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Appliance Load Profile Assessment for Automated DR Program in Residential Buildings

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Abstract

The automated demand response (DR) program encourages consumers to participate in grid operation by reducing power consumption or deferring electricity usage at peak time automatically. However, successful deployment of the automated DR program sphere needs careful assessment of appliances load profile (ALP). To this end, the recent method estimates frequency, consistency, and peak time consumption parameters of the daily ALP to compute their potential score to be involved in the DR event. Nonetheless, as the daily ALP is subject to varying with respect to the DR time ALP, the existing method could lead to an inappropriate estimation; in such a case, inappropriate appliances would be selected at the automated DR operation that effected a consumer comfort level. To address this challenge, we propose a more proper method, in which all the three parameters are calculated using ALP that overlaps with DR time, not the total daily profile. Furthermore, evaluation of our method using two public residential electricity consumption data sets, i.e., REDD and REFIT, shows that our energy management systems (EMS) could properly match a DR target. A more optimal selection of appliances for the DR event achieves a power consumption decreasing target with minimum comfort level reduction. We believe that our approach could prevent the loss of both utility and consumers. It helps the successful automated DR deployment by maintaining the consumers' willingness to participate in the program.

■ Keywords : Demand Response | Energy Management Systems | Load Profile | Residential Buildings | Smart Appliances

I. INTRODUCTION

Utilities suffer from excessive demand in peak hours due to the behavior of electricity consumers, especially when most people are at home and massively activate electric appliances. On the other hand, massive integration of distributed renewable energy sources (DRESs) and distributed energy storage devices (DESs) on the internet of energy era added new challenges to power grid management [1]. Hence, advanced energy management systems (EMS) with the capability to balance power consumption with dynamic power production is indispensable to avoid grid instability or failure. To this end, EM S can be integrated with the demand response (DR) program application [2]. The DR program can be used to curtail customers' demand during a critical period that can be divided into the following three groups: manual, semi-automated, and automated [3].

It should be noted that the automated DR (ADR) is widely acknowledged as a key approach for ensuring reliable grid operation with growing electricity demand. ADR technology has already progressed substantially with worldwide project implementations and standards [4]. In this context, consumer appliances are selected automatically in grid operation in order to minimize the peak-to-average ratio of power consumption. Moreover, the massive penetration of smart metering technologies [5] enables real-time monitoring of appliances load profile (ALP) data in a non-intrusive manner. This ALP data is the key to the successful deployment of ADR. The EMS may process this data to assess the habit of cusumers, then select their deferrable appliances to be joined in the DR event.

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Although many works have been done to optimize the ADR program, most of them focused only on maintaining system reliability and mitigate price spikes at peak times. The consumer preference in the context of occupant's comfort has not taken into account yet. Whereas, as mentioned in [6,7], a reduction of consumers' comfort caused by improper ADR schemes affects consumers' willingness to participate in the DR program.

In this paper, we develop a method to select potential consumer appliances for the ADR program using the ALP data assessment in the context of residential buildings. In order to achieve an accurate selection, which decreases the total power consumption with a minimum of consumers' comfort level reduction, we enhanced the existing assessment methods in [8,9]. The methods using daily APL data computes the following parameters of each appliance: (1) frequency of usage, (2) consistency of usage, and (3) peak time usage. The consumer appliance' s potential score for ADR is calculated as the multiplication of these parameters.

As the daily ALP might be different from the DR time ALP, the existing method lead to an inappropriate calculation to select appliances for the automated DR operation. Therefore, we should take into account that DR mainly focuses on appliances that most likely active at peak hours. Thus, it would be better that we turn the focus to calculate all three parameters from the entire daily ALP data to the peak time ALP. In other words, the system takes into account the appliance consumption pattern at only the peak demand period. This would help the system to predict correctly which profile will be repeated at the next DR time. In this context, the main contributions of this paper are as follows:

(1) We develop a technique that estimates how stable an appliance in repeating the same consumption habits at peak time. This will allows the EMS to predict consumer's possible consumption patterns for the next DR event.

(2) We examine a broader spectrum of deferrable appliances. We evaluate our proposed method using two public data sets of residential electricity consumption, i.e., REDD dataset from US households [10] and REFIT dataset from UK residential buildings [11].

(3) We analyze the contribution of several types of appliances to grid aggregate demand. The outcomes show that appliances with small power consumption like lighting bulbs may be reasonably potential for the ADR event.

We believe that this work may contribute to optimize ADR to identify proper consumer appliances that give a significant reduction of grid overall load in critical condition by automatically shifting appliance operation. Furthermore, it also helps successful automated DR deployment by maintaining consumers' willingness to participate in the program.

The remaining part of this paper is organized as follows: Section II explains reletad literatures in consumer selection methods for the DR program. Section III outlines issues in the previous researches, and section IV explains our proposed method in detail. Section V discusses the experimental outcomes and performance analysis of the proposed approach. Finally, section VI concludes the paper.

II. RELATED WORK

According to [12], the participation of residential consumers in the DR program is expected to provide almost half of the overall peak demand reduction potential in the United States. Therefore many research works have been conducted on DR management for smart residential buildings [2, 3, 8]. Moreover, to select relevant residential customers optimally, integration of smart appliances and their DR opportunities have been investigated in some literature [8, 9, 12].

Rashid et al. [8], proposed a method which selects a potential group of consumers with consistent appliance operation habit among a set of consumers. They suggested the use of the mean and standard deviation value of the appliance power consumption at each same time window during observation days. It is to assess its operation consistency. They also provide a guideline to step by step find consumers that have peak power consumption at DR time among these consistent consumers.

As mentioned in the previous section, Afzalan et al. [9] proposed interesting techniques to sort residential customers with a deferrable appliance to be involved in the DR event. Consumers are compared by their ALP characteristics as mentioned above, and only those who have a potential score higher than a particular threshold will be selected for the ADR event.

III. PROBLEM STATEMENT

Taking advantage of the existing approach in the literature [9], the following ALP characteristics of each residential consumer appliances can be analyzed:

1) Is this appliance operating frequently?

2) How consistent is it repeating the same operation habit across several days?

3) How much energy does it consume during DR time?

However, this method estimates the frequency of operation and the consistency of usage values of appliances using daily ALP. It should be noted that, in fact, the consistency value can be used to measure the predictability of the power profile that an appliance will repeat during the DR event. Thus, the consistency at the peak-time power demand is more important and may differ from the consistency of the total daily ALP. Moreover, we noted above that the DR program considers only peak periods, so it does not care about appliances that frequently operate out of peak time-period.

It also should be taken into account that the frequency of operation value is most likely higher in a daily ALP comparing to the DR time. It is because the more extended time allows the more higher probability of operation. Thus these two values in the existing approach lead to an improper selection of appliances for the DR event.

Also, the existing work in [9] evaluated their proposed method on the historical load consumption data set, which contains consumers with a single type of deferrable appliances. It is impossible to conclude that their proposed technique would give an acceptable result when it is deployed to assess heterogeneous appliances.

Focusing on all the mentioned issues above, we present an improved technique that asses all three ALP characteristics, i.e., frequency, consistency, and amount of usage at DR time operation. Furthermore, we also evaluate our method on two public data sets, REDD and REFIT, which measure real-world load consumption in US and UK residential buildings. Both datasets have several heterogeneous appliances consumption records.

IV. PROPOSED METHOD

To maintain consumers' willingness to participate in the automated DR program, we need to minimize the decrease of consumer comfort level at the time of demand shedding as described in [6], as

$$Min \sum_{n=1}^{N} \Delta C, \tag{1}$$

where ΔC is the decrease of operational comfort level of each appliance, N is the number of appliances involved in the DR event in the household. Hence, to prevent inappropriate selection of appliances for the automated DR program, our complete procedure is illustrated in Fig. 1. It consists of the data acquisition, the appliance selection, and the DR deployment stages. This paper mainly focused on the appliance selection stage, in which the EMS performs four following steps.

First, it sorts appliances with deferrable operation habits that have a reasonably higher frequency of operation at a system-peak time across K observation days. Second, the EMS follows to calculate the magnitude of appliances' power usage at DR time. Third, the EMS determines the consistency of the appliances' operation in repeating the same consumption pattern at peak time. Last, the potential of each appliance to participate in the DR event is defined in Step 4 as the multiplication of these three values.

Hereafter we explain these four steps in detail:

i. Frequency of usage score. The frequency of usage (FS) score is the ratio of the number of days that an appliance operated at DR time to the number of total observed days.

$$FS_{ij}^{(peak\ time)} = \frac{\{n \mid \sum_{t_1}^{t_2} P_{ijk}\ (t) > Thre_j, k \in (1:K)\}}{K}, \tag{2}$$

where n is the number of days that an appliance has been operated at DR time, K is the number of entire observed days, k is the historical daily profile index, and j is the appliance index in the household i. The peak-time power profile $P_{ijk}\ (t)$ is compared against the threshold to eliminate measurement noises from being counted as the appliance was operated between starting (t_1) and

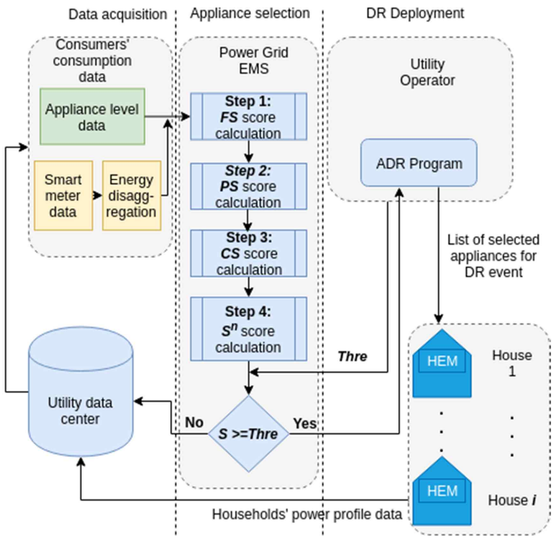


Fig. 1. Appliance selection for DR event

end (t_2) time of the DR event.

ii. Peak time usage. The next parameter to determine the appliance's contribution to grid aggregate demand is peak time usage. Each appliance is considered based on its energy consumption at peak time, which the DR program aims to curtail. The EMSr assigns the higher score to an appliance which has higher consumption amount during the considered peak time interval $[t_1:t_2]$. Peak time usage score is calculated as follows:

$$PS_{ij} = \sum_{k\in K} \int_{t_1}^{t_2} P_{ijk}(t)\,dt, \tag{3}$$

The values of PS score of all appliances are normalized to [0:1] interval.

iii. Consistency of usage – Although an appliance operates most of the days, it is desirable from the point of an operator to happen at the time when there is less demand than supply in the power grid. As we mentioned above, DR is intended to curtail the power load of consumers who show peak consumption at the DR time. Operators believe that selected consumer appliance indeed shows the same consumption habit at peak time on the DR operation. Consistent operation across the past several days allows the system to predict whether an appliance repeats its peak power usage at the next DR time. Calculation of consistency value is similar to in the assisting literature, but we limit the testing time interval of operation from a whole day to only desired DR time. The reason is that the stability of an appliance's daily power profile may differ from the profile at DR time. Thus, the EMS could predict a more precise power profile of the appliance for the next DR time and successfully involve this appliance in the DR event. To measure the consistency of consumption, we calculate root mean square (RMS) error over K days power profile at DR time interval. To eliminate small noises in measured data, we perform max normalization across power profile:

$$P_{ijk}^{n}(t) = \frac{P_{ijk}(t)}{\max(P_{ijk})},\ t \in [t_1:t_2], \tag{4}$$

$$RMS_{ij} = \sum_{k\in K} \sqrt{\sum_{t_1}^{t_2} \left[P_{ijk}^{n}(t) - \overline{P}_{ij}^{n}(t)\right]^2}, \tag{5}$$

where $\overline{P}_{ij}^{n}$ is the mean of the normalized power profile during the DR time interval over K days. we perform a $min-max$ normalization to normalize RMS_{ij}^{n} to $[0:1]$ for all appliances. Consistency of usage at peak time is defined as follows:

$$CS_{ij}^{(peak\ time)} = 1 - RMS_{ij}^{n}. \tag{6}$$

(RMS) allows us highlighting deviation of power at an observed time window from the mean of power during a total DR period. Thus, it has a smaller value for more stable operation but higher value for the more sporadic operation. Consistency value is contrary to (RMS) so, less (RMS) value shows that the appliance's operation is more consistent during the considered time interval.

iv. Potential score. Potential of the targeted appliance is estimated by multiplying these three parameters:

$$S_{ij} = FS_{ij}^{(peak\ time)} \times PS_{ij} \times CS_{ij}^{(peak\ time)}. \tag{7}$$

The above formula depicts that all of the three parameters have a direct impact on the final score. A small value among any of them brings to decrease in the potential score of the appliance. For instance, an appliance with considerably higher frequency and power usage score may have a small final potential score as it has low operation consistency value. To ease the comparison, a $min-max$ normalization is performed across the potential score of all appliances. Then, the final metric $S_{ij}^{n} \in [0:1]$ is used to sort consumer appliances for the ADR program. For consumers that have several deferrable appliances, they may receive a demand request signal from the operator, which includes a list of appropriate appliances in the household to shift their operation to a later time.

V. EXPERIMENTAL RESULTS AND PERFORMANCE EVALUATION

In this section, we present the evaluation of our proposed method along with the baseline method [9] using both REFIT [10] and REDD [11]datasets, as mentioned in the previous section. As depicted in Table 1, we denote House 1 and House 3 in REDD dataset as Consumer A and B; House 1 and House 3 in REFIT dataset as Consumer C and D.

For assessment, we set the number of observation days as K = 30. Starting from Apr.18, 2011 for appliances of Consumer A and Consumer B, from October 23, 2013, for appliances in Consumer D, and from November 9, 2013, for appliances in Consumer C. Data sets provided a limited spectrum of deferrable appliances like dishwasher, washing machine, bathroom water heater, electric space heater, tumble dryer, and electric furnace. Although a residential lighting element consumes a small amount of power, it shows competent yield power as it is turned on a long time at the DR period across the days. Most of high power kitchen outlets like a kettle, microwave and toasters are not selected as appliances with shiftable operation behavior, as they are active for a short time from 2 to 10 minutes only when it is dining time. Refrigerators are not included, because they are an always-on type of appliance. We down-sampled the data into a 15-minute resolution. DR period is selected from 5 pm to 9 pm, as the aggregate ALP of all participating appliances in both datasets has a peak in this time interval.

To ease the comparison between the results of proposed and existing methods, Table 1 shows FS and CS, and final scores S^n of each appliance in both approaches. For simplicity, Table 1 does not depict PS values information because it contains the same value in both methods. Instead, we include that information in Table 2 of appendix A for further reading.

It can be seen from Table 1 that the proposed method is assessing the ALP at the DR time interval, which is much shorter than the daily ALP. Thus, it most likely has smaller FS values for all appliances. Moreover, most appliances have a more consistent daily profile, while they show lower consistency at the DR time. The change in both values affected the final potential results of appliances.

Table 1. Comparison of evaluation results of existing and proposed appliance selection methods.

Consumers	Appliance name	Previous method			Proposed method		
		FS	CS	S^n	FS*	CS*	S^n
A	Washer dryer	0.37	0.8	**0.76**	0.33	0.28	**1**
	Light 1	0.92	0.6	**0.42**	0.57	0.3	**0.55**
B	Electric furnace	0.91	0.8	**1**	0.67	0.2	**0.78**
C	Electric heater	1	0	**0**	0	1	**0**
D	Tumble dryer	0.87	0.2	**0.24**	0.66	0.15	**0.57**
	Dishwasher	0.67	0.9	**0.5**	0.54	0.18	**0.34**
	Washing machine	0.88	0.9	**0.44**	0.4	0.1	**0.08**

Abbreviations: FS – frequency of usage; FS^* –frequency of usage at DR time interval; CS – Consistency of usage; CS^* - Consistency of usage at DR time interval; S^n – Potential score (normalized); Shaded cells represent appliances with S^n score higher than the system threshold value ($thre$ = 0.4).

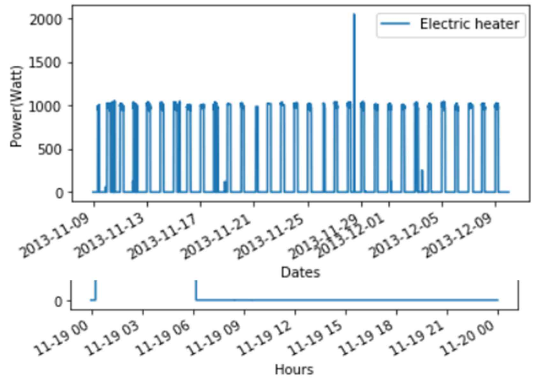
We give the system a sample threshold ($thre$ = 0.4) to compare the result in consumer appliance selection based on the existing and our proposed method. In real automated DR program operation, this threshold value can be different depends on the utility operator's intention.

Although FS and CS values of appliances in the household of consumer A and B are decreasing in the proposed method, appliances with significant peak time usage metrics are remaining to be potential for the DR event. The significant change is among the appliances of Consumer D. In the previous method, the daily power profile of "Dishwasher" ($FS = 0.67$) and "Washing machine" ($FS = 0.88$) appliances of Consumer D were very consistent ($CS = 0.9$), and these high values made the appliances to be potential ($S^n = 0.5$ and $S^n = 0.44$ respectively) for the DR event. These two appliances have less power consumption comparing to the "Tumble dryer" element in the same household ($PS = 0.32$, $PS = 0.18$ comparing to $PS = 0.53$ in Appendix A). In contrast, our proposed approach proves that the part of the power profile of these two appliances which overlaps with DR time duration was more sporadic ($CS^* = 0.18$ and $CS^* = 0.1$ respectively), causing to have the final potential score below the system threshold ($S^n = 0.37$ and $S^n = 0.15$). Consistency value of "Tumble dryer" appliance decreased slightly from $CS = 0.2$ to $CS^* = 0.15$, but its higher consumption amount during DR time was the main reason to make it one of the potential appliances for the DR program.

To be more detail, we provide the example ALP analysis of several types of appliances as follows. "Electric heater" element of Consumer C has maximum consistency value ($CS = 1$), or in other words, has minimum RMS value ($RMS = 0$). It is shown that this appliance is never active at DR time during the entire observation days. Thus it has no peak time usage to be potential for DR operation as depicted in Fig. 2.

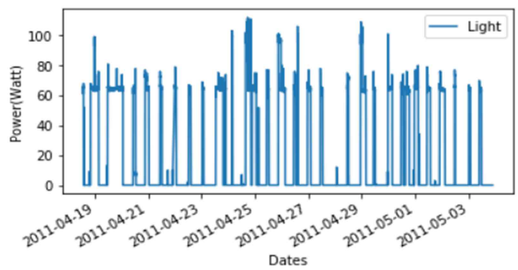
Furthermore, Table 1 highlights that most high rated power appliances with a heating element like "Washer dryer", "Tumble dryer", and "Electric furnace" with reasonably consistent usage patterns are the main target of the DR event at peak time. In fact, on the other hand, appliances with low rated power, like the "Light 1" element of Consumer A may contribute aggregate demand as they are active during total DR time in most cases, as depicted in Fig. 3. Also, a single house may have one or two same types of home appliances like washing machine, dishwasher or HVAC elements but tens of lighting elements that may be active at peak time without occupant's necessity.

Furthermore, to assess the performance of both that the power grid operator that runs the DR event has the intent to curtail peak power usage to $\Delta P\ kW$. Therefore, the operator assigns a particular threshold to the EMS to select consumer appliances to defer their operation. For instance, in Table 1, with $thre$ = 0.4, it selects five ($N_{assisting} = 5$) appliances based on the previous method and four ($N_{proposed} = 4$) appliances based on our proposed technique. We compare the possible amounts of power reduction, which can be curtailed by deferring the operation of the selected appliances in existing and proposed approaches. This power amount is directly proportional to the sum of peak time usage scores PS of selected appliances. Thus, the peak-time power consumption of five DR potential appliances relying on existing approach is $\Delta P_{assisting} \approx \sum PS_{assisting} = 2.34$, while the for selected four appliances in the proposed approach is $\Delta P_{proposed} \approx \sum PS_{proposed} = 2.37$ ($\Delta P_{proposed} \geq \Delta P_{assisting}$).

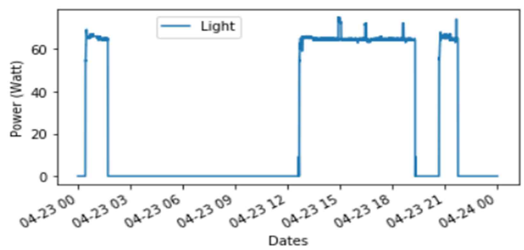


a) Monthly consumption profile (30 days active from November 09, 2013, to December 09, 2013
b) Daily consumption profile (single day, 24-hour time format)

Fig. 2. Consumption profile assessment and analysis of Electric heater appliance in Consumer C



a) Monthly consumption profile (18 days active period from April 19, 2011, to May 3, 2011)



b) Daily consumption profile (single day, 24-hour time format)

Fig. 3. Consumption profile assessment and analysis of Light 1 appliance in Consumer A

As shown above, there is a small difference between the existing approach and our proposed approach in the numbers of selected appliances and the total curtailed energy. In practice, utility serves several thousands of consumers with the number of deferrable appliances. Thus the numbers increase proportionally.

Moreover, we also compare both methods in terms of consumer's comfort level reduction caused by appliance operation shifting during the DR event. As explained in the previous section, the total decrease of the consumer comfort level at DR event time is the sum of operational comfort level reduction of its all DR participating appliances (see Eq. 1). In Table 1, only consumer D has a difference among selected appliances. Based on the existing method, the decrease of consumer D's comfort level is the sum of the operational comfort level of "Dishwasher" (more sensitive to operation shifting, $\Delta C = 4$) and "Washing machine" (more tolerant, $\Delta C = 1$). Hence, the total $\Delta C = 5$ during 4 hours DR event. On the other hand, based on our proposed method, the operational comfort level reduction can be minimized, in which only the single "Tumble dryer" element is needed to be shifted. In most cases, "Tumble dryer" follows the "Washing machine" operation. Hence it has the same tolerance to operation shifting as "Washing machine" $\Delta C = 1$. The results prove that the proposed method allows a more optimal selection of appliances with minimum consumer comfort level reduction.

VI. CONCLUSION

In this work, we presented a selection technique of consumer appliances for the automated DR program. The method is based on their ALP assessment, which is the multiplication of the frequency and consistency of usage, and amount of consumption of each appliance at the DR event. Furthermore, we have tested our method along with the baseline method using two renowned public data sets, i.e., REFIT and REDD. The comparison of consumers' potential scores against a selected threshold shows that our method allows the EMS to match DR target better than the compared method.

Furthermore, the results also showed that our method achieved less reduction in consumer comfort level compared to the existing method. Interestingly, evaluating our method on the data sets with heterogeneous appliances showed that lower power loads might have a noticeable effect in peak time consumption curve as they are active at DR event time in most cases. In contrast, high rated power appliances with sparse usage habits may have less effect on consumer aggregate demand at peak time.

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APPENDIX

A. Power profile characteristics

Table 2. Power profile characteristics of appliances

Consumers	A				B	C			D		
Appliances	Dishwasher	Bathroom GFI	Washer dryer	Light 1	Electric furnace	Washing machine	Dishwasher	Electric heater	Tumbel dryer	Dishwasher	Washing machine
PS	0.09	0.01	1	0.3	0.54	0	0.09	0	0.53	0.32	0.18

Abbreviations: *PS* -Peak time usage score

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