An Efficient Home Energy Management System for Automated Residential Demand Response

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***Abstract*—Due to the emerging of smart grid, residential consumers have the opportunity to reduce their electricity cost (EC) and peak-to-average ratio (PAR) through scheduling their power consumption. On the other hand, it is obviously impossible to integrate a large scale of renewable energy sources (RES) without extensive participation of the demand side. We are looking for a way to provide the system operators with the capability of increasing the penetration of RES besides maintaining the reliability of the power grid via load management and flexibility in the demand side. The primary aim is to provide consumers with a simple smart controller which can result in EC and PAR reduction with respect to consumer preferences and convenience level. In this paper, first we present a novel architecture of home EMS and automated DR framework for scheduling of various household appliances in a smart home, and then propose a genetic algorithm (GA) based approach to solve this optimization problem. The real-time price (RTP) model in spite of its privileges has the tendency to accumulate a lot of loads at a pretty low electricity price time. Therefore, in this paper we use the combination of RTP with the inclining block rate (IBR) model which has the capability to remarkably decrease the PAR and eliminate rebound peak during low price periods. We present three different case studies with diverse power consumption patterns to evaluate the performance of our approach. The simulation results demonstrate the terrific impact of this method for any household load shape.**

Keywords- automated demand response; home energy management system; real time price; inclining block rate; peak to average ratio; smart grid.

I. INTRODUCTION

Rising demand for electricity, growing share of intermittent renewable energy sources, increasing energy costs and environmental concerns are just a few of the challenges that face the energy industry. With such a diverse set of issues, it is essential to adopt a comprehensive approach to overcome these barriers through transitioning to a smart grid [1]. The emerging smart grid by use of advanced metering infrastructure (AMI), which can deliver real-time electricity prices to consumers and simultaneously send back their power consumption data to the utility companies, can address the major part of these issues [2], [3]. Demand response (DR) as one of the main topics in the smart grid, can provide the system operators with the capability of increasing the penetration of renewable resources besides maintaining the reliability of the power grid via load management and flexibility in the demand side. At the same time, consumers will have the opportunity to control their power usage as well as reducing their costs. In some cases, this can even lead to consume more electrical energy, but pay less for it [4].

Early demand side management (DSM) programs have been implemented via techniques such as Direct Load Control (DLC). In this program, customers should permit the utilities to disconnect selected appliances or curtail a certain load remotely on short notice when needed. Consequently, the consumers will receive a rebate or incentive on their electricity bill [5]. Although DLC is a simple and effective approach for DSM, it cannot happen frequently and provide little flexibility for alleviating the uncertainty of renewable resources integration. Furthermore, it is not proper for load management in systems comprising a large number of appliances with relatively low power consumption [6].

Real-time pricing can be the most efficient and practical DR program that reflects wholesale power market conditions. On the other hand, it is the most inexpensive way of managing electricity demand. In this method, the load control is done indirectly via sending appropriate price signals according to energy consumption, power market and other economic and technical factors. Utilities can affect resident decisions by changing the electricity price in real-time with no incentive payment. Similarly, consumers have a chance to decline their costs based on their own desire [7]. Despite the mentioned advantages of RTP, it has the tendency to cause even more volatility and instability in the electricity market and power system, due to customers respond to these signals. If all the customers receive the same RTP signals, the entire householders will schedule the appliance utilization by shifting demand to the hours with lower price which would lead to a new peak load and higher peak-to-average ratio (PAR) at these times. Multiple approaches have been presented in order to avoid such a rebound peak which include, having a period of flat price at night and randomized scheduling at home, exerting different prices to different homes at night and signaling maximum allowable power consumption to homes [8]. The adopted method in this paper is the combination of RTP with the inclining block rate (IBR) which can be the most efficient pricing model to replace the current flat rate tariffs. In IBR model, the electricity price would reach a higher level than the normal condition when the total energy consumption of residents exceeds a predetermined threshold. This model can remarkably reduce the PAR and eliminate rebound peak spikes during low price periods [9].

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Since traditional DR is often done manually, it is difficult for residential customers to track hourly price signals and respond to them by changing the daily schedule of their appliance usage, whereas they do not have sufficient knowledge and time. Thus, automated DR is necessary for attracting more householders to take part in DR programs. Obviously it is impossible to profit from all of its various privileges without extensive and pervasive participation of the demand side [10], [11]. Hence, energy management system (EMS) has been presented to control home power consumption with regard to DR signals, real-time price (RTP), consumer preferences and specific comfort level. In recent years, several architectures for home EMS and power scheduling have been proposed that authors attempt to design optimal software and hardware schemes [12]-[16].

In the literature, substantial research effort has been devoted to investigate optimal residential load management techniques. Nevertheless, a few of them have considered a realistic view of various initial power consumption profiles. Reference [17] has studied a residential energy consumption scheduling to achieve a desired trade-off between minimizing the EC and the waiting time for the operation of each appliance in a household based on the simple linear programming. In [18], the presented demand management scheme takes into account the consumer comfort level to minimize the energy cost and PAR while maximizing the comfort level of consumers. However, it seems impractical and irrational to set a time for appliances such as TV and computer before using them or control the critical loads like freezer, because it can extremely affect consumer convenience. In [19], the authors investigate the impacts of charging a large-scale electric vehicle on residential distribution network and a DR strategy was proposed as a load shaping tool. In [20], an intelligent home EMS algorithm was presented for managing high power consumption household appliances according to their preset priority and certain maximum allowable energy consumption.

In this paper, the primary aim is to provide consumers with a simple smart controller which can result in cost reduction with the least inconvenience to residents. Nowadays, the emergence of smart home appliances which can communicate with one another and EMS over the home area network (HAN), has facilitated achieving of this goal. Once the EMS is set, it will constantly communicate with smart meter (AMI) to send and receive home energy consumption and RTPs in order to plan the use of appliances for the next day.

The rest of this paper is organized as follows. Section II presents the proposed architecture of home EMS in a HAN. Section III has been devoted to define the optimization problem and its formulation via genetic algorithm (GA) for the purpose of reducing the EC and PAR with respect to consumer constraints. In section IV, we propose three separate case studies with various energy consumption patterns. Finally, the conclusions of this study are expressed in section V.

II. Architecture of Home Energy Management System

In the proposed model, we assume a smart home consisted of smart appliances having the adequate communication interfaces to handle information exchange with the EMS. Fig. 1 shows this architecture which enjoys three data communication domains, including the smart meter domain (AMI), the internet domain and home area network (HAN). The smart meter domain represents tens of millions of networked smart meters so-called "AMI" deployed and controlled by utilities to transmit DR signals and load information between the smart homes and power market. The internet domain provides consumers with the ability of controlling and monitoring their power consumption profile, appliance usage schedule and etc. through an in-home display (computer, tablet or smart phone). The home EMS schedules the pattern of electricity consumption for the next day based on the received 24 hours RTP signals day ahead and acts as a central gateway to both the internet and smart meter domain. According to consumer preset time intervals, power consumption and complete operation duration of each smart appliance, EMS determines the most suitable start time and send it to all of them via wireless HAN for minimizing the expense of electricity usage [21].

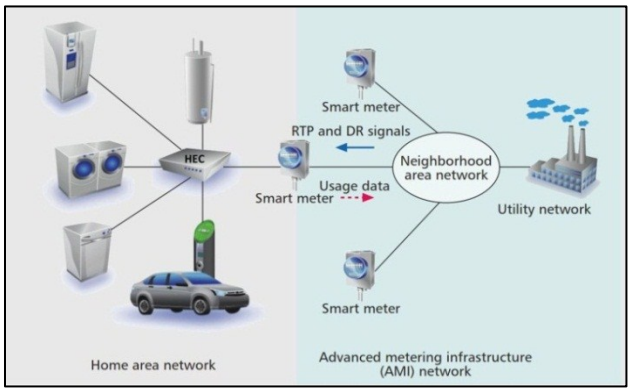

Fig. 1. Architecture of energy management system [29]

At first, a thorough study must be done on the residential load profile in order to find out different home appliance capabilities to be controlled. Due to this fact, home appliances classified into two major types as follows [11]:

1) Schedulable appliances: This kind of appliances can be operated automatically without manual control and divided into two categories based on their operating characteristics, including time-shiftable and temperature-shiftable appliances. The utilization of first type appliances (e.g., plug-in hybrid electric vehicle (PHEV), dishwasher) can be delayed or shifted earlier by a few time slots without much impact on consumer convenience. In fact, any of the above mentioned loads can adapt themselves with time shift in their operation to some extent and this tolerance varies for each device. The second type appliances (e.g., Heating Ventilation Air Conditioning (HVAC), refrigerator) are almost always in running state for a long time period and changing the temperature setting will alter their power consumption rate. The operation of these loads can be interrupted intermittently in an acceptable temperature shift interval. An accurate management of these appliances is a crucial task that can

significantly influence on energy efficiency, peak load and EC on demand side [18].

2) *Unschedulable appliances*: In different papers, these loads have been referred as manually operated appliances, baseline loads and real time appliances that all of these names indicate the inherent nature of their operation manner [2], [7], [22]. The power consumption of these appliances (e.g., lighting, TV, vacuum cleaner) must be supplied immediately at any time on resident's request and it is impossible to offer a predetermined schedule for them.

The European Smart-A project investigates how smart domestic appliances can contribute to load management in future energy systems and provides a detailed assessment of the acceptance of smart appliance operation by users [23]. The outcome of this survey illustrates that there is a clear tendency up to 90% regarding consumer acceptance of smart appliances. The National Energy Modeling System (NEMS) in the USA employs end use load shapes to build the overall system load shapes in each region. These load profiles consist of data for 3 day types (weekday, weekend day and peak day), each with 24 hourly values, for each of 12 months. Regional load shapes for space heating and space cooling are constructed using regional weather information [24]. Also, the Residential Energy Consumption Survey (RECS) is conducted in order to collect statistical data of energy consumptions and usage patterns from households. According to RECS data and reasonable assumptions, the alternative load shapes have been built for all of the home appliances in each region [25]. In this paper, we use these load patterns in region 1 (including Illinois state) for two months of summer (June and July). Fig. 2 illustrates some examples of these profiles.

Based on these real statistical data, we attempted to define three various power consumption patterns in two states (weekday and weekend day) regarding the difference in peak time and consumption rate during the typical hours of usage. In each case, different kinds and numbers of appliances with

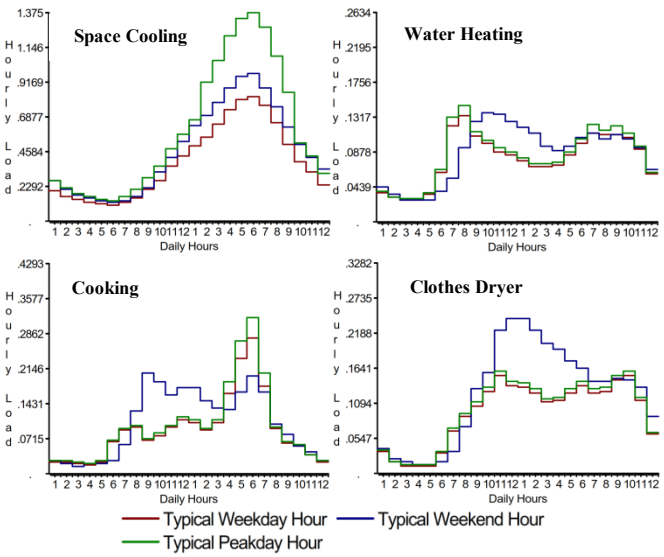

Fig. 2. Load shapes for July (hour loads as percent of annual loads)

diverse times of use have been considered. The RTP data are obtained from the Ameren Illinois Power Company for the period of June 1st 2013 to July 31st 2013 [26]. Due to the assumption, utilities have the predicted RTP of 24 hours of the next day. Concerning pricing issues, the interested reader can refer to [27] and references therein.

III. Proposed Scheduling Method for Household Appliances

After transmitting RTP and DR signals to smart meters from the aggregator or utility company, the home EMS specifies the operation time of household appliances for the following day. In the proposed scheduling method, the main goal is minimizing the EC related to the energy consumption of appliances under EMS control with respect to consumer constraints. Therefore, it is required to determine three parameters for each schedulable appliance including the utilization time range (UTR) during which the appliance must be run and its operation period be completed, the operation time duration (OTD) from start to finish the cycle, the average power consumption (APC) per hour. These parameters (UTR, OTD and APC) are the inputs of our scheduling algorithm that can be set regarding the resident's desired comfort level, lifestyle and consulting with expert persons in this field. Obviously, as much as the UTR is longer, the home EMS has more chance to decrease the cost; on the contrary, setting a strict limited UTR cannot lead to a notable decline.

A. Optimization Model and Formulation

We assume that 1 hour is divided into 10 time slots (i.e., the time resolution is 6-minute), thus the home EMS is executed once every 240 time slots a day. The resolution is set 6-minute because it is short enough as a time unit for the operation periods of all the home appliances such as, electric kettle or rice cooker. Therefore, the shortest OTD of any appliance is set to be 6 minutes and generally, the OTD will be the integer multiples of the 6-minute. It is easy about HVAC loads; however, for appliances with fixed certain OTD like washing machine or dishwasher, it must be set greater than and the closest number to the actual OTD of the appliance. In this method, the OTD indicates the number of time slots. On the whole, the errors are just some minutes and small enough to be ignored. For each use of any appliance along a day, we define a characteristic vector:

$$\mathrm{Char}_a \equiv [\, t_s \,,\, t_f \,,\, d \,,\, p \,] \tag{1}$$

where $a \in A$ is the sequence number of the set of smart appliances A, t_s and t_f are respectively the indexes of the start and the finish time slots, d indicates the OTD and p represents the APC value per time slot. Due to the fact that currently we do not have access to the energy use profile of the all home appliances, the average power consumption has been considered fixed during the operating cycle.

B. Pricing Model

As mentioned before, RTP in spite of its benefits, has the aptitude to accumulate a lot of loads at a pretty low electricity price time. Hence, we combine RTP with IBR as follows [22]:

$$\text{price}_h(c_h) = \begin{cases} P_h & \text{if } 0 \le C_h \le \text{thr} \\ \beta \cdot P_h & \text{if } C_h > \text{thr} \end{cases} \quad (2)$$

where P_h denotes the real-time electricity price prediction for the hth hour in day ahead, C_h is the total power consumption of schedulable appliances during the hth hour, thr is the given threshold for the maximum allowable power consumption during the hth hour. As long as the power consumption C_h is less than or equal to the threshold, the electricity price, $\text{price}_h(c_h)$, would be P_h; otherwise, it would be multiplied by coefficient β in order to impose more expense and prevent the formation of new peaks. Regarding to our formulation method, the hourly C_h and threshold have to be divided into 10 time slots, while the RTP values remain the same as before during an hour [9].

The IBR model plays an important role in peak shaving and PAR reduction. Besides, it is a crucial task to assign proper optimal values to the threshold and β since it can be extremely effective. These two parameters must be determined based on a trade-off between cost reduction and PAR decline. In this paper, we assume β= 1.5 according to the ratio of the two electricity price levels in British Columbia Hydro [28]. The selected threshold is about 25% to 30% of the whole power consumption of schedulable appliances along the day (from 7 am to 11:59 pm); but during the night (from 12 am to 6:59 am) due to turning off most of the consumer electronics and the baseline load decrease, it is considered 40%.

C. Genetic Algorithm

In this paper, we adopt an enhanced GA to solve our optimization problem. The fitness function is defined as follows:

$$\text{Min} \quad F = \sum_{h=1}^{240} \text{price}_h\left(P_{total}^h\right).P_{total}^h \quad (3)$$

$$\text{S.t.} \quad t_s \le t_{set}^{(a)} \le t_f - d \quad (4)$$

where $P_{total}^{(h)}$ is the total power consumption of all the appliances ($a \in A$) in the hth time slot after scheduling. The final goal is to obtain the decision variable $t_{set}^{(a)}$ i.e., the optimal time to begin the operation of the appliance *a*. Furthermore, this variable must be greater than or equal to t_s and less than or equal to $t_f - d$; because the operation cycle has to be completed in this time interval.

The initial population is 50 and double vector type, the scattered crossover rate equals to 0.9 and the mutation rate decreases adaptively with generation growth. We consider two elitisms in order to guarantee the best result and use the tournament selection method. The GA finds the optimal t_{set} for each appliance after 50 to 60 generations. The stopping criteria are set as no changes in the fitness function up to 6 decimal places. For each case study, the GA program has been executed several times to ensure about achieving the global optimum time setting. All the simulations are implemented in MATLAB.

IV. Simulation Results

In this section, we present three different case studies to assess the performance of our proposed approach for home EMS and compare the simulation results.

A. Case Study 1

We choose 7 kinds of appliances that are available in most homes. Although some of them may be used more than once a day by residents e.g., air conditioner will be operated several times along a day; therefore, in our simulation 13 times uses of appliances are considered. Table I shows the parameters of all the appliances under EMS control in case study 1. The threshold is set to 25% of the whole power consumption during the day that is equal to 0.3^{kWh} per time slot and 35% during the night that is equal to 0.4^{kWh} per time slot.

Fig. 3 shows the initial power consumption pattern of schedulable appliances (before scheduling) in two types (weekday and weekend). According to this load shape, the average daily EC for two months is 73.72 cents and the PAR is equal to 6.65 that is considered as a high peak load. Since only 7 numbers of appliances have been assumed for scheduling, the daily EC is not high; however, consumer could save 1681.5 cents with the use of our proposed method after two months. The average daily EC with a 37.4 % reduction becomes 46.14 cents and the PAR declines to 4.3 with a 35.4% reduction. As Fig. 4 shows, in addition to decreasing the cost, this approach has a terrific ability of peak shaving that is very significant for the utilities.

B. Case Study 2

In case study 2, we select 8 appliances through adding PHEV and replacing Microwave oven with Rice cooker. We consider 15 times operations of appliances per day; thus, the average daily EC increases to 102.78 cents due to involving more schedulable appliances in home EMS and consequently,

TABLE I. Defined Operation Pattern by the Residents

		Weekday Schedule		Weekend Schedule	
Appliances	***APC*** ^{kw}	***UTR***	***OTD***	***UTR***	***OTD***
Air Conditioner	1.2	105~125	8	95~135	16
Air Conditioner	1.2	126~155	12	136~155	8
Air Conditioner	1.2	156~180	10	156~175	8
Air Conditioner	1.2	181~205	9	176~205	11
Air Conditioner	1.2	206~225	7	206~235	10
Water Heater	1.5	65~105	15	80~115	14
Water Heater	1.5	175~205	9	116~145	12
Water Heater	1.5	206~230	6	180~220	12
Microwave Oven	1.3	165~195	3	100~120	3
Electric Kettle	1.2	65~85	1	85~105	1
Clothes Dryer	2.4	1~70	10	1~80	10
Dishwasher	1.2	1~70	18	1~80	18
Washing Machine	0.96	210~240	8	195~240	8

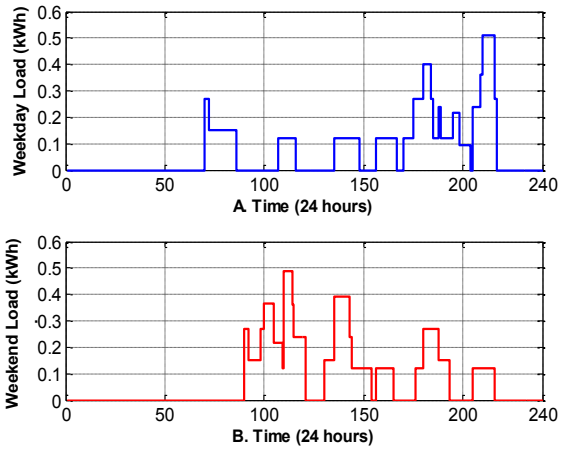

Fig. 3. The initial power consumption pattern without scheduling: (A) weekday; (B) weekend

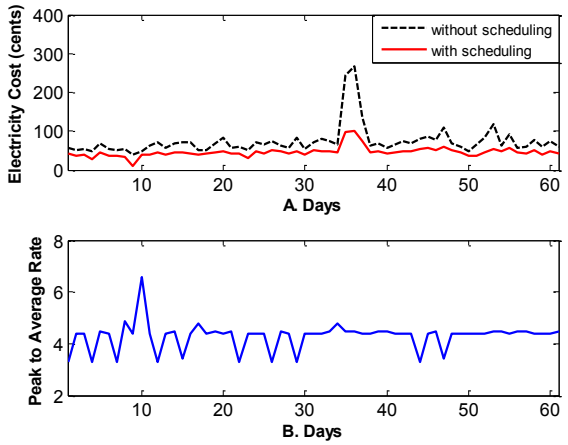

Fig. 4. The impact of the proposed approach on: (A) daily EC; (B) PAR

more chance of decreasing the cost. Moreover, the PAR of the assumed load shape is 5.11 that indicates a medium peak load. Fig. 5 illustrates simulation results that have been led to 41.2% reduction in EC and 30.63% reduction in PAR. Because of this scheduling algorithm, residents could decrease their EC to 60.42 cents and save 2584.2 cents in two months. Similar to case study 1, the PAR has been also diminished; however, the reduction in PAR is less than EC. Regarding to the initial power consumption pattern, most of the times, the peak load has been occurred during the highest electricity price hours; therefore, a slightly load shifting could result in an enormous EC reduction.

In order to have a sensible perception of the IBR model effectiveness on decreasing PAR, Fig. 6 is presented. Fig. 6(A) demonstrates the real-time electricity price on July 3th 2013 adopted from [28]. According to the profile, from 2 am to 5 am, the RTP is about 0.018 $/kWh which is the lowest price during that day. Fig. 6(B) shows the load profile without scheduling and with scheduling when RTP model is used alone, plenty of load would be aggregated during these hours. Fig. 6(C) shows power scheduling based on RTP combined with IBR model. In this case, the power consumption is scattered due to the applied threshold. As a result, the

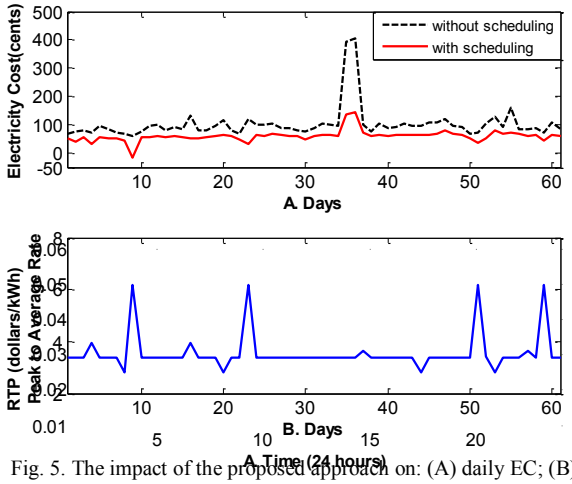

Fig. 5. The impact of the proposed approach on: (A) daily EC; (B) PAR

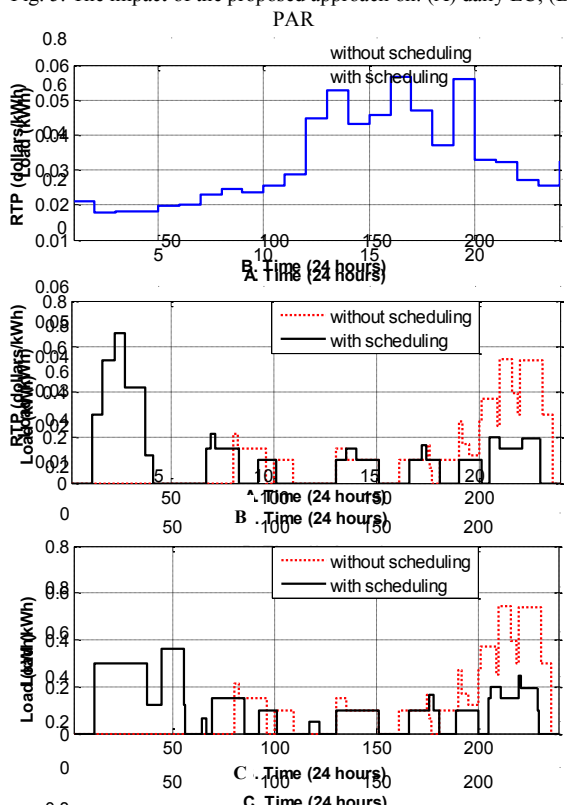

Fig. 6. (A) RTP profile on July 3th 2013; (B) Power scheduling based on RTP alone; (C) Power scheduling based on RTP combined with IBR model

phenomenal performance of our method in the aspect of eliminating the peak demand is proved.

C. *Case Study 3*

In this section, the load shape is altered again by removing the Clothes dryer and PHEV; nonetheless, we have both the Microwave oven and Rice cooker. Besides, the usage time of appliances is determined differently from the other case studies in order to achieve a new initial power consumption pattern. Although we still have 7 kinds of schedulable appliances, because of omitting two loads with pretty high power consumption, the average daily EC lessens to 58.15 cents. In the assumed load shape, PAR is about 3.98 that indicates a low peak load and the profile is approximately

uniform. In this section, we are willing to assess the performance of our proposed method in such strict situations.

The average daily EC with a 25% reduction becomes 43.57 cents and the average PAR declines to 3.96 which is almost the same as before. The results show, although the primary load profile is relatively flat with a low PAR, the proposed scheduling algorithm still has the ability to decrease the EC. Despite the fact that PAR is almost unchanged, a proper scheduling with high flexibility in demand side can shift the time of the peak load to lower electricity price hours. Sometimes, this can lead to PAR enhancement; still, the average value remains fixed.

Since the domestic appliances assumed in these simulations are all typical appliances for common residents, and enough combinations with diverse conditions were considered, we believe that the proposed approach can be effective and practical for any household.

V. CONCOLUSION

In this paper, we presented a novel architecture of home EMS for load scheduling of various household appliances in a smart home. We considered the profits of both the consumers and utility companies via minimizing the EC as well as the PAR which leads to interest residents to participate in DR programs, and simultaneously improve the reliability of the entire power system. The GA proposed method acts based on the consumer preferences and convenience level. Through the combination of RTP with IBR pricing model, we could eliminate the rebound peak and flatten the load profile.

Regarding the simulation results, our proposed approach for power consumption scheduling can feasibly control and manage diverse kinds of load shapes. For future work, discovering an optimal reasonable value for the threshold and β is suggested since it can be notably influence the results. There are still barriers to home EMS such as expensive smart appliances or lack of sufficient knowledge about EMS benefits on the demand side; however, with advancement in both the wireless and embedded system technologies, home EMS is expected to grow in the coming decades, particularly for new residential buildings.

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