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# Optimal residential load scheduling under dynamic pricing and demand-side management

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## Abstract

Balancing electricity consumption and generation in the residential market is essential for power grids. The imbalance of power scheduling between energy supply and demand would definitely increase costs to both the energy provider and customer. This paper proposes a control function to normalize the peak cost and customer discomfort. In this work, we modify an optimization power scheduling scheme by using the inclined-block rate (IBR) and real-time price (RTP) technique to achieve a desired trade-off between electricity payment and consumer discomfort level. For discomfort, an average time delay between peak and off-peak is proposed to minimize waiting time. The simulation results present our model more practical and realistic with respect to the consumption constrained at peak hours.

**Keywords:** Demand side management; Energy management system; Load scheduling; Smart grid; Optimization; Dynamic response

## 1. Introduction

With rapid population growth and limited generation potentials, the electricity power system is facing volatile conditions and constant stress due to the high fluctuations electricity demand. The domestic consumption of electricity increases by 30-40% of global consumption [1]. Residential sector greatly contributes to peak demand at 45% in the UK, 50% in New Zealand and 50% in South Australia. The increasing rate of residential demand necessitates to develop a balancing strategy for supply and demand. The SG ensures a two-way communication between utility providers and consumers that make power system more secure and efficient [2][3] [4]. Since, the SG system develops a mutually beneficial, sustainable and accessible approach for companies and consumers through the DR programs. The DR is an integral part of smart grid, and plays an important role ensuring a balance between generation and consumption. There are two major types of DR, price-based and incentive-based demand response [5][6]. The household end-user schedules appliances in ways that minimize the peak consumption and cost by shifting time intervals [7]. In more cases, customer tends to shift the consumption pattern from peak to off-peak to avoid the peak energy expenses; however, this may lead to a new peak on off-peak hours [8][9][10]. Therefore, a moderate power load and sustainable power grid are achievable through financial incentives such as time-varying electricity tariff, or $CO_2$ footprint for environmentally-friendly consumers[11]. In extant literature, many works have been done on DR for smart grid system [12][13].

Literature on DSM has focused on dynamic pricing and residential appliance optimization. Table 1 shows a summary of related work that has been done in previous literature. The work in[14], has proposed an automated optimization-based residential load control scheme in retail electricity market with real-time price (RTP) and incline block rate (IBR). A simulation was carried out in [15] to optimize the household appliance operations. For instance, an optimal scheduling

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of household appliance was developed to achieve a trade-off between payment cost and the delay time[16]. The paper [17] discussed rebound peak and cost minimization describing how to use peak to average ratio (PAR) and linear programming problem (LPP) in DSM programs. The methods constrained consumers by not choosing a usage time freely, especially, when talking about rebound peak, customers are not allowed to shift their consumption from peak to off peak, by choice. In [18], an optimal load scheduling algorithm is used and simulation results showed up to 20% and 100% reduction in the payment cost and peak demand, respectively. The paper in [19] discussed the RTP and customers' preferences as an approach to reduce energy expenses and delay time while operating the appliances but the approach is less focused on peak moderation. A priority-induced DSM strategy using HEMC based on GA, EDE, BPSO and OSR scheme is proposed in [18] to minimize consumers' electricity payment cost while maintaining user comfort. The paper has focused only on three scheduling appliances. In [20] home energy controller (HEC) is used to calculate optimized time slots for the schedulable appliances to reduce cost of energy and peak to average ratio (PAR). A convex programming DR optimization is used in [21], to regularize the schedulable appliances in a smart home. The demand response is formulated as optimization problem in [22], and a power control with RTP is developed to match between supply and demand in different time slots a day. In [23], the demand response (DR) control strategy is proposed to control the total power consumption under the specified power limit during DR period. Recent studies have shown that despite several advantages that RTP and IBR can offer, the lack of knowledge among the users about how to respond to time-varying prices and the lack of effective home automation systems are two major barriers for fully utilizing the benefits of real-time pricing tariffs [24].

In this work, we modify the residential energy scheduling by using a control function to minimize cost and discomfort. For discomfort, an average time delay between peak and off-peak is proposed to minimize waiting time. The previous literature has discussed more about the RTP, flat rates, DAP and time of use (TOU) that on the other hand results for rebound peaks and a marginal loss for utilities. Shifting the residential load from peak to off-peak results in creating of rebound peaks during off-peak time intervals. This situation also increases peak-to-average ratio (PAR), where consumers prefer to execute their home appliances at off-peak hours. For IBR pricing, the marginal price increases by each quantity consumed [24]. That is, based on certain power thresholds in the total monthly/daily/hourly load, the electricity prices are going high with rate of high load block. In addition, IBR helps in load balancing and also reducing the PAR [25]. The residential scheduling and optimization study in this work is partly similar to the work done in[25]. In this paper, we consider a time-varying pricing combined with day-ahead price (DAP) to mitigate the trade-off between payment cost and customer discomfort. In addition, the simulation results present our model more practical and realistic concerning with consumption constrain at peak hours.

Our main contributions are as follows:

- To minimize the payment cost by using a control function that works in both cases increasing or decreasing the consumption of electricity.
- An average time delay parameter is proposed (for time flexible appliances) that works twofold; minimize discomfort or waiting time and minimize rebound peak during off interval.
- Real-time price (RTP) combined with inclined block rate (IBR) is observed as a general pricing scheme to minimize consumption by setting a power threshold.
- A certain amount of Renewable energy (as constant) is used to minimize the trade-off between payment and customer discomfort.

The remaining parts of the paper are organized as follows: Section 2 focuses on system structure and load modeling. Section 3 discusses the problem formulation mathematically. Section 4 analyzes the optimization problem and its solution. Section 5 presents simulation results and Section 6 concludes the paper.

## 2. Demand Response

Demand response (DR) is defined as changes in the electricity consumption by users from their usual consumption pattern in response to changes in prices. In our problem, the household users execute their appliances within the study time horizon 24 hours. Appliances are characterized with time-flexible and power-flexible and they are working within their time and power limits. Though, customers are free to choice the reasonable and cheapest price for the application of schedulable appliances at home. Since, every user wants to pay less payments and select the least price interval for running appliances. That, on the other hand, create some new peak demand at that specific time slot. To meet the peak demand, high cost generators are needed to put into operation. More investments are planned to construct additional power plants and meet the peak demand. The adding generation approach directly affects our environment circle by fueling carbon omission which again needs investment to fight the emerging pollution issues at large level. At the moment, the utility companies are paying their attention on demand-side management (DSM) to reduce their additional cost and peak demand. Demand response is the key concept in DSM which is helpful in curbing peak demand at peak hours[26]. According to the U.S. Department of Energy (DOE), demand response is a program established to incentivize the end-use customers to change their normal consumption in response to change in the electricity prices or when there is an emergency situation in the system [27]. In the U.S, as of 2015, DR programs alone were estimated to have the potential of 31,754 MW, accounting for 6.6% of total peak demand of all ISO/RTO, and it was estimated that demand response would probably shave 38,000 MW off the country's peak demand in the year 2019 [28].

### 2.1. Benefits under DR

#### *2.1.1. Customer perspective*

The cost minimization and utility maximization are two core concerns of customers while using the electrical appliances. In conventional system, customers are charged flat or fixed rates with flexible consumption approach. With the invention of smart grid, customers receive price signals and likewise the meter information are received by smart grid at each interval. Customers remains update about each varying prices through installation of advance metering infrastructure (AMI). Appliances are connected through a wide home area network (WHAN) with smart meters to transmit demand information to the energy controller. DR is one of the cost effective and reliable techniques used by utilities for customer load shifting. Appliances are scheduled in response to varying price signals in a cheaper time slot to achieve maximum cost savings [29]. The flexibility of consumers moving from peak to off-peak hours, against incentives may help to tackle difficult situations in current and future electric systems.

#### *2.1.2. S*upplier perspective

Demand response program can help in developing a mutual consensus between customers and suppliers on setting the amount of energy consumption within given parameters of power and price. Moreover, DR has considerable potential to reduce the system cost and improve system reliability. Under dynamic price and demand-side management (DSM), the electricity distribution network operators (DNOs) become more efficient in providing power security in transmission and distribution of energy supply. The prices further reduce the discrepancies between supply and demand in smart grid system. In that, the energy suppliers offer financial incentives and awards on power reduction during peak hours, thereby improving the stability and lowering production costs in the power market [30]. Utility suppliers usually set their rates in accordance with demand characteristics and consumption patterns of customers. With dynamic pricing, customers face two types of time interval; peak and off-peak and are charged accordingly. The customers' responsiveness on high price is an indication of reducing electricity demand which, in turn, reduces the additional investment cost for the utilities, as well.

## 3. System structure

We consider a smart power system that consists of one service provider with several users. Consumers are equipped with an energy controller system (ECS) in smart meter to their power consumption. The ECS devices are connected to the service provider through a communication network such as a local area network (LAN). In this scenario, our focus is to formulate the energy consumption-scheduling problem in each household as an optimization problem that aims to minimize the cost, customer discomfort, PAR, peak shaving and an average customer electricity price.

A residential unit has various household appliances such as air-conditioners, space heaters, washers, refrigerators, plug-in hybrid vehicles, oven and lights etc. Let $a$ denote an appliance and $A$ denote the set of appliances. For each appliance $a \in A$, we assume that an energy consumption-scheduling vector $X$ is defined as

$$X_a \triangleq \left[ x_{am}^1, \ldots, x_{am}^T \right] \quad (1)$$

where scalar $x_{am}^t$ denotes the corresponding one-hour energy consumption that is scheduled for appliance $a_m, \ m=1,2,\ldots,M$ ,where $M$ is the total number of appliances. $T$ is the scheduling horizon that denotes the number of time $t$ units ahead of which the scheduling decision on energy consumption is to be made. The scheduling horizon T is 24 hours in this scenario.

The appliance includes non-schedulable and schedulable. Non-schedulable appliances remain operational until their work is completed. Smart meters receive on/off status through networking infrastructure installed into system. In this study, we focus on two important types of schedulable appliances. Let $A_1$ and $A_2$ denote time and power flexible appliances, respectively.

### 3.1. Appliance classifications

House hold appliances are categorized into two main categories with respective to their type, characteristics and the customer requirement.

#### *3.1.1. Time flexible appliances*

In the family of schedulable appliances first type is time flexible that can be delayed in the scheduling horizon $[\alpha_a, \beta_a]$ including washing machines, dish dryer and plug-in hybrid electric vehicle (PEHV). The term $\alpha_a$ indicates starting time of the appliance $a$ and $\beta_a$ denotes the ending time. We assume that,

$$x_{am}^t = 0, \quad \forall t \in T \setminus [\alpha_a, \beta_a] \tag{2}$$

because power consumption is not needed outside the scheduling horizon $[\alpha_a, \beta_a]$. Clearly we always have $\alpha_a < \beta_a$. For instance, after loading a dishwasher with the dishes used at the lunch table, the user may select $\alpha_a = 2PM$ and $\beta_a = 6PM$ for scheduling the energy consumption for the dishwasher as he/she expects the dishes to be ready to use by dinner time in the evening. As another example, the use may select $\alpha_a = 10PM$ and $\beta_a = 7AM$ ( the next day) for his/her PHEV after plugging it in at night such that the battery charging finishes by early morning time when he/she needs to use the vehicle to go to work. Here, operation start time (OST) is denoted as $t_a^b$ that can be delayed within scheduling horizon. Appliances operate continuously with fixed power $r_a$ and length of operation time (LOT) $T_a$. Given the pre-determined parameters $r_a, \alpha_a$ and $\beta_a$, in order to provide the needed energy for each schedulable appliance $a \in A_1$ in the given intervals $[\alpha_a, \beta_a]$, it is required that

$$\sum_{\alpha_a}^{\beta_a} x_{am}^t = r_{am} \tag{3}$$

Let $r_a$ denote the total energy needed for the operation of appliance $a$. For instance, in case of plug-in hybrid electric sedan, in total $r_a = 16kWh$ is needed to charge the battery for a 40-miles driving range [31]. As another example, for typical front-loading clothes washing machine with warm/rinse setting, we have $r_a = 3.6kWh$ per load [32]. Further to constraint (4), it is expected that $x_{am} = 0$ for any $t < \alpha_a$ and $t > \beta_a$ as no operation (thus energy consumption) is needed outside the time frame $[\alpha_a, \beta_a]$ for appliance $a$. We note that the time length $\beta_a - \alpha_a$ needs to be larger than equal to the time duration required to finish the normal operation of appliance $a$. For instance, for a single phase PHEV, the normal charging time is 3 hours [31]. Therefore, it is required that $\beta_a - \alpha_a \geq 3$. Clearly, if $\beta_a - \alpha_a = 3$ the timing imposed by the user would be strict and any energy consumption scheduling strategy has no choice but arranging full power charging within the whole interval $[\alpha_a, \beta_a]$. On the other hand, if $\beta_a - \alpha_a$ □ $3$, it is possible to select certain hours within the large interval $[\alpha_a, \beta_a]$ to schedule energy consumption such that the energy payments can be minimized.

#### *3.1.2. Power flexible appliances* $A_2$

The second type of appliances operate with a flexible power $x_a^t$ in the scheduling horizon $[\alpha_a, \beta_a]$ and stop working outside the scheduling horizon. The appliances including air conditioners, bulb and electric fans have certain maximum power levels denoted by $r_a^{\max}$, for each $a \in A_2$. We assume that each appliance has some minimum and maximum power values, $r_a^{\min}$ and $r_a^{\max}$, respectively in subinterval $t$. For example, a PHEV may be charged only up to $r_a^{\max} = 3.3kW$ per hour [31]. Some appliances may also have minimum stand-by power level $r_a^{\min}$, for each appliance $a \in A_2$.Therefore, the following lower and upper bound constraints are needed on the choices of the energy scheduling vector $x_a$ for each appliance $a \in A_2$.

$$r_a^{\min} \le x_a^t \le r_a^{\max}; \forall t \in [\alpha_a, \beta_a] \quad (4)$$

Together constraints (2) -(4) determine all valid choices for the energy consumption scheduling vector. Therefore, we can define a *feasible scheduling* set $\chi$ for all possible power consumption scheduling vectors as

$$\begin{aligned}\chi = \{ x \mid\ & x_a^t = r_a, \forall t \in \{t_a^b, \ldots, t_a^b + T_a - 1\} \subset [\alpha_a, \beta_a], \forall a \in A_1, \\ & x_a^t = 0, \forall t \in T \setminus \{t_a^b, \ldots, t_a^b + T_a - 1\}, \forall a \in A_1, \\ & r_a^{\min} \le x_a^t \le r_a^{\max}, \forall t \in [\alpha_a, \beta_a], \forall a \in A_2, \\ & x_a^t = 0, \forall t \in T \setminus [\alpha_a, \beta_a], \forall a \in A_2, \\ & x_s^t < x_{\max}^t \} \qquad (5)\end{aligned}$$

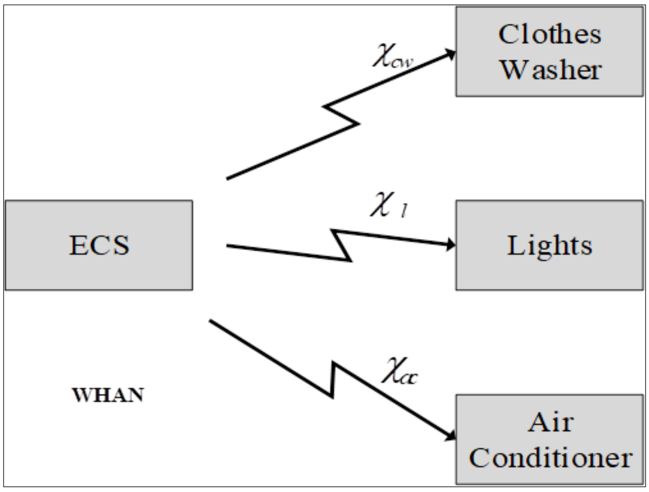


**Figure 1** The power consumption scheduling strategy by the ECS device can be applied to the application with commands over the WHAN using ZigBee transceivers

The selection of $\chi$ depends on the electricity price and the character parameters of the appliances $(\alpha_a, \beta_a, r_a, T_a, r_a^{\min}, r_a^{\max})$. The ECS determines the optimal scheduling strategy for home appliances. Then, the customer with the help of DAP schedule the energy requirement with certain constraints vector $\chi$. The scheduling strategy then applied to control the appliances via commands. The resulting energy consumption schedule is then applied to all household appliances in form of on/off commands with specified power levels over a wired or wireless *home area network* among the appliances and the smart meter. These commands specify the power level and the starting time for each appliance and transmit over a *wireless home area network* (WHAN). As shown in Fig. 1.

### *3.1.3. Real-time pricing and Incline Block Rates*

In this section, we provide a general mathematical pricing representation which combines RTP and IBR models. We also assume that the future pricing parameters are known for the users ahead of time. This is somehow similar to DAP but the only difference is the block rate structure that user may assemble load according to the time slot pricing.

Let $l^t \triangleq \sum_{a \in A_1 \cup A_2} x_a^t$ denote the *total* hourly household energy consumption at each upcoming timeslot $t \in T$.

We consider a general hourly pricing function $p^t\left(l^t\right)$ which depends on three parameters $a^t$, $b^t$, $c^t \geq 0$ and is formulated as follows:

$$p^t\left(l^t\right) = \begin{cases} a^t, & \text{if } 0 \leq l^t \leq c^t, \\ b^t, & \text{if } l^t > c^t. \end{cases} \tag{6}$$

Where $a^t$ is the real-time electricity price at timeslot $t$ in a day, and $b^t$ is the price greater than $a^t$ when $l^t$ exceeds the threshold $c^t$ of IBR. When the total electricity consumed is less than or equal to $c^t$, the price will be $a^t$. Otherwise, the electricity price will be $b^t$. For example, BC Hydro applied inclining block rates (IBR)[33]. BC hydro has decided the rates of electricity as from 7.52 cents/kWh to 11.27 cents/kWh as per the energy consumption of customer. They have decided the rate based on following rule i.e. if the electricity consumption of consumer for 2-month period is less than 1300 kWh, he/she will pay first slot price 7.52 cents/kWh; otherwise consumer have to pay second slot price 11.27 cents/kWh.

$$a^t = b^t, \quad \forall\, t \in T. \tag{7}$$

That is, although the prices vary every time slot $t$, they are indeed flat within each hour. On the other hand, for the IBR used by British Columbia Hydro Company, we have

$$a^1 = a^2 \ldots\ldots = a^{H-1} = a^H, \tag{8}$$

$$b^1 = b^2 \ldots\ldots = b^{H-1} = b^H, \tag{9}$$

$$c^1 = c^2 \ldots\ldots = c^{H-1} = c^H, \tag{10}$$

That is, although the prices are dependent on consumption level, they do not change over time; thus, they cannot reflect the fluctuations in the wholesale prices. By combining the two prices scenarios in (6), both wholesale prices as well as consumption levels are taken into account.

## 4. Problem formulation and proposed solution

In demand response, residential load scheduling and the alignment of the stochastic demand under the utility and dynamic pricing are challenging tasks to customers. The different technique has been proposed in the literature addressing load scheduling for household energy management. For instance, a genetic algorithm (GA) based DR scheme is studied in this system, the real-time price (RTP) combined with inclined block rate (IBR) is assumed to be the electricity price and it is announced one day before the operation. Then consumer schedules power consumption in response to day-ahead price. Initially, users' interest is two-fold. First, each user wishes to minimize his/her payments cost. It is reasonable to assume that all users care about the amount on their electricity bills. Second, depending on the appliance, some users may also care about their comfort and getting the work done (washing dishes, charging PHEV, or drying clothes) as soon as possible. These two objectives can be conflicting in many scenarios. For example, the consumer wants to start washing dishes at 9:00 AM right after finishing breakfast, he may choose to wait for 5 hours and postpone the operation of the dishwasher (with $r_a = 3.6kWh$ per load) to 2:00 PM to reduce the corresponding electricity payment from $3.6 \times 4.1 = 14.8$ cents to $3.6 \times 2.9 = 10.6$ cents and save 4.2 cents. However, for some reason, the user may prefer to pay the extra 4.2 cents and finish the work by 10:00 AM. As an alternative, the user might be willing to wait for 2 hours only and save 1.5 cents instead. We can see that there is a trade-off involved between payment cost and discomfort minimization in our problem. Next, we can explain how this trade-off can be minimized in our optimization problem by using alternative energy sources like, use of solar panel by demand-side.

The electricity payment corresponding to all appliances in the upcoming scheduling time slot is derived as

$$\sum_{t=1}^{T} p^t\left(l^t\right) \times \left( \sum_{a \in A_1 \cup A_2} x_a^t \right) \tag{11}$$

where the price function $p^t(.)$ is as in (6).

In (6), two types of appliances time and power flexible appliances which operate within scheduling horizon $\left[\alpha_a, \beta_a\right]$ and power interval $\left[r_a^{\min}, r_a^{\max}\right]$, that further impacts on electricity payments. Customer prefers for shifting appliances to the low price interval that indirectly increase power consumption at a specific time slot. Ultimately, a pressure built on utility companies by installations or hiring of additional generators on meeting extra power demand. As a result, customers are charged with high rates and power fluctuations or outages become commonplace. Therefore, to meet an optimum scheduling approach within a given time and power interval, the customer may avail of various types of renewable energy resources (RERs) that are available such as, solar, biomass and wind energies. However, among them, solar is the cheapest and most abundant source for residential energy consumption. According to [2], the Earth receives 174,000 terawatts (TW) of incoming solar radiation in the upper atmosphere. Approximately 30% is reflected space, while the rest is absorbed by clouds, oceans, and landmasses. To take benefit from RERs, we fix the available amount of RE during peak demand to mitigate the cost as well as the level of discomfort. To model the impacts of RE energy on payment cost and discomfort is driven (12) as new cost function as follows;

$$\sum_{t=1}^{T} \sum_{a \in A_1 \cup A_2} p^t\left(l^t\right)\left(x_a^t - x_s^t\right) + \sum_{t=1}^{T} \sum_{a \in A_1 \cup A_2} \lambda^t \times \left(x_s^t\right) \tag{12}$$

s.t.

$$x_s^t < x_{\max}^t \tag{12a}$$

$$0 < \lambda^t < \rho^t\left(l^t\right) \tag{12b}$$

where $x_s^t$ denotes the power amount produced by renewable sources that customer consumed together with grid power $x_a^t$ during the delay time interval. The term $\lambda^t$ represents the unit price of the energy received from RES and the customer utilizes during power delaying at peak hours. $x_{\max}^t$ shows the power capacity stored in the battery.

### 4.1. PAR minimization

PAR is defined as the ratio of peak load to the average load consumed over the scheduling time horizon. PAR tells us about the energy consumption behavior utility peak plants; it is beneficial for both utility and consumers. The PAR is calculated as follows;

$$\text{Peak} = \max\left(x_a^t\right), \tag{13}$$

$$\text{Average}=\frac{1}{24}\sum_{t=1}^{T}\left(\sum_{a\in A_1\cup A_2} x_a^t\right), \quad (14)$$

$$\text{PAR}=\frac{\text{Peak}}{\text{Average}}. \quad (15)$$

## 4.2. User discomfort minimization

### *4.2.1. User discomfort with time flexible appliances*

User comfort in a smart home is a crucial factor. Several user comfort factors can be considered. In this work, two factors are studied: waiting time and availability of power per time slot. The first type of appliances $A_1$, the discomfort caused by delaying operation can be modeled as

$$\rho_a^t\left(t_a^b-\alpha_a\right)=\frac{\left(t_a^b-\alpha_a\right)\cdot\left(\sigma_a\right)}{r_a}, \ \forall a\in A_1,\ t\in\left[\alpha_a,\beta_a\right] \quad (16)$$

s.t.

$$0<\sigma_a\leq 1 \quad (16a)$$

where $\sigma_a$ is an adjustable control parameter. The higher value of $\sigma_a$, the higher will be the discomfort cost. The customer discomfort happens when power scheduling interval widen by minimizing the billing cost at time interval $t$. In the home energy control system (HECS), an alternative energy window is open for providing the sufficient renewable power amount while the power from grid decreases while delaying interval.

Here in (16), the term $r_a^t$ is a discomfort function of time delay that as long as the waiting time, the discomfort cost increases accordingly. Clearly, $r_a^t=0$ for all $t<\alpha_a$ and $t>\beta_a$ as the concept of waiting may only be defined within the valid scheduling interval $\left[\alpha_a,\beta_a\right]$. The term $t_a^b$ shows appliance operation start time (OST) and it should be greater than or equal to $\alpha_a$, and less than or equal to $\beta_a-T_a$. In other words, the range of OST of $a$ is

$$t_a^b\in\left[\alpha_a,\beta_a-T_a\right] \quad (17)$$

In (17), appliance starting time is $t_a^b$ that is a hard option for users operating appliance as early to minimize waiting time or discomfort. Usually, it is not possible for each user for operating a washing machine at $\alpha_a$. For that, it depends on the customer to set the expected time according to the price that could be near to the actual operating time $\alpha_a$. Ultimately, it minimizes the discomfort within the interval. For instance, within the given interval from 10:00 PM to 7:00 AM (the next day), the user expects to load dishes into the dishwasher at 10:00 PM to wash earlier but by any reason got late and able to load them at 11 PM. In this example, both situations, loading dishes at 10:00 PM and/or later at 11:00 PM user can minimize discomfort level. As the schedulable appliance $a$ of $A_1$ operates continuously during the determined operation time $T_a$. They are controlled at their initial operating schedule but cannot stop or interrupt while working.

That is, the cost of waiting increases as more energy consumption is scheduled at later hours. Therefore, for easing customer waiting time or discomfort, we can use a renewable source, like a solar panel. The solar power setup cost is thought to have a negligible operating cost. The HECS manages the power in such a way to relay power from solar resources through minimizing the equal amount of power from the utility. At the time interval $t$, we define the available solar power generation as $r_s$, required power from the utility as $r_g$ and the total power required for the appliance $a \in A_1$ is $r_a$. The generation and load balancing equation is expressed as $r_a = r_g + r_s$ and the total cost of waiting across all appliances, we rewrite (16) as

$$\sum_{t=1}^{T}\sum_{a \in A_1} \rho_a^t \left(t_a^b - \alpha_a\right) \cdot \left(x_a^t - x_s^t\right) \quad , \forall a \in A_1,\ t \in \left[\alpha_a, \beta_a\right] \tag{17}$$

*4.2.2. User discomfort with power flexible appliances*

In second type of appliance $A_2$, the discomfort incurs by power deviation from the normal power consumption. Next, we use Taguchi loss function [18] to define the discomfort cost.

$$V_a^t\left(x_a^t\right) = \omega_a^t \left|x_a^t - \hat{x}_a^t\right| \tag{18}$$

Here, customer feeling a kind of comfort while consuming a certain amount of power from solar panel during time interval $t$ when appliance $a \in A_2$ is scheduled with power delay option, to minimize the real-time cost and discomfort, and power consumed is $x_s^t$. The discomfort after consuming solar resources is derived as

$$V_a^t\left(x_a^t\right) = \omega_a^t \left|\left(x_a^t - x_s^t\right) - \hat{x}_a^t\right| \tag{19}$$

s.t.

$$\left(x_a^t - x_s^t\right) > 0 \tag{19a}$$

where $\omega_a^t$ is a parameter that varies with different time slots, and $\hat{x}_a^t$ denotes the normal power consumption of appliance $a$. We also define $V_a^t\left(x_a^t\right) = 0$ for $t \in T \setminus \left[\alpha_a, \beta_a\right]$.The quadratic representation of the loss function is minimum at $x_a^t = \hat{x}_a^t$, increases as $x_a^t$ deviates from normal consumption $\hat{x}_a^t$. The Taguchi loss function defines the relationship between the economic loss and the deviation of the power consumption from the normal power consumption. For an appliance with normal power consumption $\hat{x}_a^t$, $\hat{x}_a^t \pm$ deviation at which consumer preference or desire involves to operate the appliance beyond the power limit. When an appliance is operated with the power consumption at the extremes, $\hat{x}_a^t$ + dev or $\hat{x}_a^t$ -dev, at this moment consumers face an additional cost to minimize the power deviation from normal load.

Here, the total discomfort caused by using the two types of appliances can be modeled as

$$\sum_{t=1}^{T}\sum_{a \in A_1} \rho_a^t \left(t_a^b - \alpha_a\right) \cdot \left(x_a^t - x_s^t\right) + \sum_{t}\sum_{a \in A_2} V_a^t\left(x_a^t - x_s^t\right) \tag{20}$$

Based on the objective functions in Eq (12), (17), (20), the scheduling problem of power consumption is modeled in Eq (21) as optimization problem.

$$\text{mini}\,\alpha 1 \sum_{t=1}^{T} \sum_{a \in A_1 \cup A_2} p^t\left(l^t\right)\left(x_a^t - x_s^t\right) + \sum_{t=1}^{T} \sum_{a \in A_1 \cup A_2} \lambda^t \times \left(x_s^t\right) + \alpha 2 \left(\sum_{t=1}^{T}\sum_{a \in A_1} \rho_a^t \left(t_a^b - \alpha_a\right) \cdot \left(x_a^t - x_s^t\right) + \sum_{t}\sum_{a \in A_2} V_a^t\left(x_a^t - x_s^t\right)\right) \tag{21}$$

Subject to:

$$\{x \mid x_a^t = r_a, \forall t \in \left\{t_a^b,...,t_a^b + T_a - 1\right\} \subset \left[\alpha_a, \beta_a\right], \forall a \in A_1,$$

$$x_a^t = 0, \forall t \in T \setminus \left\{t_a^b,...,t_a^b + T_a - 1\right\}, \forall a \in A_1,$$

$$r_a^{\min} \le x_a^t \le r_a^{\max}, \forall t \in \left[\alpha_a, \beta_a\right], \forall a \in A_2,$$

$$x_a^t = 0, \forall t \in T \setminus \left[\alpha_a, \beta_a\right], \forall a \in A_2,$$

$$x_s^t < x_{\max}^t \}$$

*Variables*

$$t_a^b \left(a \in A_1\right)$$

$$x_a^t \left(a \in A_2, t \in T\right)$$

The first term in the objective function denotes the electricity payments, and the second term denotes the total discomfort. The weights $\alpha 1$ and $\alpha 2$ $\left(\alpha 1 + \alpha 2 = 1\right)$ are used for achieving the trade-off between the payments and the discomfort. Next, we will solve the optimization problem (21) that includes both integer and continuous variables.

### 4.3. Appliance scheduling with varying rates

A category of schedulable appliances, time flexible (6), operates within given time interval $\left[\alpha_a, \beta_a\right]$. The question is: How the appliances can deal with peak and off-peak prices, at morning and night time, when they are entitled to operate within day-ahead (DAP) price? Before answering this question, we first argue the users' interest is twofold. First, each user wishes to minimize the billing cost. Second, to minimize the discomfort level, that is also assumed as part of cost in the work. In general, some customers prefer comfort level on billing cost and some prefers the payment cost on discomfort. But in this model, we prefer to minimize both the payment and discomfort by using dynamic price combined with DAP. The users prefer to operate the appliances at comfortable time that usually create peak or rebound peak condition. For example, if user wants to wash the clothes at 9:00 AM, knowing that it's a peak time and have high prices than off-peak interval. In this circumstances, he has only option to wait and postpone the washing operation up to 5 hours late the off-peak time. Here, let's suppose the morning payment for the electricity is 4.5*3.6kWh=16.2 cents and the payment for the same power quantity after 5 hours is 2.5*3.6kWh= cents, so there is a difference of 7.2 cents waiting after 5 hours. It implies that, with the passage of time rates change over the consumption of electricity. Table 2 presents the characteristics of appliances along with price and waiting time.

To minimize waiting discomfort, we prefer the average price for time flexible appliances that is acceptable and affordable for users at different time intervals. For user as well as for the utility, average price performs twofold; firstly, it decreases users discomfort and secondly, minimizes rebound peak. In this model, user feel satisfaction in executing appliances.

**Table 1** A summary of related work (n/a shows not available)

| Technique | Objectives | Tariff | Limitations | Results | | |
|---|---|---|---|---|---|---|
| | | | | Cost (%) | PAR (%) | Discomfort (%) |
| MINLP by using TOU tariff [14] | Minimize cost and inconvenience | TOU | Limited inconvenience with limited appliances | 25 | n/a | n/a |
| MILP [34] | Minimize cost | TOU | Lack of PAR and discomfort in scheduling | n/a | - | - |
| Automated optimization based load control [35] | Minimize cost | RTP & IBR | Discomfort is ignored | 25 | n/a | 38 |
| An optimal power scheduling equipped with ECS [36] | Minimize cost and discomfort | DAP | A simple cost reduction is observed | - | - | 16 |
| MILP [37] | Minimize cost | RTP & FTP | PAR and discomfort is ignored | 20 | - | - |
| GWDO [38] | Minimize cost & PAR | RTP & IBR | Discomfort is not discussed | 49 | - | 35 |
| MINLP [39] | Minimize cost & discomfort | RTP | Increased consumption time and ignored PAR | 32 | - | - |
| MINLP [40] | Minimize cost | TOU & CPP | Considering multiple appliances | - | - | - |
| WDO and min-max regret based Knapsack algorithm [41] | Minimize cost & PAR | TOU | Peak scheduling of appliance is lack along with cost | - | - | - |
| Min-Max Load Scheduling (MMLS) algorithm [42] | Minimize cost & PAR | DAP | | - | - | - |
| Optimal residential load scheduling system [43] | Minimize cost & discomfort | TOU | PAR is not thoroughly studied | 31 | 35 | - |

## 5. Results and discussions

In this section, we highlight the simulation results and evaluate the performance schedulable appliances by using the inclined-block rate (IBR) as tariff price. We consider three schedulable appliances (e.g., clothes washer (CW), lights (L) and air conditioner (AC). The clothes washer belongs to the first type of appliances, and the other two appliances belong to the second type of appliances. The parameters of the schedulable appliances are shown in Table 2. The time horizon used in the study is 24 h, starting time from 8 am to 8 am in the next day. Fig. 2. Shows the day-ahead electricity price, which is obtained from the Daily Report of Midwest Independent System Operator (MISO) from the Federal Energy Regulation (FERC) [44].

The simulation results on power consumption for schedulable appliances under IBR is shown in Fig. 3, where peak consumption at 12pm is reduced by 70% than that under the DAP program. The power consumption of CW, L and AC under IBR price are shown in Fig. 4 and Fig. 5. We can see the appliance execution behaviors before and after applying IBR as tariff price. Except CW, because of its fixed power consumption characteristic, the electricity consumption of L and AC react different with varying price intervals. The light executes of 0.8kw power before using price limits and reduced power by 0.2kw under the IBR are also lower than that under DAP. Similarly, the AC operated at 0.9kw and reduced with a minimum of 0.4kw. Thus, the incline-block rate is more effective in not only reducing the peak consumption but also decreasing the peak-to-average ratio (PAR). Fig. 6 shows the electricity payments under the incline-block rate and day–ahead price which is declined by 77% than that the day-ahead price. Table 3 compares the performance between the incline-block rate and day-ahead price in detail. After all these simulation results, we can conclude that the power scheduling under IBR block rate scheme achieves a desired trade-off between the electricity payments and the discomfort. In the day-ahead, customer is charged a constant price. The customer schedules the appliances without considering the marginal cost incurs during peak hours. For instance, the clothes washer is assumed to start working at the beginning of the scheduling horizon $\left[\alpha_a, \beta_a\right]$, and the lights and air conditioner works with random power levels around $\hat{x}_a^t$. As we have seen in Fig. 3, the peak under the IBR price is much lower than that under the DAP. Thus, the IBR price can reduce peak consumption, the PAR, the electricity payment, the average price and customer discomfort level during scheduling appliances.

**Table 2** Parameters of schedulable appliances

| | CW | L | AC |
|---|---|---|---|
| $a$ | 6 pm | 6 pm | 8 am |
| $s_{\exp}$ | 7 pm | 7 am | 9 am |
| $b$ | 7 am | 11 pm | 8 am |
| $r_a^{\min}\left(kW\right)$ | | 0.2 | 0 |
| $r_a^{\max}\left(kW\right)$ | - | 0.8 | 1.4 |
| $\hat{x}_a^t\left(kW\right)$ | - | 0.8 | 1.4 |
| $r_a\left(kW\right)$ | 0.7 | - | - |
| $T_a\left(h\right)$ | 2 | - | - |
| $r$ | 0.001 | - | - |
| $w_a^t$ | - | [0.5,1] | [0.4,1] |

**Table 3** Comparison between limit (IBR) and without limit (Flat rate and DAP) prices

| | Flat rate | DAP | IBR |
|---|---|---|---|
| Peak demand (kW) | 2.68 | 2.10 | 1.80 |
| PAR | 1.74 | 1.33 | 1.33 |
| Electricity payments ($) | 13.79 | 13.56 | 10.50 |
| Average price ($/kWh) | 0.37 | 0.36 | 0.32 |
| Discomfort level | - | 17.66 | 13.04 |

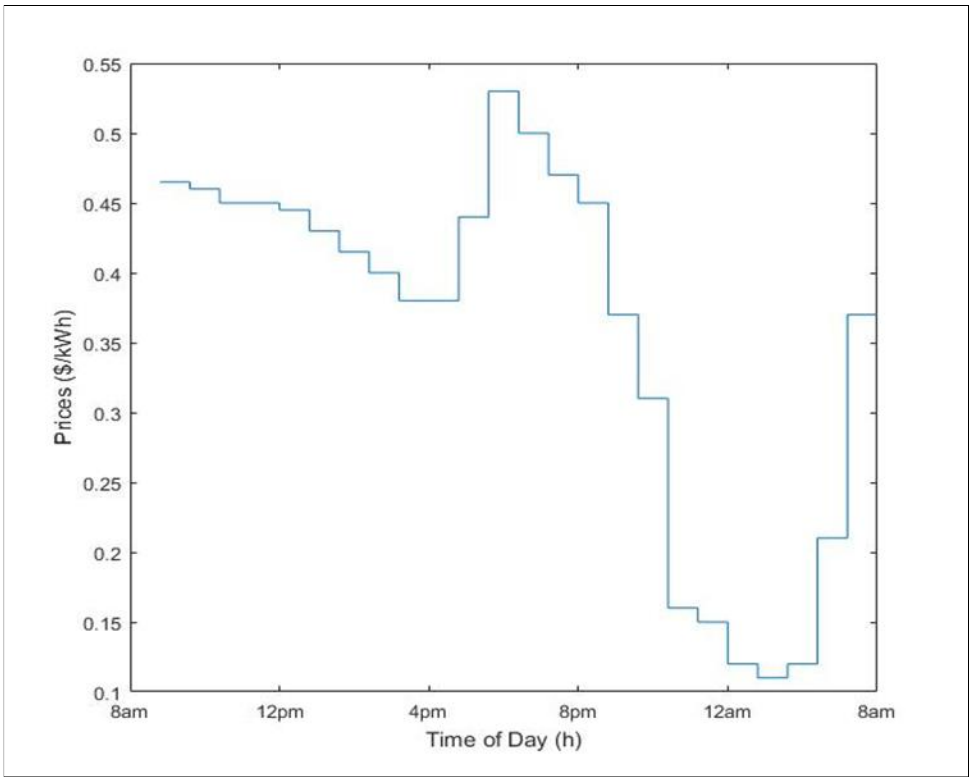


**Figure 2** Day-ahead electricity price

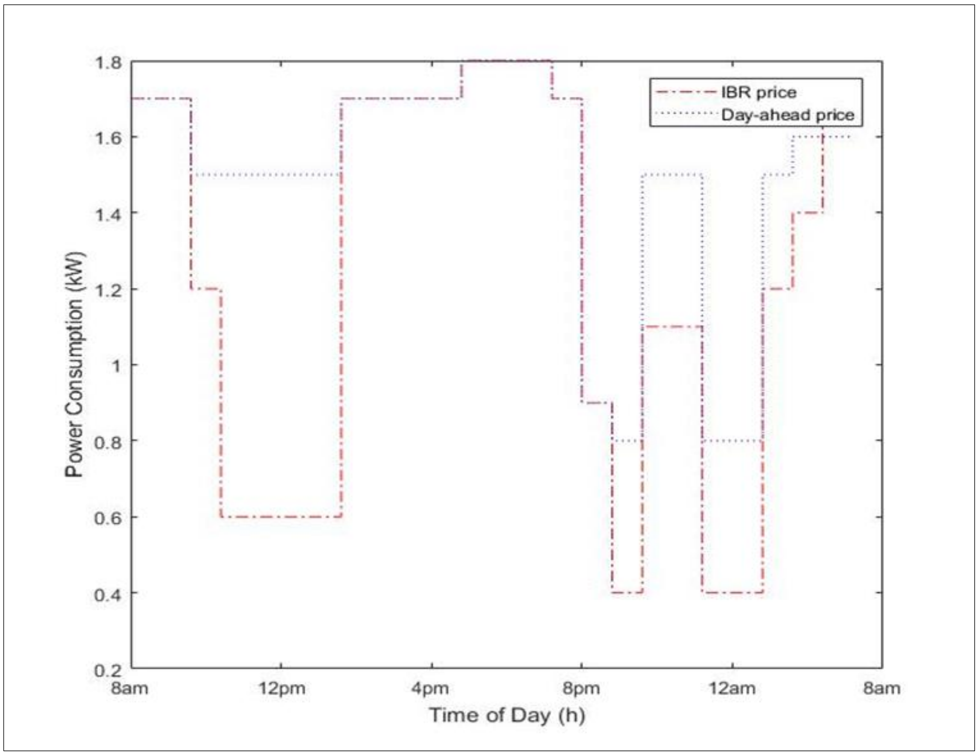


**Figure 3** Power consumption under (IBR) price

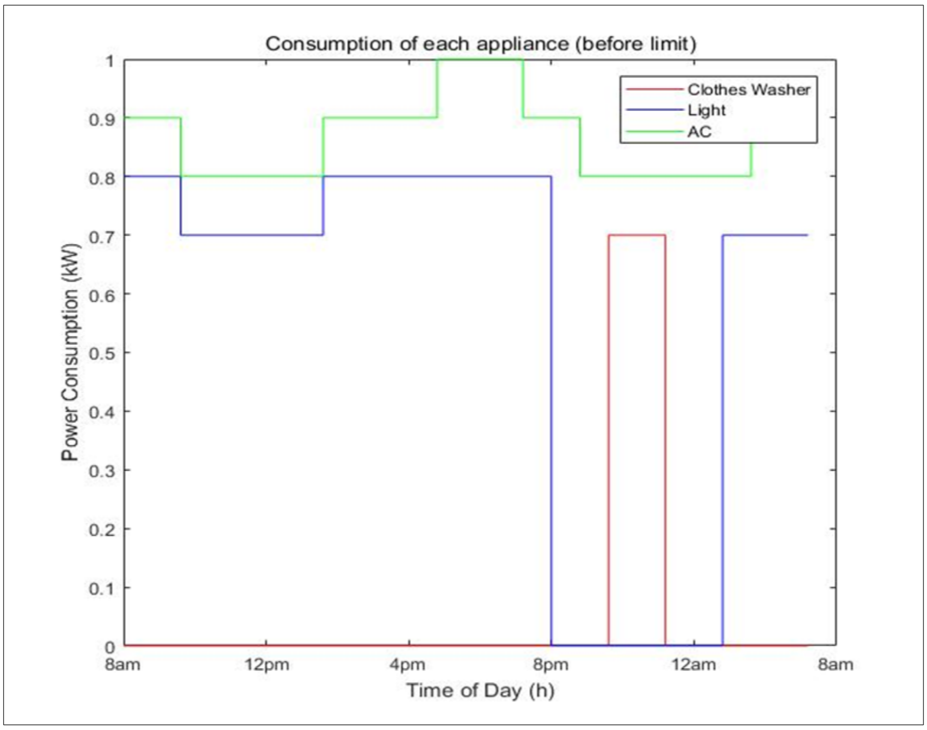


**Figure 4** Consumption of CW, L and AC before application of IBR prices

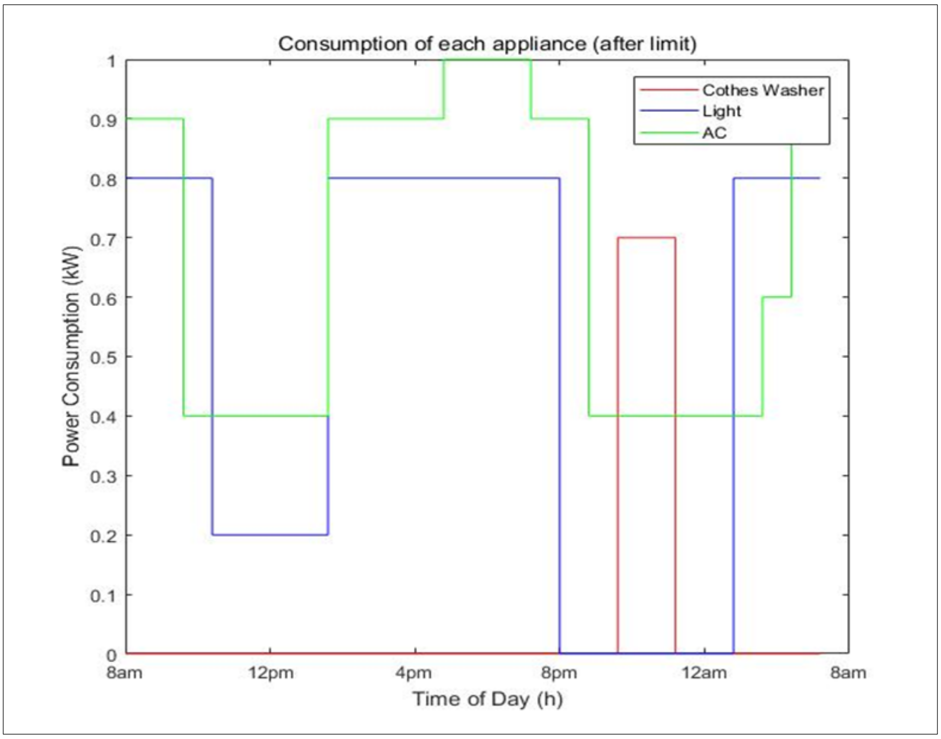


**Figure 5** Consumption of CW, L and AC under IBR price

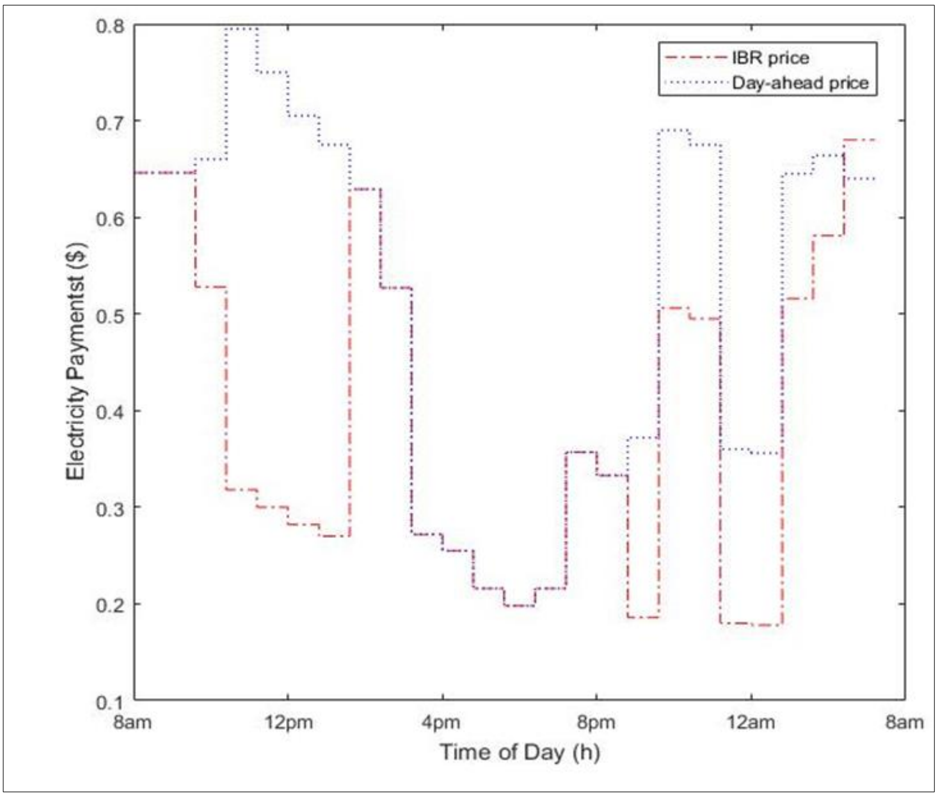


**Figure 6** Electricity payments with (IBR) and without limit (DAP)

## 6. Conclusion

In this work, we modify an optimization power scheduling scheme by using real-time price (RTP) with incline block rate (IBR) pricing technique to achieve a desired trade-off between electricity payment and consumer discomfort level. The work aims to minimize payment cost and peak consumption at residential side as well as discomfort caused by shifting peak load during peak hours. Home use appliances are characterized by un-schedulable and schedulable appliances. The schedulable are under study by categorizing further into time and power flexible. The paper assumes the problem as an optimization problem and adopts the IBR pricing scheme to optimize consumption and comfort level at peak hours. In this scheme, the electricity price is announced before hours and operating appliances. Though our experiment is based on some schedulable appliances but more effective for a large system. It is shown that the consumption declined by 70% and the discomfort level is also decreased by 30% but it was 70% in the day-ahead price. Under the proposed pricing scheme, we have a 77% declined in our payment cost. Simulation results illustrate the importance of block rates in scheduling appliances within incentive and comfort level.

The results show that the largest benefits are obtained with RTP and IBR because this form of pricing minimizes consumers' energy costs and maximizes the aggregator's profit. Consumer response, driven by monetary incentives, enables the shifting of demand from overloaded to no overloaded periods. Consumers that respond to incentives significantly lower their energy costs. The results also show the damages to the distribution system can be avoided if optimal consumer participation levels in DR are maintained.

This study has certain limitations that can be handle and addressed explicitly in future by including universal power scheduling data for better results.

## Compliance with ethical standards

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*Disclosure of conflict of interest*

The authors declare that there are no conflicts of interest regarding the publication of this paper.

*Data Availability*

The data that supports the findings of this study are available within the article.

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