Energy Policy 133 (2019) 110909

Contents lists available at ScienceDirect

Energy Policy

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

Who is sensitive to DSM? Understanding the determinants of the shape of electricity load curves and demand shifting: Socio-demographic characteristics, appliance use and attitudes

S. Yilmaz[a,*], S. Weber[b], M.K. Patel[a]

[a] *Chair for Energy Efficiency, University of Geneva, Institute for Environmental Sciences (ISE) and Department F.-A. Forel for Environmental and Aquatic Sciences (DEFSE), Faculty of Science, Switzerland*
[b] *Institute of Economic Research, University of Neuchâtel, Switzerland*

ARTICLE INFO

Keywords:
Household electricity load profiles
Load shifting
Demand response
Cluster analysis
Multinomial regression
Hurdle model

JEL classification:
C38
C93
D12
L94
Q41

ABSTRACT

To date, research on demand side management has mostly focused on the determinants of electricity consumption and stated preference experiments to understand social acceptability. Further experimental research is needed to identify the determinants for demand response schemes. This paper contributes to addressing this gap by making use of data from a randomised control trial which contains 15 months of smart meter electricity data combined with household characteristics and differences in incentives to shift their electricity use between 11am and 3pm. Cluster analysis performed on electricity data identified three distinct electricity daily load profiles. Each cluster was then linked to household characteristics by means of a multinomial logistic regression to identify the determinants of the load curves' shapes. Findings show that occupancy presence at home, age and appliance ownership were strong predictors. Finally, this paper is among the first to provide experimental evidence on the determinants of load shifting. We find that households with head aged above 65, households who belong to the cluster exhibiting a load profile characterised by a relatively high peak at noon and a low peak in the evening, and those who received money incentives were more likely to shift electricity use towards middle of the day (11am-3pm).

1. Introduction

Renewable electricity generation capacity grew at a rate of more than 8% per annum globally between 2010 and 2017. Currently, it represents 22% of worldwide generation (IEA, 2018; IRENA, 2018). The European Commission (2018) reached a political agreement on increasing renewable energy use, with the objective of covering at least 32% of the final energy consumption in the EU by renewables by 2030. Similarly, Switzerland has made pledges to increase average domestic renewable electricity generation (excluding hydropower) from 1260 GW h in 2015 to around 4400 GW h by 2020 and to around 11,400 GW h by 2035 (Federal Council of Switzerland, 2016; SFOE, 2018). These targets include a considerable proportion of intermittent renewables (18% are targeted by 2035), and in particular photovoltaics (Prognos, 2012). Hence, one of the key challenges of this massive reconfiguration is to balance supply and demand in order to accommodate the increasing penetration of intermittent renewable power into the grid.

Load shifting is defined as the process where consumers time-shift demand, either through behaviour change or automation, in response to particular conditions within the electricity system, and is therefore a potential solution to equilibrate the network. More generally, demand flexibility is seen as an integral part of the system to support the integration of renewable energy technologies (Ofgem, 2010; Barton et al., 2013; Torriti et al., 2015; IEA DSM, 2018; Darby, 2018). As it represents the largest percentage of many countries' final electricity consumption (e.g. 31% in Switzerland and in the EU) (Prognos et al., 2017; Eurostat, 2017), the residential sector has become a primary focus to integrate demand flexibility into the grid system.

However, not all households can be expected to respond equally to demand response programmes. Households have different use patterns, appliances and systems that have operational constraints and advantages, so that their potential for demand response and peak reduction will differ. In order to maximise the uptake of demand response schemes, different approaches were employed in the literature. First, research has mainly focused on data mining of large-scale smart meter

---

[*] Corresponding author.
E-mail address: selin.yilmaz@unige.ch (S. Yilmaz).

https://doi.org/10.1016/j.enpol.2019.110909
Received 19 February 2019; Received in revised form 24 July 2019; Accepted 28 July 2019
Available online 01 August 2019
0301-4215/ © 2019 Elsevier Ltd. All rights reserved.

data, in order to discover and understand patterns in electricity consumption, and ultimately try to enhance targeting and tailoring of demand response and energy efficiency programmes (Kwac et al., 2014; Benítez et al., 2014; Quilumba et al., 2015). Cluster analysis was frequently applied to segment households according to their electricity demand profiles and illustrate how each segment can be targeted with specific demand response programmes such as time-of-use tariffs or critical peak pricing (Chicco et al., 2004; Figueiredo et al., 2005; Verdú et al., 2006; Tsekouras et al., 2007). For example, according to Dent et al. (2014), households with most variability in regular activities (defined from electricity meter data) may be the most receptive to incentives to change the timing of electricity use. However, in absence of such information, these studies could not consider building characteristics, socio-demographics and appliance use, which might reflect on the uptake of demand response schemes. Second, several researchers focused on more disaggregated analysis of demand flexibility sources. They investigated the impact of availability and use of electrical appliances on the timing and magnitude of a household's electricity consumption to set up priorities and design control strategies for demand response. They have identified appliance types that are capable of shifting such as refrigerators, electrical water heaters with storage, or schedulable appliances (washing machines, dishwashers and tumble dryers) (Paatero and Lund, 2006; Kamilaris and Pitsilledes, 2011; THINK Project, 2013; Yu et al., 2013; Zhu et al., 2012). Third, several studies designed stated-preference experiments and opinion surveys to study social acceptability and willingness-to-participate in demand response programmes. On this basis, they segmented households to help developing tailored strategies that more effectively target consumers' preferences and needs, and thus increase the uptake rates of demand response programmes (Oseni et al., 2013; Andrey et al., 2014; Fell, 2016; Nicolson et al., 2017; Hille et al., 2019). However, the studies mentioned above are either based on stated preferences or on people beliefs rather than actual or observed choices. Finally, studies focus on different types of interventions to increase the success of the demand response. Financial incentive-based interventions have long been used in demand response studies and have proven successful across studies (Voulis et al., 2017; Friis and Christensen, 2016; Bartusch et al., 2011; Faruqui et al., 2016). Similarly, many studies found that information feedback is also effective in fostering shifts of electricity use (Woo et al., 2013; Abrahamse et al., 2007; Carroll et al., 2014; Vassileva et al., 2013). However, studies comparing the two approaches are scarce (Nilsson et al., 2018). Further experimental field research is therefore needed to unravel the main actual determinants of demand shifting.

To address these limitations, we use data from a field experiment conducted in northern Switzerland (Weber et al., 2017a), in which both smart meter electricity consumption data and household characteristics were collected. They performed a randomised control trial (RCT) with the objective of aligning electricity consumption with solar energy production. Two interventions were implemented to encourage households to shift their electricity demand toward 11am-3pm. These data allow us to investigate two key questions. First, *what are the main determinants of the daily load curves' shape?* To this end, a cluster analysis was performed to identify patterns of electricity load curves and the clusters thus obtained were linked to socio-demographic variables (e.g. age, tenure, education level), building characteristics (e.g. type of housing) and appliances (e.g. ownership of wet appliances and Information and Communication Technologies (ICT) appliances) by a multinomial logistic regression. Second, *who shifts, that is, what characteristics distinguish households who altered their load curve in response to the interventions from those who did not?* We then used electricity consumption data monitored before and after the implementation of the interventions and linked changes in the proportion of electricity consumed between 11am and 3pm to the household characteristics, type of intervention, type of cluster and variability.

The remainder of this paper is structured as follows. Section 2 presents the experimental design. Section 3 describes the empirical approach and provides descriptive information on the dataset. The results of the clustering and regressions explaining the composition of clusters and load shifting are presented in Section 4. Section 5 discusses the policy implications and Section 6 concludes.

2. Experimental design

The data used in this paper originally come from a field experiment, which was dedicated to assess the efficiency of various demand-response measures on residential electricity usage and conducted in a small city located in northern Switzerland.[1] All households involved were customers of the electricity provider *Groupe e* and were equipped with smart meters recording electricity usage in 15-min intervals. Monitoring of electricity usage started in October 2013 for a total of 323 households, which were all invited to answer an online survey designed to collect information on socio-demographic characteristics, dwelling attributes, and appliance ownership. The survey also included questions on respondents' thoughts and feelings on energy conservation, renewable energy and climate change (detailed information on the collected variables is provided in Section 3.3). For the purpose of the field experiment, respondents to the online survey were randomly allocated by Weber et al. (2017a) to form one control and three treatment groups. The households included in the treatment groups then received incentives (either financial incentives or information feedback, with or without access to an online platform) to shift their electricity use toward the period between 11am and 3pm. Treatments started on January 2014 and remained in operation until December 2014. October–December 2013 thus constitute the pre-treatment period, while January–December 2014 constitute the treatment period.

Data cleaning was carried out on the 15-min meter readings prior to analysis. First, a few missing values were imputed by copying the electricity consumption observed for the same household at the same time one week later.[2] In some cases, recorded consumption totalled less than 0.5 kW h for an entire day, which is implausibly low compared to the expected electricity consumption of a typical household. Such days were excluded from the database. For 14 households, there were 30 days or more with electricity usage below this threshold over October–December 2013, and we decided to completely discard these households from the analysis. Hence, the sample dropped from 323 to 309 households. In addition, yearly electricity consumption was suspiciously low (less than 500 kW h/year) for 4 additional households, and we also excluded them. The final sample for which we have electricity data is thus composed of 305 households, and the sample for which we have both electricity and survey data of 123 households.

Fig. 1 shows the evolution of average monthly electricity usage of the 305 households in our final sample, over the observation period. We observe substantial variation over the year, which is mainly due to seasonality and weather-related reasons. We also note that electricity consumption averages around 3200 kW h per household, which matches well other figures available for Switzerland. For instance, Boogen (2017) obtains 4000 kW h/year for an average household in 2010, EnergieSchweiz (2018a) provide a figure of 3000 kW h/year for a typical 3-person household without electric heating in 2016, and numbers provided in EnergieSchweiz (2018b) reveal an average household consumption around 3200 kW h/year (CHF 53 per month, transformed using a price of 20 cents/kWh) for 2016–2017. The differences between these values are mostly explained by the inclusion or exclusion of households with electric heating. The average proportion of electric

---

[1] The primary objective of the field experiment was to assess responsiveness of residential electricity users (households) to financial incentives and information feedback. A detailed presentation and analysis of the field experiment is provided in Perret et al. (2015) and Weber et al. (2017a).

[2] Out of a total of more than 14 million electricity readings in 15-min intervals, there were 24,084 missing values, i.e. less than 0.2% of the observations.

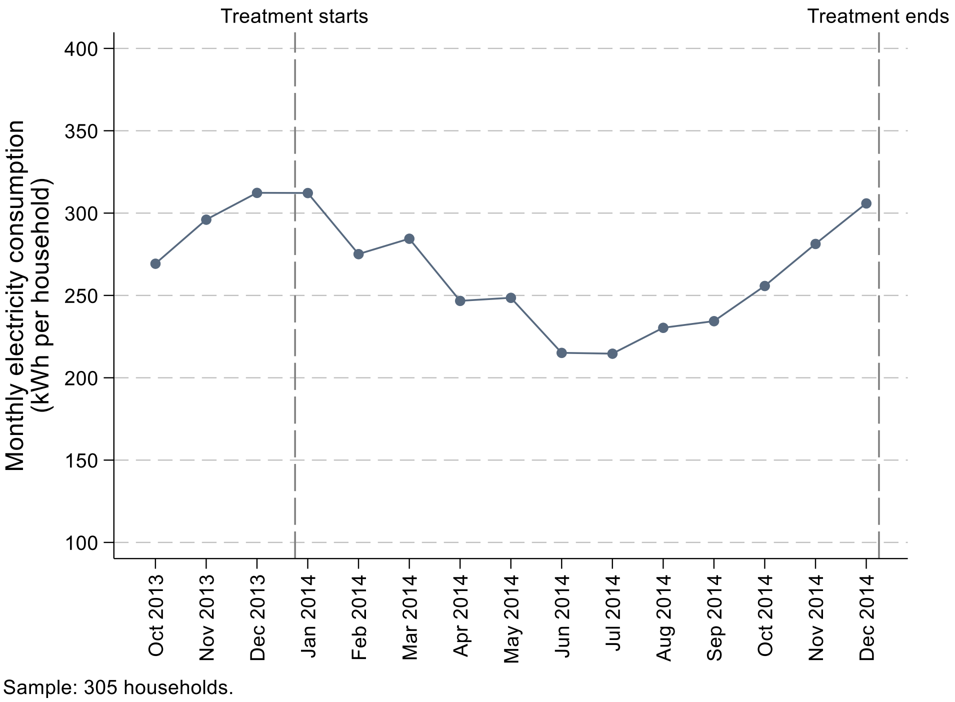


Fig. 1. Monthly electricity consumption per household and the monitoring period of the households.

heating is around 9% in Switzerland but virtually zero in our sample.

For our purposes, the samples we use depend on the steps of our analysis. In the first step, we want to cluster households based on their load profiles. For this, we do not need to know any characteristics of the households and therefore rely on the sample (305 households) for which we have valid electricity data. At the same time, we want to avoid our cluster analysis to be biased by the treatments that were implemented in the field experiment. The observation period for the cluster analysis is therefore restricted to the pre-treatment period (October–December 2013).

In the second step, we will investigate the composition of the clusters. To this end, we need the characteristics of the households, so our sample will be reduced to households who have valid electricity data and answered the online survey (123 households). This analysis being static (only one observation per household), the observation period is not relevant.

Finally, we will explore the determinants of flexibility, defined as the proportion of electricity that was shifted toward 11am-3pm, in accordance with the target assigned during the field experiment that took place from January to December 2014. Our measurement of flexibility is thus observed rather than expected or simulated, and this implies we can only use households who were included in the treatment groups. For this step of the analysis, the sample is thus composed by the households included in either of the three treatments implemented in the field experiment (see Table 1), while those in the control group are excluded. The observation period corresponds to October–December 2013 and October–December 2014, from which a difference not influenced by seasonal effects can be computed. During the treatment period, two households moved out and we exclude them from this part of the analysis, so that our sample for this step of the analysis encompasses 60 households.

3. Empirical methods

3.1. Overview

Our analysis is structured in sequential steps. A cluster analysis is conducted first in order to identify groups of households who display similar load curves. A multinomial logit regression is then used to explain the composition of clusters obtained in previous step. Finally, a hurdle model (combining a selection model and an ordinary least square model) is estimated to identify the characteristics that influence households' flexibility. Table 2 presents an overview of the analysis performed in this study and displays the samples and dataset used in each step. A schematic overview of the number of households available for each step of the analysis is provided in Fig. 2.

3.2. Cluster analysis

The cluster analysis is based on the load curves of 305 households, considering only the pre-treatment period (1 October 2013–31 December 2013) in order to have load profiles unaltered by the treatments.[3]

One daily average profile is created for each household by averaging the daily profiles of each household during the pre-treatment period. In other words, the typical load profile of a household is obtained by averaging all days of monitoring before the treatment start. In order to have figures comparable for all households and focus on the load shape rather than the consumption level, daily profiles are then normalised by dividing each hourly consumption by the daily consumption, such that the integral of the normalised profile for each household is equal to 1 in Eqn (1):

$$N_{ih} = \frac{E_{ih}}{\sum_{h=1}^{24} E_{ih}} \qquad (1)$$

---

[3] Note that the cluster analysis is based on the largest possible number of households, i.e. all households for which we have (valid) electricity data regardless of whether we have survey data for these households or not. We did not want to restrict the clustering analysis to those who happened to answer the questionnaire (123 out 305). Rather, we prefer the cluster analysis on a larger sample size as it is more robust when the sample size increases. As a robustness check, we nevertheless ran the cluster analysis for the sample of 123 households; the cluster analysis yielded very similar results (see Appendix 2).

Table 1
Types of intervention during the treatment period.

Treatment 1 (financial incentives)	Treatment 2 (information feedback)	Treatment 3 (information feedback + online platform)	Total
21	20	21	62
	−1 mover	−1 mover	−2 movers
Useable: 21	**Useable: 19**	**Useable: 20**	**Useable: 60**

Notes.
Within the 123 households for which survey data is available, 43 households constituted the control group for the field experiment and 18 households faced a two-part electricity tariff. These households were not assigned any objective about their electricity usage and are therefore not included in this step of the analysis.
Treatment 1 is implemented as a contest, in which cash prizes are awarded to the 15 top-ranked households on a monthly basis. Money worth of CHF 50, 30, and 10 (1 CHF is approximately equivalent to 1 USD) were given to households ranked 1–5, 6–10, 11–15, respectively. The ranking condition, which the households are aware of, is to maximise the proportion of electricity consumed during the period from 11am to 3pm, while keeping total consumption unaltered.
Treatment 2 consists of information feedback designed to foster shifts of electricity usage toward the period from 11am to 3pm. The feedback is delivered via monthly letters and intended to enhance households' knowledge and awareness of their electricity usage and load profile (See sample letter in Weber et al., 2017a). The letter emphasises the importance of shifting load toward the period from 11am to 3pm and provides a tip on how to shift electricity usage.
Treatment 3 is identical to treatment 2, but households in this group additionally had access to an online platform where they could follow their real-time electricity consumption. They are hence considered separately.

Table 2
Overview of the analysis performed in this study.

Analysis performed	Sample	Data	Purpose
Cluster analysis	305 households	Load curves from October to December 2013	Identify various patterns of electricity load curves and segment households.
Multinomial regression	123 households	Clusters' composition and household characteristics	Investigate the composition of clusters obtained from the cluster analysis.
Linear regression (Hurdle model)	60 households	Average increase in electricity consumed in 11am-3pm from October–December 2013 to October–December 2014, and household characteristics	Investigate the determinants of the percentage of electricity use increase between 11am and 3pm by treated households during the field experiment.

where:

N_{ih} = normalised load profile for household i in hour h.
E_{ih} = electricity used by household i in hour h.

For clustering the normalised load profiles, we have taken the approach of feature-based clustering. The principle of this approach is to extract few features to explain the shape of the load curve, thereby reducing the dimensionality of the time series (originally 24 hourly data points) to avoid “*curse of dimensionality*”, which refers to the fact that many algorithms become intractable when the input is high-dimensional (see e.g., Bellman, 1961 and Haben et al., 2016). Several studies demonstrate that feature-based clustering significantly improves cluster quality relative to using raw profile data (Räsänen and Kolehmainen, 2009; Huebner et al., 2016; Yilmaz et al., 2019).

We retain five features from the normalised values to characterise the shape of household electricity demand profiles using the approach proposed in Yilmaz et al. (2019). First, we divide the daily profiles into four time periods (Fig. 3): night time (10pm-7am), morning (7am–11am), day time (11am-3pm) and evening (3pm–10pm). The average values of the normalised profiles are calculated for each period, and these constitute the first four features to be included in the cluster analysis. The periods are usually determined depending on the level of the mean demand. In addition, we enforced period 11am-3pm to be separate, as it is the target period defined in the treatments. However, it is important to note that Yilmaz et al. (2019) and Huebner et al. (2016) found that cluster outcomes did not change if the periods were shifted by ± 1 h. Then, the mean standard deviation over the four periods gives the fifth feature. This feature expresses how much the electricity usage varies around the daily mean. A large standard deviation implies more variability, i.e. more ‘curving’ of the profile over the day whereas a small standard deviation indicates little variability. K-means clustering is applied using standard Euclidean distance as the similarity metric, using the implementation in the scikit-learn software package in Python (Pedregosa et al., 2011). The performance of the cluster model is evaluated by Silhouette index.

We run the cluster analysis on the normalised values of electricity consumption without including the magnitude of electricity consumption as a feature as our interest is in the effect of household characteristics on the shape of the daily curves. Many other studies discuss the determinants of total electricity consumption itself (see for instance Bedir et al., 2013; Kavousian et al., 2013; Tso and Yau, 2003; Wyatt, 2013; Jones and Lomas, 2015; Jones and Lomas, 2016).

3.3. Variables included as determinants in the regression analyses

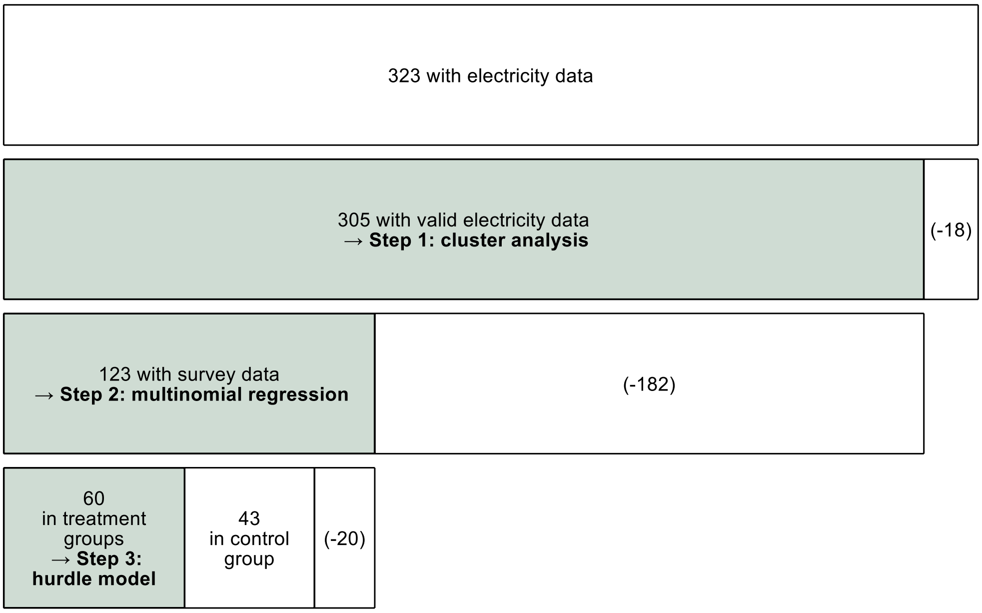
3.3.1. Household characteristics

This section describes the variables that are used as predictors in subsequent regression analyses. Table 3 shows the socio-economic characteristics, dwelling characteristics, and appliances that were considered as determinants of the clusters’ composition and load shifting. The table also shows the descriptive information with percentages for categorical variables, or mean values and standard deviation for continuous variables, separately for the two samples used in the different steps of the analysis. Number of appliances cannot be counted precisely as only availability of appliances was asked and not their number. Still, for some appliances (TVs, PCs, radios, consoles) the number is available, and for most others (e.g., washing machines or dishwashers), it seems legitimate to assume that households own no more than one unit, so that it is possible to calculate an approximate number.

Note that the number of covariates introduced in our estimations is relatively small, as it is constrained by the limited size of our sample. Further covariates were nevertheless tested in some models, but finally excluded because they correlated strongly with others, which prevented their effects from being identified accurately. This was in particular the case for dwelling size (strongly correlated with dwelling type), number of people (strongly correlated with presence of children), or income (strongly correlated with dwelling type and education level).[4] We

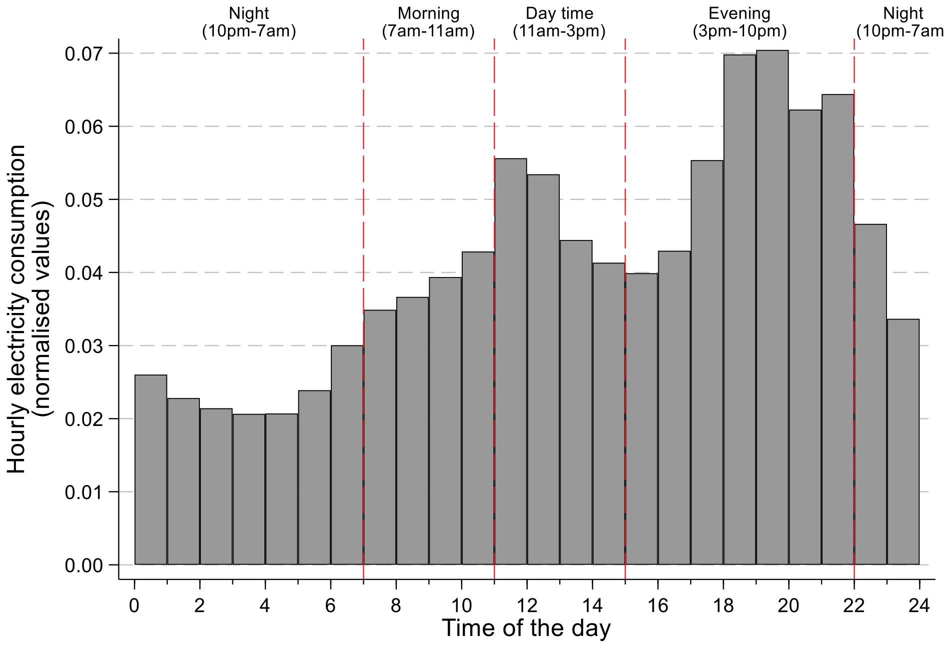
---

[4] A further reason for excluding income from the analysis is that more than



Note: negative numbers indicate how many households were discarded.
- 18 displayed implausible electricity data.
- 182 did not respond the survey.
- 20 either faced a two-part electricity tariff or moved out (further details in Table 1).

Fig. 2. Samples used for the different steps of the analysis.



Sample: 305 households.

Fig. 3. Average normalised profile for the households included in the cluster analysis.

discarded dwelling type (house vs. flat) as there was a clear overlap with the tenure type; all but one of the households living in a house were also owners.

Table 4 shows the variables about attitudes on energy conservation, climate change and renewable resources that were asked in the online survey. These variables were measured on a five-point Likert-scale. Mean values and standard deviations are indicated, separately for the two samples. Due to small size of the samples, only one variable is calculated by averaging the answers to the seven questions. It is then interpreted as the "environmental attitude" towards energy conservation, climate change, and renewable resources.

3.3.2. *Other variables*

In addition to the households' and dwellings' characteristics defined above, we use information directly extracted from the load curves as a possible determinant of the change in electricity consumption. In particular, the amount of variability in electricity use of each household has been considered as an important determinant for potential load

---

(*footnote continued*)
10% of the respondents have not provided an answer to this question.

Table 3
Socio-economic characteristics, dwelling characteristics and appliances.

Variable	Multinomial logistic regression	Hurdle model
Tenure type		
Tenant	0.38	0.40
Owner	0.62	0.60
Age of respondent		
18–29	0.11	0.13
30–39	0.15	0.17
40–49	0.25	0.22
50–64	0.31	0.33
65 +	0.18	0.15
Education level		
Low-Medium	0.61	0.67
High	0.39	0.33
Presence of children		
No	0.55	0.53
Yes	0.44	0.46
Number of wet appliances	1.92	1.92
	(1.08)	(1.12)
Number of ICT appliances	4.61	4.52
	(2.03)	(2.01)
Presence 8am-6pm (person-days)	6.49	5.85
	(5.41)	(5.19)
Number of observations	**123**	**60**

Notes.
Percentages for binary variables; means and standard deviations in parentheses for continuous variables. Totals do not necessarily sum to 100% because of rounding.
High education level includes university/college and any higher training. Low-medium education level includes high school, vocational school and lower.
Wet appliances include dishwashers, washing machines and tumble dryers.
ICT appliances include TVs, PC/laptops, radio hi-fi and consoles.

shifting (e.g. Dent et al., 2014; Kwac et al., 2014). In this paper, we define household's variability (interchangeably used with intra-household variation) as the variation in electricity use within the household during the pre-treatment period (October 2013 to December 2013), and we measure it by the entropy, as defined by Kwac et al. (2014) and calculated as shown in Equation (2). To do so, a clustering method similar to that presented in Section 3.2 is applied to daily profiles independently from the household ID (instead of average single profiles as before). It follows that the profile of each day for a given household is assigned to a cluster, and this cluster is allowed to change over time. For instance, Household 1's profile may be classified in Cluster 2 in the first day of observation, while it may be classified in Cluster 3 in the second day, etc. A distribution of daily clusters is therefore obtained for each household i, which allows to compute its entropy as follows:

$$Entropy_i = -\sum_{k=1}^{K} p(C_k)\cdot\ln[p(C_k)] \tag{2}$$

where:

$p(C_k)$ = probability of each cluster k in household's daily series.
K = total number of clusters.

Entropy is highest if inclusion in all clusters is equally likely for a household and lowest if all daily profiles of the household fall in a single cluster. In other words, high entropy characterises households with a load profile that differ substantially day after day and therefore indicates high variability in electricity use. Determining the impact of entropy on load shifting allows us to investigate the hypothesis that more variable households are more likely to change electricity use.

Finally, the treatment groups in which some households were allocated during the field experiment was also used as a determinant for load shifting. Categorical variables indicate for 60 households which treatment (financial incentives, information feedback, or information feedback combined with online platform) they received. Indeed, considering the differences in incentives across treatment groups, we can expect different intensity in their reactions. The goal is thus to assess whether monetary rewards without any precise information related to electricity usage and/or information feedback (possibly combined with access to an online platform) can induce households to shift their load profile.

3.4. Dependent variables

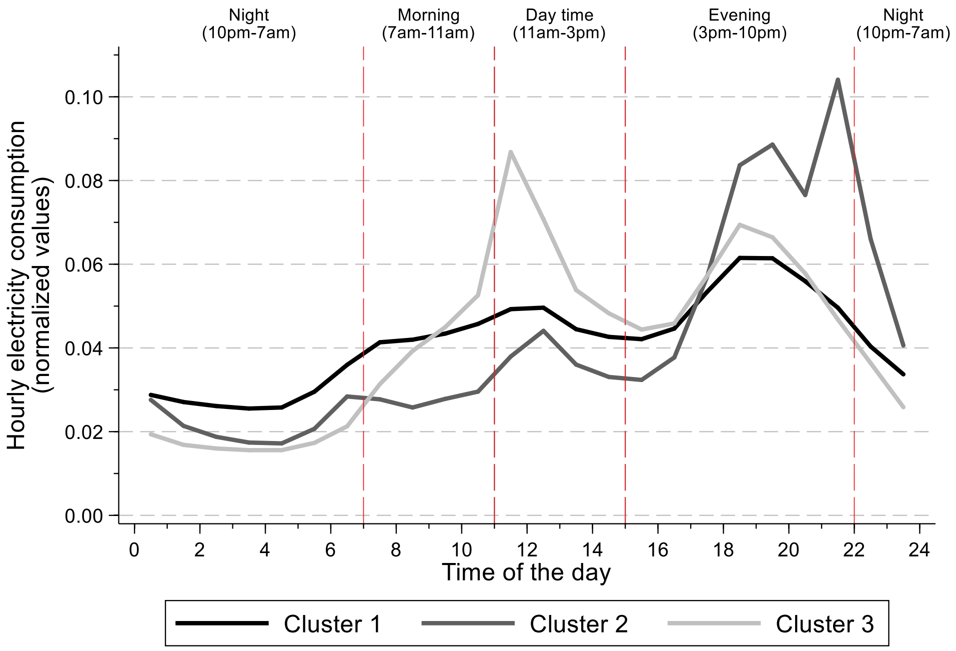
In the first regression analysis, the cluster categories are used as the dependent variable of a multinomial logistic model and linked to household characteristics. The results of this regression will unravel the factors driving the shape of the load profile.

The amount of load shifted will then be investigated, using the percentage increase of electricity consumed from 11am to 3pm calculated as the difference between the mean of normalised profiles in the pre-treatment period (October 2013–December 2013) and in (part of) the treatment period (October 2014–December 2014). Identical months are chosen from each of the pre-treatment and treatment period so as to avoid weather-related differences: in winter, days are shorter (implying more lighting use) and colder (implying more cooking and heating). The change in the proportion 11am-3pm is then used as the dependent

Table 4
Variables on attitudes.

Variable	Answer scale	Multinomial logistic regression	Hurdle model
Are you concerned about the effect of the energy consumption on the climate change?	1 = not at all, …, 5 = very concerned	3.94 (0.96)	3.83 (0.98)
Do you think your habits might have an influence on fighting the climate change?	1 = no influence at all, …, 5 = big influence	3.53 (1.02)	3.53 (1.03)
Do you pay attention to your energy consumption?	1 = not at all, …, 5 = very much	3.94 (0.91)	3.90 (0.97)
What do you think about renewable energy?	1 = not necessary, …, 5 = necessary	4.41 (0.83)	4.35 (0.86)
Do you give importance that your supply comes from a renewable energy source?	1 = not at all, …, 5 = very much	3.41 (1.22)	3.37 (1.28)
When you are buying an appliance, are you giving attention to its energy consumption?	1 = not at all, …, 5 = very much	4.28 (0.95)	4.12 (1.08)
When you are buying a car, are you giving attention to its fuel consumption?	1 = not at all, …, 5 = very much	4.09 (1.01)	4.08 (1.09)
Environmental attitude	Average of the answers to the seven questions above	3.94 (0.67)	3.88 (0.75)
Number of observations		123	60

Notes: means and standard deviations in parentheses. The Cronbach's alpha coefficient for the 7 items composing the environmental attitude scale is 0.799, which shows that there is good internal consistency and therefore that averaging these items is justified.



Sample: 140/87/78 households in cluster 1/2/3.

Fig. 4. Centroids of the load profiles, by cluster.

variable in a second regression analysis, namely a hurdle model. Cluster categories then become independent categorical variables. The objective is to determine whether certain cluster profiles are more likely to successfully shift their usage to the afternoon.

3.5. *Statistical analysis*

3.5.1. *Multinomial regression*

To investigate the characteristics influencing the clusters' composition, multinomial regression models (logit) were used to explain the probability that household i is assigned to cluster k shown in Eqn (3):

$$\Pr(y_i = k|x_i) = \begin{cases} \dfrac{1}{1+\sum_{j=2}^{3}\exp\left(x_i\beta_j\right)} & \mathit{for}\ k = 1\ \text{(reference category)} \\ \dfrac{\exp(x_i\beta_k)}{1+\sum_{j=2}^{3}\exp\left(x_i\beta_j\right)} & \mathit{for}\ k = 2,\ 3 \end{cases} \tag{3}$$

where x_i is a row vector of independent variables for household i, and β_k is the vector of coefficients for cluster k. The interested reader can find a detailed description of multinomial logit models in Greene (2018, chapter 18).

The coefficients of a multinomial logit do not represent changes in probabilities and are difficult to interpret per se. Therefore, marginal effects are usually computed, for instance for covariate x_i and cluster k shown in Eqn (4):

$$\frac{\partial \Pr(y_i = k|x_i)}{\partial x_i} = \Pr(y_i = k|x_i)\cdot\left[\beta_k - \sum_{j=2}^{3}\Pr(y_i = j|x_i)\cdot\beta_j\right] \tag{4}$$

Precisely, the marginal effects can be interpreted as the effect of a one-unit increase in the independent variable on the probability of a household being included in cluster k. For binary covariates, marginal effects indicate the effects of a change from 0 to 1. The marginal effects of each variable on the different alternatives sum up to zero by definition.

3.6. *Hurdle model*

In a second regression analysis, we seek to unravel which individual characteristics influence load shifting. The first step of our analysis shows that households in the treatment groups were only partly successful, the average proportion increasing by less than 0.5 percentage point. Almost half of the households included in the treatment groups (29 out of 60) in fact did even *decrease* their proportion of electricity consumed between 11am and 3pm while their stated objective was the opposite.

Since we are not interested in proportions that decreased, we distinguish between two types of households as the unsuccessful (i.e. the ones who did not increase the proportion) and the successful (i.e. the ones who were able to increase the proportion). We then rely on a hurdle model (see Cragg, 1971; Belotti et al., 2015), which combines a selection model with an outcome model. The selection model thus allows us to distinguish between successful and unsuccessful households, while the outcome model focuses on the successful households and explains the extent of the proportion changes.

The hurdle model is characterised by the relationship $y_i = s_i y_i^*$, where y_i^* is the change in proportion 11am-3pm realised by household i if it was successful in increasing this proportion. The selection variable s_i takes the value 1 if the household was successful and 0 if it was unsuccessful, so the selection equation shown in Eqn (5) writes:

$$s_i = \begin{cases} 1 & \mathit{if}\ z_i\gamma + \varepsilon_i > 0 \\ 0 & \mathit{otherwise} \end{cases} \tag{5}$$

where z_i is a vector of explanatory variables, γ is a vector of coefficients, and ε_i is an error term that follows a standard normal distribution. The outcome variable y_i^* is only observed when it is positive, that is when $s_i = 1$, and the outcome equation shown in Eqn (6) then writes:

$$y_i^* = x_i\beta + \nu_i \tag{6}$$

where x_i is a vector of explanatory variables, β is a vector of coefficients, and ν_i is an error term that follows a truncated normal distribution with lower truncation point $-x_i\beta$. The output of the hurdle model is hence composed of two equations: the selection equation (i.e. the hurdle), and the outcome equation, a linear model based only on households who passed the hurdle. The software Stata is used to estimate both multinomial regression (Section 3.5.1, command mlogit) and the hurdle model (command churdle).

Table 5
Mean values of the five features considered in the cluster analysis, by cluster (N = 305).

Cluster	Number of households	Morning (7am–11am)	Day time (11am-3pm)	Evening (3pm–10pm)	Night (10pm-7am)	Std. dev.
1	140 (45.9%)	0.043	0.047	0.053	0.030	0.012
2	87 (28.5%)	0.028	0.038	0.069	0.029	0.021
3	78 (25.6%)	0.042	0.065	0.055	0.020	0.021

4. Results

4.1. Cluster analysis

The cluster analysis of the households' average load profiles yielded three distinct groups, respectively composed of 140 (45.9% of the sample), 87 (28.5%), and 78 (25.6%) households. As shown in Fig. 4, the daily profile shapes are clearly distinguishable (average silhouette score = 0.28; see Appendix 1 for the silhouette scores calculated for varying number of number of clusters). All clusters display a relatively standard load profile, with morning and evening peak. However, households in Cluster 1 have morning and evening peaks that are both less sharp. Cluster 2 has comparatively lower morning peak, and a sharp evening peak. Finally, Cluster 3 shows a relatively high use of electricity centred around midday, with a considerably lower evening peak.

Table 5 shows the mean values of the five features (mean of morning, day time, evening, night and standard deviation), by cluster. Cluster 1 daily profiles have the lowest variation (std. dev. 0.012) with a relatively smoother electricity use profile and represents the largest cluster with 46% of the sample. Clusters 2 and 3 have higher variation, both with a standard deviation of 0.021.

4.2. Determinants of load profile shape

We investigate the determinants of the load profile shapes using a multinomial regression. Since the coefficients of such models are not directly interpretable (see Section 3.5.1) and for the sake of space, only the marginal effects at the means obtained in the logit model are reported in Table 6.[5] In the following, the influence of each characteristic on the composition of each cluster is discussed.

4.2.1. Cluster 1

Households which own more wet appliances are more likely to be included in Cluster 1 compared to Clusters 2 and 3. No other coefficients are significantly estimated for this cluster.

4.2.2. Cluster 2

Older age categories are under-represented in this cluster, with significant coefficients for the households with head aged above 65. Households in Cluster 2 are also less likely to be home during the day. Hence, these households are most often composed of young and active (less present at home between 8am and 6pm) individuals, who only come home at the end of the day, which explains the relatively low consumption during the day and the high peak in the evening. Finally, households who have this cluster profile possess relatively fewer wet appliances.

4.2.3. Cluster 3

Households in Cluster 3 are composed of relatively old individuals, with the age category above 65 years old being a strongly significant predictor. The number of people present at home between 8am and 6pm also exerts a positive and (weakly) significant influence. The presence of children has a positive impact as well. All these determinants make sense in view of the load curve shape of this cluster, which exhibits a large peak during the day compared to the other clusters.

Table 6
Multinomial logit regression for socio-demographic, dwelling and appliance characteristics (marginal effects) (N = 123).

	Cluster 1	Cluster 2	Cluster 3
Status (1 = owner)	−0.068	0.087	−0.019
	(0.131)	(0.108)	(0.118)
Age of respondent: 30–39	−0.029	−0.127	0.157
	(0.226)	(0.142)	(0.254)
Age of respondent: 40–49	−0.147	−0.083	0.230
	(0.217)	(0.132)	(0.241)
Age of respondent: 50–64	−0.149	−0.194	0.342
	(0.210)	(0.129)	(0.234)
Age of respondent: 65 +	−0.226	−0.268*	0.494**
	(0.225)	(0.157)	(0.242)
High education level	0.005	0.005	−0.010
	(0.103)	(0.082)	(0.094)
Presence of kids in HH	−0.157	−0.070	0.227*
	(0.134)	(0.098)	(0.126)
Presence 8am-6pm (person-days)	0.004	−0.018**	0.014
	(0.010)	(0.009)	(0.009)
Wet appliances (number)	0.110*	−0.109**	−0.001
	(0.059)	(0.046)	(0.054)
ICT appliances (number)	−0.035	0.029	0.006
	(0.028)	(0.024)	(0.025)
Environmental concerns (index)	−0.011	0.037	−0.025
	(0.072)	(0.053)	(0.068)
# Obs. in cluster	57	28	38

Notes: Standard errors in parentheses. */**/*** significant at 10/5/1%. Marginal effects computed at the sample means (discrete change from the base level for binary variables).

4.3. Determinants of load shifting

Table 7 shows the results obtained with the hurdle model. As could be expected considering the small number of observations, only few variables are significant. In the selection model, only the presence of children is significant (at the 10% level), which indicates that households are more likely to be successful electricity use shifters if they have children. Presumably, this effect is indirect and caused by the fact that parents use to come home at noon to have lunch with their children. It should be emphasized that entropy, albeit showing a positive point estimate, does not appear to be a significant determinant of success in load shifting. This non-result tends to contradict the usual assumption according to which households with more variability may be more receptive to incentives to load shifting.

Among the households who were successful in increasing their proportion of electricity used between 11am and 3pm, the extent of the increase is described by the outcome equation. As expected, it appears that households in Cluster 3 were able to shift a larger proportion. On average, they shifted above 11 percentage points of their load curve more than households in Cluster 1. Cluster 3 has a large peak at noon which implies the occupancy presence in the time period therefore increases the probability of participating in the demand response programme. Similarly, load shifting was more pronounced when the head of household is aged 65 or more, which is likely due to the less stringent time constraints faced by these households. Presence of children also appears to be raising the proportion of load shifting, but the statistical

---

[5] All results' tables are available on request.

Table 7
Coefficients of hurdle model.

	Outcome equation	Selection equation
Cluster 2	3.797	–
	(4.989)	
Cluster 3	11.358**	–
	(4.476)	
Treatment 1	6.067^{+}	–
	(3.977)	
Treatment 3	0.064	–
	(4.204)	
Status (1 = owner)	−7.221**	–
	(3.341)	
Wet appliances (number)	0.414	–
	(1.566)	
Presence of kids in HH	5.804^{+}	0.730*
	(3.835)	(0.437)
Age of respondent: 30–39	4.788	−0.277
	(4.500)	(0.632)
Age of respondent: 40–49	0.776	−0.836
	(5.892)	(0.605)
Age of respondent: 50–64	−3.812	−0.345
	(5.314)	(0.538)
Age of respondent: 65+	11.650*	0.267
	(6.592)	(0.703)
Presence 8am-6pm (person-days)	-0.739^{+}	−0.006
	(0.460)	(0.040)
Entropy	–	1.930
		(1.880)
Environmental concerns (index)	–	−0.108
		(0.237)
Intercept	−6.298	−0.448
	(7.106)	(1.208)
Pseudo-R^2	0.180	
# Obs.	60	

Notes: Standard errors in parentheses. $^{+}$/*/**/***: significant at 15/10/5/1%. Marginal effects computed at the sample means (discrete change from the base level for binary variables).

significance is low. Households submitted to monetary incentives during the field experiment (Treatment 1) have increased their percentage more than households who received monthly information feedback (Treatments 2, i.e. omitted category, and 3). While this coefficient is relatively large, it is only weakly significant (significant at the 15% level). It moreover appears that homeowners have shifted less, which might be interpreted as an indirect effect of income. Wealthier households can indeed be expected to be less sensitive to incentives (in particular financial ones) and would therefore tend to react less. All other coefficients appear statistically non-significant.

5. Discussion

5.1. Implications of the study findings

The cluster analysis on average household profiles identified three distinct patterns of electricity use over the course of the day. Cluster 1, composed by almost half of the sample, is characterised by a relatively low variability of electricity usage over the day. Its load profile displays two relatively moderate peaks at noon and in the evening. Clusters 2 and 3 exhibit a single strong peak, in the evening for Cluster 2 but at noon for Cluster 3. Different load curve shapes might reflect different ownership of appliances, presence at home and so on. Therefore, a closer look at the difference in building characteristics, socio-demographics and appliance use is of interest in this regard. The interest of our study is enhanced because such combined datasets are seldom available.

Our analysis makes it possible to classify households and the electricity use patterns based on individual characteristics (e.g. dwelling type, age). This provides a basis to pre-screen households for future studies focusing on demand response potentials based on the households' socio-demographic and dwelling characteristics. These findings may prove especially useful where metering/smart meter is not available, (Haben et al., 2016) which is currently the case of most households in Switzerland. SFOE (2015) reported the share of Swiss households equipped with smart meters at 2% in 2015. According to the latest statistics from the Swiss Household Energy Demand Survey (SHEDS; see Weber et al., 2017b), this share is roughly 9%. The Swiss government has nevertheless planned a general roll-out with a law stating that the proportion of equipped households must reach 80% by 2027.[6]

Socio-economic variables such as tenure type or education had nearly no impact on the shape of the daily curve. These variables, however, had a significant (positive or negative) effect on the level of household electricity consumption as found in more than 20 studies (Jones and Lomas, 2015). With respect to the ownership of specific appliances, ICT appliances had no effect on the load curve's shape. Wet appliances on the other hand were less likely found in cluster profile which have relatively lower use during the day (Cluster 2 compared to Clusters 1 and 3).

This study found out that attitudes reported in the survey had no effect. Many studies have found out similar results for the total electricity consumption such that self-reported attitudes on climate change and pro-environmental behaviours had a small effect on electricity consumption (Mansouri et al., 1996; Huebner et al., 2016). Through the variable indicating whether household members are present at home between 8am and 6pm during weekdays, we can infer that employment status had an impact on the shape of the load curve. Households who are less present during the day were thus more likely to have a load profile similar to Cluster 2, with low electricity use during daytime, whereas more present households were more likely as Cluster 3, with a high peak at noon.

This study relied on experimental research data with households who were actually provided with incentives to shift rather than on simulations or stated preferences. Our results should thus be of great value to utilities interested in shifting electricity use to times of afternoon when photovoltaic supply is at its maximum, thereby reducing the need for additional generation and transmission network capacity. The results did not reveal any association between the entropy (indicating variability in electricity use patterns) and the shift of electricity use. This finding challenges the two assumptions made by Kwac et al. (2014) and Dent et al. (2014). Kwac et al. (2014) argue that it could be easier to target demand response programmes to a more stable household that has the same load shape every day than one that is highly variable. Conversely, Dent et al. (2014) suggest that households showing very little variability in the timing of their regular activities can be considered as "creatures of habit", so that these households may not respond well to an incentive to change behaviour. Results also showed that households with kids (used as a proxy for families) were associated to more shifting of electricity use. This contradicts with several consumer organisations who have sometimes argued that time of use tariffs will not be popular amongst people with children (Consumer Focus, 2012; Energy and Climate Change Select Committee, 2015). Contrarily, through a stated-preference survey, Nicolson et al. (2017) found out the willingness to switch to a time-of-use tariff did not vary across people living in households with and without children and employment status.

Households showing a steep morning peak and composed of individuals older than 65 were found to perform better at load shifting. One may naturally expect such households to be more responsive, considering they have greater flexibility in their daily activities than households mostly composed of people in employment.

---

[6] See Article 31e of the *Stromversorgungsverordnung* (StromVV, in German) or the *Ordonnance sur l'approvisionnement en électricité* (OApEl, in French).

The ownership of wet appliances was not found as significantly associated with the percentage of shift of electricity use. However, many surveys have nevertheless stated higher willingness to accept demand response in wet appliances (up to 30%) compared to other appliances such as cooking (Platchkov et al., 2011; Oseni et al., 2013; Spence et al., 2015). It is important to note that there is no follow-up study to understand which appliances' use were shifted towards 11am-3pm. Last but not least, the results showed that households that receive monetary incentives are more likely to shift than those who receive information on their electricity consumption as a motivation. Therefore, money-incentive can be considered to increase the success of the demand response.

This study emphasises that cluster analysis on smart meter data alone is not sufficient to drive conclusions for policy makers. Qualitative data such as household characteristics, appliances and opinions/attitudes are important to understand the drivers and motivation behind the decision making of demand shifting. As this study found out, other factors such as incentives, can be the key factors for the success of demand response schemes not only the variation in the electricity demand profiles. The effect of these factor is also likely to differ under various network tariffs.

5.2. Limitations and future research

The results were obtained based on relatively small samples, composed of 60–305 dwellings (depending on the step of the analysis) located in a single town of western Switzerland. Extrapolating the results to the wider population of Swiss homes or even further may therefore not be appropriate. A larger national-scale study of appliance ownership and monitored electricity use data would therefore be a valuable extension to the current work and could also be used to validate the findings of the current study. Additionally, variables for which no impact could be identified with our sample such as house ownership or environmental concerns may become significant determinants with higher sample size. However, it should be noted that increasing the sample size does not mean it automatically solves the size issues as more clusters can be discovered and still the sample size within the subcategory i.e. cluster can be small. For this study, only the shifting towards the period between 11am and 3pm is considered, therefore success rate for demand response scheme is only measured by looking at the increase of the usage in this time window. For future work, a range of potential demand response schemes should be covered conducting a similar survey of household characteristics.

6. Conclusions and policy implications

In this paper, a cluster analysis was applied to average household electricity profiles of 305 dwellings in Switzerland to identify the patterns of electricity load curves. The cluster analysis on average household profiles identified three distinct patterns of electricity use over the course of the day.

A multinomial regression was then applied to 123 households to link their socio-demographic characteristics (e.g. age, presence of children, and education level) and appliances (e.g. ownership of washing machines and tumble dryers). This analysis provides a useful indication of how household characteristics affect load profile shapes. The results should be of key importance to utilities and policy makers who are interested in demand response potentials based on the households' socio-demographic and dwelling characteristics. The results suggest that characteristics such as age and presence at home during the day are strong determinants of the load profile shape. In addition, we found that households with children were significantly more likely to be included in the cluster displaying a profile with relatively higher late morning/midday electricity use. On the other hand, households who own wet appliances were less likely to be in the cluster with relatively low electricity use during the day and high peak in the evening.

The second regression analysis, based on a hurdle model, was performed to link household characteristics to those who successfully shifted their electricity use to 11am-3pm during the treatment period. The results demonstrate that presence at home was a significant determinant of load shifting. Households with head aged above 65, households exhibiting electricity use patterns that have relatively high peak at noon, and households with children (low significance) were found to be more likely to shift their load towards 11am-3pm. These results show that stronger efforts of home automation systems for load shifting should be made in order to involve households whose members are not present for most of the day. Additionally, households who received money incentives were more likely to shift than those who received information.

This paper provides a basis for advice and guidance to households, by policy makers and energy companies, that would enable them to be included in demand response programmes for the future planning of the Swiss energy supply network with increased renewable power generation. Future research should seek to understand the effects of those socio-economic, dwelling and appliance factors for different demand response programmes.

Acknowledgements

Sylvain Weber gratefully acknowledges financial support from the Swiss Federal Office of Energy (SFOE) under grant no SI/500853-01. This research is also part of the activities of SCCER CREST (financially supported by Innosuisse under grant no KTI 1155000154) as well as of SCCER FEEB&D (financially supported by Innosuisse under grant no KTI 1155002539).

Appendix 1

For this study, the performance of the cluster model is evaluated by the silhouette score shown in equation defined by Rousseeuw (1987) shown in Eqn (7):

$$Silhouette = \frac{b - a}{\max(a,\, b)} \tag{7}$$

where:

a = average intra-cluster distance,
b = average shortest distance to another cluster.

This metric compares the model parameters based on cluster geometry in terms of compactness (elements are close to one another within the cluster) and distinctness (the centres of the clusters are far away as from another cluster centre). The silhouette score has a range of [-1, +1], where a score close to +1 indicates that the object is similar to other objects in its own cluster and dissimilar to objects in other clusters. A zero or negative score indicates that an object is either not very similar to others in its own cluster or is very similar to objects in different clusters. The silhouette score may be calculated for every clustered object and as an average for the whole dataset. We calculate the silhouette score using the scikit-learn package with additional optimisations to facilitate work with large data samples.

Figure A1 shows the average silhouette scored calculated for varying number of cluster (2–20). As can be seen silhouette score is the highest (0.29) when “k” is equal to 3. Therefore, we choose “3” as the optimised number of clusters for our analysis.

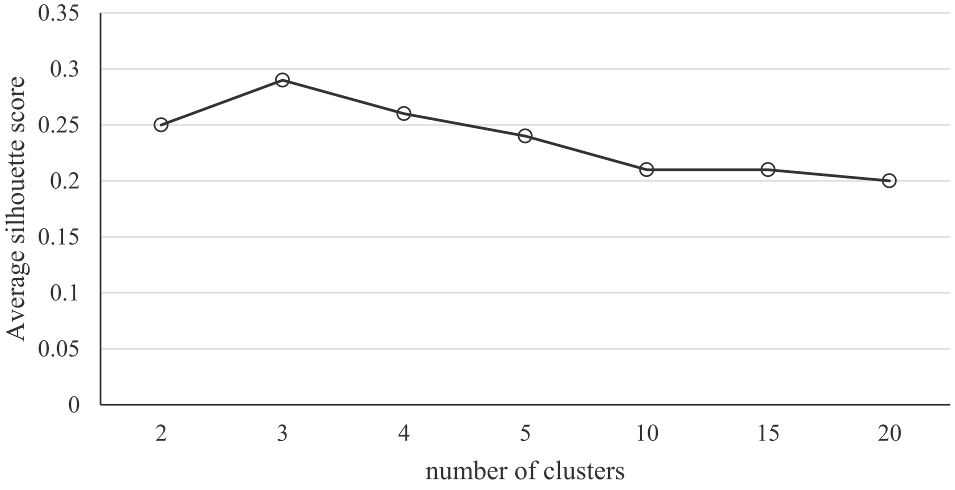
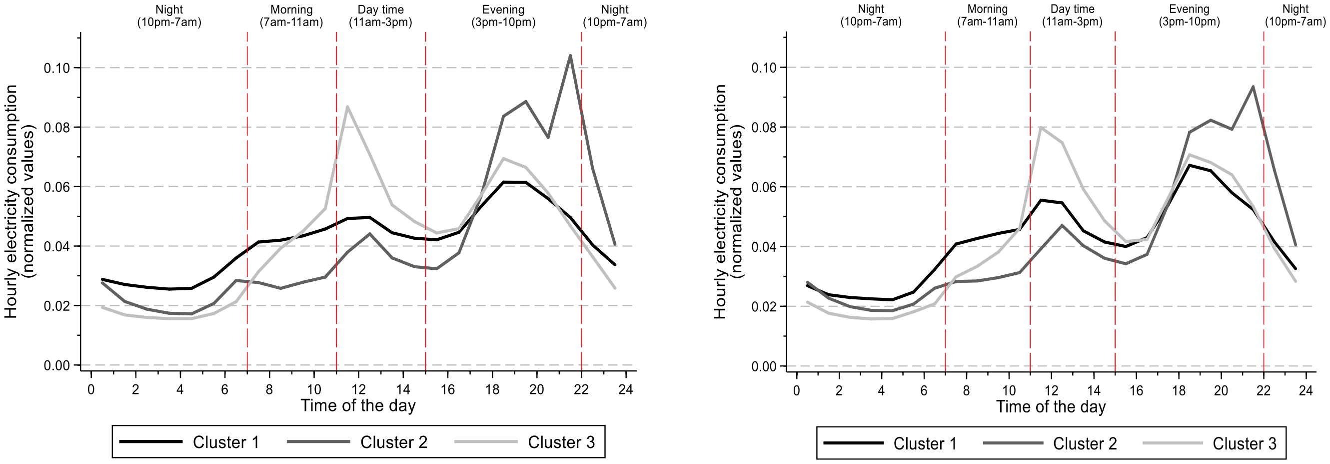


Figure A1. Average silhouette scores for varying number of clusters

Appendix 2

Figure A2shows the centroid of the load profiles by clusters based on cluster analysis of 305 and 123 households.



Sample: 140/87/78 households in cluster 1/2/3.

Sample: 58/34/31 households in cluster 1/2/3.

Fig. A2. Comparison of the centroids of the load profiles, by cluster based on 305 and 123 households2

Table A1 and Table A2 show the mean values of the five features (mean of morning, day time, evening, night and standard deviation), by cluster for cluster analysis based on 305 and 123 households, respectively.

Table A1
Mean values of the five features considered in the cluster analysis, by cluster (N = 305)

Cluster	Number of households	Morning (7am–11am)	Day time (11am-3pm)	Evening (3pm–10pm)	Night (10pm-7am)	Std. dev.
1	140 (45.9%)	0.043	0.047	0.053	0.030	0.012
2	87 (28.5%)	0.028	0.038	0.069	0.029	0.021
3	78 (25.6%)	0.042	0.065	0.055	0.020	0.021

Table A2
Mean values of the five features considered in the cluster analysis, by cluster (N = 123)

Cluster	Number of households	Morning (7am–11am)	Day time (11am-3pm)	Evening (3pm–10pm)	Night (10pm-7am)	Std. dev.
1	58 (47.2%)	0.043	0.049	0.054	0.028	0.013
2	34 (27.6%)	0.029	0.041	0.066	0.029	0.018
3	31 (25.2%)	0.037	0.066	0.057	0.022	0.021

References

Abrahamse, Wokje, Steg, Linda, Charles, Vlek, Rothengatter, Talib, 2007. The effect of tailored information, goal setting, and tailored feedback on household energy use, energy-related behaviors, and behavioral antecedents. J. Environ. Psychol. 27 (4), 265–276. https://doi.org/10.1016/j.jenvp.2007.08.002.

Andrey, C., Babonneau, F., Haurie, A., 2014. Time of Use (TOU) Pricing Adaptive and TOU Pricing Schemes for Smart Technology Integration". Available at: http://ordecsys.com/files/TOU_Final.pdf, Accessed date: 1 November 2018.

Barton, J., Huang, S., Infield, D., Leach, M., Ogunkunle, D., Torriti, J., Thomson, M., 2013. The evolution of electricity demand and the role for demand side participation, in buildings and transport. Energy Policy 52, 85–102.

Bartusch, Cajsa, Wallin, Fredrik, Odlare, Monica, Vassileva, Iana, Wester, Lars, 2011. Introducing a demand-based electricity distribution tariff in the residential sector: demand response and customer perception. Energy Policy 39 (9), 5008–5025. https://doi.org/10.1016/j.enpol.2011.06.013.

Bedir, M., Hasselaar, E., Itard, L., 2013. Determinants of electricity consumption in Dutch dwellings. Energy Build. 58, 194–207.

Bellman, R.E., 1961. Adaptive Control Processes. Princeton University Press, Princeton, NJ.

Belotti, F., Deb, P., Manning, W.G., Norton, E.C., 2015. twopm: two-part models. STATA J. 15, 3–20.

Benítez, I., Quijano, A., Díez, J.L., Delgado, I., 2014. Dynamic clustering segmentation applied to load profiles of energy consumption from Spanish customers. Electr. Power Energy Syst. 55, 437–448.

Boogen, N., 2017. Estimating the potential for electricity savings in households. Energy Econ. 63, 288–300.

Carroll, James, Lyons, Seán, Denny, Eleanor, 2014. Reducing household electricity demand through smart metering: the role of improved information about energy saving. Energy Econ. 45, 234–243. https://doi.org/10.1016/j.eneco.2014.07.007.

Chicco, G., Napoli, R., Piglione, F., Postolache, P., Scutariu, M., Toader, C., 2004. Load pattern-based classification of electricity customers. IEEE Trans. Power Syst. 19, 1232–1239.

Consumer Focus, 2012. From Devotees to the Disengaged. Consumer Focus, London.

Cragg, J.G., 1971. Some statistical models for limited dependent variables with application to the demand for durable goods. Econometrica 39, 829–844.

Darby, S.J., 2018. Smart electric storage heating and potential for residential demand response. Energy Effic. 11 (1), 67–77.

Dent, I., Craig, T., Aickelin, U., Rodden, T., 2014. Variability of behaviour in electricity load profile clustering; who does things at the same time each day? In: Proceedings of Industrial Conference on Data Mining: Advances in Data Mining. Applications and Theoretical Aspects, pp. 70–84.

EnergieSchweiz, 2018a. Energieeffizienz im Haushalt, EnergieSchweiz, Bundesamt für Energie BFE. available from: https://pubdb.bfe.admin.ch/de/publication/download/7386, Accessed date: 31 May 2019.

EnergieSchweiz, 2018b. Energieverbrauch der Haushalte in der Schweiz, EnergieSchweiz, SCCER CREST. available from: https://www.sccer-crest.ch/research/swiss-household-energy-demand-survey-sheds/, Accessed date: 31 May 2019.

Energy and Climate Change Select Committee, 2015. Ninth Report Smart Meters: Progress or Delay?, Energy and Climate Change Select Committee.

European Commission, 2018. "Europe Leads the Global Clean Energy Transition: Commission Welcomes Ambitious Agreement on Further Renewable Energy Development in the EU", European Commission Statement, 14 June 2018. (Strasbourg).

Eurostat, 2017. Household consumption by purpose. Available from: https://ec.europa.eu/eurostat/statistics-explained/index.php/Household_consumption_by_purpose, Accessed date: 10 July 2018.

Faruqui, Ahmad, Lessem, Neil, Sergici, Sanem, 2016. "Analysis of Ontario ' S Full Scale Roll -out of TOU Rates – Final Study,". pp. 1–39.

Friis, Freja, Christensen, Toke Haunstrup, 2016. The challenge of time shifting energy demand practices: insights from Denmark. Energy Res. Soc. Sci. 19, 124–133. https://doi.org/10.1016/j.erss.2016.05.017.

Federal Council of Switzerland, 2016. Ordonnance sur l'énergie. Le Conseil Fédéral. Available from: https://www.admin.ch/opc/fr/classified-compilation/20162945/index.html, Accessed date: 19 March 2018.

Fell, M.J., 2016. Taking Charge: Perceived Control and Acceptability of Domestic Demand-Side Response. PhD thesis. University College London.

Figueiredo, V., Rodrigues, F., Vale, Z., Gouveia, J., 2005. An electric energy consumer characterization framework based on data mining techniques. IEEE Trans. Power Syst. 20 (2), 596–602.

Greene, W.H., 2018. Econometric Analysis, eighth ed. Pearson, New York.

Haben, S., Singleton, C., Grindrod, P., 2016. Analysis and clustering of residential customers energy behavioral demand using smart meter data. IEEE Trans. Smart Grid 7 (1), 136–144.

Hille, S., Weber, S., Brosch, T., 2019. Consumers' preferences for electricity-saving programs: evidence from a choice-based conjoint study. J. Clean. Prod. 220, 800–815.

Huebner, G., Shipworth, D., Hamilton, I., Chalabi, Z., Oreszczyn, T., 2016. Understanding electricity consumption: a comparative contribution of building factors, socio-demographics, appliances, behaviours and attitudes. Appl. Energy 177, 692–702.

IEA, 2018. World Energy Outlook 2015. IEA, Paris Available from: https://www.iea.org/weo2017/, Accessed date: 13 May 2018.

IEA DSM, 2018. Implementing Agreement on Demand-Side Management Technologies and Programmes-2017 Annual Report.

IRENA, 2018. Rethinking Energy 2018: Accelerating the Global Energy Transformation. International Renewable Energy Agency, Abu Dhabi Available from: http://www.irena.org/documentdownloads/publications/irena_rethinking_energy_2017. pdf, Accessed date: 1 June 2018.

Jones, R.V., Lomas, K.J., 2015. Determinants of high electrical energy demand in UK homes: socio-economic and dwelling characteristics. Energy Build. 10, 24–34.

Jones, R.V., Lomas, K.J., 2016. Determinants of high electrical energy demand in UK homes: appliance ownership and use. Energy Build. 117, 71–82.

Kamilaris, A., Pitsilledes, A., 2011. Exploiting Demand Response in Web-Based Energy-Aware Smart Homes.

Kavousian, A., Rajagopal, R., Fischer, M., 2013. Determinants of residential electricity consumption: using smart meter data to examine the effect of climate, building characteristics, appliance stock, and occupants' behavior. Energy 55, 184–194.

Kwac, J., Flora, J., Rajagopal, R., 2014. Household energy consumption segmentation using hourly data. IEEE Trans. Smart Grid 5 (1), 420–430.

Mansouri, I., Newborough, M., Probert, D., 1996. Energy consumption in UK households: impact of domestic electrical appliances. Appl. Energy 3 (211), 211–285.

Nicolson, M., Huebner, G., Shipworth, D., 2017. Are consumers willing to switch to smart time of use electricity tariffs? The importance of loss-aversion and electric vehicle ownership. Energy Res. Soc. Sci. 23, 82–96.

Nilsson, Anders, Lazarevic, David, Brandt, Nils, Kordas, Olga, 2018. "Household responsiveness to residential demand response Strategies : results and policy implications from a Swedish field study. Energy Policy 122 (February), 273–286. https://doi.org/10.1016/j.enpol.2018.07.044.

Ofgem, 2010. Demand side response: a discussion paper. Available from: https://www.ofgem.gov.uk/publications-and-updates/demand-side-response-discussion- paper, Accessed date: 10 February 2018.

Oseni, M.O., Pollitt, M.G., Reiner, D.M., Richter, L.-L., Chyong, K., Baddeley, M., 2013. 2013 EPRG Public Opinion Survey: Smart Energy – Attitudes and Behaviours. Available from: goo.gl/kcb4hG, Accessed date: 5 July 2016.

Paatero, J.V., Lund, P.D., 2006. A model for generating household electricity load profiles. Int. J. Energy Res. 30 (5), 273–290.

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., Duchesnay, E., 2011. J. Mach. Learn. Res. 12, 2825–2830.

Perret, L., Fahrni, J., Wyrsch, N., Riesen, Y., Puddu, S., Weber, S., Pacheco, D., 2015. FLEXI: Determining the Flexibilization Potential of the Electricity Demand. Swiss Federal Office of Energy SFOE publication 291032.

Platchkov, L., Pollitt, M.G., Reiner, D., Shaorshadze, I., 2011. In: 2010 EPRG Public Opinion Survey: Policy Preferences and Energy Saving Measures, EPRG Working Paper. University of Cambridge, Energy Policy Research Group, Cambridge, UK Available from: goo.gl/9h2hN, Accessed date: 4 April 2016.

Prognos, A.G., 2012. Die Energieperspektiven für die Schweiz bis 2050. Available from: https://www.prognos.com/publikationen/alle-publikationen/292/show/7f9a4382d75cc40032147306d423aaca/, Accessed date: 1 April 2017.

Prognos, A.G., Kemmler, A., Koziel, S., 2017. Der Energieverbrauch der Privaten Haushalte 2000 – 2016, Ex-Post-Analyse nach Verwendungszwecken und Ursachen der Veränderungen. Available from: http://www.bfe.admin.ch/php/modules/publikationen/stream.php?extlang = de&name = de_176890762.pdf, Accessed date: 1 November 2017.

Quilumba, F.L., Lee, W.J., Huang, H., Wang, D.Y., Szabados, R.L., 2015. Using smart meter data to improve the accuracy of intraday load forecasting considering customer behavior similarities. IEEE Trans. Smart Grid 6 (2), 911–918.

Räsänen, T., Kolehmainen, M., 2009. Feature-based clustering for electricity use time series data. In: In: Kolehmainen, M., Toivanen, P., Beliczynski, P. (Eds.), Adaptive and Natural Computing Algorithms. ICANNGA 2009. Lecture Notes in Computer Science, vol.5495 Springer, Berlin, Heidelberg.

Rousseeuw, P.J., 1987. Silhouettes: a graphical aid to the interpretation and validation of cluster analysis. J. Comput. Appl. Math. 5, 53–65.

SFOE, 2015. "Smart Metering Roll Out – Kosten und Nutzen". Swiss Federal Office of Energy.

SFOE, 2018. Energy strategy 2050 once the new energy act is in force. Swiss Fed. Office Energy Available from: http://www.bfe.admin.ch/php/modules/publikationen/stream.php?extlang = en&name = en_543838858.pdf, Accessed date: 1 August 2018.

Spence, A., Demski, C., Butler, C., Parkhill, K., Pidgeon, N., 2015. Public perceptions of demand-side management and a smarter energy future. Nat. Clim. Chang. 5, 550–554.

THINK Project, 2013. Shift, Not Drift: towards Active Demand Response and beyond. Available from: http://goo.gl/rJMBk8, Accessed date: 5 October 2018.

Torriti, J., Hanna, R., Anderson, B., Yeboah, G., Druckman, A., 2015. Peak residential electricity demand and social practices: deriving flexibility and greenhouse gas intensities from time use and locational data. Indoor Built. Environ. 24 (7), 891–912.

Tsekouras, G.J., Hatziargyriou, N.D., Dialynas, E.N., 2007. Two-stage pattern recognition of load curves for classification of electricity customers. IEEE Trans. Power Syst. 22, 1120–1128.

Tso, G.K.F., Yau, K.K.W., 2003. A study of domestic energy usage patterns in Hong Kong. Energy 28 (15), 1671–1682.

Verdú, S.V., García, M.O., Senabre, C., Marín, A.G., Franco, F.J.G., 2006. Classification, filtering, and identification of electrical customer load patterns through the use of self- organizing maps. IEEE Trans. Power Syst. 21 (4), 1672–1682.

Vassileva, Iana, Dahlquist, Erik, Wallin, Fredrik, Campillo, Javier, 2013. Energy consumption feedback devices' impact evaluation on domestic energy use. Appl. Energy 106, 314–320. https://doi.org/10.1016/j.apenergy.2013.01.059.

Voulis, Nina, Warnier, Martijn, Frances, M., Brazier, T., 2017. Impact of service sector loads on renewable resource integration. Appl. Energy 205 (May), 1311–1326. https://doi.org/10.1016/j.apenergy.2017.07.134.

Weber, S., Puddu, S., Pacheco, D., 2017a. Move it! How an electric contest motivates households to shift their load profile. Energy Econ. 68, 255–270.

Weber, S., Burger, P., Farsi, M., Martinez-Cruz, A.L., Puntiroli, M., Schubert, I., Volland, B., 2017b. Swiss Household Energy Demand Survey (SHEDS): Goals, Design, and Implementation. SCCER CREST Working Paper WP2 – 2017/04.

Woo, C.K., Li, R., Shiu, A., Horowitz, I., 2013. Residential winter KWh responsiveness under optional time-varying pricing in British columbia. Appl. Energy 108, 288–297. https://doi.org/10.1016/j.apenergy.2013.03.042.

Wyatt, P., 2013. A dwelling-level investigation into the physical and socio-economic drivers of domestic energy consumption in England. Energy Policy 60, 540–549.

Yilmaz, S., Chambers, J., Patel, M.K., 2019. Comparison of clustering approaches for domestic electricity load profile characterisation and their applications for demand side management. Energy 180, 665–677.

Yu, T., Kim, D.S., Son, S.Y., 2013. Optimization of scheduling for home appliances in conjunction with renewable and energy storage resources. Int. J. Smart Home 7 (4), 1–5.

Zhu, Z., Tang, J., Lambotharan, S., Chin, W.H., Fan, Z., 2012. An integer linear programming based optimization for home demand-side management in smart grid. In: Proceedings of IEEE PES Innovative Smart Grid Technologies. ISGT), Washington, DC, United States.