Development and Clustering of Rate-Oriented Load Metrics for Customer Price-Plan Analysis

Preprint

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Development and Clustering of Rate-Oriented Load Metrics for Customer Price-Plan Analysis

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***Abstract*—One of the few methods electric utilities can use to motivate and change customer energy consumption is through retail rate structures. Utilities are increasingly moving toward more dynamic rate plans to encourage energy conservation, utilization of onsite renewable generation, peak demand reduction and flattening of demand profiles. This paper creates a set of rate-oriented load metrics that are the determinants of customers' bills under four unique rate plans. These metrics are not only indicative of which rate structure can provide customer bill reductions based on their load profile characteristics, but also convey useful information about load consumption behavior. With these metrics, utilities can analyze their customers and identify classes that are rewarded under each rate plan. This can help inform utilities whether the customers rewarded under each rate plans are meeting their original objectives. To develop these customer classes, we calculate these rate-oriented load metrics for each customer and perform k-means clustering. The analysis is conducted on a set of 300 customer profiles, examining four different rate plans, different numbers of clusters, customer bills and cluster load profile characteristics.**

***Index Terms*—Customer Clustering, Distribution Networks, Load Analysis, Price-Plans, Retail Tariffs**

I. Introduction

Major changes on the demand side— the adoption of distributed energy resources (DER), increased levels of automated demand response, and the adoption of smart-meters— are challenging the use of flat-retail rates for electricity. Increasingly, utilities are transitioning away from the traditional model for pricing electricity consumption historically priced at a flat rate per unit of energy consumed ($/kWh), towards time-varying rates structures. These time-variant, or dynamic pricing structures, include time-of-use pricing (TOU), day ahead pricing (DAP), real-time pricing (RTP) and critical peak pricing (CPP) and have been identified as a tenet of demand response [1]. Further, these rate structures have been used to motivate the use of self generation and decarbonization [2].

These new tariff schemes have been designed with the intention to help decarbonize the electricity system, and they have implications for behind-the-meter renewable generation adoption, energy efficiency, and cost recovery for utilities [2]. The design of future tariffs, both for the consumption and production of electricity by customers, will have a major impact on the uptake of DER [3]; however, studies have repeatedly shown that the demand side can be considered price inelastic, meaning that consumer behavior will not have a large reaction to these price plans, with studies showing demand exhibiting a short-run same-year price elasticity of -0.1 [4]. Studies of TOU introduction in Ontario, Canada, have shown only moderate responses with on-peak and mid-peak reductions, when controlling for weather, of -2.6 % and -2.5 % respectively [5]. Although TOU pricing has been shown to motivate energy conservation, studies of TOU in the Northeastern United States have not been shown to produce evidence of load shifting, with roughly proportional decreases in on-peak and off-peak electricity usage [6].

Given that customers exhibit an inelastic response to time-varying price signals, i.e. a poor response to changes in price, the main determinant customer bills will be their existing energy usage patterns and consumption. Much research has focused on clustering customer profiles to help identify customer archetypes and distinguish customer classes. This research has included k-means, k-medoid, and self organizing maps to cluster smart metering data and provide information on energy segmentation [7], [8]. Clustering techniques have also been used to determine the drivers of energy consumption, and to identify statistically representative load profiles [9]. In [10], customers are clustered based on their load profiles to identify different classes, including industrial and commercial customers, and they use these clusters for tariff design.

Most clustering research to date has performed the analysis based on load profile shapes and load metrics. These load metrics—including peak demand, diversity factors, after-diversity maximum-demand—have traditionally been used in distribution planning [11], in particular for sizing and evaluating the performance of distribution network service transformers [12]. Although important for distribution planning and operation, many traditional load metrics have little to no impact on customer bills, even under time-varying retail rates. For example, customers are not charged directly based on their instantaneous peak demand, although this has an important impact on the capacity requirements in distribution networks.

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The introduction of time-varying rates has the impact that some customers will be financially rewarded based on the characteristics of their time-varying consumption profiles due to their natural preferences and appliances used, rather than the price response they exhibit, which is the focus of this paper. In this paper, we create load metrics specifically related to customer payments under a set of defined retail structures, namely, flat-rate tariffs, incremental step rates (also known as inclining block rates), TOU tariffs and time-of-use tariffs with a demand charge component (TOUD). Clustering is then performed on a set of customers for these metrics to identify customer classes that are most suited to each tariff scheme and to identify the type of customer class that utilities are financially rewarding by examining each customer's levelized cost of electricity. These metrics are used as they are the direct determinants of customer bills - allowing the clustering to reveal the types of customers who are rewarded under each rate-plan rather than traditional clustering on load profiles that is independent of bill determinants.

To illustrate the developed methodology, a publicly available data set of 300 customers with residential load and photovoltaic (PV) profiles from Australia is used [13], [14]. The four pricing schemes used are set such that the average customer from the entire set of customers has the same bill under each pricing signal, ensuring the pricing schemes are equitable.

The key contributions of this paper are as follows:

- Creation of the key rate-oriented load metrics that are the determinants of customer bills
- Clustering analysis of customer load profiles based on rate-oriented load metrics.
- Using these tools for mapping of customer characteristics to utility rate plans and analysis of the objectives of rates coupled to the customer profiles they reward.

II. Methodology

The methodology clusters customers to determine the characteristics of those who perform best under each of four unique rate structures; flat-rate, inclining step rate, TOU rate, and TOUD. The clustering is not performed directly on load shapes or traditional distribution network load metrics rather on the direct attributes that impact customer rates for which a set of rate-oriented load metrics are created. This section explains in details the structure and billing under each of the four rate plans under study, identifies load metrics based on those attributes, and outlines the clustering methodology.

A. Determinants for Rate Designs

Traditional load metrics—such as diversified maximum demand, non-coincidental maximum demand, peak-to-average ratio—are not direct determinants of customer bills despite these metrics being crucial for distribution planning and operation. The metrics that actually determine customer bills are identified here for each of four rate structures.

1) Flat Rate: Flat rate structures are the most basic and simple rate design traditionally employed by utilities. Under this structure, a single rate is charged for every kWh consumed by the customer. This \$/kWh price of electricity typically lumps both the charges for fixed and variable utility costs — such as the capacity related to generation, transmission and distribution — with variable costs mainly being attributed to actual energy production. The customer bill, C, is then a function of the energy consumption for each billing period, E_t, for each time-step, t, across the entire billing period, T, multiplied by a fixed flat rate, c, see (1).

$$C = \sum_{t=1}^{T} E_t c \tag{1}$$

2) Inclining Step Rates: Inclining step rates are similar to flat rates and were introduced and adopted as a default rate design by many utilities in an attempt to encourage customers to conserve energy. Under this design, as the energy consumption increases above a certain threshold, E_{thresh}, the pricing of that energy consumption shifts to a higher tariff, c_{block1} to c_{block2}, [15], presented here for a two-step inclining rate; see (2). For these rate designs, the bill is a stepped function of total energy consumption.

$$\begin{aligned} C = \textstyle\sum_{t=1}^{T} E_t c_{block1} \left[\sum_{t=1}^{T} E_t \leq E_{thresh}\right] + \\ \textstyle\sum_{t=1}^{T} E_t c_{block2} \left[\sum_{t=1}^{T} E_t > E_{thresh}\right] \end{aligned} \tag{2}$$

3) Time-Of-Use Tariffs: Utilities that wanted to motivate energy conservation and reduce peak consumption, facilitated by advanced metering infrastructure (AMI) and smart-meter rollouts started to move away from traditional volumetric pricing. Installation of AMI enabled utilities to record electricity consumption of a customer at defined time intervals in a day, instead of getting the total consumption at the end of the billing period. This infrastructure facilitated the introduction of TOU rate designs. This rate structure divided a day into two or three time blocks, depending on the utility, and charged a different rate for each block. For a three-rate tariff with a peak, shoulder and off-peak pricing periods, the customer would be charged a higher rate for peak usage periods, N_{peak}, and lower rates for shoulder, $N_{shoulder}$, and off-peak, $N_{off\,peak}$, pricing periods. This was done to encourage the customer to reduce usage during peak periods in turn reducing stress on the network. Hence, for TOU, the consumption during each of the time blocks is the determinant of the customer bill, here formulated for a three-period TOU, see (3).

$$C = \sum_{i_{peak}=1}^{N_{peak}} E_i c^{peak} + \sum_{i_{shoulder}}^{N_{shoulder}} E_i c^{shoulder} + \sum_{i_{off\,peak}}^{N_{off\,peak}} E_i c^{offpeak} \tag{3}$$

4) Time-Of-Use Tariffs with Demand Charges: More recently, to help recover fixed costs, some utilities have migrated to rate structures with a demand charge component in addition to the TOU structure [16]. The demand charge, c^{demand}, is applied to the peak demand, $P_{i\,peak}$, during the peak usage periods and generally is based on the highest corresponding kW consumption for a billing window over the peak demand period, giving a demand charge cost C_{peak}. The energy-based TOU component, $/kWh, for this design is less than the TOU only rate design to account for this. Customer bills for this rate design are determined by demand during peak period in addition to consumption in each time block.

$$C_{peak} = max(E_i : i_{peak}, ..., N_{peak}) * c^{demand} \tag{4}$$

B. Rate-Oriented Load Metrics

Based on the key determinants of customer bills under each rate plan we create a set of rate-oriented load metrics for clustering. For both flat rate and inclining step rates this component is simply the total energy consumption, E_{total}, which is used as our first metric. For TOU, having E_{total} captures the first element required, meaning that the actual peak energy consumption, E_{peak}, shoulder energy consumption, $E_{shoulder}$, and off-peak energy consumption, $E_{off\,peak}$, are not needed in addition, but rather their ratios are; see (5).

$$\begin{aligned} E_{total} &= \sum_{t=1}^{T} E_t \\ E_{peak} &= \sum_{i_{peak}=1}^{N_{peak}} E_i \\ E_{shoulder} &= \sum_{i_{shoulder}}^{N_{shoulder}} E_i \\ E_{off\,peak} &= \sum_{i_{off\,peak}}^{N_{off\,peak}} E_i \end{aligned} \tag{5}$$

As a result of having energy consumption as our first metric, the ratios of peak to shoulder, and off-peak to peak energy consumption are used as our next two key metrics; see (6, 7).

$$R_{peak/shoulder} = \frac{E_{peak}}{E_{shoulder}} \tag{6}$$

$$R_{peak/off\,peak} = \frac{E_{peak}}{E_{off\,peak}} \tag{7}$$

For TOUD, the maximum customer peak demand that occurs within the defined peak hour windows must be used. This is the final metric used in the clustering analysis; see (8).

$$P_{i\,peak} = max(E_i : i_{peak}, ..., N_{peak}) \tag{8}$$

These four rate-oriented load metrics —E_{total}, $R_{peak/shoulder}$, $R_{peak/off\,peak}$, and $P_{i\,peak}$—are the sole reduced determinants of customer bills on any rate structure and convey useful information on customer consumption behavior to rate design.

C. Clustering

To determine rate-plan customer classes clustering is used. Clustering is an unsupervised data mining technique that groups data objects based on defined attributes. Various techniques have been used for clustering customer load profiles, such as self-organizing maps, k-means, and k-medoids [7], [9]. In this work, k-means has been used to group customers based on the proposed load metrics. K-means is a partitional clustering method that aims to minimize the total distance of data objects from their cluster centroid, also known as sum of squared error (SSE). The number of clusters, k, is predefined in this method, so the data set is divided into k clusters, and the intra-cluster SSE is minimized by assigning a data object to its closest cluster centroid [17].

III. Case Study

For this analysis, a publicly available smart meter data set from an Australian distribution utility, Ausgrid, is used, that has both energy consumption and PV generation data available for 300 residential customers at half-hourly resolution [13], [14]. Calculating customer bills under the two original rate plans offered to customers, an inclining step rate and TOU tariffs, the pricing schemes were such that almost all the customers fared better when on a TOU tariff; see Fig 1, [13].

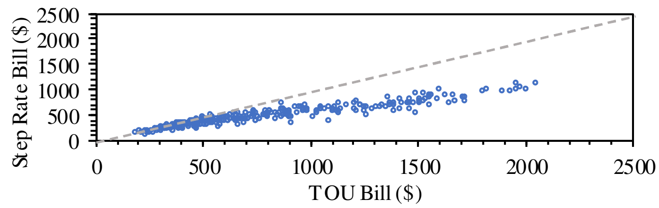

Fig. 1. Scatter-plot of each customers bill under the original time-of-use and step-rate tariffs, with a unity lined (dashed line) illustrate that customer bills were lower (beneath unity line) under the TOU plan. [14].

Four rate structures are considered; flat rate, inclining step rate, TOU rate, and TOUD. The 2010-11 Ausgrid inclining step rate pricing is used as a reference and the other rate structures are created such that the average customer's bill remains constant, ensuring the rate plans are equitable; see Table I. In terms of $/kWh prices all price-plans are comparable bar the TOUD, as traditionally utilities price the energy component much lower to cater for the demand charge. For all price-plans the average customer's bill was exactly $695.78 per year. The clustering analysis is presented solely for customer consumption patterns without solar PV. For TOU and TOUD the off-peak times are 00:00-07:00 and 22:00-0:00, the shoulder times are 07:00-14:00 and 20:00-22:00 and the on-peak times are 14:00-20:00.

IV. Results

We first examine the correlation between the created rate-oriented load metrics. If these attributes were highly correlated, either positively or negatively, this would indicate they did not provide unique information and would be poor for

TABLE I
PRICE PLANS

Price Scheme:	Details:
Flat-Rate	11.413 cents/kWh
Inclining Step-Rate	Step 1: 9.7814, Step 2: 15.1757 cents/kWh, Limit: 575 kWh
Time-of-Use	Off Peak: 3.0425, Shoulder: 6.4847, On Peak: 30.3113 cents/kWh
Time-of-Use with Demand Charge	Off Peak: 1.2376, Shoulder: 2.6377, On Peak: 12.3296 cents/kWh, On Peak Demand: 8.5674$/kW

clustering. For the created metrics, all except two pairs of attributes—E_{total}, $P_{i,peak}$—were poorly correlated (all < 0.6 Pearson correlation coefficient), indicating their suitability as attributes containing unique information.

The analysis performed k-means clustering on the rate-oriented metrics, compared for four clusters, one for each rate plan, and nine clusters, using a value close to the knee-point of the SSE plot cluster numbers. This was to see if there were four ideal customer classes for each rate plan or if there were a larger group of classes that shared attributes. The load profiles of the four cluster centroids are plotted in Fig 2 (a).

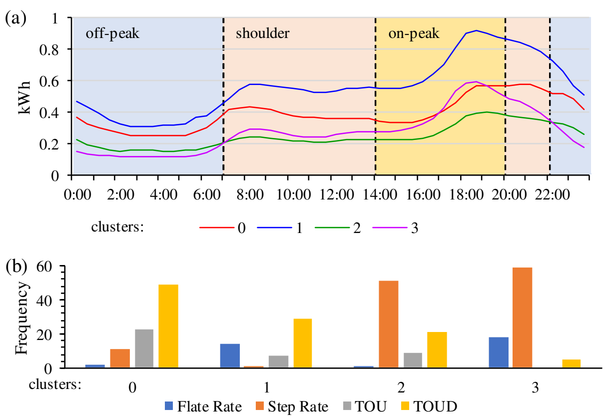

Fig. 2. Four cluster analysis examining (a) Load profiles of each cluster centroid, (b) frequency of price plan for the lowest bill for each customer for each cluster.

From the customer centroids and customer attributes, each of the four clusters had a unique load profile with distinguishing attributes, see Figures 2 (a) and 5. Some clusters had predominately lower bills on a single rate plan. For example, customers in cluster 3 performed best on the step-rate plan because a large fraction of their consumption was during peak hours, meaning they would have had higher bills on the TOU or TOUD plans, see Fig. 2 (b). Further, these customers were low-energy customers with the majority of their consumption priced at the lower component of the step-rate.

Cluster 2 and 3 have low-energy characteristics, but because they had a lower peak demand these customers also performed well on the TOUD. Cluster 0 features mid-consumption customers, but a lower peak consumption to off-peak consumption ratio, meaning they benefit from the low energy costs on

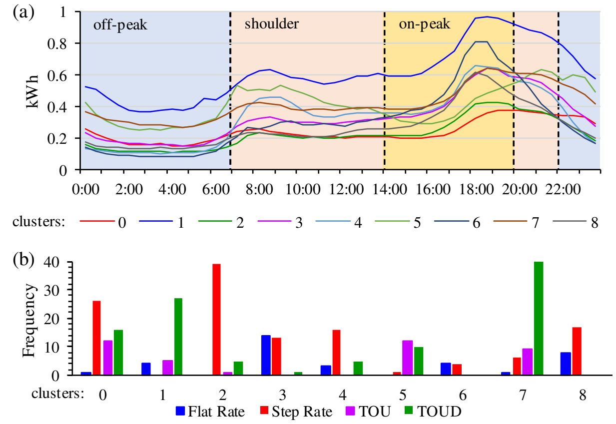

Fig. 3. Nine cluster analysis examining (a) Load profiles of each cluster centroid, (b) frequency of price plan for the lowest bill for each customer for each cluster.

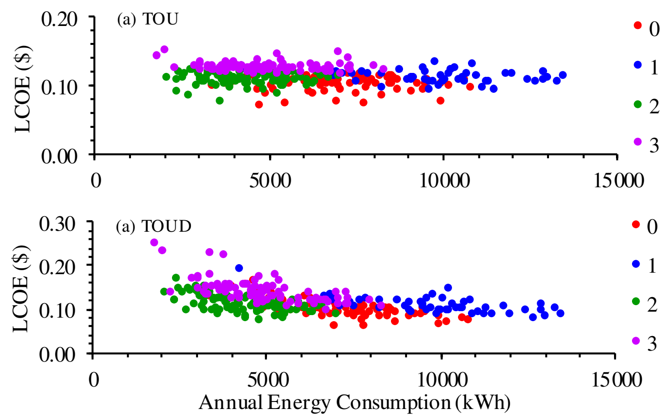

Fig. 4. LCOE of each customer in each cluster under (a) time-of-use (TOU) and (b) time-of-use with a demand charge (TOUD) for the 4 cluster analysis.

TOUD. Cluster 1 are high-energy consumption customers, meaning that these customers are not suited to the step rate as a majority of their consumption would be at a higher rate.

Comparing the four cluster analysis to that of nine clusters identifies that there are different customer archetypes who perform best on the same rate plan, e.g. clusters 0, 2, 4, and 8 who predominately perform best on the step-rate, see Fig. 3 (a), (b). This type of analysis allows utilities to identify the types of customer profiles that each rate plan is rewarding, and examine those against rate objectives.

For example, the TOUD plan was introduced by utilities to recover fixed costs and to reduce network peaks. However, due to the low energy costs of this price-plan, it actually rewards high-energy consumption customers best, and even those with high on-peak peak demands. This means that this plan does not motivate energy conservation. Looking at the levelized cost of electricity (LCOE) for the four clusters if all were under the TOUD (here compared to TOU), cluster 1, high-energy customers, would have levelized costs comparable to those lower energy consumption customers in clusters 0 and 2,

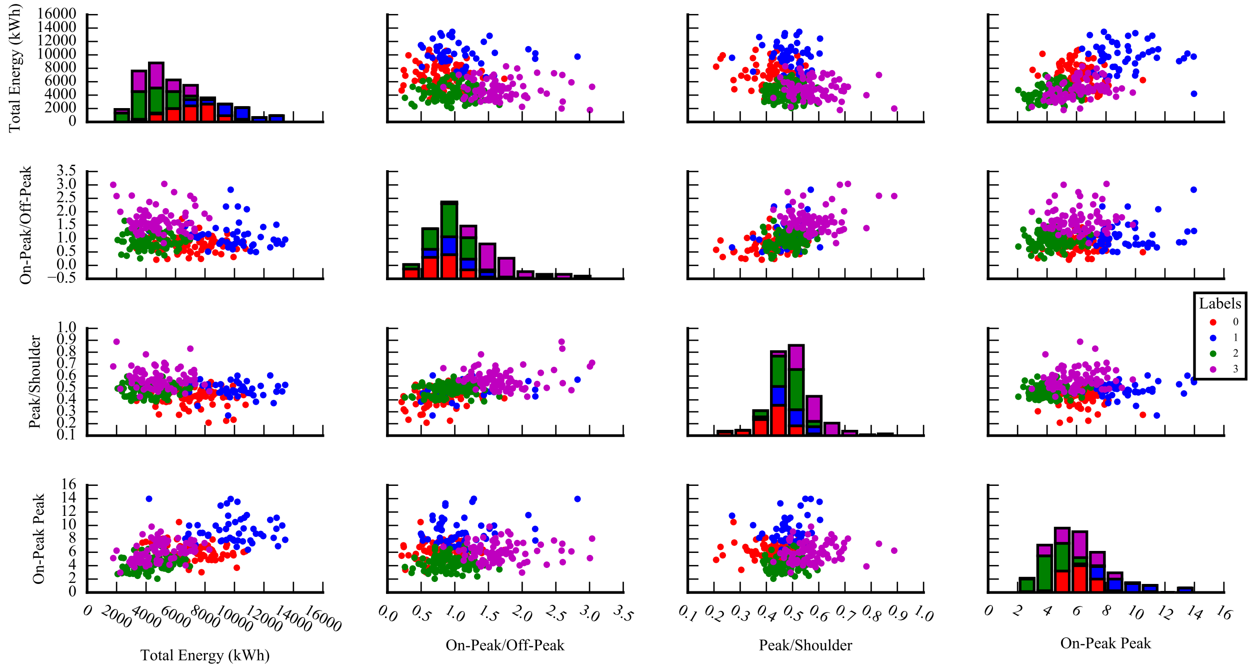

Fig. 5. Scatter plot relationship of each attribute for every customer in the 4 cluster analysis.

whereas customers in cluster 3, are penalized under this rate despite despite being mid-level consumption customers.

V. Conclusions

This paper presented a clustering and analysis framework to assist utilities in assessing the customers who benefit under each rate plan, based on a set of rate-oriented load metrics. These metrics are the key determinants of customer bills for four rate structures; flat rate, inclining step rate, TOU and TOU with a demand charge component. Clustering on these metrics, the resulting customer classes give information about which rate structure would be financially better for each customer and also enable the utility to study customer consumption behavior motivated under each rate structure. This paper highlights that utilities need to analyze whether the objectives of their rate-plans are linked to customer bill determinants to ensure that pricing structures financially reward the right customers and behavior. This analysis could be extended in future work to examine net load profiles in the presence of customer behind-the-meter DER such as solar PV and batteries, for that case the analysis would also have to include rate-oriented metrics that captured the different potential export tariff structures.

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