An Optimal Power Scheduling Method Applied in Home Energy Management System Based on Demand Response

Zhuang Zhao, Won Cheol Lee, Yoan Shin, and Kyung-Bin Song

In this paper, we first introduce a general architecture of an energy management system in a home area network based on a smart grid. Then, we 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, which is transferred to an energy management controller (EMC). Referring to the DR, the EMC achieves an optimal power scheduling scheme, which is delivered to each electric appliance by the HG. Accordingly, all appliances in the home operate automatically in the most cost-effective way possible. In our research, to avoid the high peak-to-average ratio (PAR) of power, we combine the real-time pricing model with the inclining block rate model. By adopting this combined pricing model, our proposed power scheduling method effectively reduces both the electricity cost and the PAR, ultimately strengthening the stability of the entire electricity system.

Keywords: Smart grid, energy management system, demand response, real-time pricing, inclining block rate.

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Zhuang Zhao (phone: +82 2 816 6606, lxss_007@ssu.ac.kr), Won Cheol Lee (wlee@ssu.ac.kr), and Yoan Shin (yashin@ssu.ac.kr) are with the Department of Electronic Engineering, Soongsil University, Seoul, Rep. of Korea.

Kyung-Bin Song (kbsong@ssu.ac.kr) is with the Department of Electrical Engineering Soongsil University, Seoul, Rep. of Korea.

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I. Introduction

The information and technology era has seen a rise in the demand for high quality and reliable electrical energy service. Simultaneously, the strain on global natural resources and the environment has increased. The smart grid is a system that includes a physical power system and an information system that link a variety of equipment and assets together to form a customer service platform [1]. To increase power networks' reliability and robustness and to lower energy cost, the smart grid will likely incorporate some new technologies in communications, distributed systems, advanced metering, automation, distributed storage, and safety and security [2].

With the application of the smart grid, residents can reduce their electricity cost according to the scheduling pattern of their home electricity usage, based on the real-time electricity prices (RTEPs). For this purpose, several schemes for scheduling in-home power consumption have been proposed. In [3], the authors obtained an appropriate target total power consumption for all appliances, but the specific power scheduling scheme for each appliance was not mentioned. In [4], the authors scheduled the power usage for both interruptible and non-interruptible loads so that the electricity cost was reduced, but it was shown that peak power demands could emerge when the electricity price was low. In [5], the electricity cost and the peak demand values were 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 residents' electricity demand in response to variations in the price of electricity over time. As the basis for electricity usage scheduling, DR information would be delivered to each home. With an energy management system (EMS) installed in each 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 home via a home area network (HAN). Several schemes for power scheduling-based communication protocols for in-home appliances over a 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). Since the price of electricity (POE) in TOUP and CPP is predetermined about three times a year, and the POE in RTP changes as often as hourly (sometimes more often), which may reflect the utility's cost for a generation or the wholesale price level, 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 a low electricity expense by adopting the RTP model [3]-[5]. However, the purpose of 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 POE is low. Regarding this point, RTP still has a defect: the use of RTP may cause the demand to be higher during the hours with low POE, which would lead to a higher peak electricity demand and peak-to-average ratio (PAR) at the low price time.

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

In this paper, we will 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 with the purpose of reducing the electricity cost and PAR. At last, simulation results for this approach will be presented to show its effectiveness and feasibility working in EMS.

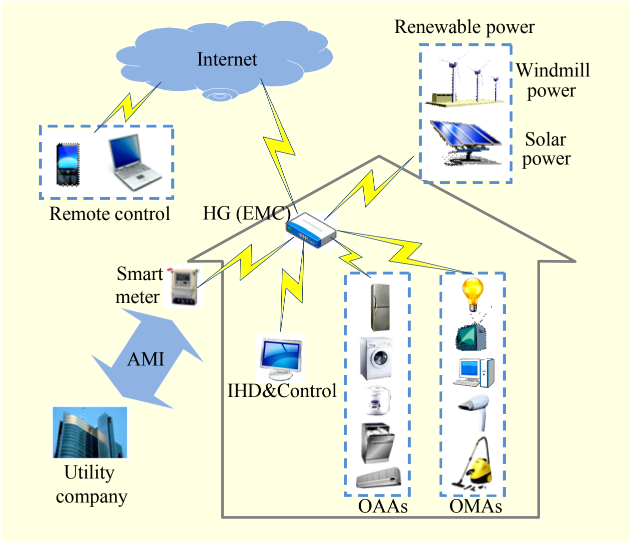

Fig. 1. Architecture of EMS in home area.

II. Architecture of Energy Management System in 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 POE to ensure that the power system is stable and secure. EMS mainly comprises an advanced metering infrastructure (AMI), smart meters, the HG, the EMC, home appliances, and in-home display (IHD) devices. The whole architecture of EMS with the help of a wireless HAN is shown in Fig. 1.

The AMI is a key factor in a smart grid treated as a central nervous system of the EMS architecture, which is an architecture for automated, two-way communication between a smart meter and a utility company [13]. Also, it is responsible for collecting and transmitting consumption data delivered from distributed smart meters to the utility company and for relaying a DR signal for pricing information from the utility company back to the smart meters almost in real time [14]. Generally, a smart meter is installed outside each residential home between the AMI and the EMC, which is responsible for reading and processing consumption data to be transferred to the utility company, simultaneously, sending the DR signal to the EMC for further analysis. In this paper, we classify two kinds of home appliances: operation automatically appliances (OAAs) and operation manually appliances (OMAs). An OAA refers to an appliance that can operate on its own, without manual control, such as a washing machine, a dish washer, or an air conditioner. OAAs are usually categorized as interruptible (for example, washing machine) and non-interruptible (for example, electric kettle) [4]. On the contrary, an OMA can operate productively only if a resident is using it manually, such as in the case of a computer, a television, or a vacuum cleaner. Since these OMAs would be switched on and off manually, the home appliances that could be scheduled are only OAAs. In our research, we embed the EMC in the HG, which receives the RTEP from a smart meter through the HG.

An optimal power usage schedule for each OAA can be exploited with the purpose of minimizing the electricity cost and reducing the PAR. There are various solutions for creating a communication link between the smart meter and the HG, such as ZigBee, Z-Wave, Wi-Fi, and a wired (HomePlug) protocol [15]. The HG transmits the power usage schedule message to OAAs via a HAN so as to control them to operate in a low POE time. In addition, residents can obtain extra power from a renewable power generator, and the message, indicating the quantity of power generated, is 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 a laptop via the Internet.

III. Proposed Approach to Manage Energy Consumption with Genetic Algorithm

In this section, an optimal approach to schedule the power usage of all OAAs in the home for the purpose of minimizing the electricity cost and alleviating PAR based on the RTP combined with IBR will be proposed.

1. Usage Pattern of Home Electric Appliances

Once the HG receives DR information and a profile of RTEP from the utility company through the smart meter, the EMC embedded in the HG can make a decision on the power schedule for all OAAs in the home. Residents usually prefer to operate every OAA in a certain time automatically to avoid peak price time or to make some appliances finish their job before a specific time. For example, when residents are sleeping at night, the washing machine may start to work because the POE 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, it is necessary for residents to set the timing parameters for each OAA, including the length of operation time (LOT) from start to end as well as its power consumption per hour and the operation time interval (OTI) during which the appliance is valid to be scheduled. These parameters can be set on the IHD device and then transmitted to the EMC via the HG.

Since every OMA is operated manually and nobody can say in advance when and for how long an OMA will be used, it seems impractical to set timing parameters for each OMA ahead of time. Therefore, in our research, we only consider the impact of OAAs on electricity cost and PAR. However, we should note a phenomenon: if at the time a resident operates an OMA the total power consumption in the home exceeds the power threshold of the IBR pricing model, then both the electricity cost and the PAR become much greater values. In this circumstance, to avoid the increase of the expense and PAR, one or several interruptible OAAs should stop operating automatically to wait for the appropriate operation times.

2. Final Goal of Our Approach

Prior to applying our proposed approach, we divide an hour into five time units, that is, we set 12 minutes as a time resolution. Therefore, one day contains 120 units, which are denoted by the symbol $u{:}u \in \boldsymbol{U} \triangleq \{1, 2, \cdots, 120\}$. Therefore, the shortest operation time of any appliance is set to 12 minutes. Hence, the LOT of the air conditioner can be set integer multiples of the 12-minute interval. However, there are also some other OAAs whose LOT for working once is fixed, such as a washing machine, a dishwasher, an electric kettle, and so on. These appliances can be operated automatically, so 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 the integer multiples of 12. Additionally, these times should be greater than and closest to the actual LOTs of these appliances. For example, if the normal operation time of a washing machine is 46 minutes, then the parameter LOT should be set as 4 (48 minutes). As another example, the LOT should be set as 1 (12 minutes) if the electric kettle needs eight minutes to boil the water. However, operating in this way produces errors in the final results. In this paper, because the difference of a few minutes is considered negligible, the errors are disregarded.

$\boldsymbol{A}$ denotes the set of OAAs. For each appliance $a \in \boldsymbol{A}$, we assume $\boldsymbol{P}_a$ as a power consumption scheduling vector (PCSV), which is

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

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

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

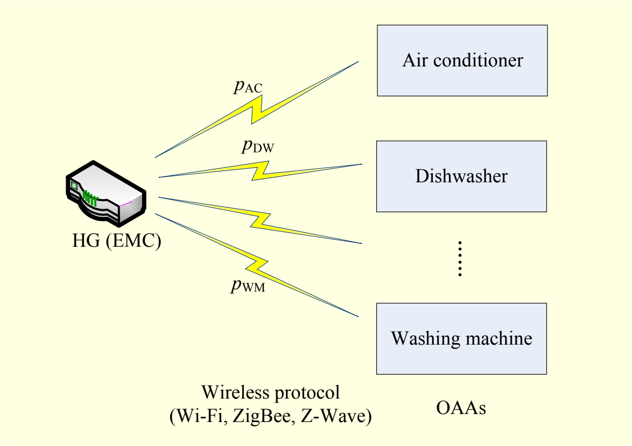

Fig. 2. Optimal PCSV can be transmitted by such wireless network as Wi-Fi, ZigBee, or Z-Wave.

As mentioned earlier, x_a must be set on the IHD device by residents; in return, it is transmitted to the EMC for further utilization.

The purpose of this paper is to optimize the PCSV $\boldsymbol{P}_a$ for each appliance $a \in \boldsymbol{A}$ so as to minimize the electricity cost and reduce PAR. The optimal $\boldsymbol{P}_a$ is transmitted to appliance a by the HG via suitable wireless solutions, as shown in Fig. 2.

3. RTP Combined with IBR

It has been mentioned that RTP has a much higher flexibility than TOUP and CPP, because the POE in RTP is dynamic in that it can change within one hour, 15 minutes, or even five minutes. However, it is much easier to concentrate the operation of several appliances at a relatively low POE time. Therefore, we combine RTP with IBR, in which the POE could be different within the same time unit based on the total power consumption. For example, because a resident wants to reduce his electricity cost, he plans to run most of the appliances at 3:00 a.m. due to the low POE at that time. However, the total power consumption at that time may exceed the threshold of IBR, so it costs a lot more than he expects. In this paper, we set two electricity price levels in IBR, and the POE is changed once every hour. The POE function is

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

Here, the total power consumption in the home during the h-th hour is denoted by s_h. The RTEP during the h-th hour in a day is denoted by a_h. The second electricity price level, which should be greater than a_h, is denoted by b_h. Furthermore, c_h represents the threshold of power consumption at the hour h of IBR. When the power consumption s_h is less than or equal to the threshold c_h, the POE is a_h. Otherwise, POE is b_h, and the unit is cents/kwh.

Considering one hour has been divided into five units, we should make a modification to the POE function. By dividing s_h by 5, we can obtain the total power consumption value for every 12-minute $\tilde{s}_u$. In the same way, we can also obtain the threshold of IBR for every 12-minute unit. Then, the POE function can be altered as

$$\widetilde{prc}_u\left(\tilde{s}_u\right)=\begin{cases} \tilde{a}_u, & \text{if } 0 \le \tilde{s}_u \le \tilde{c}_u, \\ \tilde{b}_u, & \text{if } \tilde{s}_u > \tilde{c}_u. \end{cases} \tag{4}$$

After modification, the only difference from the aforementioned function is its format, that is, the number of variables is 120 instead of 24, due to the time division, whereas the POE values are the same as before.

Now, we assume that if $\tilde{b}_u$ is a constant value greater than $\tilde{a}_u$, whenever the total power consumption exceeds the threshold, the POE is fixed at $\tilde{b}_u$. Such would be the case that if there must be a time interval for the total power consumption to exceed the threshold, this can happen at any time in the day. If this time interval arises at the low price time, that is acceptable. However, if a corresponding time interval occurs at the highest price time, the whole power system is 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 λ is a positive value. Now, in the IBR, the second price level $\tilde{b}_u$ is changed with $\tilde{a}_u$, which means that when the normal POE $\tilde{a}_u$ is the highest in the day, then $\tilde{b}_u$ turns out to be the highest. In this case, the circumstance mentioned before would not happen. However, it seems unrealistic to utilize this price function because it is impossible to get the whole POE function ahead of time. However, several electricity price prediction methods have been proposed in [5], [16]-[19].

4. Problem Formulation

As mentioned before, it is necessary for residents to set some parameters for each OAA. Toward this, we assume $\alpha_a, \beta_a \in \boldsymbol{U}(\alpha_a < \beta_a)$ as the start and the end time unit, respectively. Along this OTI, the power consumption of appliance a is assumed to be valid for appropriate scheduling. Let l_a indicate the LOT, that is, the number of time units for operation of appliance a. The above parameters must be set by residents via IHD to be transmitted to the EMC. In addition, it is confined that $\beta_a - \alpha_a$ 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 number that

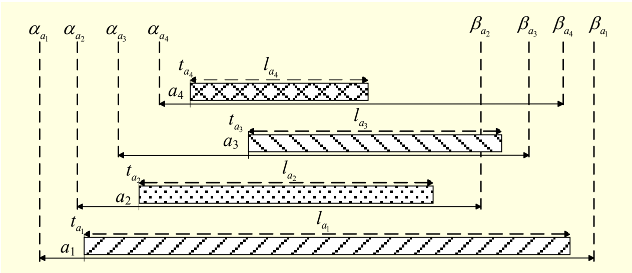

Fig. 3. Four examples to show relationship among all parameters for each appliance.

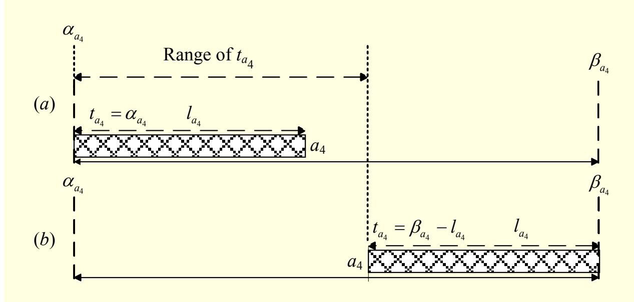

Fig. 4. Illustration for range of start time unit of home appliance a: (a) earliest start time and (b) latest start time.

is greater than or equal to 5 and less than or equal to 120. The greater $\beta_a - \alpha_a$ is, the more possible solutions there are. Define variable t_a as the start time for the operation of appliance a. Since α_a, β_a, l_a, and x_a are all known already, once we have t_a, the PCSV of appliance a is determined. In Fig. 3, the example shows the relationship of these parameters, in which four different kinds of OAAs are included.

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. The earliest start time unit and the latest finish time unit are represented by α_a and β_a, respectively. In addition, we allow start time unit t_a to be variable. Having α_a, β_a, and l_a, t_a should be greater than or equal to α_a and less than or equal to $\beta_a - l_a$. In other words, the range of the start time unit of a is

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

The range of t_a is shown in Fig. 4.

Since α_a, β_a, and l_a can be set by residents, and x_a is known as a nominal value for each appliance, (6) can be regarded as a constraint with single variable t_a. Now, we construct a variable vector $[t_1, t_2, \cdots, t_a]$, which is composed of the start times of all OAAs. Therefore, we can define a power consumption scheduling matrix (PCSM) $\boldsymbol{P}$ for all OAAs as

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

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

$$\boldsymbol{P}_{\text{scd}} = \left\{ p_{\text{scd}} \middle| p_{\text{scd}}^{(u)} = \sum \boldsymbol{P}^{(u)}, \quad \forall u \in \boldsymbol{U} \right\}. \tag{8}$$

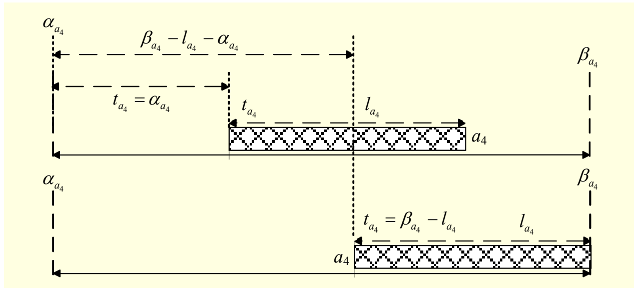

Fig. 5. Illustration of concept of DTR_a.

In (8), $\boldsymbol{P}^{(u)}$ stands for the u-th column in the PCSM. Residents usually hope home appliances can finish their work as soon as possible. Therefore, 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 DTR_a means DTR of the appliance a. Here, if the appliance operates at a later time, the later the appliance operates, the larger DTR_a becomes. The smallest and the largest values of DTR_a are set to be 0 and 1. For example, assuming that a resident sets the parameter OTI for a washing machine as $[\alpha_{\text{wm}}, \beta_{\text{wm}}]$ and the LOT as l_{wm}, if it starts operating at time unit α_{wm}, the DTR_{wm} is 0; if it starts at time unit $\beta_{\text{wm}} - l_{\text{wm}}$, the DTR_{wm} is 1. This relationship can be clearly seen in Fig. 5, wherein $DTR_{a_4} = 0$ and $DTR_{a_4} = 1$ if $t_{a_4} = \alpha_{a_4}$ and $t_{a_4} = \beta_{a_4} - l_{a_4}$, respectively. Therefore, in the final optimization formula, a delay time rate should be considered. Now, we introduce a delay parameter $\rho > 1$ and relevant formula can be expressed by

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

Since the delay parameter ρ is greater than 1, ρ^{DTR_a} geometrically increases as DTR_a continues to enlarge. For residents, the value of this formula is expected to be as small as possible. Thus, along with the accomplishment of the final optimization problem, to reduce the electricity expense, we try to minimize the above value as well.

Above all, we can clarify the power consumption scheduling problem as the following optimization problem:

$$\begin{aligned} &\text{minimize} \quad \omega_1 F_1\left(\boldsymbol{P}_{\text{scd}}\right)+\omega_2 F_2\left(DTR_a\right) \\ &\text{s.t.} \quad t_a \in\left[\alpha_a, \beta_a-l_a\right], \end{aligned} \tag{11}$$

where

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

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

In (11), ω_1 and ω_2 are the weights representing the importance of individual objectives shown in (12) and (13), where $\omega_1+\omega_2=1$, $\omega_1, \omega_2 \in[0,1]$. The weights are determined by residents. If a resident prefers to reduce the electricity cost, any weight value can be set for which $\omega_1>\omega_2$. Otherwise, the weight value should reflect $\omega_1<\omega_2$. In (12), the function $\widetilde{prc}_u$ denotes the POE at the u-th time unit.

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

$$\begin{aligned} &\text{minimize} \quad \omega_1 \frac{\sum_{u=1}^{120} \widetilde{prc}_u\left(p_{\text{scd}}^{(u)}\right) \cdot p_{\text{scd}}^{(u)}}{\left(\sum_{u=1}^{120} \widetilde{prc}_u\left(p_{\text{scd}}^{(u)}\right) \cdot p_{\text{scd}}^{(u)}\right)_{\max}}+\omega_2 \frac{\sum_{a \in \boldsymbol{A}} \rho^{DTR_a}}{\left(\sum_{a \in \boldsymbol{A}} \rho^{DTR_a}\right)_{\max}}, \\ &\text{s.t.} \quad t_a \in\left[\alpha_a, \beta_a-l_a\right]. \end{aligned} \tag{14}$$

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

5. Genetic Algorithm

In this paper, we utilize the GA method to optimize the start time units of all the OAAs to achieve our objectives. Since the start time unit 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). In the selection process, we adopt 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, the time complexity of the GA process can be represented as O(generation number∗(mutation complexity + crossover complexity + selection complexity)). Assume the maximal generation number, the size of the population, and the number of individuals are denoted by g, N, and n_a, respectively; therefore, the time complexity of our scheme is $O(gNn_a)$. In this case, the time cost increases as the three parameters become larger, and, usually, the time cost of GA optimization does not satisfy people. However, in our approach, the power scheduling process is implemented at the beginning of the day; therefore, after time parameters are determined, there is enough time for power scheduling, and the algorithm running time problem is not so important. We think a time cost of a few seconds is acceptable. In this paper, the population size is 200; the probability of crossover and the probability of mutation are 90% and 2%, respectively. Finally, when the generation number reaches 1,000, the evolution process will finish.

IV. 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 there are 16 OAAs in the home. Since residents may not use all of their appliances every day, we assume that approximately eight to 16 OAAs are used in a given home each day. According to the ratio of the two electricity price levels established by British Columbia Hydro [20], the value of λ in (5) is determined to be 1.4423. Finally, we assume the power threshold to be $\tilde{c}_u=0.4$ and the delay parameter to be ρ =5 for all cases.

1. Relationship between Electricity Cost and DTR

As mentioned previously, if residents aim to achieve the minimization of electricity cost, OAAs must be operated according to how the EMC schedules them. Therefore, in the time intervals during which the appliances are valid to be scheduled, which are set by residents in advance, the operation times of OAAs are not fixed, due to the RTEP and other OAAs' operations. Now, we define

$$DTR_{\text{ave}}=\frac{\sum_{a \in A}\left(t_a-\alpha_a\right)}{\sum_{a \in A}\left(\beta_a-l_a-\alpha_a\right)}. \tag{15}$$

The above formula denotes the average DTR of all OAAs. Figure 6 represents the simulation result of the relationship between electricity cost and average DTR.

Generally speaking, the relationship between electricity cost and DTR_{ave} is a tradeoff. In other words, as the value of DTR_{ave} increases, electricity cost decreases. However, the minimum electricity cost value would emerge at a position at which the DTR_{ave} value is about 50%, which is not definite, due to the random POE. From the result shown in Fig. 6, at the position that DTR_{ave} equals 0, it implies that the major consideration is minimizing the delay time; thus, in this case, ω_1=0, ω_2=1.

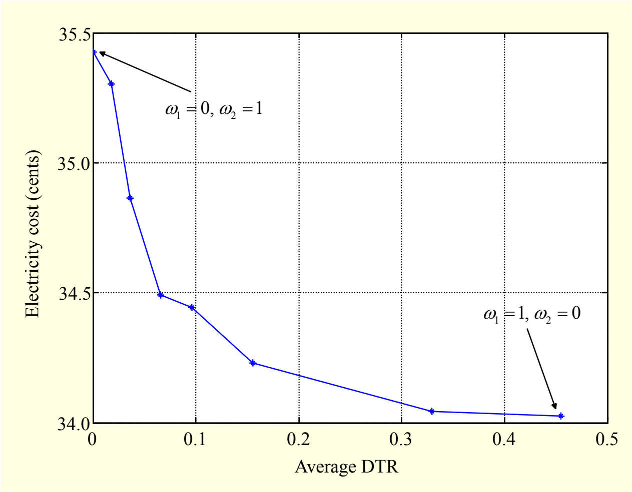

Fig. 6. Tradeoff between electricity cost and average DTR.

However, when the minimum electricity cost is reached, ω_1=1, ω_2=0.

2. Impact of Inclining Block Rates

Now, we focus on a comparison regarding electricity cost and PAR between the states of being with and without power scheduling. In this paper, the RTEP data is adopted from the Ameren Illinois Power Company, and the date range is from 1 January 2012 to 31 March 2012 (91 days) [21]. The simulation results of electricity cost and PAR with RTP combined with IBR are shown in Fig. 7.

In this simulation, we only consider minimizing the electricity cost; therefore, in this case, ω_1=1, ω_2=0. From the results shown in Fig. 7(a), it is clear that the average daily electricity cost for three months without power scheduling is 44.39 cents; however, this value is 33.89 cents with power scheduling in the home. After three months, the resident could save 955.5 cents by using the proposed power scheduling approach. Because in our simulation the home appliances considered are only OAAs, and the number of OAAs is not large, the daily electricity cost is not high. Figure 7(b) shows that PAR reduces from 5.01 to 3.44 with the application of our proposed approach, leading us to conclude that our approach is effective in reducing both electricity cost and PAR.

As mentioned previously, if only RTP is applied in our power scheduling approach, the demand for electricity at the low POE time would greatly increase, resulting in a high PAR. In this case, to demonstrate the effectiveness of our approach, a comparison between RTP only and RTP combined with IBR is shown in Fig. 8. Here, if only RTP is used, the PAR value is also very high, whereas the proposed RTP combined with IBR is a better way to reduce PAR.

The impact of IBR on peak power usage in the home is shown in Fig. 9. The power consumption in a home without power scheduling is shown in Fig. 9(a), in which there are two peak times within a day. With power scheduling using RTP only, there may be a much greater number of peak times and

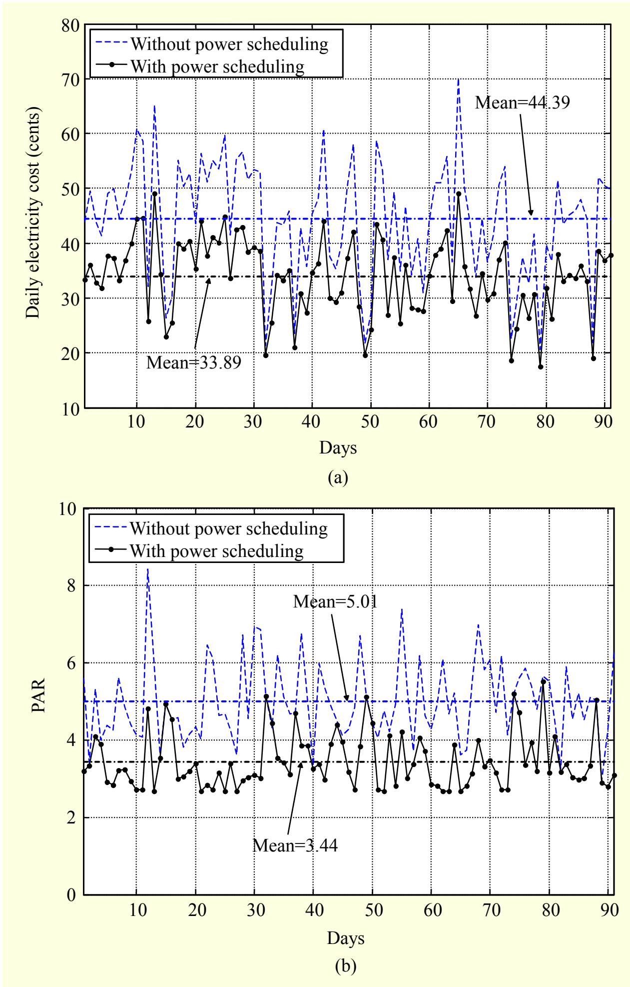

Fig. 7. Impact of proposed power scheduling approach on (a) daily electricity cost and (b) PAR.

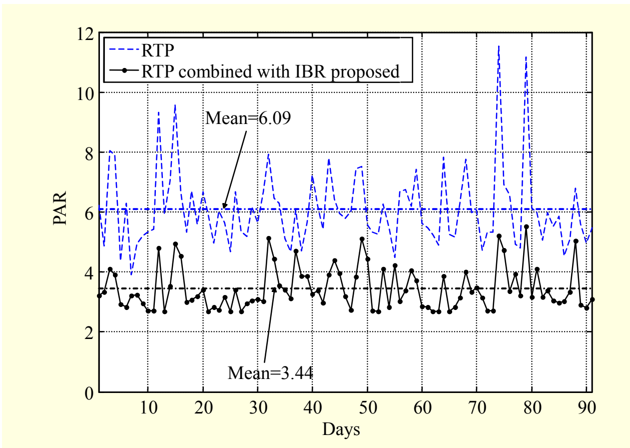

Fig. 8. Impact of IBR in proposed approach on PAR.

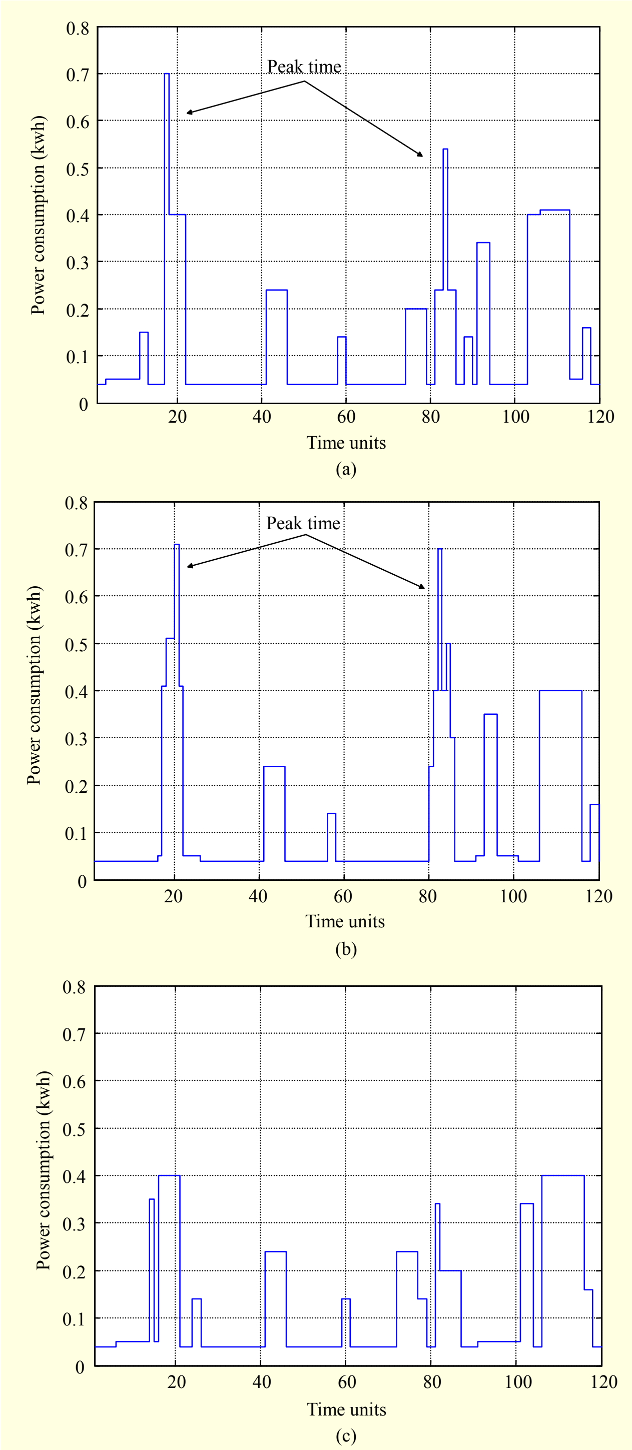

Fig. 9. Profile of power consumption (a) without power scheduling, (b) with power scheduling using RTP only, and (c) with power scheduling using RTP combined with IBR.

the peak value may become much larger, as shown in Fig. 9(b). Lastly, power scheduling using the combined RTP and IBR method proposed in this paper gives rise to superior performance in the aspect of eliminating the peak times, as

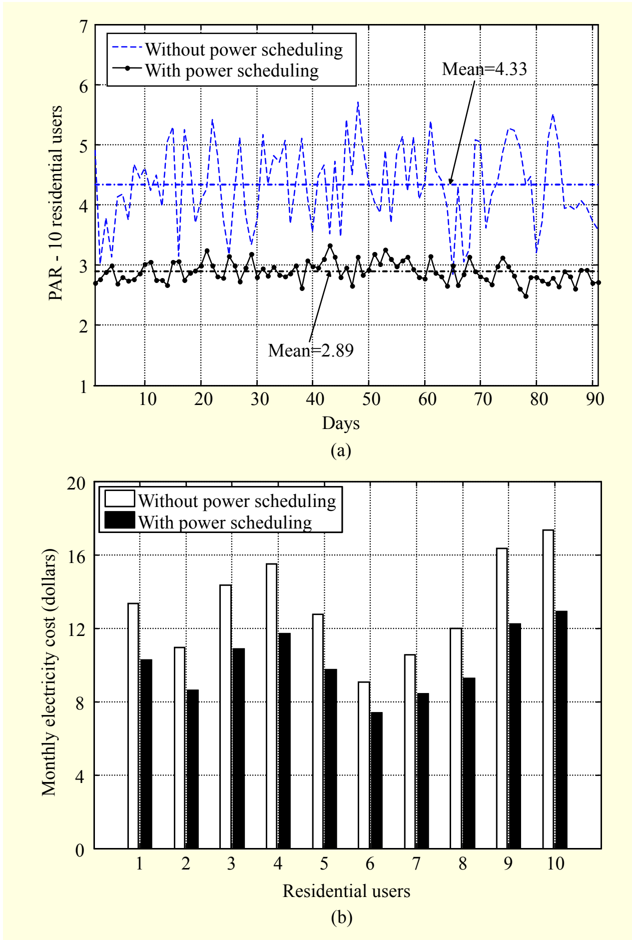

Fig. 10. Impact of multiuser on (a) PAR of aggregated power demand and (b) monthly electricity cost.

shown in Fig. 9(c). From the results, we can conclude that combining RTP and IBR will always result in electricity cost minimization and PAR reduction.

3. Impact of Multiuser

So far, we have presented the effectiveness of our proposed scheme for a single resident. Now, we will present the simulation results that show the impact of our scheme on 10 residents. Figure 10(a) shows that even if the number of residents increases, the average PAR of 10 residential users' aggregated power demand is still reduced from 4.33 to 2.89, which would lead to the stability and security of the whole electricity system. As shown in Fig. 10(b), after adopting our proposed scheme, all residents can reduce their monthly electricity cost effectively.

V. Conclusion

In this paper, we first introduced the architecture of EMS in a

HAN, then presented an approach for power scheduling in the home with the help of RTEP and residents' preferences.

There have been many algorithms proposed for home power scheduling. In [22], the authors proposed a power scheduling method to save money spent on energy consumption based on the RTEP. The researchers' goal was the same as that presented in our paper; however, they did not consider the potential damage to the power system resulting from a large PAR value. In [23], the authors achieved an optimal power consumption scheduling approach to reduce the energy cost and PAR simultaneously with game-theory optimization, showing desirable results. However, the authors did not consider the delay time of the appliances' operations, which can lead to discomfort for some residents. In [24], the authors proposed a scheme to maximize user comfort and minimize energy cost; however, the type of electricity pricing scheme and the problem of possibly having a large PAR were not mentioned. In [25], the authors only maximized the profit of the energy provider and the user's payoff; however, they neglected to consider the security and stability of the energy system. Compared with the work presented in these previous studies, the approach proposed in this paper provides all the advantages and functions of the existing schemes. For residents, the beneficial features obtained by applying our proposed approach are a reduction in the electricity cost and a reduction in the delay time rate of home appliances' operations. In addition, a benefit to the utility companies is the reduction of PAR, which increases the stability of the entire electricity system. Our approach of combining RTP and IBR can satisfy all the benefits for both the residents and the utility companies. According to the simulation results, we conclude that our proposed power scheduling approach using RTP combined with the IBR model has been proven to be a better way than using the RTP only. Surely, the proposed approach is a reliable solution for future EMS in a HAN of a smart grid.

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Zhuang Zhao was born in Shandong Province, China, on January 11, 1988. He received his BS in electronics and information engineering from Shandong University of Science and Technology, China, in 2010. He is an exchange student who is currently working toward a dual MS at Shandong University of Science and Technology and Soongsil University in the Rep. of Korea. His research interests include smart grid communication, power scheduling in home area networks, and cognitive radio.

Won Cheol Lee was born in Seoul, Rep. of Korea, on December 26, 1963. He received his BS in electronics engineering from Sogang University in 1986, his MS from Yonsei University in 1988, and his PhD from the Polytechnic Institute of New York University, New York, NY, USA, in 1994. Since 1995, he has been a professor of the School of Electronics Engineering, Soongsil University. From 2010, he has worked as a director at the Center for Intelligent Cognitive Radio Communications, Soongsil University, and he has served as the chair of the TV White Space Policy and Technical Committee at the Korea Ministry of Science, ICT & Future Planning (MSIP). To date, he is a vice-chairperson of the Cognitive Radio Standard Project Group (PG705) of the Korea Telecommunication Technology Association (TTA). His research interests include cognitive radio, TV white space, smart grid communication, dynamic spectrum access, interference management, and software-defined radio. He is a member of IEEE, IEICE, IEEK, KICS, and Sigma Xi.

Yoan Shin received his BS and MS in electronics engineering from Seoul National University, Seoul, Rep. of Korea, in 1987 and 1989, respectively, and his PhD in electrical and computer engineering from the University of Texas at Austin, Austin, TX, USA, in 1992. He has been served as an organizing/technical committee member for various prominent international conferences, including IEEE VTC 2003-Spring, ISITA 2006, ISPLC 2008, APCC 2008, ISIT 2009, APWCS 2009, APWCS 2010, APCC 2010, ICTC 2010, ISAP 2011, APCC 2012, and APWCS 2012. He has authored more than 150 refereed papers published in international journals and conference proceedings and holds 19 patents, including four international patents in the area of wireless communications. His areas of interest include cognitive radio, UWB, localization, and compressed sensing. He is a senior member of IEEE, a lifelong member of KICS and IEEK, and a member of IEICE.

Kyung-Bin Song received his BS and MS in electrical engineering from Yonsei University, Seoul, Rep. of Korea, in 1986 and 1988, respectively. He received his PhD in electrical engineering from Texas A&M University, College Station, TX, USA, in 1995. His employment experience includes the following: LG-EDS Systems, Seoul, Rep. of Korea; Korea Electric Power Research Institute, Daejeon, Rep. of Korea; Catholic University of Taegu-Hyosung, Kyungsan, Rep. of Korea; and Keimyung University, Daegu, Rep. of Korea. In 2002, he joined the faculty of Soongsil University, Seoul, Rep. of Korea, where he is currently an associate professor of electrical engineering. His interests include power system operation and control, power system economics, the optimization of the large scale systems, and the fuzzy system and its applications.