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Electric Load Shape Benchmarking for Small- and Medium-Sized Commercial Buildings

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Abstract

Small- and medium-sized commercial buildings owners and utility managers often look for opportunities for energy cost savings through energy efficiency and energy waste minimization. However, they currently lack easy access to low-cost tools that help interpret the massive amount of data needed to improve understanding of their energy use behaviors. Benchmarking is one of the techniques used in energy audits to identify which buildings are priorities for an energy analysis. Traditional energy performance indicators, such as the energy use intensity (annual energy per unit of floor area), consider only the total annual energy consumption, lacking consideration of the fluctuation of energy use behavior over time, which reveals the time of use information and represents distinct energy use behaviors during different time spans. To fill the gap, this study developed a general statistical method using 24-hour electric load shape benchmarking to compare a building or business/tenant space against peers. Specifically, the study developed new forms of benchmarking metrics and data analysis methods to infer the energy performance of a building based on its load shape. We first performed a data experiment with collected smart meter data using over 2,000 small- and medium-sized businesses in California. We then conducted a cluster analysis of the source data, and determined and interpreted the load shape features and parameters with peer group analysis. Finally, we implemented the load shape benchmarking feature in an open-access web-based toolkit (the Commercial Building Energy Saver) to provide straightforward and practical recommendations to users. The analysis techniques were generic and flexible for future datasets of other building types and in other utility territories.

Keywords

Benchmarking; load shape; representative load pattern; load profile; cluster analysis; building energy

1. Introduction

Buildings consume over 40 percent of the total energy consumption in the United States [1]. Small- and medium-sized commercial buildings less than 50,000 square feet (ft^2) (4,647 square meters [m^2]) represent 95 percent of the number of commercial buildings and consume 47 percent of the total energy of U.S. commercial buildings, excluding malls [2]. Building owners and utility managers often look for energy cost savings opportunities through installation of energy efficiency measures or by identifying and eliminating energy waste. Analysis of whole-building electric load data is an effective approach to discovering opportunities for reducing energy costs through building energy management [3]. Electric meters from Advanced Metering Infrastructure (AMI) systems provide hourly or sub-hourly interval data to utilities at a rate approximately three orders of magnitude faster than the traditional manually read data [4]. Supported by the Smart Grid Investment Grant (SGIG) program, the U.S. Department of Energy reported that by 2013, most SGIG-funded meter deployments had already started, or even been completed [5]. By mid-2014, electricity smart meters had been installed in over 50 million, or 43 percent, of U.S. households and were generating more than one billion data points a day [6]. California also has implemented state-level smart grid policies and topped the list of smart meter penetration rates, at 87.1 percent [7].

Employment of new technologies in the energy industry usually brings new opportunities regarding energy efficiency [8] and cost effectiveness [9][10]. Specifically, the use of AMI systems by utilities creates huge opportunities for novel forms of analysis and interpretation of energy use behavior in buildings. However, small- and medium-sized business owners currently lack easy access to low-cost tools that help them interpret massive amounts of data to better understand their energy use behaviors and to look for opportunities to eliminate electricity waste [11].

Benchmarking is one technique used in energy audits for targeting buildings and identifying energy-saving opportunities [12]. It refers to the comparison of the energy use in the target building to that in other buildings, and includes factors such as the magnitude of energy consumption, energy density, and consumption patterns [13]. Benchmarking policies are being pursued in many countries and at all levels of government. At present, the states of California and Washington, and many major cities in the United States, including Washington D.C., Austin, New York, Seattle, San Francisco, and Boston, have passed energy disclosure laws to transform the market for energy efficient buildings [14]. A simple floor-area-normalized Energy Use Intensity (EUI) metric is often used to assess the energy-use performance of a commercial building, and is commonly used as an Energy Performance Indicator (EPI) in the benchmarking process [15]. An EUI is a useful metric to evaluate a building's long-term aggregated energy efficiency trends [16]. For example, the 1992 Commercial Buildings Energy Consumption Survey database is used to develop distributions of electric EUIs in office buildings for the nine U.S. census divisions [12]. Individual building EUIs can be compared to these distributions as an indication of energy performance [17]. The Commercial End-Use Survey (CEUS) survey provides detailed audit data for commercial buildings, and a California-based benchmarking tool, the Cal-Arch, was developed using the database, representing the frequency distribution curve of energy intensity and the relative position of the target building [13].

Currently, the U.S. Environmental Protection Agency's Portfolio Manager is the most commonly applied tool for performing operational ratings. It allows auditors to track energy and water consumption data and benchmark results to other buildings in the same functional category and climate zone [18]. Other EPIs, such as energy per worker or energy per bed, may also be used in various building types [19,20]. However, these traditional EPIs reveal only the long-term cumulative energy consumption information, lacking consideration of the fluctuation of energy use behaviors over time. With smart meter data, time series energy usage in sub-hourly intervals allows energy customers to understand how much energy they use at different times of the day, different days of the week, and different seasons of the year. Electric load shapes convert the long-term consumption data into estimates of the hourly or sub-hourly load to determine the energy use patterns over time [21]. Comparably, the load shape reveals the time-of-use information, and the characteristics of the shapes during different time spans may represent distinct energy use behaviors. Considering this, it is also valuable to conduct load-shape benchmarking for buildings.

A *load shape* is defined as the curve that represents load as a function of time. Load shapes contain information on how electricity use changes over the day, as a composite of end uses such as lights, appliances, and heating, ventilation and air conditioning (HVAC). Load shape analysis is commonly used by building owners, operators, or energy managers to analyze the energy consumption of their buildings. Researchers have developed general methods to obtain these curves using historical electric meter data. Clustering is a common way to extrapolate load profiles representing conventional patterns of electricity consumption for commercial and residential buildings [22–24]. Chicco et al. applied the Electrical Pattern Ant Colony Clustering (EPACC) algorithm to obtain the daily electricity load patterns of non-residential customers in a typical weekday of an intermediate season and created a partitioning of the patterns into customers with non-overlapping classes [24]. Carmo and Christensen conducted k-means clustering of residential daily heat gas load profile to find the correlation between the load clusters and building characteristics such as the floor area, building type and vintage [25]. Deepak Sharma et al. also applied clustering techniques using load factor (ratio of peak load to average load) as an indicator, for the purpose of identifying similar electricity load profiles and normal peak demand among them [26].

A load shape reveals information that helps building owners and facility managers detect potential energy waste and diagnose the possible reason for it. For example, load shapes can be evaluated to determine if they are consistent with the shape one would expect for the target building business or building type. These patterns can consider hours of operation, weekday versus weekend operation, seasonal variations, and holidays. The DrCEUS system, developed by California's Commercial End-Use Survey (CEUS) project, suggests the building's load shape be examined in a whole-year period to check the inconsistency between with the load file and the time-of-use logger data [27]. More generally, researchers also have defined a variety of load shape features and parameters to interpret the load file. Mathieu et al. recommended five parameters that were useful for describing load shapes, namely near-base load (kilowatts, kW), near-peak load (kW), high-load duration (hours), rise time, and fall time [28]. These parameters were used to describe and visualize load variation from one day to the next. Capehart et al. also recommended examining the base load percent (night load/day load), peak-to-base load ratio,

and coincident peak in the facility load profile, to identify irregular energy use behaviors in buildings [29].

Previous research listed above demonstrated different interpretations of the electric load shape for individual buildings, but little work has been done to employ these load shapes as energy benchmarking features, due to the complexity of extracting performance metrics from the time series data. However, the interpretation of some facts revealed in load shapes, such as the average workday operation hours, may not be explicit by itself, but yields information when the feature is compared to the target building's peers of the same building category in the benchmarking analysis. One challenge in this analysis is that for small- and medium-sized buildings and business, electricity utility companies rarely have information on the floor area that a meter serves. Considering it is not proper to use the absolute energy consumption for peer group comparison since it ranges widely, we designed a novel approach to quantify the energy performance by interpreting the load shape without consideration of the magnitude of the total load.

This study developed a general benchmarking method to allow energy consumers to benchmark their building or business space by comparing their energy use patterns against peers using statistical methods. Specifically, new forms of benchmarking metrics and analytical methods are needed to infer the energy performance of the building based on their load shape. The study developed a simple tool to perform the benchmarking analysis for general commercial buildings, to present straightforward interpretations of the result, and to provide practical recommendations on energy efficiency improvements. The benchmarking results can be used by the building owners and facility managers to improve how they operate and schedule equipment, to find opportunities for demand response, and to better understand the link between their building's load shape and the coincident peak of the local distribution system or the larger electric grid.

2. Data and Methods

2.1 Source data sampling and labeling

Electric load meter data from thousands of randomly selected small- and medium-sized commercial buildings were obtained from Pacific Gas and Electric Company, a California investor-owned utility, along with building information such as the location and building use. Specifically, the 15-minute interval electricity usage meter data were collected from a total of 2,353 accounts. Since the time span of the raw data varies from record to record, to perform peer analysis and benchmarking, we selected a period of one continuous year, from January 1, 2015, to December 31, 2015, for data analysis. During this period, 1,907 buildings have full records without missing values.

To categorize the buildings for peer group analysis, we labeled them based on building type, the amount of electricity use, vintage, and climate zone. Building type was determined according to the building's North American Industry Classification System (NAICS) codes, which indicate the building usage. Based on the sampled dataset, we classified the buildings into three groups: Office, Retail, and Other. Building floor area was not available, and considering this limitation, the annual rolling premise usage was used to determine the building size category. In particular,

buildings with electric usage less than 40,000 kilowatt-hours (kWh) were labeled as "small-sized buildings" and the rest as "medium-sized buildings." The year-built information was partially available by looking up the property information from a real estate data source website (such as PropertyShark), and we categorized them as five groups: "before 1900," "1900–1949," "1950–1979," "1980–1999," and "after 2000." Forty-two percent of the buildings were labeled with one of the five vintage categories. Climate zone was defined by California Building Energy Efficiency Standards Title 24 by mapping the building ZIP code to one of the 16 zones. Via the resources mentioned above, all sample buildings were labeled with one of the three building types, one of the two building size categories, and one of the sixteen climate zones. In the study, we analyze each feature using the buildings with available labeled data.

Figure 1 shows the distributions of the 1907 sample data records on the climate zone map (left) and by pie charts (right), categorizing the source data by its building type, building size, building vintage, and climate zone. The majority of the analyzed buildings are small offices, built after 1950 and before 2000, and are mainly located in the San Francisco Bay Area.
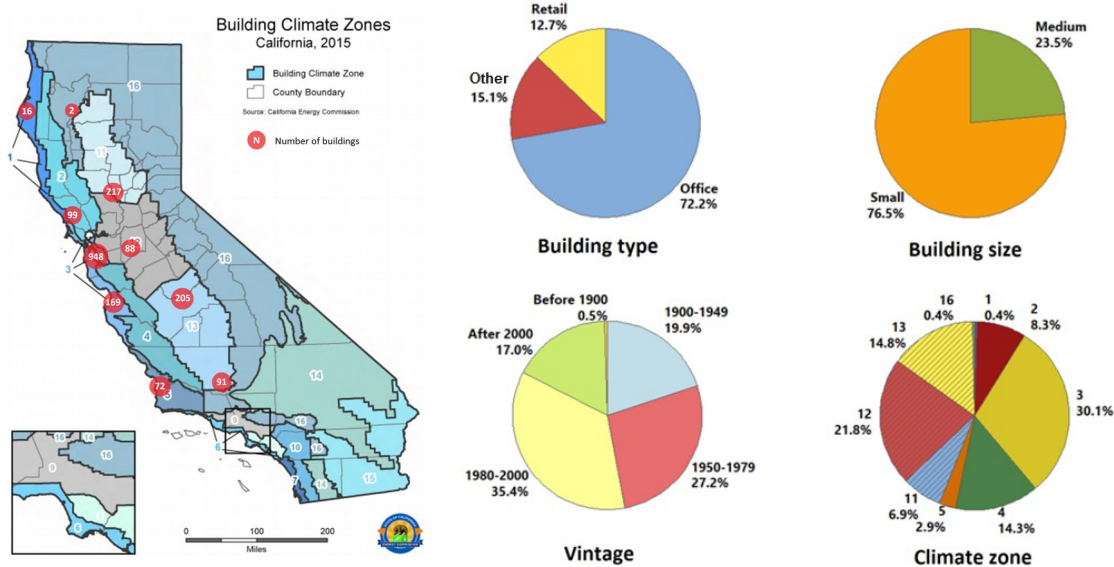

Figure 1 Distributions of the source data

The data were labeled with these features, and these factors were considered as potential clustering features for the load shape benchmarking.

2.2 Deriving load shapes from meter data

To evaluate the hourly load shape from the metered data, daily chronological load curves were examined, clustered, and generalized. As suggested by our literature review, load shapes in commercial building are dominated by factors such as the day of the week and the season of the year [30]. Hence, for each meter record, we first clustered the daily records into four seasons: Winter (Dec, Jan, Feb), Spring (Mar, Apr, May), Summer (Jun, Jul, Aug), and Fall (Sep, Oct, Nov). This allows the customers to identify different characteristics of the energy use pattern in each season. For each group of time series, we derived basic statistics of the daily data, namely the hourly mean load, the daily mean load, and the load at the 5, 15, 50, 85, and 95 percentiles. To capture the behavior on typical days, the "mean of the medians" is calculated for each statistic, by finding the median value for each day of the week and taking the mean of the results.

Given the seasonal load shapes derived for each time series record, quantified features of those curves were extrapolated. Naming the load at *n* percentile as *"pct_n,"* we especially defined three examined load shape features in this study, including:

- **Peak load**: pct_95

- **Base load**: pct_15

- **On hour**: the period of time when building's load is higher than the threshold. The threshold is defined as pct_5 + 0.25 * (pct_95 – pct_5).

Further, to identify the energy use pattern during the days when the buildings are in operation for each season, the data were clustered into workdays and non-workdays based on its load pattern during the day, as shown in Figure 2 [31]. Specifically, we adopted the k-means clustering algorithm in the workday and non-workday clustering, considering features including daily mean load, mean on-hour load, mean off-hour load, on-hour duration, and the 5, 15, 50, 85, and 95 percentiles of the daily load curve. Based on the results, the hourly representative load curve, along with the three concerned load shape features, are derived for each cluster, representing a typical workday and a typical non-workday for each building.
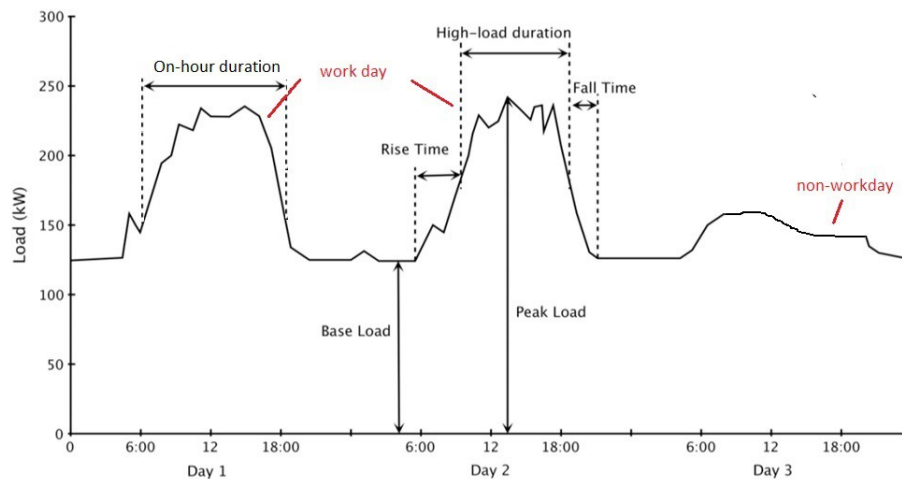

Figure 2 Load shape features and parameters [31]

2.3 Load shape parameters analysis

Building load shapes can vary greatly, but a group of buildings may share similar characteristics in their shapes [32]. For small- and medium-sized commercial buildings, the timing and amount of energy use are the most significant indications of the building's operating patterns. To examine a facility load and compare it to its peers, we normally care about the magnitude of day load, night load, and operation and non-operation load, as well as the duration during which these loads occur. We developed a set of dimensionless parameters to interpret the load patterns. Specifically, the three load shape parameters listed in were considered in this study. The concepts of peak load, base load, typical workdays, and on-hour were defined in the previous section.

Table 1 Definition of load shape parameters

Load shape parameters	Definition
Peak-base load ratio	Ratio of peak load to base load on typical workdays
Workday/non-workday load ratio	Ratio of total daily load on typical workdays to non-workdays
On-hour duration	Duration of a building's operating hours on typical workdays

As the base load is the amount of power always on, a low peak-base load ratio may indicate that many unnecessary loads are left on in the building during the night hours. Similarly, a low workday and non-workday load ratio may suggest many unnecessary loads are left on during non-operating days in a week. Apart from these, the on-hour duration can imply the amount of time in a day that the building is in full or main operation, and the customer can justify whether the duration is as expected.

2.4 Representative load patterns clustering

A more nuanced way to look at hourly energy consumption is a load duration curve. The curve is the graphical representation of hourly electric demand from highest to lowest over a certain time interval. Clustering load curves are based on the shape of a load curve, and are usually normalized scaled to a specific range, such as [0.0, 1.0]. To normalize the vector of the shape, we divided the load of every hour by the annual average daily near-peak load, which was calculated by taking the average of the daily peak load (pct_95) across all working days of a building.

Suggested from previous work, the normalized curves can then be clustered to obtain the representative load patterns (RLPs). The RLPs represent the conventional patterns of the electricity consumption of a building group. We used the RLPs to understand the normal load shape in similar load profiles and to identify irregular load shapes. To recognize a building's RLPs for each studied period (a season in this case), we clustered the hourly load curves based on the shape of the curve. The cluster analysis groups the load profiles into classes according to their load characteristics. The k-means clustering algorithm is the most widely applied for the purpose of load curve clustering [33], and was adopted in the analysis. The algorithm includes iterated selection of k centroids of k patterns, and the objective function is to minimize the overall Sum of Squared Errors (SSE) given by Equation (1):

$$SSE = \sum_{k=1}^{K} \sum_{x_j \in C_k} d^2(w_k, x_j) \quad (1)$$

where C_k is the k-th cluster with $C_1 \cup C2 \cup \ldots \cup C_k = X$ and $d(\bullet, \bullet)$ is the Euclidean distance norm. The Calinski-Harabasz (CH) criterion was used to evaluate the optimal number of clusters. The CH criterion calculates the CH clustering index for cluster validation, and tests the validity based on the average distance between and within cluster sum of squares [34]. The corresponding functions in the Statistics and Machine Learning Toolbox™ in MATLAB were applied.

Conducting the experiment using 2 to 5 clusters, Figure 3 shows the results of the clustering performance evaluated by the CH criterion. Comparing the performance of clustering solutions containing two to five clusters, we chose to group the load curves of office buildings into three clusters, and the retail buildings into two, as suggested by the optimal cluster numbers for each subgroup.
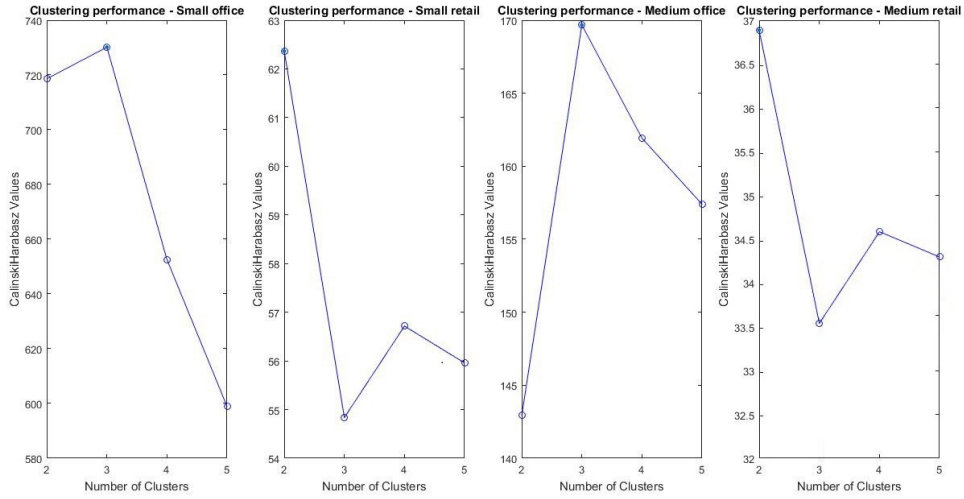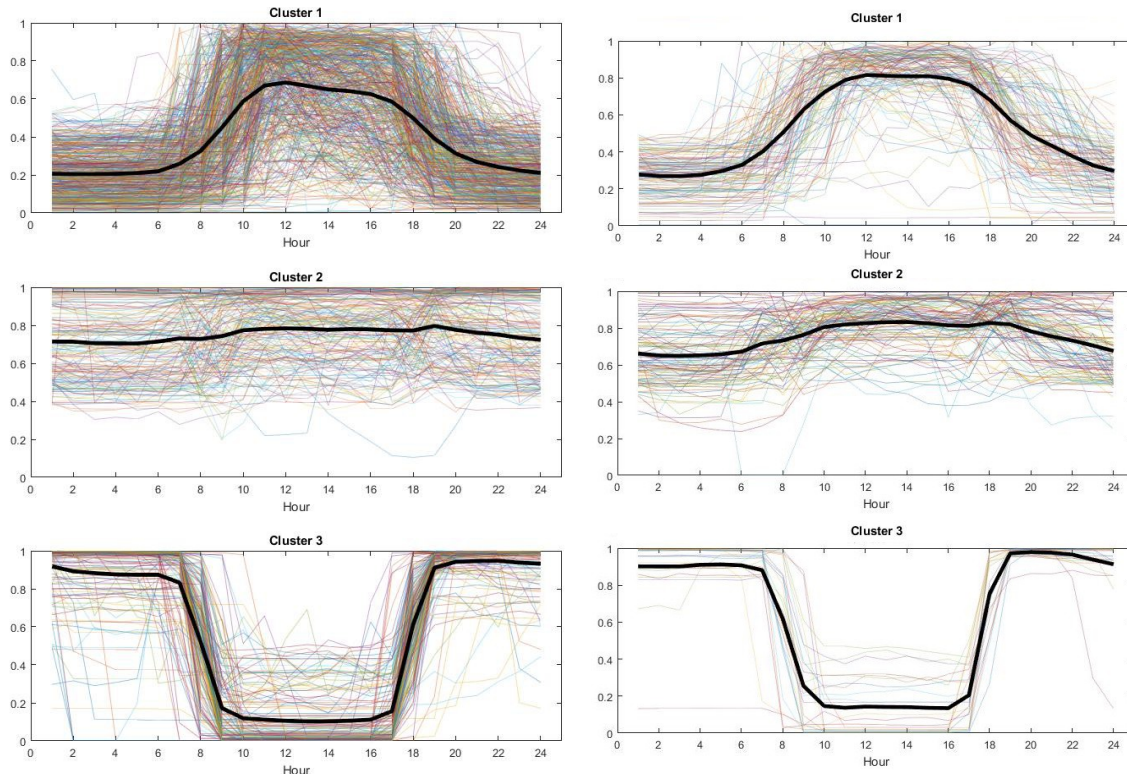
Figure 3 Clustering performance of different number of clusters

After clustering, the RLPs are developed by calculating the centroid of a cluster of normalized load curves. Figure 4 Example clustering results for each subgroup shows an example of clustering the load curves based on peer groups into an optimal number of clusters.

(a) Clustering results for small office - winter   (b) Clustering results for small retail - winter
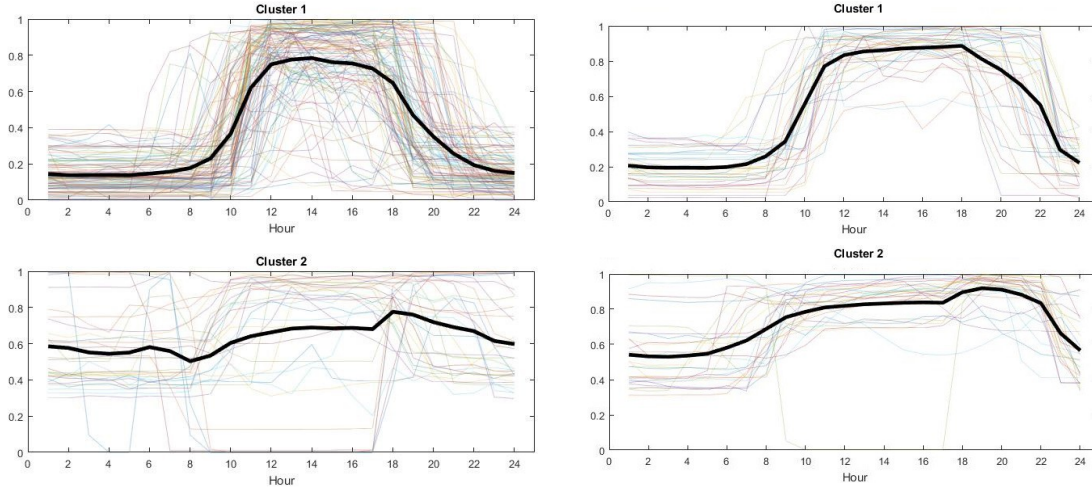
(c) Clustering results for medium office - winter   (d) Clustering results for medium retail - winter

Figure 4 Example clustering results for each subgroup

3. Experiment and Results

3.1 Data categorization for peer group analysis

To enable energy benchmarking of a building in peer groups, we first categorized the sample buildings based on the data labels. To select features for categorization, we individually tested the significance of each data labels listed in Chapter 2.1 to those mentioned above three statistical load shape parameters. Table 2 lists the p-value for each term, testing the null hypothesis that the coefficient is equal to zero (no effect). Testing at a significant level (α-value) of 0.05, a predictor that has a low p-value less than the α-value was likely to be a meaningful addition to the corresponding response variable and vice versa. In the output below, we can see that the predictor variable of building size was significant for all tested responses, and the building type was associated with the peak-base load ratio and on-hour duration. Finally, the climate zone had an effect on load ratios in summer.

Table 2 Significance of building labels to load shape parameters

Factor	P-value of general linear model					
	Peak-base load ratio		Workday / non-workday load ratio		On-hour duration	
	Winter	Summer	Winter	Summer	Winter	Summer
Building size category	0.000	0.000	0.000	0.045	0.000	0.000
Building type	0.000	0.034	0.201	0.382	0.000	0.015
Vintage	0.789	0.744	0.701	0.495	0.252	0.477
Climate zone	0.695	0.002	0.276	0.000	0.343	0.227

Table 2 suggested categorizing sample buildings based on their size category, type, and the climate zone in summer. However, except for Climate Zone 3, the source data we had was limited. According to the central limit theorem, a sample size less than 100 will construct a 95 percent confidence interval with a margin of error of over ±13 percent (for very large populations as in our case)—too large a range for estimating the true population proportion with any accuracy [35]. For benchmarking analysis, we usually desire a sample size level of about 500

to optimally estimate the population parameters, constructing a 95 percent confidence interval with a margin of error of about ±4.4 percent. To ensure the sample size was sufficiently large in each cluster for benchmarking, we only categorized the sample buildings with their type and size. Besides, in this analysis, the buildings labeled "Other" as a building type were excluded from benchmarking analysis since energy usage can vary from type to type, and it is irrelevant to compare the usage of office and retail buildings to other types of buildings. As a result, we sampled four groups of 928 small office, 148 medium office, 532 small retail, and 124 medium retail buildings for peer comparison. With more labeled data available in the future, the peer group could be categorized in more detail according to the significance of the data label to the benchmarking parameters concerned, and more detailed sensitivity analysis should be conducted regarding the significance of each parameter [36].

3.1.1 Analysis of load shape parameters

Based on the methodology described in the previous chapters, we derived the statistics and distributions for each load shape benchmarking parameter. Figure 5 shows the probability distribution of the peak-base load ratio of the four building categories: namely, small office, small retail, medium office, and medium retail. The X-axis shows the load ratio ranging from 1 to 30, and the Y-axis shows the percentage of all analyzed buildings within a certain range. The results indicated that more medium-sized buildings had a lower peak-base load ratio than the small buildings, and more office buildings had a lower peak-base load ratio than the retail buildings. Among all sample buildings in our analysis, small office buildings and small- and medium-sized retail buildings tended to shut down more completely during non-operation hours.
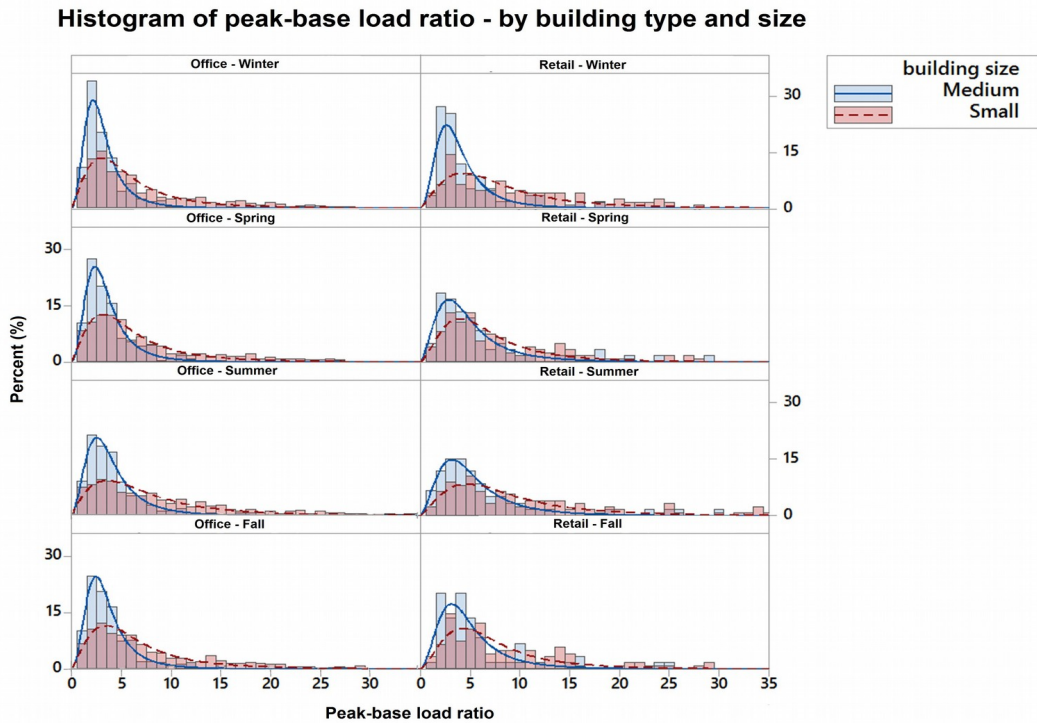

Figure 5 Histogram of peak-base load ratio for each building category

Similarly, Figure 6 plots the probability distributions of the workday and non-workday load ratio. It was clear from Figure 5 that more retail buildings have a lower workday / non-workday load ratio than office buildings, because retail buildings tend to operate all days of a week. In particular, the statistics of small- and medium-sized office buildings were close; while the load ratio of medium-sized retail buildings was significantly lower than other groups, indicating these buildings did not have an obvious difference in operation patterns between workdays and non-workdays.
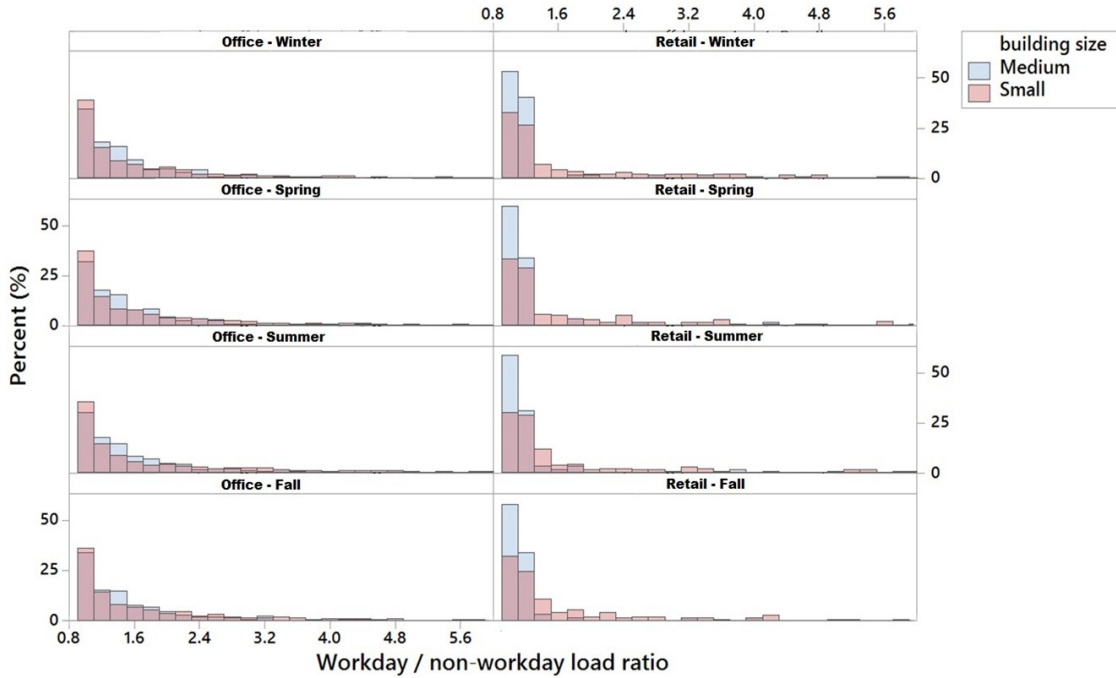

Figure 6 Histogram of workday / non-workday load ratio for each building category

The duration of operation hours also varied from group to group, as shown in Figure 7. The difference was found between small buildings with an average "on" duration of around 10 hours and medium buildings at around 13 hours. Detailed operation start and end time can be found from representative load pattern analysis, as described in the following chapter.
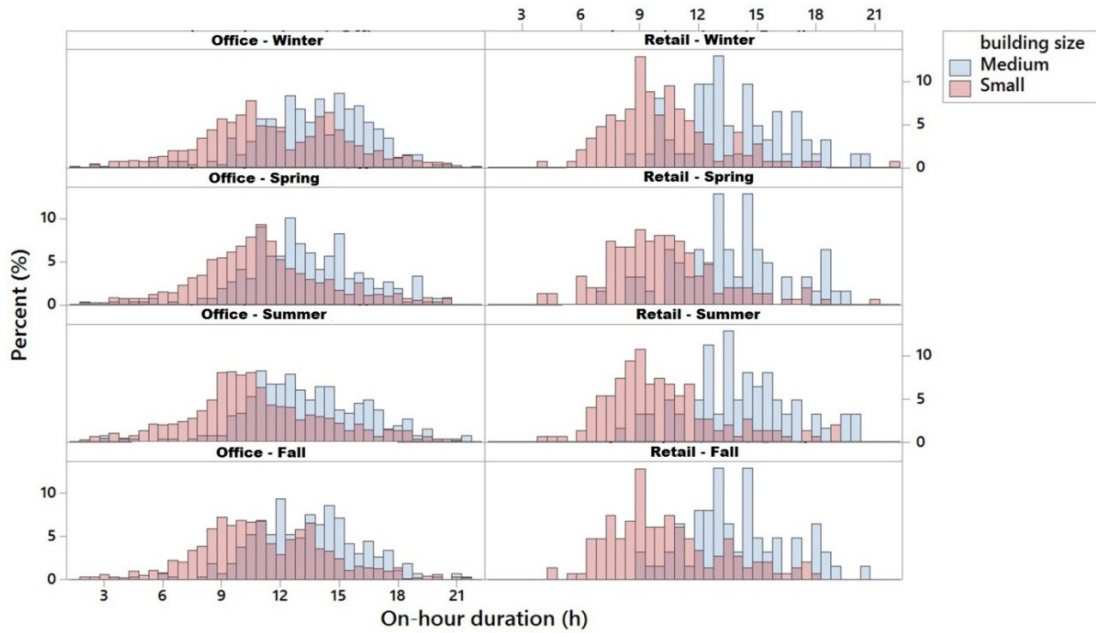
Figure 7 Histogram of peak-base load ratio for each building category

3.1.2 Representative load patterns

Representative load patterns (RLPs), derived from the centroid of load curves of each building group, were used to identify more detailed building energy use patterns, involving the start and end time of operation hours, as well as the period of rise time, high-load duration, and fall time.

Figure 8 lists all the clustered RLPs for the four building categories. The percentage marked for each load shape on the figures represents the percentage of the buildings falling into this kind of RLP. Taking small offices for instance, 65 percent of the RLPs have a normal curve corresponding to the normal operation schedule, rising at 8 am and falling around 6 pm, and this cluster accounts for the largest proportion of all buildings. And 18 percent of the buildings had a flat and high curve, which does not have an obvious rise or fall time, indicating the building is operating the whole day. A few office buildings had a load curve that is "on" during the night and "off" during the day. This likely represents a meter serving part of a building that only operates at night. A large number of these meters may be parking lots or exterior lighting.
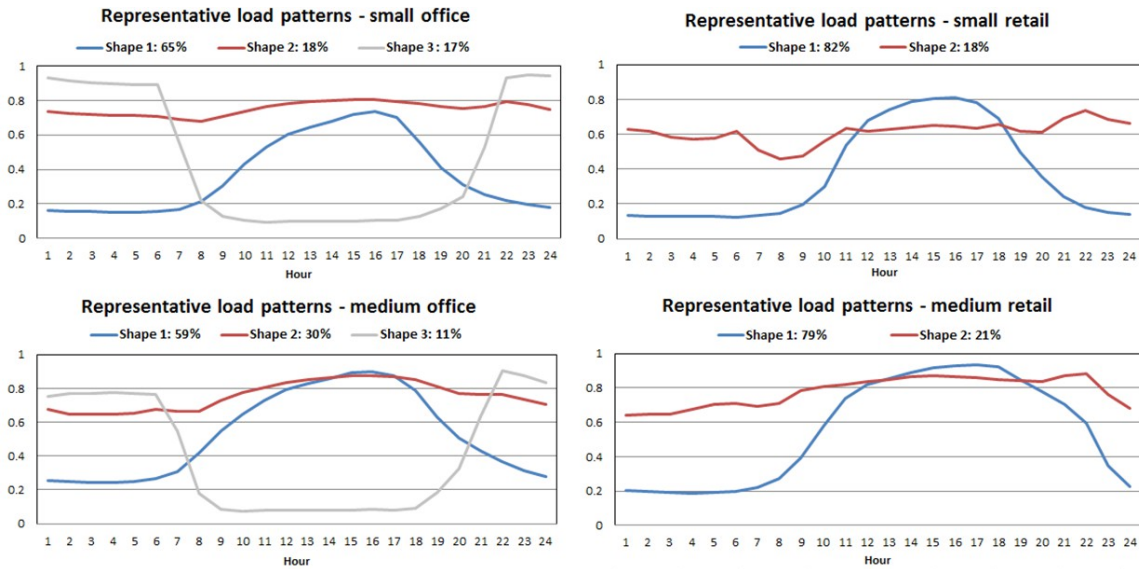
Figure 8 Clustered representative load patterns for each building category in summer

Plotting the seasonal RLPs in one figure, as shown in Figure 9, it was clear that in retail buildings, the load patterns are similar between seasons. Across different seasons, for small and medium offices, the afternoon "fall time" (as defined in Figure 2) is shorter in winter than that in other seasons, as the peak load in the cooling seasons usually appears at 3 pm. The load shape in winter during working hours (9 am to 5 pm), however, stays at a relatively constant level and does not show a particularly high peak load in the afternoon. Across different building groups, medium office and retail buildings tended to have a longer high-load duration, when the load ratio was higher than 0.8, which makes sense because larger buildings have more people, and the diversity of times people come and go is likely larger. Each group of buildings had its own normal operation hours different from one another.
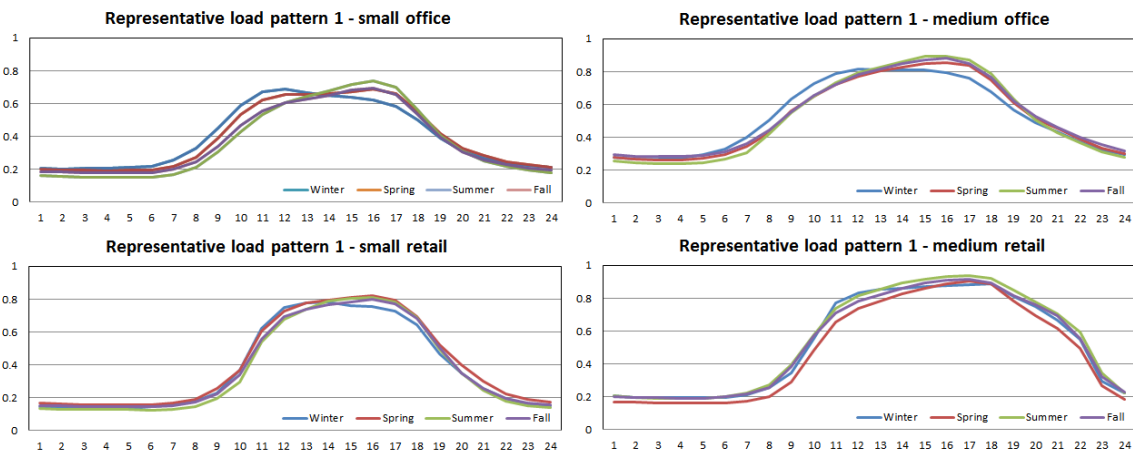

Figure 9 Seasonal representative load patterns of each building category

The RLPs and the percentage of buildings they represented were also included in the database for benchmarking.

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4. Application

Based on the previous analyses, we purposed benchmarking a building's load shape from their utility meter data according to two metrics, the load shape parameters, and the clustered representative load patterns. The load profile database and analysis methods were programmed and implemented into a web-based toolkit, the Commercial Building Energy Saver (CBES: http://cbes.lbl.gov) [3]. CBES is intended use for small- to medium-sized office and retail buildings in California, providing energy benchmarking and three levels of retrofit analysis that consider the project goal, data availability, and user experience. CBES offers prototype building models for seven building types, six vintages, in 16 California climate zones and roughly 80 energy conservation measures (ECMs) for lighting, envelope, plug-in equipment, HVAC, and service hot water retrofit upgrades. The CBES Preliminary Retrofit Analysis utilizes the DEEP database, a data bank for screening and evaluating retrofit measures for commercial buildings generated from 10 million building energy simulations conducted using EnergyPlus on the U.S. National Energy Research Scientific Computing (NERSC) supercomputer. The CBES Detailed Retrofit Analysis employs advanced automated calibration algorithms to attune inputs before simulating energy savings of ECMs. For the detailed retrofit analysis, on-demand energy simulations using OpenStudio [37] and EnergyPlus [38] calculates the energy performance of the building with user-configurable ECMs. CBES is flexible enough that the user can jump to any level of evaluation after the common inputs are provided.

The CBES toolkit can be used to generate a benchmarking report by input building type and building size category and upload the annual meter data file. For the load shape parameter benchmarking, the user can compare the operation and performance of an individual building against its peers to determine whether the building is in the normal range. The CBES toolkit is compatible with multiple meter data intervals, as it ultimately aggregates the load data to a reasonable interval length. For example, if the load data at 1-second timescale, the tool aggregates it to the 10-minute timescale, to avoid carrying around tens or hundreds of times more data than needed. However, to generate more accurate hourly load shapes using the methodology described in Section 2.2, the tool also requires the data interval of the input daily chronological loads to be short enough for clustering based on shape, and preferably to be hourly or sub-hourly.

We conducted a case study with the CBES toolkit using the AMI data from a medium-sized retail building in San Francisco to demonstrate the benchmarking feature. The studied dataset contains electricity meter records of the building from Jan 1, 2015, to Dec 31, 2015, in a 15-minute interval. The toolkit first generates a normalized load curve of the target building and compares it to the RLPs of its peer group—the database of all medium-sized retail buildings. Figure 10 shows the sample report generated by the toolkit, including the benchmarking results of the three parameters, namely peak-base load ratio, workday / non-workday load ratio, and on-hour duration in summer. The building was benchmarked with its peer medium-sized retail buildings, and the parameter distributions of the whole database are shown as the histograms. The red dashed line indicates the medium level of all medium retail buildings, and the blue shadow shows the range from the first to the third quartile, marked as the interquartile range (IQR). The report provides the user with the message that this building's peak-base load ratio and work / non-workday load ratio are 2.0 and 1.33, respectively, which are lower than 81.9 percent and 7.0 percent of its peer buildings. The on-hour duration is 14.4 hours per day, and is only longer than 64.6 percent of its peer buildings. So compared with its peer buildings,

this building's workday / non-workday load ratio and on-hour duration (operation hours) are normal. The building's peak-base load ratio is significantly lower though, indicating that the building may not fully shut down during the non-working hours at night.
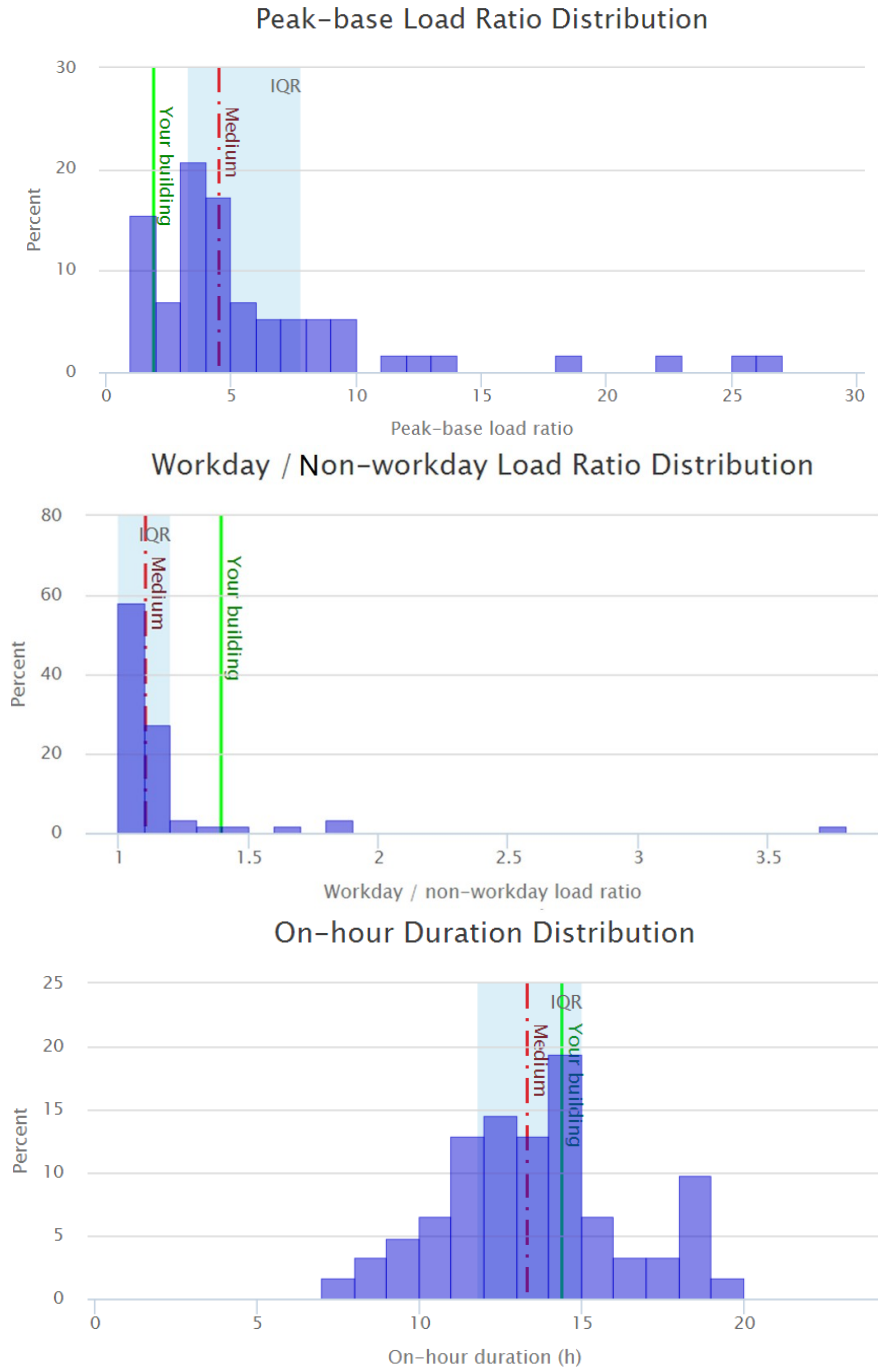

Figure 10 Results of a load shape benchmarking case study for a retail building in San Francisco

The CBES toolkit then generates normalized load curves of the target building and compares them to the RLPs of its peer group. Figure 11 shows the two clustered RLPs of medium retail buildings in dashed line and the target building in solid line. Cluster 1 had a normal load pattern

with regular on and off hours, while Cluster 2 had a flat and high curve. In all medium retail buildings from the database, 79 percent were grouped into the first cluster, while the rest were clustered into the second. The user can further compare the load shape with the RLPs across the four seasons to understand the building's operation performance in all seasons. Take the sample building in Figure 11 as an example, the load curve is closer to the RLP of the first cluster, and shows a normal on-off schedule. The load curve indicates the building's working hour starts at around 7 am and ends at around 8 pm, and the rise and fall times are normal. However, the curve during the off-work hours deviates from the shape of the majority of its peer buildings, which can inform building operators to check the operating schedule of the building systems.
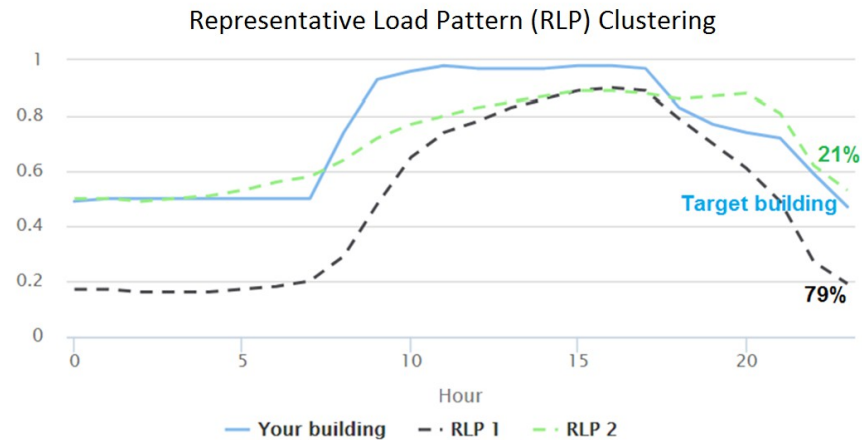

Figure 11 Clustered representative load patterns clustering

In this way, a building owner or facility manager can compare a building's load shape patterns against peer buildings in the same type and size category to identify irregular load shapes and to evaluate the building's operation performance.

5. Discussion

As pointed before, the smart meter data of a small business may correspond to only a portion of a building rather than the entire building. Utility companies do not have accurate data of their customers' total floor area. Floor area data are hard to acquire. Consequently, the load profiles were not normalized by floor area, and thus it was not eligible to compare the buildings' absolute amount of energy use against peers. Considering this limit, the benchmarking metrics proposed in this study were based on the normalized hourly load profile (by their own peak loads), considering only the shape of the curves, regardless of the actual energy use amount. Specifically, the quantified metrics marks represent mostly the variation of electricity load over time during a day, or the distribution of energy demand. Besides, as utility companies do not have the information of the exact serving area of a meter, the usage category of an analyzed record can be ambiguous for the peer grouping and benchmarking analysis. Another major limitation due to the limited data source is that the gas consumption was not provided along with the electricity data, while the seasonal daily electricity profile of a building would differ based on whether or not the building has gas heating. Future work is suggested to consider this as a potential peer grouping parameter for seasonal load shape analysis.

Fifteen-minute electricity data for 2,000 smart meter accounts were acquired in this study, and used as the database for the benchmarking analysis. Due to the practical limitations of data availability and reliability, the analysis was based on a simplified grouping of buildings in California. As justified in the paper, to ensure the sample size was large enough in each cluster for benchmarking, the sample buildings were categorized by their use type and size category based on annual electricity consumption. However, it might be worthwhile to further group the benchmarked buildings by climate zone and building vintage if an adequate sample of buildings have smart meter data available. Furthermore, the current datasets were sampled only from small- and medium-sized commercial buildings in California, but the analysis techniques may also be applied to other building types and in other utility territories and locations. With more meter data from AMI available in the future, the benchmarking database can be replenished gradually to cover broader existing building stock and for a wider range of applications.

6. Conclusions

In this study, a general approach was developed to allow load shape benchmarking for small- and medium-sized commercial buildings and businesses to interpret and benchmark their electricity use patterns with statistical approaches. The paper discussed the method of benchmarking metric selection, peer group categorization, and the selection of desired sample size for benchmarking. Normalization and cluster analysis techniques were proposed. Three quantified shape-based parameters were proposed to characterize a building's electricity use patterns from interval load data, namely the peak-base load ratio, the on-hour duration, and the workday and non-workday load ratio. The analysis techniques are generic and flexible for future datasets of other building types and in other utility territories. The methodology and results were implemented in the CBES web tool, allowing users to perform the analysis easily and obtain a better understanding with the visualized benchmarking results.

The methodology and the tool can be useful for the energy benchmarking of buildings with AMI data, where the available vast amount of raw data needs to be processed effectively, to acquire useful information about the energy use behaviors and the potential application in energy saving, utility cost saving and waste elimination. Moreover, recognizing representative load shapes for peer group buildings would benefit demand response, which aims at usage reduction at peak that is offset by usage during off-peak hours. Energy customers can use the tool to benchmark their building operation performance against other peer buildings. Owners will be able to identify opportunities for operational improvements, energy retrofit, and utility cost saving. The potential benefits also rest upon energy policy pillars associated with economic objectives to reduce the cost of energy supply by a targeted response to electricity market conditions.

Load shape benchmarking implies a step forward in energy benchmarking as a comparative appraisal of the energy performance of an existing building. With the massive amount of AMI data flowing into the industry in the future, the benchmarking techniques may allow building owners and facility managers to improve building operations to reduce energy use and utility cost. Further work is needed to understand the practical application of this tool and its usefulness for customers. As mentioned, further work is also needed to explore these trends with a larger dataset, and to conduct additional related research in other climate zones and regions with different end-uses and electricity consumption patterns. For example, it would be very worthwhile to attempt to group peers by climate zones, and by construction and retrofitting

history aligned with the changes in building regulations and codes. As techniques to collect hourly occupancy data improve, it will be useful to revisit this methodology to understand how energy use and occupancy can be compared.

Acknowledgments

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