A comparative analysis of patterns of electricity use and flexibility potential of domestic and non-domestic building archetypes through data mining techniques

Selin Yilmaz1, Jonathan Chambers1, Xiang Li1, Martin K. Patel1
Chair for Energy Efficiency, Institute for Environmental Sciences and Department F.-A. Forel for Environmental and Aquatic Sciences, University of Geneva, Uni Carl-Vogt, 1211 Genève 4, Switzerland
Selin.Yilmaz@unige.ch

Abstract The large-scale deployment of smart meters has led to significant amount of electricity demand data available, driving it into the realm of Big Data. It is a major challenge to exploit this Big Data in order to characterise electricity use patterns and to support demand response policies. In this paper, we perform a featured-based cluster analysis on nine building archetypes (hospitals, schools, offices, hotels, flats, houses etc.) to identify electricity use patterns. Then, four metrics are developed, which are entropy, load curviness, peak intensity and index of hourly ramp rates, to measure these archetypes' suitability to be involved in demand response schemes. A significant difference in electricity use patterns between the archetypes is found, as well as among the seasons and days of the week. We present a number of metrics for each archetype to establish which type of archetype should be prioritised for demand response programmes in terms of peak management, ramp rates as well as demand flexibility. A key finding of our study is that households offer more demand flexibility than the non-domestic sector and should therefore be incentivized to participate in dynamic electricity tariffs.

1. Introduction

Buildings have become a primary focus to integrate demand flexibility into the grid system as they are responsible for 31% of final energy consumption and more than 55% of global electricity demand [1]. Demand response is defined as the process where consumers time-shift demand, either through behaviour change or automation, in response to specific conditions within the electricity system [2]–[4]. However, there is currently no overview or insight into how much different building archetypes may be able to offer to the future energy systems in the sense of minimizing congestion problems, increase the stability of the energy networks by providing flexibility, decreasing generation costs and CO₂ emissions [5]. Buildings such as schools, hospital and households have different electricity use patterns resulting in different opportunities and operational constraints, and therefore their offer will differ. Therefore, there is a need for increasing knowledge on what different building archetypes can provide to energy networks. Against this background, this paper performs a k-means cluster analysis to identify distinct electricity use patterns in nine building archetypes based on a dataset of hourly electricity readings from 1000 sites including both domestic (flats and single houses) and non-domestic (mansions, schools, hospitals,
commercial offices, restaurants, hotels) sectors. We then derive four metrics characterizing electricity use patterns: load curviness and entropy to quantify the flexibility potential, peak intensity (for peak reduction), and index of hourly ramp rates to measure these archetypes’ suitability to be involved in demand response schemes. We then provide a comparative analysis of each building archetype using these metrics and discuss the implications for the energy networks in terms of peak demand management, ramp rates, as well as the flexibility for each archetype in both domestic and non-domestic buildings.

2. Methods

2.1 Datasets

Electricity readings from both domestic and non-domestic buildings in Switzerland were used, as displayed in Table 1. No socio-demographic or dwelling characteristics were collected. It is known that none of the dwellings has electric heating, that they are all served by central (whole building) heating (as in most buildings in Switzerland) and that each reading belongs to an individual household.

Table 1. Description of the variables in the datasets

| Number of sites | Location | Resolution |
|-----------------|----------|------------|
| Domestic         |          |            |
| Houses           | 42       | Neuchatel  | 15-minutes |
| Regular flats    | 656      | Martigny   | 15-minutes |
| Minergie flats   | 71       | Suurstoffi | Hourly     |
| Non-domestic     |          |            |
| Schools          | 41       | Ticino     |            |
| Commercial offices | 82     | Ticino     | 15-minutes |
| Banks            | 32       | Ticino     |            |
| Hospitals        | 31       | Ticino     |            |
| Restaurants      | 29       | Ticino     |            |

2.2 Methods

Our analysis is structured in two sequential steps. A cluster analysis is conducted first in order to identify clusters of households with similar load curves for each of the nine building archetypes presented in Table 1. These clusters are analysed for three demand response strategies, i.e. flexibility potential, peak demand reduction and ramp rates. Flexibility potential is generally defined as the possibility to adapt the electricity demand profile in order to better match supply profiles. Demand flexibility is being explored in the form of demand response as part of load shifting initiatives. Peak demand reflects the greatest demands on both the capacity of the transmission network and the generation infrastructure. Ramp rate reflects the need for electricity demand and supply to match on the grid when either changes rapidly. For each demand response strategies, metrics were defined to evaluate the suitability for the scheme. Table 2 presents an overview of the analysis and the metrics defined, and it displays the samples used.

Table 2. Overview of the analysis performed in this study

| Aspects               | Metric                        | Clustered profiles used |
|-----------------------|-------------------------------|-------------------------|
| Flexibility           | Entropy                       | Daily profiles over one year |
|                       | Load curviness                | Average daily profile   |
| Peak demand reduction | Peak intensity and duration   | Average daily profile   |
| Ramp rate             | Index of hourly ramp rates    | Average daily profile   |
2.1.1 Clustering method: Feature-based clustering was applied for the average daily values. This approach extracts a small number of features from the time series which explain the shape of the load curve, thereby reducing the dimensionality of the time series (originally 24 data points for hourly monitored electricity use) [6]. Five features are derived from the normalised values to define the shape of household electricity demand profiles. The first four features are defined by dividing the daily profile into four time periods and calculating the relative average value of the normalised profiles for each period. The normalised daily profile shape was determined by dividing each measurement in a day by the sum of electricity consumed during that day, such that the integral of the normalised profile for each day is equal to one:

\[ N_{ht} = \frac{E_{ht}}{\sum_{h=1}^{24} E_{ht}} \]  

where:
\( N_{ht} \) = normalised electricity use in hour \( h \) of day \( t \)  
\( E_{ht} \) = electricity use in hour \( h \) of day \( t \)

K-means clustering is applied using standard Euclidean distance [7] as the similarity metric, implemented using the scikit-learn software package [8]. The performance of the cluster model is evaluated using the Silhouette index.

2.1.2 Flexibility: We define the variability in electricity use within the household during the monitoring period. Entropy defined by (2) is used to calculate the amount of variability in load curves throughout the monitoring period and is calculated for each household.

\[ Entropy_n = -\sum_{i=1}^{K} p(C_i) \log p(C_i) \]  

2.1.3 Peak intensity: Peak intensity is calculated as the ratio of the building’s peak power demand over average daily power, as defined in (3):

\[ \text{Peak intensity} = \frac{\text{peak power (normalised)}}{\sum_{t}^{24} \text{power (normalised)}} \]  

2.1.4 Ramp rates: The index of hourly ramp rates (RR) is expressed as a percentage of the household’s power demand per unit of time differential:

\[ RR = \frac{P_{\text{normalised}(t)} - P_{\text{normalised}(t-\Delta t_R)}}{\Delta t_R} \]  

where \( P_{\text{normalised}}(t) \) is the household’s power demand at a given point in time \( t \) and \( \Delta t_R \) is the time differential of the ramp rate. In our case, the time differential \( \Delta t_R \) is one hour as a consequence of the available data (hourly load curves).

3. Results
Figure 1 displays the shape of the cluster centroids (normalised values) for both domestic and non-domestic buildings. Legends shows the number of distinct profiles for each archetype that were found by k-means clustering i.e. optimum number of class with the highest silhouette score). For example, cluster analysis revealed three and two distinct profiles for regular flat and houses.
Figure 1. The centroids of the clusters of normalised values found for each archetype.

Figure 2 shows the distribution of the calculated metrics for demand flexibility for all archetypes in terms of variability across the days (calculated by entropy). The entropy was found to be highest (i.e. highest variability) for the domestic sector meaning that the electricity patterns were changing day by day during the monitored period, whereas non-domestic buildings had relatively lower entropy which means they mostly follow inflexible schedule each day monitored.

Figure 2. The variability of the electricity use across the days (entropy)
Figure 3 shows the calculated peak intensities for each cluster belonging to each archetype. Archetypes are listed in order of increasing median. The domestic sector has mostly a higher peak intensity than the non-domestic sector, with houses having the highest peak intensity.

![Figure 3](image-url)  
**Figure 3.** Peak intensities calculated clusters existing in each archetype

The morning and evening peaks are reached at approximately the same time for all archetypes, but the ramp up and down is faster for some archetypes. Figure 4 shows the calculated index of hourly ramp rates for each cluster belonging to each archetype.

![Figure 4](image-url)  
**Figure 4.** Hourly ramp rates calculated for clusters existing in each archetype

4. Discussion and Conclusions

A k-means clustering analysis performed on an electricity demand dataset of 1,000 homes in Switzerland over a year resulted in significantly different clusters of electricity use patterns for each archetype. An important finding was that occupancy schedules affect not only the shape of load profiles but also peak intensity and ramp rates. Many households are empty during daytime and afternoons on weekdays (relatively lower electricity), while they consume actively during the morning or evening causing higher peak intensity and ramp rates. The presence of different peak intensities and demand flexibility potentials may have important implications for peak management and demand supply matching and minimizing congestion problems. For instance, the domestic sector - houses, regular and Minergie flats - have high peak intensities compared to the non-domestic sector. This calls for targeting the domestic sector by tariffs aiming for peak demand reduction such as Time of Use and Critical Peak Pricing (CPP).
On the other hand, most archetypes of non-domestic buildings have lower peak intensity. They offer more potential for flexibility (i.e. higher variability). Schools, mansions and commercial offices not only they have relatively lower peak intensity but also offer lower flexibility potential, implying that demand response schemes may not be successful for these households due to their fixed schedules. Results of the calculated entropy and load curviness show that households (flats and houses) offer more demand flexibility as opposed to non-domestic sectors (schools, hotels etc.). Households should therefore be incentivized to participate in dynamic electricity tariffs given its variability. However, it is important to note that the acceptance of dynamic tariffs by the public are quite low, therefore tailored programmes which are carefully designed that incorporate the financial with the social, is required to promote the acceptance of dynamic tariffs.

References
[1] IEA, “Energy Technology Perspectives 2017 - Catalysing Energy Technology Transformations,” 2017.
[2] S. Juneja and Ofgem, “Demand side response,” Japanese J. Clin. Hematol., vol. 54, no. 1, pp. 79–80, 2010.
[3] G. Owen and J. Ward, “Smart tariffs and household demand response for Great Britain. Co-author with Judith Ward. Sustainability First, March 2010,” Response, no. March, p. 93, 2010.
[4] J. Torriti, M. G. Hassan, and M. Leach, “Demand response experience in Europe: Policies, programmes and implementation,” Energy, vol. 35, no. 4, pp. 1575–1583, 2010.
[5] S. Ø. Jensen et al., “IEA EBC Annex 67 Energy Flexible Buildings,” Energy Build., vol. 155, no. 2017, pp. 25–34, 2017.
[6] S. Yilmaz, J. Chambers, and M. K. Patel, “Comparison of clustering approaches for domestic electricity load profile characterisation - Implications for demand side management,” Energy, vol. 180, 2019.
[7] S. Yilmaz, J. Chambers, S. Cozza, and M. K. Patel, “Exploratory study on clustering methods to identify electricity use patterns in building sector,” J. Phys. Conf. Ser., vol. 1343, no. 1, 2019.
[8] F. Pedregosa et al., “Scikit-learn: Machine Learning in Python,” vol. 12, pp. 2825–2830, 2012.