DEMAND AND FLEXIBILITY OF RESIDENTIAL APPLIANCES: AN EMPIRICAL ANALYSIS

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***Abstract*—Smart metering and submetering technologies make energy data available at the granularity of individual appliance. Based on a real-world data set, we characterize energy consumption of individual appliances, and quantify the flexibility for demand response as realizable increase and decrease of energy consumption. Results show significant flexibility potential in residential appliances and substantial cost savings for customers under time-of-use pricing.**

***Index Terms*—data analysis, demand response, flexibility, residential appliance.**

I. INTRODUCTION

Deployment of advanced metering infrastructure (AMI) enables residential demand response (DR). Smart meters and submeters produce detailed data of electricity consumption by end use. Such granular data opens up new opportunities to promote residential DR programs. Measurements of individual appliances and circuits enable better understanding of consumption patterns and utilization of DR resources. However, the methodologies that discover the underlying structure of AMI and submeter data and convert the fine-grained energy data into useful information to support decision-making for DR have not been formalized.

In this paper, we study the electricity consumption behavior of individual appliances and quantify their flexibility potentials for offering DR. In particular, we use statistical techniques to analyze energy consumption data of various appliances and produce distributions of demand flexibility in individual appliances. Such statistics can be translated into actionable insights for DR providers to identify and select appropriate appliances and users.

First, we characterize the consumption pattern by extracting descriptive statistics from the appliance-level data. Specifically, the variation in the energy consumption is analyzed across different types of appliances as well as different temporal factors for individual appliances. Aiming at flexibility estimation, we also quantify the availability and reliability of each appliance as DR resource.

We then evaluate the flexibility potential of individual appliances using a quantifiable definition — the increase and decrease of energy that can be realized with user-specified constraints [3]. The empirical flexibility is calculated for different appliances by either shifting or shedding the load. We note that the flexibility is not only estimated in the form of a nominal value but also a *distribution*.

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Finally, a case study is provided to estimate the potential cost saving for customers using time-of-use (TOU) rates [4]. Numerical results show significant flexibility potential in residential appliances and substantial cost savings for customers from DR participation.

There is a substantial body of literature on studying demand and flexibility of residential appliances. Most analyses [5]–[12] only focus on a particular type of appliance. Thermostatically controlled loads (TCLs), such as AC, clothes washer and dryer and water heater, receive the most attention due to their high energy consumption and suitability for DR. Physical and statistical models are usually adopted by fitting the available appliance-related data for flexibility quantification. Such analyses cannot provide insights in selecting the appropriate type of appliance to offer DR, due to the lack of comparison between various appliances.

A few studies [3], [13] investigate and compare the demand and flexibility of multiple residential appliances. Such analyses usually require survey information or customer interaction to characterize the demand flexibility. However, the requirement of intensive inputs from customers limits the scale and diversity of appliances being analyzed.

In this study, more than 20 distinct appliances are studied from their hourly energy consumption data. The cross-appliance comparison can provide valuable insights in identification and selection of appropriate resources for DR offering.

II. DATA

A. Data Set

The data set used in this study is the hourly electricity consumption of individual appliances. Data is collected from 345 homes with each having complete record for at least one appliance, mainly located in Austin, Texas, in 2016 [2].

The data is pre-processed before the analysis to guarantee reliable statistics. First, appliances owned by less than 20 users are excluded. Second, we aggregate the consumption on different units of the same appliance. For example, if a user has multiple AC units, then the hourly consumption of AC is the total use of all units. Finally, for each appliance, users who have negligible consumption (maximum hourly consumption is less than 0.1 Wh) or incomplete record (unavailable records are more than 100 hours in the year) are excluded.

B. Classification of Appliances

Appliances can be categorized into three types according to operating characteristics: inflexible loads, flexible deferrable loads, and flexible non-deferrable loads. Inflexible loads cannot be deferred in time or curtailed during operation. Flexible

TABLE I
APPLIANCE CLASSIFICATION AND NUMBER OF OWNERSHIP

Inflexible	Flexible	
	Deferrable	Non-Deferrable
bathroom (78), bedroom (63), cook top (57), disposal (92), garage (35), microwave (149), kitchen (32), living room (54), office (32), oven (121), vent hood (27)	clothes washer (193), dishwasher (183), dryer (214), EV (60), hot tub (23), pool pump (21)	AC (274), furnace (225), light (101), refrigerator (205), water heater (27)

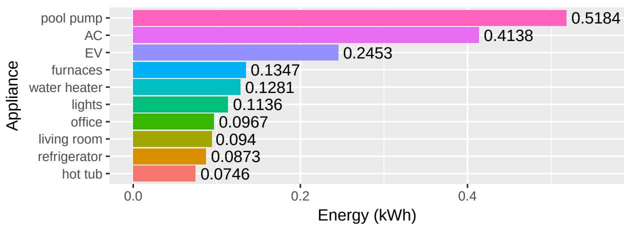


Fig. 1. Top 10 appliances ranking by average hourly energy consumption.

loads can be further divided into deferrable and non-deferrable loads according to the temporal flexibility. Deferrable loads can be shifted in time but not changed in magnitude while non-deferrable loads can only be curtailed in magnitude.

The classification of the appliances analyzed in this study is given in Table I along with the number of owners. We note that inside and outside lights are separately monitored in the data set. Only outside lights are assumed to be curtailable.

III. CHARACTERISTICS OF APPLIANCE ENERGY USE

A. Variation across Appliances

The purpose of analyzing consumption variation across appliances is to identify flexibility potential and provide a preliminary guidance on appropriate appliance selection when DR is needed. To determine how much electricity each appliance use, we first calculate the average hourly energy consumption of individual appliances.

Let $x_{i,j}(t)$ be the hourly energy consumption of appliance i for user j at time t, where t is the hour index of year 2016, *i.e.*, $t \in \mathcal{T}_{\text{year}} \triangleq \{1, 2, \cdots, 8784\}$. The average hourly energy consumption $\bar{x}_i$ of appliance i is given by

$$\bar{x}_i = \frac{1}{|\mathcal{T}_{\text{year}}||\mathcal{J}_i|} \sum_{j \in \mathcal{J}_i} \sum_{t \in \mathcal{T}_{\text{year}}} x_{i,j}(t) \tag{1}$$

where $\mathcal{J}_i$ is the set of users who own appliance i.

Fig. 1 presents the top 10 energy-consuming appliances with the average hourly energy consumption. Since the majority of high energy-consuming appliances are flexible loads, there is a substantial fraction of residential energy consumption can be used to provide DR.

Since the average hourly energy consumption does not reveal the actual electricity usage *when the appliance is in use*, it alone may not be sufficient for efficient identification and selection of DR resource when the demand reduction is needed at a certain time. To exclude idle time of appliances, we use the average power as another measure.

Estimating the on or off status of an appliance from hourly energy consumption data is non-trivial. Here we use a simple

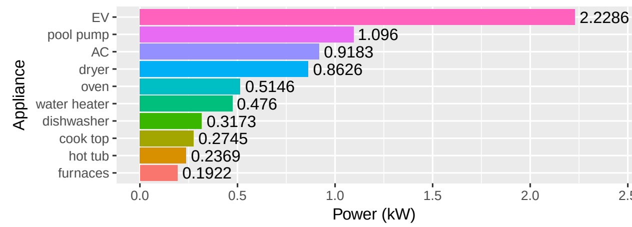


Fig. 2. Top 10 appliances ranking by estimated average power.

criterion to detect if an appliance is actually in use. Specifically, a small threshold θ is chosen to rule out the hours when the hourly energy consumption is below it. Mathematically, the average power $\tilde{x}_i$ of appliance i is estimated by

$$\tilde{x}_i = \frac{\sum_{j \in \mathcal{J}_i} \sum_{t \in \mathcal{T}_{\text{year}}} x_{i,j}(t) \mathbb{1}_{\{x_{i,j}(t) > \theta\}}}{\sum_{j \in \mathcal{J}_i} \sum_{t \in \mathcal{T}_{\text{year}}} \mathbb{1}_{\{x_{i,j}(t) > \theta\}}} \tag{2}$$

where $\mathbb{1}_{\{s\}}$ is the indicator function whose value is one if the statement s is true and zero otherwise.

The average power of the top 10 appliances is presented in Fig. 2, where the threshold θ is set to be 0.01 kW. The rank of appliances by average power $\tilde{x}_i$ is completely different from that by average hourly energy consumption $\bar{x}_i$. When high power appliances are in use, they can provide more flexibility than appliances with high energy consumption.

B. Variation over Time

In general, the energy consumption of appliances changes over time. Variation in electricity use may present daily, weekly, or seasonal patterns due to regularity in human activities. The analysis of temporal variation in appliance demand provides prior knowledge into load modeling and prediction, which are essential inputs of decision making algorithms for DR.

The analysis of temporal variation is based on the normalized consumption data of each appliance. Formally, the normalized hourly energy consumption $\bar{x}_i(t)$ of appliance i at time t is given by

$$\bar{x}_i(t) = \frac{1}{|\mathcal{J}_i|} \sum_{j \in \mathcal{J}_i} x_{i,j}(t). \tag{3}$$

According to time of day, day of week, and month of year, temporal patterns of the normalized average hourly energy consumption have been identified.

The effect of time of day on electricity use is observed in all studied appliances. Daily variation in energy consumption can reflect human activities. Here we highlight daily consumption profiles of some representative flexible loads. Since the top energy-consuming appliances have the most DR potential, we choose AC, EV, light and pool pump to illustrate their variation characteristics.

As shown in Fig 3, daily load shapes vary widely across appliances, where diamond represents the mean value. As a TCL, the load profile of AC bears strong similarity to the temperature profile. This explains the observation that the average consumption of AC reaches the peak around 5 PM and the bottom around 7 AM. Another reason for the peak time being around 5 PM can be the fact that the room temperature is much higher than the desired level when people arrive at

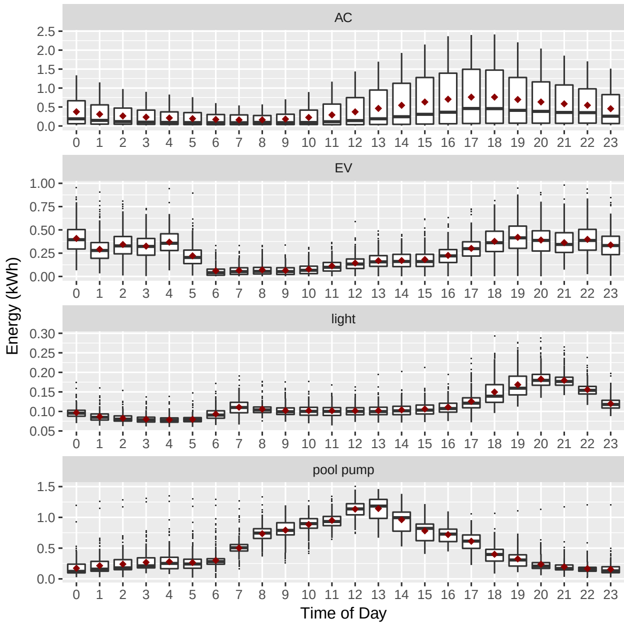


Fig. 3. Daily variation in energy consumption of selected flexible appliances.

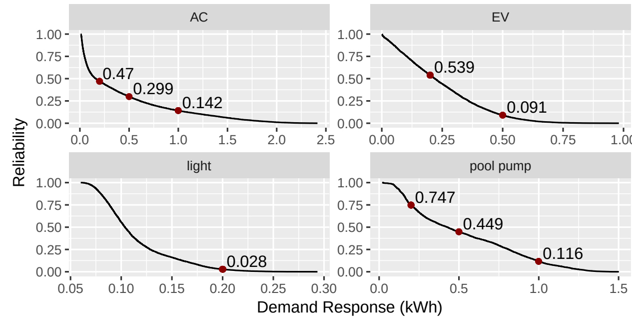


Fig. 4. Normalized empirical reliability curve of selected flexible appliances.

home from work. The big variance at the peak might indicate the uncertainty of time when people come back home. The home-work commuting pattern is more obvious in the load shape of EV charging — the majority of EV charging activities happen during night time. Since a single charge usually does not exceed 3 hours, substantial DR can be provided, especially during the evening when most inflexible appliances, such as kitchen appliances and room plugs, are being used. Lights are mostly used during the evening, as expected. But the non-zero consumption during the day time seems to be unnecessary, thus being curtailable. The load shape of pool pump seems to be similar to that of solar generation. Such similarity indicates the possibility of aligning pool pump use with solar generation.

Compared with time of day, the other two seasonal factors only affect a few appliances. For day of week, only clothes washer, dryer, hot tub and some room plugs consume more energy on the weekend than on weekdays. For example, the average hourly energy consumption of clothes washer on Sunday is more than 60% of that on Wednesday, while no significant difference is observed across weekdays. Month of year is influential on energy consumption of TCLs due to temperature seasonality. An interesting finding of the monthly pattern is that the electricity use of lights in December is much higher than other months, ranging from 16% to 35%. This is most likely caused by lighted holiday decorations.

C. Availability and Reliability

In order to estimate the demand flexibility of each appliance, we need to quantify how much power is available for DR and how reliable each resource is. To this end, we introduce the concepts of availability and reliability.

The availability $a_{i,j}(t)$ of appliance i in home j at time t is defined by the maximum amount of energy can be used for DR. The value of availability $a_{i,j}(t)$ is equal to the hourly energy consumption $x_{i,j}(t)$.

The reliability $r_{i,j}(a)$ measures how reliable the appliance i in home j is when DR a (in kWh) is needed. Mathematically, we define the reliability $r_{i,j}(a)$ by the probability that the random availability $A_{i,j}$ of appliance i in home j exceeds the required DR level a, *i.e.*,

$$r_{i,j}(a) = \mathbb{P}[A_{i,j} \geq a]. \tag{4}$$

Note that the reliability $r_{i,j}(a)$ is essentially the complementary cumulative distribution function of $A_{i,j}$, which can be estimated by

$$\hat{r}_{i,j}(a) = \frac{1}{|\mathcal{T}_{\text{year}}|} \sum_{t \in \mathcal{T}_{\text{year}}} \mathbb{1}_{\{x_{i,j}(t) \geq a\}}. \tag{5}$$

The normalized reliability curve $\hat{r}_i(a) = \frac{1}{\mathcal{J}_i} \sum_{j \in \mathcal{J}_i} \hat{r}_{i,j}(a)$ of selected appliances is shown in Fig. 4 with highlighted DR levels at 0.2, 0.5 and 1.0 kWh. Decay rates vary significantly across appliances as well as DR levels. A plausible conclusion can be drawn is that the rank of average hourly energy consumption has positive correlation with reliability *within certain range*. For example, if we need 0.2 kWh demand reduction, pool pump is the most reliable resource for DR as $\hat{r}_{\text{poolpump}}(0.2) = 0.747$.

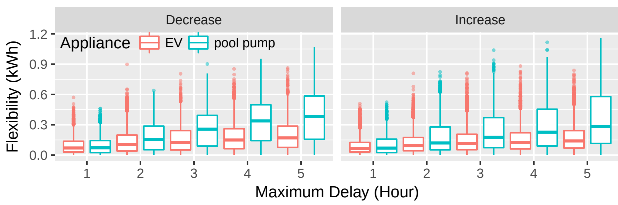
IV. Flexibility

For residential appliances, the demand flexibility indicates how much load can be shifted or reduced within user-specified limits. Here we adopt the quantifiable definition of flexibility in [3]. Formally, the demand flexibility of appliance i in home j at time t is defined as the realizable increase $\Delta x_{i,j}^{+}(t)$ and decrease $\Delta x_{i,j}^{-}(t)$ of energy.

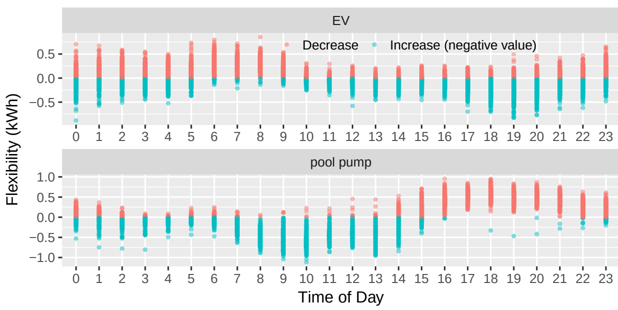
To estimate flexibility, we use two naive measures to represent user-specified limits. We adopt the maximum delay $\tau^{\max}$ (in hour) to represent the consumer tolerance for deferrable loads. The maximum curtailment ratio $\lambda^{\max}(t)$ at time t is used for non-deferrable loads. We note that the flexibility is estimated at the normalized consumption values, *i.e.*, $\Delta \bar{x}_i^{+}(t)$ and $\Delta \bar{x}_i^{+}(t)$, with the assumption of the expected consumption being $\bar{x}_i(t)$ for appliance i at time t.

A. Deferrable Load

For deferrable loads, we investigate the impact of maximum delay and time of day on flexibility. Specifically, the flexibility is calculated by shifting the year-long load profile by the maximum delay. Results of EV and pool pump are shown in Fig. 5. As shown in Fig. 5(a), the flexibility grows with the maximum delay for both appliances. When the delay bound



(a) Impact of maximum delay



(b) Impact of time of day ($\tau^{\max} = 5$)

Fig. 5. Flexibility of selected deferrable loads.

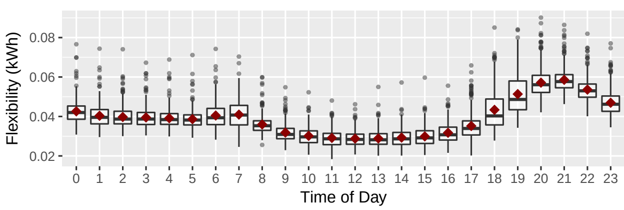


Fig. 6. Flexibility (demand reduction) of light.

is tight ($\tau^{\max} < 3$), the increase and decrease flexibility seem to be symmetric. As the maximum delay increasing, the decrease flexibility is slightly greater than the increase flexibility. Comparing Fig. 5(b) with Fig. 3, the shape of availability and flexibility seem to be closely related: the shape of decrease flexibility looks similar to the availability profile while the shape of increase (in positive value) is complementary to the availability curve. This observation implies that the availability is a reasonable indicator of flexibility for deferrable loads.

B. Non-Deferrable Load

Since the flexibility of non-deferrable loads arises from curtailment, the flexibility is essentially the demand reduction. The flexibility of non-deferrable loads is thus calculated by reducing the energy consumption by the maximum curtailment. Due to space limit and numerous studies on TCLs in the literature, we only present the result of light here. The fraction of outside light consumption, *i.e.*, $\bar{x}_{\text{out}}(t)/(\bar{x}_{\text{out}}(t) + \bar{x}_{\text{in}}(t))$ is used as the maximum curtailment ratio $\lambda^{\max}(t)$. Fig. 6 shows the flexibility profile of light. In contract to deferrable loads, the flexibility profile of light differs from its availability shape in Fig. 3. This is caused by the *time-varying* maximum curtailment ratio $\lambda^{\max}(t)$.

We note that the flexibility is not only a nominal value as energy increase or decrease but also a distribution. Based on the availability and reliability of appliance demand, more sophisticated methods can be to used to estimate flexibility

TABLE II
TIME-OF-USE PERIODS AND CHARGES ($/KWH) [4]

	Period	Charge	
		Jun.-Sept.	Oct.-May
Off-Peak	Sat-Sun, Mon-Fri: 10PM-7AM	0.02108	0.01959
Mid-Peak	Mon-Fri: 7AM-3PM, 6PM-10PM	0.02829	0.02556
On-Peak	Mon-Fri: 3PM-6PM	0.12887	0.02727

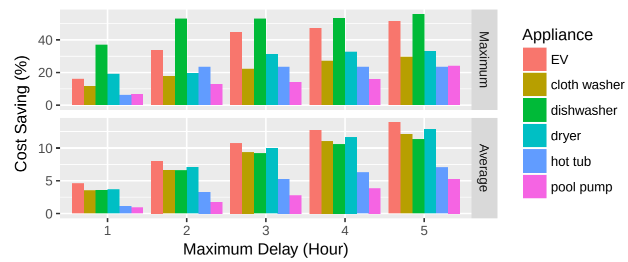


Fig. 7. Cost savings in flexible deferrable appliances.

and schedule appliances to achieve desired DR level. In the next section, we use a case study to illustrate the potential savings for customers by scheduling deferrable loads.

V. OPTIMIZATION FOR CUSTOMER

TOU rate of energy consumption provides economic incentives for customers to shift or reduce consumption during high-priced periods. Below we show how much saving can be achieved by utilizing the flexibility in deferrable loads under the TOU pricing in Table II.

Since the deferrable load can only be shifted in time, the load profile of a task of the appliance cannot be changed. Therefore, the scheduling problem is essentially to determine the optimal start time of each task within the maximum delay. Consider the kth task of appliance i in home j within the billing period. Let $\{x_{i,j}(t)\}_{t\in[t^{\text{start}}_{i,j,k}, t^{\text{end}}_{i,j,k}]}$ be the load profile of this task, where $t^{\text{start}}_{i,j,k}$ and $t^{\text{end}}_{i,j,k}$ are the original start and end time, and $x_{i,j}(t) > \theta$ for all $t \in \left[t^{\text{start}}_{i,j,k}, t^{\text{end}}_{i,j,k}\right]$. Given the maximum delay $\tau^{\max}_{i,j}$, the optimal delay $\tau^*_{i,j,k}$ of this task is given by

$$\tau^*_{i,j,k} = \underset{\tau\in\{0,1,\cdots,\tau^{\max}_{i,j}\}}{\operatorname{argmin}} \sum_{t=t^{\text{start}}_{i,j,k}}^{t^{\text{end}}_{i,j,k}} c(t+\tau)x_{i,j}(t) \tag{6}$$

where $c(t)$ is TOU rate at time t.

Fig. 7 shows the maximum and average cost savings of each appliance at different maximum delay values, where the maximum and average are taking over all owners of each appliance. As expected, the cost saving is highly positively correlated with the flexibility. This suggests that consumers can benefit significantly from DR participation.

VI. CONCLUSION

We present an empirical analysis of demand and flexibility of different appliances using a real-world data set. Various metrics are used to characterize load profiles of individual appliances. These descriptive statistics provide valuable insights in identification and selection of appropriate appliances as DR resource. The quantification of flexibility shows how much power can be used and when it can be used for DR.

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