# An Optimal Power Scheduling Method for Demand Response in Home Energy Management System

Zhuang Zhao, Won Cheol Lee, *Member, IEEE*, Yoan Shin, *Senior Member, IEEE*, and Kyung-Bin Song

***Abstract*—With the development of smart grid, residents have the opportunity to schedule their power usage in the home by themselves for the purpose of reducing electricity expense and alleviating the power peak-to-average ratio (PAR). In this paper, we first introduce a general architecture of energy management system (EMS) in a home area network (HAN) based on the smart grid and then propose an efficient scheduling method for home power usage. The home gateway (HG) receives the demand response (DR) information indicating the real-time electricity price that is transferred to an energy management controller (EMC). With the DR, the EMC achieves an optimal power scheduling scheme that can be delivered to each electric appliance by the HG. Accordingly, all appliances in the home operate automatically in the most cost-effective way. When only the real-time pricing (RTP) model is adopted, there is the possibility that most appliances would operate during the time with the lowest electricity price, and this may damage the entire electricity system due to the high PAR. In our research, we combine RTP with the inclining block rate (IBR) model. By adopting this combined pricing model, our proposed power scheduling method would effectively reduce both the electricity cost and PAR, thereby, strengthening the stability of the entire electricity system. Because these kinds of optimization problems are usually nonlinear, we use a genetic algorithm to solve this problem.**

***Index Terms*—Demand response, energy management system, genetic algorithm, inclining block rate, real-time pricing, smart grid.**

## I. Nomenclature

| | |
|---|---|
| LOT | Length of operation time. |
| AOA | Automatically operated appliance. |
| AOM | Manually operated appliance. |
| OST | Operation start time slot. |
| OTI | Operation time interval. |
| $\alpha_a$ | Start time slot of the OTI for appliance $a$. |
| $\beta_a$ | End time slot of the OTI for appliance $a$. |
| $l_a$ | LOT of appliance $a$. |
| $t_a$ | OST of appliance $a$. |
| $\boldsymbol{P}_a$ | Power consumption scheduling vector of appliance $a$. |
| $\boldsymbol{P}$ | Power consumption scheduling matrix. |
| $\boldsymbol{P}_{scd}$ | Total power consumption scheduling vector of all AOAs. |

## II. Introduction

WITH THE arrival of the information and technology era, residential demand for high quality and reliability of electrical energy increases day by day. At the same time, the pressure of global natural resources and environment is also increasing rapidly. Smart grid is a system that includes a physical power system and information system that links a variety of equipments and assets together to form a customer service platform [1]. Smart grid will likely incorporate some new technologies in communications, distributed systems, advanced metering, automation, distributed storage, safety, and security, to allow a considerable increase in the reliability and robustness of the power network, which will in turn lower the energy costs [2].

With the emergence of the smart grid, residents can reduce their electricity cost by scheduling the pattern of their home electricity usage, based on the real-time electricity prices (RTEP). With this motivation, several schemes for scheduling in-home power consumption have been proposed. In [3], the authors obtain an appropriate target total power consumption for all appliances; however, the specific power scheduling scheme for each appliance is not mentioned. In [4], the authors schedule the power usage for both interruptible and non-interruptible loads so that the electricity cost is reduced; however, peak power demands may emerge when the electricity price is low. In [5], the electricity cost and peak demand values are reduced simultaneously, but the assumptions of the scenario seem impractical. The power consumption of each appliance should be nearly constant over time. Demand response (DR) generally refers to actions taken to change residential electricity demand in response to variations in the electricity prices over time. As the basis for electricity usage scheduling, the DR information would be delivered to each home. With an energy management system (EMS) installed in the home, residents can make use of this information via an in-home energy management controller (EMC), which uses both prices and user preferences to schedule power usage. In our research, an EMC is embedded in the home gateway (HG), which is able to transmit the control signal to smart appliances in the

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home via a home area network (HAN). Several schemes for power-scheduling-based communication protocols for in-home appliances over HAN have been proposed [3],[6]–[9].

The most common DR includes time of use pricing (TOUP), critical peak pricing (CPP), and real-time pricing (RTP). The electricity price (EP) in TOUP and CPP are previously determined, and this work may be conducted only once for more than a quarter of a year. In contrast, the EP in RTP changes as often as hourly (exceptionally more often), which may reflect the utility's cost for generation or the wholesale price level. Hence, RTP has a much higher flexibility than TOUP and CPP, although CPP adds a peak price to TOUP [10]. Several ideas and methods have been proposed to achieve low electricity expenses by adopting the RTP model [3]–[5]. However, the purpose of the DR is not only to lower electricity demand from customers at peak demand times, but also to prevent higher power demand peaks even if the EP is low. From this point of view, RTP still has one defect: the use of RTP may cause the demand to be shifted to hours with low EP, which would lead to a higher peak electricity demand and peak-to-average ratio (PAR) during the low price time.

The overloads would result in instability in the system or even blackout. Therefore, a combination of RTP with inclining block rates (IBR) is necessary. In the IBR model, the EP would reach a higher level than the normal situation when the total electricity consumption exceeds a fixed threshold. After being combined with IBR, the RTP model would effectively reduce the PAR and increase the stability of the entire electricity system. There have been several methods proposed to solve the optimal in-home power scheduling problem: linear programming [3],[5]; particle swarm optimization (PSO) method [11]; and game theory [12]. Normally, the formulas for most of these optimization problems are nonlinear, so we anticipate that these problems can be solved easily by a genetic algorithm (GA).

In order to apply the EMS to residential houses, smart home appliances must be put into wide use. For existing home appliances, all we need to do is to add a wireless transceiver and data processor to each appliance. The data processor can analyze the data received by the transceiver and make the appliance operate during an appropriate time interval. Actually, some of these types of appliances have already emerged. Some smart refrigerators allow users to get connect with the appliance with a tablet or mobile phone. Moreover, novel Wi-Fi laundries that can be controlled by users from anywhere with a smart phone or tablet application have been produced. However, we think it would be a better idea if users could centralize the management of all smart appliances in the home via the HG which acts as a window, rather than connecting home appliances separately.

In this paper, we introduce the general architecture of EMS in a HAN and how the EMS works in the home, and then present an approach to schedule the electricity usage in the home for the purpose of reducing the electricity cost and PAR. Finally, the simulation results for this approach are presented to show its effectiveness and feasibility for working in the EMS.

## III. Architecture of Energy Management System in a Home Area Network

The objective of deploying EMS in the home is to minimize the expense of electricity and reduce the PAR by scheduling the pattern of electricity usage based on a priori supplied EP to ensure power system stability and security. EMS mainly comprises advanced metering infrastructure (AMI), smart meters, HG, EMC, home appliances, and in-home display (IHD) devices. The entire architecture of EMS with the help of wireless HAN is shown in Fig. 1.

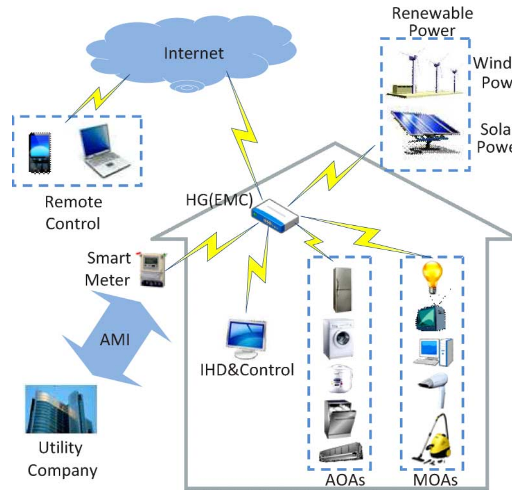


Fig. 1. Architecture of energy management system in the home.

The AMI is a key factor in smart grid treated as a central nervous system of the EMS architecture, which is the architecture for automated, two-way communication between a smart meter and the utility company [13]. In addition, the AMI is responsible for collecting and transmitting consumption data delivered from distributed smart meters to the utility company as well as for relaying a DR signal for pricing information from the utility company back to the smart meters in almost real time [14]. A smart meter is generally installed outside residential homes between the AMI and the EMC, which is responsible for reading and processing consumption data to be transferred to the utility company and simultaneously sending the DR signal to the EMC for further analysis. In this paper, we classify two kinds of home appliances: automatically operated appliances (AOAs) and manually operated appliances (MOAs). AOAs refer to the appliances that can be operated by themselves without manual control, such as washing machines, dish washer, or air conditioners. AOAs are usually categorized as interruptible (e.g., washing machines) and non-interruptible (e.g., electric kettle) [4]. On the contrary, MOAs can operate meaningfully only if residents are using them manually, such as a computer, television, and vacuum cleaner. Because these MOAs would be switched on and off manually, the home appliances that could be scheduled are only AOAs. In addition, we assume that the AOAs mentioned in this paper are smart home appliances. In our research, we embed the EMC in the HG, which receives the RTEP from a smart meter through the HG. In the architecture of the EMS proposed in this paper, the AOAs do not interact with each other; they only interact with the HG instead. This relationship can be found in Fig. 2. The HG acts as a window for residents to control all smart appliances in the home. All the operations of AOAs would have been scheduled by the EMC at the beginning of the day.

There are various wireless solutions for communication links between the smart meter and the HG, such as ZigBee, Z-Wave,

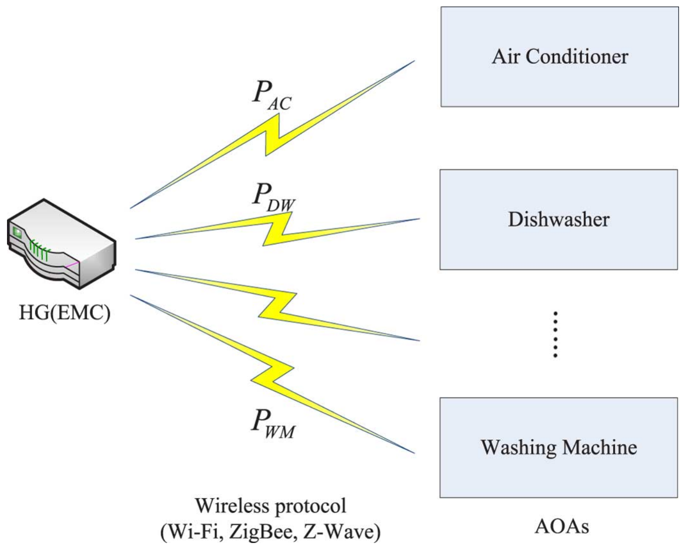


Fig. 2. The optimal power consumption scheduling vector can be transmitted by a wireless network such as Wi-Fi, ZigBee, or Z-Wave.

Wi-Fi, or a wired (HomePlug) protocol [15]. An optimal power usage schedule for each AOA can be exploited and transmitted to each AOA by the HG via a HAN. In addition, residents can obtain additional power from a renewable power generator, and the message, indicating the quantity of power generated, would be sent to the smart meter through the HG for further analysis. The scheduling process can be monitored for modification either by an IHD device or by a remote control such as a mobile phone or laptop via the internet.

## IV. Proposed Approach To Manage Energy Consumption With Genetic Algorithm

In this section, an optimal approach for scheduling the power usage of all AOAs in the home is proposed based on the RTP combined with IBR pricing scheme.

### A. Usage Pattern of Home Electric Appliances

Once HG receives DR information and the profile of RTEP from the utility company, the EMC can make decision on power schedule for all AOAs in the home. Residents usually prefer to operate each AOA at a certain time automatically to avoid peak price time or schedule appliances to finish their job before a specific time. For example, when residents are sleeping at night, the washing machine may start to work because the EP is low. In another example, if residents want to have dinner as soon as they arrive home in the afternoon, they must ensure that the electric rice cooker finishes its job before they arrive home. From this point of view, it is necessary for residents to set the time parameters for each AOA including the length of operation time (LOT) from start to end, the operation time interval (OTI) during which the appliance is valid to be scheduled, and its power consumption per hour. These parameters can be set on the IHD device and then transmitted to the EMC via HG.

Since each MOA is operated manually and nobody can tell in advance when and for how long time they will use a MOA, it seems impractical to set time parameters for each MOA ahead of the time. Therefore, we only consider the impact of AOAs on electricity cost and PAR. However, in the simulation results, we show that our scheme is still effective when MOA operation is involved.

### B. Final Goal of Our Approach

Before applying our proposed approach, 1 hour is divided into 5 time slots; in other words, the time resolution is 12-minute, and 1 day has 120 slots, which are denoted by the symbol $u$ : $u \in \boldsymbol{U} \triangleq \{1, 2, \ldots, 120\}$. The resolution is set to be 12-minute because it is short enough as a time unit for the operation intervals of all the home appliances, and it is much more convenient to solve the optimization problem using GA in which situation 1 day has 120 time slots (the binary number 1111111 is 128 in decimal). Therefore, the shortest operation time of any appliance is set to be 12 minutes. Hence, the LOT of the air conditioner can be set to integer multiples of the 12-minute interval. However, there are also some other AOAs whose LOTs for operating once are fixed, such as a washing machine, dishwasher, and electric kettle. These appliances can be operated automatically so that their operation times do not need to be controlled manually. Therefore, the LOTs of these appliances should be set strictly; that is, the operation times should be the numbers that denote integer multiples of 12. At the same time, these should be greater than and be the nearest numbers from the actual LOTs of these appliances. In this paper, we assume that the unit of LOT is the number of time slots. For example, if the normal operation time of a washing machine is 46 minutes, then parameter LOT should be set as 4 (48 minutes). In another example, the LOT should be set as 1 (12 minutes) if the electric kettle needs 8 minutes to boil water. If we apply this scheme, there must be some errors in the final results. However, the errors are just several minutes and are small enough to be ignored.

$\boldsymbol{A}$ denotes the set of AOAs. For each appliance $a \in \boldsymbol{A}$, we assume that $\boldsymbol{P}_a$ is the power consumption scheduling vector:

$$\boldsymbol{P}_a \triangleq [p_a^{(1)}, p_a^{(2)}, \ldots, p_a^{(120)}] \tag{1}$$

where $p_a^{(u)}$ denotes the power consumption value for appliance $a$ during the $u^{th}$ time slot, and the unit is kWh. Considering that there is a specification for each electric appliance, we assume that the power consumption values per hour for all appliances are all fixed. When the power consumption value per hour of appliance $a$ is denoted by $x_a$, during the $u^{th}$ time slot, the corresponding power consumption is

$$p_a^{(u)} = \frac{x_a}{5}. \tag{2}$$

Our purpose is to optimize the power consumption scheduling vector $\boldsymbol{P}_a$ that is transmitted to appliance $a$ by HG via a suitable wireless network as shown in Fig. 2.

### C. RTP Combined With IBR

We previously mentioned that RTP has much higher flexibility than TOUP and CPP, whereas it is much easier to concentrate a lot of appliances' operations at a relatively low EP time. Therefore, we combine RTP with IBR, in which the EP could be different within the same time slot based on the total power consumption. For example, a resident wants to reduce his/her electricity cost and then plans to run most of the appliances in the home at 3:00 A.M. due to the low EP at that time. However, the total power consumption at that time may exceed the threshold of IBR, hence, it costs a lot more than expected. In this paper, we set two electricity price levels in IBR, and the EP changes every hour. The EP function is given as

$$prc_h(s_h) = \begin{cases} a_h, & \text{if } 0 \le s_h \le c_h \\ b_h, & \text{if } s_h > c_h \end{cases} \tag{3}$$

where $s_h$ denotes the total power consumption in the home during the $h^{th}$ hour, $a_h$ is the RTEP during the $h^{th}$ hour in a day, $b_h$ is the second electricity price level that should be greater than $a_h$, and $c_h$ is the threshold of power consumption at hour $h$ of IBR. When the power consumption $s_h$ is less than or equal to the threshold $c_h$, the EP would be $a_h$. Otherwise, the EP would be $b_h$, and the unit is cents/kWh.

Considering that one hour has been divided into five time slots, we should make a modification on the EP function. By dividing $s_h$ and $c_h$ by 5, we can obtain the total power consumption value $\tilde{s}_u$ and the IBR threshold $\tilde{c}_u$ in every 12-minute, respectively. Then, the EP function can be altered as

$$p\tilde{r}c_u(\tilde{s}_u) = \begin{cases} \tilde{a}_u, & \text{if } 0 \le \tilde{s}_u \le \tilde{c}_u \\ \tilde{b}_u, & \text{if } \tilde{s}_u > \tilde{c}_u. \end{cases} \tag{4}$$

After modification, the only difference from the afore mentioned function is its format, i.e., the number of variables becomes 120 instead of 24 due to the time division, whereas the EP values would be the same as before.

If $\tilde{b}_u$ is a constant value greater than $\tilde{a}_u$, the EP would be fixed at $\tilde{b}_u$ whenever the total power consumption exceeds the threshold. This would be the case that if there is a time interval where the total power consumption exceeds the threshold, this can happen at any time during the day. If this time interval arises at the low price time, that would be acceptable. However, if the corresponding time interval occurs during the highest price time, the entire power system seems to be overloaded such that it may damage the system and yield to a blackout. Therefore, in this paper, we assume that

$$\tilde{b}_u = \lambda \cdot \tilde{a}_u \tag{5}$$

where $\lambda$ is a positive value. In the IBR, the second price level $\tilde{b}_u$ is changed with $\tilde{a}_u$, which means when the normal EP $\tilde{a}_u$ is the highest in the day, then $\tilde{b}_u$ is also the highest. In this case, the circumstance mentioned before would not arise. But it seems unrealistic to utilize this price function because it is impossible to obtain the entire EP function ahead of the day. However, several electricity price prediction methods have been proposed in [5],[16]–[19].

### D. Problem Formulation

As mentioned before, it is necessary for residents to set some parameters for each AOA. Toward this aim, we assume $\alpha_a$, $\beta_a \in \boldsymbol{U}(\alpha_a < \beta_a)$ as the indexes of the start and the end time slots, respectively. Along this OTI, the power consumption of appliance $a$ is assumed to be valid for appropriate scheduling. Let $l_a$ indicate the LOT, i.e., the number of time slots for the operation of appliance $a$. The above parameters need to be set by residents via an IHD to be transmitted to the EMC. In addition, $\beta_a - \alpha_a$ must be greater than or equal to $l_a$. For example, if the washing machine needs one hour to finish its work, then the value of $\beta_a - \alpha_a$ could be any numbers that are greater than or equal to 5, and in the meantime less than or equal to 120. The greater the value of $\beta_a - \alpha_a$ is, the more possible solutions there would be. We define a variable $t_a$ as the operation start time (OST) of appliance $a$. Since $\alpha_a$, $\beta_a$, $l_a$ and $x_a$ are all known already, the power consumption scheduling vector of appliance $a$ would be determined once we have $t_a$. In Fig. 3, the example shows the relationship of these parameters, in which four different kinds of AOAs are included.

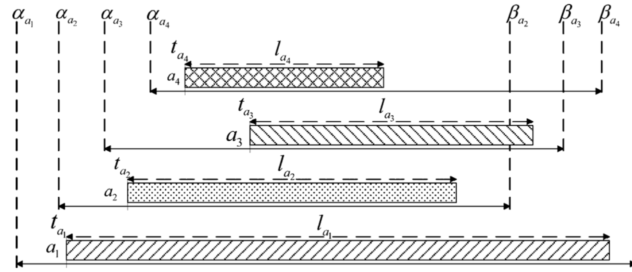

Fig. 3. Four examples to show the relationship among all parameters for each appliance.

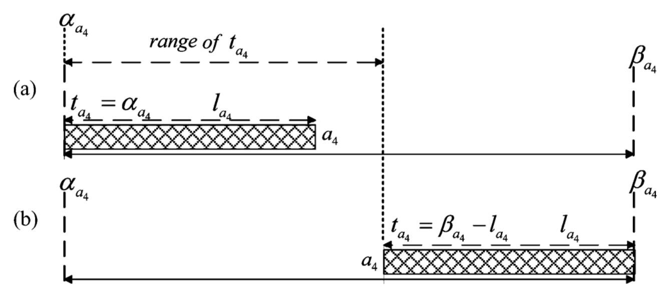


Fig. 4. Illustration for the range of OST of home appliance a: (a) the earliest start time and (b) the latest start time.

Now for each appliance $a \in \boldsymbol{A}$, there exists a group of parameters comprising the OTI $[\alpha_a, \beta_a]$, LOT $l_a$, and power consumption value per hour $x_a$. In addition, we also set OST $t_a$ as a variable. Having $\alpha_a$, $\beta_a$, and $l_a$, $t_a$ should be greater than or equal to $\alpha_a$, and less than or equal to $\beta_a - l_a$. In other words, the range of OST of $a$ is

$$t_a \in [\alpha_a, \beta_a - l_a]. \tag{6}$$

The range of $t_a$ is shown in Fig. 4.

We construct a variable vector $[t_1, t_2, \ldots, t_a]$ which is composed of the OSTs of all AOAs. Therefore, we can define a power consumption scheduling matrix $\boldsymbol{P}$ for all AOAs as

$$\boldsymbol{P} = \left\{ \begin{array}{lll} p \mid p_a^{(u)} = & \frac{x_a}{5}, & \forall a \in \boldsymbol{A}, u \in [t_a, t_a + l_a] \\ p_a^{(u)} = & 0, & \forall a \in \boldsymbol{A}, u \in \boldsymbol{U} \setminus [t_a, t_a + l_a] \end{array} \right\} \tag{7}$$

where $\boldsymbol{P}$ denotes a matrix in which each row stands for the power schedule of a certain appliance. $u$ is the index of column. The expression $u \in \boldsymbol{U} \setminus [t_a, t_a + l_a]$ indicates that $u$ belongs to $\boldsymbol{U}$ excluding the range $[t_a, t_a + l_a]$. By summing up all the values of each column vector in the power consumption scheduling matrix, a total power consumption scheduling vector $\boldsymbol{P}_{scd}$ would be determined as

$$\boldsymbol{P}_{scd} = \{p_{scd} \mid p_{scd}^{(u)} = \sum \boldsymbol{P}^{(u)}, \quad \forall u \in \boldsymbol{U}\}. \tag{8}$$

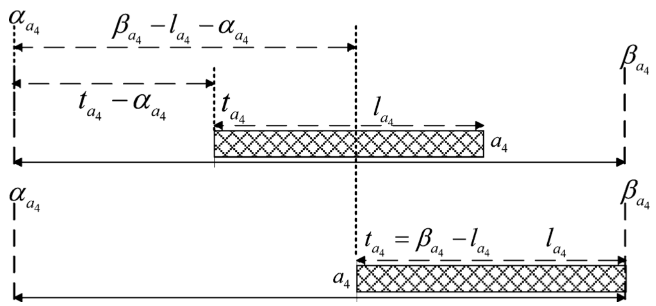

Fig. 5. Illustration of the concept of $\mathrm{DTR}_a$.

In (8), $\boldsymbol{P}^{(u)}$ stands for the $u^{th}$ column in the power consumption scheduling matrix. Residents usually hope that home appliances can finish their work as soon as possible. Thus, we consider lowering the delay time rate (DTR) of home appliances. The definition of DTR emerges as

$$DTR_a = \frac{t_a - \alpha_a}{\beta_a - l_a - \alpha_a} \tag{9}$$

where $\mathrm{DTR}_a$ denotes the DTR of appliance $a$. Here, if the appliance operates at a later time, the later the appliance operates, the larger the $\mathrm{DTR}_a$ becomes. The smallest and largest values of $\mathrm{DTR}_a$ are set to 0 and 1. For example, assuming that a resident sets the parameter OTI for a washing machine as $[\alpha_{wm}, \beta_{wm}]$ and LOT as $l_{wm}$, if it starts operating at time slot $\alpha_{wm}$, the $\mathrm{DTR}_{wm}$ would be 0; if it starts at time slot $\beta_{wm} - l_{wm}$, the $\mathrm{DTR}_{wm}$ would be one. This relationship can be easily seen in Fig. 5 where $\mathrm{DTR}_{a_4} = 0$ and $\mathrm{DTR}_{a_4} = 1$, if $t_{a_4} = \alpha_{a_4}$ and $t_{a_4} = \beta_{a_4} - l_{a_4}$, respectively. Now we introduce a delay parameter $\rho > 1$ and the relevant formula can be expressed by

$$\sum_{a \in \boldsymbol{A}} \rho^{DTR_a}. \tag{10}$$

Since the delay parameter $\rho > 1, \rho^{DTR_a}$ geometrically increases as $\mathrm{DTR}_a$ continues to increase. For residents, the value of this formula is expected to be as smaller as possible. Thus, in the final optimization problem, along with the reduction of the electricity expense, we also try to minimize the above value as well.

We clarify the power consumption scheduling problem as the following optimization problem:

$$\begin{aligned} minimize \quad & w_1 F_1(\boldsymbol{P}_{scd}) + w_2 F_2(DTR_a) \\ s.t. \quad & t_a \in [\alpha_a, \beta_a - l_a] \end{aligned} \tag{11}$$

where

$$F_1(\boldsymbol{P}_{scd}) = \sum_{u=1}^{120} \tilde{prc}_u(p_{scd}^{(u)}) \cdot p_{scd}^{(u)}, \tag{12}$$

$$F_2(DTR_a) = \sum_{a \in \boldsymbol{A}} \rho^{DTR_a}. \tag{13}$$

In (11), $w_1$ and $w_2$ are the weights representing the importance of the individual objectives shown in (12) and (13) where $w_1 + w_2 = 1$, and $w_1, w_2 \in [0, 1]$. In (12), function $\tilde{prc}_u$ denotes the EP at the $u^{th}$ time slot.

After normalization, we can construct the final optimization formula as follows:

$$\begin{aligned} minimize \quad & w_1 \frac{\sum\limits_{u=1}^{120} \tilde{prc}_u(p_{scd}^{(u)}) \cdot p_{scd}^{(u)}}{\left(\sum\limits_{u=1}^{120} \tilde{prc}_u(p_{scd}^{(u)}) \cdot p_{scd}^{(u)}\right)_{max}} \\ & + w_2 \frac{\sum\limits_{a \in \mathbf{A}} \rho^{DTR_a}}{\left(\sum\limits_{a \in \mathbf{A}} \rho^{DTR_a}\right)_{\max}} \\ s.t. \quad & t_a \in [\alpha_a, \beta_a - l_a]. \end{aligned} \tag{14}$$

For each appliance $a \in \boldsymbol{A}$, since the maximum value of $\rho^{DTR_a}$ is $\rho$, the value of $(\sum_{a \in \boldsymbol{A}} \rho^{DTR_a})_{max}$ is equal to $n_a p$ where $n_a$ indicates the number of AOAs.

### *E. Genetic Algorithm Module*

In this paper, we adopt GA to optimize the OSTs of all AOAs to achieve our objectives. The GA randomly creates a solution population consisting of a certain number of individuals. Each individual contains a solution set of all kinds of variables represented as a chromosome. After calculating fitness values, selecting individuals, crossover, and mutation, we can get the new solutions that include both the old and the new individuals. After judging whether the expected generation number $N_{gmax}$ has been satisfied or not, we can obtain the new generation or the best fitness solution. In order to better illustrate the proposed approach, the GA optimization and the specific calculation process of our scheme is shown in Fig. 6. Since the OST is the only variable in our scheme and the constraint parameters are set in the beginning, we assume that the total fitness function is (14). Referring to the selection process, we use a roulette selection method in which the individual with a better fitness value has a higher probability to be selected for further processing. In general, chromosomes are represented by binary strings which are considered easy to split and recombine [20].

## V. Simulation Results

In this section, we present the simulation results to show the superior performance of our proposed approach for in-home power scheduling. In this paper, we assume nine kinds of AOAs in the home. However, considering some AOAs may be used more than once by users in a day, we assume that the number of AOAs' operations in one day is up to 16. The information of all AOAs is shown in Table I. Since residents may not use all of the appliances in one day, therefore, in our simulation, 8–16 AOAs' operations are considered. According to the ratio of the two electricity price levels in British Columbia Hydro [21], the value of $\lambda$ in (5) is determined to be 1.4423. We also assume the power threshold $\tilde{c}_u = 0.4$ and the delay parameter $\rho = 5$ for all cases. For GA optimization, the population size of each generation, $N_s$, is 200. The probability of crossover between two strings, $P_c$, is 90%. In addition, all strings have a probability of 2% to mutate, which is denoted by $P_m$. Finally, when the generation number reaches 1000, the evolution process will finish. All

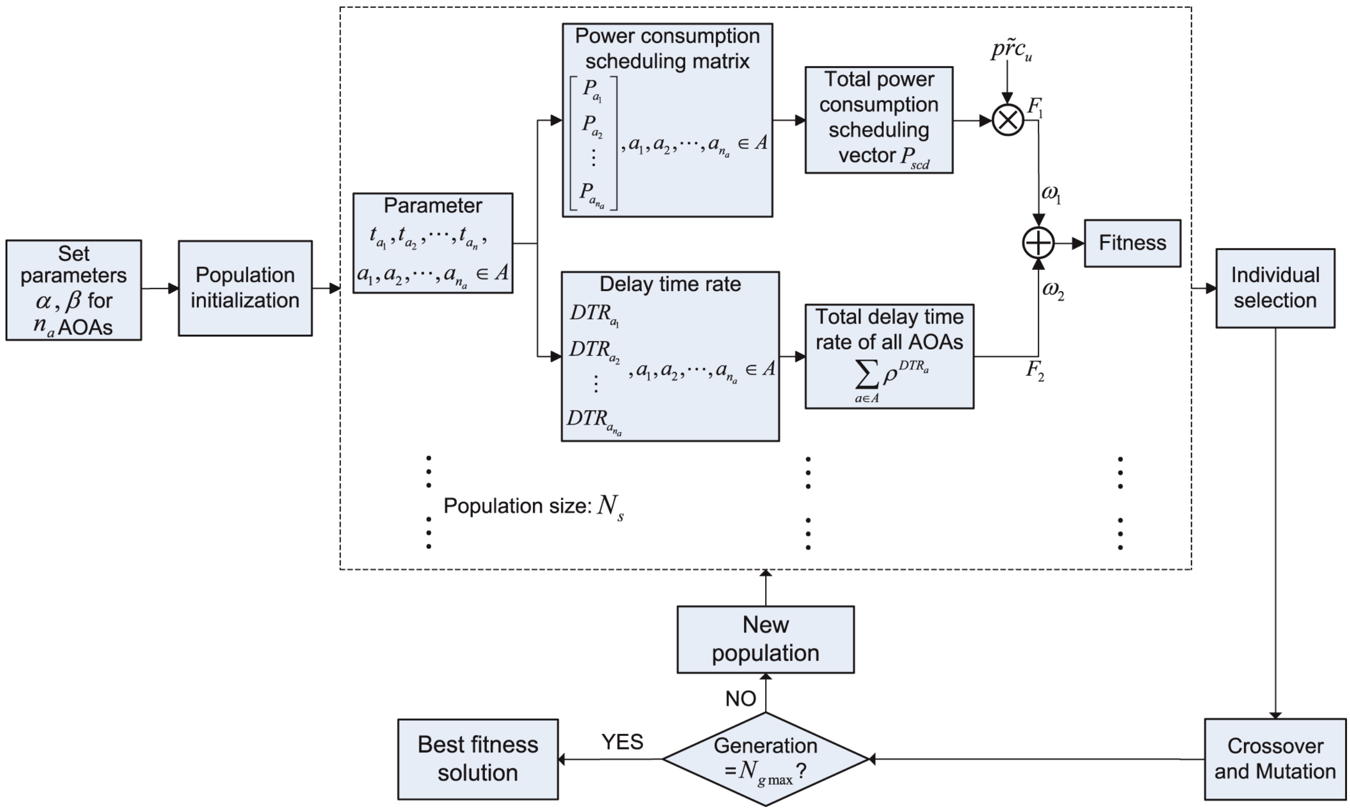


Fig. 6. Flowchart of GA optimization and the calculation process of the proposed approach.

TABLE I
PARAMETERS OF AOAS USED IN THE SIMULATION PROCESS

| AOA | OTI | LOT | Power($kWh$) | AOA | OTI | LOT | Power($kWh$) |
|---|---|---|---|---|---|---|---|
| Air conditioner$^1$ | 41∼60 | 5 | 1 | Water heater | 86∼105 | 3 | 1.5 |
| Air conditioner$^2$ | 61∼85 | 5 | 1 | Dishwasher | 101∼120 | 2 | 0.6 |
| Air conditioner$^3$ | 86∼120 | 10 | 1 | Washing machine | 1∼60 | 5 | 0.38 |
| Electric radiator$^1$ | 1∼30 | 5 | 1.8 | Electric kettle$^1$ | 1∼25 | 1 | 1.5 |
| Electric radiator$^2$ | 91∼115 | 10 | 1.8 | Electric kettle$^2$ | 66∼85 | 1 | 1.5 |
| Rice cooker$^1$ | 1∼25 | 2 | 0.5 | Humidifier$^1$ | 1∼30 | 10 | 0.05 |
| Rice cooker$^2$ | 41∼60 | 2 | 0.5 | Humdifier$^2$ | 91∼120 | 10 | 0.05 |
| Rice cooker$^3$ | 71∼90 | 2 | 0.5 | Clothes dryer | 71∼91 | 5 | 0.8 |

$*^1$,$*^2$ and $*^3$ denote that appliance $*$ is used three times within different OTIs in one day.

parameters used for the proposed approach are listed in Table II. In our paper, all simulations are implemented in MATLAB.

### A. Relationship Between Electricity Cost and DTR

As mentioned before, if residents aim to achieve the minimization of electricity cost, AOAs must be operated according to how the EMC schedules them. Within the OTI, the operation times of AOAs are not fixed due to the RTEP and the operations of other AOAs. Now we define

$$DTR_{ave} = \frac{\sum\limits_{a \in \boldsymbol{A}} (t_a - \alpha_a)}{\sum\limits_{a \in \boldsymbol{A}} (\beta_a - l_a - \alpha_a)}. \tag{15}$$

The formula in (15) denotes the average DTR of all AOAs. Fig. 7 shows the simulation results of the relationship between the electricity cost and the average DTR.

Generally speaking, the relationship between the electricity cost and $\mathrm{DTR}_{ave}$ is a trade-off. In other words, as the value of $\mathrm{DTR}_{ave}$ increases, the electricity cost decreases. However, the minimum electricity cost value emerges at a position where the $\mathrm{DTR}_{ave}$ value is approximately 50%, which is not definite due to the random EP. From the results shown in Fig. 7, at the position that $\mathrm{DTR}_{ave} = 0$, it implies that the major consideration is minimizing the delay time, so in this case $w_1 = 0$, and $w_2 = 1$; whereas, when the minimum electricity cost is reached, $w_1 = 1$, and $w_2 = 0$.

TABLE II
PARAMETERS USED FOR THE PROPOSED OPTIMIZATION APPROACH

| Parameter | Value | Parameter | Value |
|---|---|---|---|
| $n_a$ | 16 | $N_s$ | 200 |
| $\lambda$ | 1.4423 | $P_c$ | 0.9 |
| $\tilde{c}_u$ | 0.4 | $P_m$ | 0.02 |
| $\rho$ | 5 | $N_{gmax}$ | 1000 |

### B. Impact of Inclining Block Rates

Now we focus on the comparison about the electricity cost and PAR between the states of being with and without our power

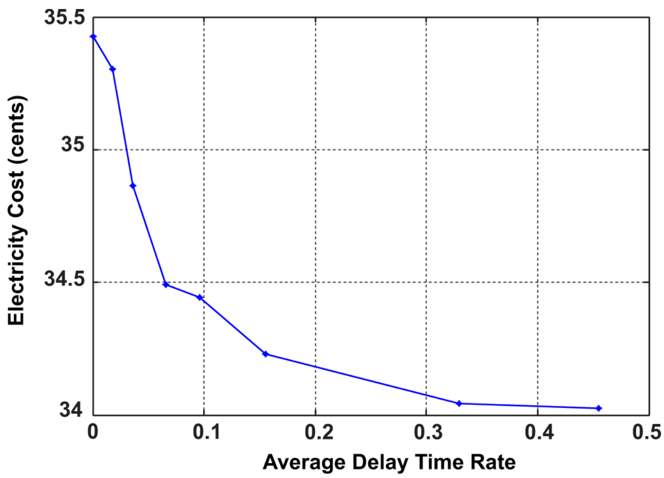


Fig. 7. Trade-off between electricity cost and average delay time rate.

scheduling scheme. The RTEP data is adopted from the Ameren Illinois Power Company, and the date ranges from August 1st, 2012 to October 31st, 2012 (92 days) [22]. The simulation results for the electricity cost and PAR with RTP combined with IBR pricing scheme are shown in Fig. 8.

In this simulation, we only consider minimizing the electricity cost; therefore, in this case, $w_1 = 1$, and $w_2 = 0$. From the results in Fig. 8(a), we find that without power scheduling in the homw, the average daily electricity cost for three months is 48.65 cents; however, this value becomes 35.97 cents with our power scheduling scheme. After three months, the resident could save 1166.6 cents with the proposed power scheduling approach. Because the home appliances considered are only AOAs, and the number of AOAs is not large, the daily electricity cost is not high. Fig. 8(b) shows that PAR reduces from 5.22 to 3.37 with the application of our proposed approach, leading us to conclude that our approach is effective in reducing both the electricity cost and PAR.

In order to demonstrate the effectiveness of RTP combined with IBR pricing scheme, the comparison between which and RTP scheme alone is shown in Fig. 9. Here, if only RTP is used, the PAR value would also be very high, whereas the proposed RTP combined with IBR is a better way to reduce PAR.

Now we present the impact of IBR on peak power usage in home. Fig. 10(a) shows the RTEP profile in the United States on August 7th, 2012. From the profile, we know that the EP within the 16th–20th time slots on that day is 1.646 cents/$kWh$, which is the lowest during the day. Two power consumption profiles in a home, without power scheduling and with power scheduling based on RTP, are shown in Fig. 10(b). With the power scheduling using RTP scheme alone, even if the electricity cost would reduce, a large amount of power demand would be shifted to the 16th-20th time slots due to the low EP at that time. However, with our power scheduling approach based on the RTP combined with IBR pricing scheme, the power demand could be dispersive due to the constraint of the power threshold. The superior performance of our scheme in the aspect of eliminating the peak power demand is shown in Fig. 10(c).

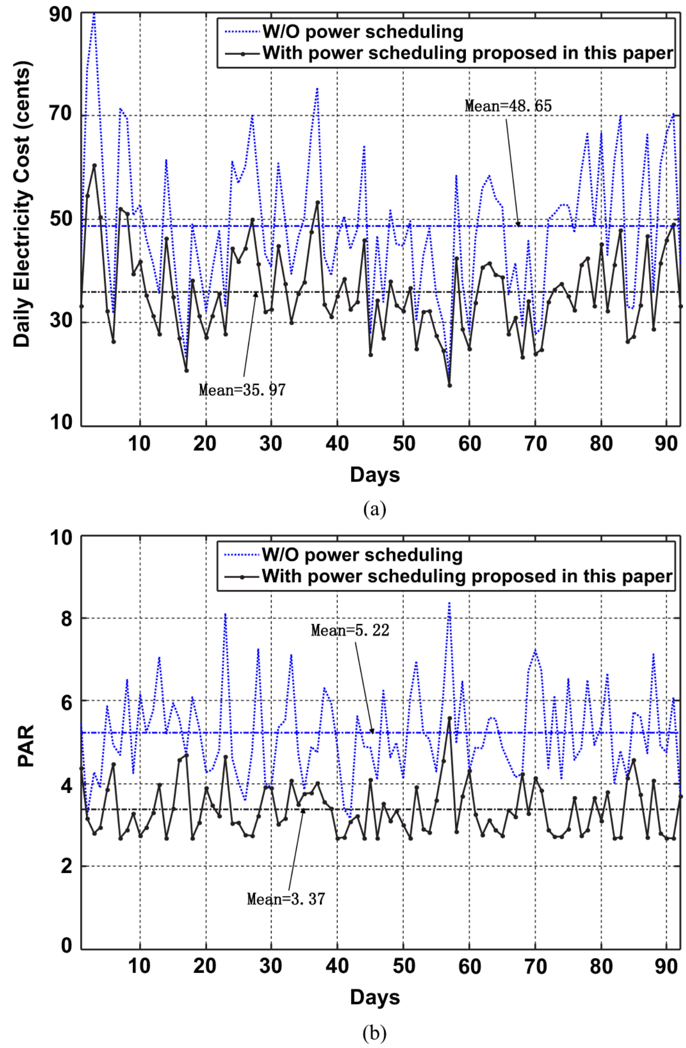


Fig. 8. The impact of the proposed power scheduling approach on: (a) daily electricity cost and (b) PAR.

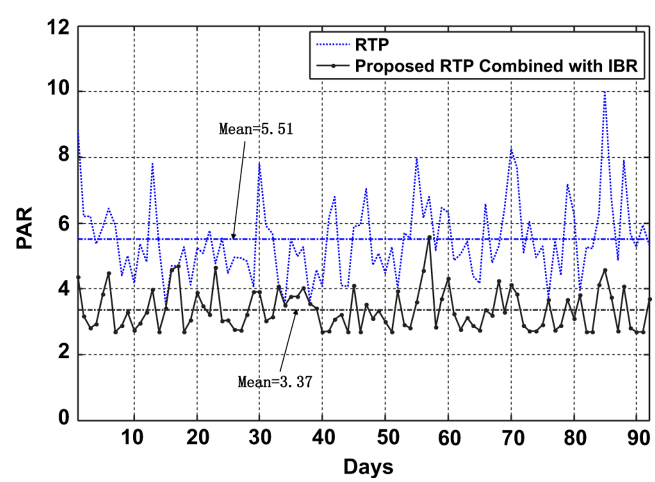


Fig. 9. The impact of IBR in the proposed approach on PAR.

## C. Impact of MOAs

We also consider the impact of MOAs on the performance of our proposed scheme. The simulation results are shown in Fig. 11. Seven kinds of MOAs are involved, and we consider

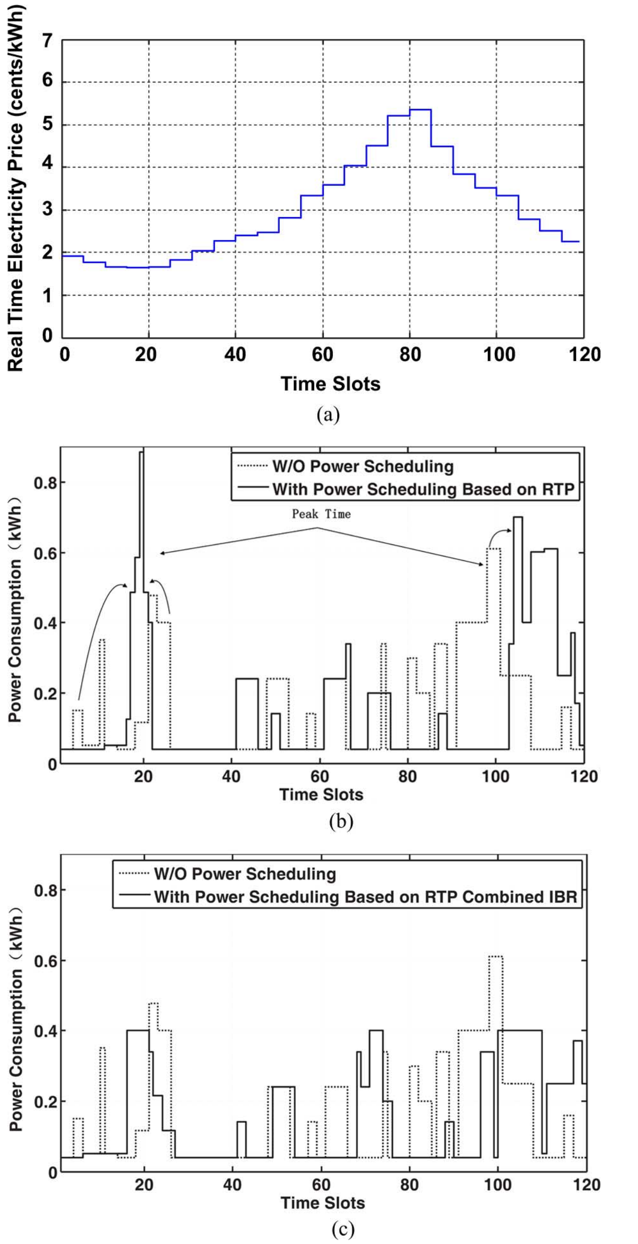


Fig. 10. (a) RTEP profile on August 7th, 2012. (b) Comparison between the power consumption profile without power scheduling and with power scheduling based on RTP alone. (c) Comparison between the power consumption profile without power scheduling and with power scheduling based on RTP combined with IBR.

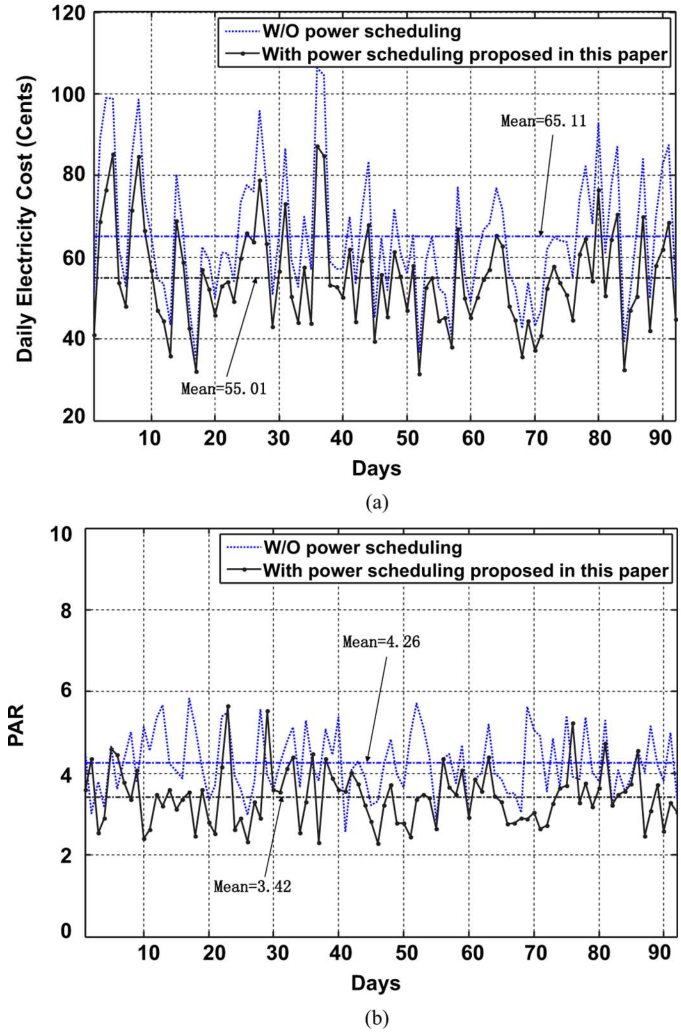


Fig. 11. The impact of MOAs' operations on: (a) daily electricity cost and (b) PAR.

4-8 MOAs' operations in one day that are detailed in Table III. We assume these MOAs operate in a relatively random time slot during a probable OTI. In Fig. 11(a), because MOAs are involved, the electricity cost is much greater than that in Fig. 8(a). In Fig. 11(b), due to the increase of the average power level, the PAR value is relatively smaller than that in Fig. 8(b). With our power scheduling scheme, the average electricity cost during three months is reduced from 65.11 cents to 55.01 cents, and the PAR is reduced from 4.26 to 3.42. Depending on these results, we find that our scheme is also effective even if MOAs' operations are involved. Since the home appliances assumed in this simulation are all typical appliances for ordinary electricity consumers, and enough combinations of AOAs and MOAs are considered, we believe that the proposed approach is always feasible and effective for any residential houses.

### D. Impact of Multiple Users

Thus, we have presented the effectiveness of our proposed scheme for a single resident. Now we present the simulation results that show the impact of our scheme on 10 residents. Fig. 12(a) shows that even if the number of residents increases, the average PAR of 10 residential users' aggregated power demand is still reduced from 4.34 to 2.84, which leads to the stability and security of the entire electricity system. In Fig. 12(b), all the residents can reduce their monthly electricity cost effectively by adopting our proposed scheme.

## VI. Conclusion

In this paper, we first introduce the architecture of EMS in a HAN, and then present an approach for power scheduling in the home with the help of the RTEP and residents' preferences. For residents, the beneficial features obtained by applying our proposed approach are the reduction of the electricity cost as well as the delay time rate of home appliances' operations simultaneously. In addition, the benefit rewarded to utility companies

TABLE III
ASSUMED PARAMETERS OF MOAS USED IN THE SIMULATION PROCESS

| MOA | Probable OTI | LOT | Power($kWh$) | MOA | Probable OTI | LOT | Power($kWh$) |
|---|---|---|---|---|---|---|---|
| Light | 81∼120 | 30 | 0.24 | TV | 91∼120 | 25 | 0.1 |
| Computer[1] | 31∼60 | 20 | 0.4 | Electric iron | 61∼70 | 2 | 1.5 |
| Computer[2] | 61∼90 | 20 | 0.4 | Hair drier | 101∼110 | 1 | 1 |
| Cleaner | 31∼40 | 2 | 1.5 | Fan | 61∼70 | 6 | 0.05 |

$*^1$ and $*^2$ denote that appliance $*$ is used twice within different OTIs in one day.

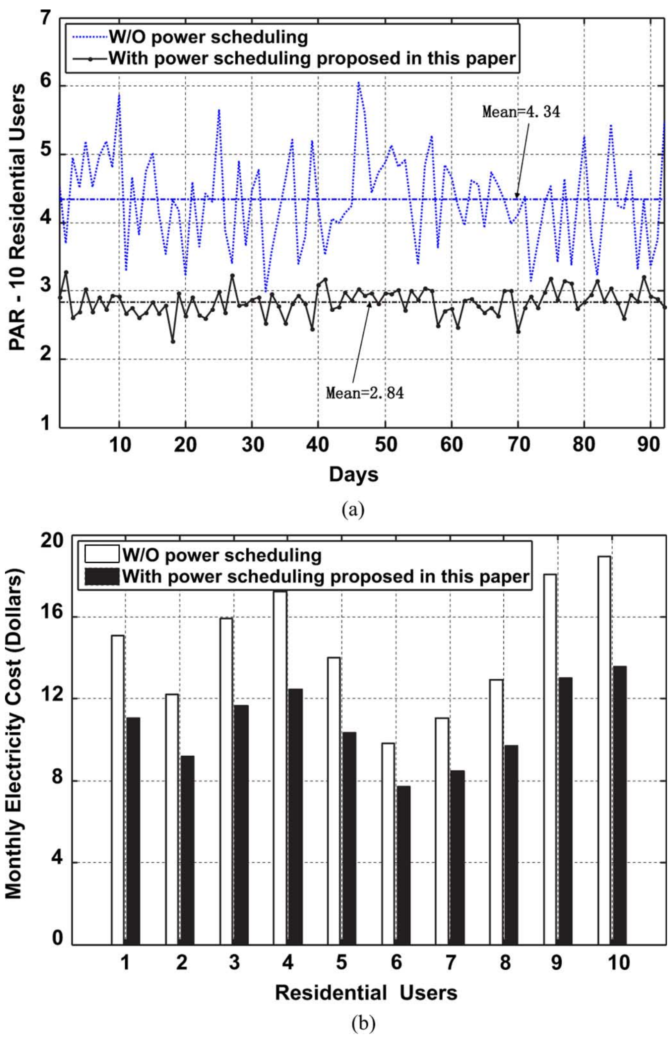


Fig. 12. The impact of multiple users on: (a) PAR of aggregated power demand and (b) monthly electricity cost.

is the reduction of the PAR which would increase the stability of the entire electricity system. By combining RTP and IBR together, our approach could satisfy all the benefits not only for residents but also for utility companies. In the simulation results, it can be concluded that our power scheduling approach using RTP combined with the IBR pricing model has been proved to be a better way compared with the RTP alone pricing scheme. Surely, the proposed approach can be a reliable solution for future EMS in HAN of smart grid.

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