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# Improving Energy Management System based on Internet of Things and Optimization Algorithms in Smart Buildings

Mohsen Nasri, Hassen Maaref
Monastir University, Faculty of Sciences of Monastir,
Micro-Opto-electronics and Nanostructures Laboratory LMON,
LR99ES29, Monastir 5000, Tunisia.

***Abstract-*** **One of this biosphere's most important resources is energy. However, due to the population's rapid growth and growing reliance on energy for daily use as a result of smart technologies and the Internet of Things (IoT), the limited resources that are currently available are becoming scarce. Therefore, new methods and algorithms are being developed and employed in the smart grid's (SG) energy optimization process to ensure that consumers are making the best use possible of the available energy resources. The new methods must take into account all aspects of the electrical grid to make it more intelligent and flexible. In this paper, we suggest three meta-heuristic algorithms which uses alternating operation among home appliances to schedule appliances while balancing User Comfort. The suggested algorithms are a Bacterial Forging Algorithm (BFA), Hybrid of Genetic and Bacterial foraging (HBG) and Genetic Algorithm (GA). It aims to efficiently manage load demand in order to reduce power costs and the peak-to-average ratio while ensuring user comfort by coordinating home appliances. We schedule loads on a day-ahead and real-time basis to fulfill the load demand of power consumers. This method avoids undesirable user behavior like forcing a device to start or stop, which defeats the objective of device programming. In order to solve this issue, the home energy management system uses the alternating operation process to coordinate the rescheduling of appliances. This helps the scheduler in determining the appropriate ON/OFF status of appliances in order to balance electricity among appliances. For this purpose, we adopt the dynamic programming to formulate our real-time rescheduling problem. In weekdays, we can get an extra electricity charge. This quantity is asked Outside of the scheduling process. This research also analyzes the performance of the proposed method under three pricing models: Time of Use, Real-Time Pricing, and Critical Peak Pricing.**

***Keywords: Energy management system; Internet of Things; Smart Grid; Demand side management; Alternating Operation.***

## 1. INTRODUCTION

During the last decades, the rapid change in the environment has led to a massive growth in electricity demand. The traditional grid is increasingly inefficient in the face of such massive demand, and it faces numerous challenges such as reliability, sustainability and energy management. Moreover, 65% of the power produced in a conventional grid is lost during generation, transmission, and distribution.[1]. The Smart Grid (SG) concept is established to solve the aforementioned issues. The SG has innovative power system features such two-way power flow, bidirectional communication, auto-monitoring, auto-healing, and greater compatibility. The energy demand-supply gap is being addressed through Demand Side Management (DSM) and Supply Side Management (SSM). Fundamentally, the DSM aims to educate electricity customers on how to change their electricity usage patterns in order to alleviate strain on the main grid and provide a continuous supply of power to consumers [2]. As depicted in Fig.1, the suggested DSM techniques include load shifting, strategic conservation, peak clipping, and valley filling to deal with variations in the consumer load profile.

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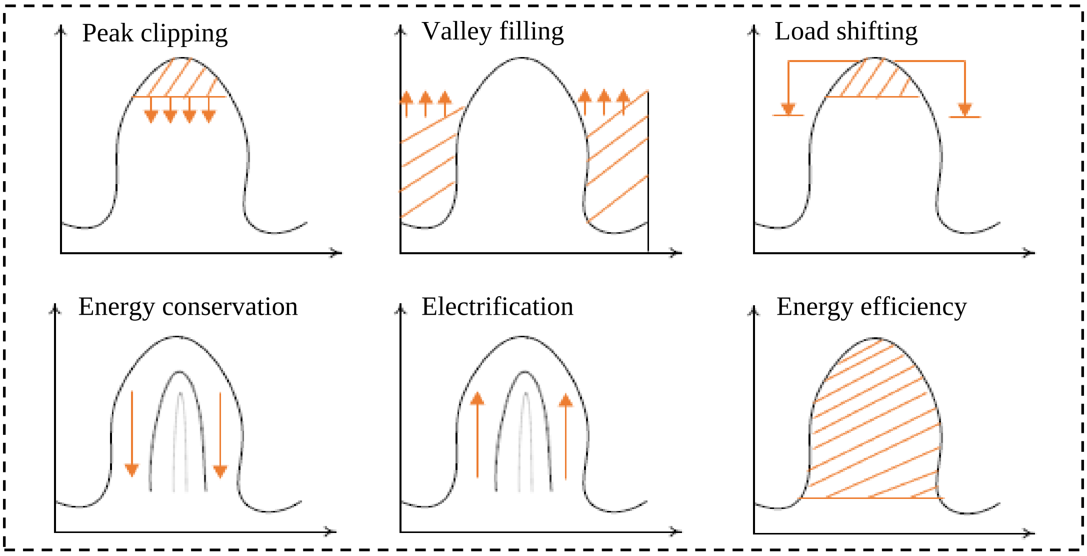


Fig.1. DSM's strategic planning

The conventional load management methods include peak clipping, valley filling, and load shifting. The DSM's energy efficiency strategies include strategic conservation, strategic load growth, and flexible load shaping [3]. However, in the literature, load shifting is the most commonly used approach for managing load using Demand Response (DR) [4].

The DR's primary objective is to influence electricity customers to alter their energy consumption habits in response to the present power prices signal. Usually, users benefit by relocating load demand from peak to off-peak hours, allowing the upstream main power grid to alleviate stress and lower the Peak to Average Ratio (PAR) [5]. The above techniques are mainly intended to persuade consumers to reduce their electricity use during peak hours and shift their load to off-peak hours, hence reducing electricity costs and PAR. The most of DSM solutions use DR programs to transfer the load in order to optimize the demand pattern. This encourages electricity users to adjust their load in accordance with the price tariff [6]. This could be accomplished through bidirectional communication, intelligent computing infrastructure, intelligent devices, and renewable energy sources. The systematic model of the SG is depicted in Fig. 2. However, implementing the SG and DSM into practice is challenging since the system must define and accomplish the objective on its own. The DSM must manage a huge number of controllable loads from various regions, including residential, commercial, and industrial areas, in order to deal with power outages.

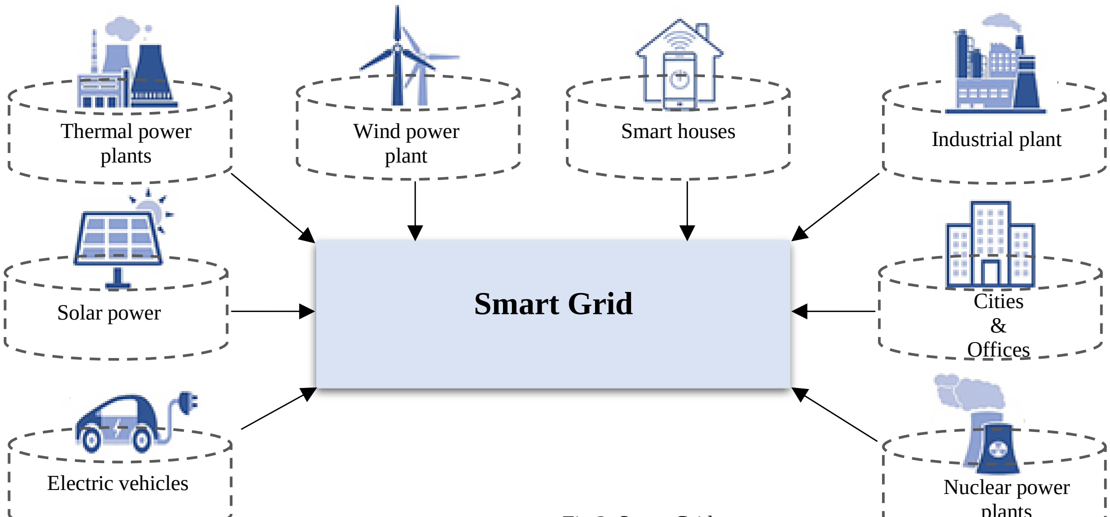


Fig.2. Smart Grid.

Established price signals include, day-ahead pricing, Real Time Pricing (RTP), Time of Use (TOU), hourly peak and Critical Peak Pricing (CPP), and non-critical peak pricing [7]. A flat rate tariff known as TOU pricing is a price that stays constant for a predetermined period of time. Typically, there are three peaks with different prices: off-peak, mid-peak, and high-peak. In the case of flat pricing, CPP is similar to TOU tariff signals. However, due to pressure events in the power system, the price for a certain time period may change. At the beginning of each time period, consumers are informed about the RTP pricing structure, and it is updated following each time period. This pricing's rate method is defined by the preceding time period's energy usage, generation, and consumer response. Since it is adjusted at the start of each hour, the RTP is a commonly examined pricing scheme [8].

In this paper, a new load shifting method is proposed. Moreover, coordination among the scheduled appliances enables for the avoidance of schedule deterioration produced by user uncertainty, such as forcing the start or stop of a scheduled appliance. A proposed Alternating Operation (AO) is used to load shifting, resulting in a full Home Energy Management System (HEMS) for a smart home. The HEMS's idea is to decrease the electricity price. The system's flexibility is enhanced by integrating coordination among appliances based on available space in order to achieve alternating operation. Users can reschedule appliances in real time without disrupting their entire day's schedules thanks to coordination. The choice of calls from urgent applications is respected after performing alternate operations.

The paper's main contributions are:

- Implementation of GA, BFA and Hybrid Bacterial Foraging and Genetic Algorithm (HBG) for load shifting.
- Comparison of the proposed techniques is established according to the electricity cost, electricity consumption and PAR.
- Alternating operation among appliances is considered to increase system flexibility and increase comfort.

The remainder of the paper is structured as follows: Related work is listed in Section 2. Section 3 describes the suggested system model and its components. Scheduling techniques and coordination with Alternating Operation among appliances are explained in Section 4. Section 5 describes results and discussion of both cases: coordination with Alternating Operation and without Alternating Operation. The conclusion and future work are listed in Section 6.

## 2. RELATED WORK

Many existing strategies for the scheduling of home load using various optimization techniques are investigated in the literature. Numerous approaches have been put forth and carried out with the intention of achieving Single Objective Optimization (SOO) or Multi Objective Optimization (MOO) with trade-offs between several desired objectives.

For Demand Side Management in Smart Buildings, Adia Khalid et al. [9] suggest Dynamic Coordination Among Home Appliances Using Multi-Objective Energy Optimization. The authors of this proposal present a fitness criterion for the proposed hybrid approach, which aids in load balancing during ON-peak and OFF-peak hours. The concept of home appliance coordination for real-time rescheduling is also presented by the authors. In [10], a system model is presented for integrating Renewable Energy Sources (RESs) and scheduling home appliances. To do this, the authors employ dynamic programming to schedule household appliances and Game Theory (GT) to sell excess energy to neighbors and utilities. In Ref. [11], the authors have proposed a novel Home Energy Management System (HEMS). The authors use the Genetic Algorithm (GA), CSA, and crow search techniques to control the load in a smart building with thirty homes. To reduce the PAR and consumers' bill, HEMS was proposed in Ref. [12], using heuristic optimization techniques for scheduling. Particle Swarm Optimization (PSO) and GA are applied for meeting the required requirements. The authors address the challenge as a multiple knapsack problem and employ three pricing tariffs: ToU, CPP, and RTP. An expert energy management system based on SSM is provided in Reference [13]. The authors schedule the different energy resources using the Bacterial Foraging Algorithm (BFA). The operational cost of energy resources and carbon emissions were decreased by their suggested solution, according to simulation results. Logenthiran et al. [14] consider residential, commercial, and industrial users. Using the Evolutionary Algorithm, the authors offer a solution to reduce PAR and electricity costs (EA). Simulation results show that the presence of a high number of devices has no impact on EA performance.

Muralitharan et al. [15] present a model that uses multi-objective EA to reduce costs and waiting time. A threshold limit is used to implement this strategy in order to balance the load and avoid peaks. If the consumer's load exceeds the utility's stated threshold limit, the consumer will be charged an additional fee. According to Ref [16], efficient household load is divided into two main categories: flexible and essential load. A home load management system is developed based on this categorization to reduce appliance costs and delays. The considered optimization problem is solved using a centralized solution built by adaptive dynamic programming. To deal with the uncertainties associated with customer behavior, Wang et al. [17] propose a Robust-Index Method (RIM). One of the main goals is to improve user comfort. This integration has assisted the scheduling system in achieving the possible best scheduled load. Ref [18] presents a DR program based on mixed-integer non-linear programming. The authors make use of the ToU pricing mechanism as well as the IDR program.

Nikolaos et al. [19] propose HEMS for optimal day-ahead controlled appliance scheduling in a dynamic pricing scenario, including distributed generation system. The suggested HEMS improves the amount of electricity needed to meet the load demands of the consumers. However, as the population, buildings, and industries grow, so does consumer demand. As a result, the utility is unable to meet the consumers' requirements. As a result, the utility must address the issue of load balancing and thresholds.

Efficiency includes more than just lowering demand during on-peak hours or cutting costs; additional considerations are also taken into account. Top of that, the flexibility of the scheduler can handle unexpected changes without affecting the required load or total cost. Scheduling modifications made by the user were addressed by researchers in [20]. However, requested adjustments are carried out during the course of the following day. Authors in [21] achieved rescheduling based on power demand. As a result, high priority appliances are turned on in accordance with user needs in real-time and switched to any other scheduled appliance during a different hour, which can result in peak on end hours due to static inputs for day-ahead scheduling.

The appliance's operation needs to be rescheduled with flexibility so that it doesn't produce peak demand or have a considerable impact on the overall cost and PAR in order to enable alternate operation in accordance with consumer requirements. In this study, we introduce home appliances alternating operation which is suitable for smart building.

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## 2. PROPOSED SYSTEM MODEL

Demand side management is the key element of the smart grid. The DSM confronts various challenges, including those related to fairness, security communication, load shifting, and privacy [22]. DSM aims to manage the load on the smart power system. For DSM to succeed in achieving its objectives, electricity users must take part in this program. The DSM techniques aim to regulate requirement between consumers and the electric network. At particular times, there is a higher demand for electricity, which requires more expensive additional electricity generation. In this direction, the strategy is efficient and powerful for HEMS, allowing customers to change their load from peak hours to off-peak hours in a fair manner.

A control, monitoring, and management unit make up the HEMS' overarching framework. The monitoring system keeps track of electricity production, price signals, and user power demand at any given moment. Home appliances are scheduled by the management unit, and the control unit selects which appliance to switch ON or OFF in accordance with the allocated working hours. Equitable coordination between the user and the system is necessary for effective use of the HEMS. In this way, the suggested system model focuses on an administrator who reports to the management unit. An administrative unit of management is responsible for handling user autonomy requests and programming electrical devices. This context is appropriate for this paper's objective. The purpose suggests a brand-new HEMS system variant called AO-HEMS. In this scenario, electrical device programming is based on Alternating Operation. Fig. 3 depicts an overview of the proposed system model and the data flow between the system's components. The proposed model demonstrates how information and energy are transferred between the service provider and the intelligent home. In order to assure the consistency of the power supply, the service provider enables the transfer of electricity from power producing facilities to transmission lines. Every smart home has an AO-HEMS, and the upstream utility sends the electricity price produced to the smart meter deployed in each one.

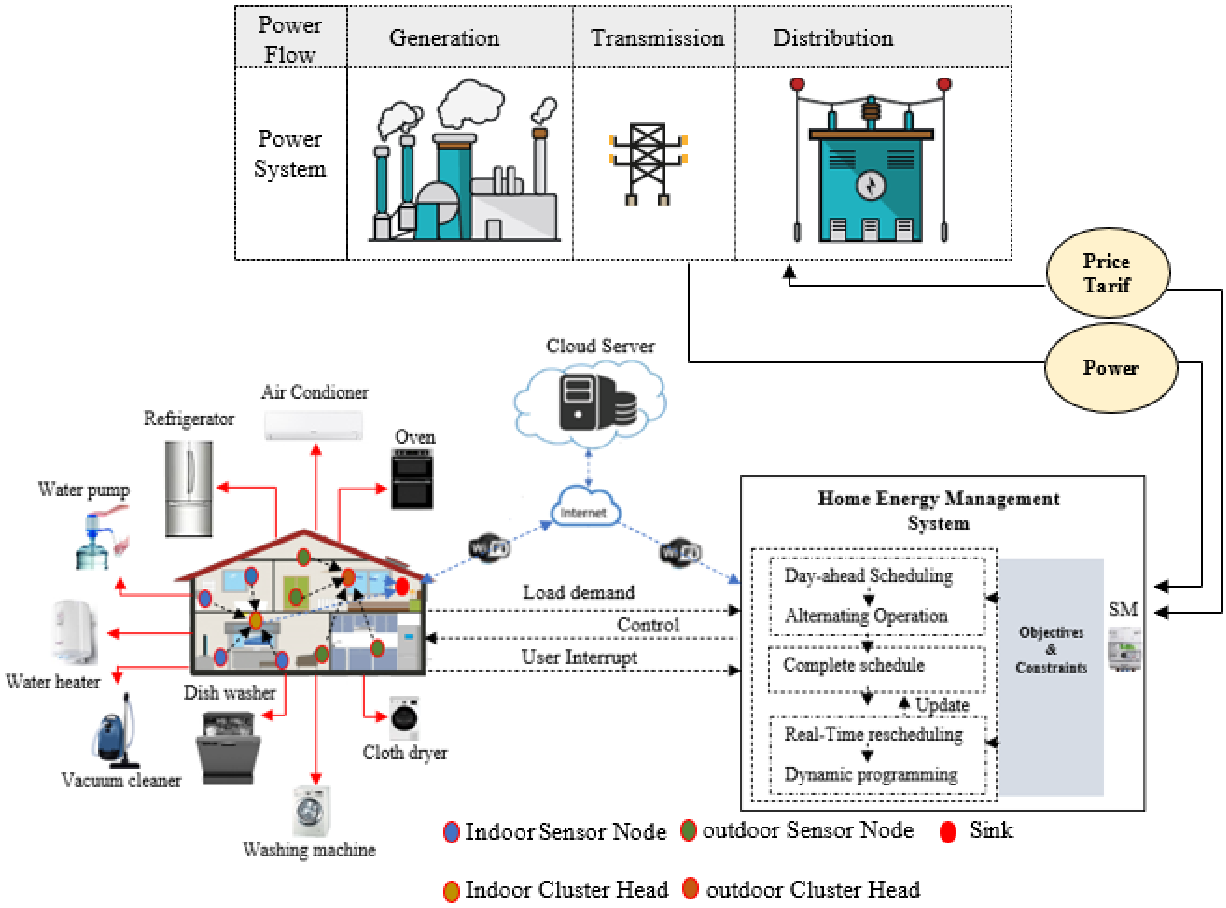


Fig. 3. Overview of the suggested control system and data flows between the service provider and the smart house user.

Streamlining scheduling appliances are divided into three different categories: Base Load Interruptible (BLI), Interruptible Burst Load (IBL) and Uninterruptible Burst Load (UBL). Every smart home has a WSN to control the operation of Base Load Interruptible appliances like air conditioner and refrigerator. Wireless sensor nodes are in charge of sensing the temperature and transmitting it to the sink node. The sensed temperature will be collected to a cloud server for high performance computing and remote the data storage. Remote controllable appliances operate when a predetermined threshold is reached. As depicted in Table1, the refrigerator should only be used for up to 18 hours at the recommended temperature. The air conditioner should only run for 15 hours at the required temperature.

The smart meter enables information exchange between the utility and the customer. Additionally, a smart meter is composed of a variety of components, including an embedded computing platform. The embedded computing platform schedules the smart meter's activities. Furthermore, the suggested optimization method for AO-HEMS uses meta-heuristics and dynamic programming to schedule a consumer's load demand in real-time and on a day-ahead basis. Dynamic programming is used to enable real-time scheduling, allowing the user and scheduler to cooperate together when the user creates an interruption still respecting the alternating operation.

The proposed framework's major goal is load shifting, which will reduce both the PAR and the electricity cost. During load shifting, the load curve should resemble the objective load curve as closely as possible. According to the proposal, if decreasing electricity costs is the main aim, the objective load curve should be inversely related to electricity costs. In our scenario, the fitness function's established constraints provide the basis of the targeted objective load curve, as shown in Equation 4a. Real-time scheduling is the second main objective of our proposed methodology. This will improve the system's adaptability, which will eventually benefit consumers' comfort.

## 3. PROBLEM FORMULATION

The proposed AO-HEMS adjusts the load using real-time and day-ahead scheduling. We focus on reaching a number of goals while taking into account both scheduling strategies. The day-ahead objective involves minimizing the cost of power, PAR, and the difference between the objective load curve and the actual pattern of energy consumption.

Table 1 provides an overview of the notations used in the manuscript to analyze the relevant parameters.

Table 1. Summary of the used notations.

| Notation | Meaning |
|---|---|
| $\breve{I}$ | User interrupt |
| $App$ | Appliance |
| $App^{d}_{D_h}$ | User requested a particular appliance within an hour. |
| $App^{d}_{DS_h}$ | Scheduled hour for a specific appliance |
| $App^{d}_{w_t}$ | Appliance waiting time |
| $App^{d}$ | a specific appliance |
| $\mathrm{App}^{on}$ | Application in on state |
| $\mathrm{App}^{off}$ | Application in off state |
| $App^{\alpha_i}_{c}$ | Rescheduled appliances list. |
| $App^{\alpha_i}$ | Appliance rescheduled from $App^{\alpha_i}_{c}$ |
| $App^{d}_{p_{rate}}$ | Appliance power rate d |
| $E^{sch^{hour}}_{load}$ | Scheduled load for specific hour |
| $E^{hour}_{price}$ | Hourly cost of electricity |
| $E^{i\in PoP}_{load}$ | Load of population |
| $E^{total}_{cost}$ | Day's amount of cost |
| $(E^{hour}_{cost}$ | Cost of a day per hour |
| $E^{sch^{N}}_{load}$ | Scheduled electrical loads per hour |
| $E^{unsch}_{load}$ | A list of the day's unscheduled electricity loads |
| $F_f$ | Fitness function |
| $F_{PoP}$ | Fitness of population |
| $Obj^{hour}_{l_{curve}}$ | Per hour objective load |
| Sch | Complete schedule of 24 hours |

### 3.1. The Load shifting

The proposed methodology schedules the appliances in a manner which brings the objective load curve closer to the consumption schedule load curve. The load shifting algorithm is defined by [23]:

$$O_1 = \min\left(E^{sch^{hour}}_{load} - Obj^{hour}_{l_{curve}}\right) \tag{1}$$

The price of the electrical market's $E^{hour}_{price}$ must be inversely proportional to the objective load curve $Obj^{hour}_{l_{curve}}$, which is determined by:

$$Obj^{hour}_{l_{curve}} \propto \frac{1}{E^{sch^{hour}}_{price}} \tag{2}$$

Where, $E^{sch^{hour}}_{price}$ is the scheduled electric power load per hour calculated by Eq. 3.

$$E_{load} = \begin{cases} \sum_{d=1}^{M} App^{d}_{P_{rate}}, & if\ \mathrm{App}^{on} \\ 0, & if\ \mathrm{App}^{off} \end{cases} \tag{3}$$

Where, $E_{load}$ is the total load of appliances that are ON status at any particular time.

The constraints in the Fitness Function ($F_f$) indicated in Eq.4 are used to obtain the intended $Obj^{hour}_{l_{curve}}$ mentioned above. In order to avoid the peak during off-peak hours, this defined function $F_f$ selects the fittest individual from the given population *PoP* in order to find the best solution from the search space.

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$$F_f = \min(F_{PoP}) \tag{4}$$

Where, the $F_{PoP}$ is defined by Eq.5,

$$F_{PoP} = \begin{cases} E_{load}^{i \in PoP} \geq P_{l_1}, & if\ H_p^{off} \\ E_{load}^{i \in PoP} > P_{l_2} \wedge E_{load}^{i \in PoP} < P_{l_3}, & if\ H_p^{on} \end{cases} \tag{5}$$

$$P_{l_1} = sum(load_N^h) - std(E_{load}^{unsch}) \tag{5a}$$

$$P_{l_2} = std(E_{load}^{unsch}) + \eta \times min(E_{load}^{unsch}) \tag{5b}$$

$$P_{l_3} = min(E_{load}^{unsch}) \tag{5c}$$

$$load_N^h = \frac{E_{load}^{unsch}(h) - min(E_{load}^{unsch})}{max(E_{load}^{unsch}) - min(E_{load}^{unsch})} \tag{5d}$$

Where, the value of $\eta$ is selected so that the minimum load limit for on-peak hours should be lower than the minimum limit for off-peak hours. In our scenario $\eta = 2$. $P_{l_1}$ is the off-peak power limit and $P_{l_2}$ is the on-peak power limit, $E_{load}^{unsch}$ is the load computed for a single population using the solution space defined by Eq. 3, $H_p^{on}$ is the On-Peak hour, which is higher than the Electric Price List mean $E_{price}$, and $H_p^{off}$ is the Off-Peak hour, which is equal or less than the Price List mean. The $load_N^h$ has been normalized for uniform distribution $\forall\ h \in \{1, 2, 3, \ldots..24\}$.

### 3.2. Reducing electricity cost

The second objective is to decrease the electricity cost, which can be expressed quantitatively as follows:

$$O_2 = \min(E_{cost}^{total}) \tag{6}$$

The objective load curve below minimizes the cost of electricity, so $O_1$ from Eq. 1 is used as a restriction in this scenario.

$$E_{cost}^{total} = \sum_{hour=1}^{24} (E_{cost}^{hour}) \tag{7}$$

where the cost of a $E_{cost}^{hour}$ per hour is determined using Eq.8.

$$E_{cost}^{hour} = \begin{cases} \sum_{d=1}^{M} E_{price}^{hour} \times App_{prate}^{d}, & if\ \text{App}^{on} \\ 0, & if\ \text{App}^{off} \end{cases} \tag{8}$$

Each appliance's $App_{prate}^{d}$ is listed in Table 2.

Table2. Appliances used during simulations.

| Group | | Appliances | | Power Rating (kWh) | Daily Usage (hours) |
|---|---|---|---|---|---|
| 1 | Base Load Interruptible (BLI) | Remote controllable appliances | Refrigerator | 0.27 | ≤18 According to RT |
| | | | Air Conditioner | 1 | ≤15 According to RT |
| | | Oven | | 1.8 | 7 |
| 2 | Interruptible Burst Load (IBL) | Vacuum cleaner | | 0.225 | 6 |
| | | Water heater | | 2.15 | 8 |
| | | Water pump | | 5 | 8 |
| | | Dish washer | | 1.5 | 8 |
| 3 | Uninterruptible Burst Load (UBL) | Washing machine | | 0.7 | |
| | | Cloth dryer | | 5 | 4 |

### 3.3. PAR improvement

Maintaining the grid's stability is one of the main goals, which is accomplished by minimizing the PAR which can be represented mathematically as follows:

$$O_3 = \min(PAR) \tag{9}$$

This is carried out using Eq.1 automatically. The PAR may be expressed formally as follows:

$$\text{PAR} = \frac{max\left(E_{load}^{sch^N}\right)^2}{(avg\left(E_{load}^{sch^N}\right))^2} \tag{10}$$

Where $E_{load}^{sch^N}$ represents a list of the scheduled electrical loads per hour determined by Eq. 3, $\forall\ N \in \{1, 2, 3, \ldots..24\}$.

### 3.4. User comfort enhancement

Customers need some flexibility when scheduling their home appliances in order to be able to turn one appliance off and request to reschedule any other appliance in accordance with their needs. Each group's alternate operation must be respected as the rescheduling is done using the AO-HEMS technique. The user's wait time to turn ON the required appliance is somehow reduced by this rescheduling. Regardless of the user's previous demand time, an appliance's waiting time is considered zero when it is rescheduled on demand. The purpose of the technique is integrated in this framework. The aim and objective, which focuses on improving consumer comfort, can be computed by:

$$O_4 = \max(confort) \quad (11)$$

Whereas comfort is accomplished by including coordination between the scheduler and the user through an intelligent monitoring system, when the scheduler receives an interruption from the user to turn off an appliance and a request for real-time rescheduling from the $App^{\alpha_i}$, this can be defined as follows:

$$App^{\alpha_i} = \begin{cases} 1, & if\ \breve{I} \\ 0, & \text{otherwise} \end{cases} \quad (12)$$

The user's comfort and waiting time $App_{w_t}^{d}$ have an inverse relationship that can be represented mathematically as follows:

$$Confort \propto \frac{1}{App_{w_t}^{d}} \quad (13)$$

Where $App_{w_t}^{d}$ represents the waiting time for a specific appliance d, the formula is:

$$App_{w_t}^{d} = \min\left|App_{D_h}^{d} - App_{DS_h}^{d}\right| \quad (14)$$

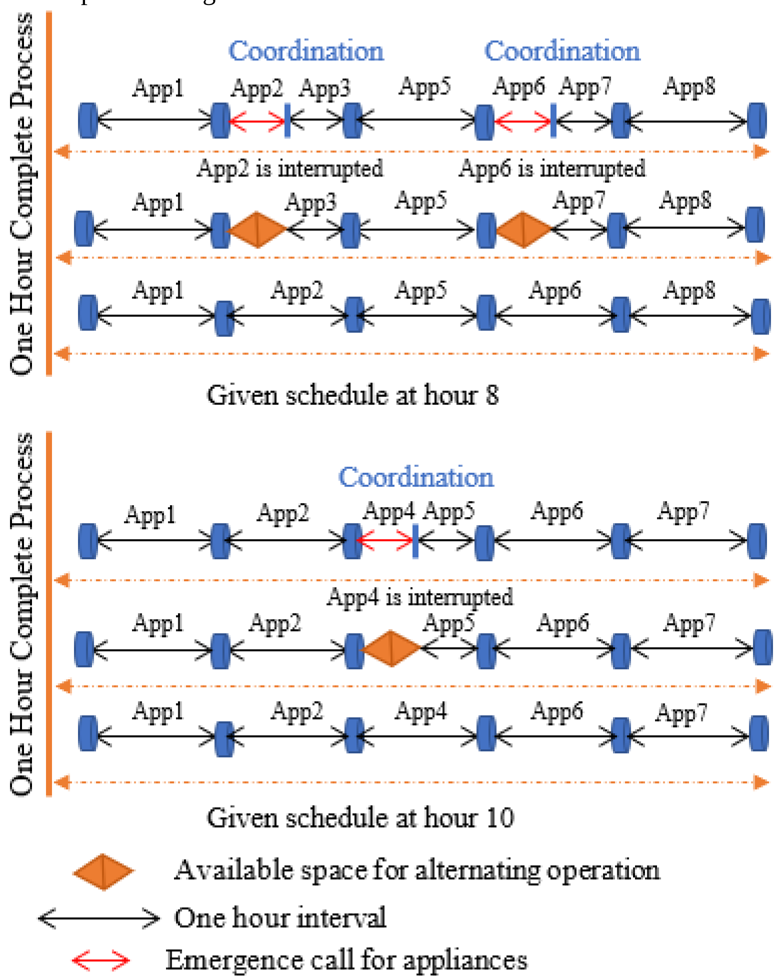
Two distinct algorithms are included in the suggested house pregnancy administration scheduling, and they are as follows:

(i) *Day-ahead scheduling*.

The proposed paper primary objective is to integrate scheduling and promote coordination between consumers and schedulers. To achieve and enhance the coordination, IoT home automation was used to connect with the smart home information technology systems. Through two-way communication between consumers and schedulers, the IoT smart grid offers scheduling flexibility. The sensor devices are connected to the internet and communicate with each other using wireless communication to sense the temperature in the smart house. The sink node collects temperature from the sensors nodes and sends the fused information to the cloud server. Using the proposed approach, we will continuously monitor the temperature remotely. Since, in the summer, the basic elements of a smart house are a refrigerator and an air conditioner, the process of rescheduling is dependent on the temperature data collected from different sensor nodes. The sensed data will be remotely gathered and stored on a cloud server for high performance computing. In this scenario, the sensed temperature must be transmitted periodically to the local server in a short time period. Furthermore, the proposed work is characterized by giving consumers the flexibility to reschedule specialized devices at any time through operating while respecting alternating operation.

*(ii) Real-time scheduling.*

Scheduling electrical devices during operating hours is a challenging task. The user's comfort must be taken into account while converting an apparatus's working hours. Furthermore, peak hours, beyond, and the electricity cost are not considered. The coordination between devices is depicted in Fig. 4.



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The scheduler receives a list of the devices that the user wants to reschedule. Rescheduling electrical devices is a challenging problem, therefore it can be compared to a backpack problem, where the available time corresponds to backpack capacity. As depicted in Fig.5, the objective is to select a collection of items with the highest possible profit overall while staying within the limits of each knapsack's capacity.

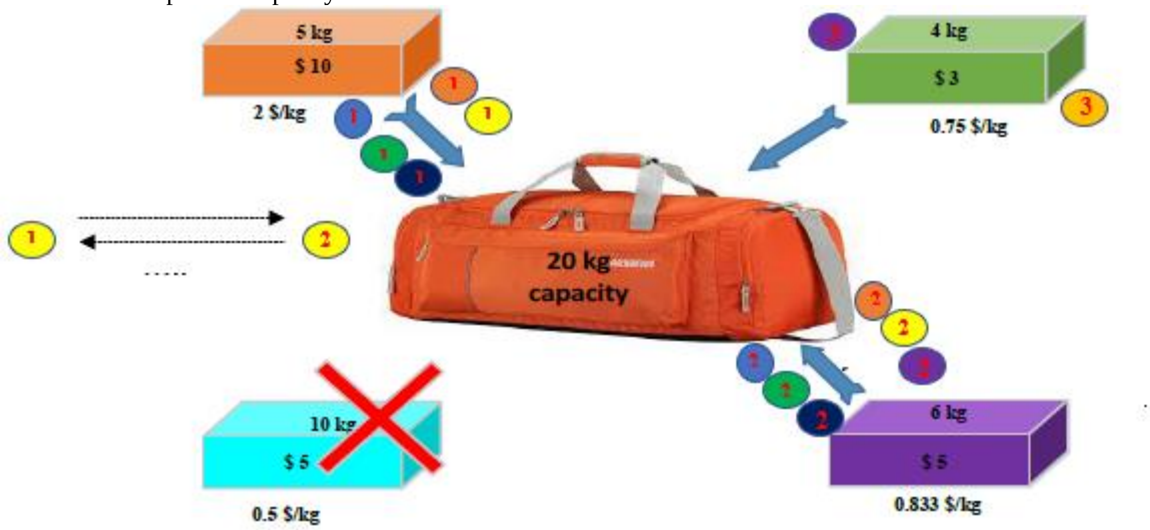


Fig.5. The multiple knapsack problem (MKP) formulation.

## 3. THE PROPOSED TECHNIQUE

Our research attempts to integrate scheduling and enhance coordination between a user and the scheduler. The best solution is selected to depend on Eq.4 from the search space submitted by Hybrid Bacterial Foraging and Genetic algorithm (HBG), genetic algorithm (GA) and Bacterial Foraging Algorithm (BFA) algorithms. Fig.6 shows the schematic flowchart of the proposed technique. Since appliances like air conditioners and refrigerators use a lot of energy, it is critical to set up a method for reducing energy consumption in buildings by controlling the temperature to provide comfort. In our case study, we were considering an IoT system that could control the room temperature. For the system model, the sensor nodes are organized into clusters. Both indoor and outdoor sensor nodes make up the network's two main sections. The inside sensors enable measurement of the indoor temperature. Indoor sensors are employed to determine the outdoor temperature. The sink node collects the indoor temperature and outdoor temperature via Cluster heads installed inside and outside to compare the temperatures and sends the fused information to be processed. For high performance computing and remote data storage, the sensed information will be collected and sent to a cloud server through the smart meter. In this scenario, the sensed data need to be transmitted periodically to the local server in a short time period. Additionally, the suggested strategy based on intelligent systems provides the capability of remotely controlling the home's temperature system, enhancing communication between a user and the scheduler.

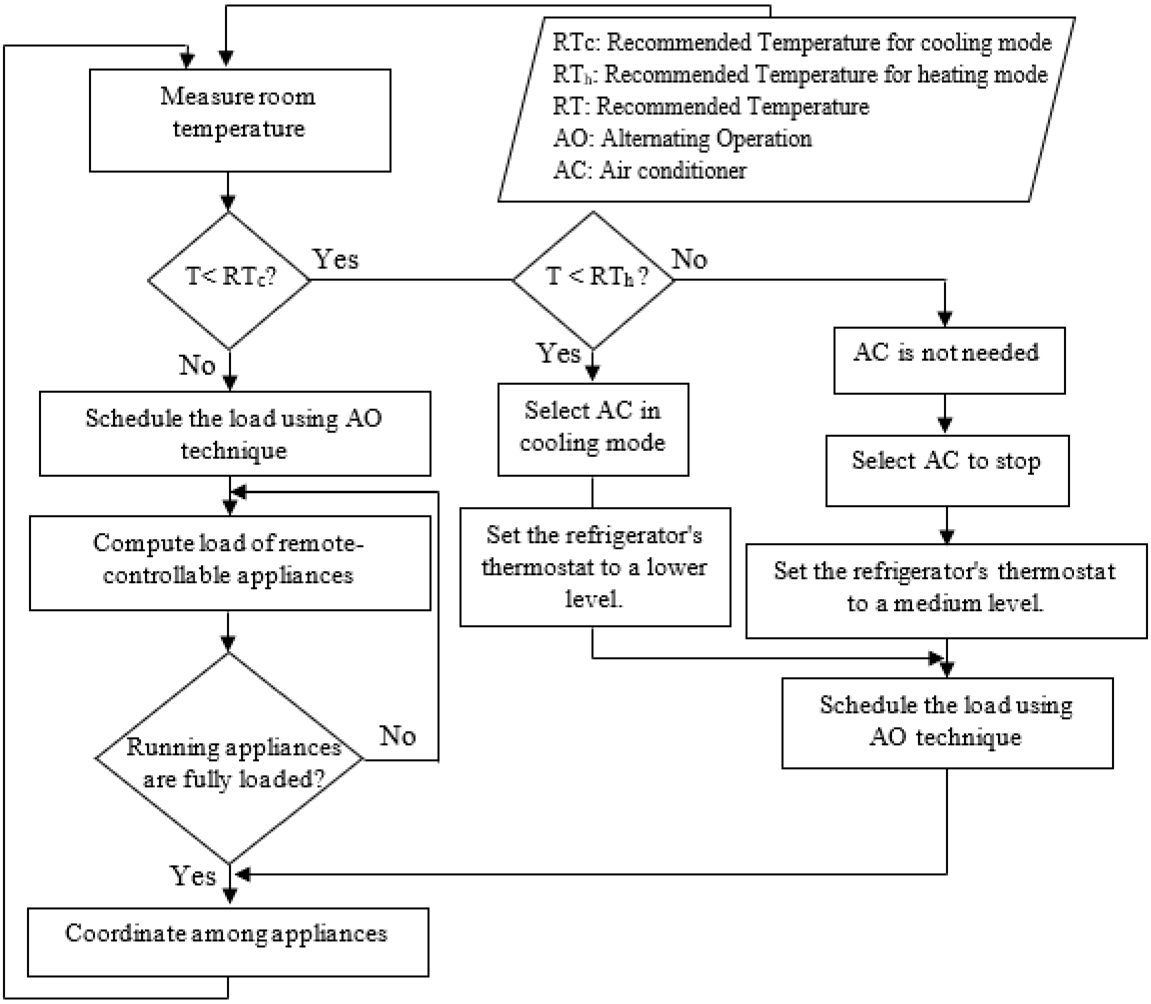


Fig.6. Schematic flowchart of the proposed technique

## 4. SIMULATION PARAMETERS

In this section, the effectiveness of the proposed system is evaluated using MATLAB simulations. Results have been generated using HBG, GA, and BFA without and with Alternating Operation for the considered pricing tariffs in order to evaluate these efficacies of the three algorithms in smart homes. We are considering a single home with nine appliances that requires scheduling. As depicted in Table1, considered appliances are divided into three categories: group 1, group 2, and group 3, including remote controllable appliances being a subcategory of group 1. Due to their frequent use throughout the year, remote controllable appliances are monitored continuously. The devices must be operated alternately in each group. In consideration of alternate operation, devices may be turned on at any time during the day. However, any appliance could be turned off at any time by the user.

In this propose, due to the shortest working hours and ability to be called in 6 to 8 times per day, the vacuum cleaner and dish washing are chosen for rescheduling in order to incorporate coordination. The user should specify the operational time for a particular time slot before scheduling; for simulations, the operational time is assigned alternatively. In this scenario, the maximum available time interval is the knapsack weight capacity which is computed as follows:
$Time_{aval} = 60\text{-}interp_{t,}$ where *Interpt* is the time when a user requests to turn ON an appliance while requesting the rescheduling of another. The available working time-slot of an appliance in the list $\alpha_i$ is the item's knapsack weight. Where the value of the item is the cost during a particular interrupted hour defined by Eq 8. Table 2 lists the power rating of each appliance and daily usage.

Three price tariffs are used to evaluate the performance of the proposed system, as was previously discussed. The considered pricing tariffs are RTP, TOU and CPP. There are three time zones in the price tariff: On-peak 11:00am-4:00pm, MID-peak 7:00am-10:00am and 5:00pm-6:00pm, and Off-peak 1:00am-6:00am and 7:00pm-12:00pm. According to the CPP rate taken from [24], the pricing tariff has 11:00am-4:00pm on-peak hours and 1:00am-10:00am and 5:00pm-12:00pm off-peak hours. Only On-peak and Off-peak hours are taken into consideration when running simulations for the TOU tariff. whereas on-peak hours are considered as shoulder or MID-peak hours

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**4.1. RTP**

In [25], RTP is the rate of dynamic price which is determined by the amount of electricity consumed per hour. Electric utilities regulate the RTP in two ways, and the overall price is the sum of these two parts:

(i) Depending on Client Baseline Load (CBL), the base bill is determined using the standard specified tariff for a specific customer.

(ii) Hourly prices are determined by consumer usage, which is the difference between actual and CBL usage. Regardless of the chosen price strategy, each user is must pay a $wQ_*$specified amount per hour.

When a consumer selects a pricing structure like RTP, it implies that they are saving $(P_h - W_s)\Delta Q_h$, where $P_h$ is the requested energy rate by the applicant, $Q_h$ is the electricity unit. The market price and the charges of a standard energy tariff, $W_s$, are used to determine the RTP energy rate $P_{RTP}$ listed in Eq 15. The RTP standard specifies when the energy rate is $P_L$ and the consumer wants to increase their electricity usage above the level $Q_L$.

$$P_{RTP} = \begin{cases} wQ_* & if\ E_{load} \leq Q_*, \\ wQ_* + P_L & otherwise. \end{cases} \quad (15)$$

**4.2.TOU**

The TOU refers to the time-based pricing concept. Prices for the peak and off-peak hours are determined by [26]. Where a day is divided into different blocks, and the price for each block remaining fixed. The total amount of savings shared by the customer and the Local Distribution Company (LDC) is represented by the $D_{TOU}$. Shifting a maximum load demand and the overall cost ζ savings fraction that LDC passes results in a cost reduction ($\sigma_0$ - $\sigma_1$) for the system.

$$D_{TOU} = \zeta\,(\sigma_0 - \sigma_1)\, Q_{TOU} \quad (16)$$

**4.3. CPP**

Critical events may actually occur at a specific time when utilities detect an increase in the market price or when a system emergency, which typically happens in hot weather, occurs. In general, electricity prices rise during this time.

## 5. SIMULATION RESULTS AND DISCUSSION

Two subsections are used to analyze the simulation results: Scheduling's effect on electric load, electricity cost and PAR after coordination without and with alternating operation.

**5.1. Results after coordination without alternate operation**

Figs. 6, 8, 10(a), and 11(a) show the simulation results after coordination without alternating operation. The electricity load for 24 hours is revealed in Fig. 7. As seen in Fig. 7, the load shifting made possible by the adopted optimization methodologies has a direct impact on the price. For high peak hours, BFA displays comparatively low-price signals. It's also important to note that the scheduled load curve and the objective load curve are is almost nearby.

Fig. 9 (a) shows the electricity cost per hour during a day after coordination without alternating operation. The results demonstrate that on-peak cost is less expensive than off-peak cost for scheduled load. Using RTP, the unscheduled, GA, BFA, and HBG algorithms have the rate of 1830, 1620, 1420, and 1630 cents, respectively. Considering the TOU pricing tariff, for the unscheduled, GA, BFA, and HBG algorithms these values are 1820, 1550, 1400, and 1540 cents respectively. GA, BFA, and HBG algorithms reduce the cost by 38%, 44.8% and 39 % over the unscheduled CPP respectively. Therefore, BFA is better than the other considered algorithms in terms of electricity cost.

The trade-off between the price and the PAR is depicted in Table 3. The CPP signal has reduced the cost by 44.8% for BFA, where it has a PAR 2.73 which is 70.8% less as compared to unscheduled PAR. Since reducing the cost of electricity is one of the main keys for smart home applications the BFA performs better as it provides a significant cost savings in additional to PAR, compared to the other two techniques.

Table 3. Scheduling methods' performance trade-offs following coordination without alternating operation.

| Techniques | Tarif | Electricity cost decreasing (%) | PAR reduction (%) |
|---|---|---|---|
| | RTP | 11.47 (Fig.10(a)) | 75 (Fig.11(a)) |
| GA | TOU | 14.83 (Fig.10(a)) | 71.85 (Fig.11(a)) |
| | CPP | 39 (Fig.10(a)) | 73.79 (Fig.11(a)) |
| | RTP | 22.4 (Fig.10(a)) | 68.91 (Fig.11(a)) |
| BFA | TOU | 23 (Fig.10(a)) | 65.25 (Fig.11(a)) |
| | CPP | 44.8 (Fig.10(a)) | 70.8 (Fig.11(a)) |
| | RTP | 10.92 (Fig.10(a)) | 74.74 (Fig.11(a)) |
| HBG | TOU | 15.38 (Fig.10(a)) | 65.25 (Fig.11(a)) |
| | CPP | 40 (Fig.10(a)) | 70.8 (Fig.11(a)) |

**5.2. Results after coordination with alternate operation**

The suggested work uses a variety of coordination loads according to the manner of the random consumer. As illustrated in Figs 7 and 8, the interconnectivity between the curves of the objective load and the curves of the scheduled load was unaffected by any modifications made through coordination with alternating operations. Fig. 7 shows that the electricity cost is fairly low during On-peak hours. Fig. 7 depicts the grid load for a single home over period of a day using three different pricing tariffs. This shift in load from peak to off-peak hours reflects the impact on total cost as shown in Fig. 11 (b) and on PAR as shown in Fig. 12 (b).

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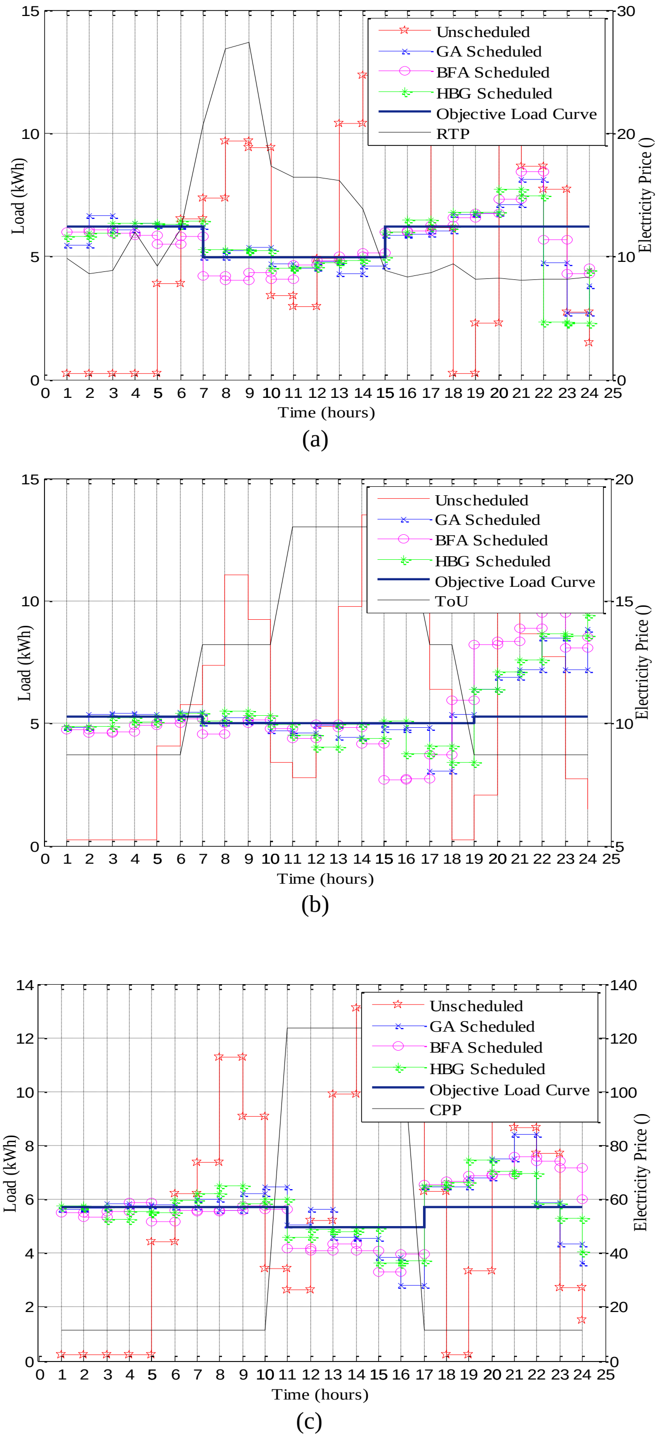


Fig.7. Electricity load profile. (a) RTP, (b) TOU, (c) CPP: Coordination without Alternate Operation

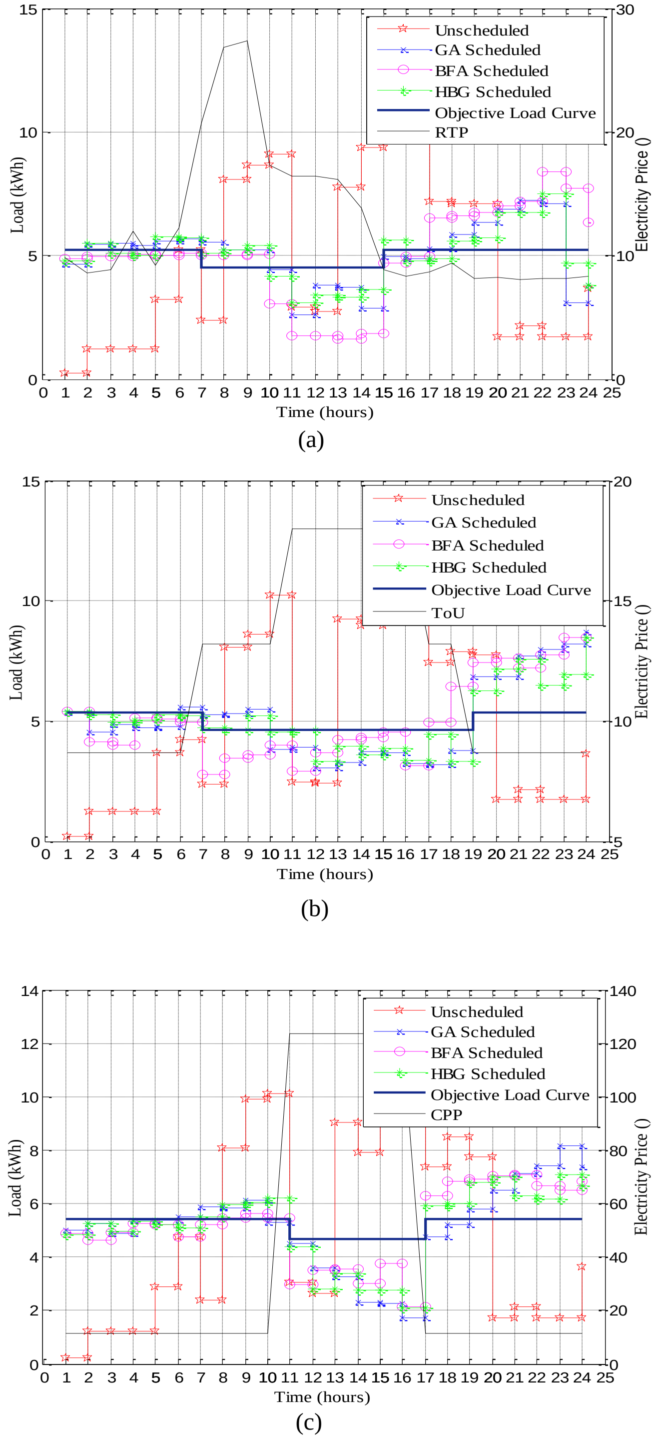


Fig.8. Electricity load profile. (a) RTP, (b) TOU, (c) CPP: Coordination with Alternate Operation

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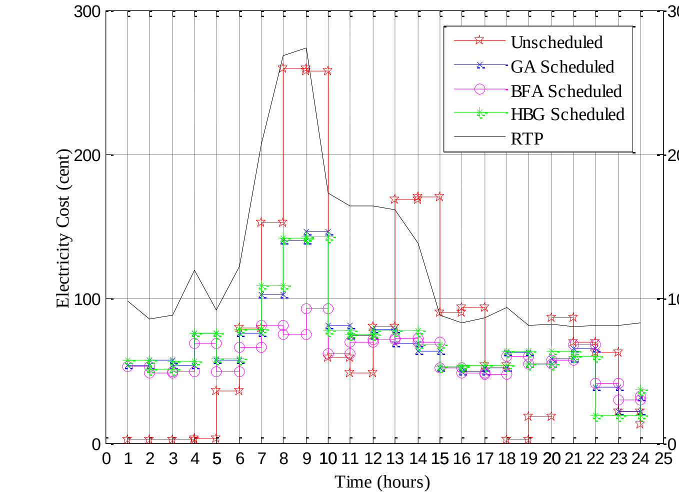
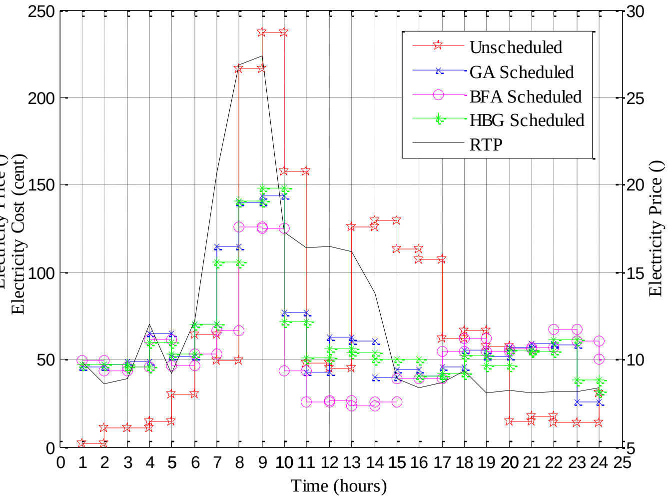
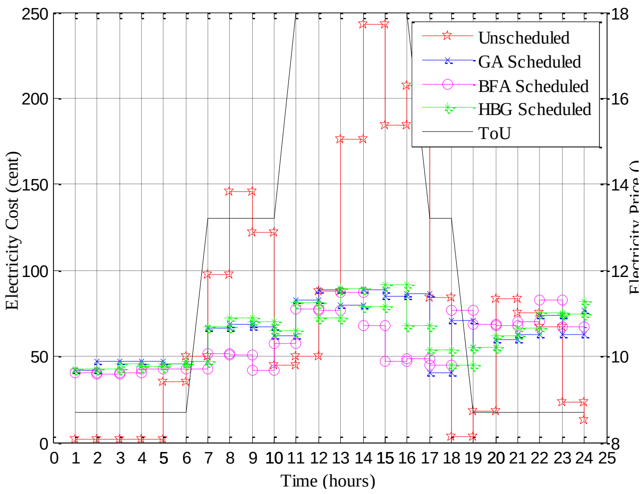
Fig. 11 (a) evidently revealed 8.6%, 1.4% and 9.8% less cost than the without alternating operation scheduled for GA, BFA and HBG, respectively, using RTP. Using coordination with alternating operation, the electricity cost is improved by 24%, 13%, and 23.28% for GA, BFA and HBG, respectively regarding CPP. This improvement is matched by an increase in PAR as shown in Fig. 12 (a). The global graphs clearly show the difference between coordination both with and without alternating operation of operation due to the decrease in the total charge requested and the decrease in the point charge. During coordination, the load is reduced which reduces costs, but the PAR increases because sometimes it passes heavy load appliances and remote controllable appliances, demonstrating the tradeoff between cost and PAR.




(a)




(a)

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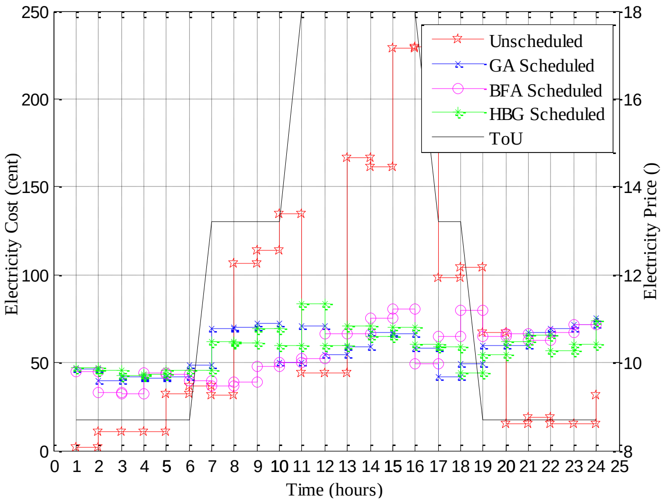


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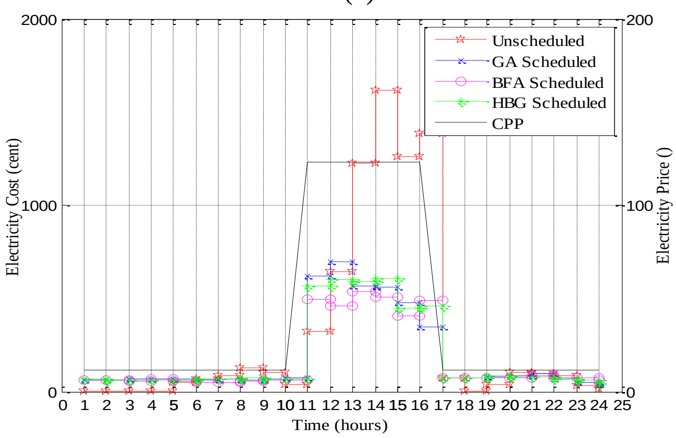
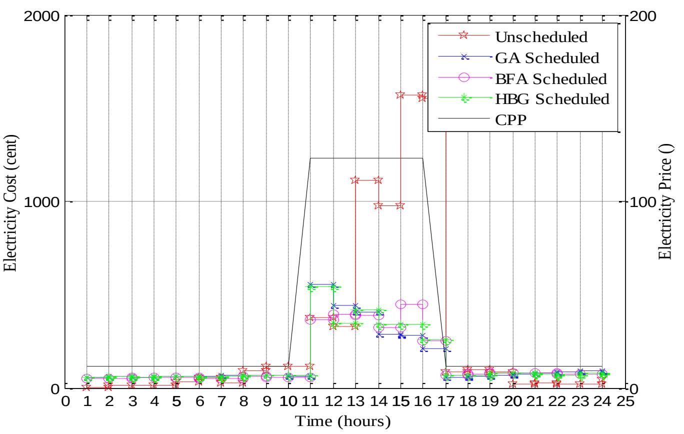



(c)

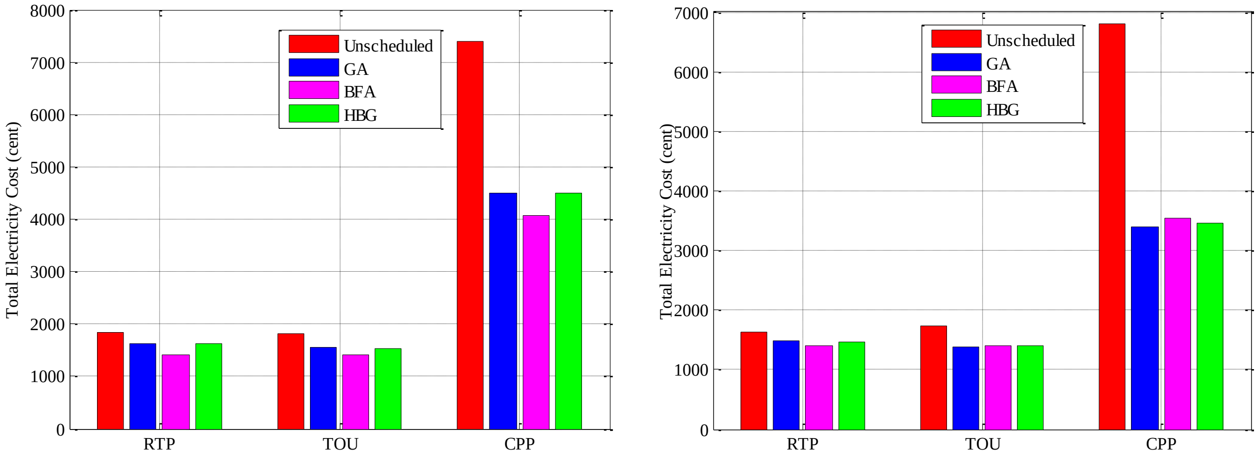



(c)

Fig. 9. Price signals for the daily cost of electricity per hour. (a) RTP, (b) TOU, (c) CPP: Coordination without Alternating Operation

Fig. 10. Price signals for the daily cost of electricity per hour. (a) RTP, (b) TOU, (c) CPP: Coordination without Alternating Operation

The waiting times for appliances are depicted in Figs. 13 and 14. It is envisioned that waiting times with alternating operations will be less than those without alternating operations when using the HBG algorithm for different tariffs taken into consideration. This effect is clearly seen with interruptible load. The waiting time for appliances that can be controlled remotely depends on the control system.



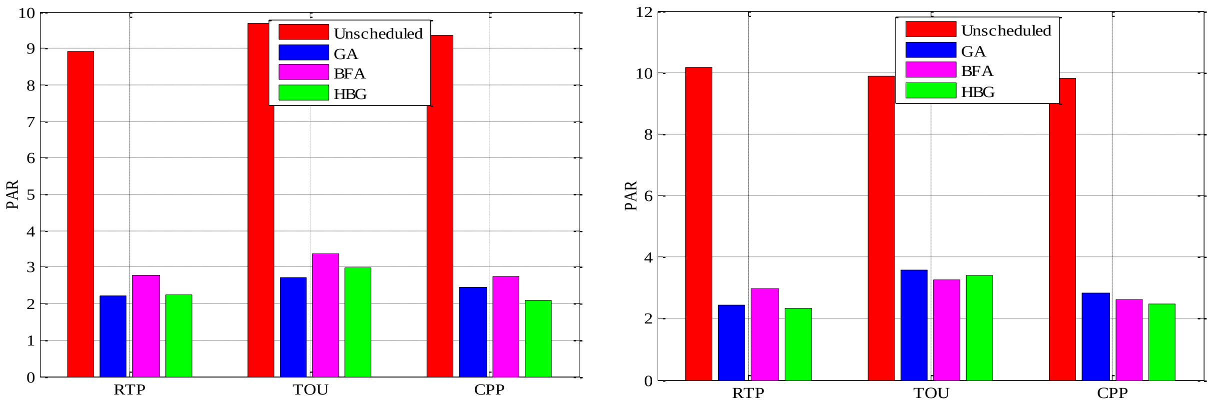

(a) (b)

Fig.11. Total electricity cost: (a) Coordination without Alternating Operation; (b) Coordination with Alternating Operation

Results show that a specified $F_f$ not only decreased the electricity cost as well as PAR during day-ahead scheduling, preventing real-time rescheduling. Furthermore, the results show a trade-off between many performance factors, including comfort, electricity cost, and PAR. Additionally, in order to improve user comfort, our suggested strategy uses a smart system to enable coordination between scheduler and user. The impact of coordination with alternating operation on electricity cost, PAR, and waiting time is presented in Table 4.

Table 4. Coordination with alternating operation effects on different performance parameters.

| Technique | Tarif | Electricity cost | PAR | Waiting Time |
|---|---|---|---|---|
| | RTP | 8.64% **decrease** | 9.9% increase | 13.95% **decrease** |
| GA | TOU | 10.32% decrease | 30.76% increase | 2.51% increase |
| | CPP | 24.44% **decrease** | 15.91% increase | 30.11% **decrease** |
| | RTP | 1.4% decrease | 6.85% increase | 93% increase |
| BFA | TOU | - | 2.96% decrease | 5.66% increase |
| | CPP | 12.99% **decrease** | 4.39% **decrease** | 12.91% increase |
| | RTP | 9.5% **decrease** | 3.55% increase | 26.82% **decrease** |
| HBG | TOU | 8.44% **decrease** | 13.66% increase | 15.91% **decrease** |
| | CPP | 23.28% decrease | 18.66% increase | 7.5% increase |




(a) (b)

Fig.12. PAR for all adopted and proposed strategies: (a) Coordination without Alternating Operation; (b) Coordination with Alternating Operation

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These results suggest that, for all pricing schemes, the electricity cost is reduced. PAR and waiting time alternates between decreasing and increasing. In the case, the before and after waiting time difference is only assessed for base load interruptible appliances. In order to assess the effectiveness of the strategies under consideration, we considered a technique to be effective when it achieved at least two objectives.

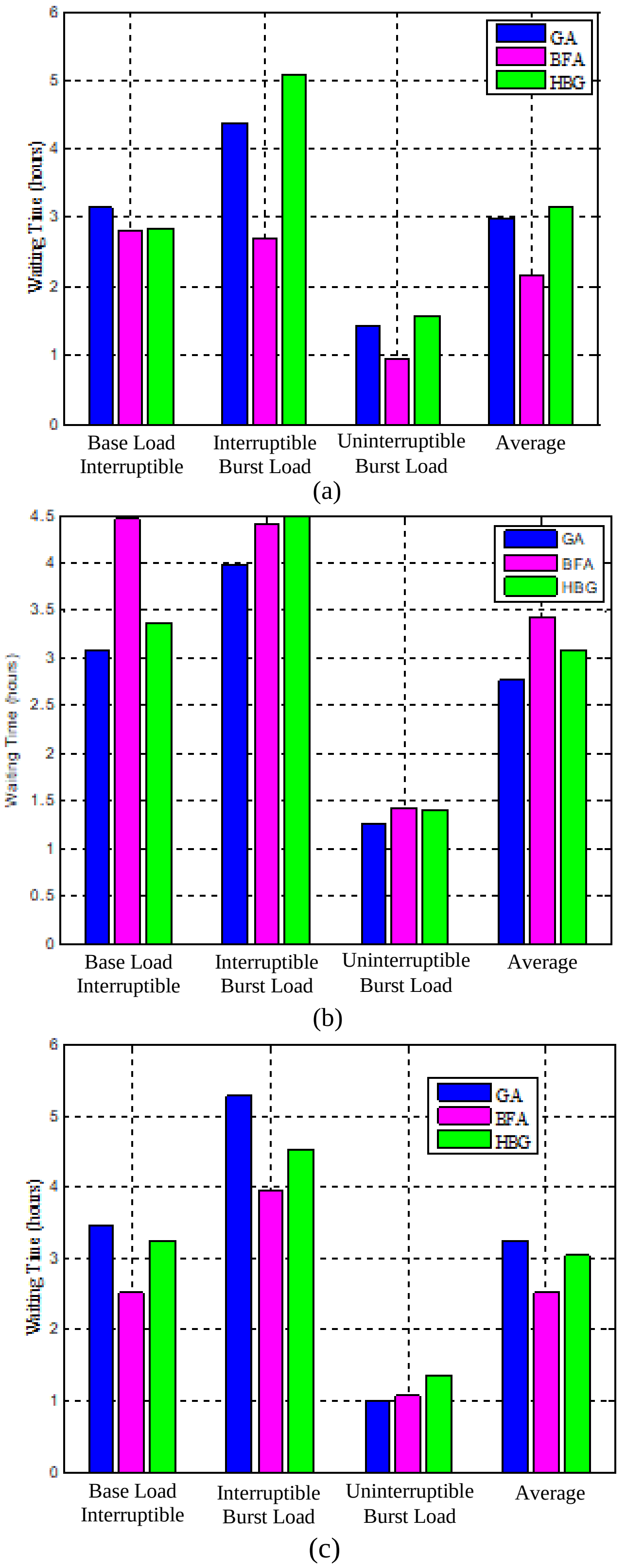


Fig.13. Average appliances waiting time according to categorization: (a) RTP. (b) TOU. (c) CPP.

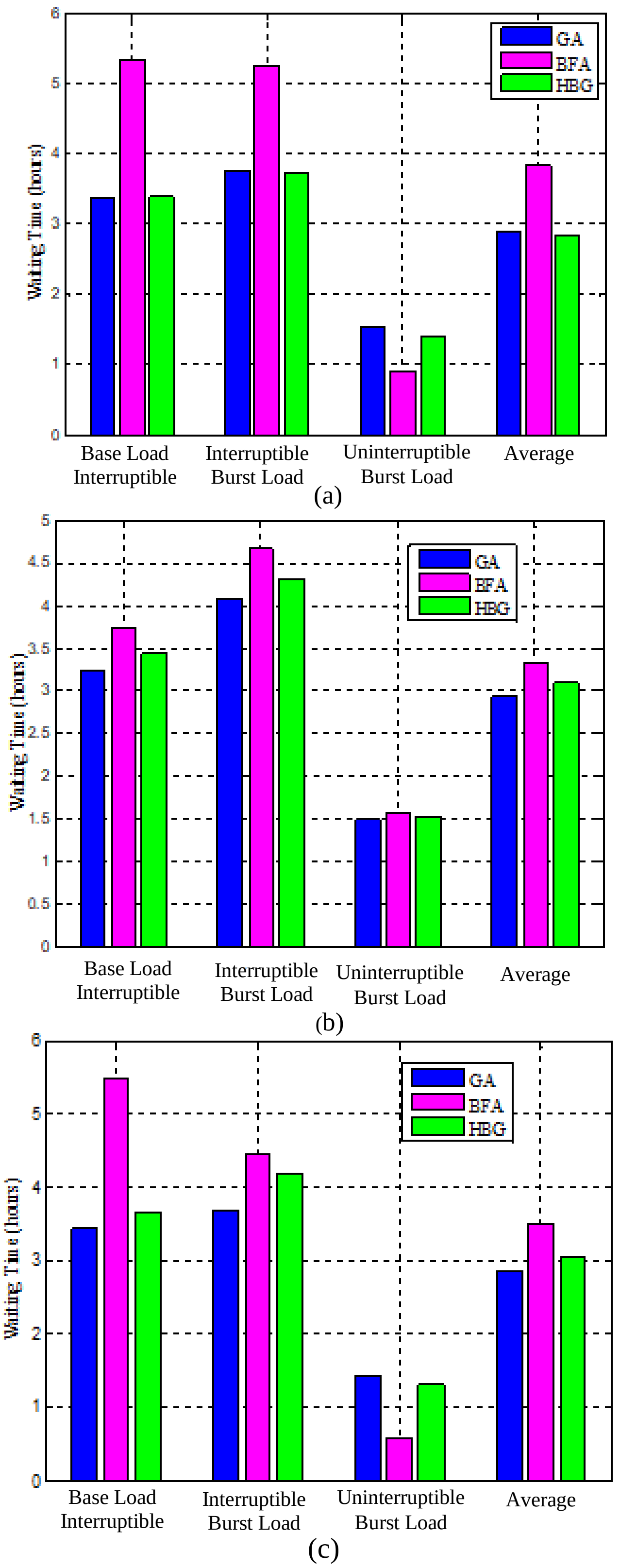


Fig.14. Real-time scheduling's effect on appliance wait time: (a) RTP. (b) TOU. (c) CPP.

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The simulation results showed the high performance of HBG when applying RTP and TOU price tariffs. For the RTP signal, a 9.5% maximum cost is decreased by HBG with a 26.82% minimized waiting time. BFA is adopted to CPP signal, which reduces the electricity cost by 12.99% and the PAR by 4.39%. For CPP, GA can save up to 24.44% for the electricity cost and 30.11% for the PAR.

The trade-off between electricity cost, PAR and waiting time in smart home is determined by the consumer. For example, one may prefer saving electricity cost and waiting time over PAR, others favor minimizing electricity costs and PAR above waiting times.

## 6. CONCLUSION AND FUTURE WORK

In order to achieve the intended objectives, AO-HEMS has been used in this study, and the strategy of load shifting has been used for DSM. In this work, a single home containing various home appliances is used. The suggested optimization technique is used to schedule each smart home device. Remote controllable appliances are scheduled based on IoT system to prevent energy waste. Considered methods are utilized to find the best optimal schedule for each home device, taking into consideration system constraints.

In order to achieve this, we've used dynamic programming techniques to incorporate coordination with alternating operation among home appliances. While several pricing models are used to analyze the AO-HEMS' performance. Our analysis of the performance of the GA, BFA, and HBG approaches, using considered pricing models, lead to the conclusion that GA is high performance using RTP and CPP to improve waiting times and electricity costs. BFA is well suited to CPP to improve electricity costs and PAR. While, HBG performs well with RTP and TOU to cut down on waiting times and electricity costs. This confirms that our suggested strategy effectively schedules home appliances considering all pricing indications.

In the future, smart appliances will be taken into consideration to enhance user comfort and reduce electricity costs.

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