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Identifying Commercial Demand Response Candidates Using Load Profile Clustering

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ABSTRACT

This study explored the use of electricity load profile clustering and load shape variability to identify potential candidates for demand response programs. A dataset from Southern California Edison's commercial demand response program from 2016-2017 was applied in the exploration. Ten types of load shapes were identified among the daily profiles of individual customers in the hot climate zone, each of which was characterized by the occurrence of peak/non-peak at different times of the day. The study found that the overlaps between peak hours and event hours are important for identifying demand response candidates. Combining the effects of load shape types, daily load consumption, and load variability, the study examined two classification models – a logistic regression model to capture the main effects, and a classification tree model to capture interactive effects. This study suggests that generalized load shape clustering and simple regression model approaches may be generalizable and practical for application to other program candidate-targeting research.

Keywords

Commercial customers
Demand response load reduction
K-means clustering

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1 INTRODUCTION

Demand Response

Demand response (DR) is a class of programs in which utility providers engage or interact with customers to reduce or shift the energy usage during periods when it is challenging for the grid to balance demand and supply. Typical DR approaches include price signaling in rate plans and/or automation control of end-uses. The load shape of a customer is an important influencer of the demand response effects. For example, if a customer has low consumption during DR periods, it does not make economic sense programmatically for this customer to sign up. Thus, customer segmentation based on load shape is a popular direction of research in DR candidate targeting. Clustering is one of the popular methods in load shape analytics. Next, a literature review is provided concerning the work of applying clustering techniques to identify DR candidates.

Literature Review of Clustering Methods in Demand Response

Clustering is a machine learning method for grouping samples based on their similarity given some features. The features are quantities that describe the samples. For example, in the case of load profiles, features can be the consumption values, timing of the occurrence of specific patterns, variation of load, etc. The output of a clustering process are cluster centers such that the samples that belong to the same cluster are similar to each other while different clusters were dissimilar to each other. K-means clustering is one of the basic algorithms in the clustering family. The K-means clustering process outputs K clusters that optimize the grouping of similar profiles.

In the past decade, clustering methods have been applied in load profile analytics. For example, McLoughlin et al. [1] used K-means clustering in residential load profiles to observe the load shape transition over months. Load profile clustering was also used to identify potential candidates for demand response. The key concept of this application was to link the variability of load to DR potential, with the rationale that higher variability may indicate higher flexibility of load shifting. The implementations of clustering method in the past differ briefly in two aspects:

- Converting load data to features for clustering
- Associating clustering results with DR potentials.

The summary of approaches found in the literature is provided below, respectively.

<u>Clustering Features:</u>

Normalized hourly load data were often used as direct input to the clustering process. The normalized hourly consumption value can be calculated relative to total daily assumption [2] or relative to maximum hourly consumption [3]. The advantage of this approach is that the cluster results explicitly show the time related characteristics, for example, the occurrence and timing of peaks. However, the clusters from this approach did not directly quantify “load variability”, therefore a post-clustering metric is needed In the work of Kwac et al. [2], the concept of "entropy" in information theory was introduced to capture how likely a customer's profiles switch between different load shapes.

Input features can also be quantities that are defined to measure load variability. Jang et al. [4] used four variability indices to quantify the consumption variability across different days and hours, followed by the clustering based on the variability indices.

Associating clustering results with DR potentials:

Kwac et al. used average quantile of usage and load shape entropy (likelihood of switching between load shapes) as two indicators to suggest high potential candidates, which suggested that customers with higher usage and higher load shape entropy may be good candidates. At the time of publication of this research, Kwac's proposal has not yet been applied to real DR programs to assess or validate performance.

In the study of Jang et al. in which load variability indices were used, the high load variability was found as a useful indicator of high impact in response to price signals in a 2013 study conducted in South Korea. The study was based on a two-month critical peak pricing program with 802 commercial and industrial customer participants. The participants received notice of upcoming events on a day-ahead basis via phone, message, email and through the utility website. The response to the signal under this program relied on the customers' change of end-use routines without utility provider controlling on the end-use equipment.

Case Study Data – Southern California Edison Commercial Demand Response Program

This case study implements a load profile clustering method in the Southern California Edison (SCE) Summer Discount Plan – Commercial (SDP-C) program. SDP-C is a central air conditioning direct load control (DLC) program for commercial and industrial customers. For each enrolled customer, a DLC device was installed free of charge on or near the outdoor compressor of the central air conditioning unit. SCE can remotely cycle the unit during the demand response events by sending a signal to the DLC device. Different plan options were available for the customers to allow different control levels by the utility.

From the record of 2016-2017, 15-min load data were available from 11,656 customers in eight climate zones (3058 in cool zones, 5550 in moderate zones, and 1556 in hot zones). This report focuses on climate zone 14 – a hot zone with 702 customers and also the hot zone with most customers. Given that most DR events were in summer a hot zone with most customers was selected for the exploration as a representative case for most reduction of A/C usage during DR.

Chapter 2 describes the process of clustering based on 24-hour load data. The identified load shape clusters and the metric to capture load shape variability are also presented in this chapter. Chapter 3 develops classification models to link the load shape clusters and variability to the impact of DR events. Chapter 4 presents the important load shape features that indicate positive/negative DR impacts. Chapter 5 describes the conclusion and next steps.

2
CLUSTERING

Preparing Daily Load Profiles

Daily kWh load data in fifteen-minute intervals were compiled into normalized hourly load profiles. In the normalization process, each hourly consumption data was divided by the average hourly consumption of the same day. For a given hour h on day d, the normalized load $\hat{a}_{h,d}$ was calculated as:

$$\hat{a}_{h,d} = \frac{a_{h,d}}{\frac{1}{24}\sum_{t=1}^{24} a_{t,d}} \quad \textbf{Eq. 2-1}$$

Where $a_{h,d}$ the original hourly consumption, and denominator is the average load over 24 hours of the same day. The value of normalized load $\hat{a}_{h,d}$ < 1, =1, or >1, corresponds to the load of this hour lower, equal, or higher than the average value. The highest normalized load value of a day is also the inverse of the load factor of the day.

The rationale behind the normalization is to prevent the differences of consumption levels from overwhelming the differences of the load shapes in the clustering process.

Clustering

For each customer, load profile of one day was treated as one sample for clustering. The features in climate zone 14, data included 702 customers from April 2016 to July 2017. K-means clustering was applied to the daily load profile samples. The normalized hourly loads of 24 hours in a sample (i.e. a day) were treated as cluster features, i.e. the clustering process quantified difference and similarity between the samples based on the normalized 24 hours loads.

The clustering process output the centers of the identified clusters, each of which represented the mean of the load shapes that were identified to belong to the center. The rest of this report refers to the identified clusters as load shape types.

Load Shape Types

Ten types of load shapes were identified in the samples of daily load profiles, as shown in Figure 2-1. For ease of reference within this report, the load shape types are described as follows, with a naming convention derived based on their peak properties:

Morning peak: the load profiles in the "morning peak" cluster have a sharp peak before 12pm followed by a dramatic drop after 12pm and then remaining flat at the level of about half the magnitude of the average load of the day (i.e. normalized load ~ 0.5).

Mid-day peak: this type of load shape is characterized by the peak round 12pm followed by a gradual drop in the afternoon.

Early afternoon peak: load of this type slowly climbs up from 6am in the morning, peaks at around early afternoon, and drops during the late afternoon.

Late afternoon peak: this type of load shape has relative low consumption during the day but has sharp peak in the late afternoon around 5-6pm.

Early evening peak: this type of load shape is similar to the "late afternoon peak" shape but with the sharp peak occurs around 7-8pm.

Daytime plateau: the consumption is higher than the average hourly consumption between 7am – 5pm. The load remains at an evenly high level in late morning, noon and early afternoon.

Afternoon foothill: the type of load shape does not have an obvious peak. The load slowly increases from the morning and reaches the highest consumption in afternoon. The hourly load level ranges between 0.5 to 1.5 times of the average hourly load of the whole day.

Flat load: the load shape of this types has an evenly loaded level throughout the whole day.

Daytime basin: the consumption is evenly at low level during the daytime and at high level during nighttime.

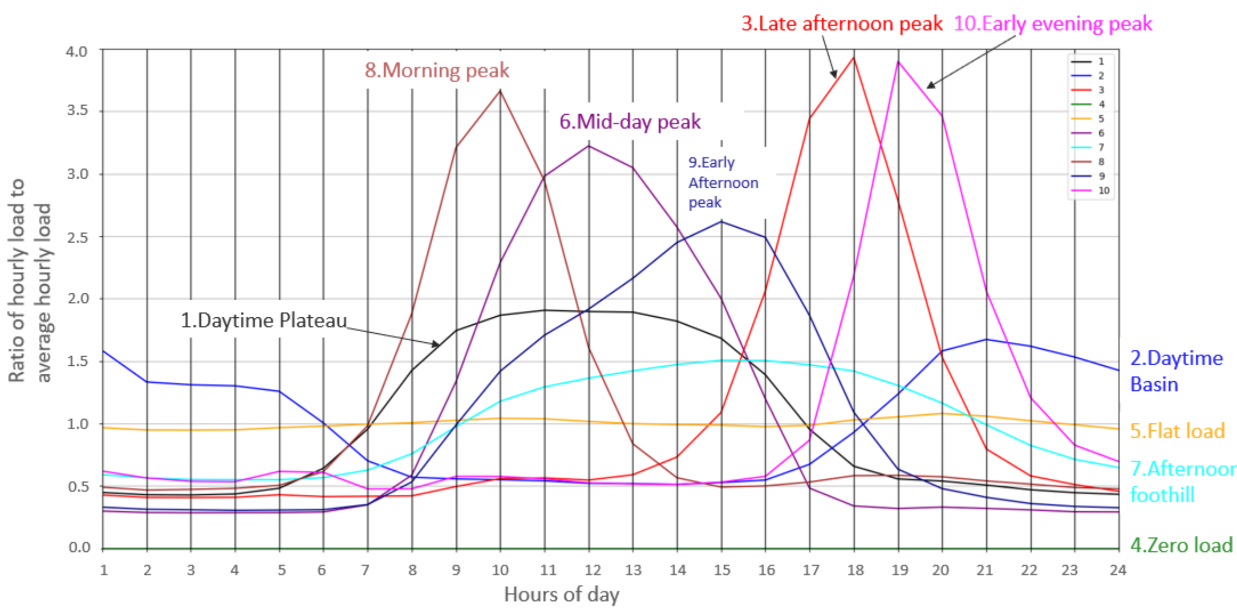

Figure 2-1
Load shape types identified by clustering based on normalized 24-hour daily load profiles

Load Shape Variability

A customer may have different types of load shapes on different days of the week in different seasons. To capture the load shape variability of a customer, the concept of *entropy* in information theory is used to quantify how the days of a customer are distributed over the different types of load shapes (the same method was used in Kwac et al. in [2]). The calculation of the load shape entropy for each customer is described below.

For the N types of load shape (N=10) $s_1, \ldots, s_N$, suppose a customer labeled as i has the probabilities of $P_{i,1}, \ldots, P_{i,N}$ to respectively have the N types of load shapes in the weekdays of June – September 2016 and 2017, i.e. the periods when the DR events occurred. The entropy E_i of the customer i is calculated as:

$$E_i = -\sum_{n=1}^{N} P_{i,n} \log P_{i,n} \qquad \textbf{Eq. 2-2}$$

An entropy value of 0 indicates the customer only stays in one type of load shape for all days. Higher entropy value indicates higher variability – more types of shapes occurs in the customer's history and/or the occurrence of the types are distributed more evenly over the history.

3 CLASSIFICATION MODEL

Measuring Customer-Specific Demand Response Impact

Baseline model

The measure of demand response impact was based on the reduction of consumption during demand response hours, as in Equation 3-1.

$$r_{DR} = a_{h,baseline} - a_{h,actual\ DR}, \text{for each } h \text{ in demand response hours} \qquad \textbf{Eq. 3-1}$$

$a_{h,baseline}$ is the load consumption of hour h in the baseline estimation. $a_{h,actual}$ is the actual load consumption of hour h recorded on the day of a demand response event.

This study used a within-subject baseline, calculated by averaging the load consumption of two most recent days with the same day-of-week of the same customer, then multiplying by a day-of factor. The day-of factor was used in SCE Scheduled Load Reduction Program for non-residential customers, in which the day-of adjustment is a ratio of the 4 hours prior to the event to the average load of the same hours from the baseline.

Several rationales are behind the approach. First, the dataset did not provide the control group of customers that match up with the participating customers, therefore the baseline was based on within-subject consumption. Second, commercial customers may have different load shapes on different day-of-weeks, therefore the baseline referenced the same day-of-week. Third, the day-of factor was one approach that SCE had used to adjust the baseline in summertime Scheduled Load Reduction Program.

Significance

Significance testing was used to justify whether the load reduction is likely due to the reduction from the load which "would have been" (the baseline load), other than just the fluctuation across the same day of week. A set of "reference" samples was generated, which was populated with the errors generated by applying the baseline model to the non-DR days with the same day-of-weeks of the DR days. For example, if there is a DR day as Wednesday, the reference samples also included other non-DR Wednesday.

For a given customer, the samples of reduction on DR days were tested against the samples of error on the non-DR days. The DR reduction was considered significant only if the DR reduction significantly differs from the error of the baseline at the P value level <0.05. The Kolmogorov-Smirnov two-sample test was used for the testing and obtaining the P value. Kolmogorov-Smirnov two-sample was a method for testing significance of difference between two sets of samples without knowing the distribution of the samples [5].

Input and Output

The modeling process used 12 features observed in the period of June-September:

- The average daily load across the weekdays
- The probabilities that a customer has each of the 10 types of load shape
- The entropy of the load shape types distribution

Each customer sample in the model fitting was labeled as "positive" or "negative". "Positive" means that the customer has an average positive reduction (i.e. baseline load higher than actual load in DR hours) with significance level <0.05. "Positive" includes the cases of "Significant negative", "negative but not significant", and "positive but not significant". Under this categorization, about 10% customers were labeled as "Positive" in Zone 14.

Given the input of a customer's features, the output is a propensity probability that represents the likelihood of being a "positive" customer. Next, two classification models are introduced, a logistic regression model that captures the main effects of each load shape and a classification tree model that enables interactive effects between features.

Logistic Regression Model

For each customer sample, logistic regression fits a propensity probability function given the set of 12 feature values, labeled as $x_1, \dots, x_{12}$., mathematically written:

$$P = \frac{1}{1+\exp-(\beta_0+\beta_1 \cdot x_1+\cdots+\beta_{12} \cdot x_{12})} \quad \textbf{Eq. 3-2}$$

Where β_0 is the intercept term of a linear model component, and $\beta_1, \dots, \beta_{12}$ are weights on the features representing the effects of each feature on the output probability. The linear component is often referred to as "decision function". The higher value the decision function has, the closer the propensity probability approaches 1 while lower value results in a probability approaching 0. The estimates of the feature weights can show whether the feature has a positive or negative effect.

Classification Tree Model

The classification tree model is trained by searching among the features to find the most information gain by branching, such that the positive vs negative samples can be separated as much as possible using a sequence of feature checkpoints. The benefit of a classification tree model is that it can automatically identify interactive features and hence can improve the predictive power. For example, if a load shape is a good indicator only if it is at some kWh level, this model can show that without knowing it in advance. Figure 3-1 illustrates a simple example of a classification tree, which has three feature checkpoints, leading to the end leaves as the probabilities of being positive in the bucket of samples that pass the same feature checks along the path to the same end leaf.

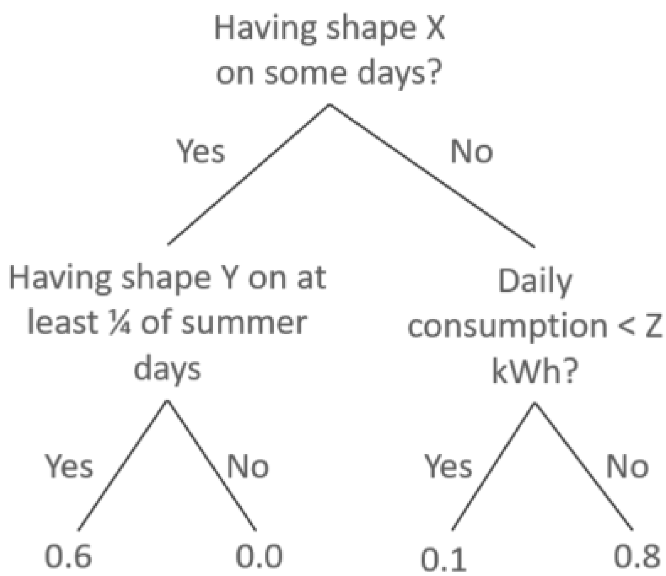

Figure 3-1
Example of classification tree

Training Set and Test Set

Overfitting is a phenomenon in which an over-complex model is developed to fit a particular set of data for training and fails to fit additional data. Overfitting will undermine the reliability of a model to well perform in new data. The typical machine learning approach to detect overfitting is to divide the pool of available samples into a training set and a test set with sample sizes approximately 2:1 respectively. The logistic model and classification tree model were trained using the training set and the predictive performance was validated in the test set.

For the logistic regression model, the training means optimizing the fixed number of parameters in Equation 3-2 to fit the data. For the tree model, the tree can keep branching until each "leaf" is one sample, a stopping rule is needed to prevent overfitting. The complexity of the tree structure increases to maximize the predictive power in the training set and test set until the predictive power in the test set started to decrease.

4

MODEL RESULT AND DISCUSSION

Feature Main Effects

Logistic regression model estimated the main effects of the load features – average daily load in summer, the probabilities of occurrence of the 10 types of load shapes in summer, the load shape entropy (likelihood to switch between different load shapes). Figure 4-1 shows the features that have significant effects on the outcome of positive/negative DR impacts, ranked by the magnitude of the weights on the features (the estimates and statistics are also summarized in Appendix A). The top significant effects are the feature related to negative impact, i.e. negative weights. Entropy and early afternoon peak and average daily load have the top positive effects.

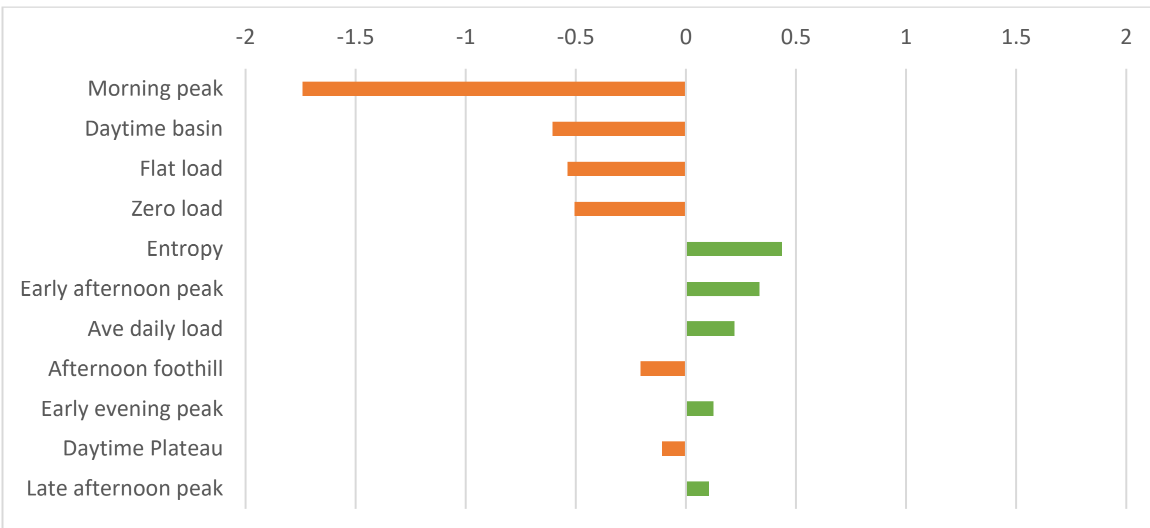

Figure 4-1
Significant positive and negative effects sorted by the magnitude of the effect

Features of Negative Effects

Five load shapes features are indicators of negative candidates, which are described below. Each load profile shown is the mean of the customer load profiles that belong to the same cluster.

- **Morning peak**
  Morning peak is the strongest indicator of the negatives. This may be due to the DR hours all occurred in the afternoon. The more often the load shape only has high consumption in the morning and flat in the afternoon, the more likely the customer is a bad candidate.

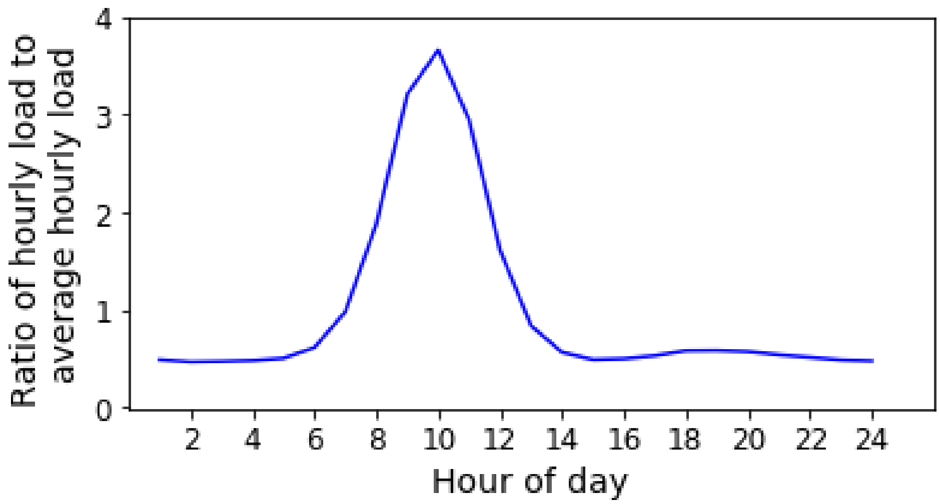

Figure 4-2
Load shape of morning peak

- **Daytime basin**
  The daytime basin pattern indicates that the customer used about half of the average hourly load of the day while in the evening after 8pm and the usage tripled the consumption during the day.

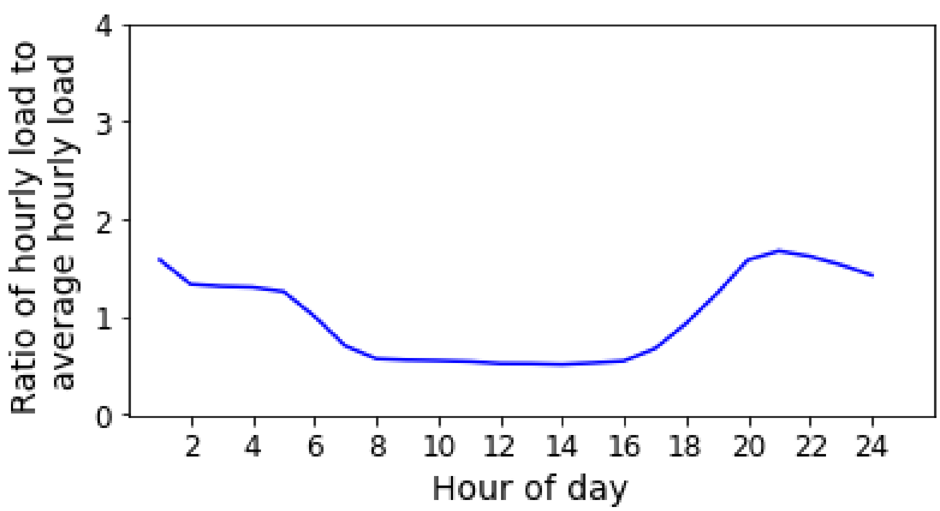

Figure 4-3
Load shape of daytime basin

- **Flat load**

  Customers who showed flat load consumed electricity evenly throughout 24 hours. Flat load may indicate HVAC not in use, thus automatically turning off the HVAC may not be effective for this type of customers.

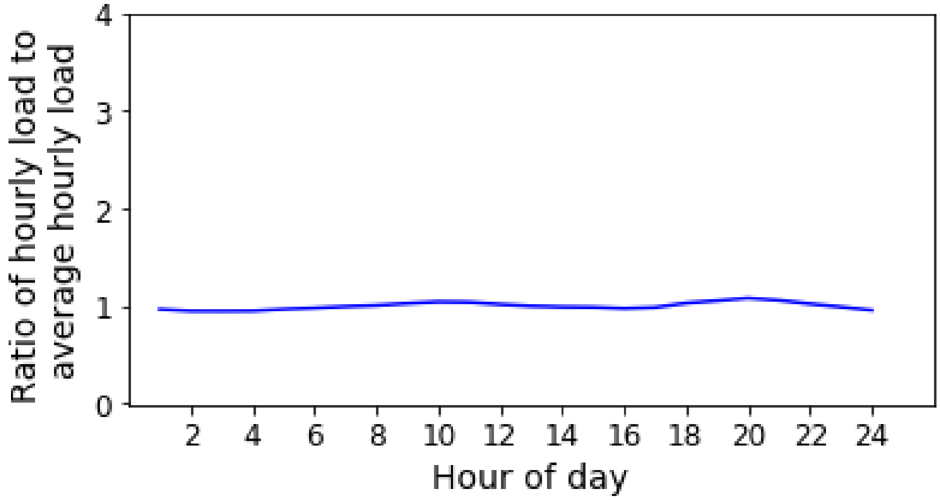

Figure 4-4
Load shape of flat load

- **Zero load**

  More frequently a customer has zero consumption throughout a day, less room for the DR strategy to make reductions.

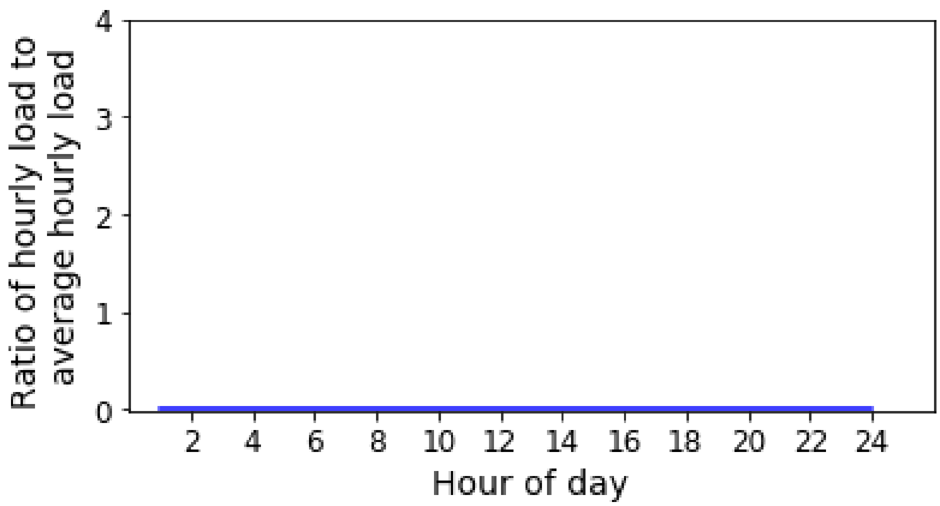

Figure 4-5
Load shape of zero load

- **Afternoon foothill**

  Afternoon foothill pattern has slightly higher consumption in the afternoon and even consumption in the night and early morning. The afternoon foothill does not have a sharp peak pattern and has a weak negative effect DR impact.

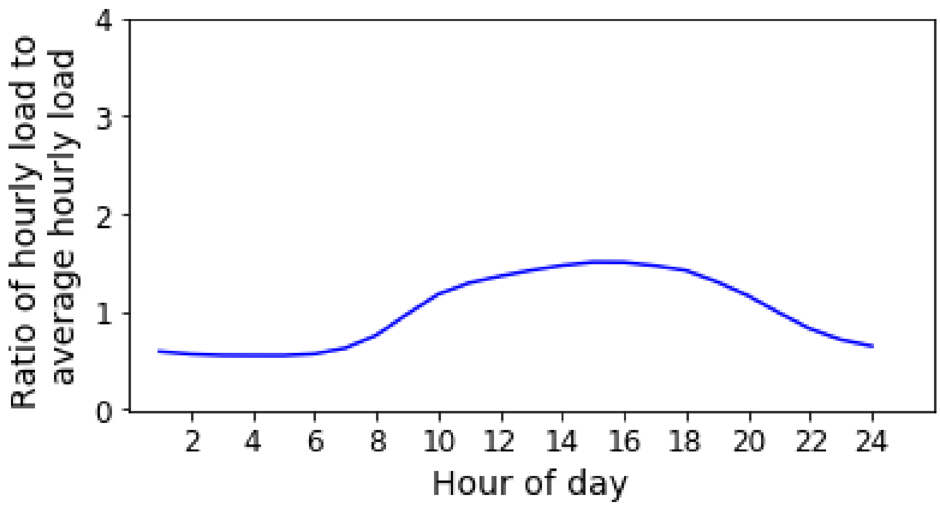

Figure 4-6
Load shape of afternoon foothill

- **Daytime plateau**

  Daytime plateau refers to the load shape that slowly climbs up after 6am then maintains about the same high level during 9am-4pm, then slowly drops.

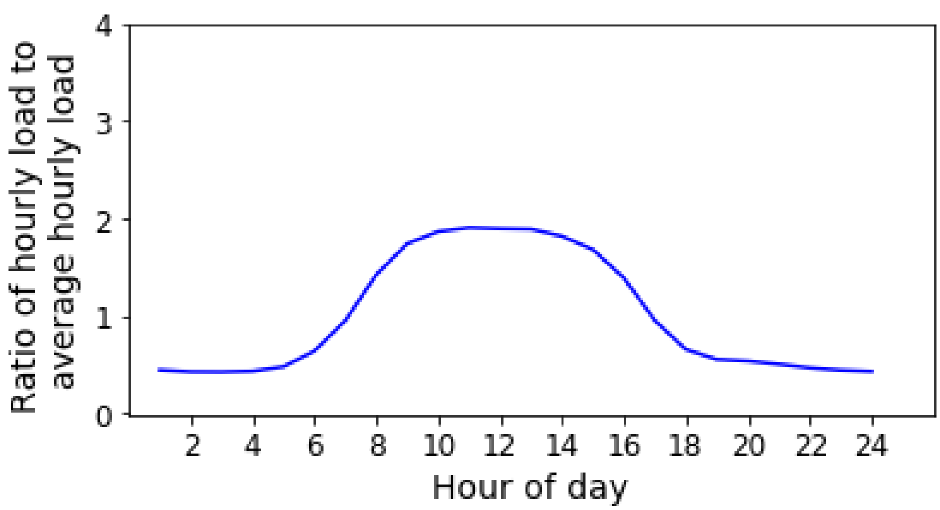

Figure 4-7
Load shape of daytime plateau

Features of Positive Effects

Load shape entropy, summer average daily consumption and three load shapes were identified as features that indicate good candidates.

- **Load shape entropy**

  Load shape entropy shows as the top feature among the positive effects. That is, the variability of load shape and the switch between load shapes helps identify positive candidates. But magnitude of the effect is behind the negative indicator shapes.

- **Average daily load in summer**

  High daily consumption is among the features of a positive effect. This may due to low daily consumption in the summer and may indicate less running of the HVAC.

- **Early afternoon peak**

  Load shape with this pattern has increasing load from around 6am. Between 2-4pm, it reaches the peak at about 2.5 times of the average hourly load of the day. The high consumption period overlaps with the early period of DR hours in the events starting at 3pm.

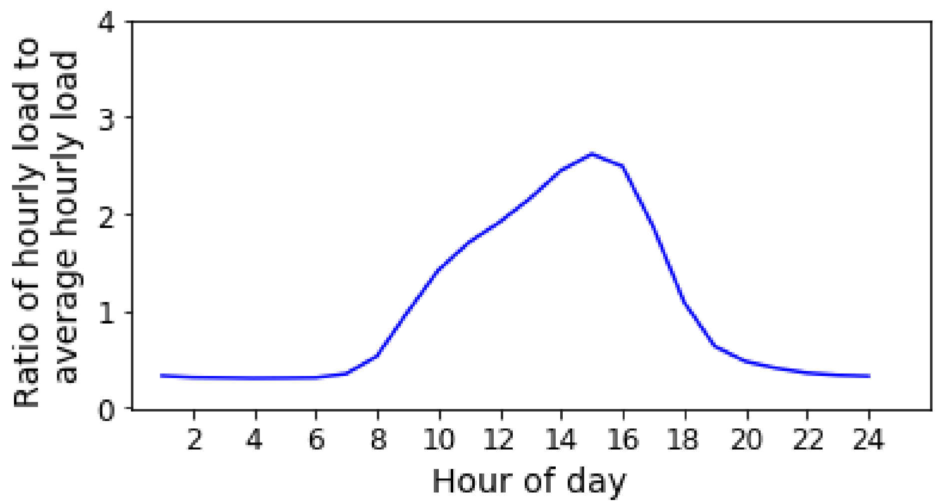

Figure 4-8
Load shape of early afternoon peak

- **Early evening peak**
  The shape of early evening peak is characterized by the sharp peak load between 7-8pm, which is often a period overlaps with the tail of a DR event.

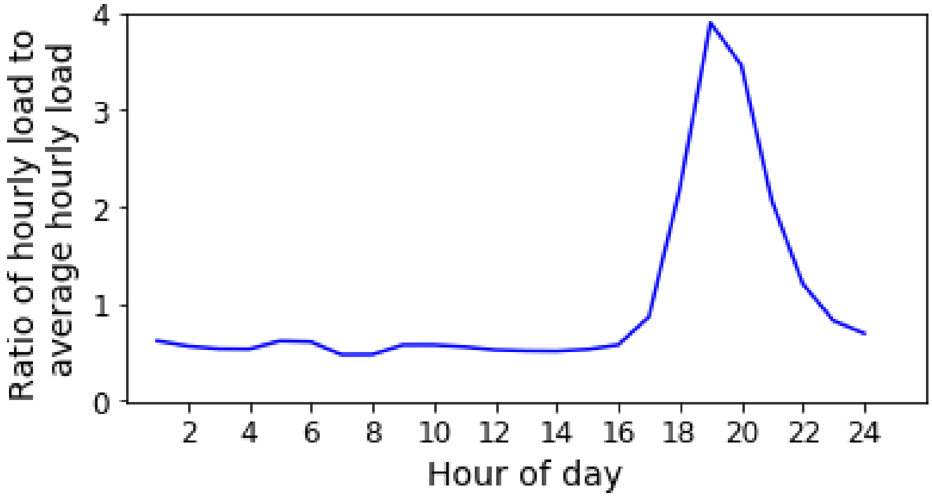

Figure 4-9
Load shape of early evening peak

- **Late afternoon peak**
  The shape of late afternoon peak is similar to the early evening peak, but the peak occurs between 5-6pm, which overlaps with the mid-period of typical DR events.

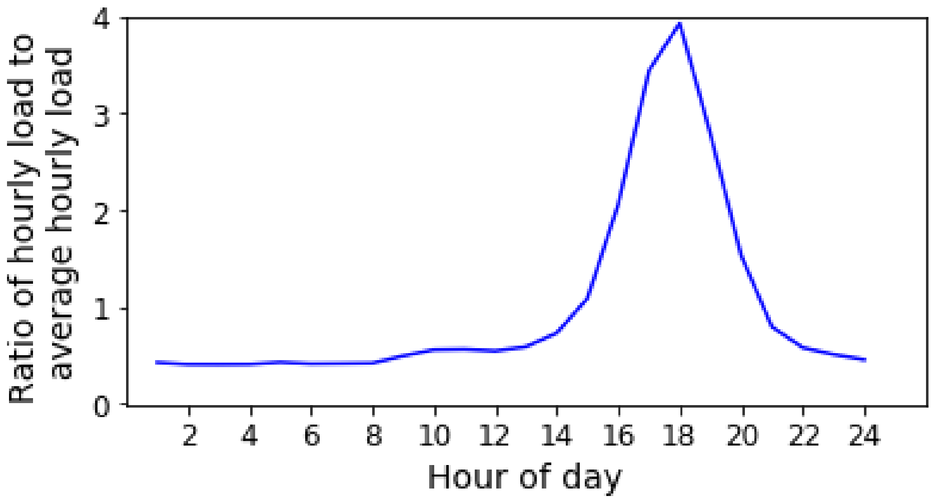

Figure 4-10
Load shape of late afternoon peak

Classification Model Performance

In addition to the logistic regression model, a classification tree model was built to explore the interactive power between features, if there is any. Classification performance of both models was evaluated in the training set and the test set. The Receiver Operation Characteristics (ROC) diagram, Figure 4-11, is used to visualize the model capability to identify positive samples at the same time avoiding false alarms. Table 4-1 explains the true positive and false positive rate in the ROC diagram. The true positive rate (TPR) captures the capability to capture the positive samples. The false positive rate (FPR) captures the false alarm. Good prediction should maximize the true positive identification without increasing the false alarm (i.e. the ideal performance would display on the upper left corner in the ROC).

Suppose a model outputs a propensity score between 0.0 to 1.0 for each sample in a dataset, a criteria propensity score can be set to separate between “positive” and “negative”. For example, >0.5 identified as positive and <0.5 as negative or using a more relaxed criteria to tolerate false alarms, such as >0.3 identified as positive and <0.3 as negative. Given a decision criteria, one pair of TPR and FPR can be obtained. The ROC curve is a trace of TPR and FPR as the decision criteria moved from 0.0 to 1.0, with x-axis as FPR, and y-axis as TPR The perfect predictive performance means the positive/negative samples are completely separated using the model, i.e. achieving identifying all the positive samples (100% PTR) and at the same with zero false alarm (0% FPR), mapping to the up left corner of the ROC diagram.

Indicators of bad performance are low TPR or high FPR. An extreme example is that predicting all samples as positive would capture all true positives (100% TPR) but mistake all the negatives as positives (100% FPR). If predicting all samples as negatives would miss all positives but generate zero false positives.

Table 4-1
The calculation of true positive rate and false positive rate

		Data Observation	
		True	**Negative**
Model Prediction	True	True Positive (TP)	False Positive (FP)
	Negative	False Negative (FN)	True Negative (TN)

$$\text{True Positive Rate} = \frac{TP}{TP + FN}$$

$$\text{False Positive Rate} = \frac{FP}{FP+TN}$$

Figure 4-11 compares the ROC diagrams of the simple logistic regression model (only capturing main effect of individual features) and the more complex classification tree model (capturing interactive effects between features). The closer a curve to the up-left corner in the coordinates, the better performance the model has. The overfitting, if any, will be indicated by the ROC in training closer to the ROC in the testing.

The classification tree model fits better than the logistic model in the training set. The tree model can achieve about 90% true positive rate with only 20% false positive rate, while the logistic regression model is able to identify about 55% true positives given the same level of false positive rate level. However, the tree model significantly overfits. In the test data set, the tree model drops to about 55% true positives at 20% false positives, performs similarly as the logistic regression model. In the test data set, both logistic model and decision tree model can identify about 90% true positives at the level of 50% false positives.

Considering overall the tested performance, overfitting, complexity and interpretability, the regression model is a practical approach worthwhile to generalize in the future application, given that has much simpler structure and straightforward interpretation of the effect of each feature.

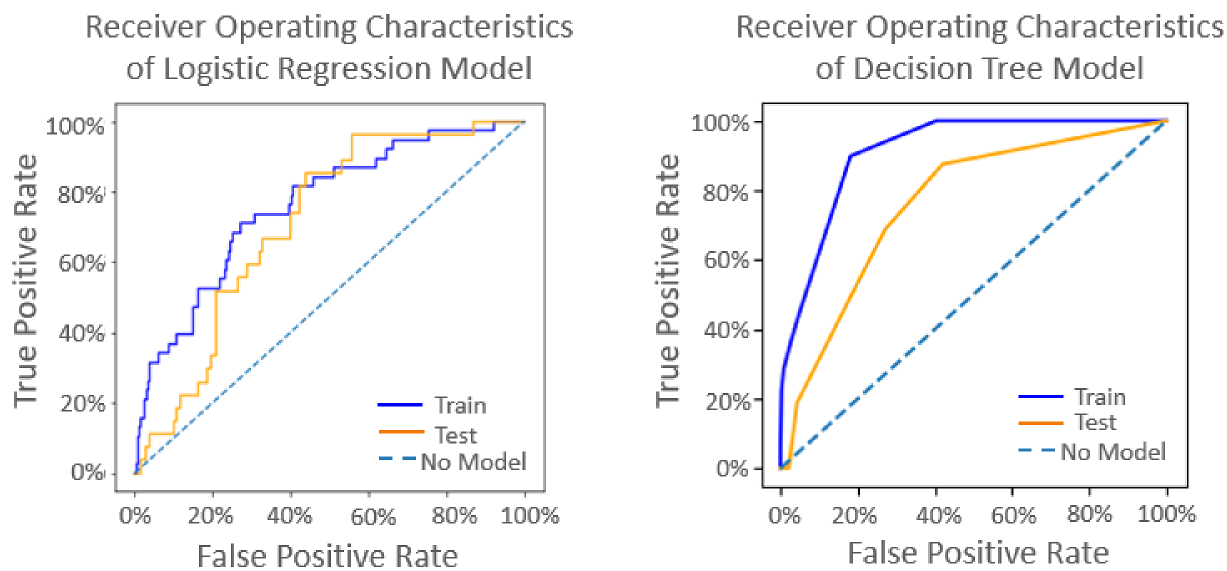

Figure 4-11
Model performance in training set and test set. Left: Logistic Regression Model. Right: Classifcation Tree Model

5 CONCLUSION

This study explored the use of load shape clustering and load shape variability to identify potential candidates for demand response programs. A dataset from SCE commercial demand response program were applied. This study approached clustering similarly to the work of Kwac et al. in 2014, which clustered customers based on 24-hour load data and used information entropy to quantify load shape variability.

This study found that not only the load shapes but also the timing of the peak is important to identify good candidates. The demand response program used direct control of HVAC during the events which mostly occurred after 3pm and before 8pm. If a customer usually did not use heating or cooling during DR hours, the control would not be effective on reducing load consumption. Thus, the timing of high consumption of a day was observed to be important. The load shapes identified as positive indicators all have peak hours overlapped part of DR event periods (such as afternoon peak and early evening peak), while the negative indicators did not have high consumption during the DR periods (such as morning peak, flat load, daytime basin, daytime plateau).

This study also found that load consumption and load variability are two important indicators. Higher load consumption and higher variability of switching between load shapes point to more likely DR candidates. Consumption and load variability also appeared in the previous literatures as positive features, which our finding is consistent with. However, avoiding the bad indicator load shapes were found to be more important – features of negative effects were estimated to have higher weights in the logistic model than positive features.

The clustering method in this study is generalizable in other DR targeting studies, or other customer segmentation research in which customer specific load shape plays as an important influencer of the benefit, cost, and efficiency for the customer or utility. Different customer populations are likely to generate different representative clusters. Thus, the clusters found in this study may not fully represent a different customer population. However, the lessons learned about the coincidence of peak periods and DR periods are still applicable. The generalizability of learnings also depends on the mechanism of different programs. This study has a context of HVAC control mechanism, which is different from the behavioral programs that signal customers to shift the end-use routines. Therefore, the clustering and load variability method could apply but would need tailoring for the program mechanism.

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LOGISTIC REGRESSION ESTIMATES

Logistic regression was used to capture the main effects of the features – average summer daily load, load shapes and load shape entropy (likelihood switching between load shapes). Table A-1 summarizes the coefficients and significance of the logistic regression estimates. All features have significant level <0.05 except the mid-day peak load shape.

Table A-1
Logistic regression estimates

Feature	Coefficient value	Standard Error	t	P value
Const	-2.1503	0.0735	-29.2743	0.000
Average daily load	0.2196	0.0112	19.5255	0.000
1.Daytime plateau	-0.1074	0.0374	-2.8734	0.004
2.Daytime basin	-0.6045	0.0336	-17.9898	0.000
3.Late afternoon peak	0.1029	0.0413	2.4917	0.013
4.Zero load	-0.5044	0.0819	-6.1600	0.000
5.Flat load	-0.5381	0.0447	-12.0332	0.000
6.Mid-day peak	-0.0079	0.0376	-0.2094	0.834
7.Afternoon foothill	-0.2056	0.0456	-4.5127	0.000
8.Morning peak	-1.7399	0.0370	-47.0342	0.000
9.Early afternoon peak	0.3342	0.0387	8.6361	0.000
10.Early evening peak	0.1253	0.0460	2.7246	0.0066
Entropy	0.4352	0.0503	8.6552	0.000

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