Applied Energy 254 (2019) 113693

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Residential loads flexibility potential for demand response using energy consumption patterns and user segments

Milad Afzalan, Farrokh Jazizadeh*

The Charles E Via Jr., Department of Civil and Environmental Engineering, Virginia Tech, 750 Drillfield Dr., Blacksburg, VA 24061, USA

HIGHLIGHTS

- A data-driven segmentation approach using individual loads for demand response is presented.
- The segmentation approach successfully distinguishes users based on demand reduction potential.
- Presented a cross-appliance comparison of flexibility assessment for different segments of users.
- Presented feasibility evaluation on real-world data for more than 300 households.
- Findings show high variation of demand reduction potential based on consumption patterns.

ARTICLE INFO

Keywords:
Demand response
Smart appliances
Connected homes
Flexibility
Residential buildings
Grid-interactive efficient buildings

ABSTRACT

Demand response (DR) is considered an effective approach in mitigating the ever-growing concerns for supplying the electricity peak demand. Recent attempts have shown that the contribution from the aggregate impact of flexible individual residential loads can add flexibility to the power grid as ancillary services. However, current DR schemes do not systematically distinguish the varying potential of user contribution due to the highly-varied usage behaviors. Thus, this paper proposes a data-driven approach for quantifying the potential of individual flexible load users for participation in DR. We introduced a metric to capture the predictability of usage in a future DR event using the historical consumption data for different load types. The metric helps to sort the users with flexible loads in a community according to their potential for load shifting scenarios. We then evaluated the applicability of the metric in the DR context to assess the extent of energy reduction for different segments of users. In our analysis, we included electric vehicle, wet appliances (dryer, washing machine, dishwasher), and air conditioning. The analysis of real-world data shows that the approach is effective in identifying suitable user segments with higher predictive potential for demand reduction. We also presented a cross-appliance comparison for assessing the flexibility potential of different user segments. As a case study based on Pecan Street Project, the findings suggest that potentially ~160 MWh reduction might be achieved in Austin, TX through only 20% participation of the selected flexible loads for the residential sector during a 2-h event.

1. Introduction

With moving towards distributed and decentralized energy management [1,2], it is important to add flexibility to the power consumption patterns at the individual household-level to enable efficient operation of the power system, grid-interactive buildings, and self-adaptive smart grids. Accordingly, demand response (DR) is considered as a cost-effective technique for demand reduction and ancillary services in comparison to conventional and cost-intensive techniques for expanding generation capacity or network augmentation. From the automation perspective, DR schemes vary from methods based on direct user engagement to more automated ways, in which the load operation can be automatically scheduled with Home Energy Management (HEM) systems. The advances in communication technologies and embedded communication modules in appliances [3–5] have paved the way for automation of flexible load operation, which in turn could reduce the users' burden for manual load shifting [6] and response fatigue [7]. Specifically, automation scenarios could enable the implementation of effective and acceptable dynamic pricing [8–10] in the electricity market such as real-time pricing (RTP), which is typically difficult to

* Corresponding author.
E-mail addresses: afzalan@vt.edu (M. Afzalan), jazizade@vt.edu (F. Jazizadeh).

https://doi.org/10.1016/j.apenergy.2019.113693
Received 30 April 2019; Received in revised form 12 July 2019; Accepted 2 August 2019
Available online 22 August 2019
0306-2619/

implement for manual scheduling of energy use due to high uncertainty in user response [8,11]. From the HEM automation perspective, several energy-intensive devices, such as wet appliances (tumble dryers, washing machines, and dishwashers), electric vehicles (EV), air conditioning (AC) systems, and water heaters could be adopted for flexible operation by receiving the signal from an operator. For example, wet appliances or EV can shift their operation or charging time to a later time during peak demand, or AC systems can adjust the temperature setpoint within the users' preference ranges. In this context, flexibility has been formally defined as the potential for modification of appliance power profile by adjusting power draw, the operation duration, and/or the activation time [12]. Several experimental studies have shown the applicability of load control through automation by leveraging the flexibility of individual loads at needed times with little or no impact on users' convenience [3,13,14].

In recent years, several research efforts have shown that the aggregate contribution of deferring individual loads in residential units could facilitate the peak demand reduction and provide ancillary services (e.g., [3,14–17]). These studies have focused on assessing and quantifying the flexibility, offered by individual loads, as well as the associated response from users for automated DR on networks of households. In assessing load flexibility potentials, a number of factors should be taken into account. (1) Diversity in appliance types and interactional behaviors [18] makes the aggregate load profiles widely different and brings about a high level of uncertainty in estimating flexibility across different households [7]. Even for users with the same appliance type, the user-load interaction patterns could be considerably different, which results in differences in load flexibility potential. (2) In the adoption of automated DR technologies, targeted and stratified engagement of users is of economic importance in incentivization under the constraints of limited resources [19]. Specifically, introducing DR dynamic pricing scheme comes with constraints such as additional costs for enabling technologies and customer enrollment and marketing investment [20,21]. Such barriers necessitate the identification and enrollment of only high-potential users, whose price responsiveness to dynamic pricing can be more beneficial [22]. (3) In idealistic scenarios through an unjustified selection of individual loads, the DR objective might not be satisfied, and the rebound effect (generating a new peak) can occur [23]. Synchronized activation of a large number of deferrable appliances to target a peak time [24] could actually jeopardize the system reliability and create another unforeseen peak [6]. Therefore, justified selection of participants under the uncertainty constraints of load type, load demand, and user behavior is the objective of our study on self-sustained smart grid operations.

Accounting for the above factors, it is imperative to consider the users' historical consumption and their variation of usage to effectively leverage the opportunities for load flexibility potentials. Specifically, individual loads' usage patterns have shown to be an important factor for energy demand characterization while its influence on DR objectives has been less explored [25,26]. Although smart meter aggregate-level data analysis has been used for user segmentation in DR applications (e.g., [18,27,28]), such investigations on an individual load basis, with applications for automated DR programs, has been less explored. Accordingly, in this paper, we have proposed a data-driven approach for user segmentation by leveraging individual load consumption patterns and statistical indicators of user-load interactions. Relying on the proposed segmentation strategy, through a case study by using the data from the Pecan Street Project [29], we have further investigated the DR capacity of the targeted selection of households according to user-appliance interactions and their associated usage pattern. Furthermore, using the proposed segmentation approach, we presented and evaluated a comprehensive cross-appliance comparison of demand reduction potential at a community level using real-world data. The method is applied to a sample of more than 300 households, primarily located in Austin, TX.

The rest of the paper has been structured as follows. Section 2 covers the related literature. Section 3 defines the segmentation approach for ranking users and its constituent parameters. Section 4 presents the applicability of the method through empirical assessment for estimating lower DR capacity and peak load reduction. Section 5 discusses the implications of the study, followed by concluding remarks and future research directions.

2. Research background

The research background in this study has been presented from two perspectives of (1) residential load flexibility assessment for different types of loads regardless of user consumption behavior, and (2) leveraging users' consumption behavioral patterns in DR targeted operations.

2.1. Flexibility potential assessment of residential loads

Residential loads could contribute to the flexibility of grid operation through two classes of deferrable and thermostatically-controlled loads (TCL) [30]. Accordingly, one of the primary directions of research has been focused on assessing the potential of smart appliances operation for load shifting regardless of the patterns of user-load interaction/consumption. In what follows, a number of the major studies are described to provide an insight on the research directions into this domain. In one of the leading efforts, through a field study on 77 households with solar power in the Netherlands, Kobus et al. [14] have explored the demand shift from smart washing machines in a field experiment. They used dynamic pricing to encourage user compliance for automated load shifting within a 24-h window at an optimum time. The user acceptance to shift the demand was found to be relatively low (14%) given the extended window for shifted operations. In a later study, D'hulst et al. [3] investigated the flexibility potential of all wet appliances, as well as EVs and water heaters, in more than 180 households in Belgium. Compared to the previous study, the engagement in smart and automated operation was increased (varying between 30% to 50%), mainly due to the increased incentive and authority of users in defining the allowable operational delay window. They have stated that varied levels of demand change could be observed from different load types at different times of the day. In this regard, EV and water heaters showed higher potential compared to wet appliances [3]. Klassen et al. [31] performed a field experiment for flexibility potential assessment of 188 households in the Netherlands for smart washing machines for both manual and automated DR. They showed the potential of automated DR and reported success in shifting the load to off-peak pricing times resulting in 31% of load reduction during the evening.

In addition to investigating the flexibility potential of deferrable appliances, studies have also sought to quantify the flexibility of thermostatically controlled load (TCL) (e.g., [17,32,33]). Assessing the load flexibility for different ambient temperatures and setpoints of air conditioning systems [17,33], as well as refrigerator and water heaters [17] for different building types comprise the main direction of research for flexibility quantification of TCLs. The use of elasticity component of the residential loads is another alternative for creating flexibility capacity [34]. Elasticity refers to reducing the power demand (e.g., reducing the heating load of a dryer) at the cost of increasing the duration time assuming that smart appliances could offer such flexibilities. These efforts have adopted simulation as a methodology for assessing flexibly potential for different building types and geographical locations without explicitly accounting for diversity in user consumption patterns, which stems from differences in interaction habits of users with appliances.

In recent years, in order to leverage the aforementioned load flexibility potentials, Home Energy Management (HEM) systems have been introduced and explored (e.g., [13,14,35–44]). These efforts mainly have focused on optimal load scheduling for a single user and adopting effective DR dynamic pricing. In this work, looking at a network of buildings, we have quantified the load flexibility potential from the user segmentation perspective as the first step of targeting and prioritizing homes for distributed energy management initiatives.

2.2. User identification for DR: Consumption data analysis

Several previous efforts have focused on the identification of suitable users for DR (e.g., [18,28,45,46]) by using historical behavior of households, reflected in aggregate power consumption data. To this end, studies that leveraged historical data are mainly categorized based on clustering the daily load profiles or developing DR selection functions. In the first category of studies [18,47–49], clustering has been used on daily aggregate consumption profiles of households to identify representative load shapes. Different techniques such as two-stage k-means [18,47], hierarchical clustering [50], self-organizing maps (SOM) [51], and fast search and find of density peaks (FSFDP) [48] have been used for the user segmentation purposes. The selection of suitable users for participation has been carried out based on the shape and power magnitude of clusters, the variability of load shapes, and the distribution of different load shapes in each household [18,47,48]. Within this context, the rationale for user selection for direct DR control is to identify households with high-consumption and low-variability (i.e., less variation across subsequent days) load shapes [48]. Therefore, the user selection through aggregate load profiling has been mainly focused on visual analytics of load profile clusters. However, the potential opportunities for demand reduction based on user selection have not been explored in a new set of data as a test set for further evaluations. On the other hand, selection functions as a quantitative approach for identification of user consumption patterns have been also investigated. For example, using aggregate power, Mammen et al. [28] proposed a function that couples the consistency of consumption, peak consumption, and customer response (learned from the historical events) to categorize user behavior. They studied the potentials of the proposed function by investigating the trade-off between participation fairness and the selection of users with higher consumption using a historical dataset from 60 apartments to simulate DR event. In another example, Holyhead et al. [52] proposed a residential DR approach based on mixed integer programming to target users based on relevance (the likelihood of using deferrable appliances at peak times) and willingness to respond positively to DR requests.

As a common trend, the research efforts on user selection according to consumption patterns have focused on aggregate power data, which could mask the information from individual loads and thus reduce the potential for context-aware automated DR applications. Analysis of individual loads' dynamics could bring about higher information gain on user behavior for context-aware operations. Although several efforts have looked into individual load contributions for DR (as discussed in Section 2.1), they have not accounted for variance in user interactions with different load types and their impact on the efficacy of the DR process. In other words, all the users and their interaction with the flexible appliances were treated similarly. Nonetheless, there has been a number of research efforts that explored the data-driven impact of individual loads. In a recent effort, Malik et al. [32] investigated the contribution of AC units in summer on peak demand reduction using data from selected houses in Australia. Clustering was used to characterize different consumption patterns for AC units in different households, and a load control strategy was employed to assess the possible demand reduction for each cluster type. It was concluded that around 9% of total peak demand can be reduced trough moderate change in temperature setpoints. In another study [53], a comparison on flexibility potential of different appliances such as EVs, ACs, pool pumps, and lights was performed. However, this study did not account for differences among households in providing flexibility potential.

As the review of the literature shows, in DR operations, behavioral patterns of users in interacting with individual appliances have been less investigated. A Large body of segmentation methods in literature has looked at the aggregate (i.e., whole-house) segmentation, except few recent studies [32,54] that focused on AC load segmentation. In other words, to the best of our knowledge, there is no comparative study on flexibility potential of different appliance types according to the user interaction patterns with individual loads. Therefore, we have proposed to leverage human-appliance interaction patterns as another level of information in identifying suitable users for DR engagement. We specifically look at the load flexibility potentials from the perspective of engaging users with different behavioral patterns. To this end, we have proposed a multi-dimensional metric to characterize user behavioral patterns for targeted engagement of users. The objective was to investigate the impact of user interaction with each flexible appliance separately by envisioning emerging Demand-Side Management (DSM) technologies [55] for the smart operation of individual loads. We have further evaluated the DR capacity of engaging users with different interaction patterns while accounting for the probability of compliance to accept DR requests.

3. Methodology

As noted, in this study, we have proposed to learn from the user-appliance interaction patterns to characterize user behavioral traits for effective user segmentation and more informed user engagement. Therefore, the methodology in this study describes a multi-dimensional metric for user behavior identification, as well as simulation studies for evaluating the DR capacity of engaging different groups of households in the load shifting process by accounting for user behavior and compliance.

3.1. Data-driven user behavior characterization

In this method, by assuming that the historical data at the appliance level are available, we have proposed to leverage the historical consumption data to quantitatively identify the behavioral patterns of user-appliance interactions that could benefit the goal of load shifting across a community. Through statistical analysis of the historical interactions, we have sought to create a potential score for each household for different load types or appliances. To this end, considering N users in a community, we assign a score S_{ij}^{n} in which i is the user and j is the appliance type. S_{ij}^{n} is calculated by leveraging the daily power consumption for different households and appliances (P_{ijk}) for day k. $P_{ijk}(t)$ is defined as the daily power consumption profile for user i ($i \in [1, .., N]$), appliance type j ($j \in [1, .., J]$), day index k ($k \in [1, .., K]$), and t is time index of the day ($t \in [1: T]$, e.g., $T = 24$ for the hourly

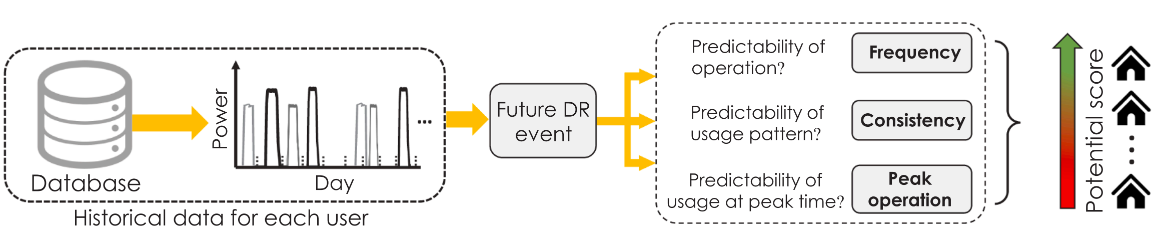


Fig. 1. Data-driven scoring system for characterization of user-appliance interactions.

electricity consumption data). In order to characterize the user-appliance interaction patterns as S_{ij}^n, as illustrated in Fig. 1, we have considered three attributes (i.e., dimensions) [56], namely (i) frequency of use, (ii) consistency of use, and (iii) magnitude of demand during the peak time. All these attributes are measured for a specific load type (j):

Frequency of operation: It is intuitive that some of the targeted appliance types might not be operated by some users on a regular basis. Therefore, it is important to understand the frequency of operation and the tendency of users to use an appliance on a regular basis. Therefore, we have quantified the frequency of operation (FS_{ij}^n), in the range of [0,1] as follow:

$$FS_{ij} = \frac{|\{k|\ \max(P_{ijk}(t)) > \tau_j, k \in (1{:}\ K)\}|}{K} \tag{1}$$

in which τ_j is a threshold value related to the minimum power draw that an appliance class has. Therefore, FS_{ij} measures the ratio of the number of days that an appliance has been activated compared to the total number of historical days (K) in the analysis. τ_j is used to eliminate the inherent impact of noise in the data or standby power to avoid false detection of operations.

Consistency of operation: An important factor in targeting users in a DR scheme is to understand the consistency of usage [57]. This attribute aims at measuring the extent to which a user's behavior is deterministic or stochastic across subsequent days. Accordingly, from the utility perspective, it is more effective to invest in users with higher consistency, as this factor reflect the likelihood of following the expected usage pattern during the DR event. As a demonstration, we have shown the charging patterns of EVs for two users across 10 days in Fig. 2. As shown, user 1 has shown to be more consistent by repeating the same pattern for different days, while user 2 is more sporadic and less predictable in usage patterns. We have defined the consistency of operation (CS_{ij}^n), measured in the range of [0,1], as follows:

$$CS_{ij}^n = 1 - RMS_{ij}^n \tag{2}$$

in which RMS_{ij}^n is the root mean square error (RMS_{ij}), normalized across all users in the community using min–max normalization. The non-normalized RMS_{ij} is defined as follows:

$$RMS_{ij} = \begin{cases} \sum_{k\in K_{op}} \sqrt{\sum_{t=1}^{T} [P_{ijk}^n(t) - \bar{P}_{ij}^n(t)]^2} & j \in \left\{\begin{matrix} EV,\ dryer,\ washingmachine,\ dishwasher \\ or\ other\ deferrable\ loads \end{matrix}\right\} \\ \sum_{k\in K_{op}} \sqrt{\sum_{t=t_1-\frac{t_2-t_1}{2}}^{t_2+\frac{t_2-t_1}{2}} [P_{ijk}^n(t) - \bar{P}_{ij}^n(t)]^2} & j = AC\ or\ TCLs \end{cases} \tag{3}$$

in which K_{op} is the set of days that an appliance was operational (defined in the numerator in Eq. (1)), $\bar{P}_{ij}^n(t)$ is the average of normalized daily profiles over the span of K historical days, [t_1: t_2] is a potential DR timeframe, and $P_{ijk}^n(t)$ is the normalized values of power consumption profile on each given day as calculated as follows:

$$P_{ijk}^n(t) = \frac{P_{ijk}(t)}{\max(P_{ijk}(t))},\ k \in K_{op} \tag{4}$$

The RMS_{ij} (Eq. (3)) measures the deviation of the observed value compared to the average across all days that an appliance was operated. For AC or in general TCL loads, we limit the consistency measurement to the vicinity of DR timeframe, due to the fact that they might have multiple daily cycles. For deferrable loads, since the number of activations is limited per day, the consistency could be measured across the entire day. The normalization in Eq. (4) is performed to avoid biases in comparing the errors given the same appliance class shows varying levels of power draw across multiple users.

Peak time operation: using a pre-defined demand management timeframe, for example, a DR event timeframe, the historical usage pattern during the event timeframe could be characterized. Accordingly, users with higher consumption during DR timeframes are more suitable for load shifting or shedding. Assuming a DR timeframe of [t_1: t_2], we define PS_{ij} as:

$$PS_{ij} = \sum_{k\in K_{op}} \int_{t_1}^{t_2} P_{ijk}(t)dt \tag{5}$$

PS_{ij} indicates the energy consumption during the DR timeframe across historical days. Using min–max normalization for all users, the $PS_{ij}^n \in [0, 1]$ is calculated to account for power draw variations for the same load type.

Potential score: Using the aforementioned attributes of frequency (FS_{ij}^n), consistency (CS_{ij}^n), and peak time use (PS_{ij}^n), we define S_{ij} as:

$$S_{ij} = FS_{ij}^n * CS_{ij}^n * PS_{ij}^n \tag{6}$$

The attributes are multiplied to penalize the S_{ij} if either of them is low (e.g., users that show frequent and consistent use with low energy consumption during DR timeframe). The superscript n for all attributes indicate that all values are mapped to the range of [0:1] over the entire community.

For better interpretability, the min–max normalization of S_{ij} across the entire community is performed to obtain the normalized potential score $S_{ij}^n \in [0, 1]$:

$$S_{ij}^n = \frac{S_{ij} - \min(S_{ij})_{\forall i}}{\max(S_{ij})_{\forall i} - \min(S_{ij})_{\forall i}},\ i \in [1, \cdots, N] \tag{7}$$

S_{ij}^n is applied to rank the users for different load types (j). As the first stage of user engagement, this metric has been intended to be used for user engagement prioritization in a DR scheme for different load types. In other words, the score is used to consider the *relevance* factor, as the suitability for providing flexibility. However, user compliance should be also considered. If the consumption patterns are driven by operational urgency, it is less likely that users comply. On the other hand, if consumption patterns are habitual, it is more likely that users comply. Nonetheless, the level of flexibility in compliance is another factor that should be considered. The compliance could be quantified through direct communication or through statistical analysis in historical user response to DR events.

3.2. User-centered load shifting framework

In order to quantify the aggregate impact of load shifting/shedding

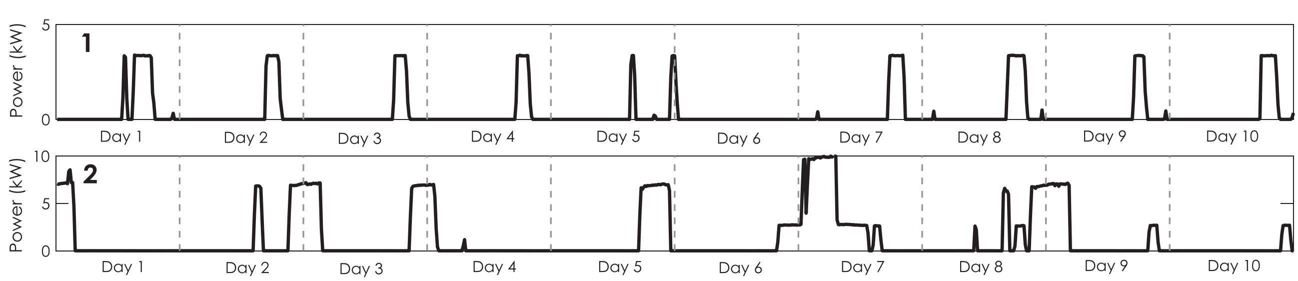


Fig. 2. Consistency of usage pattern for two users across 10 days.

across a community for different groups (i.e., segments) of users, we have adopted a load shifting framework that leverages the user characterization model in Section 3.1. Fig. 3 illustrates the general framework, which leverages the ground truth data to simulate the impact of load shifting/shedding to off-peak time following a set of standard protocols, described in the following sections.

3.2.1. Load shifting/shedding simulation scenarios

To quantify the DR capacity of the proposed score in load shifting, we have simulated the use of the above framework through a case study of a real-world community. In this simulation, for each DR event day, we retrieved the daily consumption profile for user i and appliance j. During the DR timeframe [t_1: t_2], the operational status of an appliance class is examined by searching for available continuous activation load sequences (i.e., adjacent data points) above the limiting τ_j. If no operation is detected, the power profile remains the same. Otherwise, the activation profile, Γ_{ij}=[t_{beg}: t_{end}] is identified, in which $t_1 \leq t_{beg} < t_2$ (i.e., activation start is within the DR timeframe), and t_{end} could be either within DR timeframe or stretched to a later time. For load shifting from Γ_{ij}, we have considered two scenarios:

Scenario 1: Minimum temporal deferral: In this scenario, we have assumed that the deferred load will be immediately operated once the DR timeframe (i.e., the peak time) is over. Studies have shown that there is a higher probability that users shift the loads to an immediate timeframe after the DR event [58]. In other words, users prefer the minimum delay in the activation start. In this case, we assume the new activation cycle will happen at the Γ^*_{ij} = [t_2: $t_2 + t_{end} - t_{beg}$] timeframe.

Scenario 2: Temporal deferral in a user flexibility window: In this scenario, each user defines an allowable flexibility window for each load type upon agreement for load deferral [3]. The flexibility window is within the comfort limit of users. In this way, the loads could be shifted to off-peak time when the electricity price is lower. Therefore, the new activation cycle will happen at the Γ^*_{ij} = [$t_{beg^{'}}$: $t_{end^{'}}$] in which $t_{beg^{'}} > t_2$ and $t_{end^{'}} - t_{beg} < max_d$. Here, max_d is the maximum allowable delay time defined by the user.

3.2.2. User compliance simulation scenarios

To present the applicability of the method, we select multiple days that were *not* previously considered as the historical days for ranking the users. To this end, we have randomly selected five days after the historical days to quantify the energy reduction at the peak time and reported the average result. We select multiple days to impose adequate variations for empirical demonstration. In quantifying the energy reduction during peak time, we have considered two alternatives for emulating user response:

Scenario 1: Maximum potential:

In this scenario, to evaluate the maximum load shifting potential, we allow for the load shifting of a load only if its consumption time coincides with the peak timeframe. In other words, it was assumed that users always comply with a DR request signal. Therefore, the results represent the upper bound for energy reduction potential. Since deferring the load to an immediate timeframe after the DR window is more consistent with user tendency [58], we used the minimum deferral scenario (described in Section 3.2.1) for shifting the operation cycle for deferrable loads right after the DR timeframe ends (t_2).

Scenario 2: User-compliance factor:

Successful DR events consider users' preferences. User compliance and the flexibility window (allowable time for load deferral) are contextual attributes that drive the users' response to a DR event. User compliance indicates whether a user accepts a DR signal or configurations for automated operations of smart appliances for participation. The flexibility window defines the allowable timeframe for load deferral without compromising user comfort. In the literature, there exist a few experimental and field studies on characterizing users' response for automated load deferral. In our simulations, we have adopted the user response output from a large-scale experimental pilot project over a community of houses monitored for 3 years [3]. The compliance factor, reflecting the average of acceptance to DR signals for each load, are as presented in Table 1. For the flexibility window, the probability distributions shown in Fig. 4 were adopted from the same study, which reported the average flexibility windows for EV, dryer, washing machine, and dishwasher as 5.6, 8.1, 7.3, and 8.5 h, respectively [3]. AC was not included in Fig. 4 as the control mechanism is different and is based on temperature setpoints.

For each owner of the deferrable loads, we used the *compliance threshold* specified in Table 1 as the average fixed response of community for engaging in a DR event. A random number from a uniform distribution (between 0 and 1) was generated for each user as the *compliance response*. If the compliance response was lower than the

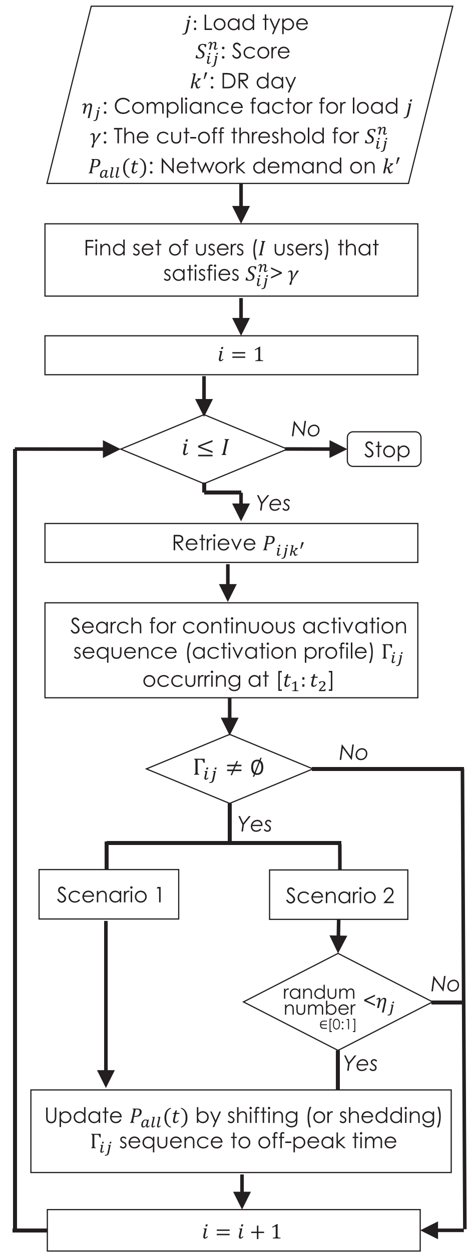


Fig. 3. Load shifting/shedding simulation framework based on user-appliance interaction patterns.

Table 1
Compliance factor (parameters partially adopted from [3]).

Device	Compliance factor threshold
EV*	0.60
Dryer	0.31
Washing machine	0.29
Dishwasher	0.56
AC**	0.50

* Was not specified in Ref. [3] and we assumed its compliance factor threshold. In the reference, it was stated that a majority of smart configurations occurred in the evening.

** AC was not included in the pilot study, and we assumed its compliance factor threshold.

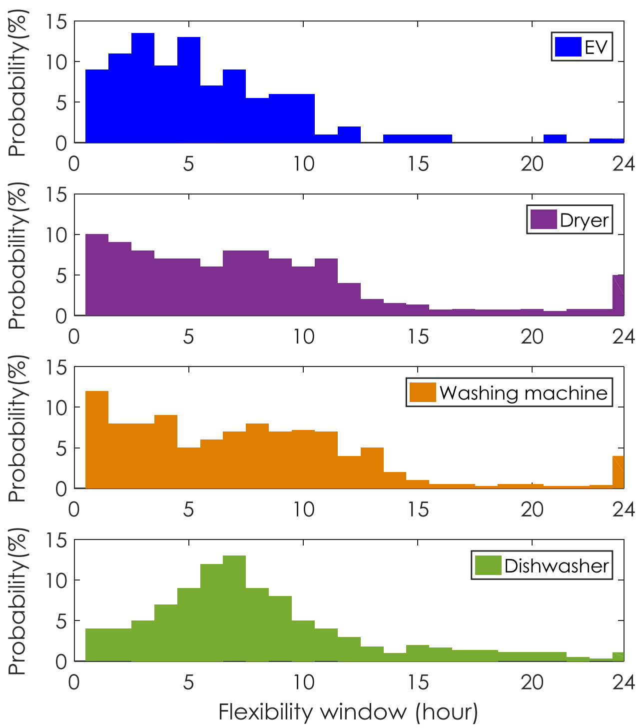


Fig. 4. The probability distribution of flexibility windows for different load types (adopted from [3]).

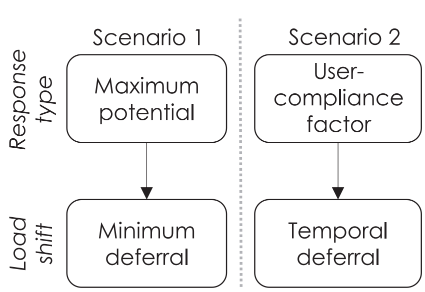


Fig. 5. Combination of scenarios in simulation analyses.

compliance factor threshold, DR participation (i.e., agreement) was positive. Upon agreement, the value of the flexibility window (duration of load deferral) was selected from the probability distribution function (shown in Fig. 4). We ran the results 10 times on each DR day in order to account for the fact that different users have varying compliance factors, and the values shown in Table 1 are used as the average of the community. In this scenario, to account for the possibility of load shifting to a next day (if the flexibility window allows), we extracted 48-h power profiles. Fig. 5 shows different combinations of scenarios

Table 2
Characteristics of the selected community data set.

Device	# of owners	# of viable datasets	# of daily profiles
EV	85	78	4909
Dryer	184	175	10,797
Washing machine	190	108	11,220
Dishwasher	224	176	13,208
AC	282	276	16,560

from Sections 3.2.1 and 3.2.2.

3.2.3. Case study community

We hypothesized that user selection based on human-appliance interactions could be effective in realizing a large ratio of possible demand reduction in the entire community by engaging a small portion of users (for a specific load type). To assess this hypothesis, we used the real-world consumption data from the Dataport Pecan Street project [29], which is an ongoing project on monitoring the appliance-level and aggregate-level data for more than 1000 households, primarily located in Austin, TX, from 2011. Monitored houses have participated at different time periods. Therefore, some of them have opted-in and opted-out from the beginning of the project, and the number of houses has been subject to change over the years. In this study, we have retrieved the data for all households that were monitored during July and August 2015, reflecting high AC use as well. We used 15-min resolution data, indicating that each daily profile includes $T = 96$ datapoints. 15-min resolution data was used since (1) it was enough to capture the operation/charging of considered flexible appliances in this study and (2) could be acquired through smart meters [59]. Daily power profiles of appliances were used to examine the complex human-building interaction at the level of individual loads.

Consumption daily profiles for EV, dryer, washing machine, dishwasher, and AC were extracted for different users. The total number of households that participated in the data collection process during the period of our study was 307. The data set information is presented in Table 2. The second column shows the number of households or owners, and the third column shows the number of households with viable datasets. In some of the houses, either the devices were not used over a long span of time or the datasets had considerable missing data points. The last column shows the number of daily profiles for different load types.

4. Data analysis and results

The assessment of the hypothesis, the demonstration of the potential score, the results of load shifting under different scenarios, and a cross-comparison of the flexibility for different load types at different time-of-use across a 24-h period have been presented in this section.

4.1. The effectiveness of the potential score

In this study, except otherwise specified, a DR timeframe of $[t_1: t_2]$ from 17:00 to 19:00 was used. This timeframe is compatible with our peak time observations in the aggregate consumption patterns of the case study community, as well as the common timeframe in practice (e.g., [60]). The 2-h duration has been also commonly investigated in the literature [27,52,61]. Nonetheless, the selected timeframe is an input to the model, and the score S^n could be calculated accordingly. Through a sensitivity analysis (described in Section 4.1.1), we selected one month of historical days (K) in the analysis. For τ_j, values of 1 kW, 0.8 kW, 0.3 kW, 0.5 kW, and 0.5 kW were used for EV, dryer, washing machine, dishwasher, and AC, respectively. These values were selected based on typical power draw values of appliances [62,63] in addition to visual inspection of the dataset.

The distribution of the potential scores (S^n) for EV, dryers, washing

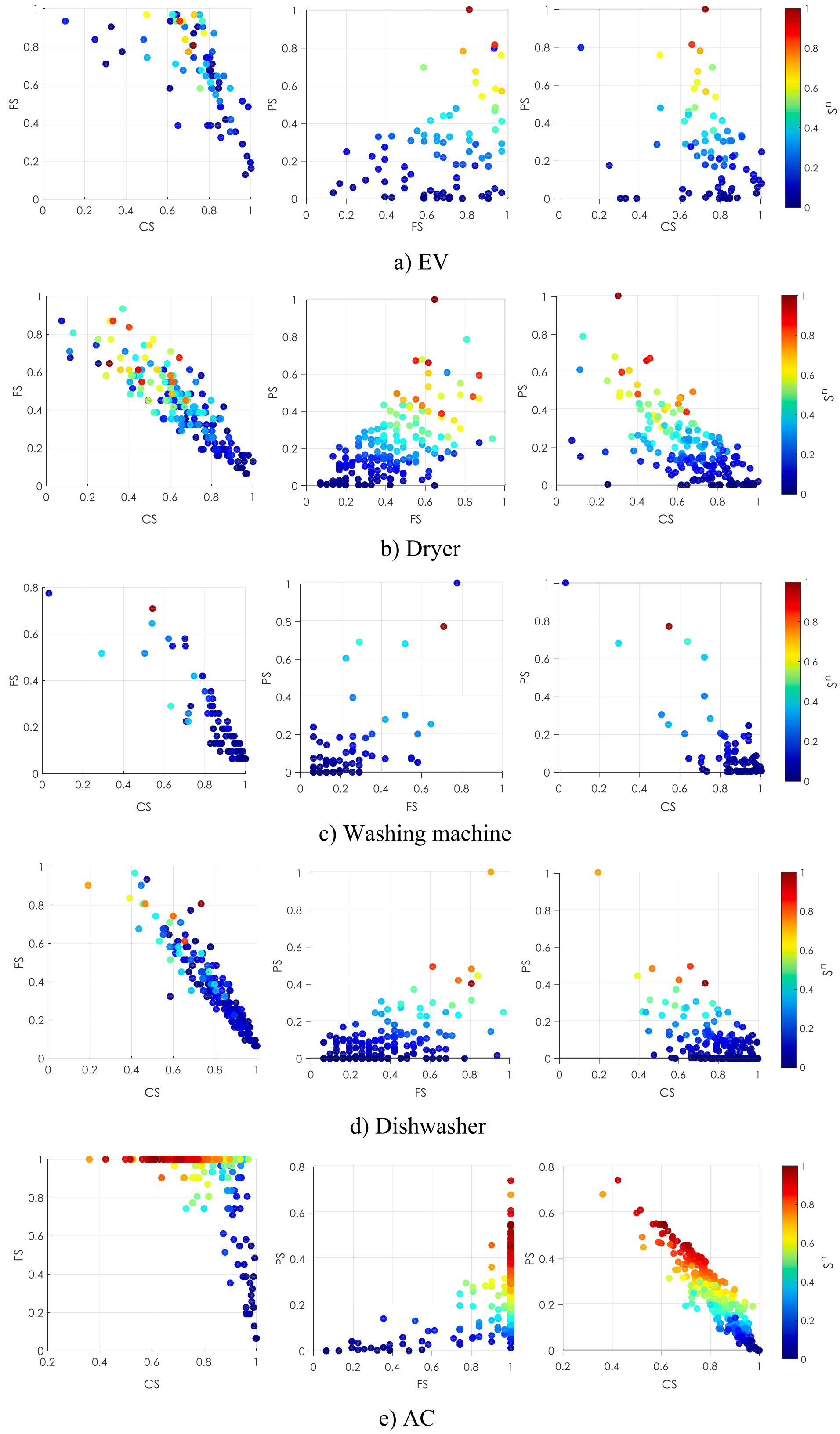
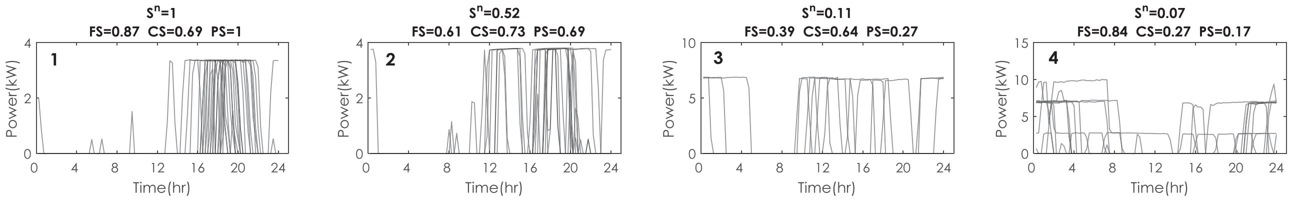
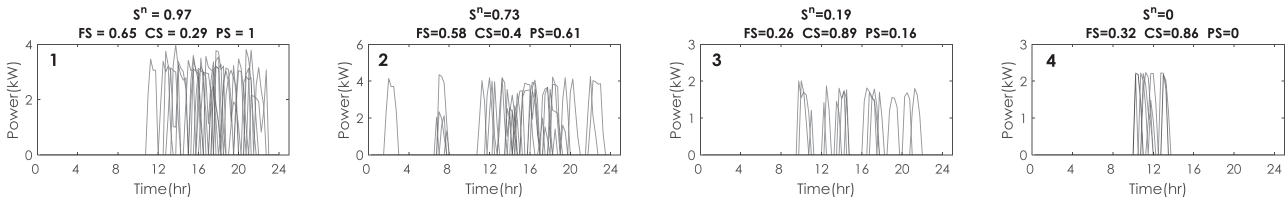


Fig. 6. Distribution of S^n for different (a) EV owners, (b) dryer owners, (c) washing machine owners, (d) dishwasher owners, and (e) AC owners.

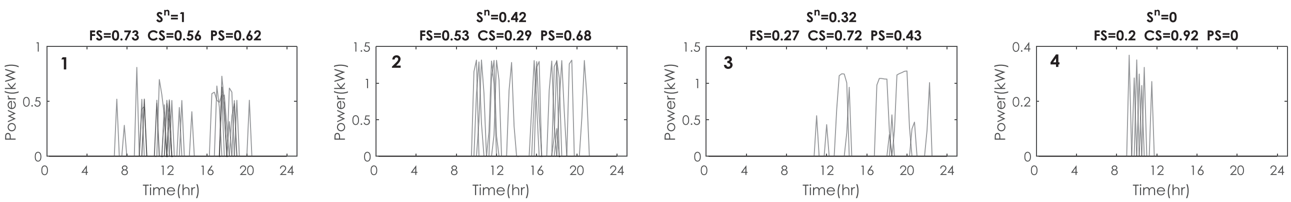
machine, dishwasher, and AC are presented in Fig. 6. Each subplot represents one load type and each data point represents one of the households in the community. Each of the axes represents one of the dimensions (i.e., FS^n, CS^n, PS^n) and variations of S^n values have been illustrated by a color heat map. In subplot (a), it could be seen that the potential scores for EV charging are distributed across all three attributes in the community, indicating highly varied usage styles and operational frequencies in the community. In subplots (b–d), which



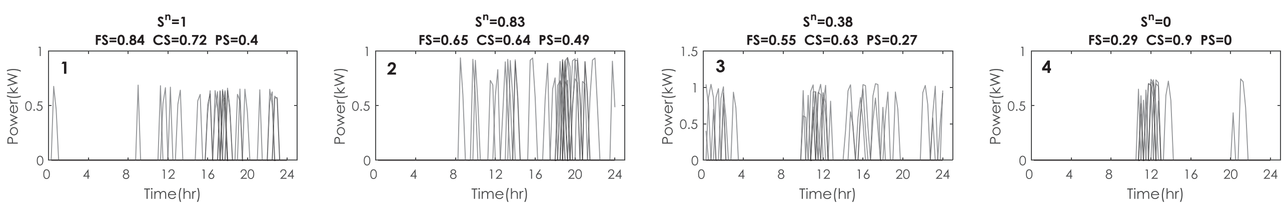
a) EV



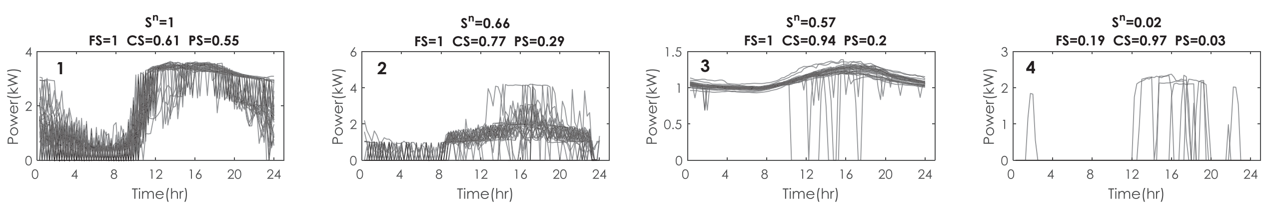
b) Dryer



c) Washing Machine



d) Dishwasher



e) AC

Fig. 7. The daily consumption profiles of four representative users with varied potential scores on 30 subsequent days and their associated dimensional values for: (a) EV, (b) dryer, (c) washing machine, (d) dishwasher, and (e) AC.

represent wet appliances, there is a higher concentration in distribution of houses around lower values of FS^n, indicating these appliances are mainly not operated on a regular basis. This is also consistent with the expected daily routines of users. However, higher CS^n values could be observed, reflecting on consistency of the time-of-use of the appliances by users. In the case of AC in subplot (e), a majority of data points show higher values of FS^n, reflecting regular use of AC on a daily basis. Given that the data set is associated with summer days, the remaining few data points with low FS^n could be associated with unoccupied houses.

The power variations for different potential scores have been presented in Fig. 7 to provide an insight into their interpretation for several representative users. Each subplot illustrates the consumption profiles across all historical days ($K = 30$) with their associated potential scores and relevant dimensional values. To provide an example explanation of these visualizations, we have elaborated the observations for the EV data. User 1 charges the EV almost every day (26 out of 30 days, $FS^n = 0.87$) with a relatively consistent pattern ($CS^n = 0.69$), with the highest consumption in the community during the desired DR timeframe ($PS^n = 1$) resulting in a potential score of $S^n = 1$. User 2 has a relatively high potential score ($S^n = 0.52$). Compared to User 1, this user charges EV less frequently ($FS^n = 0.61$), with lower consumption values ($PS^n = 0.69$) while being more consistent across the activation days ($CS^n = 0.73$). User 3 and user 4 both have lower a potential score ($S^n = 0.11$ and $S^n = 0.07$, respectively). User 4 charges EV on a regular basis (higher FS^n) with low temporal consistency (lower CS^n) with a charging time that rarely coincides with the DR timeframe (lower PS^n). Therefore, utilities will be less interested in involving these users in a DR event. As can be seen from usage patterns for different load types in Fig. 7, user 1 and 2 with higher S^n are more suitable for getting involved in a DR event as they have high frequent peak usage and more predictable behavior while user 3 and 4 manifest lower values for either of the dimensions.

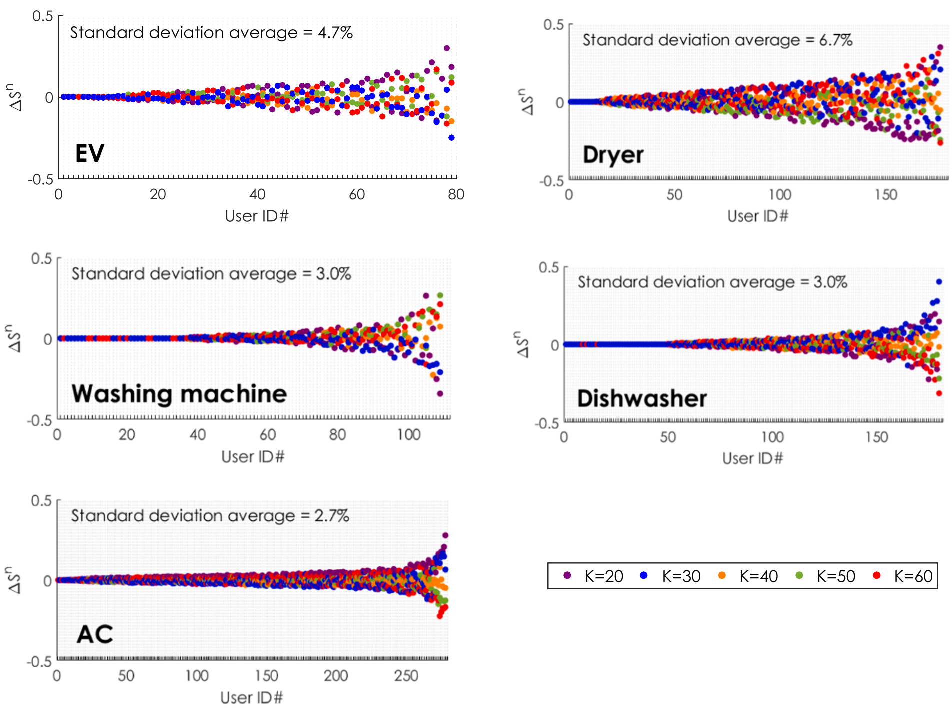


Fig. 8. Sensitivity analysis result for quantifying S^n across 20, 30, 40, 50, and 60 days for different load types.

Table 3
Kruskal-Wallis test on the set of K (different number of days).

	EV	Dryer	Washing machine	Dishwasher	AC
P-value*	0.99	0.10	0.30	0.23	0.70

* P-value > 0.05 indicates the equal population medians of ΔS^n for the set of K.

4.1.1. Sensitivity analysis:

In order to show the sensitivity of S^n on the number of historical days K, we performed a sensitivity analysis for different K values of 20, 30, 40, 50, 60 days. Fig. 8 illustrates the results for different load types. For each user ID# (i.e., house ID) on the horizontal axis, 5 different data points corresponding to different K values have been plotted on a vertical line. Users were sorted according to the lowest deviation from the average values of S^n over all K days. In some cases that houses have opted out from the program during a longer timespan ($K > 30$), data points are missing. In some cases, variations of K could result in changes in frequency, consistency, and peak usage, given the potential changes in behavioral traits in user behavior. Nonetheless, the results in Fig. 8 show a low amount of sensitivity in terms of change in S^n in total. Specifically, the average amount of standard deviation for S^n across all households varied between 2% and 7% for different considered load types, as shown in Fig. 8.

Based on the trend in Fig. 8, we hypothesized that, through varying K, S^n do not show significant changes for each user. We performed the Kruskal-Wallis test to examine whether distributions of ΔS^n for different households are significantly different for different K values ($K = \{20, 30, 40, 50, 60\}$). The Kruskal-Wallis was selected for the comparison of multiple groups of days (different K values) as a non-parametric method since ΔS^n values did not follow the normal distribution. For each user, we measured the deviation of S^n for each specific K from its average (over the entire K vector). The Kruskal-Wallis test was performed on the considered 5 groups (different K values), in which each group contained ΔS^n values for users in the community. The null hypothesis was that the population medians for all groups of K values are all equal for the case-study community. The *p-values* in analysis for all flexible appliances were above 0.05 (as shown in Table 3), indicating the fact that the null hypothesis is accepted and ΔS^n belongs to the same distribution in all cases.

4.2. Empirical assessment of DR capacity

In this section, we have evaluated the efficacy of the proposed scoring system in the smart engagement of the users in a DR event. To this end, we selected five DR days, *not* included in historical days to avoid *a priori* biases in DR flexibility assessments. Using different cut-off threshold values for S^n(0, 0.05, 0.1, 0.2, 0.4, 0.6, 0.8), different groups of users were selected for participation in DR events. We have quantified the potential energy reduction for each user and each load type by measuring the differences between consumed energy at the peak timeframe $[t_1{:}t_2]$ (using ground truth) and the resultant time-series obtained by load shifting/shedding. Numerical integration was used on the power time-series to calculate the energy consumption.

We used load shifting for deferrable loads (i.e., EV, dryer, washing machine, and dishwasher). For AC, as a TCL load, we used partial load shedding through changing the temperature setpoint for simulation. In doing so, we adopted the assumptions and findings outlined in [32,64] – a 25% power reduction during peak time by 1 °C increase in temperature setpoint of AC. Although the findings of these studies were dependent on their context, we used their assumptions to be able to estimate the aggregate contribution of different segments of users in demand reduction. Sophisticated models for thermal behavior of these houses could be developed by using simulation tools such as EnergyPlus. However, such model require detailed information from the buildings and is out of the scope of this study. Using the load shifting/shedding framework described in Section 3.2, we considered different scenarios as presented in Fig. 5.

4.2.1. First scenario – maximum potential

Fig. 9 illustrates the achievable energy saving for different S^n values and load types. The right and left vertical axes show the achievable energy reduction during the peak (from the entire community) and the percentage of engaged users, selected according to the S^n values, respectively. The horizontal axis shows different cut-off values for user

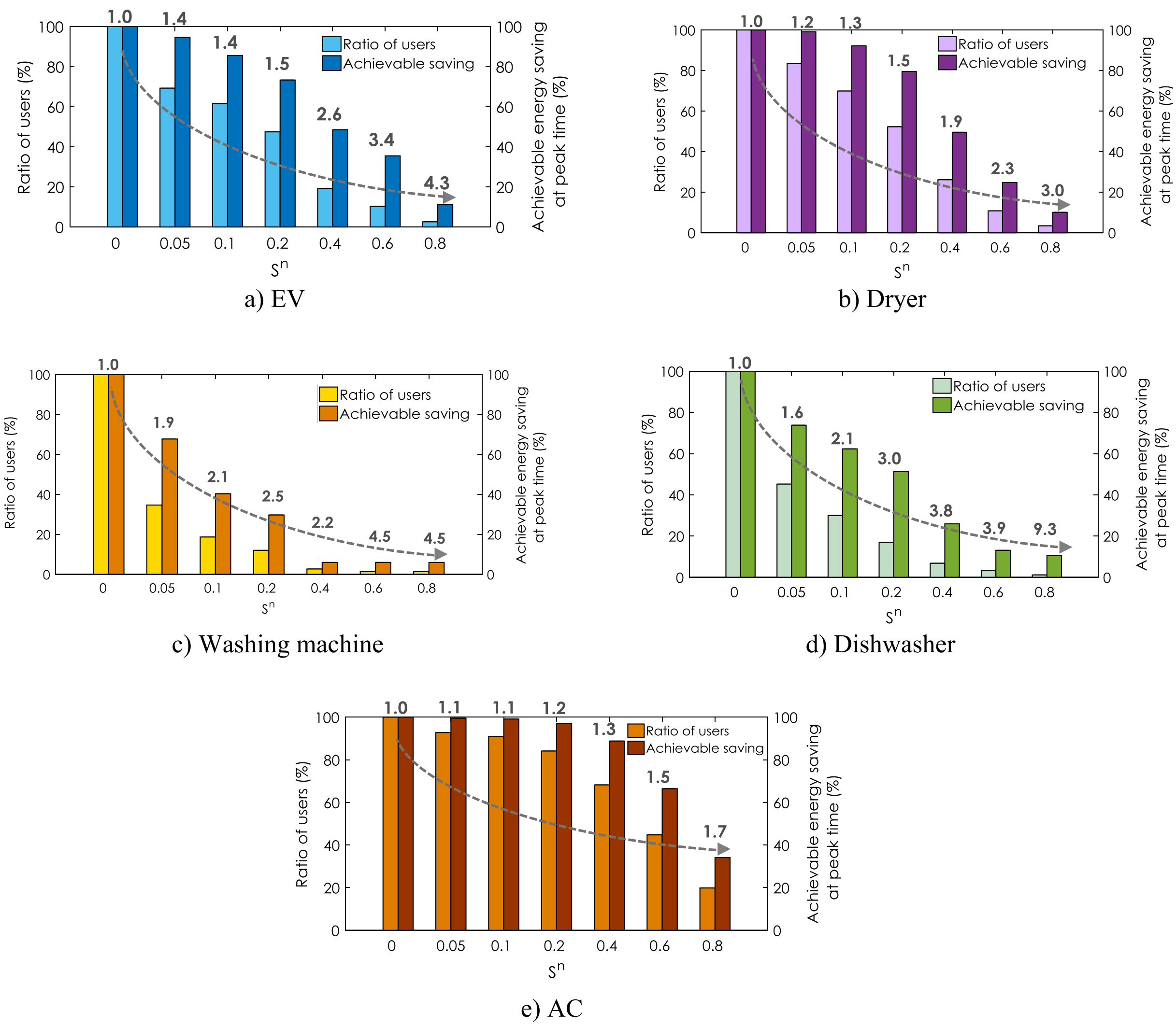


Fig. 9. Load shifting potential for scenario 1 (averaged over 5 days) across different subsets of users. The value on top of the double-bar shows the ratio of 'achievable saving' to 'ratio of users' for each case (a higher value is desired).

segmentation based on the S^n values. In these graphs, $S^n = 0$ indicates the participation of the entire community and the maximum load shifting potential for activated loads without accounting for the human-appliance interaction patterns. As shown in Fig. 9, for all load types, as the S^n cut-off increases, we generally observe that the demand reduction drops with a lower rate compared to the ratio of engaged households. Therefore, it is shown that we could identify and select a small portion of users to achieve demand reduction goals. For example, for EVs (Fig. 9(a)), by selecting users with S^n higher than 0.8, 0.6, and 0.4, energy reduction of 11%, 35%, and 49% could be achieved, respectively. These values correspond to only 3%, 11% and 19% of all the households in the community, respectively.

In order to provide a cross-appliance comparison of the energy reduction potentials, Fig. 10 shows the individual contribution of users for different load types. The horizontal axis shows the user IDs, sorted based on ascending values of S^n, and the vertical axis shows the energy reduction potential during the DR timeframe, averaged across five DR days. As the results in Fig. 10 show for different load types, if the loads have been activated during the peak, there is an increasing trend in saving potential as S^n increases. As can be seen, many users have not operated/charged the deferrable loads on DR test days during the peak time. On the other hand, given the regularity of usage, AC provides the highest energy reduction potential after EV. Among the deferrable loads, EV provides the highest potential for energy reduction followed by the dryer. Washing machine and dishwasher have shown to provide the least potential for DR operation on the selected test days.

As noted earlier, unjustified and synchronized compensation through engaging all categories of loads immediately after the DR event could result in a rebound effect – the creation of a secondary peak. To demonstrate the applicability of the method for load selection to avoid the rebound impact, we have shown the aggregate power profile from the entire community on a DR test day in Fig. 11. Fig. 11(a) illustrates the results from the contribution of all deferrable loads while Fig. 11(b) also includes the AC. The ground truth line shows the actual aggregate power for the test day. The resultant load profiles from load shifting according to different segments of S^n are shown with dash lines. The percentage values in the legend of Fig. 11 shows the average ratio of users engaged in DR. A hypothetical baseline of 1000 kW was considered. As shown in subplot (a), the cut-off value of $S^n = 0.2$, corresponding to the participation of 30% of users, can result in the balance between the primary and the secondary peak and achieving the hypothetical baseline. On the other hand, if the setpoint control of AC will be considered in addition to deferrable loads (subplot (b)), the same objective can be achieved by selecting $S^n = 0.8$, corresponding to 5% of users. As the results show, engaging users according to their previous interaction patterns could help us achieve the targeted energy reduction without creating a rebound effect compared to engaging all users.

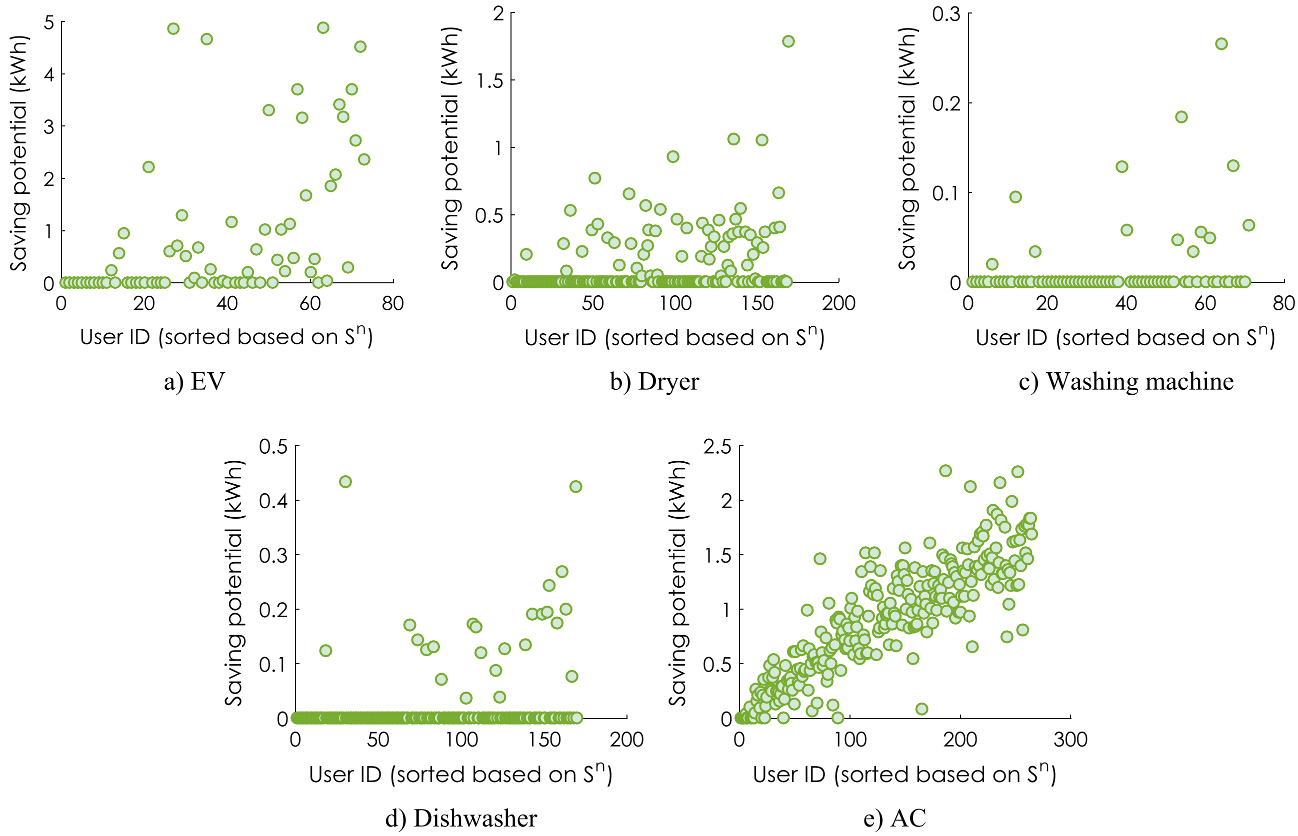


Fig. 10. Demand reduction potential for scenario 1 (averaged over 5 days) for each user.

4.2.2. Second scenario – user compliance driven

Fig. 12 shows the achievable energy reductions according to different S^n values for the second scenario, which represents a more realistic user engagement. Therefore, the maximum achievable reduction was observed to be a portion of reductions in the first scenario. The ratio between these two observations is close to the associated compliance factors. The user response to DR request could be negative, even if the activation indeed contributes to high peak demand, and therefore the maximum achievable saving will be limited. Nonetheless, the same trend that a high percentage of achievable energy reductions can be realized by a lower rate of targeted participation was also observed in most cases for this scenario.

Similar to the previous scenario, Fig. 13 illustrates the energy reduction potential for the 2-h DR timeframe for each user. The results for this scenario also revealed the efficacy of the proposed scoring method in the targeted engagement of users in DR events. Given the lower probability of the user compliance for dryer and washing machine, the reduction of flexibility potential for these loads has been relatively higher while AC and EV manifest better opportunities for load shifting.

Table 4 presents the numeric values of demand reduction for different scenarios. It is expected that some users might not operate their deferrable loads at all during the DR test events, and in this case, the associated energy reduction will be zero. Accordingly, the averaged values in Table 4 could be interpreted as the realizable demand reduction for different segments of users. Given the high variance among different user quantiles for each load type, the potential of the peak shaving could be estimated and prioritized for different load types. For our case study community, EVs, ACs, dryers, dishwashers, and washing machines show the highest potentials, respectively.

The energy saving potentials, presented in Table 4, could be also used as weight factors in case of combining the potential score of individual appliances into a metric at the household level. In that case, the metric would characterize the overall flexibility of the user and reflects the overall evaluation of household potential for individual load flexibility.

4.3. Diurnal variation of flexibility

Defining the temporal flexibility of loads (as a function of the time of the day) could provide opportunities for the integration of renewables and maintaining the power balance in addition to the peak demand reduction. Accordingly, analyzing the historical patterns of temporal variations of load-specific demands provides insight into load targeting. To demonstrate the demand reduction potential of the considered load types with respect to different segments of users and according to time-of-use, we presented the results in Fig. 14 for maximum potential scenario and based on S^n values on a 1-h basis. Each bar represents the range of average demand reduction between upper and lower user quantiles for a given hour, and each marker shows the average demand reduction for the associated user quantiles. A longer bar indicates high variation in usage style and vice versa. Moreover, a higher concentration of the markers on the lower parts indicate that only a small portion of users could provide a higher power reduction potential. For example, the top quantile of users with EV in the 80–100% quantile (associated with high S^n values) at 18:00 are highly suitable for shifting their demand, while the rest are not contributing as much.

For EV, the diurnal charging pattern reflects a typical home to work commuting lifestyle as the charging time mainly starts in the late afternoon and stretches to early morning hours. For AC, the potential for demand reduction across the entire day is observed. The demand reduction potential reflects the occupancy pattern as well as the typical temperature variation pattern. In general, compared to deferrable loads that show a high uncertainty for demand reduction potential across different classes of the users, AC shows a lower variance and more predictable behavior. Wet appliances manifest a bi-modal distribution with a double peak around noon and the evening. The peak around noon indicates opportunities for solar power integration.

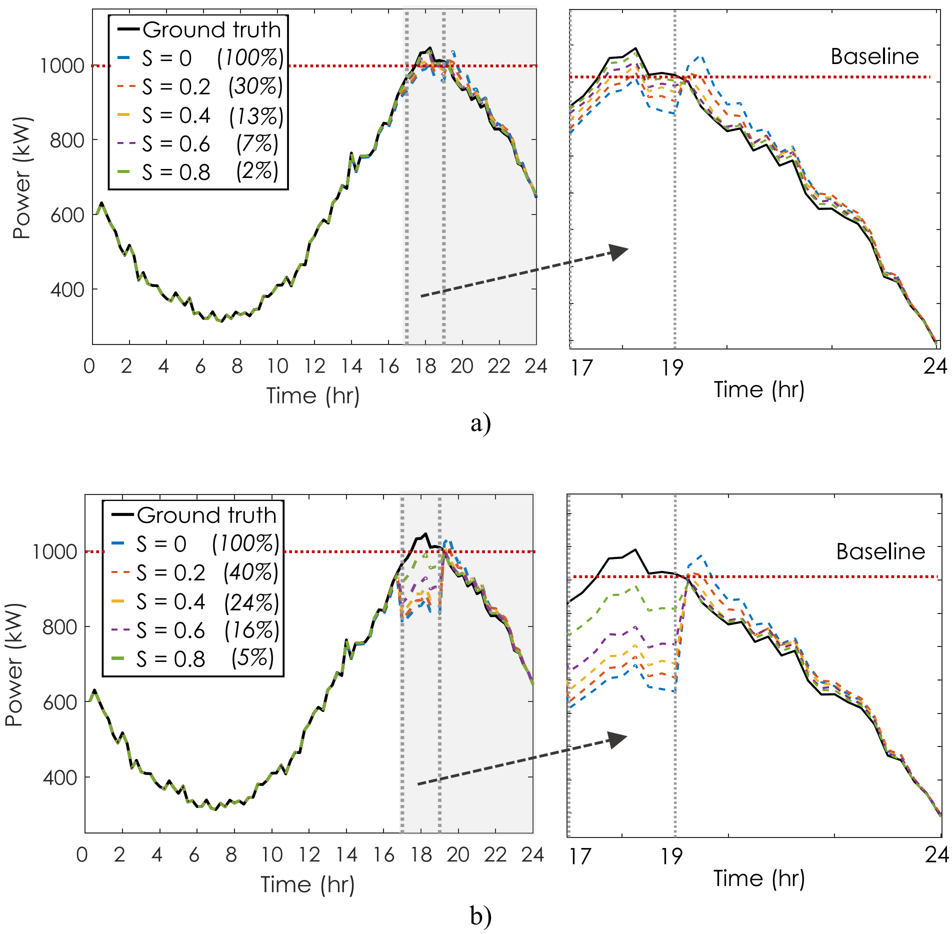


Fig. 11. Impact of load shifting/shedding (peak and secondary peak) across different subsets of users for (a) all deferrable loads and (b) all deferrable loads plus AC on a DR test day. Numbers in parentheses show the percentage of users engage (averaged over considered loads) in DR.

5. Implications and limitations

5.1. Large-scale potential for demand reduction

The findings in this study could provide insight for planners and utilities to identify and target potential candidates for automated DR. To this end, we have estimated the potential for Austin TX, as a demonstration of city-scale assessment. According to the U.S. Census Bureau, the number of households in Austin was about 360,000 in 2017 [65]. Although the appliance ownership rate in Austin could be different from our sample, we used the same rate as a basis for a rough estimate of demand reduction at a city-scale. Therefore, by assuming the same appliance ownership rate (Table 2) and the information in Table 4, it is estimated that participation of only 20% of users with higher demand reduction potential, during a 2-h DR event, could result in up to 41.7 MWh, 11.2 MWh, 1.8 MWh, 3.2 MWh, and 100.2 MWh for EV, dryer, washing machine, dishwasher, and AC, respectively. This suggests a total of 158.1 MWh reduction for all loads combined.

5.2. User segmentation and fairness

An important consideration in DR programs is *fairness* to ensure that a specific set of users are not targeted on a regular basis and avoid the risk of user fatigue [66], which could result in reduced willingness for participation. In our segmentation scheme, given that DR events might be selected at different time intervals for different days as operatorial decisions dictate, the S^n values for users could vary across different days. Therefore, the same user could be assigned to a different subset of targeted users for each DR event, which in turn helps to alleviate the fatigue problem. To demonstrate how users will be assigned to different subsets (sorted based on their potential score), we have considered three DR time intervals of 16–18, 17–19, and 18–20. For each interval, based on the S^n values, each user will be assigned to a different quantile (i.e., a subset), which contains the set of users such that $\frac{i}{100} < S^n < \frac{i+10}{100}$, $i \in \{0, 10, \cdots, 90\}$. Therefore, users will be assigned to 10 different quantiles.

The results are presented in Fig. 15. Each polyline spanning the x-axis represents one user across different DR events. Darker lines are associated with a higher frequency of occurrence. A horizontal polyline indicates that the user is always assigned to the same quantile at different DR times, while each inclined line indicates the allocation of the user to a different quantile as DR timeframe varies. In Fig. 15, considerable variations across the community are observed, implying that users are allocated to varying levels of priority for participation for different DR timeframes. Heuristic-based methods, which iteratively update the record of DR participation for each user at each event, have been used as an alternative method for improved fairness [28].

5.3. Data availability

In our proposed segmentation scheme, data at the individual load level (i.e., appliance-level) is used for analysis. In the context of smart grid, smart appliances will be capable of providing such information and respond to DR signals for load shifting. Furthermore, considering the appliances mentioned in this study, recent efforts based on disaggregation methodologies have achieved reasonable accuracy for load disaggregation from smart meter data. For example, disaggregation of EV loads [67,68], dryer, washing machine, dishwasher [69], or AC [70,71], with relatively acceptable accuracy (~70–100%) have been reported in

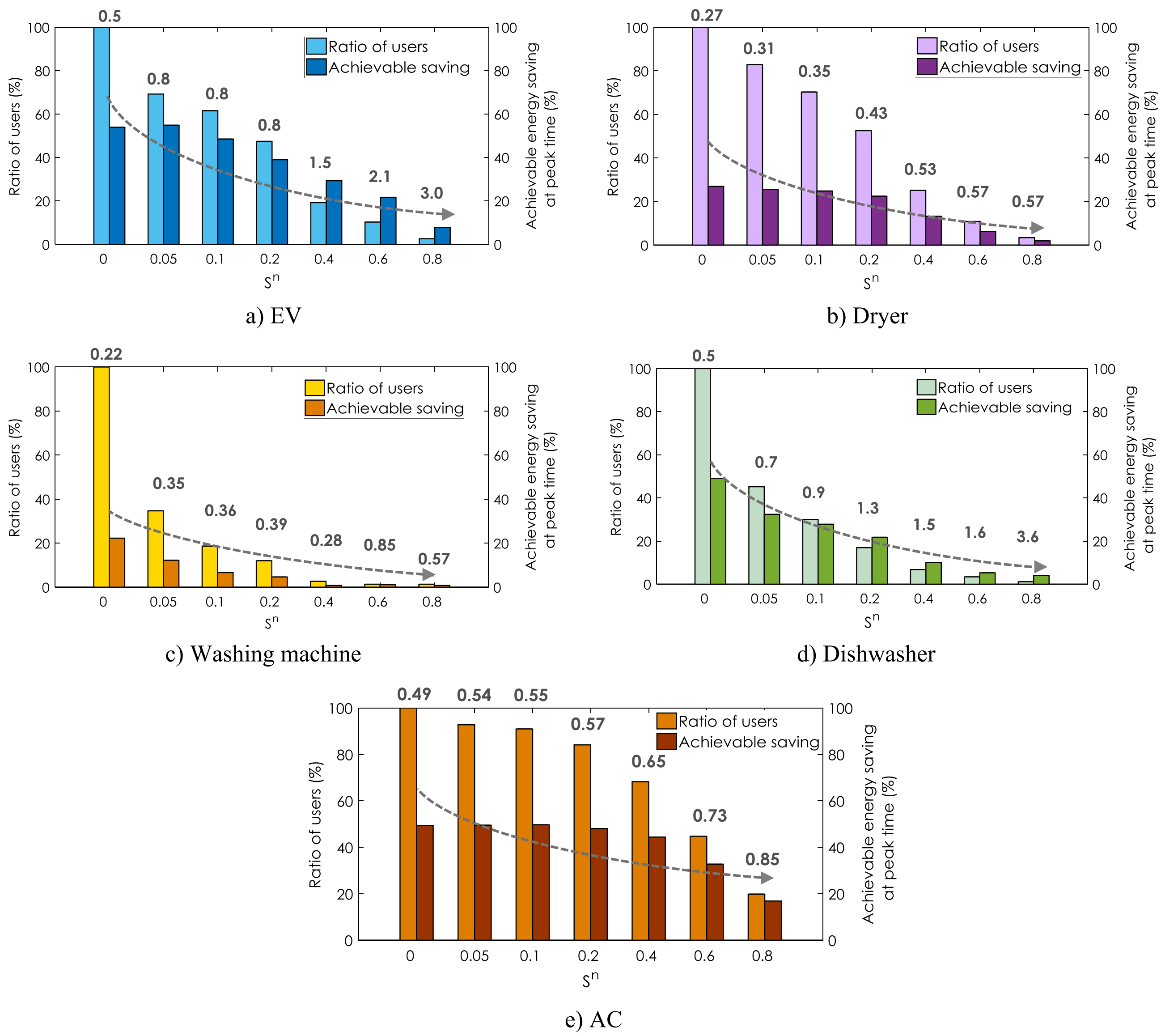


Fig. 12. Load shifting potential for scenario 2 (averaged over 5 days) across different subsets of users. The value on top of the double-bar shows the ratio of 'achievable saving' to 'ratio of users' for each case (a higher value is desired).

recent studies. Accordingly, the proposed segmentation scheme, coupled with disaggregation on smart meter data could be used for incentive programs or for an economic feasibility assessment of offering smart appliance rebates to suitable candidates under budget constraints.

We evaluated our method based on a case study analysis from the Pecan Street project [29], which is currently the largest available energy consumption dataset at both aggregate and appliance levels. More specifically, we used a sample of more than 300 households to ensure that the analysis covers diversity in energy consumption styles and interactional behaviors of users. However, this approach is considered a generalized approach as it includes two main steps: (1) quantifying the differences between users by using the proposed scoring metric, and (2) providing quantified energy demand variations. As long as the datasets that enable examining the complex human-building interaction at the level of individual loads characteristics are available, these metrics could be quantified.

5.4. Opportunity for EV load coordination

Smart EV charging scheduling has received attention due to the high penetration of EVs that resulted in increased stress for the distribution system [72–74]. As elaborated in a representative survey work [75], most studies have assumed the availability of charging pattern; however, the impact of load uncertainty is necessary for developing coordination algorithm for shaving peak loads. In this work, we looked at the participation of user segments based on their potential contribution to a DR event, which has applications for efficient load shifting from the peak time. For such purposes, the presented data-driven quantified energy demand variation for each segment of users and each time-of-day can be an additional information layer for estimating EV charging pattern.

EV scheduling algorithms typically leverage optimization-based methods to balance the demand versus supply. However, constraints in the optimization either require perfect knowledge on EV charging patterns (known *a priori*) or an estimate of charging pattern. Studies that estimate EV charging pattern typically select distribution models (such as Gaussian distribution) (e.g., [76]), which might not be an effective estimate/forecast for the aggregator, given the high energy use difference amongst users. Therefore, an effective estimate of EV charging patterns through statistical analysis could be a potential solution [75]. In this direction, an implication of our approach is to provide an estimate of charging pattern of EV at different times-of-day for different segments of consumers based on our potential score. Specifically, the

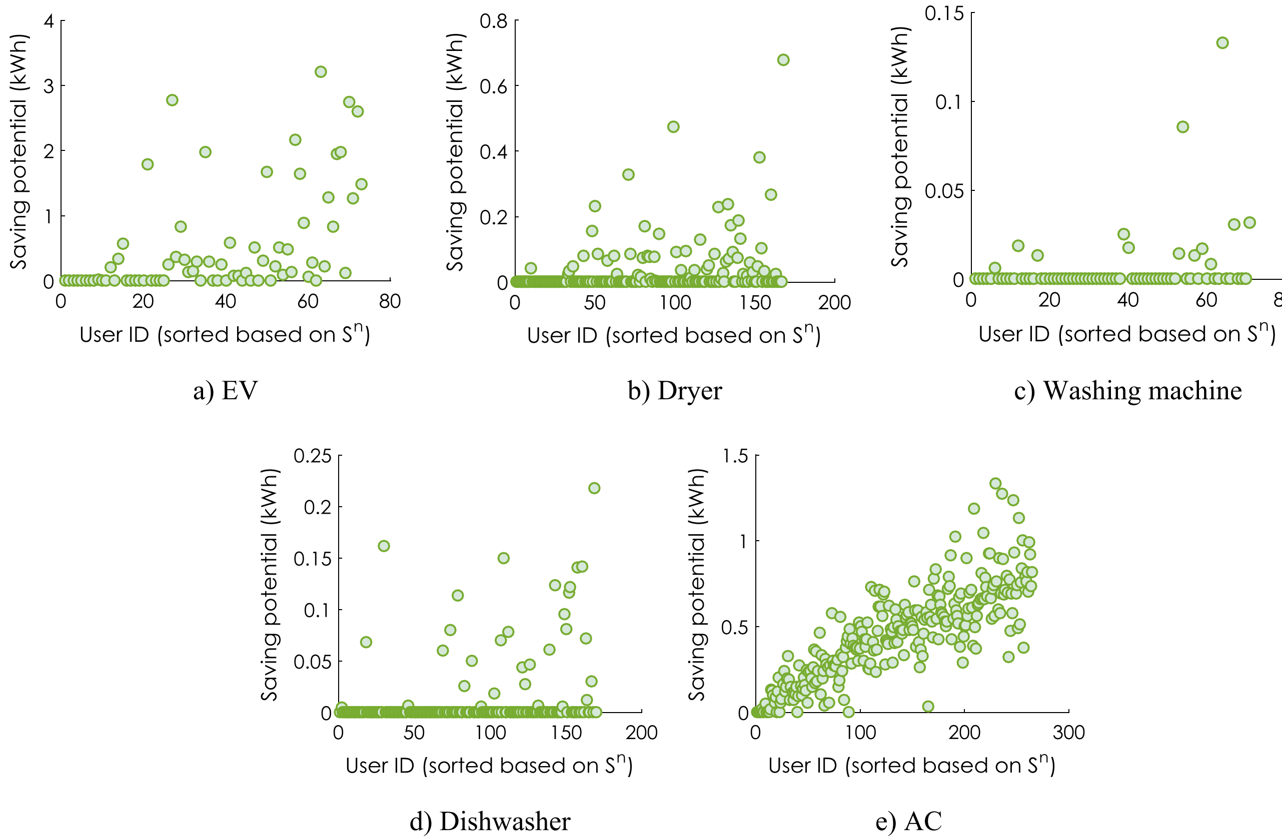


Fig. 13. Demand reduction potential for scenario 2 (averaged over 5 days) for different users.

Table 4
Average demand reduction potential over a 2-h afternoon DR event based on different quantiles of users for different loads.

Load Type	User quantile based on S^n	Maximum potential (Wh)	User response-driven (Wh)
EV	80–100	2095	1260
	60–80	1065	550
	40–60	495	280
	20–40	700	435
	0–20	120	75
Dryer	80–100	260	70
	60–80	145	40
	40–60	140	50
	20–40	90	25
	0–20	20	5
Washing machine	80–100	40	15
	60–80	20	10
	40–60	10	5
	20–40	0	0
	0–20	10	0
Dishwasher	80–100	60	35
	60–80	20	15
	40–60	20	10
	20–40	0	0
	0–20	15	5
AC	80–100	1515	760
	60–80	1195	590
	40–60	1010	485
	20–40	620	310
	0–20	210	105

presented variation in energy needed by different segments of users at each timeframe can be used to estimate the probability distribution of EV charging. Such results could shed light on the impact of load uncertainty compared to generic distribution models for developing personalized EV charging estimates for users.

5.5. Limitations

There are a number of limitations associated with this work as outlined here: (1) Daily routines and occupants' lifestyle is impacted by the day of the week (working days or weekends). Accordingly, consumption styles can be reflected differently on weekends compared to weekdays. For the computation of potential score in this work, we have not distinguished between such differences. Nonetheless, given larger duration and availability for the data, S^n values can be calculated separately on weekdays and weekends and separately evaluated for DR events. (2) We have looked at the flexibility based on potential demand reduction that can be realized by the participation of individual loads. However, the potential increase in power demand is also deemed as a flexibility attribute, which was not investigated in this work. (3) Looking at the results in Fig. 14, the increasing trend in demand reduction potential based on higher S^n values are not observed in all cases. This is due to the fact that the usage styles in the future (used as test events) are not always dependent on previously shown historical behaviors and uncertainties are involved. Nonetheless, the results in most cases appear to agree with our expectation, and regular or seasonal upgrade in calculating the scores could be effective. (4) We accounted for user compliance using previous community-level empirical studies. However, the average compliance factor for each load type might not be the best representation of the community, and varying levels of willingness in complying with the DR requests for each household need more sophisticated model compared to the implemented distribution function. For example, it is possible that users with frequent and consistent usage pattern will be less willing to shift their loads. Therefore, the causality of behavioral patterns is an important factor to consider. Investigation of the association between user

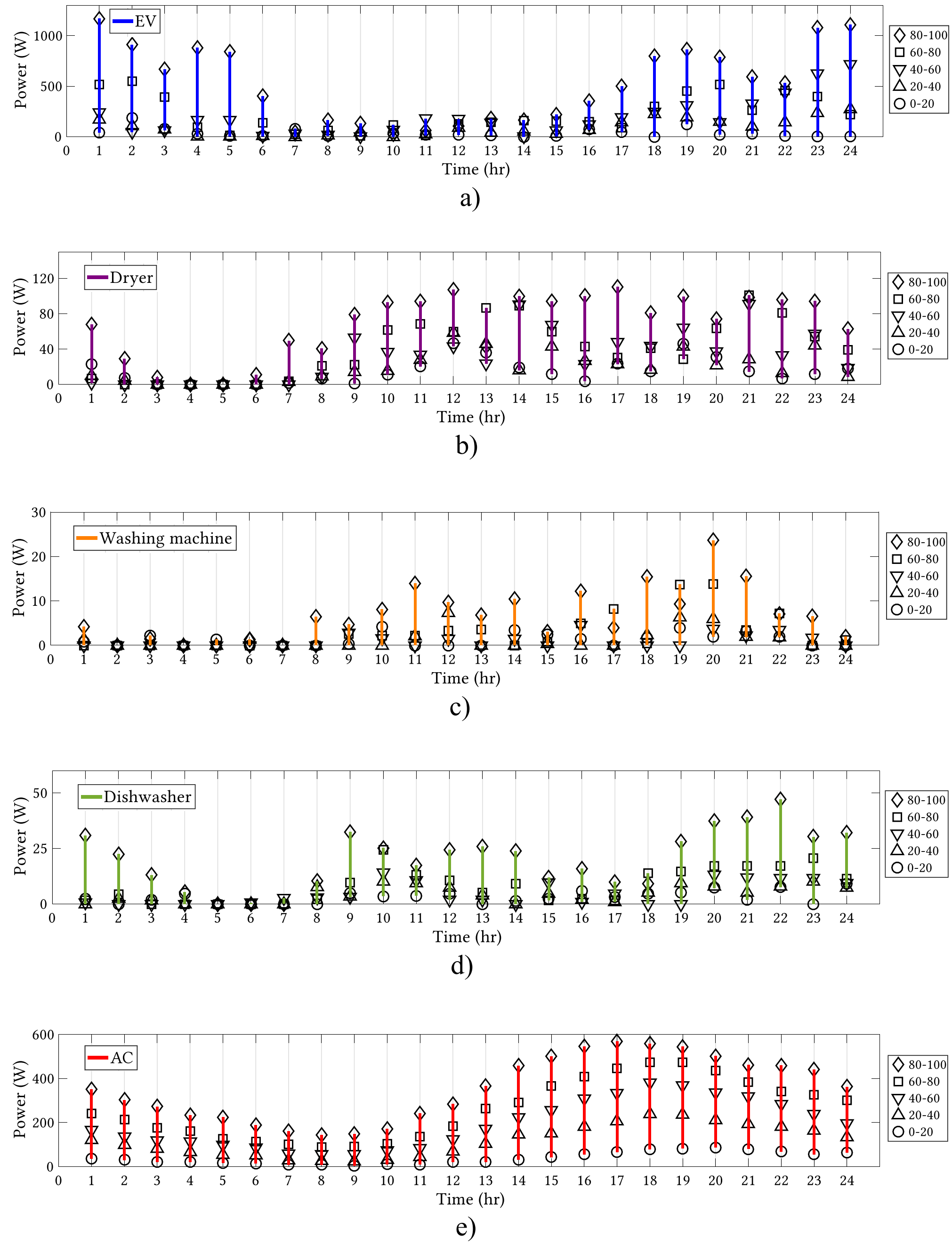


Fig. 14. Average diurnal demand reduction potential for different user segments: (a) EV, (b) dryer, (c) washing machine, (d) dishwasher, and (e) AC – The legend shows different quantiles of selected users based on their S^n score.

compliance and historically observed consumption behavior is among our future research directions. (5) We used the same timeframe for all the households with respect to the same benchmark calendar days for the evaluation. In our sample in this study, there were cases with missing data (e.g., hours of missing data for a day) in which we opted for eliminating the specific day from our analysis. In practice, missing data points, such as every 15-min data, could be interpolated with adjacent points as long as such data points are scarce and not continuous. However, continuous metering failures that limit the measured data could hinder the evaluation process for a specific customer. An interesting research direction is to develop a data-driven technique that considers a certain duration of data and measures when the behavior of a customer has changed. As a result, if the behavior has not changed over the considered duration, a practical solution could be referring to existing alternate days (e.g., same day of the week) in the historical dataset for the same customer as a replacement alternative. (6) In specific cases such as the presence of outmoded or anomalous appliances, higher electricity consumption could be incurred. However, such improper functionality does not necessarily imply increased/proper engagement of users for DR program. Nonetheless, a two-tier scenario can be considered: (I) The customers can be suitable for energy-efficiency programs such as being targeted for appliance replacement and not necessarily DR programs that look at imposing temporal changes in the dynamic patterns of consumption. Recent data-driven methods for identifying outmoded or anomalous appliances for historical data includes Ref. [77] that looked into identifying potential households with outmoded and inefficient appliances such as HVAC or Ref. [78] that identified anomalous appliances through examining their load signatures. Relying on such existing methodologies from the literature, it is possible to filter out potential customers with such specific cases in

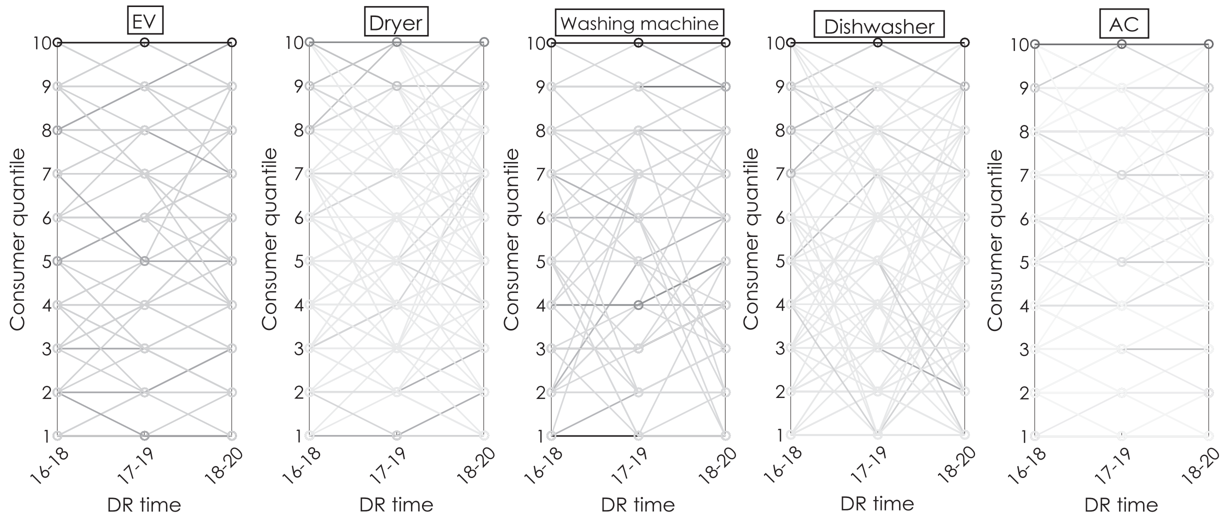


Fig. 15. Association of different users to different quantiles based on varied DR timeframes. Each line represents the output for a user. Darker lines are associated with a higher frequency of occurrence.

the data pre-processing step and filter them in the evaluation step. (II) The findings can be used for incentivizing right customers for automated technology adoption. In the case of having outmoded appliances, the operation time could still be shifted. In other words, shifting the operation time does not depend on the technology in the appliance. Therefore, although users with outmoded appliances cannot be integrated into DR programs such as Direct Load Control (DLC), they can be targeted for adopting smart appliances.

6. Conclusion

In this study, we systematically investigated the demand reduction potential for different individual residential loads according to historical consumption styles. A data-driven scoring approach was used to characterize and rank the users based on the patterns of their interaction with different loads. The empirical assessment in the context of DR shows the applicability of the score for user segmentation for automated DR. The investigations were conducted for a variety of deferrable loads including EV, dryer, washing machine, dishwasher, as well as AC. In a comparative analysis of flexibility potential, we used two scenarios: (1) maximum potential of load shifting/shedding and (2) user compliance modeling. The findings show that households manifest high variations in providing demand reduction potential and the proposed scoring approach could capture those variations. Furthermore, the scoring approach has shown to be effective in the targeted engagement of the users for effective demand reduction without a rebound effect. EV and AC were shown to provide a higher level of flexibility compared to wet appliances. A demand reduction projection for households in Austin, TX, proposes that justified selection of considered loads for DR during the afternoon timeframe could potentially provide around 160 MWh reduction, with only 20% participation of residential users in the community.

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