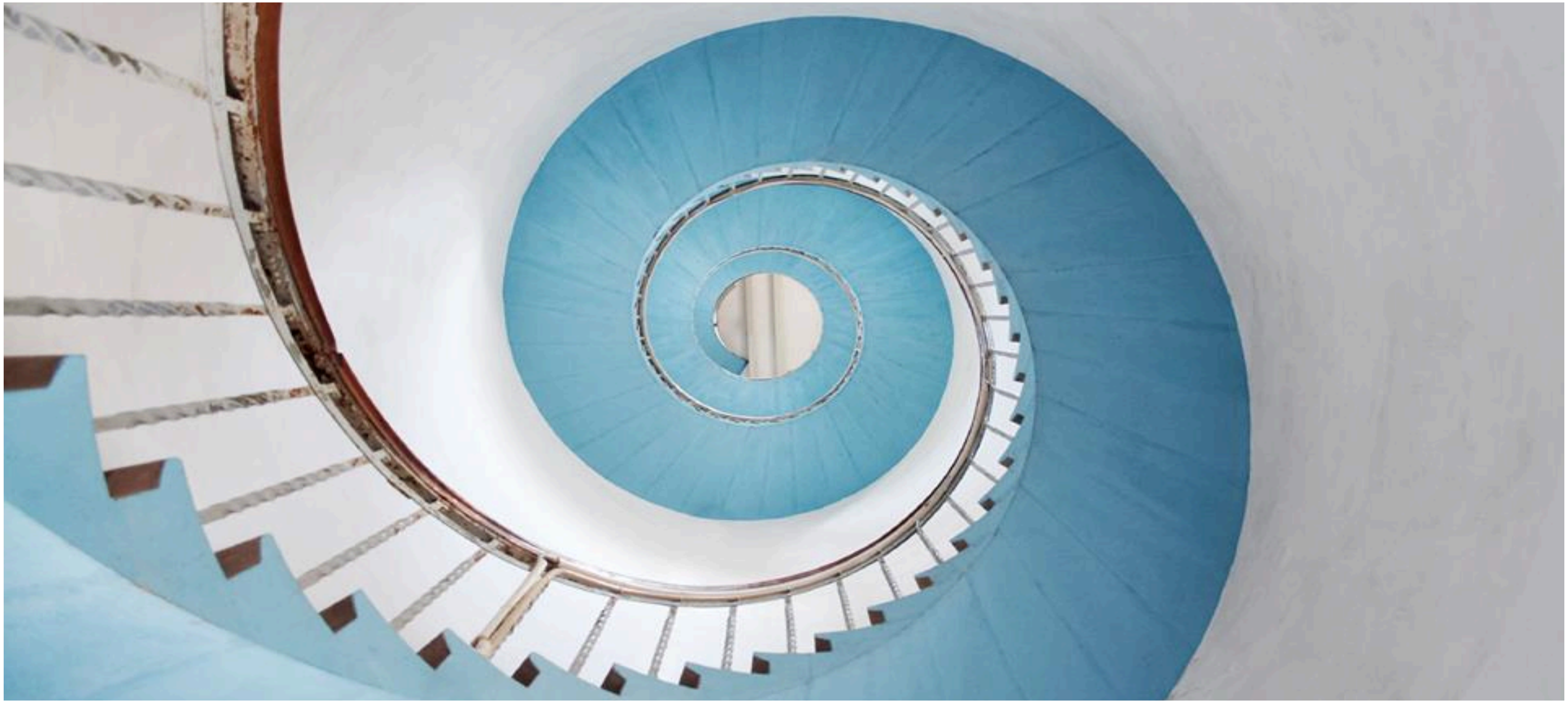

Understanding electricity consumption patterns in households through data fusion of smart meters and door to door surveys

FACULDADE DE CIÊNCIAS E TECNOLOGIA UNIVERSIDADE NOVA DE LISBOA

CENSE center for environmental and sustainability research

João Pedro Gouveia (jplg@fct.unl.pt)
Júlia Seixas; Shiming Luo;
Nuno Bilo; António Valentim

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Problem framing

In Portugal, Residential buildings consume approximately one third of total electricity, with a growth of 70% from 1995 to 2012.

This consumption is a complex issue that can be explained by a combination of physical, technological, demographic, climatic and behavioral characteristics of building and its occupants.

Smart meters have been gaining higher interest in demand side management initiatives and for utilities and are seen as an important instrument for giving energy consumption feedback to households and for consumers' profiles analysis.

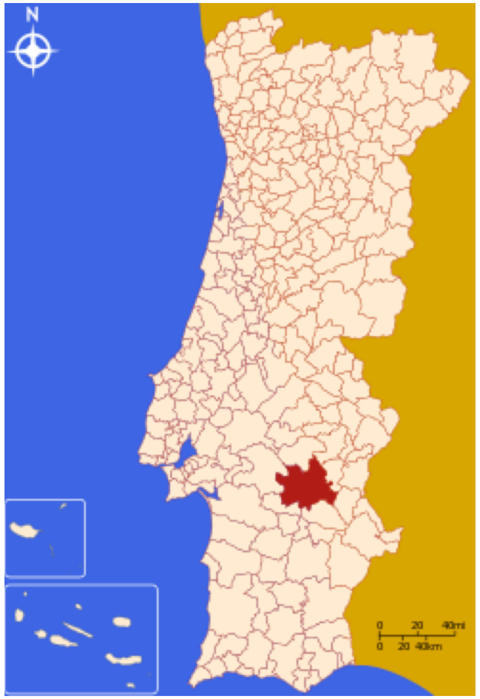
The tailoring of energy efficiency measures based on consumers segmentation enables the change of behavior and equipment towards the ultimate goal of an effective energy consumption reduction and load curve consumption peaks minimization.

Work features

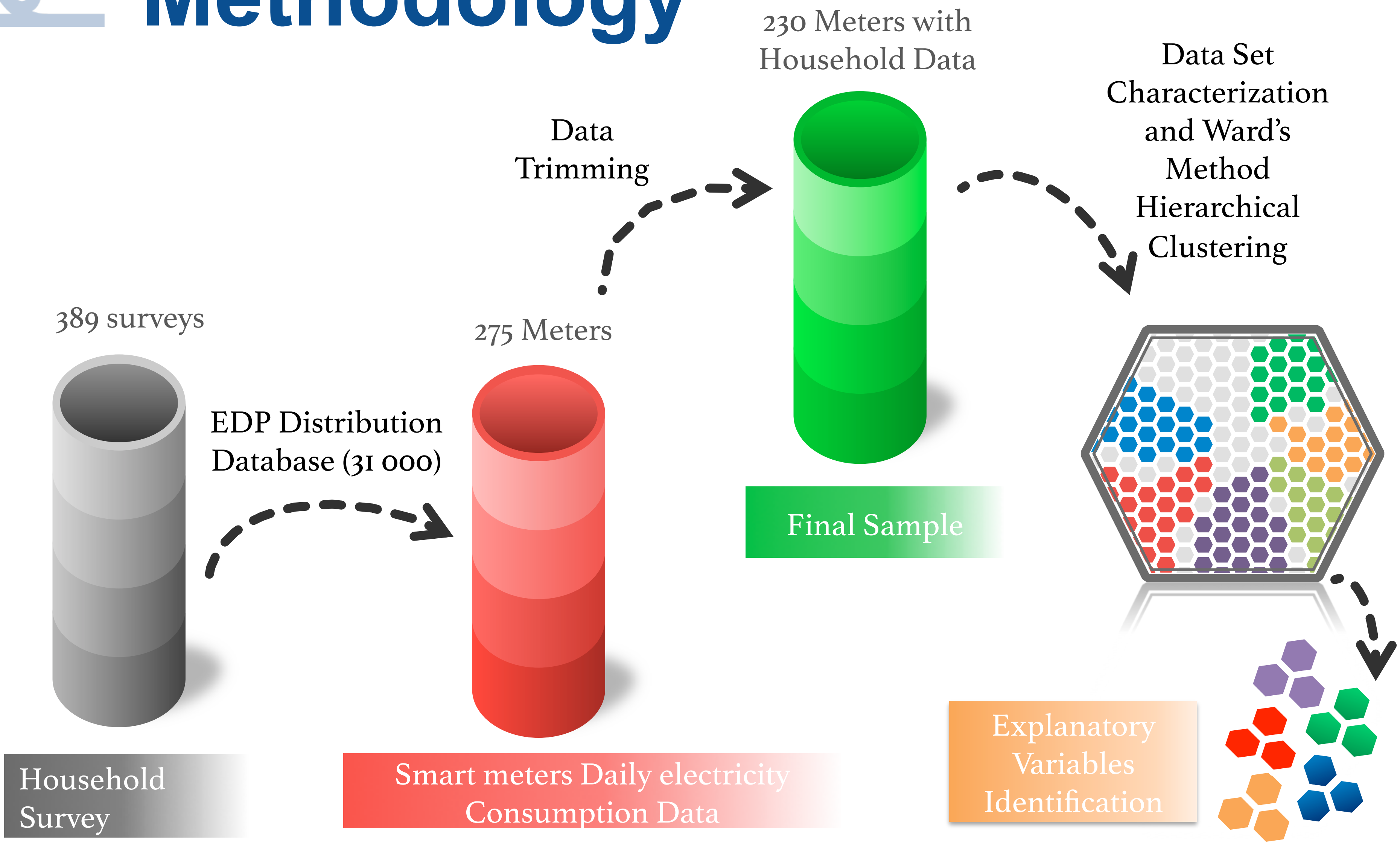
WHERE? Évora city (Portugal)

WHY? Identify specific profiles of different types of electricity consumers and the drivers beneath them in a Southwest European city.

HOW? Exploratory data analysis through segmentation of consumers based on clustering electricity consumption profiles identifying similar electricity consumption determinants per cluster.



Methodology



Household surveys

389 door-to-door, extensive 110–question surveys (June - September 2014), for **residential buildings**, spread across urban and rural areas.

✧ **Buildings Characterization**
- Location,
- Floors,
- Floor area,
- Bearing structure,
- Insulation and glazing,
- Roof type.

✧ **Heating and Cooling Systems and Electrical Appliances**
- Number, hours of use,
- Power.

✧ **Households Characterization**
- Persons per household
- Income,
- Age and gender,
- Education levels,
- Working status.

Smart meters data set

- Of the total number of surveys collected (i.e. 389) we were able to identify and link 64% of them with the smart meter number (275).

- Extensive data from smart meters (sample from the 31000 EDP Distribution S.A., INOVGRID project).

- Data from these smart meters are available since 2010, but are dependent on the smart meters rollout in the municipality. Therefore to have a more complete database; electricity data consumption was retrieved for 2011 to 2013.

Data trimming

- Meters with daily readings below 80% in the year were discarded, the 275 meters were therefore reduced to 250.

- Daily electricity consumption data were averaged for the three years, preserving the intra-annual variability for each household.

- Sample size reduced to 230 households, since, where at least 5% of the data over the 3-year period average was missing from a particular meter, that meter was excluded from the study.

Data characterization

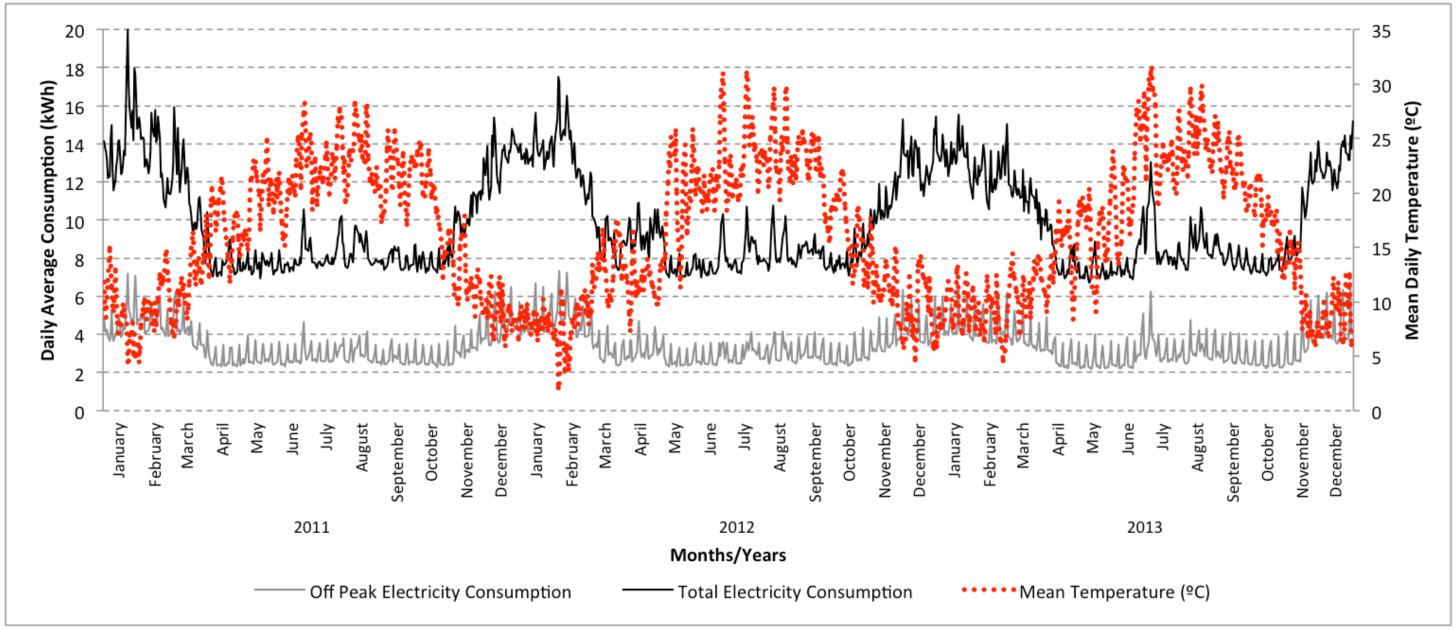


Fig. 1 - Daily average consumption (off peak and total) for 250 sampled households (2011 to 2013)

- Daily average consumption of 9.82 kWh per day, with seasonal peaks in winter days.
- No significant inter annual changes in the electricity consumption patterns and temperature clearly distinguishing the three years of analysis .

Cluster analysis I

10 clusters - similar distribution of meters within clusters with mean daily electricity consumptions below 15kWh (cluster 1 to 6), totaling 200 meters (more than 86%).

Distribution of consumption data from C1 to C6 is similar, with C1 presenting the lowest statistics and C2 the higher variance.

Cluster C7 shows the highest data variability while C8 the highest consumption.

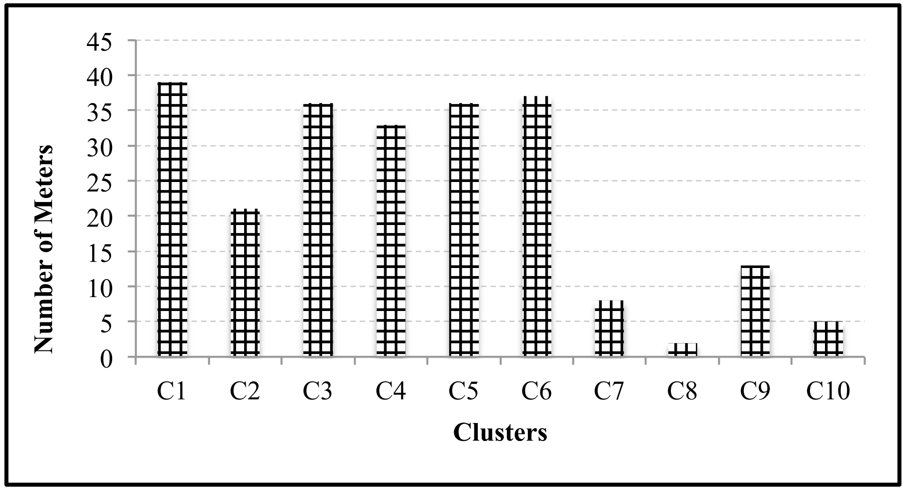


Fig. 2 – Number of smart meters allocated per cluster

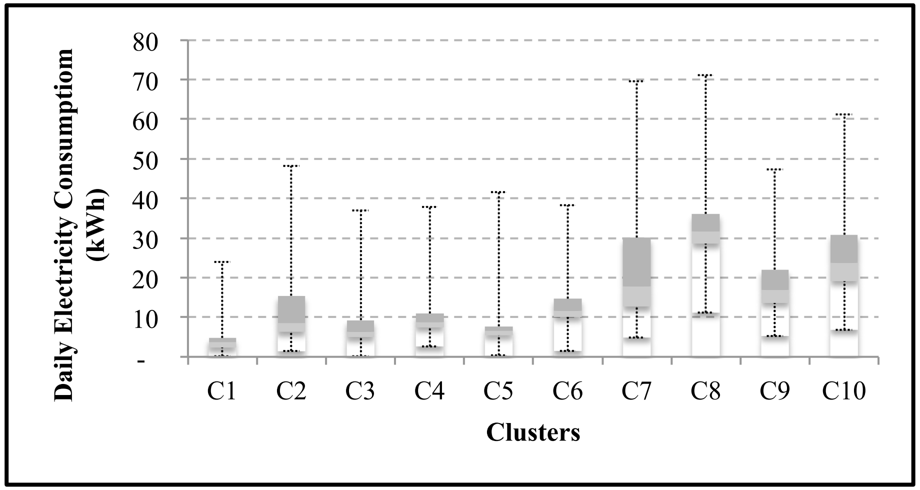


Fig. 3 – Box and whisker plot with clusters distribution

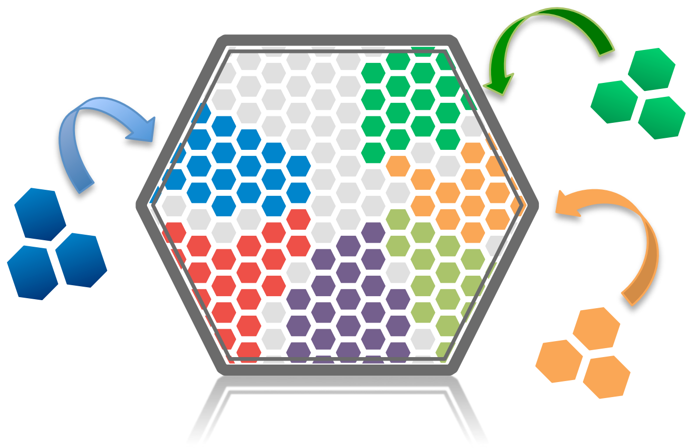
Cluster analysis II

Three clusters selected as examples for an in-depth analysis:

- ✧ very distinct profiles regarding the mean (low, medium, high);
- ✧ dispersion (low and high);
- ✧ annual profile (similar along the year or different in winter and/or summer months).

Screening of the surveys allocated to each cluster to identify the parameters that explain the electricity consumption patterns and similarities.

- ✧ dwelling characteristics,
- ✧ occupants profiles,
- ✧ electrical appliances ownership and use.



Results – Electricity data clusters I

Under similar climate conditions, the consumers have different profiles of electricity consumption, meaning a diversity of drivers behind those segments of consumers.

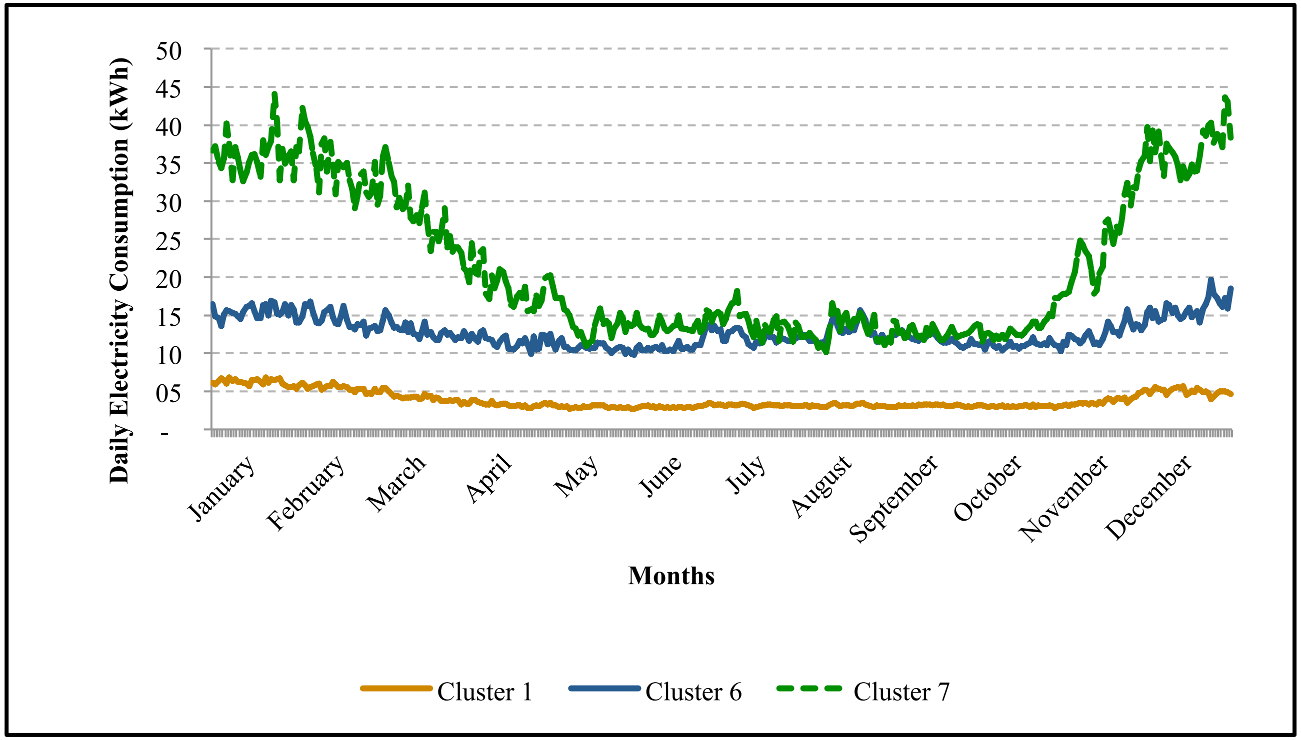


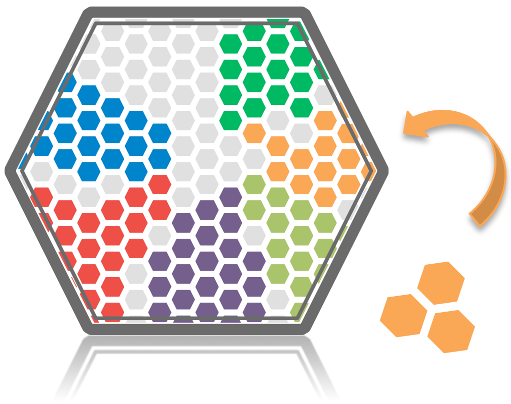
Fig. 4 – Daily electricity consumption profiles of Clusters 1,6 and 7 (2011-2013 average)

Results – Electricity data clusters II

Explanatory Variables	Cluster 1	Cluster 6	Cluster 7
Characteristics of Dwellings			
Location			
Urban	68%	68%	87%
Rural	32%	32%	13%
Type			
Detached	24%	30%	12%
Semi Detached	30%	35%	38%
Terraced	46%	35%	50%
Age			
Before 1945	22%	14%	50%
Between 1946 and 1990	70%	51%	38%
After 1991	8%	35%	12%
Size			
Under 100m²	66%	26%	17%
Between 100m² and 150m²	31%	48%	50%
Higher than 151m²	3%	26%	33%
Type of Glazing			
Single	91%	43%	62%
Double	9%	57%	38%
Type of Window Framing			
Aluminium	39%	81%	50%
Wood	58%	16%	38%
PVC	3%	3%	12%

Explanatory Variables	Cluster 1	Cluster 6	Cluster 7
Occupants Characteristics			
Number of Occupants			
1 or 2	73%	24%	37%
3 or more	27%	76%	63%
Age			
Under 18	5%	16%	0%
Between 18 and 50	39%	46%	27%
Older than 50	56%	38%	73%
Education of the Head of the Family			
Before 9th Grade	49%	41%	17%
Between the 9th and 12th grade	35%	41%	0%
Graduation, MSc or PhD	16%	19%	83%
Monthly Average Income			
Below 750€	52%	21%	0%
Between 751€ and 1500€	34%	33%	50%
Above 1501€	14%	46%	50%
Employment Status			
Working Full Time	34%	48%	41%
Retired	41%	20%	41%
Student	21%	24%	9%
Other	4%	8%	9%

Cluster 1 – Explanatory variables

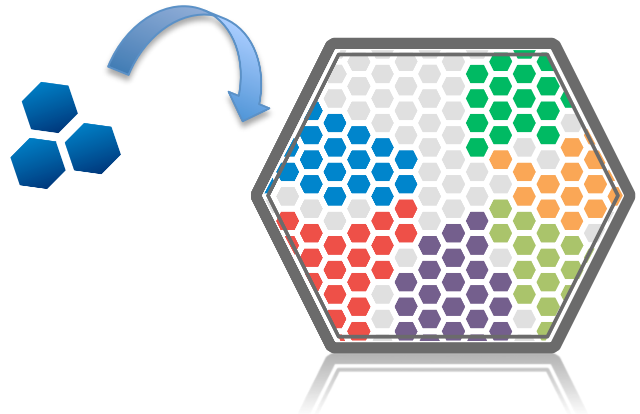


Lowest average electricity consumption (3.86 kWh) and standard deviation (1.76) of all the clusters.

- Age of buildings - 67% with a period of construction between 1946 and 1990
- House size - average of $71m^2$.
- Occupants' characteristics - 70% of the households with just 1 or 2 residents; 60% of the occupants aged above 50 years old, retired and with low levels of education, monthly average incomes below 750€.

- Windows framing and type of glazing, 82% of the households having single glazing and the majority (54%) of wooden framing in windows.
- Type of heating, cooling and domestic hot water appliances. 97% have electric heaters for space heating.
- High share of houses with just fan coils for space cooling.
- Low penetration of dish washing machines (i.e. 30%) and freezers (60%).
- 81% of the houses have installed power lower than 3.45 kVA.
- 69% of the houses still have single tariff.

Cluster 6 – Explanatory variables



- Middle of the defined smart meters clustering:
  - Average electrical consumption of 11.7 kWh
  - 3.9kWh of standard deviation.

- Yearly consumption profile in this cluster does not present significant differences between winter months and the rest of the year.

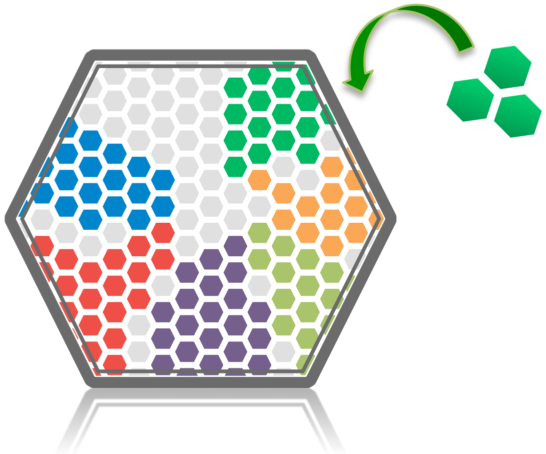
- Similar distribution of urban and rural households as Cluster 1, even distribution of the three types of households therefore not being factors of difference between the clustering.

- Average size houses with floor areas between 100 and 150m², built after 1946 but with a high share built after 1991. Similarly distribution of single and double-glazing but the majority of them have aluminium framing in the windows (81%).

- Higher number of household occupants (3.2), also contrasting with Cluster 1 regarding the age of occupants, household income and employment status. 62% of the occupants aged below 50 years and 48% working full time reflected on higher levels of monthly income (i.e. 46% of houses with incomes above 1501€).

- Highest penetration of Fireplaces (38%). 78% of the houses own equipment for cooling.

Cluster 7 – Explanatory variables



- Combines a high average consumption (17.9kWh) with a high dispersion (standard deviation of 11.3kWh).
- As Cluster 1, this cluster presents important differences of consumption in winter months (around more 230%).
- Predominantly located in urban areas (87%), with a strong predominance of old houses (50% built before 1945) with high floor areas.
- 65% of the households have **more than 2 persons** per household; **73% older than 50 years old; 83% with high education levels** and the majority working **full time professionals.**
- **Non-linear relationship** between household electricity consumption and the number of occupants. With **larger households having higher aggregate electricity consumption but lower per capita consumption**.
- No similar building characteristics as bearing structure, type of wall and windows. Probably explained by the high standard deviation of consumption.
- **Electric appliances for heating and cooling are dominant** in this cluster, with only one house having gas equipment for heating purposes.
- **Very high penetration** white appliances: microwaves (113%), DWM (100%) and freezers (86%).

Conclusions

Combining detailed smart meters data with an extensive survey on household data provides a **coherent dataset for household electricity consumption analysis**.

Identification of significant differences and similarities within cluster groups could be useful: Market segmentation to feed specific energy reduction recommendations (e.g. tariff design for utilities, demand side management strategies).

3 major groups of determinants influence:

- ✧ physical characteristics of a dwelling especially year of construction and total floor area;
- ✧ electrical heating/cooling equipment and fireplaces ownership and use;
- ✧ occupants profiles (mainly number of occupants and monthly income).

Not paramount for distinguishing household profiles:

- ✧ tariff and contracted power;
- ✧ urbanisation levels and bearing structure.

Future Work

Include in the analysis daily electricity consumption for the year 2014.

Statistical analysis evaluating the significance in the differences across the clusters

Assessment of the households electricity consumption determinants to identify the relative importance of each one within this smart meters data set

?

1) Which is the most suitable method for the identification of electricity consumption determinants?
2) Assessment for the total dataset and/or within clusters?
3) Who are the policy and market agents which might take advantage from detailed knowledge on electricity profiles?

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INSMART
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