FINAL REPORT

for project

Large Scale Smart Meter Data Assessment for Energy Benchmarking and Occupant Behaviour Profile Development of Building Clusters

Objectives

The project aimed at profiting from the new and unique opportunity for accessing and processing the high resolution representative dataset being developed within the preceding national smart-meter implementation pilot project ("Central Smart Grid Pilot Project") conducted by KOM Zrt.

In the past only some segments of the building stock's and building users' energy performance could be analysed simply because of lacking consumption related information. This dataset is an enormously rich source of information and opens new perspectives to obtain a much more advanced knowledge compared to the state of the art.

Research focus points were as follows:

1. Analysis of real energy consumption of building types and comparison to models based on the physical characteristics of buildings.
2. A better representation of occupant behaviour for the Hungarian building stock such as representative occupancy schedules (e.g. seasonal, monthly, weekly, and hourly electricity, gas and water consumption profiles).
3. Comparative analysis of electricity production daily trends and demand side profiles.

Literature review

A fundamental part of the literature review aimed to outline the research currently conducted on smart meter (SM) adoption and its connection to building occupant behaviour to better understand both SM technology and SM customers. We've compiled our findings from the existing literature and developed a holistic understanding of the socio-demographic factors that lead to more or less energy use, the methods used to group and cluster occupants based on energy use, how occupant energy-use profiles are developed, and which socio-psychological determinants may influence of SM adoption. Our results highlighted 11 demographic variables that impact building energy use, found 9 methods utilize to profile occupants based on energy usage, and highlighted 13 socio-psychological variables than can be utilized to better understand smart meter adoption intentions. The review pointed out two major deficiencies in existing literature. First, the review highlighted the lack of existing interdisciplinary research that combines occupant behaviour with smart meter data and a clear socio-psychological framework. Second, the review underscored certain data limitations in existing smart meter research, with most research being conducted only on residential or office buildings, and geographically, in North America or Western Europe. Our recommendations centred on increased need for interdisciplinary smart meter research and the need for an expanded understanding of occupant behaviour and smart meter research across different geographies. The results of the review have been summarized in two papers [6, 12].

To analyse the energy consumption data different methods are applied in practice. This area have been reviewed within the project in detail as well. We've concluded that data clustering techniques are suitable for our purposes and it has been highlighted that no universally applicable clustering technique exists; their suitability depends on the input parameters [1–4].

Dataset

In a precedent national demonstration project conducted by KOM Ltd., 128 634 smart meters were installed in different regions of Hungary (Figure 1). The main goal of that demonstration project was to install meters in as many buildings as possible of different types (residential, public, commercial, and industrial) and different settlements (capital, cities, towns, and villages). However, statistical representativeness was not targeted. The installed meters according to measured carrier are presented in Table 1. KOM Ltd. provided us the anonymised data for research purposes within the framework of a bilateral cooperation agreement.

Table 1. Number of meters deployed in the KOM project for the different consumption types

Consumption type	Total no. meters deployed	Residential meters deployed
Natural gas	22079	7368
Heat	53447	53432
Electricity	*28993*	*24917*
Water	24115	22231
Σ	128634	107948

One of our research goals was to analyse the possible differences between building types and settlement types, so further elaboration of the datasets was necessary. Our analysis focused on smaller amount of data after data quality check, data filtering and collection of supplementary building information, e.g. the electricity supplier provided us with the exact address only for 9 237 meters. In the next step, preliminary filtering was applied to remove unreliable datasets, which resulted in 4 454 useful datasets. The buildings corresponding to these addresses were afterwards surveyed with the help of a GIS mapping tool to gather qualitative information that may be relevant for further analysis. An expert identified the building and assessed the building function, building type, covered area, number of stories, general condition of the building, visible retrofit measures (change of windows, additional insulation on façade), type of roof (flat roof, pitched roof occupied or unoccupied) and the presence of solar panels/collectors. Finally, roughly 2000 datasets were selected for analysis where both metered data quality was high, and further information on the building was available. The sampling time for electric meters was 15 minutes. Other type of data applied daily time steps. In addition to KOM we used further data as well, e.g. from district heating companies.

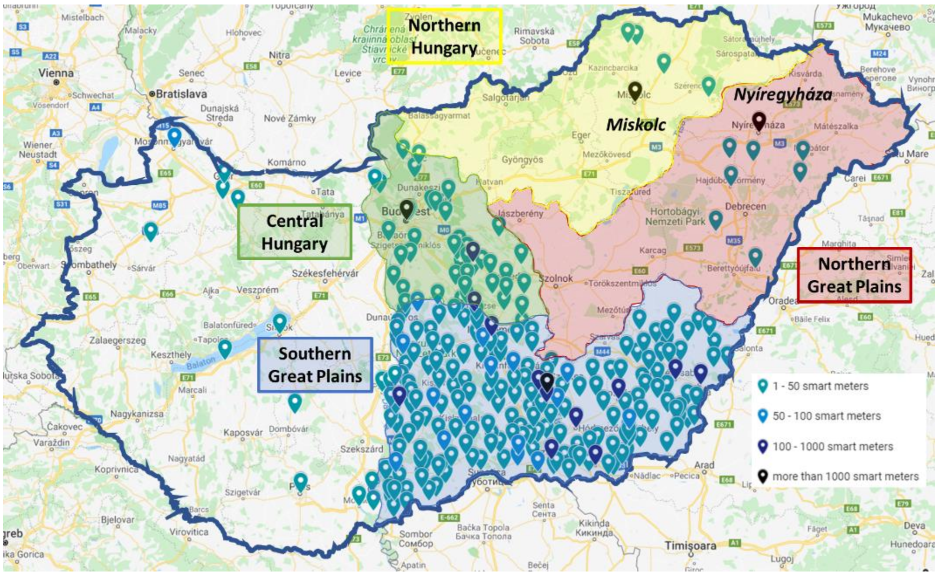

Figure 1. The geographical distribution of the installed smart meters.

District heating consumption profiles [5,6]

The DHW (domestic hot water) consumption data of 6 years (March 2014 – March 2020) was analysed in 115 Hungarian residential buildings. These buildings are prefabricated large panel system buildings located in Budapest.

The monthly and daily DHW consumption data were and examined. Figure 2 presents the boxplot diagram of the annual variation.

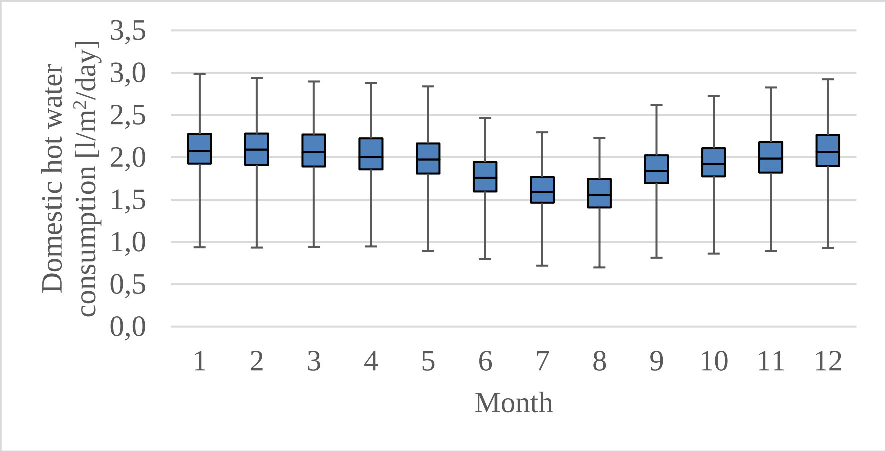

Figure 2. Daily DHW consumption in large panel system buildings

The DHW consumption increases when the outdoor temperature decreases, due to this fact the DHW consumption is approximately 30% higher in winter than in the summer months. The impact of economic indicators, travelling habits and outdoor temperature was also investigated. On the basis of the available data, the economic indicators (gross income, share of employed people) do not have significant effect on the DHW consumption. The travelling habits clearly influence the hot water usage, the effect of the summer holidays could be observed. The outdoor temperature also has a significant effect on the DHW demand. On the outdoor temperature – DHW consumption data third degree polynomial trend line was fitted. The net DHW consumption per heated area values were calculated for every building. The distribution of the heat consumption data is normal and the average value is 28.2 $kWhm^{-2}a^{-1}$. This value approximates the 30 $kWhm^{-2}a^{-1}$ data determined by the national building code in force accurately.

Gas consumption profiles [7]

Gas consumption data were assessed for a database of 76 educational buildings with at least 1 year long hourly data each. The energy consumption data were examined by using different clustering techniques: k-means, fuzzy k-means, and agglomerative hierarchical clustering methods. The methodology of our research is summarized in Figure 3.

First, the optimal clustering method was selected. Second, different clustering methods were compared. Third, the optimal number of clusters was searched. In conclusion the most accurate clustering results are obtained if the normal data type was used and fuzzy k-means clustering method was applied. The optimal number of clusters could be determined the most reliable with elbow method. Finally, the obtained typical profiles were observed to find explanations in building operation on the shapes of the graphs (see an example in Figure 4).

The proposed methodology opens new perspectives in building operation. Analysing the energy consumption results the operation of the buildings and the behaviour of the consumers could be concluded. The energy-wasting buildings could be filtered out, the gas consumer equipment and the physical status of the building could be predicted without knowing the examined building. The knowledge of any kind of energy consumption could help the decision makers to develop effective DSM strategies and determine energy tariffs which encourage people to save energy.

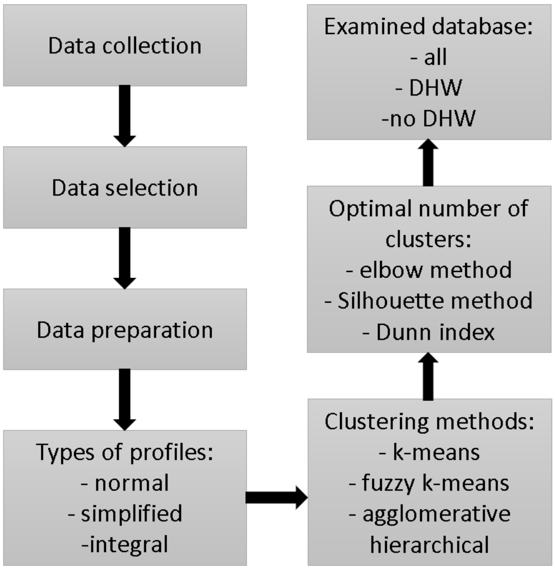

Figure 3. Flowchart of the examination process of gas meters

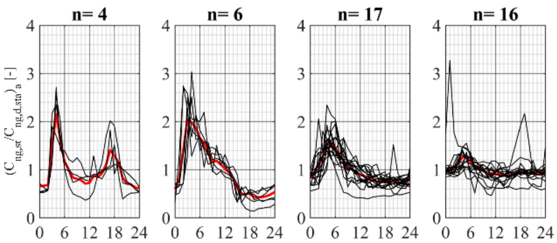

Figure 4. Clustering results of educational buildings with heating and domestic hot water production based on gas in ‚winter' period

Electricity profiles

In this work phase, the objective was to determine energy consumption profiles from time series of daily and annual electric load. Several papers were published based on different datasets using different methods [1,2,4,8]. Here, the latest results are detailed based on a high-resolution electric load dataset provided by KOM Ltd., collected from nearly a thousand households in Hungary, many of them single-family houses.

Based on the preliminary data filtering, we narrowed our research to 816 residential units (more than half of them are family houses). For this population, we determined daily electricity consumption profiles and examined how different parameters influence the shape of the profiles.

Methodology is summarized in Figure 5. The meters were residential electricity meters. Five subgroups were established for the clustering process according to the sub-metering principle: A) regular electricity meters; B) off-peak meters only; C) regular meters only (in these housing units there is also an off-peak meter); D) regular meters and accompanying off-peak meters summed up (sum of B and C meters); E) merge of group A) and D), which includes all investigated apartments.

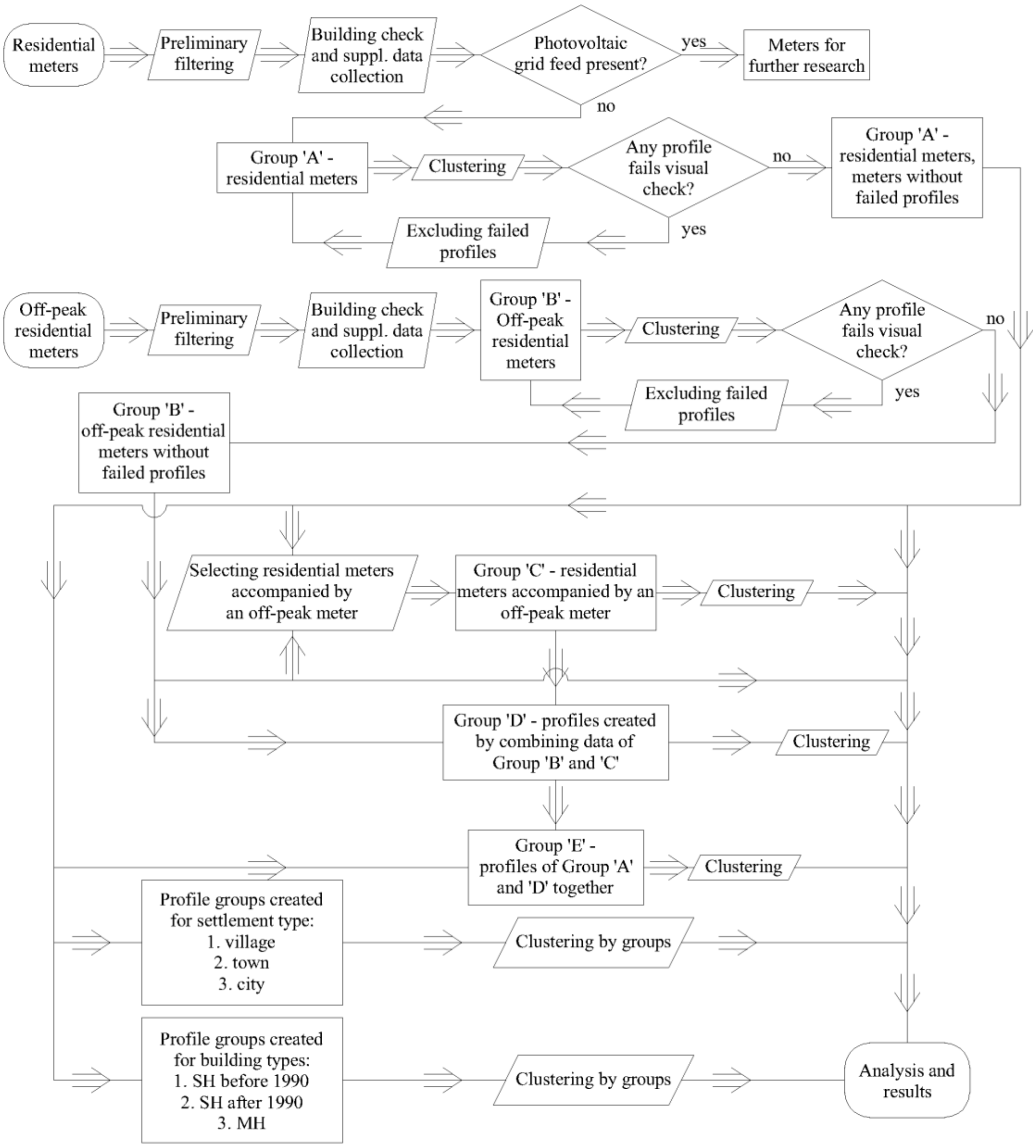

Figure 5. Workflow for creating the different groups for further analysis of data

After representativity check of dataset daily and annual energy consumption profiles were developed, applying three different clustering methods (k-means, fuzzy k-means, agglomerative hierarchical) and three different cluster validity indexes (elbow method, silhouette method, Dunn index) in MATLAB environment. To determine the similarity of the energy profiles, the Euclidean distance metric was used. The optimal clustering method and the optimal number of clusters were determined based on cluster validity indices and the shape of the cluster centroids. The best clustering method for our examination proved to be the k-means clustering technique. Analyses were carried out to identify different consumer groups, as well as to clarify the impact of specific parameters such as meter type in the housing unit (e.g. peak, off-peak meter), day of the week (e.g. weekend, weekday), seasonality, geographical location, settlement type and housing type (single-family house, flat, age class of the building). Furthermore, four electric user profile types were proposed, which can be used for building energy demand simulation, summer heat load and winter heating demand calculation.

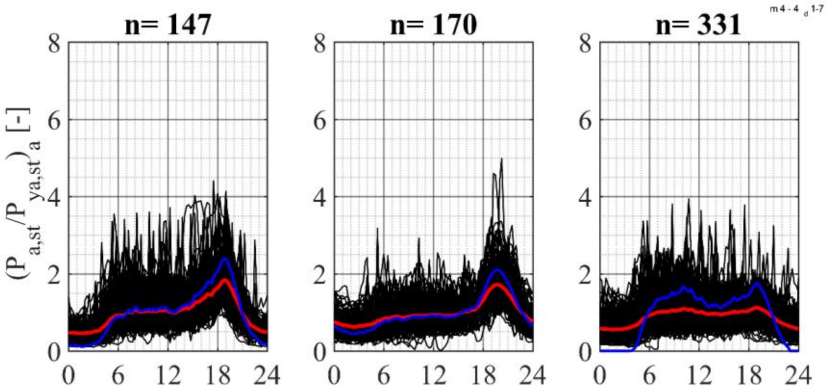

Figure 6. Simulation profiles using Method A (group A for three cluster for m_4-4_d_1-7, month April)

The main findings are as follows:

- Concerning the daily profiles, three types of definite profiles can be distinguished, which can be justified by the different occupancy schedules and behavioural habits. One of these can be characterised by a more even consumption throughout the day; the two others had definitive peaks in the morning or/and in the evening.
- In the case of off-peak meters, it was impossible to explain the differences between the profiles by demand-side drivers. Instead, it can be read from the profiles during which periods the service providers intervene to supply electricity. This is helpful information to consider when modelling DHW systems with storage.
- In terms of seasonality, the summer-day profiles clearly separated the units using mechanical cooling. Still, where there was no mechanical cooling, the profiles showed a similar course as in the rest of the year.
- There was only a moderate difference between the types of settlements (village, town, city).
- Similarly, there was only a slight difference between the profiles of condominiums, old single-family houses and new single-family houses.

In the annual analysis, three distinct profiles could be distinguished as well. A more balanced consumption can characterise one with a summer peak (presumably due to mechanical cooling), one with a winter peak (presumably electric heating or somewhat heating assistance).

Based on the annual off-peak consumption profile, the hot water consumption is lower than average in summer and higher than average in winter. The average can be best characterised by consumption in April, followed by October. The determined numerical data can be well used for the monthly distribution of consumption when only annual data is available.

Finally, we proposed electrical profiles for dynamic simulation after finding that the April data were most suitable for this purpose. There have been fours profile types determined, which can be used for building energy demand simulation, summer heat load and winter heating demand calculations. An example for the proposed profiles are presented in Figure 6.

Applications

The developed profiles have been used in several own studies. In [9] we've examined the impact of simplifications in user profiles influence results in dynamic building simulation using Design Builder software. In paper [3] we have emphasised the significance of real usage profiles in comfort test methods. In papers [10,11] transpired solar collectors were modelled taking into account our proposed user profiles.

Future work

There are further opportunities to continue the research, of which the following would be highlighted:

- Questionnaire surveys could clarify the reasons influencing the development of individual profiles; during the project, questionnaire surveys were hampered by the COVID situation and the GDPR requirements.
- The calculation model could be applied for other countries and regions even for smaller datasets to see whether electric consumption habits are similar or different. Our hypothesis is that the achieved results can be generalised for other countries as well, at least in the region, because not significant difference could be detected between different building and settlement types.
- The profile analysis can be implemented for residential units with solar meters in the future, for which we have a large number of measurement data.

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