Applied Energy 302 (2021) 117543

Contents lists available at ScienceDirect

Applied Energy

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

Demand charges and user flexibility – Exploring differences in electricity consumer types and load patterns within the Swedish commercial sector

Vera van Zoest [a,*], Fouad El Gohary [b], Edith C.H. Ngai [c], Cajsa Bartusch [b]

[a] Uppsala University, Department of Information Technology, Division of Computer Systems, P.O. Box 337, SE-751 05 Uppsala, Sweden
[b] Uppsala University, Department of Civil and Industrial Engineering, Division of Industrial Engineering & Management, P.O. Box 534, SE-751 21 Uppsala, Sweden
[c] The University of Hong Kong, Department of Electrical and Electronic Engineering, Pokfulam Road, Hong Kong, China

HIGHLIGHTS

- Assessment of a demand charge on electricity consumption in the commercial sector.
- A clustering technique is applied to generalized electricity consumption patterns.
- Electricity consumption decreased after implementation of a demand charge.
- Effects of demand charge vary between cluster segments in the commercial sector.

ARTICLE INFO

Keywords:
Peak demand response
Commercial electricity consumption
Commercial peak demand
Clustering

ABSTRACT

Demand-based charges have been employed as a tool intended to reduce electricity users' maximum demand but there is a lack of consensus regarding their efficacy. One reason for this may be the diversity in the flexibility potential of different types of users. This study explores the flexibility potential of different types of electricity consumers in the small to medium-sized commercial sector (35-63A) in response to a compulsory demand charge. The objective is to characterize varying levels of flexibility with respect to different types of commercial users with different load patterns. A multivariate clustering technique was used to group commercial users with comparable load patterns based on a year of hourly data before the tariff change was introduced. This method was used to: (1) match users from the intervention area and reference area with similar load patterns, without losing any user data, and (2) compare how users with different load patterns react differently to the tariff change. We found clear distinctions in the types of commercial users in each cluster and their response to the tariff, demonstrating the extent to which demand flexibility may be dependent on the nature of an organization's activities and its respective load patterns. The highest demand flexibility was found in clusters which had a large share of users in the IT sector, commerce and public administration. The lowest demand flexibility was found in the real estate and education sectors. Future research should further investigate these variations and explore the possibilities of tailoring interventions to the specific types of users.

1. Introduction

1.1. Background

A decarbonized electricity sector is fundamental to any transition towards a sustainable energy system. As countries strive to reduce their CO_2 emissions through increased electrification, they face new challenges in adapting their electricity grids to higher levels of renewable energy penetration. The problem of intermittency, where the supply of power from renewable energy sources like wind and solar is much more volatile due to the chaotic nature of atmospheric conditions, creates vulnerabilities in the power system that pose a threat to the continued expansion of renewables [1]. Parallel to that, electricity grids are becoming increasingly strained by bottlenecks in the grid's transmission capacity. Capacity shortages, induced by high surges in demand during peak hours of consumption, are also responsible for vulnerabilities in the electricity system that require expensive upgrades in infrastructure. One proposed remedy to both these problems is increasing the flexibility of

* Corresponding author.
E-mail address: vera.van.zoest@it.uu.se (V. van Zoest).

https://doi.org/10.1016/j.apenergy.2021.117543
Received 17 March 2021; Received in revised form 28 July 2021; Accepted 3 August 2021
Available online 10 August 2021

the demand side, through demand side management (DSM) measures that involve motivating users to shift their electricity usage [2]. Demand response (DR) is a subset of these measures that typically relies on using the price of electricity to incentivize end users to make changes in their electricity usage [2].

The residential sector has been the focal point of research in demand response. Despite the broad range of literature, this research has yet to converge on a common resolution regarding the magnitude of response that can be expected from price-based policies and the role that demand response can play in the electricity sector at large [3]. The policies being tested and implemented are usually financial, and the wide disparity in their outcomes point to the prospect of pricing as an instrument that is too crude in incorporating the variety of complex elements that drive human behavior [4]. The assumption of forward-thinking rational agents is arguably more apt for the commercial sector. Though studied less frequently, the commercial sector has been identified as a candidate with a large potential for demand-response participation, and one that could be more responsive to prices [5,6]. One U.S. study with a time-of-use (TOU) pricing scheme characterized by low peak to off-peak price differentials shows minimal effects on peak demand [7]. In contrast, a Korean study on the effects of a critical-peak-pricing (CPP) scheme with more extreme peak to off-peak ratios detected larger effects, as well as a correlation between the magnitude of response and a given firm's expenditure share on electricity [8]. As in the residential sector, a consensus is yet to emerge on the efficacy of price-based demand response measures in the commercial sector.

1.2. Problem statement

The heterogeneity of the commercial sector makes it difficult to generalize an evaluation of any price-based intervention. The constituents of this sector vary widely in their size, the activities they conduct, their reliance on electricity and the flexibility of their consumption. Segmenting this sector and outlining these differences allows for a sharper understanding of the aspects relevant to commercial demand response. In the context of this study, the "commercial sector" refers to users that have a small to medium-sized electricity connection (35-63A), and are either businesses, organizations or public institutions. This study then explores the effects of a rolled-out demand charge on the consumption patterns of these users.

Demand charges, which apply a per-kW fee to a given user's monthly maximum rate of energy consumption (in kW) have an extensive history in the industrial sector but have been used less frequently in the residential and service sectors [9,10]. Renewed interest in these charges stems from the heightened need to contain costs in the distribution of electricity, mainly through "incentivizing smarter load management" and "improving utility cost recovery" [11]. The extent to which these charges can in fact influence behavior so as to meet these goals remains to be established. Accordingly, our aim is to explore the flexibility potential of different types of commercial users, map out their load patterns and measure changes in their consumption behaviors in response to a demand charge. In doing so, we aim to quantify the effect of the demand charge, segment users into distinct groups based on their load characteristics, and differentiate the effect of the demand charge between these segments while examining their composition.

The measure through which different users can be compared are numerous, i.e. size and type of business, operating hours, etc. Among these different factors, the load pattern is one of the most illuminating measures. Profiling the different loads and evaluating their variability allows for an assessment of a given user's contribution to demand peaks in the local grid. Furthermore, characterizing this variability has been demonstrated to be effective in estimating the potential degree of demand response [12]. While distribution system operators (DSOs) are forbidden from discriminatory pricing and therefore need to uniformly apply their pricing schemes to their designated areas, the ability to distinguish between different user and load types can influence how and to whom demand response policies should be communicated.

In this study, the analysis is conducted by clustering the users according to their distinct load patterns and evaluating the quantitative effect on the monthly mean and maximum demand (measured hourly) within the different clusters. We match the clusters between the intervention area and the reference area to understand the effect of the demand charge. We also study the industrial classification codes of the companies in each cluster to understand which types of business are present in each cluster and investigate their flexibility to adapt to the demand charge.

1.3. Profiling users

Clustering is one technique that has commonly been used to categorize users. A form of unsupervised learning, it can be used to classify electricity users according to certain properties of their consumption patterns. Clustering has been used quite extensively in the residential sector, mainly to characterize, identify and classify the different types of users [13–15]. It has also been used to distinguish users who are higher contributors of peak demand [16]. Research that considers mixed or industrial sectors has been more focused on the performance of the algorithms and models used for classification rather than the interpretation of their outcome [17–19]. Clustering has also been used to improve load-forecasting models, with one study looking at a case in Finland where a sample of mixed users is used to generate load profiles for different customers [20]. One study targets a non-residential sample in the U.S. and uses clustering to generate 16 different load patterns for different types of commercial users [21], but otherwise, research that strictly applies clustering techniques to the commercial sector is scarce. The commercial sector represents a much more diverse set of users, with variations that are highly contingent on the type of commercial or service activity a given user engages in. Applying these clustering techniques could therefore lead to a more comprehensive understanding of user heterogeneity within the sector, and in turn, more precise demand response policies. In this paper, we cluster the users based on their load patterns using their hourly electricity consumption data. We adopt multivariate clustering techniques to match users with different load patterns by considering their mean, standard deviation, and skewness of total energy consumption, as well as the mean and standard deviation of their power spectral density to capture the periodicity in electricity consumption.

2. Data

2.1. Data collection

It is important to note that electricity in Sweden, the location of the empirical setting, is paid for through two different bills. The first goes to a retailer, and covers the cost of procuring and supplying the electricity, while the second goes to the distribution system operator (DSO) and covers the cost of transmission and distribution. This study strictly deals with the second of these bills, that of the DSO.

The set of users consists of two groups that fall into an intervention and a reference area. The reference area is the city of Sundsvall, Sweden and has an energy-based distribution tariff that consists of a volumetric charge of 0.13 SEK/kWh and a fixed fee that ranges from 8210 to 14795 SEK/year, depending on the fuse size. The intervention area is the city of Sandviken (227 km south of Sundsvall). Prior to the intervention, users were subject to a two-part tariff similar to that in the reference area, with a volumetric charge of 0.225 SEK/kWh and a fixed charge that ranged from 5250 to 10,000 SEK/ year, also depending on fuse size. The DSO for the intervention area replaced this two-part tariff with one centered on a demand charge. Users were now subject to a fixed fee of 5250 SEK/year (increased to 5426 SEK in the third year) and a demand charge that varied in each month. This applied to all users with a fuse size of 35–63 A. The various rates are displayed in Table 1.

Table 1
Monthly demand charge rates (SEK/kWh/h) over the evaluation period.

Month	Year		
	2015	2016	2017
January		93	89
February		83	85
March		80	78
April		65	65
May	55	55	56
June	53	53	53
July	51	51	51
August	53	53	51
September	66	66	63
October	75	75	74
November	76	76	86
December	95	95	94

The first thing to note is that users would pay according to their maximum monthly demand, which is calculated at an hourly rate. A temporal resolution of one hour means that a user's maximum "peak" is taken to be their monthly maximum hourly consumption in kWh, hence the units in Table 1. A user who's highest hourly consumption is 1 kWh for some arbitrary hour in January 2016 would then pay 93 SEK. The second point to note is that this rate varies with each month, priced in accordance to the average peak load during that respective month over the past two years. Months where aggregate demand is typically higher (winter months) are therefore priced at higher rates.

The aim of this tariff was to encourage users to reduce their maximum demand, and therefore reduce the strain imposed on the local grid. Electricity consumption data in kWh/h were collected on an hourly timescale for all users in the intervention (212 users) and reference (1055 users) areas spanning the period from May 1st, 2014 to April 30th 2017. This includes one year of data before the introduction of the new tariff (pre-treatment) and two years of data after the introduction of the tariff (post-treatment). More information about the dataset can be found elsewhere [22]. In addition to consumption data, each user was matched by a Swedish Standard Industrial Classification (SNI) code [23] in order to map them to their respective commercial activity category.

2.2. Data preprocessing

The pretreatment period of hourly electricity consumption data from each user was checked for extremely low or high consumption values, extremely low variability in the time series, and long periods of missing data. These data were cleaned from the dataset to avoid having them influence the results. Following Öhrlund, Schultzberg and Bartusch [22], users were removed from the dataset when either of the following conditions were met: i) their annual mean hourly electricity consumption was lower than 0.1 kWh, ii) their minimum consumption was higher than 13 kWh, iii) their maximum consumption was lower than 2 kWh, iv) their variance in electricity consumption was smaller than 0.05 kWh and v) their data was missing for more than 100 days. In the intervention area, data from 15 out of 212 users (7.1%) were excluded based on these criteria. In the reference area, data from 91 out of 1055 users (8.6%) were excluded. The clustering of the users and analyses of the effects were performed on the remaining 1161 users, of which 197 in the intervention area and 964 in the reference area.

3. Methods

3.1. Clustering users

To explore the effects of the tariff change, the electricity consumption in the posttreatment years of the intervention area and reference area have to be compared. We are aiming for causal inference, i.e. attributing changes in electricity consumption behavior to the changes in the tariff scheme. This requires, however, that the electricity consumption in the pretreatment year was similar for the users in both areas. Due to intrinsic differences between the users in both areas and other area characteristics such as outdoor temperature, this is not necessarily the case. Therefore, some kind of matching is required to pair users in the intervention area and reference area with similar electricity consumption patterns. There are multiple ways to do such pairing, e.g. one-to-one pairing or finding a subset in the larger reference group which matches with the smaller intervention group [22]. However, in both cases, data will be lost. Also, when matching is based on single statistical values such as the mean electricity consumption, large differences in variance or periodicity could be neglected.

In this study, we propose using a multivariate clustering technique to be able to avoid the beforementioned problems, as well as to be able to explore the effects of the tariff change on different types of users, characterized by the clusters. Note that for the clustering, only the data from the pretreatment year was used. We denote the hourly energy consumption of each user c at hour h by $x_{c,h}$. First, summary statistics were computed for each user c: mean (m_c), standard deviation (s_c) and skewness (b_c) of total energy consumption based on its hourly electricity consumption data, as well as the mean (μ_c) and standard deviation (σ_c) of the power spectral density (PSD) plot of each user. Welch's PSD was used as a measure of periodicity within the electricity consumption of each user. The mean electricity consumption for user c is calculated as:

$$m_c = \frac{1}{H_c}\left(\sum_{h=1}^{H_c} x_{c,h}\right) \quad (1)$$

where H_c is the number of hours for which data is available for user c. The sample standard deviation is then defined as:

$$s_c = \sqrt{\frac{1}{H_c - 1}\sum_{h=1}^{H_c}\left(x_{c,h} - m_c\right)^2} \quad (2)$$

and the skewness is calculated as:

$$b_c = \frac{\frac{1}{H_c}\sum_{h=1}^{H_c}\left(x_{c,h} - m_c\right)^3}{\left(s_c\right)^3} \quad (3)$$

Welch's PSD was calculated by dividing the time series of the hourly electricity consumption of each user into 10 equally-sized segments with zero overlap. The Hamming window function was applied to smooth the autocovariance function:

$$w(n) = \alpha - (1-\alpha)\cos\left(\frac{2\pi n}{N-1}\right), 0 \le n \le N-1$$

with $\alpha = 0.54$ and N equal to the size of the output window [24]. A periodogram was calculated based on the discrete Fourier transformation [25]. Welch's PSD is mainly used in signal processing. In this study, we treat the fluctuating energy consumption pattern as a signal, to determine the periodicity in the energy consumption. Welch's PSD returns two vectors: a vector containing frequency bins and a vector containing the power in each of the frequency bins. An example of a PSD plot is shown in Fig. 1. The frequency bins represent periods such as days, weeks and months. A stronger periodicity in the electricity consumption, for example weekday/weekend patterns or day/night patterns, will return higher peaks in power. Although the frequency bins themselves are not interpretable in this form, they are similar for each user. This means that we can use the power vectors to compare the periodicity of different users. Given the power vector $\boldsymbol{p}_c = \left\{p_{c,1}\cdots p_{c,F}\right\}$ for user c, consisting of the power for each frequency bin $f \in 1\cdots F$, we can then compute the mean (μ_c) and standard deviation (σ_c) of each PSD as:

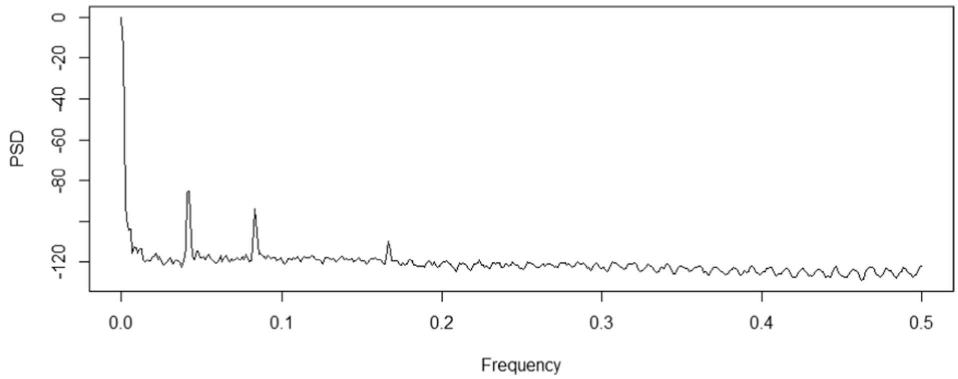

Fig. 1. Example of a Welch PSD plot.

$$\mu_c = \frac{1}{F}\left(\sum_{f=1}^{F} p_{c,f}\right) \tag{4}$$

$$\sigma_c = \sqrt{\frac{1}{F-1}\sum_{f=1}^{F}\left(p_{c,f}-\mu_c\right)^2} \tag{5}$$

Next, consider $\boldsymbol{v}_c = \{m_c, s_c, b_c, \mu_c, \sigma_c\}$ to be the vector of summary statistics for user $c \in 1\cdots C$, where C is the total number of users. Using k-means clustering, the set of all observations $\{\boldsymbol{v}_1, \cdots, \boldsymbol{v}_C\}$ is partitioned into k number of sets or clusters, where $k \leq C$. The sets $\boldsymbol{S} = \{S_1, \cdots, S_k\}$ are chosen such that the within cluster sum-of-squares is minimized:

$$\min\left(\sum_{i=1}^{k}\sum_{\boldsymbol{v}_c\in S_i}\|\boldsymbol{v}_c - \boldsymbol{m}_{S_i}\|^2\right) \tag{6}$$

where $\boldsymbol{m}_{S_i}$ is the mean of $\boldsymbol{v}_c$ in set S_i, where $i \in 1\cdots k$. This makes $\boldsymbol{m}_{S_i}$ the center of cluster i. The Hartigan-Wong method was used for minimization of the within cluster sum-of-squares [26]. First, the observations are divided into random sets S_i. Each observation is assigned to the nearest cluster center. Then, in each iteration, the within cluster sum-of-squares is calculated for each observation in a cluster, as well as the case in which the observation would have been assigned to a different cluster. The observation is then assigned to the new cluster if that cluster has a smaller sum-of-squares:

$$\frac{N_i\sum_{\boldsymbol{v}_c\in S_i}\|\boldsymbol{v}_c - \boldsymbol{m}_{S_i}\|^2}{N_i - 1} < \frac{N_1\sum_{\boldsymbol{v}_c\in S_1}\|\boldsymbol{v}_c - \boldsymbol{m}_{S_1}\|^2}{N_1 - 1} \tag{7}$$

where N_i is the number of observations in the candidate cluster S_i and N_1 is the number of observations in the current cluster S_1. In each iteration, $\boldsymbol{m}_{S_i}$ is updated. The algorithm terminates when no changes can be made to further minimize the within cluster sum-of-squares. As the randomization in the first step may influence the results, it is strongly suggested to run the Hartigan-Wong algorithm multiple times with new random starting sets. In this study we used three runs.

Note that the clustering is performed on the summary statistics of the complete pretreatment dataset including both the users in the intervention area and reference area. Users from the intervention area and reference area are combined in the same cluster based on similar amounts and patterns in their electricity consumption. To minimize the chance of clusters having no or only a few users from the smaller intervention area group, the number of clusters k should not be too high. In this study, we found $k = 4$ to be a suitable number of clusters for a good balance between minimizing the within-cluster variability and maximizing the between-cluster variability. Results for other values of k are included in Figure S1 in the Supplementary Materials. The between-cluster variability and within-cluster variability were visually inspected based on the time series plots of the pretreatment period. The aim was to obtain large differences between clusters in terms of mean electricity consumption and periodicity, while minimizing the within-cluster differences of the users in the intervention area and the users in the reference area. The goal of the latter is to have comparable user groups in the reference area and intervention area, such that the effects in the post-treatment period can be attributed to the tariff change and not to other within-cluster differences between the user groups.

3.2. Evaluating the effects of the demand charge on consumption patterns

Within each cluster $S_1, \cdots, S_4$ we compared the electricity consumption before and after the tariff change. Note again that each cluster contains users from the intervention area and from the reference area. To minimize the effects of within-cluster variability on differences between the users in the intervention area and reference area, we do not compare their absolute differences, but the relative differences between the pretreatment period and posttreatment period for the intervention area vs. the reference area. We considered relative differences in the mean for the full year as well as for the summer only, to eliminate possible bias due to differences in wintertime heating between the reference area and intervention area. We also considered differences in monthly peaks, i.e. the average monthly maximum energy consumption of the users in each group, and the peak-to-average ratio (PAR), where PAR is defined as the ratio between the monthly maximum of the hourly energy consumption and the monthly mean of the hourly energy consumption for each user. The relative change in peaks and the PAR in the posttreatment period compared to the pretreatment period is evaluated for the intervention area users and reference area users within each cluster. The monthly peaks and PAR are used, because the demand charge is also based on monthly peak consumption. A decrease in monthly peaks would demonstrate a positive effect of the demand charge.

3.3. Evaluating the types of user in each cluster

To further explore the clusters, the Swedish Standard Industrial Classification (SNI) codes [23] were used to map the users to their respective commercial activity category. At the most general level, a letter between A to U is given to designate an entire sector (agriculture, mining or manufacturing for instance). Each letter corresponds to a set of two-digit codes that then specify certain sub-sectors. The general agricultural sector (A) can be split into agriculture, forestry and fishing for example, each represented by a unique two-digit code. Each additional digit provides a further level of specification and the full five digits will give a highly detailed classification ("retail sale of pet animals, and pet food in specialized stores" for example). The guide of SNI codes and their respective categorizations was downloaded from Statistics Sweden (SCB) and was then used to match users from the dataset to their associated commercial activity.

Compositional bar charts were then generated for each cluster, showing the distribution of different user types. The 2-digit SNI codes were used to create these charts. While using the 5-digit codes could provide a higher data granularity, it severely limited the ability to identify wider patterns and draw any conclusions due to the limited number of users that fall into each specific business type. The charts generated provided the proportional representation of the different commercial activities in each sector and allowed us to visualize the distribution of users across the clusters.

4. Results

4.1. Clustering results

The clustering based on the mean, standard deviation, skewness, mean of PSD and standard deviation of PSD led to four distinct clusters. The algorithm converged after 4 iterations. Cluster 1 contained 328 users, of which 73 were located in the intervention area and 255 in the reference area. Cluster 2 contained 345 users, of which 52 were located in the intervention area and 293 in the reference area. Cluster 3 is the smallest cluster with 178 users, of which 23 were located in the intervention area and 155 in the reference area. Cluster 4 consisted of 310 users, of which 49 were located in the intervention area and 261 in the reference area. The time series for each group were visually inspected to evaluate whether the within-cluster variability was small enough to make the intervention group and reference group comparable in terms of their average electricity consumption, weekly consumption patterns and seasonality. Fig. 2 shows the time series in the pretreatment year for all clusters. For visualization purposes, a 24-hour rolling mean was used. The actual analysis was performed using hourly values.

As can be seen in Fig. 2, the patterns in the electricity consumption of the users in the intervention area and reference area largely overlap. This will allow comparability in the posttreatment period. In clusters 1 and 2, the mean electricity consumption was slightly higher in the intervention area compared to the reference area. In cluster 4, the electricity consumption was slightly higher in the reference area. Since we are comparing relative differences, these small differences are negligible. In Fig. 2 we can also see that the between-cluster variability is large, showing good effectiveness of the clustering algorithm. Clusters can be distinctly differentiated in terms of mean electricity consumption, weekly periodicity patterns and seasonality throughout the year. In cluster 1, the mean electricity consumption is low, around 2 kWh per hour. The consumption stays relatively constant throughout the year and there are no strong weekday/weekend patterns, suggesting a low periodicity. Cluster 2 has a medium mean electricity consumption with a strong seasonal pattern. The consumption is lowest in summer with a demand around 4 kWh per hour, and higher in winter with a demand around 8 kWh per hour. There are some signs of weekday/weekend patterns with a medium strength. Cluster 3 contains the users with the highest electricity consumption. Additionally, in this cluster there is a strong effect of seasonality, with a demand around 7 kWh per hour in summer and around 13 kWh per hour in winter. Here, the weekday/weekend effect is very clear with a strong increase in demand during the week and a strong decrease in demand during the weekend. Cluster 4 is characterized by a low and stable demand of around 3 kWh per hour throughout the year, with a small increase during winter. However, compared to cluster 1 there is a large difference in periodicity. Whereas cluster 1 had a low periodicity, cluster 4 clearly shows strong weekday/weekend patterns.

4.2. Effects of the demand charge

Fig. 3 shows the electricity consumption of the different clusters throughout the posttreatment period. The posttreatment period covers a period of two full years. Compared to Fig. 2, two winter peaks are visible and the periodicity of the weekly patterns is more compressed. The effects of the tariff change can be distinguished most clearly in the second year of the posttreatment period of clusters 3 and 4, where the red line of the intervention area clearly drops below the line of the reference area, both during summer and winter.

In Table 2, the differences are quantified. When the difference indicates a positive value, the consumption was higher in the intervention area compared to the reference area. As this was already the case for 3

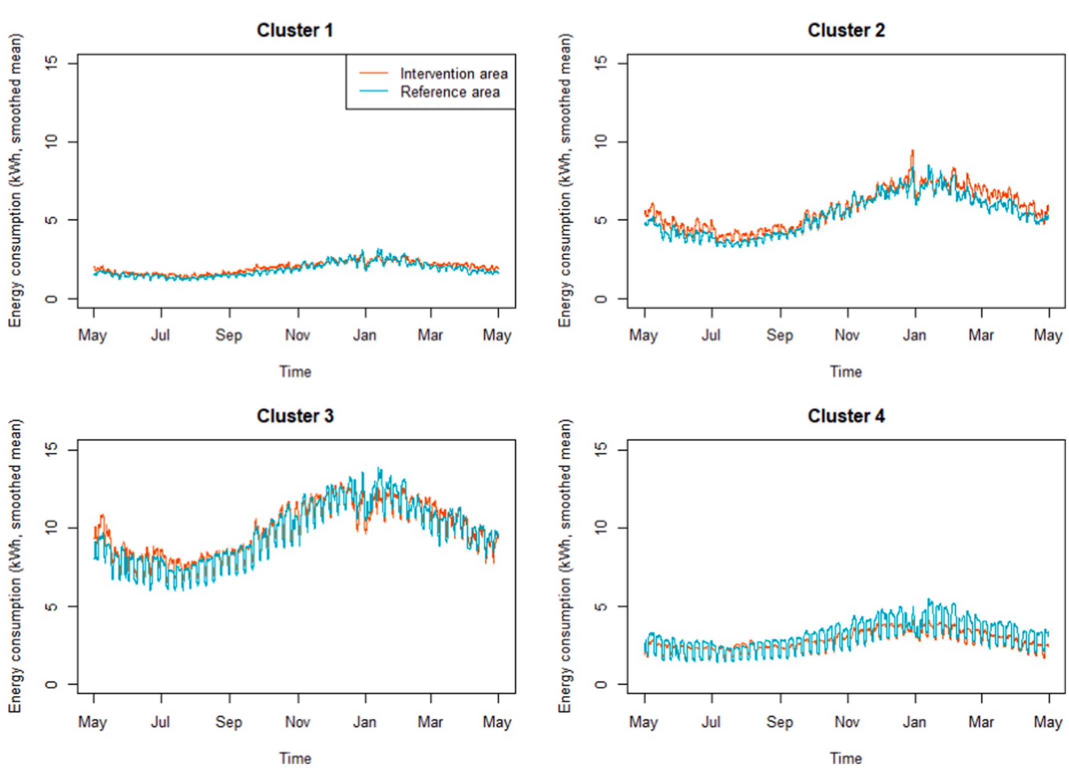

Fig. 2. Energy consumption in the pretreatment year for each cluster. For visualization purposes, a 24-hour rolling mean is used.

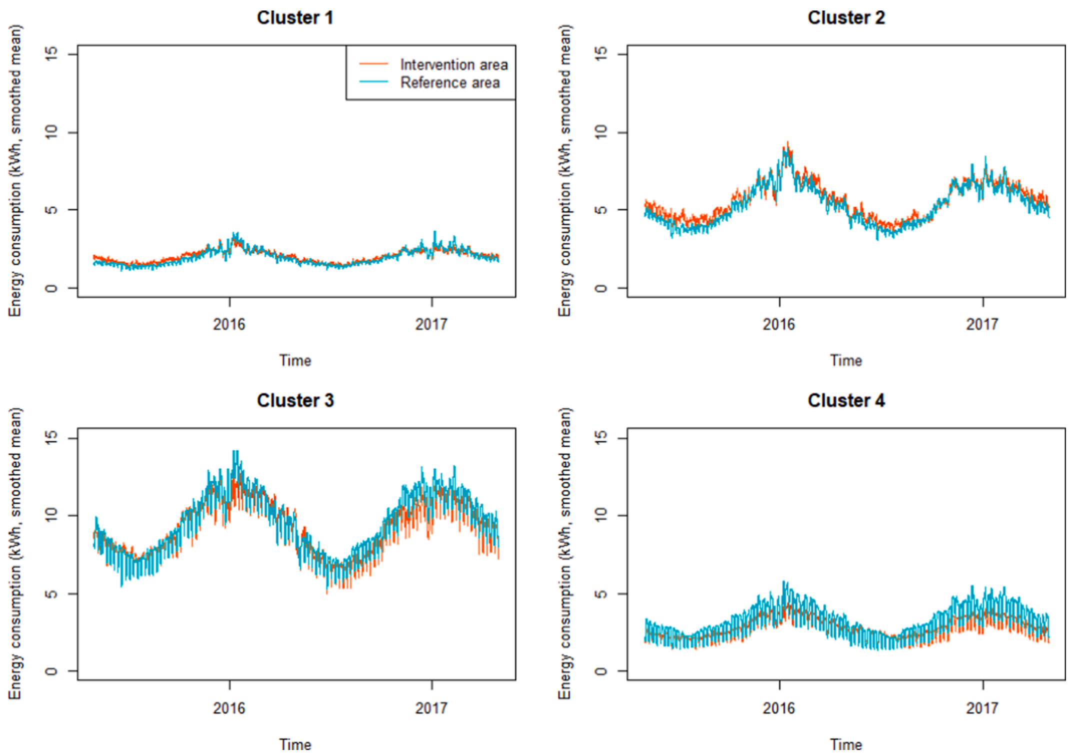

Fig. 3. Energy consumption in the posttreatment years for each cluster. The red line represents the intervention area. The blue line represents the reference area. For visualization purposes, a 24-hour rolling mean is used.

Table 2
Differences in electricity consumption between the intervention area and reference area, throughout the pretreatment and posttreatment periods.

Cluster		Pretreatment	Posttreatment year 1	Posttreatment year 2	Posttreatment overall
Cluster 1	Intervention area	1.95 kWh	2.03 kWh	1.99 kWh	2.01 kWh
	Reference area	1.81 kWh	1.91 kWh	1.97 kWh	1.94 kWh
	Difference	7.62 %	6.35 %	1.01 %	3.71 %
Cluster 2	Intervention area	5.71 kWh	5.73 kWh	5.46 kWh	5.60 kWh
	Reference area	5.31 kWh	5.37 kWh	5.22 kWh	5.30 kWh
	Difference	7.52 %	6.81 %	4.53 %	5.7 %
Cluster 3	Intervention area	9.83 kWh	9.41 kWh	8.83 kWh	9.12 kWh
	Reference area	9.65 kWh	9.54 kWh	9.38 kWh	9.46 kWh
	Difference	1.81 %	−1.41 %	−5.88 %	−3.59 %
Cluster 4	Intervention area	2.73 kWh	2.72 kWh	2.68 kWh	2.70 kWh
	Reference area	3.12 kWh	3.17 kWh	3.22 kWh	3.19 kWh
	Difference	−12.60 %	−14.38 %	−16.79 %	−15.55 %

out of 4 clusters, we are mostly interested in the change in this difference throughout the years. For all clusters, we see that the energy consumption decreased in the intervention area compared to the reference area. The effect of the tariff change is visible in the first posttreatment year and becomes stronger in the second year. For example, in cluster 1 we see that the average consumption in the intervention area was 7.62 % higher than in the reference group during the pretreatment period. After the tariff change, this reduced to 6.35 % in the first year and even to 1.01 % in the second year, indicating a large effect of the tariff change on the average consumption. In cluster 2 we see a similar pattern, although less strong. In cluster 3, where the electricity demand in the intervention area was 1.81% higher than in the reference area during the pretreatment period, the electricity demand in the intervention area dropped in comparison to the reference area, such that the electricity demand in the intervention area was even 5.88 % lower in the intervention area than in the reference area during the second year after the tariff change. In cluster 4, the electricity demand in the intervention area was already much lower than that of the reference area in the pretreatment period. However, even in this case, the effect of the tariff change is visible through an increase in the difference.

To validate that the effects were actually caused by the tariff change and not by other factors such as seasonal temperature variations, which differ between the intervention area and reference area and from year to year, we carried out the same analysis only on the summer months of June-August. The results are shown in Table 3, which shows that the demand charge also had an effect on electricity consumption in summer only, at least for clusters 1, 3 and 4. We don't see an effect in cluster 2, which also had the least strong effect visible in Table 2. For completeness, Table 3 also includes the results during the winter months December-February. Due to possible temperature differences between the areas, these should be used for comparison only, and not for evaluation of the effect of the tariff change.

As the demand charge is based on a given user's maximum monthly consumption (kWh/h) an effect would also be expected users' "peaks". This effect can clearly be seen for clusters 1, 2 and 3 (Table 4). Again, we look at the change in difference between the two areas over time rather

Table 3
Differences in electricity consumption between the intervention area and reference area, throughout the summer periods (June-August) and winter periods (December-February) in the pretreatment and posttreatment periods.

Cluster		Pretreatment summer	Posttreatment summer	Pretreatment winter	Posttreatment winter
Cluster 1	Intervention area	1.48 kWh	1.56 kWh	2.42 kWh	2.44 kWh
	Reference area	1.35 kWh	1.44 kWh	2.38 kWh	2.56 kWh
	Difference	9.35 %	8.59 %	1.65 %	−4.51 %
Cluster 2	Intervention area	4.24 kWh	4.31 kWh	7.36 kWh	7.01 kWh
	Reference area	3.79 kWh	3.86 kWh	6.95 kWh	6.86 kWh
	Difference	11.75 %	11.83 %	5.90 %	2.22 %
Cluster 3	Intervention area	7.83 kWh	7.06 kWh	11.69 kWh	11.03 kWh
	Reference area	7.43 kWh	7.18 kWh	11.92 kWh	11.73 kWh
	Difference	5.40 %	−1.74 %	−1.88 %	−5.98 %
Cluster 4	Intervention area	2.19 kWh	2.09 kWh	3.44 kWh	3.44 kWh
	Reference area	2.26 kWh	2.24 kWh	4.09 kWh	4.23 kWh
	Difference	−3.08 %	−6.70 %	−16.06 %	−18.54 %

Table 4
Differences in monthly maximum electricity consumption averaged over the users in the intervention area and reference area, throughout the pretreatment and posttreatment periods.

Cluster		Pretreatment	Posttreatment year 1	Posttreatment year 2
Cluster 1	Intervention area	8.58 kWh	8.35 kWh	8.27 kWh
	Reference area	8.47 kWh	8.73 kWh	8.79 kWh
	Difference	1.31 %	−4.35 %	−5.97 %
Cluster 2	Intervention area	15.13 kWh	14.55 kWh	14.08 kWh
	Reference area	13.79 kWh	13.88 kWh	13.71 kWh
	Difference	9.68 %	4.82 %	2.67 %
Cluster 3	Intervention area	21.42 kWh	20.71 kWh	19.49 kWh
	Reference area	21.11 kWh	20.78 kWh	20.24 kWh
	Difference	1.48 %	−0.30 %	−3.70 %
Cluster 4	Intervention area	7.43 kWh	7.29 kWh	7.48 kWh
	Reference area	8.78 kWh	8.92 kWh	8.81 kWh
	Difference	−15.42 %	−18.28 %	−15.11 %

than the absolute peak values, which would fluctuate too much over time to draw conclusions only based on those. In clusters 1 and 3, the peaks were a bit higher in the intervention area than in the reference area within the pretreatment period. However, in the posttreatment period, the peaks were lower in the intervention area compared to the reference area, indicating an effect of the tariff change. In cluster 2, the peaks were substantially larger in the intervention area than in the reference area during the pretreatment period. During the posttreatment period, the difference became considerably smaller. The peak consumption of users in cluster 4 did not seem to be affected by the tariff change. No difference in the PAR was found after the tariff change, indicating that the mean and peak consumption decreased with a similar magnitude.

4.3. User types

Given that the mean of a user's monthly electricity usage was one of the parameters on which the clustering was based on, one would expect to detect a relationship between a user's fuse size and the cluster in which they were placed. The heatmap in Fig. 4 illustrates this relationship.

It is evident that a majority of the users in clusters 1 and 4, which were the clusters with the lowest average consumption, have the smallest possible fuse size and so are indeed "low-energy" consumers. Cluster 2 was characterized as a cluster of "medium" energy usage, with its users distributed roughly evenly among all three fuse sizes. Cluster 3 which had the highest average energy usage places most of its users in the largest possible fuse size. Fig. 4 confirms the role played by fuse size in the clustering outcomes but provides little additional insight. Even though the majority of users in cluster 3 have the largest fuse size, less than 30% of all users with the largest fuse size fall into cluster 3. That is to say, a user in cluster 3 is likely to have the largest fuse size, but having the largest fuse size is not necessarily an indicator of being in cluster 3. Further insight on the type of users in each cluster must be drawn from other factors.

Using the SNI codes, users could be matched to the type of activities associated with their organization. The SNI codes provide a high level of classification for each user type, but users were grouped into their broader sectors as the data was too sparse to detect general patterns using the more detailed codes. Fig. 4 shows how each sector is distributed among the clusters, with each cluster represented by a different color. The left segment of Fig. 5 shows the frequency chart of the sector composition, with the x-axis corresponding to the total number of organizations that fall within a given sector and cluster. The sectors are organized in decreasing order, starting with those occupying the largest share of the total sample. Sectors beneath "Hotel and restaurant" each make up less than 5% of the total sample and are increasingly difficult to explore. To ease a visual understanding of the data, the right segment of Fig. 5 shows the normalized sector composition, with an x-axis that represents the proportion of each cluster in the sector. The numbers in brackets to the right of Fig. 5 represent the total number of organizations that fall within the corresponding sector, and the numbers centered in each bar show how many organizations fall within each cluster.

The main deduction to be made from Fig. 5 is the sharp contrast between the real estate and commerce sectors. It should be stressed that users contained in the real estate sector are not private households but a combination of housing or tenant-owner associations and a variety of other types of property rentals and management. Nonetheless, electricity usage associated with this sector is "residential" because it primarily involves activities carried out by or for residents. This could be lights and heating used in common areas, or laundry rooms and common gyms, for example. This sector makes up almost half of the total sample (48.5%) and so when looking at the clusters individually, it is difficult to identify any patterns because each cluster has a high share of the real estate sector. Fig. 5 also illustrates the proportions of each sector that fall into each cluster. More than half the real estate sector (56%) for example falls into the low consumption and seasonal periodicity clusters, clusters 1 and 4. In contrast, the proportion of the real estate sector that falls into cluster 3, which is characterized by high energy use and strong periodicity is extremely low (12.4%). These proportions are virtually

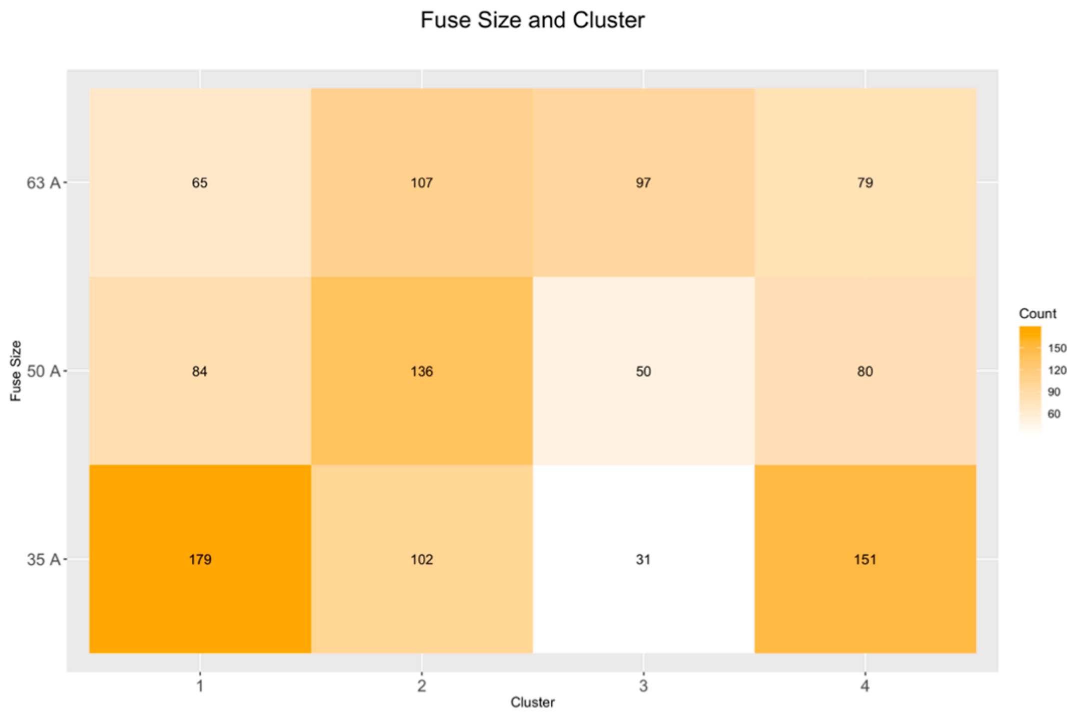

Fig. 4. Heatmap of user's fuse size and corresponding cluster.

Fig. 5. Distribution of clusters among sectors.

reversed in the commerce sector, where less than 7% of users fall into the cluster 1 with low consumption and periodicity, and almost 30% fall in cluster 3 with high consumption and periodicity. The hotel and restaurant sector mostly consists of restaurants and largely falls into clusters 2 and 3 (76%) with medium–high consumption and strong periodicity. While distinct from the commerce sector, restaurants are also regarded as part of the commercial sector and so reinforce the finding that users in this sector tend to fall in clusters with stronger periodicities. A similar divide can be found among the education sector, predominantly made up of primary schools. 70% of this sector falls into clusters 2 and 4, which is reflective of schools being low-medium energy consumers with strong periodicity. Sectors smaller than the hotel and restaurants category each form less than 5% of the total sample. The number of users in these sectors becomes too small and too varied to draw general observations. A full proportional breakdown of clusters and sectors can be found in Table S1 in the Supplementary Materials.

5. Discussion

A set of commercial users were categorized into four clusters based on their consumption patterns. Within each cluster we see clear trends in electricity consumption with respect to fuse size and the sectors representing each cluster. In cluster 1, we see users with low energy consumption and a small fuse size. The periodicity within the time series is low, indicating no strong weekday/weekend peak effects. In cluster 2, we find users with a medium energy consumption and a large variability in fuse sizes. The periodicity in cluster 2 is also medium while the seasonality is stronger, with an increase in electricity consumption in winter. Both clusters 1 and 2 only responded mildly to the change in tariff scheme. This is partially explained by the composition of these clusters, which consist mostly of the real estate sector. As stated, this sector refers not to the end-users in the residential buildings, but the common facilities as well as shared lighting and heating in the common areas, elevators, laundry rooms and gyms. These are usually on 24/7, which explains the low periodicity in the time series. The lack of user engagement and direct accountability regarding electricity consumption in this sector explains the low response to the tariff change. Cluster 3 consists of users with a high electricity consumption, large fuse sizes and a high periodicity, showing a strong increase in consumption during weekdays and a drop in consumption during weekends. Cluster 4 consists of low electricity consumers with small fuse sizes and a high periodicity. The users in clusters 3 and 4 showed the strongest response to the new tariff.

The clusters differed not only in their load patterns but also in their composition. While the real estate sector made up half the entire sample, it predominantly fell into clusters 1 and 2. Moderate electricity consumption and low periodicity are in line with expectations as the activities associated with this category are mostly base-load activities that occur in the public spaces of buildings (e.g. lighting, HVAC, etc.). The decrease in the average and peak consumption described in section 4.2 was only expressed at the cluster level. It is therefore not entirely clear "who" reduced their consumption within a given cluster. All the units in a cluster might have decreased their consumption by small amounts or a few units could have made substantial changes while a majority made little to no change. Given the large representation of the real estate sector in each cluster, at least some residential units are very likely to have played a role in this decrease. This may be overlooked as a straightforward consequence of the demand charge but it should raise a serious question - how and why was this reduction achieved? As previously mentioned, these units are not households, but various forms of associations that manage and administer buildings and properties. If the reduction was due to behavioral changes in activity, then the residents necessarily played a role, perhaps through their usage of the common facilities. In turn, this implies an exchange of information between the residents and the property's management, who consequently must have informed them. If this is the case, then what and how they communicated to their residents should be a question of major interest. If on the other hand these reductions came from managers and administrators carrying out specific passive changes themselves (e.g. retrofitting, switching to more efficient lighting, HVAC, etc.) then this is also an interesting finding that reflects an unusual amount of effort exerted to save costs that have historically just been pushed onto the residents (through higher monthly fees).

Primary schools make up the second largest share of the sample, 41% of which fell into cluster 4, a cluster with high periodicity and the least responsive to the tariff. There is little flexibility in the activities that take place in a primary school, which are centered around a rigid schedule with a regimented set of routines. Education is distinct in that it is a public good, not a purely commercial activity. While the cost of electricity might be a factor to consider in the operation of a business, it is not something that is likely to bear a heavy influence on the operation of a school. Similar to the real estate sector above, the direct users of the facilities (students, teachers, workers) have no direct incentive to reduce their electricity consumption as they incur no cost. While property managers in the residential sectors could hypothetically use their electricity savings to make their properties more attractive through advertising reduced monthly fees, it is unclear if a similar incentive would exist for the facility managers of a school. Whether the facility managers have any incentive to reduce their electricity consumption is ambiguous and likely depends on if and how they pay for their electricity use. Variations in these details between schools are likely too wide to draw general conclusions. Additionally, primary schools do fall within the other clusters as well, but their low representation in those clusters (around 10%) make it difficult to decipher whether they played any role in the cluster's response.

Less than 7% of all users registered under the commerce SNI code fall into cluster 1. Around 20% fall into cluster 2 and the remainder fall into clusters 3 and 4. One conclusion is that it is highly unlikely that a business in the commercial sector has both low energy use and low periodicity. A business in the commercial sector is very likely to have a medium–high energy consumption with a medium–high periodicity. If a business is a low energy user, it is very likely that it has a high periodicity and so falls within cluster 4. The high periodicity associated with the commercial sector points to loads driven by activities, contrary to the more stable base-loads of the real estate sector. If we disregard the 7% of commercial units that fall in cluster 1, we find that the remainder are almost evenly split between the clusters 2 and 3, which were more responsive with peak consumption (Table 3) and the less responsive cluster 4. An attempt to describe this disparity was made through further unpacking the commercial sector to see if there were different distributions between its constituents. The three subdivisions of the commercial sector are wholesale, retail and the automotive sector. All three were similarly distributed among clusters, with a slight underrepresentation of the automotive sector in cluster 3. There were no clear patterns as to which companies fall into a more or less responsive cluster. Further dividing the companies into more specific categories lowers the count of each user-type to a degree where it is difficult to make any generalizable conclusions. One could, for example, unpack the retail sector and count four grocery stores in cluster 3 and four stores that specialize in "eyeglasses and optics" in cluster 4, but these figures are too small to generalize. On the one hand, one could presume the commercial sector to be more responsive to a demand charge, given that electricity is a running cost that affects the operation of a business. On the other hand, flexibility in the timing of electricity use is not something one would expect of all businesses. Certain sets of activities might be more difficult to shift in time and so regardless of what sort of tariff a business has, it cannot be compelled to make changes if there are detrimental effects on its operations. Given an extensive set of barriers and challenges to demand response in the commercial sector [27], identifying which businesses reduced their consumption and how they did it is a particularly interesting question that requires going further than analyzing SNI codes.

A final note with important implications is the fact that while reductions were detected in the intervention area's maximum hourly demand (users' peaks), the PAR remained constant. Users must therefore have necessarily also decreased their average monthly energy usage. If users had responded to the demand charge by load-shifting, one would expect their average energy usage to remain constant, and therefore detect a decrease in the PAR. A stable PAR points to users responding through reducing their average energy usage instead of load-shifting, and indirectly reducing their maximum monthly demand through a general overall reduction in electricity use. While this may be glossed over as a minor technical detail, it raises important questions concerning how users respond to demand charges. Given that the tariff lacked a volumetric charge, there was no incentive for users to decrease their average energy consumption, only to decrease their maximum hourly demand in a given month. If users resorted to an indiscriminate decrease in energy because they misunderstood the tariff or its implications, then this points to potential issues with communication, and demands attention be channeled into ensuring users are better informed and guided with practical advice on how to best respond to their tariff. One may argue that this is a pedantic concern, given that there was still a detectable overall response. But if users "missed the point" of load-shifting, then it may be possible that users who are able to load-shift but unable to decrease their average energy usage were left out, non-responsive due to a misunderstanding or a lack of guidance.

6. Conclusion

In this paper, a multivariate clustering technique is used to incorporate more statistical parameters in the evaluation of the demand charge while also classifying users in accordance to their consumption patterns. Using SNI codes that match users to their associated activities, we tried to explore the distributions of user-types among clusters and detect patterns in the data. By doing this, we aimed to develop a more detailed understanding of the tariff's effects along with the heterogeneity of its subjects.

The users were divided into four clusters, each with distinct characteristics. Effects of the new tariff through decreases in mean and maximum monthly electricity consumption were detectable in three of the four clusters. Both these results point to disparities between users who make up the sample that are overlooked when the sample is treated homogenously. The clearest result in the user-type investigation was the stark divide between the real estate and commercial sectors. The real estate sector predominantly fell into clusters 1 and 2, characterized by low to moderate energy consumption and periodicity. In contrast, the commercial sector predominantly fell into clusters 3 and 4, characterized by high periodicity, while restaurants largely fell into clusters 2 and 3, indicating a medium–high energy use and a medium–high periodicity. While the more detailed 5-digit SNI codes allow one to match each user to more specific types of activity, no clear patterns were identified due to limitations in the sample size.

Price tariffs are geographically indiscriminate. Users of the same local network will receive the same tariff regardless of their load patterns or consumption habits. While we refrain from making a judgment on this state of affairs, a demand-response policy would likely be strengthened by catering to the diversity of the users in a target sample. This need not take the form of differentiated pricing but could be applied in the communication strategies used in parallel to demand charges. One could be content with the moderate overall effect detected in [22] but this study reveals the heterogeneity of users and varying degrees of response that underlies the average. Demand response policies could therefore be strengthened if specific strategies are adopted for different user types. The real estate sector was characterized by low periodicity and low to medium consumption. Despite this, the real estate sector makes up half the sample, and so minor changes in its overall levels of demand could be more substantial for the local grid's system peaks than smaller but more volatile users. Moderate improvements in energy efficiency and performance can have effects on demand response that outweigh those achieved by behavioral changes [28]. If the patterns associated with this sector are in fact due to base-load energy usage and not driven by resident activity, then it could perhaps be appropriate to emphasize retrofitting and the adoption of more energy efficient systems in public places instead of targeting behavior in public spaces.

One posited explanation for the predominant share of primary schools in the least responsive cluster was that those who use electricity are not the same as those who pay for the costs incurred. Bridging this gap would require a realignment of incentives and a strategy that goes beyond a basic price signal. In the case of the commercial and hospitality sectors (restaurants and hotels), demand is very likely to be driven by activity as evidenced by the higher periodicities. The tariff creates an incentive to decrease or shift activities peaks, but the efficacy of this incentive is uncertain, as many of these users fall into cluster 4 which was unresponsive when it comes to monthly maximum electricity consumption. Whether some businesses fail to respond due to limited knowledge on the implications of the tariff or weak financial incentives, or whether they cannot respond because the activities associated with their load patterns are essential to the operation of the business is another avenue for future research.

CRediT authorship contribution statement

Vera Zoest: Methodology, Software, Formal analysis, Writing – original draft. **Fouad El Gohary:** Methodology, Investigation, Writing – original draft. **Edith C.H. Ngai:** Methodology, Writing – review & editing. **Cajsa Bartusch:** Conceptualization, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This work was supported by Energiforsk AB project number EV32254.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apenergy.2021.117543.

References

[1] Rowe D, Sayeef S, Platt G. Intermittency: It's the Short-Term that Matters. In: Future of Utilities - Utilities of the Future: How Technological Innovations in Distributed Energy Resources Will Reshape the Electric Power Sector, 2016.
[2] Paterakis NG, Erdinç O, Catalão JPS. An overview of Demand Response: Key-elements and international experience. Renew Sustain Energy Rev 2016;69: 871–891.
[3] Flaim T, Neenan B, Robinson J. Pilot paralysis: why dynamic pricing remains over-hyped and underachieved. Electr J 2013;26(4):8–21.
[4] Hobman EV, Frederiks ER, Stenner K, Meikle S. Uptake and usage of cost-reflective electricity pricing: insights from psychology and behavioural economics. Renew Sustain Energy Rev 2016;57:455–67.
[5] Reiter U, Jakob M, Wohlfarth K. Demand side management-empirical data from the services sector Bibliographical data. no. 691685; 2018. p. 1–12.
[6] Wohlfarth K, Klobasa M, Gutknecht R. Demand response in the service sector – theoretical, technical and practical potentials. Appl Energy 2020;258:114089.
[7] Jessoe K, Rapson D. Commercial and industrial demand response under mandatory time-of-use electricity pricing. J Ind Econ 2015;63(3):397–421.
[8] Jang D, Eom J, Kim MG, Rho JJ. Demand responses of Korean commercial and industrial businesses to critical peak pricing of electricity. J Clean Prod 2015;90: 275–90.
[9] Taylor TN, Schwarz PM, Taylor TN, Schwarz PM. A residential demand charge : evidence from the duke power time-of-day pricing experiment published by : international association for energy economics stable URL : http://www.jstor.org/stable/41322212 Evidence from the Duke Power A Residential Demand Cha. vol. 7, no. 2, pp. 135–151, 2018.
[10] Taylor TN. The long-run effects of a time-of-use demand charge author (s): Thomas N . Taylor and Peter M . Schwarz Published by : Wiley on behalf of RAND Corporation Stable URL : http://www.jstor.org/stable/2555618 The long-run effects of a time-of-use demand char," vol. 21, no. 3, pp. 431–445, 2018.
[11] Hledik R. Rediscovering residential demand charges. Electr J 2014;27(7):82–96.
[12] Jang D, Eom J, Jae Park M, Jeung Rho J. Variability of electricity load patterns and its effect on demand response: a critical peak pricing experiment on Korean commercial and industrial customers. Energy Pol 2016;88:11–26.
[13] McLoughlin F, Duffy A, Conlon M. Characterising domestic electricity consumption patterns by dwelling and occupant socio-economic variables: An Irish case study. Energy Build 2012;48(July 2009):240–248.
[14] Haben S, Singleton C, Grindrod P. Analysis and clustering of residential customers energy behavioral demand using smart meter data. IEEE Trans Smart Grid 2016;7 (1):136–44.
[15] Melzi FN, Same A, Zayani MH, Oukhellou L. A dedicated mixture model for clustering smart meter data: Identification and analysis of electricity consumption behaviors. Energies 2017;10(10).

[16] Azaza M, Wallin F. Smart meter data clustering using consumption indicators: responsibility factor and consumption variability. Energy Procedia 2017;142: 2236–42.
[17] Al-Wakeel A, Wu J, Jenkins N. K-means based load estimation of domestic smart meter measurements. Appl Energy 2017;194:333–42.
[18] Hernández L, Baladrón C, Aguiar JM, Carro B, Sánchez-Esguevillas A. Classification and clustering of electricity demand patterns in industrial parks. Energies 2012;5 (12):5215–28.
[19] Lavin A, Klabjan D. Clustering time-series energy data from smart meters. Energy Effic. 2015;8(4):681–9.
[20] Räsänen T, Voukantsis D, Niska H, Karatzas K, Kolehmainen M. Data-based method for creating electricity use load profiles using large amount of customer-specific hourly measured electricity use data. Appl Energy 2010;87(11):3538–45.
[21] Jiang Z, Lin R, Yang F. A hybrid machine learning model for electricity consumer categorization using smart meter data. Energies 2018;11(9).
[22] Öhrlund I, Schultzberg M, Bartusch C. Identifying and estimating the effects of a mandatory billing demand charge. Appl Energy 2019;237:885–95.
[23] SCB. Swedish Standard Industrial Classification (SNI). [Online]. Available: https://www.scb.se/en/documentation/classifications-and-standards/swedish-standard-industrial-classification-sni/. [Accessed: 02-Oct-2020].
[24] Blackman RB, Tukey JW. The measurement of power spectra from the point of view of communications engineering — Part I. Bell Syst Tech J 1958.
[25] Welch PD. The use of fast fourier transform for the estimation of power spectra: a method based on time averaging over short, modified periodograms. IEEE Trans Audio Electroacoust 1967.
[26] Hartigan JA, Wong MA. Algorithm AS 136: a K-means clustering algorithm. Appl. Stat. 1979.
[27] Cardoso CA, Torriti J, Lorincz M. Making demand side response happen: a review of barriers in commercial and public organisations. Energy Res Soc Sci 2020;64 (June 2019):101443.
[28] Yilmaz S, Rinaldi A, Patel MK. DSM interactions: What is the impact of appliance energy efficiency measures on the demand response (peak load management)? Energy Pol 2020;139(February).