-peak hours. This shifting of the load from on-peak to off-peak hours help the consumers to minimize their electricity consumption cost while compromising their comfort levels. Resulting in an efficient and reliable grid operations. Different incentive based pricing tariffs are established by utilities such as, dynamic based (RTP, CPP, DAP, IBR) and time based ToU, etc.. Because of tentative behavior of optimization techniques we considering both Summer and Winter seasons, because on-peak hours and off-peak hours are different for both seasons. In Summer season, 11 am to 5 pm are on-peak hours in weekdays. Whereas in Winter season, 7 am to 8 am and 5 pm to 7 pm are the on-peak hours in weekdays [27].

### B. PROPOSED SCHEME

In the literature, numerous kinds of optimization algorithms are proposed, which vary in terms of solving the problems according to the requirements of the environment. Some of the popular algorithms GA, PSO, BFA, HSA, etc., are used to solve the problem of scheduling in SGs. However, there always exists a trade-off in exploring the search space. For instance, BFA possesses excellent local search capabilities [15], while HSA proves to be effective in global search space [16]. Now, a dire need emerges to focus on the parallel exploitation and exploration of both the search spaces. In order to maximize the benefits of scheduling, a hybrid approach HBH is proposed for comparative performance analysis of the system based on performance parameters. Merging these aforementioned techniques provides better optimal results. All three heuristic algorithms implemented in this scheme are discussed in coming subsections.

#### 1) BFA

Kevin M. Passino in 2000, introduced a bio-inspired algorithm BFA for distributed optimization problems [2] which is based on foraging behavior of E.coli bacteria. In nature, animals having better foraging strategies tend to survive more than the animals having weak foraging strategies. In BFA, healthy bacterium splits and produce their clones and replace the weak bacterium to keep population size constant [29]. The swarm of bacterium stochastically move towards the optimal solution. This algorithm follow three basic steps:

1) Chemotaxis: This phase describes the movement of an E.coli cell. The E.coli bacterium can move in two alternate ways, either it can swim in the same direction for a period of time or it may tumble. Bacterium follow these two ways for their entire lifespan. The lifespan of bacteria depend upon the number of chemotactic steps. Let's assume, $(j, k, l)$ represents $ith$ bacterium at $jth$ chemotactic, $kth$ reproductive and $lth$ elimination-dispersal step. $C(i)$ is the step size taken in the random direction specified by the tumble. The movement of bacterium is represented by the following equation [29]:
$$\theta_i[j, k, l] = \theta_i[j-1, k, l] + C(i)\frac{\Delta(i)}{\sqrt{(\Delta^t(i)\Delta(i))}} \quad (1)$$
where, $\Delta$ represents a vector in random direction and its elements lie in $[-1, 1]$ range.
2) Reproduction: This phase deals with the elimination of the weak bacteria based on the fitness values and simultaneously spilt the healthy ones into two and replace them in place of weak bacterium to keep the swarm size constant, so that they contribute in the next generation.
3) Elimination dispersal: In this phase, new random samples with low probability are inserted to compensate the discarded cells. At the end of the aforementioned steps, best bacterium is selected based on the fitness function representing the schedule of an appliance, as given in equation [29]:
$$j_i[j, k, l] = j_i[j, k, l] + j_{cc}(\theta_i[j, k, l], PoP[j, k, l]) \quad (2)$$
where, $j_{cc}$ is computed as:
$$j_{cc} = \sum_{d=1}^{d-1}(100 \times (\theta(i, d+1) - (\theta(i, d))^2)^2 + (\theta(i, d) - 1)^2) \quad (3)$$

We adopt BFA foraging strategy to find optimal energy consumption patterns for consumers in SG. This algorithm has exceptional attributes such as less computational burden, global convergence, require less computational time and also suitable for handling multiple objective functions. Basic idea and working of HSA is given in the upcoming subsection.

#### 2) HSA

This subsection presents an overview of the basic HSA. This algorithm is proposed by Yang and Geem [30] and it is inspired by the natural musical process, which searches for an ideal state of harmony just like optimization process tries to find an optimal solution for a particular problem. The HSA uses a stochastic random search and it does not require an initial value for decision variables. HSA considers all existing vectors and then generates a new vector. General working of the algorithm is given as follows:

Step 1. Define the decision variables and objective function: Initiate the system parameters. The optimization problem can be defined as follows [31]:

$$\begin{aligned} &Minimize\, f(x) \\ &\text{subject to: } x_{iL} \le x_i \le x_{iU} \end{aligned} \tag{4}$$

where $x_{iL}$ and $x_{iU}$ are the lower and upper bounds for decision variables. It has following parameters: i) harmony memory size (HMS) or the number of solution vectors in harmony memory (HM), ii) HM consideration rate (HMCR), iii) distance bandwidth (bw), iv) pitch adjusting rate (PA) and v) number of improvisations ($k$) or stopping criterion. Where, $k$ is same as the total number of iterations.

Step 2. HM is initialized, this memory stores all solution vectors (sets of decision variables). Initially, this memory is randomly generated based on the following equation [31]:

$$x_i^j = x_{iL} + rand() \times (x_{iU} - x_{iL}) \quad j = 1, 2 \ldots HMS \tag{5}$$

where, $rand()$ is a random number function which give uniform distribution of [0, 1].

Step 3. Improvise a new harmony from the HM. Generating a new harmony $x^{new}$ is called improvisation and it is based on 3 rules; memory consideration, pitch adjustment, and random selection. Initially, a uniform random number $r$ is generated in the range [0, 1]. If $r$ is less than the HMCR, the decision variable $x_i^{new}$ is generated by the memory consideration; or else, $x_i^{new}$ is produced by a random selection. Then, each decision variable $x_i^{new}$ will undergo a pitch adjustment with a probability of PA rate, if it is produced by the memory consideration. The PA is given as follows [31]:

$$x_i^{new} = x_i^{new} \pm r \times bw \tag{6}$$

Step 4. Update HM: After generating a new harmony vector $x_i^{new}$, the memory will be updated. If the fitness of the new harmony vector $x_i^{new} = (x_i^{new} + x_2^{new} \ldots x_n^{new})$ is better than that of the worst harmony, then $x^{new}$ replace worst harmony in the memory.

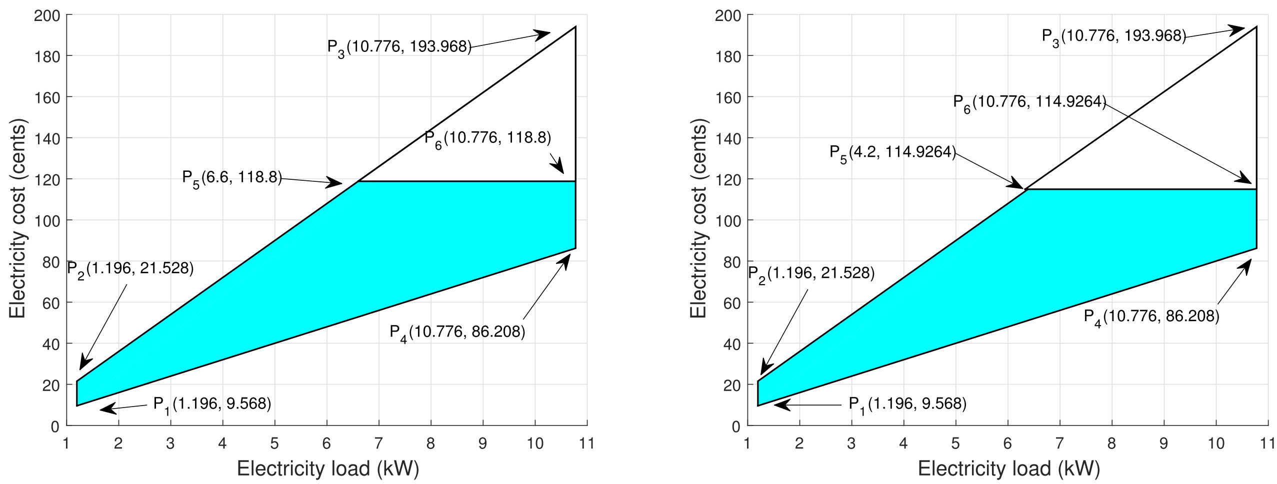
Step 5. Repeat Steps $3 - 4$ until the stopping criterion is met. This algorithm proves to be very successful for optimization processes [32].

#### 3) HBH

In this subsection, our proposed technique HBH is discussed. In order to explore and exploit the entire search space, a hybridization of BFA and HSA is performed. Both techniques are very effective and well known in handling optimization problems. However, some limitations are still needed to be addressed. BFA retains optimal results from local search space while it has limitations in exploring the search space globally [15] and [33]. In this regard, HSA proves itself to be effective and efficient. HSA has efficient global search abilities. It considers all vectors in the memory for generating a new solution. The structure of HSA is relatively easy. This makes it flexible to integrate it with other algorithms. However, it has weak local search ability. In order to obtain the optimal results, the complete search space needs to be explored both locally and globally. On the other hand, the proposed HBH follows the initial steps of BFA, exploiting the local search space by using the chemotactic operators. In HBH, the elimination and dispersal step of BFA is replaced by integrating the steps of improvising new harmony of HSA. In Algorithm 1, the working procedure of HBH is provided to understand the sequence of hybridization process. The tuned parameters of proposed algorithm are flexible which can be modified as per the requirement of the application.

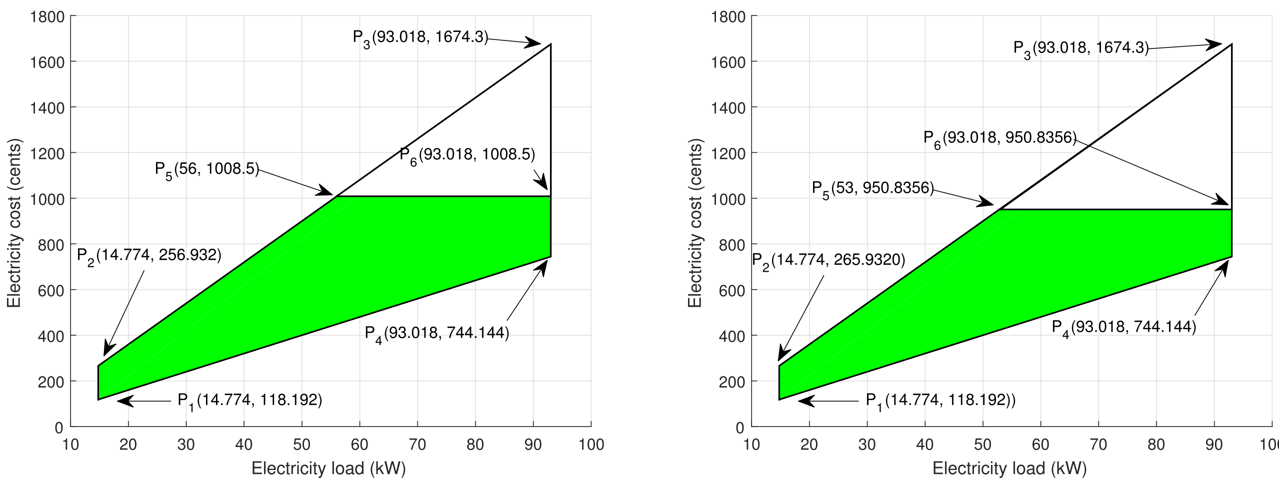
**Algorithm 1** HBH Algorithm

initialize all input parameters
**for** $l = 1 : N_e$ **do**
  **for** $k = 1 : N_r$ **do**
    **for** $j = 1 : N_c$ **do**
      **for** $i = 1 : N_p$ **do**
        Find new position $\theta_i$[j,k,l] for pop
        Evaluate the fitness of population
        **for** $s = 1 : N_s$ **do**
          **if** $j_i < j_{last}$ **then**
            $j_{last} \leftarrow J_{last}$
            **goto** *4.*
          **else**
            *Tumble direction*
            **goto** *4.*
          **end if**
        **end for**
      **end for**
    **end for**
    Evaluate the population by objective function
    select the best pattern
  **end for**
  $HM \leftarrow bestpattern$
  **if** $cost(HM) \le cost(worst(harmonies))$ **then**
    $worst(harmonies) \leftarrow HM$
  **end if**
  **goto** *2.*
**end for**




(a) (b)

**FIGURE 2.** **Feasible region for electricity cost and load consumption in Summer season (Single home). (a) Feasible region for electricity cost without coordination. (b) Feasible region for electricity cost with coordination.**

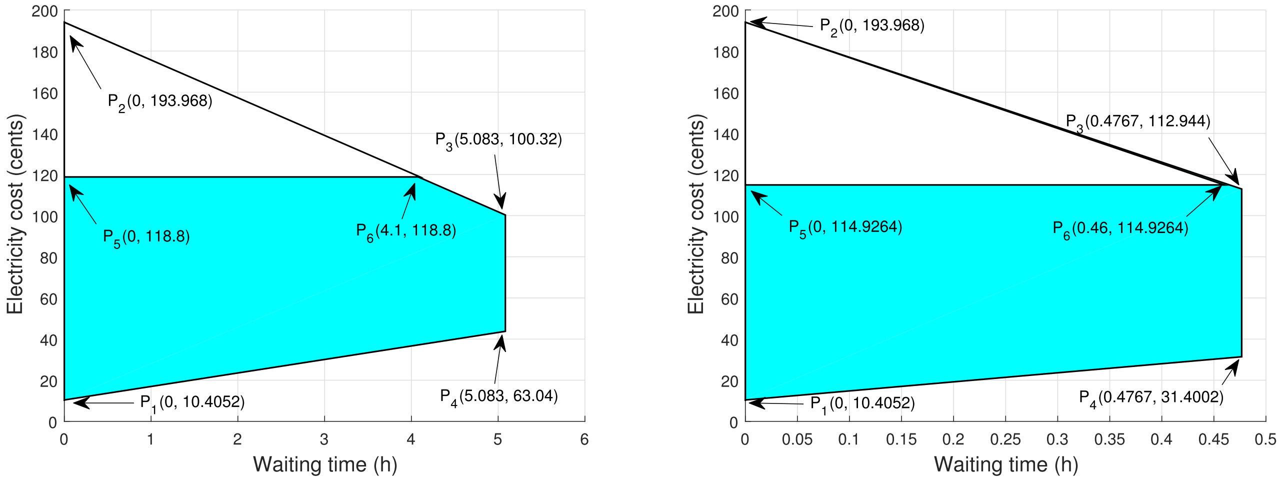



(a) (b)

**FIGURE 3.** **Feasible region for electricity cost and load consumption in Summer season (Multiple homes). (a) Feasible region for electricity cost without coordination. (b) Feasible region for electricity cost with coordination.**

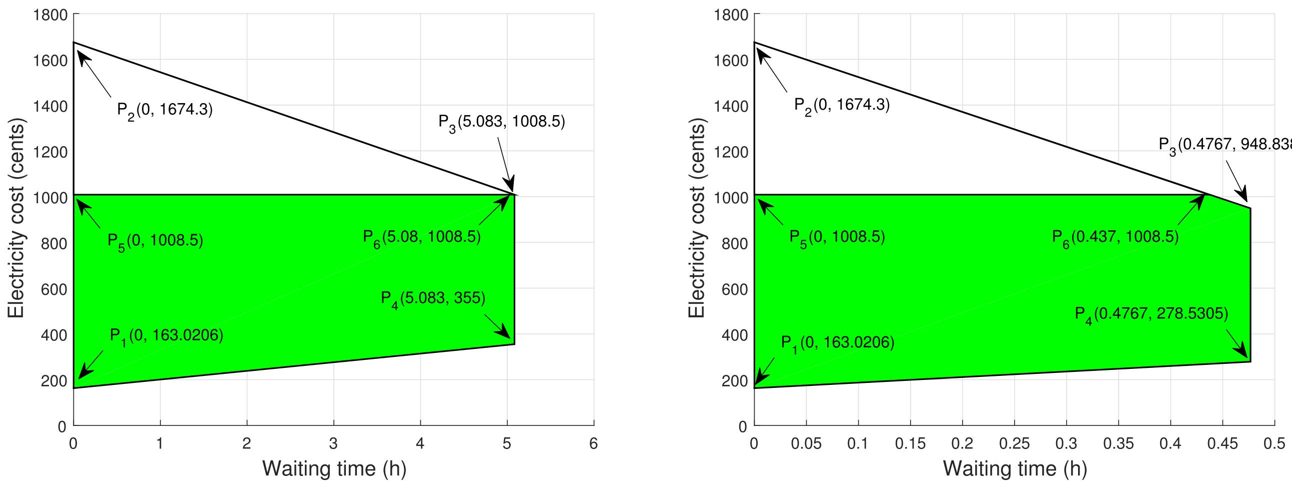
## V. FEASIBLE REGION

Feasible regions are calculated to verify the results for performance parameters such as electricity consumption cost and consumer satisfaction level in term of waiting time for single and multiple homes, considering both Summer and Winter seasons. In Fig.2(a) and (b), $P_1(1.198,\ 9.568)$, $P_2(1.198,\ 21.528)$, $P_3(10.776,\ 193.968)$ and $P_4(10.776,\ 86.208)$ represent the overall region of electricity bill before and after coordination in the Summer season for a single home. In Fig.2(a), $P_5(6.6,\ 118.8)$ and $P_6(10.776,\ 118.8)$ show the maximum limits for the electricity consumption cost i.e, 118.8 cents after scheduling all appliances without coordination, all optimal solutions are in the new region formed by points $P_1(1.198, 9.568)$, $P_2(1.198, 21.528)$, $P_5(6.6,\ 118.8)$ and $P_6(10.776,\ 118.8)$. After scheduling with coordination, feasible region is shown in Fig.2(b), created by $P_1(1.198,\ 9.568)$, $P_2(1.198,\ 21.528)$, $P_5(4.4,\ 114.9264)$ and $P_6(10.776,\ 114.9264)$, electricity consumption cost limit is further reduced to 114.9264 cents. Feasible regions for multiple homes are calculated with and without coordination in the Summer season and represented in Fig.3(a) and (b), $P_1(14.774,\ 118.192)$, $P_2(14.774,\ 256.932)$, $P_3(93.018,\ 1674.3)$ and $P_4(93.018,\ 744.144)$ show the complete region of electricity bill in unscheduled case. In Fig.3(a), points $P_1(14.774,\ 118.192)$, $P_2(14.774,\ 256.932)$, $P_5(56,\ 1008.5)$ and $P_6(93.018,\ 1008.5)$ create a new region after scheduling without coordination, maximum electricity bill reduces from 1674.3 cents to 1008.5 cents. As coordination is incorporated, the electricity consumption cost is further minimized to 950.8356 cents as it can be observed from Fig.3(b).




(a) (b)

**FIGURE 4.** Feasible region for electricity cost with waiting time in Summer season (Single home). (a) Feasible region for waiting time without coordination. (b) Feasible region for waiting time with coordination.




(a) (b)

**FIGURE 5.** Feasible region for electricity cost with waiting time in Summer season (Multiple homes). (a) Feasible region for waiting time without coordination. (b) Feasible region for waiting time with coordination.

In this article, feasible regions for consumer's satisfaction level in term of waiting time are also evaluated considering a single and multiple homes. Graphical representation of feasible region for electricity cost with waiting time is presented in Fig.4(a) and (b). The area covered by points $P_1(0,\ 10.4052)$, $P_2(0,\ 193.968)$, $P_3(5.083,\ 100.32)$ and $P_4(5.083,\ 68.84)$, shows the complete region in unscheduled case. Fig.4(a) shows the feasible region for a single home scheduled without coordination, points $P_5(0,\ 118.8)$ and $P_6(4.1,\ 118.8)$ represent the maximum cost limit i.e, 118.8 cents at the minimum and maximum waiting time 0 and 4.1 h, respectively. The desirable minimization in electricity cost with respect to waiting time is achieved. Similarly, in Fig.4(b), points $P_1(0,\ 10.4052)$, $P_2(0,\ 193.968)$, $P_5(0,\ 114.9264)$ and $P_6(0.4767,\ 114.9264)$ show the feasible region after scheduling with coordination. Points $P_5(0, 114.9264)$ and $P_6(0.4767, 114.9264)$ represent the maximum electricity limit equals to 114.9264 cents at minimum and maximum waiting time 0 and 0.4767 h, respectively. Incorporating coordination in the system, maximizes the consumer's satisfaction level by reducing the waiting time. Similarly, in Fig.5(a) and (b), area covered by points $P_1(0, 163.0206)$, $P_2(0, 1674.3)$, $P_3(5.083, 1008.5)$ and $P_4(5.083, 355)$ show the overall region for multiple homes before and after coordination. In Fig.5(a), points $P_5(0, 1008.5)$ and $P_6(5.083, 1008.5)$ represent the maximum electricity limit at minimum and maximum waiting time before coordination. While in Fig.5(b), points $P_1(0, 163.0206)$, $P_2(0, 1674.3)$, $P_3(0.4767, 948.838)$ and $P_4(0.4767,\ 278.5305)$ show overall region after

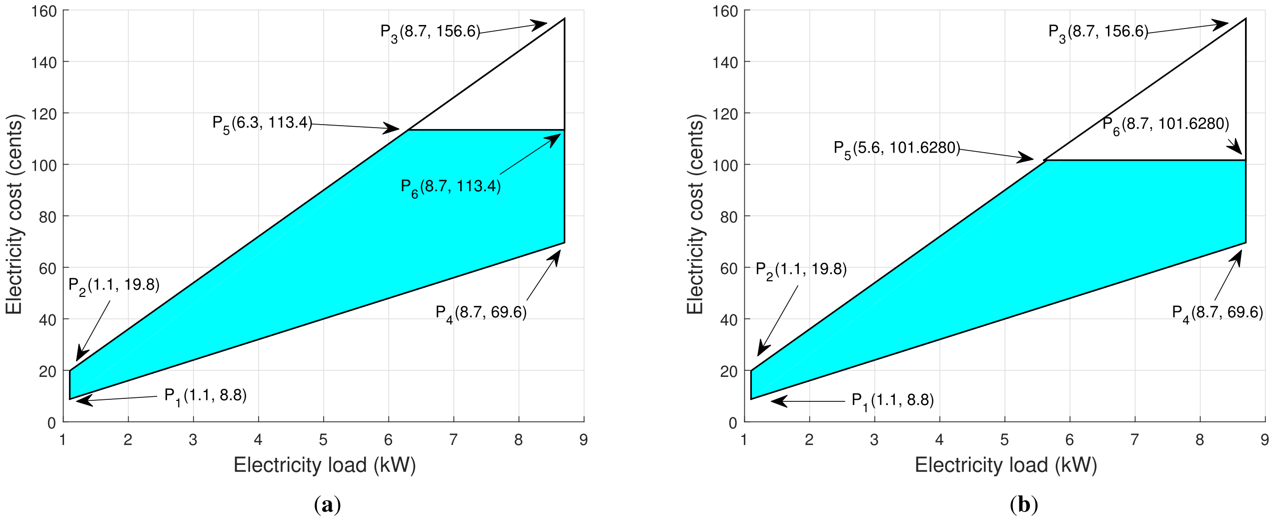



**FIGURE 6.** Feasible region for electricity cost and load consumption in Winter season (Single home). (a) Feasible region for electricity cost without coordination. (b) Feasible region for electricity cost with coordination.

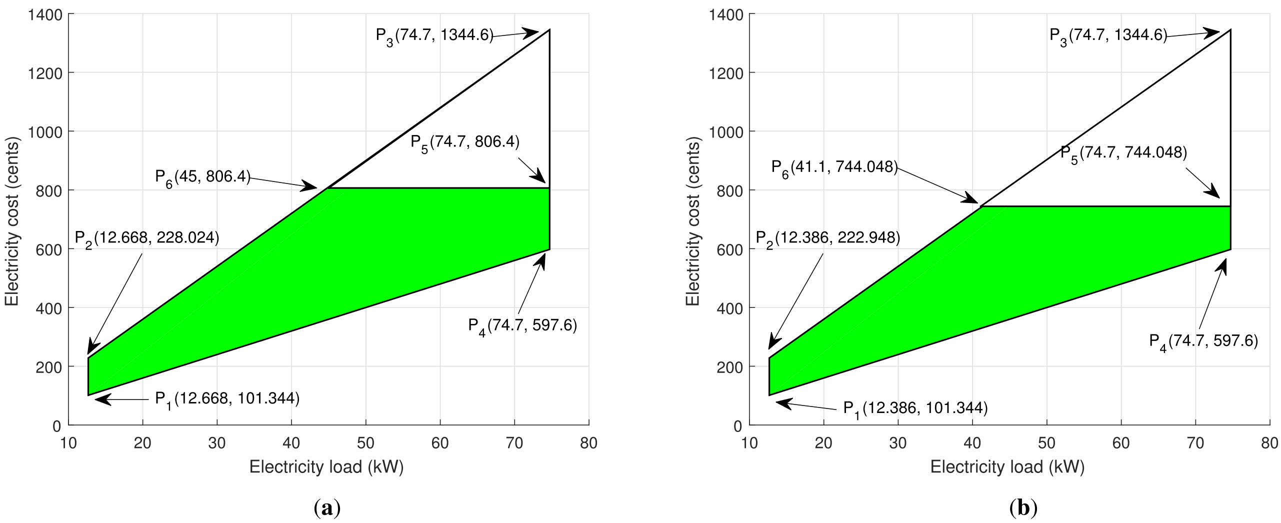



**FIGURE 7.** Feasible region for electricity cost and load consumption in Winter season (Multiple homes). (a) Feasible region for electricity cost without coordination. (b) Feasible region for electricity cost with coordination.

coordination is incorporated, while points $P_5(0, 1008.4)$ and $P_6(0.437, 1008.5)$ show the achieved reduction in waiting time after coordination is incorporated in the system which maximizes the consumer's satisfaction level.

Fig.6(a) and (b), represent the feasible regions for electricity cost and load consumption in Winter season for a single home. In Fig.6(a), points $P_1(1.1, 8.8)$, $P_2(1.1, 19.8)$, $P_5(6.3, 113.4)$ and $P_6(8.7, 113.4)$ represent the feasible region for a single home schedule without coordination. The maximum electricity cost limit is 113.4 cents as it is reduced from 156.6 cents. Fig.6(b) represents the feasible region after coordination is incorporated in the system. Points $P_5(5.6, 101.6280)$ and $P_6(8.7, 101.6280)$ show the maximum electricity limit 101.6280 cents. This shows that by incorporating coordination, a minimized electricity cost is achieved. Feasible regions for multiple homes in Winter season are represented in Fig.7(a) and (b). Area covered by points $P_1(12.668, 101.344)$, $P_2(12.668, 228.024)$, $P_3(74.7, 1344.6)$ and $P_4(74.7, 597.6)$ represent the overall region before and after coordination. Fig.7(a) represents the feasible region before coordination is employed for multiple homes. $P_5(45, 806.4)$ and $P_6(74.7, 806.4)$ are points representing the maximum electricity cost i.e, 806.4 cents, electricity cost never cross this threshold in any condition. In Fig.7(b), points $P_5(74.7, 744.048)$ and $P_6(41.1, 744.048)$ represent the maximum electricity cost after coordination is incorporated in scheduling, a clear difference is observed as the electricity consumption cost further reduced from 806.4 cents to 744.048 cents.

Fig.8 and Fig.9, represent the feasible regions for electricity cost with waiting time while considering single and multiple homes in the Winter season, respectively.

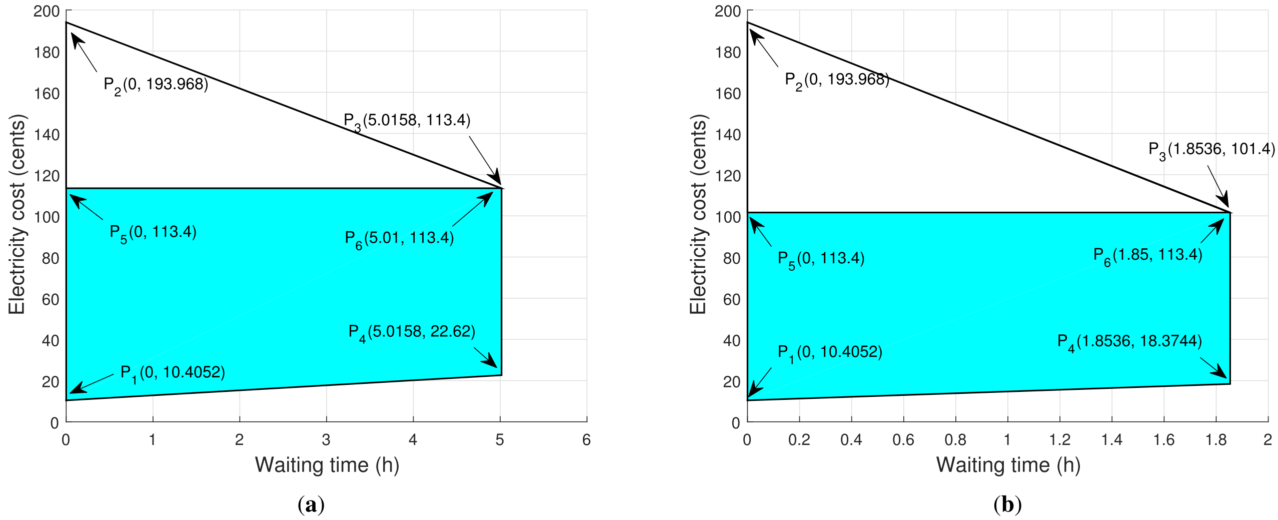



**FIGURE 8.** **Feasible region for electricity cost with waiting time in Winter season (Single home). (a) Feasible region for waiting time without coordination. (b) Feasible region for waiting time with coordination.**

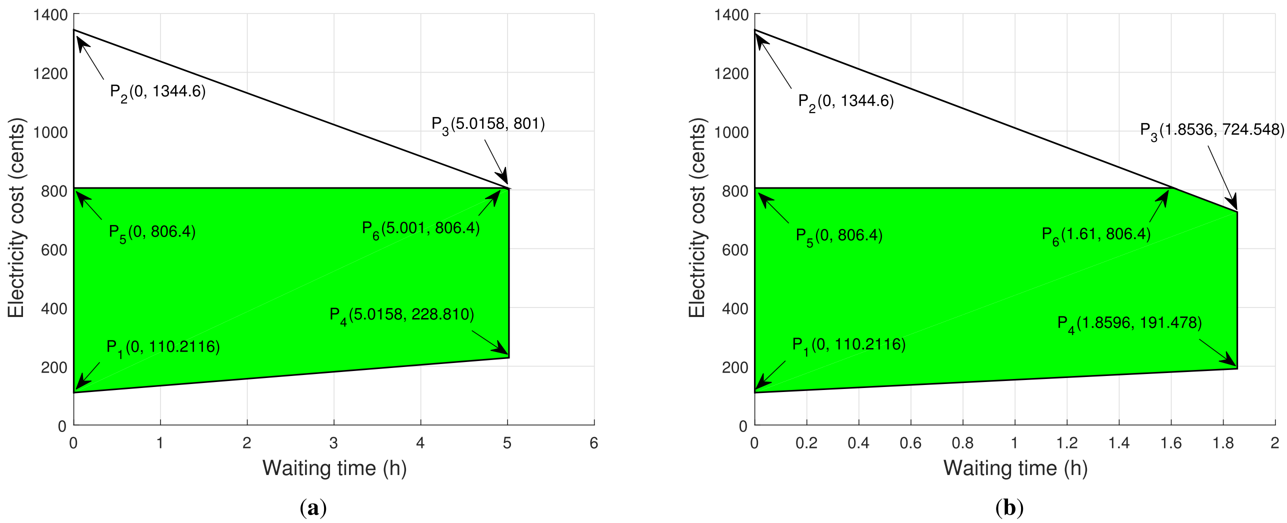



**FIGURE 9.** **Feasible region for electricity cost with waiting time in Winter season (Multiple homes). (a) Feasible region for waiting time without coordination. (b) Feasible region for waiting time with coordination.**

Fig.8(a) represents the reduction in electricity cost with waiting time without coordination. While Fig.8(b) represents the reduction in waiting time as coordination is incorporated in scheduling for a single home. Fig.9(a) and (b), represent the feasible regions before and after coordination for multiple homes. These figures clearly demonstrate that desirable reduction in electricity cost is achieved while maximizing the consumer comfort. Results for Summer and Winter seasons are discussed in simulation and discussion section in detail.

## VI. SIMULATIONS AND RESULTS

In this section, simulation results are evaluated to analyze the performance of the proposed HEM model. In order to validate our simulation results, extensive simulations are conducted in Matlab. Heuristic algorithms BFA, HSA and our proposed HBH are used to find the optimal solution of the specified problem on the basis of performance parameters, such as electricity consumption cost, energy consumption, PAR, and consumer satisfaction levels. ToU price rates for Summer and Winter seasons are used to analyze the behaviour of consumers and their electricity consumption patterns in changing seasons. Fig.10(a) and (b) show the hourly price rates in Summer and Winter seasons. 24 h time horizon is divided into three segments off-peak hours, mid-peak hours, and on-peak hours. We performed simulations for two cases: i) Single home and ii) multiple homes. A single home with eleven appliances is considered for the simulations. These appliances are further categorized into three classes while keeping in mind the consumer's need: i) fixed appliances, ii) shiftable burst appliances and iii) interruptable appliances.

**TABLE 2. Control parameters for summer season.**

| Classes | Appliances | LoT (h) | PR (kWh) |
|---|---|---|---|
| Fixed Appliances | Light | 12 | 0.1 |
| | Fan | 16 | 0.1 |
| | Oven | 9 | 3 |
| | Blender | 4 | 1.2 |
| Shiftable Appliances | Washing Machine | 5 | 0.5 |
| | Cloth Dryer | 4 | 4 |
| | Dish Washer | 4 | 1.5 |
| Interruptable Appliances | AC | 12 | 1.1 |
| | Refrigerator | 12 | 1.2 |
| | Iron | 6 | 1.1 |
| | Vacuum Cleaner | 9 | 0.5 |

**TABLE 3. Parameters of appliances used in winter season.**

| Classes | Appliances | LoT (h) | PR (kWh) |
|---|---|---|---|
| Fixed Appliances | Light | 12 | 0.1 |
| | Coffee Maker | 4 | 0.5 |
| | Oven | 9 | 3 |
| | Blender | 4 | 1.2 |
| Shiftable Appliances | Washing Machine | 5 | 0.5 |
| | Cloth Dryer | 4 | 4 |
| | Dish Washer | 4 | 1.5 |
| Interruptable Appliances | Water Heater | 12 | 1.1 |
| | Space Heater | 12 | 1.5 |
| | Iron | 6 | 1.1 |
| | Vacuum Cleaner | 9 | 0.5 |

**TABLE 4. Consumer priority appliances.**

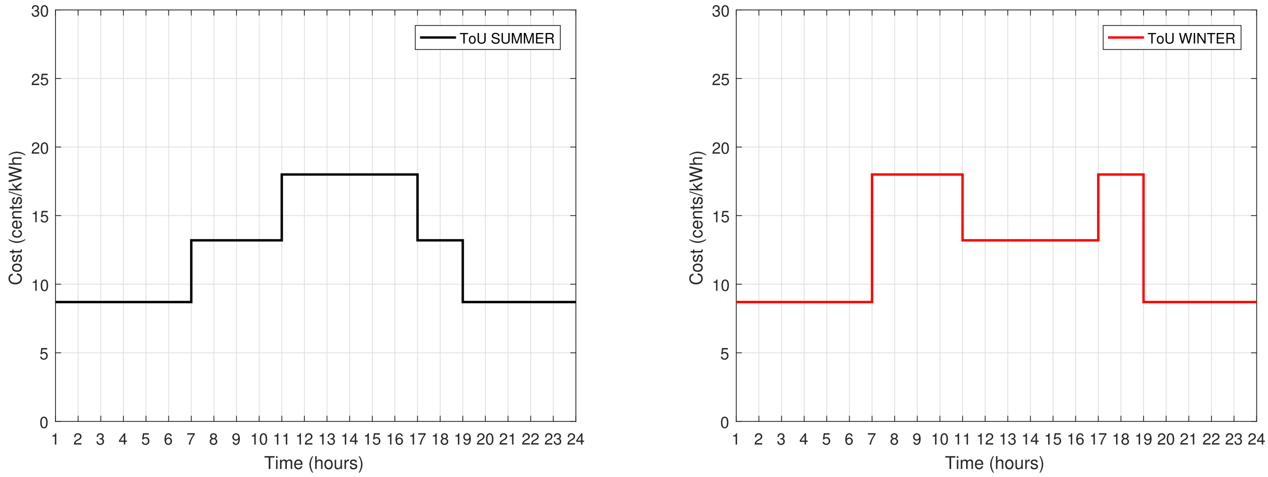
| Seasons | Appliances | LoT (h) | PR (kWh) |
|---|---|---|---|
| Summer | AC | 12 | 1.1 |
| | Vacuum cleaner | 9 | 0.5 |
| Winter | Water heater | 14 | 1.1 |
| | Vacuum cleaner | 10 | 1.5 |

Fixed appliances include; light, fan, oven and blender. Washing machine, cloth dryer and dish washer are in shiftable burst appliances class. Whereas, interruptable appliances include; AC, refrigerator, iron and vacuum cleaner. Table.2 and Table.3 represent the appliance classes, their LoT and PR used in simulations for both Summer and Winter seasons. Coordination among appliances and scheduler is established by incorporating coordination using DP approach. DP is a method of solving complex problems by breaking them down into a collection of simpler subproblems. These subproblems are solved and the results are then stored in a memory, this process is called memoization. This is a recursive process, if the same problem occurs again, instead of computing its solution again one can simply use the already stored solution by using bottom up approach. Table.4 represents the consumer preferred appliances, their LoT and PR. In case of multiple homes, the categorization of appliances remain same as in single home case. However, we have considered different PR and LoT of appliances for each home. Results for two cases are discussed in 'Summer with and without coordination' and 'Winter before and after coordination' subsections.

### A. SUMMER WITH AND WITHOUT COORDINATION

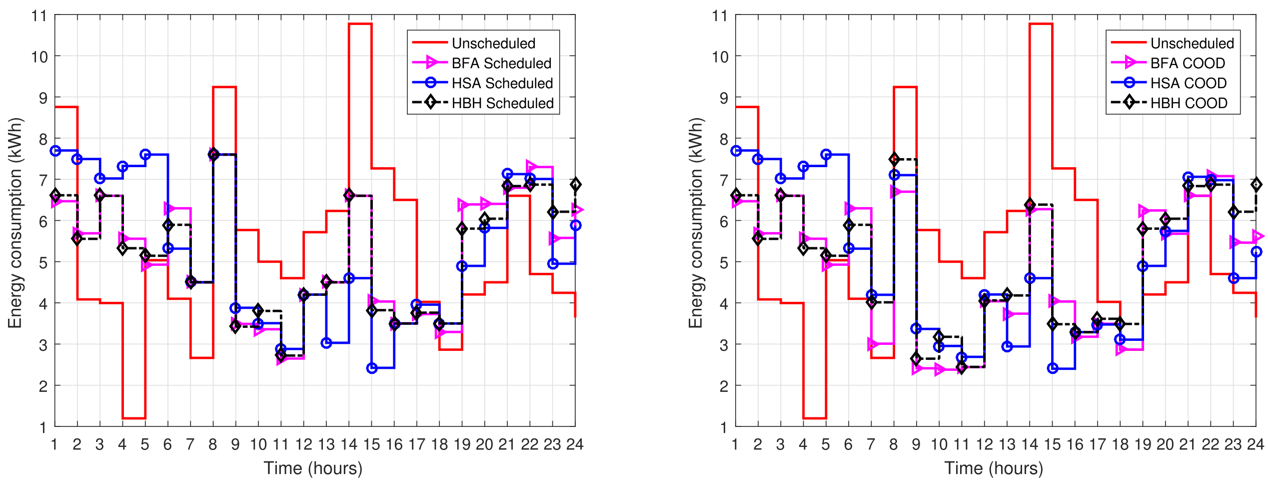
This analysis studies the energy consumption cost under ToU pricing model for which the data is available online for both Summer and Winter seasons [27]. ToU price rates are considered for the evaluation of heuristic algorithms. Fig.10(a) shows Summer season ToU price rates for a day. In Summer season, 11 am to 5 pm are on-peak hours, mid-peak hours are from 7 am to 11 am and 5 pm to 7 pm and the remaining hours are off-peak hours. Price rates for on-peak hours, mid-peak hours and off-peak hours are 18 cents/kWh, 13.2 cents/kWh and 8.7 cents/kWh, respectively. The aim of using ToU price model is to enables the consumers to make decision considering both the electricity consumption cost and their own satisfaction level. The information about ToU model is readily available to consumers having advanced metering infrastructure. Electricity consumption patterns with and without coordination are shown in Fig.11(a) and (b), respectively. All three algorithms (BFA, HSA and HBH) perform efficiently in managing and minimizing the hourly electricity consumption after scheduling with and without coordination. Minimization of consumption cost is achieved by limiting the appliances on request in on-peak hours.

Electricity consumption cost pattern for each hour using BFA, HSA, and HBH before and after coordination are shown in Fig.12(a) and (b), respectively. Electricity consumption cost is high during off-peak and mid-peak hours, whereas in the on-peak hours the electricity consumption is comparatively less than off-peak and mid peak hours. Fig.13(a) illustrates the effect on PAR, before and after incorporating coordination in the model for a single home. Significant minimization in PAR is achieved for BFA, HSA and HBH before and after coordination as compared to unscheduled case as these are designed to avoid peak formation in any hour. This proves that proposed model effectively handle the peak formation problem. Bar plots for BFA, HSA and HBH, shows that the electricity consumption of all appliances are optimally distributed in 24 h. Fig.13(a) shows the reduction in PAR achieved by BFA, HSA and HBH which is 49.17%, 47.14% and 49.79%, respectively before and after coordination 43.25%, 42.08% and 47.97% PAR minimization is achieved by BFA, HSA and HBH, respectively, for a single home. HBH outperformed both BFA and HSA in both scenarios; before and after coordination. Peak formation is one of the major problems in SG. In order to meet the high demand utility turn on extra peak generators, causing increase in electricity bills for consumers. Fig.13(b) shows the performance of the proposed model with respect to PAR when number of homes are increased. It shows that the proposed system is scalable as it reduces the PAR effectively. 24.42%, 25.91% and 24.60% minimization in PAR is achieved by BFA, HSA and HBH algorithms before coordination. BFA, HSA and HBH show 23.36%, 28.25% and 23.81% minimization in PAR after coordination. BFA and HBH after coordination have high PAR than HSA. Total electricity bill reduction before and after coordination is shown in Fig.14(a) and (b), for single and multiple homes, respectively. In both cases,




(a) (b)

**FIGURE 10.** **ToU price rates. (a) ToU in Summer season. (b) ToU in Winter season.**




(a) (b)

**FIGURE 11.** **Energy consumption per hour (kWh) (Summer season). (a) Energy consumption per hour without coordination. (b) Energy consumption per hour with coordination.**

reduction in electricity bill per day is achieved. Fig.14(a) represents electricity consumption cost for single home. Bar plots for BFA, HSA and HBH before coordination show 2.58%, 4.76% and 2.68% reduction in electricity cost per day. After coordination, 17.30%, 16.00% and 13.39% reduction in electricity bill is achieved by BFA, HSA and HBH, respectively. Fig.14(b) illustrates the result for electricity consumption cost per day after coordination for multiple homes. After coordination is incorporated in the system BFA, HSA and HBH show 2.83%, 17.15% and 13.27% minimization in electricity consumption cost per day. It is clear from results that, HSA show better results as compared to BFA and HBH for both cases.

BFA, HSA and HBH schedule with coordination show more reduction than before coordination. As in coordination, two appliances are set as priority appliances by consumer. Their LoTs may vary randomly, as per consumer's need. A consumer generate an interrupt causing schedular to kill the running interruptable appliance and allocate that particular time slot to the consumer preferred appliance without effecting the operation of rest of the appliances. It reduces the overall load which consequently reduce consumer electricity bill per day.

### *B. WINTER WITH AND WITHOUT COORDINATION*

In this section, ToU price rates for Winter season are used [27] and shown in Fig.10(b). In Winter season, 7 am to 11 am and 5 pm to 7 pm are on-peak hours, 11 am to 5 pm are mid-peak hours and remaining hours are off-peak hours. Price rates for on-peak, mid-peak and off-peak hours are 18 cents/kWh, 13.2 cents/kWh and 8.7 cents/kWh. Hourly electricity consumption patterns before and after coordination are

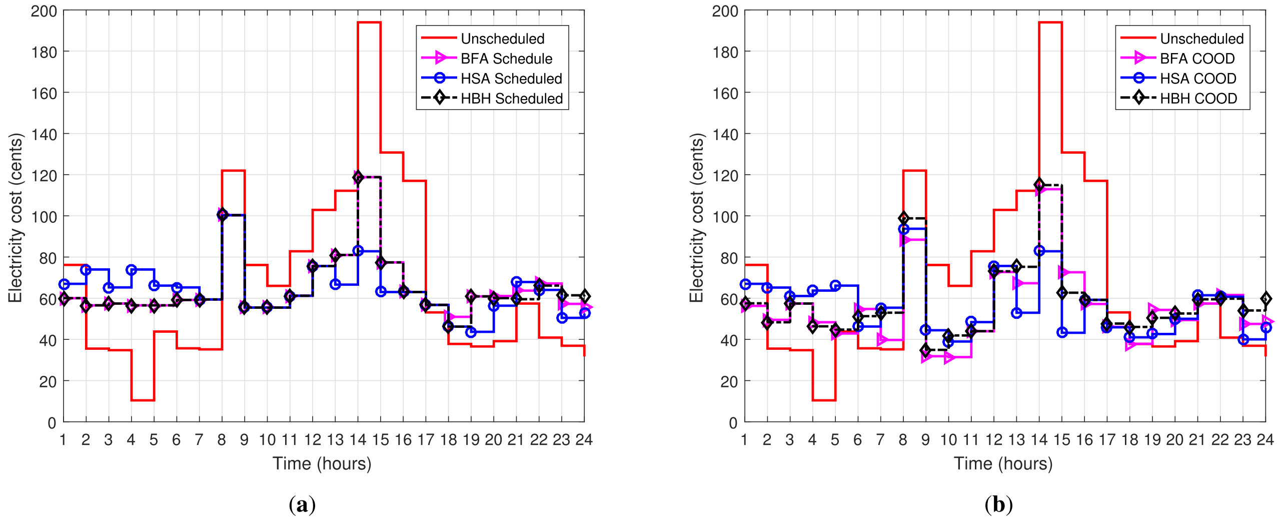



**FIGURE 12.** Electricity cost per hour (cents) (Summer season). (a) Electricity cost per hour without coordination. (b) Electricity cost per hour with coordination.

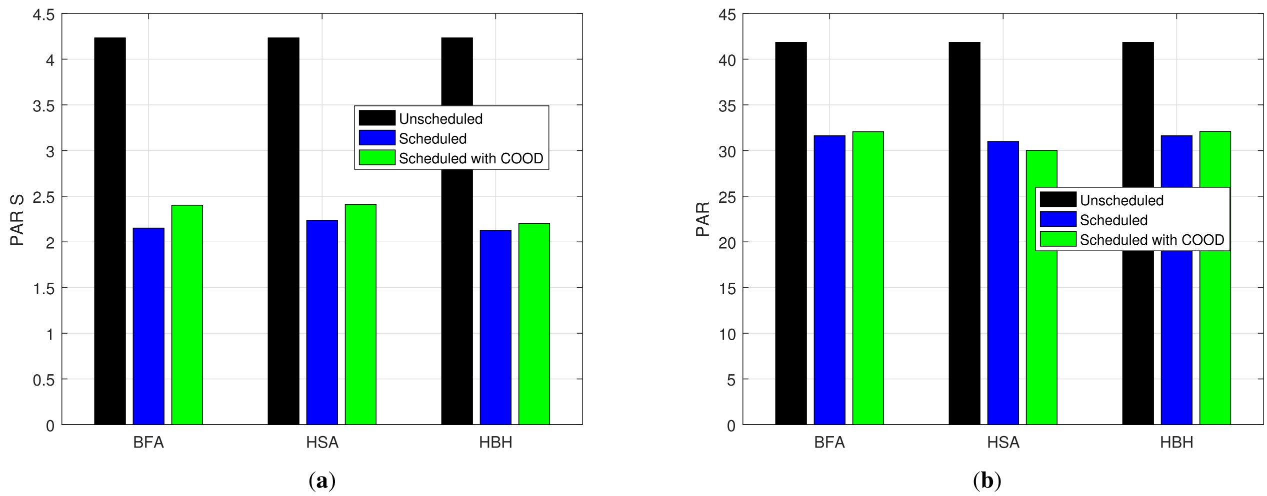
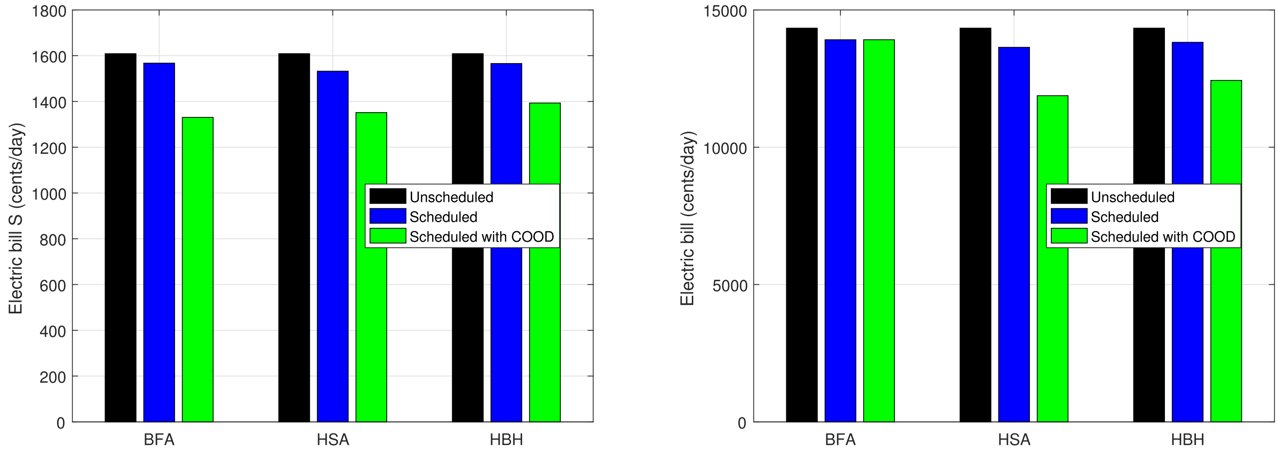



**FIGURE 13.** PAR for Summer season. (a) PAR for single home. (b) PAR for multiple homes.

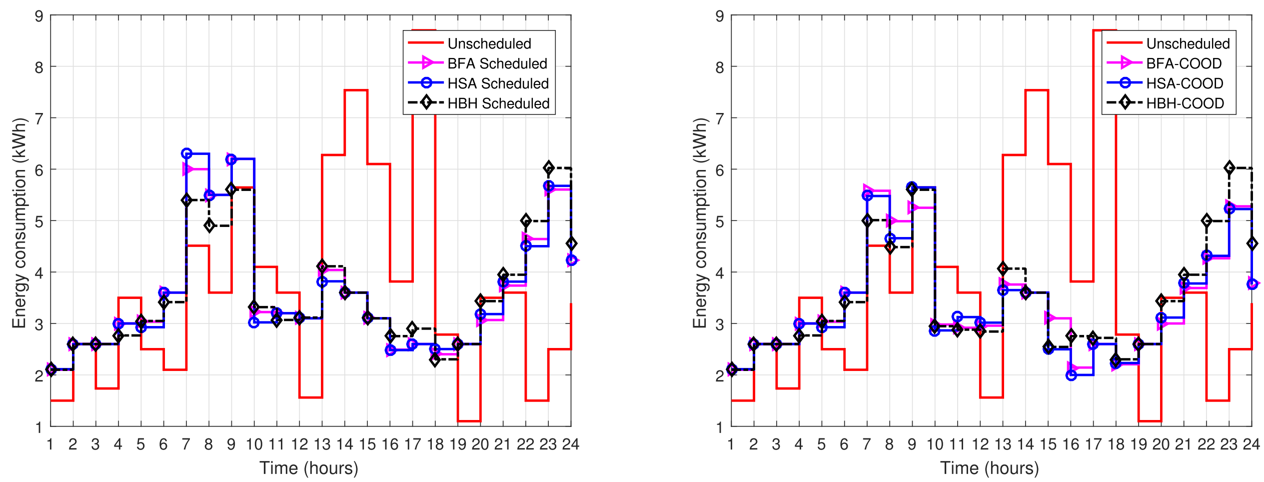
illustrated in Fig.15(a) and (b). It shows that electricity consumption of all appliances is optimally distributed within 24 h. Fig.15(a) illustrates that maximum energy consumption limited to 6.2000 (kWh), 6.3000 (kWh) and 6.0240 (kWh) for BFA, HSA and HBH before coordination. Fig.15(b) shows the maximum power consumption limits for BFA, HSA and HBH after coordination are 5.5804 (kWh), 5.6460 (kWh) and 6.0230 (kWh), respectively. Fig. 16(a) and (b), show the hourly electricity cost pattern for BFA, HSA and HBH before and after coordination is incorporated in the proposed model for single home. Reduction in electricity consumption cost is achieved by efficiently shifting the loads from on-peak hours where price rates are high to off-peak hour where prices are low.

Performance of the proposed model with respect to PAR for a single home is shown in Fig.17(a). In comparison to the unscheduled case, significant minimization in PAR is achieved for all three algorithms (BFA, HSA and HBH) before and after coordination. This shows that the proposed model prevents the peak formation causing due to high energy demand in certain time periods. The peak formation is a threat for both utility and consumers. As the consumers have to pay high price for power consumption during peak hours, whereas utility suffers from high demands that may cause blackout or load shedding. BFA, HSA and HBH algorithms efficiently minimize PAR upto 43.23%, 41.83% and 37.48% before coordination and 46.01%, 41.48% and 35.34% after coordination is incorporated in system for a single home. Fig.17(b) shows the effects of proposed model on PAR for multiple homes. The behaviour of the bar plots are almost same as in the case of single home, all three algorithms minimize the PAR in comparison to the unscheduled case. This shows that proposed model is effectively scalable. Fig.17(b) illustrates that proposed algorithms




(a) (b)

**FIGURE 14.** **Electricity price per day (cents) (Summer season). (a) Electricity price per day for single home. (b) Electricity price per day for multiple homes.**




(a) (b)

**FIGURE 15.** **Energy consumption per hour (kWh) (Winter season). (a) Energy consumption per hour without coordination. (b) Energy consumption per hour with coordination.**

(BFA, HSA, HBH) achieved 26.05%, 35.11% and 25.86% reduction in PAR without coordination. Furthermore, BFA, HSA and HBH schedule with coordination show 25.08%, 33.35% and 24.55% minimization in PAR, in case of multiple homes. Here, HSA before and after coordination performs better than BFA and HBH.

Fig.18(a) and (b), illustrate the total electricity consumption cost per day for single and multiple homes before and after coordination is incorporated in the proposed model. 7.45%, 1.22% and 2.26% reduction in electricity cost per day is achieved by BFA, HSA and HBH without coordination as shown in Fig.18(a). As coordination is incorporated with BFA, HSA and HBH electricity cost per day reduces to 13.16%, 13.96% and 11.86%, respectively in case of a single home. Fig.18(b) represents 14.43%, 13.42% and 14.65% reduction in electricity cost per day for multiple homes after coordination is incorporated with BFA, HSA and HBH. The difference in cost before and after coordination is there for all three algorithms because in coordination, two appliances are set as priority appliances by the consumers. These appliances have LoT in minutes, this reduces the overall load after coordination which consequently reduce the consumers electricity bill per day. The BFA algorithm in both scenarios, before and after coordination, outperformed both HSA and HBH.

### *C. CONSUMER COMFORT*

In this research, consumer's satisfaction level in terms of electricity bill and waiting time of an appliance is also considered. Consumers must follow the optimal appliance's schedule generated by schedular in order to minimize electricity consumption cost. Generally, there is a trade-off between waiting time and electricity consumption cost. Fig.19(a) and (b), illustrate that appliances scheduled before coordination have

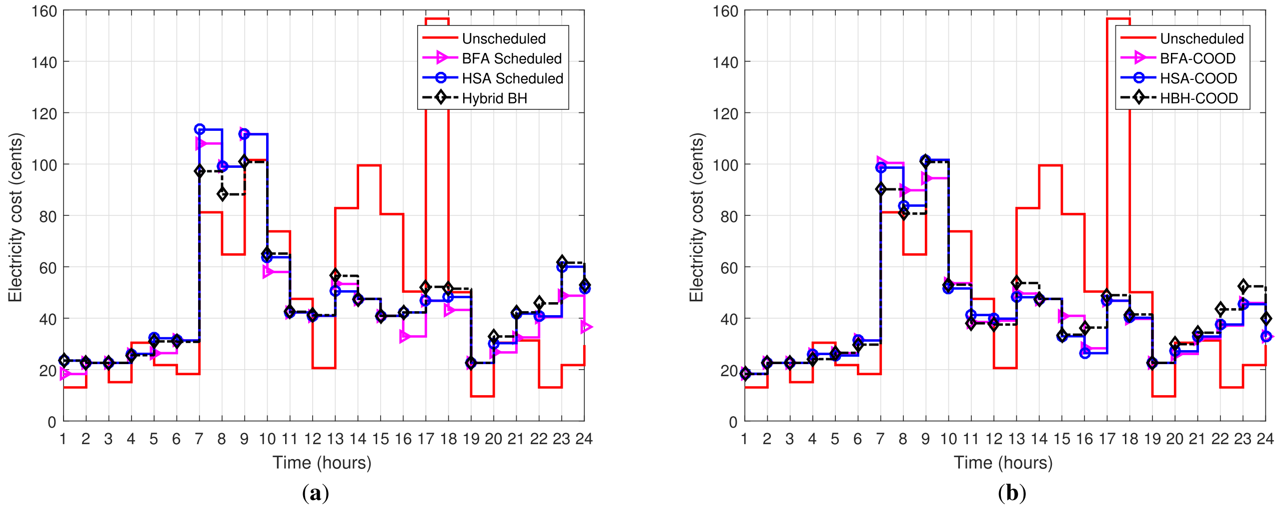



**FIGURE 16.** Electricity cost per hour (cents) (Winter season). (a) Electricity cost per hour without coordination. (b) Electricity cost per hour with coordination.

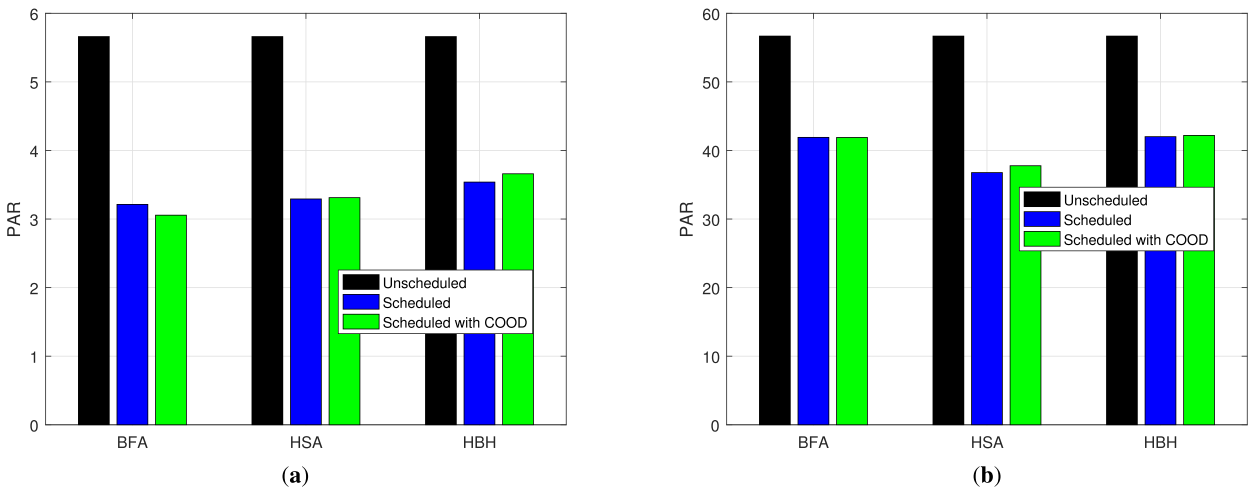



**FIGURE 17.** PAR for Winter season. (a) PAR for single home. (b) PAR for multiple homes.

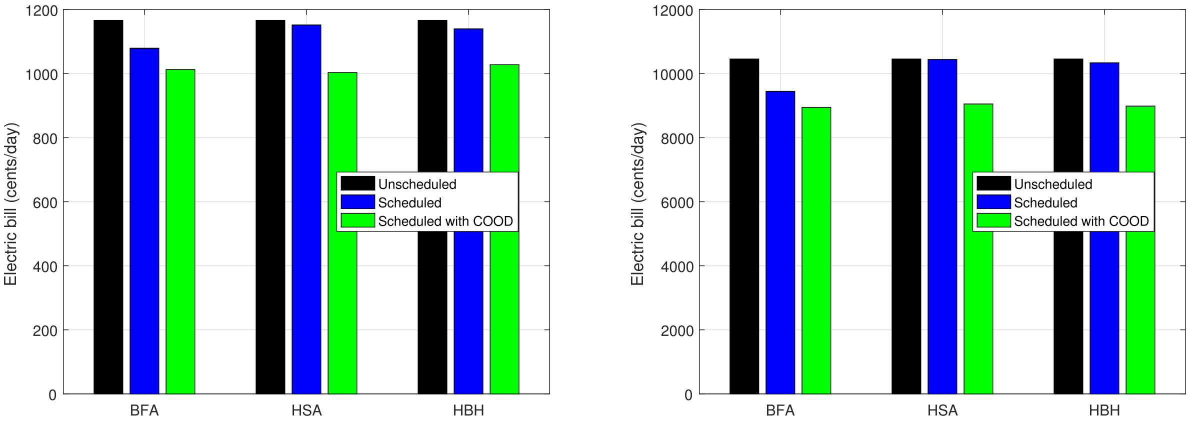
high waiting time as compared to appliances scheduled after coordination is incorporated in system. BFA and HBH have less average waiting time as compared to HSA before coordination. As coordination enables the consumers to generate an interrupt at any time to operate priority appliance. This incorporation of coordination significantly minimize the waiting time of the appliances as shown in Fig.19(b) for a single home. Similar results are obtained when simulations are performed for multiple homes. Similarly, Fig.20(a) and (b), show the average waiting time of appliances before coordination for a single home. The average waiting time for HBH is less as compared to BFA and HSA before coordination, where as, BFA show less average waiting time than HSA and HBH after coordination. In case of multiple home, similar results are achieved for average waiting time.

### D. PERFORMANCE TRADE-OFF

Figs.13-14 clearly show the trade-off between PAR and electricity consumption cost for Summer season, respectively. An inverse relationship between electricity consumption cost and PAR can be observed from Figs.18-17 in Winter season. Moreover, Figs.19-20 present the consumer comfort in terms of waiting time for both Summer and Winter seasons. It is clear from the figures that the trade-off between the electricity consumption cost and consumer comfort exists. If consumers want to minimize their electricity consumption cost then they have to sacrifice their satisfaction level (more waiting time) and vice versa.

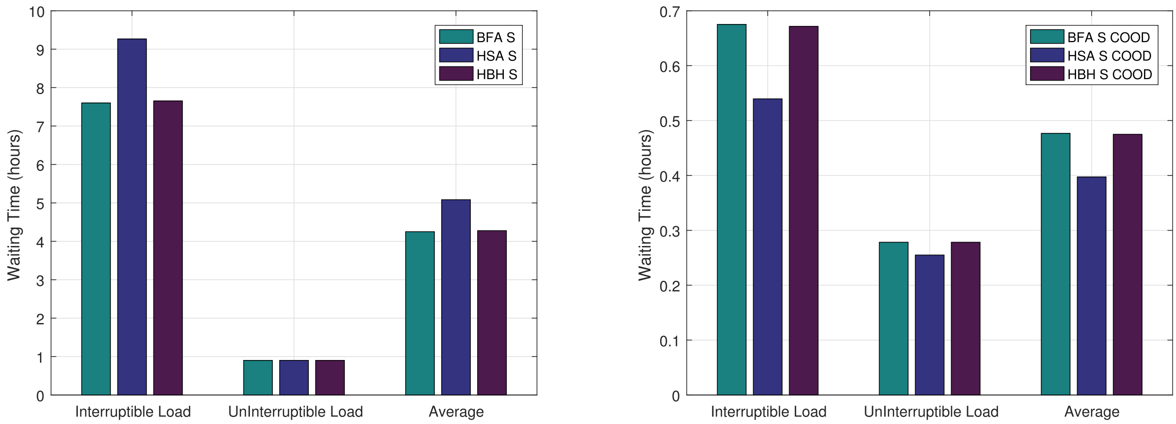
### E. PERFORMANCE ANALYSIS OF PROPOSED ALGORITHM

To analyze the behavior of the proposed algorithm HBH, two test functions: Rastrigin [34] and Ackley [35] have been implemented and compared with the existing techniques HSA and BFA. Figs. 21-22 illustrate the behaviour of all three algorithms from where it can be envisioned that HSA has acquired global optimal result, whereas, BFA outperforms in local search space. Fig. 21 depicts the low convergence of HSA, even after 100 iterations. It is not converged at



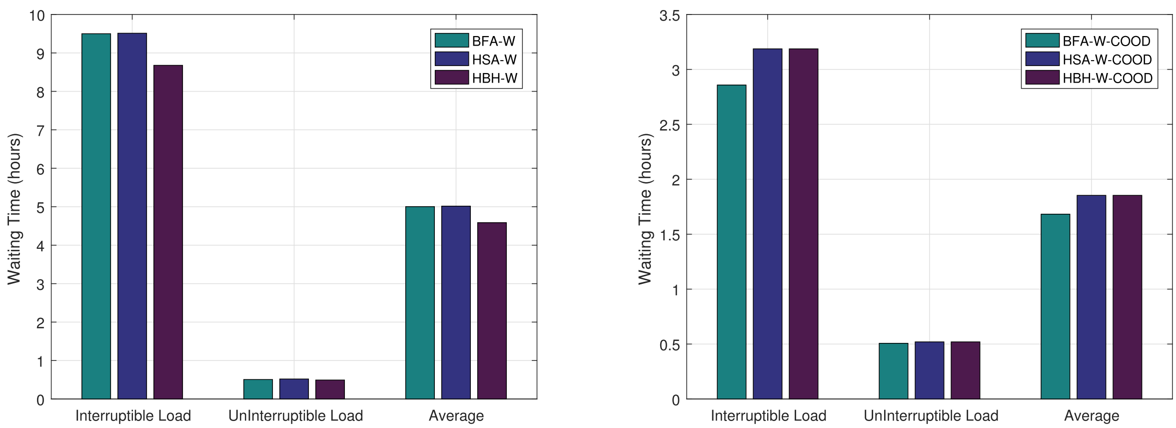

(a) (b)

**FIGURE 18.** **Electricity price per day (cents) (Winter season). (a) Electricity price per day for single home. (b) Electricity price per day for multiple homes.**




(a) (b)

**FIGURE 19.** **Consumer comfort for single home (Summer season). (a) Consumer comfort without coordination. (b) Consumer comfort with coordination.**




(a) (b)

**FIGURE 20.** **Consumer comfort for single home (Winter season). (a) Consumer comfort without coordination. (b) Consumer comfort with coordination.**

optimal point. On the other hand, BFA has shown significant amount of improvement towards optimal point after 7th iteration. While, the integration of BFA and HSA operators in HBH took advantage of both local and global convergence which is evident from the Figs. 21-22. Hence, it can be concluded from the results that the problem of local optima in

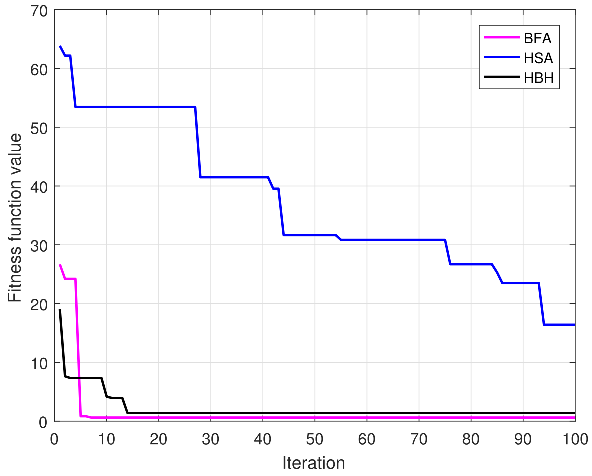



**FIGURE 21.** Analysis of Rastrigin test function.

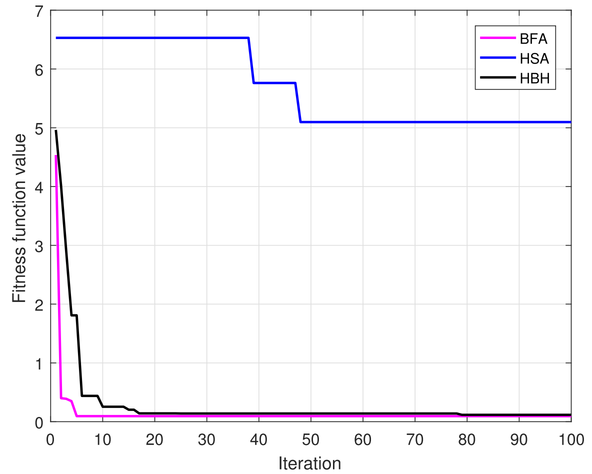



**FIGURE 22.** Analysis of Ackley test function.

BFA and global optima in HSA is tackled through hybridization of both schemes.

## VII. CONCLUSION AND FUTURE WORK

In this paper, seasonal ToU based appliance scheduling schemes for residential DSM have been proposed. Three heuristic algorithms: BFA, HSA, and their hybrid: HBH are used to evaluate the performance parameters; energy consumption cost, PAR and consumer comfort (in term of waiting time). Two scenarios are analyzed in this work to evaluate the consumer's demand and behaviour of the proposed home energy management system (HEMS) in Summer and Winter seasons. Control parameters and classification of appliances are kept the same to comparatively analyze the performance of all participating algorithms in each season; however, types of appliance and their power ratings are different in different seasons as per consumers' need. To achieve the targeted objectives, the concept of coordination among appliances is introduced. This gives consumers the ability to generate an interrupt during the schedule of the running appliances. Scheduler terminates the operations of running appliance immediately once an interrupt is generated in the system, and allocates the remaining time slot to the priority appliance. DP approach along with the heuristic technique is used on the larger data for coordination and rescheduling, ultimately increasing the consumers' comfort and minimizing the electricity cost and PAR. Simulation results of 'with coordination' and 'without coordination' scenarios in two seasons for single and multiple homes are presented in 'simulations and results' section. It is observed from the simulations that energy consumption cost is further minimized with coordination, as compared to the 'without coordination' scenario. Our proposed scheme is efficiently proved capable of managing the load in an optimal way to reduce energy consumption cost, PAR and increase the consumer comfort. However, a trade-off has been observed between the energy consumption cost and consumer comfort.

In future, case studies of real-world implementation are desirable to test the performance of this scheme. In addition, multi-objective function should be designed and integration of RES should be considered, in further extension of this work.

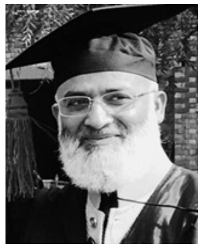
## REFERENCES

[1] Z. Wen, D. O'Neill, and H. Maei, "Optimal demand response using device-based reinforcement learning," *IEEE Trans. Smart Grid*, vol. 6, no. 5, pp. 2312–2324, Sep. 2015.
[2] D. Setlhaolo, X. Xia, and J. Zhang, "Optimal scheduling of household appliances for demand response," *Electr. Power Syst. Res.*, vol. 116, pp. 24–28, Nov. 2014.
[3] E. Shirazi and S. Jadid, "Optimal residential appliance scheduling under dynamic pricing scheme via HEMDAS," *Energy Buildings*, vol. 93, pp. 40–49, Apr. 2015.
[4] S. Rahim *et al.*, "Exploiting heuristic algorithms to efficiently utilize energy management controllers with renewable energy sources," *Energy Buildings*, vol. 129, pp. 452–470, Oct. 2016.
[5] P. Mesarić and S. Krajcar, "Home demand side management integrated with electric vehicles and renewable energy sources," *Energy Buildings*, vol. 108, pp. 1–9, Dec. 2015.
[6] J. Abushnaf, A. Rassau, and W. Górnisiewicz, "Impact on electricity use of introducing time-of-use pricing to a multi-user home energy management system," *Int. Trans. Elect. Energy Syst.*, vol. 26, no. 5, pp. 993–1005, 2015.
[7] A. G. Azar and R. H. Jacobsen, "Appliance scheduling optimization for demand response," *Int. J. Adv. Intell. Syst.*, vol. 9, nos. 1–2, pp. 50–64, 2016.
[8] Y. Huang, H. Tian, and L. Wang, "Demand response for home energy management system," *Int. J. Elect. Power Energy Syst.*, vol. 73, pp. 448–455, Dec. 2015.
[9] A. Ahmad *et al.*, "An optimized home energy management system with integrated renewable energy and storage resources," *Energies*, vol. 10, no. 4, p. 549, 2017.
[10] M. B. Rasheed *et al.*, "Priority and delay constrained demand side management in real-time price environment with renewable energy source," *Int. J. Energy Res.*, vol. 40, no. 14, pp. 2002–2021, 2016.
[11] K. Ma, T. Yao, J. Yang, and X. Guan, "Residential power scheduling for demand response in smart grid," *Int. J. Elect. Power Energy Syst.*, vol. 78, pp. 320–325, Jun. 2016.
[12] M. Marzband, E. Yousefnejad, A. Sumper, and J. L. Domínguez-García, "Real time experimental implementation of optimum energy management system in standalone Microgrid by using multi-layer ant colony optimization," *Int. J. Elect. Power Energy Syst.*, vol. 75, pp. 265–274, Feb. 2016.
[13] H.-T. Yang, C.-T. Yang, C.-C. Tsai, G.-J. Chen, and S.-Y. Chen, "Improved PSO based home energy management systems integrated with demand response in a smart grid," in *Proc. IEEE Congr. Evol. Comput. (CEC)*, May 2015, pp. 275–282.
[14] S. H. Hong, M. Yu, and X. Huang, "A real-time demand response algorithm for heterogeneous devices in buildings and homes," *Energy*, vol. 80, pp. 123–132, Feb. 2015.

[15] T.-C. Chen, P.-W. Tsai, S.-C. Chu, and J.-S. Pan, "A novel optimization approach: Bacterial-GA foraging," in *Proc. 2nd Int. Conf. Innov. Comput., Inf. Control (ICICIC)*, Sep. 2007, p. 391.
[16] Y. Jiao, J. Wu, Q.-K. Tan, Z.-F. Tan, and G. Wang, "An optimization model and modified harmony search algorithm for microgrid planning with ESS," *Discrete Dyn. Nature Soc.*, vol. 2017, Aug. 2017, Art. no. 8425458, doi: 10.1155/2017/8425458.
[17] C. O. Adika and L. Wang, "Smart charging and appliance scheduling approaches to demand side management," *Int. J. Elect. Power Energy Syst.*, vol. 57, pp. 232–240, May 2014.
[18] R. Jovanovic, A. Bousselham, and I. S. Bayram, "Residential demand response scheduling with consideration of consumer preferences," *Appl. Sci.*, vol. 6, no. 1, p. 16, 2016.
[19] H.-T. Roh and J.-W. Lee, "Residential demand response scheduling with multiclass appliances in the smart grid," *IEEE Trans. Smart Grid*, vol. 7, no. 1, pp. 94–104, Jan. 2016.
[20] P. Samadi, V. W. S. Wong, and R. Schober, "Load scheduling and power trading in systems with high penetration of renewable energy resources," *IEEE Trans. Smart Grid*, vol. 7, no. 4, pp. 1802–1812, Jul. 2016.
[21] T. Logenthiran, D. Srinivasan, and T. Z. Shun, "Demand side management in smart grid using heuristic optimization," *IEEE Trans. Smart Grid*, vol. 3, no. 3, pp. 1244–1252, Sep. 2012.
[22] C. Ogwumike, M. Short, and M. Denai, "Near-optimal scheduling of residential smart home appliances using heuristic approach," in *Proc. IEEE Int. Conf. Ind. Technol. (ICIT)*, Mar. 2015, pp. 3128–3133.
[23] I.-Y. Joo and D.-H. Choi, "Distributed optimization framework for energy management of multiple smart homes with distributed energy resources," *IEEE Access*, vol. 5, pp. 15551–15560, 2017.
[24] B. Celik, R. Roche, S. Suryanarayanan, D. Bouquain, and A. Miraoui, "Electric energy management in residential areas through coordination of multiple smart homes," *Renew. Sustain. Energy Rev.*, vol. 80, pp. 260–275, Dec. 2017.
[25] M. Senthilkumar and P. Ilango, "A survey on job scheduling in big data," *Cybern. Inf. Technol.*, vol. 16, no. 3, pp. 35–51, 2016.
[26] M. Kalra and S. Singh, "A review of metaheuristic scheduling techniques in cloud computing," *Egyptian Inform. J.*, vol. 16, no. 3, pp. 275–295, 2015.
[27] *Ontario Energy Board*. Accessed: Mar. 20, 2017. [Online]. Available: https://www.oeb.ca/rates-and-your-bill/electricity-rates
[28] K. M. Passino, "Biomimicry of bacterial foraging for distributed optimization and control," *IEEE Control Syst. Mag.*, vol. 22, no. 3, pp. 52–67, Mar. 2002.
[29] S. Das, A. Biswas, S. Dasgupta, and A. Abraham, "Bacterial foraging optimization algorithm: theoretical foundations, analysis, and applications," in *Foundations of Computational Intelligence*, vol. 3. Berlin, Germany: Springer, 2009, pp. 23–55.
[30] Z. W. Geem, Ed., *Music-Inspired Harmony Search Algorithm: Theory and Applications*, vol. 191. New York, NY, USA: Springer, 2009.
[31] K. Nekooei, M. M. Farsangi, H. Nezamabadi-Pour, and K. Y. Lee, "An improved multi-objective harmony search for optimal placement of DGs in distribution systems," *IEEE Trans. Smart Grid*, vol. 4, no. 1, pp. 557–567, Mar. 2013.
[32] O. Abdel-Raouf and M. A.-B. Metwally, "A survey of harmony search algorithm," *Int. J. Comput. Appl.*, vol. 70, no. 28, pp. 17–28, 2013.
[33] M. Motevasel and A. R. Seifi, "Expert energy management of a micro-grid considering wind energy uncertainty," *Energy Convers. Manage.*, vol. 83, pp. 58–72, Jul. 2014.
[34] L. A. Rastrigin, "Systems of extreme control," *Nauka*, 1974.
[35] D. H. Ackley, *A Connectionist Machine for Genetic Hillclimbing*. Boston, MA, USA: Kluwer, 1987.

**MUHAMMAD HASSAN RAHIM** received the B.S. degree in computer science from the COMSATS Institute of Information Technology, Islamabad, Pakistan, where he is currently involved in the M.S. thesis in computer science with the Department of Computer Science, COMSATS Institute of Information Technology, under the supervision of Dr. N. Javaid. His research interests include energy optimization in micro and smart grids and cloud computing for smart grids.

**ADIA KHALID** received the bachelor's and master's degree from the University of Azad Jammu and Kashmir, Muzaffarabad, Pakistan, in 2007 and 2010, respectively, and the master's degree from Pir Mehr Ali Shah Arid Agriculture University, Rawalpindi, Pakistan. She is currently pursuing the Ph.D. degree in computer science with the Department of Computer Science, COMSATS Institute of Information Technology, Islamabad, Pakistan, under the supervision of Dr. N. Javaid and Dr. M. Ilahi. Her research interests include energy optimization in micro and smart grid clouds and big data analytics in smart grids.



**NADEEM JAVAID** received the bachelor's degree in computer science from Gomal University, Dera Ismail Khan,, Pakistan, in 1995, the master's degree in electronics from Quid-i-Azam University, Islamabad, Pakistan, in 1999, and the Ph.D. degree in computer science from the University of Paris-Est, France, in 2010. He is currently an Associate Professor and the Founding Director of the ComSens (Communications over Sensors) Research Lab, Department of Computer Science, COMSATS Institute of Information Technology, Islamabad. He has supervised seven Ph.D. and 85 master's theses. He has authored over 600 articles in technical journals and international conferences. He is also an Associate Editor for the IEEE Access Journal and an Editor for the *International Journal of Space Based and Situated Computing*. He received the Best University Teacher Award for 2016 from the Higher Education Commission of Pakistan and the Research Productivity Award 2017 from the Pakistan Council for Science and Technology. His research interests include energy optimization in smart/micro grids, cloud computing for smart grids, IoT enabled wireless sensor networks, and big data analytics in smart grids.

**MUSAED ALHUSSEIN** was born in Riyadh, Saudi Arabia. He received the B.S. degree in computer engineering from King Saud University, Riyadh, in 1988, and the M.S. and Ph.D. degrees in computer science and engineering from the University of South Florida, Tampa, FL, USA, in1992 and 1997, respectively. Since 1997, he has been with the Faculty of the Computer Engineering, College of Computer and Information Science, King Saud University. He is currently the Founder and the Director of Embedded Computing and Signal Processing Research Laboratory. His research interests include computer architecture and signal processing and with an emphasis on VLSI testing and verification, embedded and pervasive computing, cyber-physical systems, mobile cloud computing, big data, eHealthcare, and body area networks.

**KHURSHEED AURANGZEB** received the B.S. degree in computer engineering from the COMSATS Institute of Information Technology at Abbottabad, Abbottabad, Pakistan, in 2006, the M.S. degree in electrical engineering (system on chip) from Linköping University, Sweden, in 2009, and the Ph.D. degree from Mid Sweden University, Sundsvall, Sweden, in 2013. From 2013 to 2016, he was an Assistant Professor/HoD with the Electrical Engineering Department, Abasyn University, Peshawar, Pakistan. He is currently an Assistant Professor with the College of Computer and Information Science, King Saud University, Riyadh, Saudi Arabia. His research interests include wireless visual sensor networks, design methods and implementation of embedded systems, applied image/signal processing, image compression, cloud computing, Internet of Things, smart grids, smart buildings, and traffic monitoring.

**ZAHOOR ALI KHAN** (SM'15) received the B.Sc. degree from the University of Peshawar, Peshawar, Pakistan, the M.Sc. degree in computer engineering from UET Texila, Taxila, Pakistan, the M.Sc. degree in electronics from Quaid-i-Azam University, Islamabad, Pakistan, and the Ph.D. and M.C.Sc. degrees from the Faculty of Engineering and the Faculty of Computer Science, Dalhousie University, Halifax, NS, Canada. He has been an Assistant Professor and a Post-Doctoral Fellow with the Faculty of Engineering, Dalhousie University, and a part-time Professor of computing and information systems with Saint Mary's University, Halifax. He is currently an Assistant Professor with CIS, Higher Colleges of Technology at Fujairah, Fujairah, United Arab Emirates. He has authored or co-authored a book and over 180 peer-reviewed journal and conference papers. His research interests include but are not limited to the areas of wireless (Body Area) sensor networks and software defined networks. He is a Senior Member of the IEEE Communication Society and IAENG. He serves as a Regular Reviewer/Organizer of numerous ISI indexed journals and conferences.