Investigating Underlying Drivers of Variability in Residential Energy Usage Patterns with Daily Load Shape Clustering of Smart Meter Data

Ling Jin, C. Anna Spurlock, Sam Borgeson, Alina Lazar, Daniel Fredman, Annika Todd, Alexander Sim, Kesheng Wu

Abstract—Residential customers have traditionally not been treated as individual entities due to the high volatility in residential consumption patterns as well as a historic focus on aggregated loads from the utility and system feeder perspective. Large-scale deployment of smart meters has motivated increasing studies to explore disaggregated daily load patterns, which can reveal important heterogeneity across different time scales, weather conditions, as well as within and across individual households. Such heterogeneity provides insights into household energy behavior and reveals sources and drivers of variability that is critical for utilities to understand in order to design efficient and effective demand side management strategies. This paper aims to shed light on the mechanisms by which electricity consumption patterns exhibit variability and the different constraints that may affect demand-response (DR) flexibility. We systematically evaluate the relationship between daily time-of-use patterns and their variability to external and internal influencing factors, including time scales of interest, meteorological conditions, and household characteristics by application of an improved version of the adaptive K-means clustering method to profile “household-days” of a summer peaking utility. We find that for this summer-peaking utility, outdoor temperature is the most important external driver of the load shape variability relative to seasonality and day-of-week. The top three consumption patterns represent approximately 50% of usage on the highest temperature days. Having an electric dryer and children-in-home are the leading predictors of a more variable consumption schedule, while conversely homes with elderly residents exhibit the most stable day-to-day routines. Among the customer vulnerability characteristics considered here (chronic-illness, elderly, and low-income), we find low-income households tend to have more variable consumption patterns. The variability in summer load shapes across customers can be explained by the responsiveness of the households to outside temperature. Our results suggest that depending on the influencing factors, not all the consumption variability can be readily translated to consumption flexibility. Such information needs to be further explored in segmenting customers for better program targeting and tailoring to meet the needs of the rapidly evolving electricity grid.

Index Terms—Residential load shapes; smart meter; discretionary consumption; Flexibility and time-based management; whole time series clustering; adaptive k-means.

I. INTRODUCTION

With the rise of residential Advanced Metering Infrastructure (AMI) in the past decade, increasing prevalence of high-resolution meter data has motivated more research to apply load profiling to residential customers (e.g. [1], [2], [3], [4], [5], [6], [7], [8], [9]) that have traditionally not been treated as individual entities due to the high volatility in residential consumption patterns as well as a historic focus on aggregated loads from the utility and system feeder perspective [10]. Data and evidence based insights into behavioral usage patterns hold the potential for efficient and effective load forecasting and planning, demand response management, time-of-use tariff design, and electricity settlement [11], [12], [13], [14], [9].

Despite this progress, most work have focused on load shape differences between customers and therefore applied clustering to individual households each associated with pre-averaged load shapes or attributes (e.g. averaged profiles by season, by day of week, or by month). Such an approach ignores the day-to-day variability within households, thereby overlooking fine-grained information on household attributes and sources of variation that could be valuable for subsequent classification models and segmentation. This omission can have meaningful repercussions in terms of our understanding of patterns of electricity load. A recent study by Yilmaz et al. [15] has demonstrated significant differences in clustering results between daily load profiles averaged over individual households and raw daily load profiles (with no averaging); Kwac in [6] found that although two homes might have the same average profiles, the diversity of load patterns from one day to the next could vary significantly; McLoughlin et al. in [4] applied cluster analysis to day-to-day usage patterns of individual households and found the sequence of resulting daily patterns useful for further segmenting customers; and Haben et al. in [7] demonstrated day-to-day variability in energy consumption within the household together with their average behavior was sufficient to meaningfully distinguish households.

The diversity or variability of day-to-day time-of-use patterns within households is especially important in the context of demand response and energy efficiency programs, as such information may directly relate to each household’s suitability to various demand side management strategies. For example, it is speculated that households with variable consumption schedules may be more flexible and therefore likely to respond
to time of use pricing incentives [15], whereas those with regular demand during the daytime are ideal to target for integrating solar energy [16]. However, these speculations have not been sufficiently empirically verified and specifically the underlying drivers of variability in day-to-day usage patterns are yet to be examined. Consequently there is no consensus in the literature on a comprehensive relationship between variability and flexibility ([17], [6], [15] and detailed in Section II).

In this study, we apply an efficient whole 24 hour time series clustering algorithm to each daily load profile (household-day) of a large sample of residential customers as opposed to aggregated load profiles for individual households. This approach allows us to assign each household to multiple representative load patterns that may vary from day to day, so that patterns in electricity consumption and their variability within and across households can be derived. We systematically examine this load shape variability based on distributional differences in the resulting dictionary of load shapes across underlying external (such as seasonality, day of week, outside temperature) and internal (such as socio-demographic and household properties) drivers. In contrast to previous studies which typically use load data sets ranging from a few hundred to a few thousand households (see review [9]), our load data consists of more than 30 million daily load profiles from approximately 100,000 households.

The context of our analysis is a summer-peak utility that has a time-of-use (TOU) electricity pricing option. This type of time-based pricing is an example of a mechanism, like demand response (DR) programs, designed to shift electricity consumption from the highest demand times of day through a monetary incentive. This shift relies on customers actively changing their behavior in response to these incentives. TOU pricing programs are gaining traction as attractive alternatives to more traditional flat or inclining-block electricity rates at the residential level. California, for example, has authorized their investor-owned utilities (IOUs) to institute default TOU pricing across their residential customer base [18]. Understanding underlying patterns of behavior at an individual household level and how these patterns relate to the timing relevant for a TOU program is therefore highly valuable.

Within this TOU pricing context, we focus our analysis specifically on customer-controlled electricity loads (e.g., lighting, air conditioning, computer equipment, entertainment, dishwashers, laundry equipment), rather than installed equipment demand (e.g., electric tank-type water heater or refrigerator load). Households are more able to quickly adjust these customer-controlled loads with active behaviors in a short-run response to a DR program like TOU pricing, relative to the more long-run response of replacing installed equipment with more energy efficient versions. To isolate this customer-controlled usage we introduce an additional innovation unique among the research in this area: we focus on clustering “discretionary” electricity usage profiles (further defined in Section III B) rather than profiles of total hourly electricity use.

The goal of this research is to demonstrate how daily consumption patterns and their diversity in discretionary electricity consumption within and across households can be explained by factors relevant to DR programs, such as day-of-week, season, meteorological conditions, and household characteristics. By doing so, we aim to shed light on the mechanisms by which electricity consumption patterns exhibit variability and the different constraints that may affect DR flexibility. The paper is organised as follows: Section II provides a review of clustering methods used in the literature and current understanding of load shape variability, thereby explaining the methods and approaches and defining the challenges. Section III presents the data and methods used in this study. The resulting dictionary load shapes and their distributional differences in relation to both external and internal factors are examined and discussed in Section IV. Section V concludes.

II. RELATED WORK AND OUR CONTRIBUTION

A. Direct load shape clustering

Cluster analysis is a commonly used unsupervised learning technique used for load profiling that can help discover and understand patterns in electricity consumption. This study applies whole 24-hour time series clustering to daily load profiles, which falls under the direct-clustering based approach according to [9]. As reviewed in Chicco [10], a number of direct clustering techniques, such as k-means, follow the leader, and self-organizing maps, were applied to whole-building load data to construct load profiles for non-residential (i.e., industrial and commercial) customers. Residential customers are characterized by highly volatile behavior, which challenges the application of clustering methods to individual load curves [10]. Using a large sample of residential daily load profiles (>100,000) and six performance metrics Jin et al. [19], following [20], conducted a comparative study to evaluate eleven direct clustering methods under four families of algorithms: centroid based, hierarchical, density based, and model based methods. They found whole time series clustering of residential load profiles exhibits a trade-off between cluster compactness and distinctness and the number of clusters required to achieve adequate performance was 50 to 100, much larger than that of non-residential customers. The key to data synthesis in this context using direct clustering is to identify a diverse set of typical daily shapes that can be adequately described by the cluster centroids representing different patterns in day-to-day and customer-to-customer consumption schedules. [19] found that algorithms with heuristics minimizing the within cluster scatter, such as k-means and adaptive k-means, perform better with respect to such load profiling goals. We improve upon adaptive k-means [6] and explicitly control for clustering quality with reasonable statistical affinity of cluster centroids.

As the interest in time-of-use patterns is generally and primarily the temporal aspect of the daily profile rather than absolute usage, the load profiles are usually preprocessed with normalization. Most existing studies normalize the daily usage data by a reference power value following standardizing methods reviewed in Milligan and Cooper [21]. For example, Chicco et al. [22] and Chicco [10] divided hourly usage by
the daily maximum; Piao et al. [23], Han et al. [24], and Cao et al. [3] employed min-max normalization, which subtracts the minimum from the data and divides by the maximum; and Kwac et al. [6] normalized hourly demand by the daily total. We also apply a normalize-to-one procedure, however, prior to this step we isolate discretionary electricity consumption from total hourly consumption through a “de-minning” process described in Section III.

B. Load shape variability and demand-side flexibility

Demand-side flexibility is defined as the ability for consumers to change how, when, and where energy is used [25]. As the energy system becomes increasingly supplied by variable renewable generation, predictable and/or controllable flexibility becomes increasingly important for balancing supply and demand [26]. The variability of the daily load “shapes” or the day-to-day changes in consumption schedules of households provides a reasonable indication of whether and how the households may change their energy usage in response to a utility program [15]. Note that this paper is focused on variability or diversity in the consumption schedules, i.e. the “shape” of daily loads, rather than variability in absolute electricity consumption at given times of the day (e.g. [5], [7]) or the intra-day variations in consumption levels (e.g. [27]), which are also important features to explore.

Past studies have employed load shape clustering to explicitly quantify the “shape” variability [28], [29], [6] as a measure of potential demand response flexibility. However, there has not been consensus in the literature on a comprehensive relationship between variability and demand response flexibility. Using a data set collected from a residential demand response program, [29] found that customers with more variable consumption patterns are more likely to reduce their consumption compared to those with a more regular consumption behavior. In contrast, [6] proposed that a more stable household that shows the same load shape every day should be targeted by DR programs rather than one that is highly variable. As reviewed by [26], there are significant literature gaps in both the mechanisms by which electricity consumption patterns exhibit variability and the different constraints or motivating factors that can reshape them.

Emerging studies have taken a deeper dive into the underlying drivers of load shape variability including season, day of week, temperature, and household characteristics. [30] used a Hidden Markov Model to learn the consumption dynamic behavior under the corresponding environments and concluded that customers can be grouped in three categories: normal, sensitive, and insensitive households in relation to outdoor temperature changes. [31] applied agglomerative hierarchical clustering based on proportions of different load curve categories in different seasons and found the behavioral patterns of customer groups are highly consistent across several seasons. [32] used a constrained Gaussian mixture model whose parameters vary according to the day type (weekday, Saturday or Sunday), and crossed the clustering results with contextual variables available for the households to show the close links between electricity consumption and household socio-economic characteristics.

[33], [4] correlated load profile classes with socio-economic determinants yet did not explore the variability linkage. [34] indicated that understanding DR potential of vulnerable and low-income customers was especially lacking. [35] found no evidence that vulnerable populations (low income, elderly, or chronically ill) were unduly harmed or burdened by a time-of-use pricing program, but did nothing to characterize the usage of such customers, which could provide an better understanding of the mechanisms through which such customers respond, or not, to that or similar programs. Using the dictionary of household-day load shapes derived from our study, we are able to systematically examine the correlation between load shape variability across various temporal scales and customer characteristics (including the above mentioned vulnerability characteristics) to better understand the source of variation and their implications for DR flexibility.

Lastly, entropy has been a common metric to quantify load shape variability and its application has been limited to characterizing individual customers [28], [29], [6]. Essentially, entropy quantifies the distribution or diversity of a given set of load shapes. In this paper, in addition to computing load shape entropy of individual customers, we also use this metric more flexibly to characterize load shape variability under different time scales, days, and outside temperature ranges to understand the role of these external drivers.

III. MATERIALS AND METHODS

A. Dataset

We cluster household-day load profiles based on hourly consumption data collected from a summer-peaking utility in California. The data consist of over 30 million daily load profiles (“household-days”) from approximately 100,000 households, measured between June 1st, 2011 and May 31st, 2012, prior to the implementation of time-of-use (TOU) pricing. Therefore, the data set represents consumption behavior absent any time-based rate or other related program.

In addition, household information was collected in a survey of 6413 participants in the utility service area. The household characteristic variables used in this study are processed into binary indicators on: (1) socio-demographic and lifestyle information (low-income, chronically-ill, elderly, children-in-home, college-degree, work-full-time, work-from-home); (2) dwelling information (single family home); (3) appliance ownership information (electric dryer, central air conditioner, room air conditioner, programmable thermostat). Note that we explicitly included three vulnerability indicators (low-income, chronically-ill, and elderly) in order to inform the literature gap identified in Section II B.

The clustering method employed here improves upon the method developed in [6] and is illustrated in Figure 1 and described in detail below.

B. Deriving discretionary load shapes

We first conduct data cleaning and establish the format of the object to be clustered. We apply the same preprocessing criteria as Kwac et al. [6]: dropping daily usage data with missing hour observations, or with low average demand (below
These data cleaning steps result in 32,611,421 daily load shapes (94% of the raw data) remaining. From this set of cleaned load shapes a random subsample of 100,000 as suggested by Kwac et al. [6] was drawn for purposes of clustering.

In the original adaptive k-means study, Kwac et al. [6] normalized hourly usage by its daily total, so the area under each single household’s 24-hour load shape is one. We also apply a normalize-to-one procedure, however, prior to this step we isolate discretionary electricity consumption from total hourly consumption through a “de-minning” process described below. We then normalize by dividing each hourly discretionary usage value by that day’s total discretionary usage.

A household’s “discretionary” usage captures the electricity consumption resulting from active residential behavior (e.g., lighting, air conditioning, computer equipment, entertainment, dishwashers, laundry equipment). We innovate beyond Kwac et al. [6] to isolate only discretionary consumption by “de-minning” the load profiles prior to normalization. Specifically, the daily minimum electricity usage is subtracted from each hour of that day within each household-day profile. The object to be clustered is therefore defined to be this “de-minned” and normalized profile of discretionary daily usage.

This procedure has two advantages: first, from a conceptual perspective daily minimum electricity usage serves as a proxy for “baseload” so this procedure allows us to isolate a household’s variable, or discretionary, usage from their baseload. After normalization, a load shape essentially represents a sequence of each hour’s proportional contribution to that day’s total discretionary usage, and dictionary load shapes can be interpreted in terms of the overall patterns in timing of higher and lower discretionary use.

The second advantage to this “de-minning” process is that it alleviates the distortion of consumption profiles that occurs during normalization when using the total daily electricity load for each household. In particular, a load profile with high baseload tends to be flattened when total hourly usage is divided by daily total consumption in the normalization step. To demonstrate this, the top row of Figure 2 illustrates two load shapes with the same discretionary consumption schedules but different baseloads, and the bottom row shows those same shapes after normalization without “de-minning”. This figure demonstrates that when the daily load has not been “de-minned” the normalization step causes the signal associated with the relevant variation in electricity usage stemming from the same active consumption behaviors to be significantly muted when there is high baseload and not muted when there is very low baseload. Subsequently moving to the clustering step when this is the case tends to result in one of the resulting representative dictionary clusters having a large membership consisting of undifferentiated flattened load shapes due to the nature of the distance metrics used to score shape fits into best-fit clusters. This means that any information regarding patterns of discretionary electricity consumption behavior is obscured.

By “de-minning,” we significantly reduce this problem.

C. Load shape clustering with adaptive k-means

The application of adaptive k-means to our dataset is more thoroughly documented in an earlier report [36] and can be found in the supporting materials and briefly described here.

Specifically, clustering the load profiles after normalization without “de-minning” resulted in more than 65% of the daily load profiles in the data being assigned to a single flat-shaped cluster. When the daily load profiles were “de-minned” prior to normalization and clustered into the same number of clusters, the highest concentration of load profiles assigned to a single cluster was approximately 10%.
After preprocessing, the subsample of 100,000 “de-mined” and normalized load shapes is moved into the load shape clustering step. They are first passed through an adaptive k-means algorithm (6), which splits the data set of load shapes into $K_1$ clusters, such that the relative squared error (RSE) of any load shape assigned to a cluster is not greater than an error threshold $\theta$. The RSE is defined in the equation below, where $s$ is the load shape of interest, $t$ is the hour of day index, and $C_i$ is the cluster center to which $s$ is assigned. The error threshold $\theta$ is varied from 0.05 to 0.5 to determine a suitable value that results in the most reasonable $K_1$.

$$RSE_{s,i} = \frac{\sum_{t=1}^{24}(s(t) - C_i(t))^2}{\sum_{t=1}^{24}(C_i(t))^2}$$

As the resulting clusters from adaptive k-means are typically highly correlated, in the second step we follow Kwac et al. (6), and undertake a subsequent hierarchical merging of the clusters by sequentially combining the most similar clusters until their total count reaches a target number $K_2$. Under this transformation the requirement that all RSEs fall under $\theta$ is relaxed. In particular, the target size $K_2$ is selected such that it is the smallest number of clusters for which less than 5% of the load shapes violate the $\theta$ threshold condition. Guided by the acceptable error threshold, we allow our original number of clusters to grow into the thousands before applying quantitative criteria in the post clustering processing step described in the next section.

D. Iterative dictionary truncation

In the post clustering processing phase, we implemented an iterative truncation algorithm (illustrated in Algorithm 1) to remove cluster centers with low member counts with a user-defined clustering quality metric: the overall violation rate ($V$: the fraction of load shapes with RSE $> \theta$). Dictionary truncation allows us to focus on the electricity consumption patterns that represent the majority of the household-day observations, rather than outliers. In contrast to the original adaptive k-means algorithm, the parameter $V$ we introduced here ensures the maximum reduction of final dictionary size while controlling for clustering quality. The advantage of this post-processing procedure is to avoid tuning of the number of clusters $K$ (a usual hyper-parameter in k-means-type of clustering) because an optimal $K$ is automatically determined after the iterative truncation. Without this iterative process (i.e. the original adaptive k-means implemented by (6)), the clustering quality as indicated by the violation rate generally increases by 30%.

Algorithm 1  Iterative dictionary truncation.

$V$: violation rate  
$\theta$: error threshold  

**LOOP Process**

1: while violation < V do  
2: Identify the ids of smallest clusters whose shape members comprise the fraction $V$ of the total number of shapes  
3: Remove those clusters  
4: Reassign the shapes that were members of the removed clusters into the remaining closest clusters  
5: Compute violation rate as fraction of load shapes with RSE $> \theta$  
6: end while  

Following the truncation procedure the resulting set of remaining cluster centers are defined as the “dictionary” of discretionary usage patterns (referred to as “dictionary load shapes”). Finally, each household-day in the full data set is assigned to the single closest dictionary load shape based on Euclidean distance.

E. Entropy to quantify load shape variability

We use load shape entropy (defined below) to quantify the distribution or diversity of a given set of the load shapes. Greater entropy indicates the load shapes are distributed more uniformly and therefore more diverse and variable, while smaller entropy indicates the distribution is concentrated on fewer dictionary load shapes and is therefore less variable.

$$S_i = -\sum_{c \in C_i} p_{i,c} \cdot \log(p_{i,c})$$

Where $S_i$ is the Entropy of set $i$; $C_i$ is the set of dictionary load shapes observed in set $i$; $c$ is any dictionary load shape that occurs within set $i$, and $p_{i,c}$ is the frequency of dictionary load shape $c$ that occurs within set $i$. The set $i$ is usually defined by customer, that is, $C_i$ is the set of dictionary load shapes observed for customer $i$ over a certain time period. In addition, to understand the overall relationship between variability and external factors, we also compute population-level entropy of a given temporal period. In such a case, the set $i$ is defined by season, day-of-week, days with a certain temperature levels, or by each day. For example,
of usage captured by that cluster accounts for approximately 13% of the total kWh usage; the top 38, 53, and 73 dictionary load shapes respectively cover 70%, 80%, and 90% of the electricity use underlying the approximately 30 million load shapes across households over the entire year period.

Fig. 4. Distribution of dictionary load shapes (left) and their cumulative electricity coverage (right).

The top 16 dictionary load shapes of this final dictionary ranked by their total daily electricity load coverage are shown in Figure 5 and account for more than 40% of all the household daily load shapes in the data set, and more than 50% of total daily electricity load. The utility defines their peak period for the TOU rate from 4 to 7 PM (i.e., hours 16 through 18 as indicated by the gray shaded areas in Figure 5) on non-holiday weekdays. While in aggregate, most of the high electricity usage happens during this period, Figure 5 demonstrates that the clusters exhibit considerable variability in peak timing of discretionary usage as well as number of peaks. For example, the clusters with ranks 3 through 9 and 13 through 16 in Figure 5 reflect patterns of significant discretionary usage peaks that are outside of the TOU peak period. Conventional expectation of the most common load shape may be a morning peak and an evening peak, before and after work, but only clusters 5 and 16, representing only 3.6% and 1.2% of total daily consumption, respectively, really follow this classic pattern. Other double peaking load shapes follow different peak timing from the conventional expectation: for example, the second peak in cluster 3 occurs in late evening, while clusters 9 and 14 have distinct double peaks at noon and late evening.

Figure 6 aligns the 99 dictionary load shapes on a two dimensional space governed by peak timing (x-axis) and number of peaks (y-axis). Interpreting patterns within this figure broadly, we see that of all the household-day load shapes in the full year data set, approximately 75% are assigned to dictionary load shapes that are single peaking, and approximately 22% are double peaking. Daytime (10 AM to 4 PM), TOU peak (4 to 7 PM), and evening (7 to 11 PM) are the most frequent times when major peaks occur, accounting for 23%, 26% and 27% of the full year data set, respectively.

Of particular interest in this set of results is the degree to which the system peak (defined as the TOU peak from 4-7pm) does not necessarily represent the most frequent peak in discretionary usage as represented by this dictionary of load shapes. Only 26% of all household-day load shapes are assigned to dictionary load shapes that exhibit significant discretionary usage peaking during that time period. For this
whereas the one on weekends peaks during the day, which
between weekdays and weekends, while the 6th cluster differs.

Note is that five of these six dictionary load shapes are common
customers. According to Figure 7a, the first observation of
with respect to the behavior patterns of these residential
patterns derived within and across households allow us to
are applicable only on weekdays. The representative usage
this utility.

hours on hot days represents the highest peak usage times for
summer season because increased consumption during peak
shape patterns and their diversity with temperature in the

timescales. In addition, we investigate the relationship of load
(Figure 7) and their variability (Figure 8) across these two
explore distributional differences in electricity usage patterns
primary dimensions over which these rates are defined, we
weekdays. Because the season and days of the week are
only charged during the peak hours (4-7pm) on non-holiday
weekdays. This utility’s TOU rate is to be in effect for customers
during the summer months only, and the higher peak price is
only charged during the peak hours (4-7pm) on non-holiday
weekdays. Because the season and days of the week are
primary dimensions over which these rates are defined, we
explore distributional differences in electricity usage patterns
(Figure 7) and their variability (Figure 8) across these two
timescales. In addition, we investigate the relationship of load
shape patterns and their diversity with temperature in the
summer season because increased consumption during peak
hours on hot days represents the highest peak usage times for
this utility.

B. Temporal and meteorological heterogeneity

This utility’s TOU rate is to be in effect for customers
during the summer months only, and the higher peak price is
only charged during the peak hours (4-7pm) on non-holiday
weekdays. Because the season and days of the week are
primary dimensions over which these rates are defined, we
explore distributional differences in electricity usage patterns
(Figure 7) and their variability (Figure 8) across these two
timescales. In addition, we investigate the relationship of load
shape patterns and their diversity with temperature in the
summer season because increased consumption during peak
hours on hot days represents the highest peak usage times for
this utility.

1) Day-of-week variability: most TOU rates, including the
one offered by this utility, include peak period rates that
are applicable only on weekdays. The representative usage
patterns derived within and across households allow us to
assess the degree to which weekdays differ from weekends
with respect to the behavior patterns of these residential
customers. According to Figure 7a, the first observation of
note is that five of these six dictionary load shapes are common
between weekdays and weekends, while the 6th cluster differs.
The 6th-ranked cluster on weekdays peaks in the evening,
whereas the one on weekends peaks during the day, which
indicates a slight increase of activities in the daytime at the
residence on weekends.

In the left column of Figure 8 we compare the cumulative
distributional differences between weekdays and weekends
with respect to total electricity usage. From this figure we
observe that weekend electricity consumption is slightly more
concentrated in the top clusters (i.e., the weekend cumulative
distribution is pulled slightly to the left of the weekday distrib-
ution), the entropy (right column of Figure 8) suggests usage
patterns on weekdays are relatively more diverse and variable
than weekends. However, these differences are extremely small
(difference in entropy is less than 0.07). These results suggest
that at population level, the diversity of discretionary consump-
tion schedules is not significantly informed by whether that
usage is taking place on a weekend or a weekday.

2) Seasonal distributions: according to the top 6 dictionary
load shapes based on kWh usage coverage for each season
(Figure 7b), Cluster#1, a shape with a single peak during the
TOU period, is consistently one of the top two dictionary load
shapes for all seasons and is the top dictionary load shape
except for winter. In summer, cluster#1 accounts for 21% of
summer electricity consumption of all households. In winter,
an evening peaking dictionary cluster (cluster#2) covers 9%
of the consumption while the kWh coverage of cluster#1 drops
to 7%.

As can be seen in Figure 8 electricity usage is most diverse
(i.e. more uniformly distributed across the 99 dictionary load
shapes) in the spring season and most concentrated and least
variable in summer, with autumn and winter in between.
Qualitatively, to see how significant this is, note that only
8 dictionary load shapes represent 50% of the total summer
electricity usage, while 20 dictionary load shapes are needed
to cover the same proportion of total seasonal electricity
consumption in winter. Cluster#1 makes up almost a quarter
of the summer electricity usage and is also the most populous
cluster (15% of total number of load shapes) in the summer.
The difference in entropy between seasons (0.26) is much
greater than day-of-week difference (less than 0.07).

This suggests that factors necessary (be they socio-
economic, preference-driven, or meteorological) to respond
to summer conditions tend to concentrate and reduce the
degree of variability in discretionary electricity usage patterns.
It is a reasonable assumption, particularly given the high
summer temperatures in this utility’s service territory, that this
concentration in summer usage to a relatively small number
of discretionary usage patterns is driven by the cooling needs
and resulting air conditioning usage in the summer months
which may be less variable across households than other types
of usage.

3) Distribution by outdoor temperatures within the summer
season: seasonal differences presented above indicate that
this summer peaking utility has the least variable patterns
during the peak demand season with significant cooling needs.
Household energy consumption patterns in response to outdoor
temperature itself is important to understand from the perspec-

Fig. 5. Sixteen highest electricity using dictionary load shape cluster centers.
Notes: The title of each panel is: [Cluster#] [Percentage of total daily
electricity load covered by this cluster], where “Cluster#” is the label assigned
to that dictionary cluster, ordered based on the total kWh usage of its members.
The boxes and whiskers summarize the within-hour distribution of load
members belonging to the cluster (median, inter-quartile range, and 5th to
95th percentile), with the mean normalized discretionary load marked in red.
The gray shaded area indicates the peak period for the TOU rate.

3http://esnews.wapa.gov/wordpress/tag/sacramento-municipal-utility-
district/
tive of maintaining sufficient electricity generation capacity, grid reliability, and transmission and distribution infrastructure to meet demand. The most important factor is the demand on the small number of highest consumption days. Highest electricity consumption tends to occur on the hottest weekdays.

We define daily average outdoor dry bulb temperature quartiles (<68 F, 68-71F, 71-76F, and >76F) for the summer season. The top six dictionary load shapes (Figure 7c) indicate that dictionary load shapes with peaks in the TOU period account for more electricity usage on the hottest days (“T _4”), as compared to the cooler days of the summer. In particular, cluster#1 peaks in the TOU period and represents 29% of electricity consumed on the hottest days. By contrast, on the coolest summer days, the electricity consumed within this dominant dictionary cluster reduced by almost two-thirds (from 29.1% to 10.5% in Figure 7c).

Usage patterns on the hottest days are more concentrated in the top shapes as indicated by the cumulative distribution and quantified by entropy (Figure 8). There is a marked decreasing trend of entropy with temperature and the entropy difference between hottest and coolest periods is 0.63 (nearly three times seasonal difference in entropy, and ten times the day of week difference). The top 3 dictionary load shapes on the hottest days cover almost 50% of the total electricity usage of the whole population during those days, while 18 dictionary load shapes are needed to cover the same proportion of usage during the coolest days.

The key results from these analyses are: first, the degree to which behavioral patterns vary across seasons is much more significant than how they vary across weekends and weekdays. Second, seasonal variation in distributional differences is largely driven by temperature variation. Finally, given these results, we show that a relatively small number of usage patterns dominate the underlying drivers of energy consumption on the most important days when electricity demand is likely to put pressure on the grid (i.e., the hottest summer days). We show that three dictionary load shapes alone cover close to 50% of the total energy consumption on the hottest summer days. This suggests that understanding the distribution of these three dictionary load shapes alone across households, and constructing outreach materials, messages, and programs around this information, could have a powerful impact on critical electricity load from the perspective of the grid.

C. Load shape variability within and cross customers

While overall consumption patterns are least diverse in the summer season, the variability in load shapes differ considerably among customers during this same period (Figure 9). Entropy of individual customers ranges from 0 to 3, much greater than the overall difference driven by external factors such as day of week, season, or temperature, suggesting internal factors specific to individual households are more important to understand the behaviors that generate various degrees of load shape diversity.

We assess the correlation between load shape entropy of individual households and household characteristics to understand the key predictors of variability in consumption schedules. Entropy differences between households with and without the selected household characteristics are shown in Figure 10. We can see that having an electric dryer and children-in-home are the leading factors associated with more variable consumption schedules. This may be associated with variable day-to-day laundry time and more chaotic needs of children-in-home. Low-income households, those with central AC, and full-time workers also tend to vary their pattern
of consumption from day to day. On the other end of the spectrum, elderly households tend to have the most stable day-to-day routines. Characteristics of single family homes, those working from home, and those with a college degree also tend to correlate with more stable consumption schedules relative to households without those characteristics.

Depending on the household characteristics, we can see not all the resulting variability is likely to be readily translated to consumption flexibility. Usage of appliances such as electric dryers can be flexibly moved between times of day to accommodate a time-based DR program. However, the variability of load shapes due to having children-in-home reflects a lifestyle constraint that may be more difficult to change.

[34] identified literature gaps with regard to consumption behavior and DR response potential of vulnerable and low-income customers. Our results suggest that in terms of variability in consumption schedules, households with chronic illness do not show significant differences relative to those without chronic illness. Low-income households on the other hand tend to be more variable while elderly households are the opposite. Further research is needed to test whether the variability shown in low-income households makes them desirable candidates for DR programs.

As discussed in the section IV B, there are three dictionary load shapes that cover 50% of all the electricity consumption during the hottest summer days (clusters 1, 2 and 4 in Figure 7c). To further understand the within and across customer variability we map the occurrence of these three dictionary load shapes of primary interest across the population of households in our data (a random sample of 1000 households are shown in Figure 11). The households are sorted by the overall number of times one of their days was assigned to one of the three dictionary load shapes of interest. The households farthest to the bottom of the figure had the fewest days assigned to a cluster of interest, while those at the top had the most days assigned to a cluster of interest. The average daily outdoor
temperatures and load shape entropy computed for each day are overlaid onto the bottom of this figure for reference.

In examining this figure, first the correlation of the clusters of interest with temperature is clear with counts of cluster-of-interest membership, i.e. column averages, increasing as temperatures spike. The diversity of usage patterns measured by load shape Entropy also shows sharp decreases when temperatures increase. Second, the variability in load shapes (whether in the top 3 dictionary patterns or not) can be explained by the responsiveness of the households to outside temperature, which is consistent with [30]. We see that the households in the top quarter of the figure are classified into one of the three target dictionary load shapes on a large percentage of their summer days, while the households in the bottom quarter of the figure only demonstrate these target usage patterns when temperatures spike.

These two types of behavior, and the spectrum across households in between, represent very different underlying behavioral patterns. There is a need for further research to better understand these underlying patterns. Observable patterns such as these based on AMI data alone can be used to segment customers into groups that better capture heterogeneity in how they are likely to respond to DR or time-differentiated pricing programs. These segments could be used, for example, to target relevant programs based on the needs of the utility.

V. Conclusion

In this paper we employ an innovative clustering technique to categorize daily electricity consumption at hourly resolution across a large sample of residential customers over a full year. We focus clustering on the schedules and magnitudes of discretionary consumption with an innovative “de-minning” process. Our clustering procedure results in a dictionary of 99 distinctive usage patterns that can represent more than 30 million discretionary load shapes within a reasonable error threshold.

With cluster assignment of daily discretionary load shapes over the whole year period, we are able to demonstrate how consumption patterns can be differentiated by external influencing factors such as time scales of interests (season and day-of-week) and meteorological conditions (outside temperature levels). Analysis of the temporal distribution of 99 dictionary load shapes reveals that high temperature is the single biggest external influence reducing discretionary load pattern diversity. In particular, approximately 50% of the energy use during the hottest days are covered by only three dictionary load shapes. The coincident load resulting from increased concentration of usage patterns driven by high temperatures is problematic for the grid, causing high system peaks that are expensive and threaten service stability. Variation in the concentration of discretionary usage patterns exists across seasons as well, but this is largely being driven by temperature. There is much less variations in the distribution of electricity usage across dictionary load shapes between weekends and weekdays than across seasons.

There is significant diversity of load shapes within households across days and such variability can be explained by household characteristics including socio-demographic and lifestyle information, dwelling information, and appliance ownership information. We find that having an electric dryer and children-in-home are the leading predictors of a more variable consumption schedule, while homes with elderly residents best predict stable day-to-day routines. Among the vulnerability characteristics considered here (chronic-illness, elderly, and low-income), we find low-income households tend to be more variable. This needs further research to confirm whether such variability can lead to greater DR potential.

We have demonstrated that there is significant heterogeneity across households regarding the diversity in usage patterns
and such diversity markedly decreases on hotter days. The variability in summer load shapes across customers can be explained by the responsiveness of the households to outside temperature, which is consistent with current literature. Our results motivate future work in which identifying and mapping these particular patterns across the population can potentially be used in developing targeting techniques to improve the uptake and effectiveness of demand response programs.

While utilities and system operators typically focus on aggregate residential load shapes, our findings shed light on the considerable heterogeneity and the relative importance of influencing factors that underlie such variability across days and households. We argue that finding tractable ways to map out and understand this variability, as we have begun above, can be a powerful tool for subsequently segmenting customers for better program targeting and tailoring to meet the needs of the rapidly evolving electricity grid.

ACKNOWLEDGMENT

The work described in this report was funded by Laboratory Directed Research and Development (LDRD) funds from the U.S. Department of Energy under Contract No. DE-AC02-05CH11231.

REFERENCES

[1] T. Räsänen, D. Voukantitis, H. Niska, K. Karatzas, and M. Kolehmainen, “Data-based method for creating electricity use load profiles using large amount of customer-specific hourly measured electricity use data,” Appl. Energy, vol. 87, no. 11, pp. 3538–3545, Nov. 2010.

[2] C. Flath, D. Nicolay, T. Conte, C. van Dinten, and L. Filipova-Neumann, “Cluster analysis of smart metering data,” Bus Inf Syst Eng, vol. 4, no. 1, pp. 31–39, Feb. 2012.

[3] H. Cao, C. Beckel, and T. Staake, “Are domestic load profiles stable over time? an attempt to identify target households for demand side management campaigns,” in IECON 2013 - 39th Annual Conference of the IEEE Industrial Electronics Society. ieeexplore.ieee.org, Nov. 2013, pp. 4733–4738.

[4] F. McLoughlin, A. Duffy, and M. Conlon, “A clustering approach to domestic electricity load profile characterisation using smart metering data,” Appl. Energy, vol. 141, pp. 190–199, Mar. 2015.

[5] I. Khan, M. W. Jack, and J. Stephenson, “Identifying residential daily electricity-use profiles through time-segmented regression analysis,” Energy Build, vol. 194, pp. 232–246, Jul. 2019.

[6] J. Kwac, J. Flora, and R. Rajagopal, “Household energy consumption segmentation using hourly data,” IEEE Trans. Smart Grid, vol. 5, no. 1, pp. 420–430, Jan. 2014.

[7] S. Haben, C. Singleton, and P. Grindrod, “Analysis and clustering of residential customers energy behavioral demand using smart meter data,” IEEE Trans. Smart Grid, vol. 7, no. 1, pp. 136–144, Jan. 2016.

[8] Y. Wang, Qixin Chen, Chongqing Kang, Mingming Zhang, Ke Wang, and Yun Zhao, “Load profiling and its application to demand response: A review,” Tsinghua Sci. Technol., vol. 20, no. 2, pp. 117–129, Apr. 2015.

[9] Y. Wang, Q. Chen, T. Hong, and C. Kang, “Review of smart meter data analytics: Applications, methodologies, and challenges,” IEEE Transactions on Smart Grid, Feb. 2018.

[10] G. Chicco, “Overview and performance assessment of the clustering methods for electrical load pattern grouping,” Energy, vol. 42, no. 1, pp. 68–80, Jun. 2012.

[11] K. Mosleh and R. Kumar, “A reliability perspective of the smart grid,” IEEE Trans. Smart Grid, 2010.

[12] H. Farhangi, “The path of the smart grid,” IEEE Power Energy Mag., vol. 8, no. 1, pp. 18–28, Jan. 2010.

[13] W.-C. Hong, “Electric load forecasting by seasonal recurrent SVR (support vector regression) with chaotic artificial bee colony algorithm,” Energy, vol. 36, no. 9, pp. 5568–5578, Sep. 2011.

[14] K.-L. Zhou, S.-L. Yang, and C. Shen, “A review of electric load classification in smart grid environment,” Renewable Sustainable Energy Rev., vol. 24, pp. 103–110, Aug. 2013.

[15] S. Yilmaz, J. Chambers, and M. K. Patel, “Comparison of clustering approaches for domestic electricity load profile characterisation - implications for demand side management,” Energy, vol. 180, pp. 665–677, Aug. 2019.

[16] M. E. Dyson, S. D. Borgeson, M. D. Tabone, and D. S. Callaway, “Using smart meter data to estimate demand response potential, with application to solar energy integration,” Energy Policy, vol. 73, pp. 607–619, 2014.

[17] I. Dent, T. Craig, U. Aickelin, and T. Rodden, “Variability of behaviour in electricity load profile clustering: who does things at the same time each day?,” in Industrial Conference on Data Mining. Springer, 2014, pp. 70–84.

[18] C. Public Utilities Commission, “Order instituting rulemaking on the commission’s own motion to consider alternative-fueled vehicle tariffs, infrastructure and policies to support . . . ,” California Public Utilities Commission, 2009.

[19] L. Jin, D. Lee, A. Sim, S. Borgeson, K. Wu, C. Anna Spurlock, and A. Todd, “Comparison of clustering techniques for residential energy behavior using smart meter data,” in Workshops at the Thirty-First AAAI Conference on Artificial Intelligence, Mar. 2017.

[20] I. Dent, T. Craig, U. Aickelin, and T. Rodden, “An approach for assessing clustering of households by electricity usage,” Jan. 2012.

[21] G. W. Milligan and M. C. Cooper, “A study of standardization of variables in cluster analysis,” J. Classification, vol. 5, no. 2, pp. 181–204, Sep. 1988.

[22] G. Chicco, R. Napoli, and F. Piglione, “Comparisons among clustering techniques for electricity customer classification,” IEEE Trans. Power Syst., vol. 21, no. 2, pp. 933–940, May 2006.

[23] M. Piao, H. S. Shon, J. Y. Lee, and K. H. Ryu, “Subspace projection method based clustering analysis in load profiling,” IEEE Trans. Power Syst., vol. 29, no. 6, pp. 2628–2635, Nov. 2014.

[24] J. Han, J. Pei, and M. Kamber, Data Mining: Concepts and Techniques. Elsevier, Jun. 2011.

[25] J. Torriti, R. Hanna, B. Anderson, G. Yeboah, and A. Druckman, “Peak residential and electricity demand and social practices: Deriving flexibility and greenhouse gas intensities from time use and locational data,” Indoor and Built Environment, vol. 24, no. 7, pp. 891–912, 2015.

[26] A. Satre-Meloy, M. Diakonova, and P. Grünewald, “Daily life and demand: an analysis of intra-day variations in residential electricity consumption with time-use data,” Energy Efficiency, pp. 1–26, 2019.

[27] M. B. Roberts, N. Haghdadi, A. Bruce, and I. MacGill, “Characterisation of australian apartment electricity demand and its implications for low carbon cities,” Energy, May 2019.

[28] S. Xu, E. Barbour, and M. C. González, “Household segmentation by load shape and daily consumption,” in Proc. ACM SigKDD 2017 Conf. Halifax, Nova Scotia, Canada, August 2017. urbcamp.ist.psu.edu, 2017.

[29] D. Zhou, M. Balandat, and C. Tomlin, “Residential-demand response targeting using machine learning with observational data,” Jul. 2016.

[30] H. Fang, Y. Zhang, M. Liu, and W. Shen, “Clustering and analysis of household power load based on HMM and multi-factors,” in 2018 IEEE 22nd International Conference on Computer Supported Cooperative Work in Design ((CSCWD)). ieeexplore.ieee.org, May 2018, pp. 491–495.

[31] K. Chen, J. Hu, and Z. He, “Data-driven residential customer aggregation based on seasonal behavioral patterns,” in 2017 IEEE Power Energy Society General Meeting. ieeexplore.ieee.org, Jul. 2017, pp. 1–5.

[32] F. N. Melzi, A. Same, M. H. Zayani, and L. Oukhellou, “A dedicated mixture model for clustering smart meter data: Identification and analysis of electricity consumption behaviors,” Energies, vol. 10, no. 10, p. 1446, Sep. 2017.

[33] J. D. Rhodes, W. J. Cole, C. R. Upshaw, T. F. Edgar, and M. E. Webber, “Clustering analysis of residential electricity demand profiles,” Appl. Energy, vol. 135, pp. 461–471, Dec. 2014.

[34] F. Economics and S. First, “Demand side response in the domestic sector—a literature review of major trials,” Final Report, London, August, 2012.

[35] P. Cappers, C. A. Spurlock, A. Todd, and L. Jin, “Are vulnerable customers any different than their peers when exposed to critical peak pricing: Evidence from the us,” Energy policy, vol. 123, pp. 421–432, 2018.

[36] L. Jin, A. Spurlock, S. Borgeson, D. Fredman, L. Hans, S. Patel, and A. Todd, “Load shape classification using residential smart meter data: a technical memorandum,” 2016.

[37] D. L. Davies and D. W. Bouldin, “A cluster separation measure,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 1, no. 2, pp. 224–227, Feb. 1979.