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Large scale smart meter data assessment for energy benchmarking and occupant behaviour profile development

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Abstract. This paper will present objectives and first results of the research project entitled “Large Scale Smart Meter Data Assessment for Energy Benchmarking and Occupant Behaviour Profile Development of Building Clusters,” implemented in the geographical scope of Hungary. The project seeks to utilize a new and unique opportunity for accessing and processing an enormous dataset collected by smart meters. Recently in Hungary, nearly 10 000 buildings have been equipped with smart meters within the “Central Smart Grid Pilot Project”. By means of advanced data analysis techniques, consumption trends and motivations of building users are being investigated. The aims are to help building designers and engineers design more energy efficient buildings at lower investment costs by avoiding system oversizing, and to obtain better knowledge about hourly, daily and monthly energy consumption trends. Furthermore, standard net demand values for normative energy calculations can be updated and specified more precisely since consumption habits change with time and depend on the region.

1. Introduction

There are two principal ways to analyze the energy performance of buildings. First, the asset method, which applies calculation principles and modelling tools based on the physical characteristics of buildings such as geometry, building shell attributes, features of technical systems and occupant’s behavior. The asset method provides transparent information on performance indicators and details. However, it is sensitive on the reliability of input data, and information on user behavior is often missing; thus, standardized data are used instead of actual users’ performance. The second, so called operational method, is based on real energy consumption analysis, which gives a reliable picture about the energy performance of a building, but only for the analyzed period under specific circumstances.

To perform energy analysis for a large number of buildings, both methods are applicable and relevant. In Hungary, there is greater proficiency in building stock analysis using the asset method, particularly in the housing sector. In 2013 the National Building Energy Strategy (NBES) [1] was expanded based on modeled building archetypes. Additionally, Hungary has joined the Tabula/Episcope



project, supported by the Intelligent Energy Europe Programme. In this project, building typologies have been developed for 18 EU countries, Norway and Serbia [2]. The work was further developed within the KEOP-7.9.0/12-2013-0019 project in 2015, when a representative sample of 2 000 residential buildings [3] were selected and on-site surveys were carried out by accredited experts. As a result of the work, a national level extrapolation was implemented and energy saving scenarios were proposed for policy developers.

However, these projects did not consider real occupants' behavior, and certainly a set of simplifications were applied in the analytical model. Real energy performance can only be monitored based on the operational model, although this method does not give any information about factors influencing performance and is not applicable for modeling energy saving. Nevertheless, both discussed methods have relevance and can provide supplementary information to each other.

1.1. Brief Review on Smart Meters

Smart meters (SM) are electronic devices that record occupant energy consumption and share this information with utilities, allowing two-way communication between consumers and providers [4]. At the end of 2016, there were 700 million smart meters installed globally, with over half of those in China [5]. Aside from China, Europe is a global leader in SM implementation; a European Union directive has an 80% customer penetration goal by 2020 [6]. Additionally, from 2016 – 2020 European utility companies will invest €33.4 billion to install 182 million smart meters [7].

Given the massive uptake in SM technology, methods for analyzing such data are crucial, and there is an increased focus on profiling occupants to better understand their energy behaviors. Many researchers have begun using a data mining technique known as clustering to group occupants by similar temporal (i.e. daily, weekly or seasonal) energy use patterns [8–10]. Research in this area also supplements SM data clusters with socio-demographic data to determine how factors like age, income, employment status, appliances and building retrofit, among others, influence energy use patterns [11–14].

It is also important to note that consumers have expressed privacy concerns with SM technology. Such concerns are energy data being sold to third parties like advertisers or law enforcement, decreased privacy inside households (such as family members monitoring each other's activities), or that criminals could hack SM information and determine when residents are not at home [15,16]. Recent research also suggests that social-psychological factors like trust in utility companies, perceived usefulness of the technology and perceived risk to privacy may directly impact SM support [17]. Therefore, it is important to continually refine data analysis techniques while also addressing consumer concerns as SM use surges worldwide.

1.2. Central Smart Grid Pilot Project in Hungary

Article 8 of the Energy Performance of Buildings Directive (2010/31/EU) claims that the Member States shall encourage the introduction of intelligent metering systems whenever a building is constructed or undergoes major renovation, and the Member States may furthermore encourage, where appropriate, the installation of active control systems such as automation, control and monitoring systems that aim to save energy. Furthermore, directive (EU) 2018/844 of 30 May 2018 amending Directive 2010/31/EU on the energy performance of buildings, prioritizes smart buildings and introduces the new smartness and smart readiness indicators.

Legislation related to the Third Energy Package of the EU, such as 2009/72/EC [6], and 2009/73/EC [19] required Member States to prepare an economic assessment of long-term costs and benefits of electricity and gas smart metering by 3 September 2012. In cases where the cost-benefit analysis (CBA) is positive, there is a roll-out target of 80% market penetration for electricity by 2020. The results of the CBAs are as follows [20]: for electricity smart meters, 16 states from the EU-27 have decided to roll-out smart meters by 2020, in seven states the CBAs were negative, and in four states the CBAs or roll-

out plans have not been prepared; for gas smart meters, five states from the EU-27 will proceed with large-scale roll-out of smart meters by 2020, two states have plans to proceed with a large-scale roll-out but have yet to take official decisions, in 12 states the CBAs were negative, two states have no gas network at all, and in six states the assessments have not been prepared. Overall, 72% of EU consumers are expected to have smart electricity meters and 40% smart gas meters.

In Hungary, the Central Smart Grid Pilot Project (KOM) was established in 2016 to assess the possibilities of a national smart monitoring system. Within the framework of the project, 139 901 smart metering devices have been installed throughout the country in residential, public, commercial and industrial buildings. Emphasis was placed on the representativeness of settlement and building types during the selection. The evaluation of energy consumption was not an objective in the demonstration project, only installation, maintenance and continuous data collection during a 5-year period ending in 2023. Therefore, another project entitled “Large Scale Smart Meter Data Assessment for Energy Benchmarking and Occupant Behavior Profile Development of Building Clusters” was initiated by BME in October 2018 to benefit from the opportunity by accessing and processing this enormous, representative dataset.

In the past, only some segments of the building stock and building users’ energy performance could be analyzed in the country due to the lack of consumption-related information. This high-resolution, detailed dataset opens new perspectives to supplement and complete the existing national building typology; it also provides building use schedules for different purposes such as building energy simulations or energy certifications using more reliable input data on users’ profiles.

1.3. Objectives

The main objective of this research is to evaluate the dataset collected by the smart meters installed across Hungary within the Central Smart Grid Pilot Project. This enormously rich source of information opens new perspectives in energy pattern evaluation on a building stock level. Our intention is to obtain more advanced knowledge in the following aspects:

- a more precise picture about the real energy consumption of Hungarian building stock,
- a comparative analysis can be carried out between measured and building typology based modelled data, and hence a supplement and completion in national existing bottom-up building stock modelling,
- by means of advanced data analysis techniques it is possible now to cluster building types and occupant types to determine user profiles and energy consumption patterns,
- energy demand profiles can be developed on a large scale and utilized by energy supply and utility companies to improve their production profiles by demand side management (DSM); thus, the smart-grid concept can be realized, resulting in energy savings by peak-shifting on a national level.

The current research (“Large Scale Smart Meter Data Assessment for Energy Benchmarking and Occupant Behavior Profile Development of Building Clusters”) started in October 2018 and is still in an early phase: we are working on data verification and cleaning; evaluation algorithms are being developed and tested on a small sample and supplementary data on buildings are being collected. Present paper presents the first experiences, challenges and difficulties we have faced so far.

2. Methods

2.1. Time Series Datasets

In the early stages of the project, it was decided that residential buildings would be in the focus of the research. First, the device database was filtered in order to identify the smart meters installed in residential buildings. The second step was to categorize the selected smart meter database. In the categorization process the following were considered:

- geographical diversification,

- type of settlement,
- meter type / measured consumption.

For the analysis of geographical diversification, a map was created indicating locations of installed sensors, which can be seen in Figure 1. It is apparent that the meters were mostly installed in Central Hungary and the Southern Great Plains; further, it is important to note that while there were a significant number of smart meters also installed in Northern Hungary and the Northern Great Plains, they were only in two cities (Nyíregyháza and Miskolc).

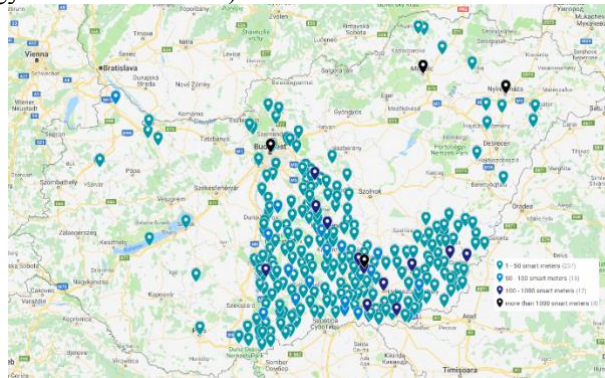


Figure 1., The geographical distribution of the installed smart meters.

The distribution of settlement types was better than the geographical distribution, which can be seen in Figure 2. While the distribution of buildings by settlement type was uniform, the number of installed smart meters by settlement type shows an uneven distribution in favour of larger cities.

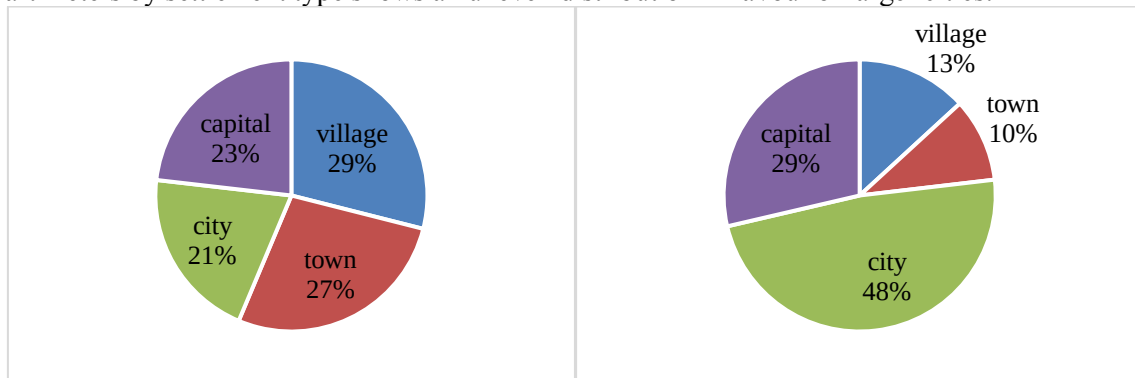


Figure 2., Distribution of residential buildings in Hungary (left) and the installed smart meters (right) by settlement type

In residential buildings a total number of 33761 smart meters were installed, measuring gas (5614), electricity (10368), heat (11715) and water (6064) consumption.

The meters were in operation between the years 2016 and 2018. For most of them, the dataset is limited to dates between 2017 and 2018 or only 2018.

It should also be noted that, depending on the sampling frequency, the possible data usage can be limited. For some meters, the sampling time was as low as 300s, but there were meters with sampling times as high as one week. Obviously, the more frequently recorded data is more suitable for daily profiles, whereas the usage of time series with high sampling time is restricted to weekly or monthly profiles. Communication problems between the smart meters and the servers result in data loss and this degrades the quality of the data. Long outages make it impossible to derive relevant observations.

2.2. Statistical Significance and Representative Sample

It is essential to ensure the validity of the results obtained from the dataset described above. In order to formulate statements on Hungarian building stock, two statistical parameters have to be investigated to determine appropriate sample size and distribution.

Firstly, the population groups were determined with the aim of having results with statistical significance. In the first round of analyses, residential apartments were tackled. Group-defining variables were: size of settlement and geographic regions of the country (see Table 1).

Table 1 - Residential apartment-based population groups used for sample-size calculations

Size of town	Nr. of apartments	Geographical region	Nr. of apartments
Villages and towns	1 227 110 (23%)	Southern Great Plain	602 819 (11%)
Cities	1 370 964 (26%)	Southern Transdanubia	409 265 (8%)
County-seat cities	925 730 (17%)	Northern Great Plain	624 091 (12%)
Capital	1 832 310 (34%)	Northern Hungary	509 790 (10%)
		Central Hungary	2 318 556 (43%)
		Western Transdanubia	435 697 (8%)
		Central Transdanubia	455 896 (9%)

Based on a national statistical dataset [21], the population of each statistical group was determined based on the number of apartments. The necessary sample size to ensure statistical significance in each group was calculated using Eq. 1 [22].

$$Ns = \frac{(Np)(p)(1-p)}{(Np-1)\left(\frac{B}{C}\right)^2 + (p)(1-p)} \quad (1)$$

Where Ns = completed sample size needed (notation often used is n)

Np = size of population (notation often used is N)

p = data diversity: 50% or 0.5 is most conservative

B = acceptable level of sampling error (0.05=±5%; 0.03=±3%)

C = Z statistic associate with confidence interval (1.645=90% confidence level; 1.960=95% confidence level; 2.576=99% confidence level)

For the sample size calculations, a sampling error of 3% and 95% confidence level were assumed.

Secondly, the representativity of the sample was ensured by preserving the ratios of population groups. For example, in Hungary, 26% of apartments are located in cities. Therefore, in this project's sample, 26% of the apartments investigated were from cities.

2.3. Qualitative Information Assigned to Smart Meter Data Points

Analysis of the measured data requires some information from the buildings where the meters were installed. First, the function of the building is relevant, but parameters such as the size or construction type influence the energy consumption and may help with further analysis. Unfortunately, such data were not recorded in the measurement campaign and only the address of the buildings were available.

For compiling further building parameters, we decided to apply a 'manual' approach. As the number of meters and the number of buildings is large, a compromise had to be found between the accuracy and the time spent for data acquisition. Physical observation of the buildings would give highly reliable data, but it would take too much time as the meters are scattered all over Hungary. Using GIS mapping tools provides a relatively fast method for data collection. Based on the address, an expert identifies the building and collects relevant information by observation and some measurements.

First, we identified the relevant parameters that are important for the characterization of a building. The necessary parameters include 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 unused or used) and the presence of solar panels/ collectors. Buildings are first classified based on the building function: residential buildings, offices, sport facilities, restaurants, educational, healthcare, cultural, industrial, commercial, religious or agricultural buildings. There are further subcategories available, for example, educational buildings are classified into kindergartens, primary and secondary schools, universities, etc. So far, only residential buildings were examined.

As most of the measured data are from residential buildings, a more detailed subcategorization based on building archetypes developed in the framework of the KEOP-7.9.0/12-2013-0019 project was applied [3]. In this project, 23 residential building types were established and for each building type, the most typical construction materials, heating systems, typical energy consumption, etc. were provided. However, it was soon realized that such a detailed classification is difficult without further information sources, so certain categories were merged. Finally, a simplified typology with 10 classes was applied, based on the type of the residential building (detached house, small apartment building, large apartment building), the approximate date of construction and the construction type (prefabricated concrete panel or not).

According to the first experiences, this process generally worked well and fast enough to identify and classify a large number of buildings in a reasonable time frame. A major problem encountered was that streetview images are not available in some villages and in some smaller streets. Such buildings were removed from the sample and substituted with new ones. Also, the identification of the building based on the address was sometimes difficult, and external obstacles such as trees blocked the view in some cases.

2.4. Time-series Data Analysis

The preliminary analysis of the data started on the time series showing the incremental natural gas consumption of different residential buildings. It is vital to discard the unusable or false datasets as they would corrupt the conclusions of the future analysis. Therefore, some series were manually analyzed to identify the typical errors. By using the findings of these investigations, algorithms will be developed to automatically categorise the time series from the different meters and only manually investigate the minimal number of datasets.

For instance by analyzing the electricity measurements time series of the energy usage measured in kWh-s was different from the same energy usage obtained from integrating the mean power measured by the same meter. The mean power values were zero sometimes, which can be the result of some software or database failures. Thus it's vital to check smart meter data carefully before any conclusion can be drawn.

2.5. Questionnaires and Interviews

In this project, time-series datasets are supplemented with socio-demographic data collected by questionnaires and interviews.

The following table contains independent variables derived from four models commonly used to determine social-psychological determinants of energy efficient technology acceptance. We have selected the variables from each model most relevant to our project. Each variable will be measured using reliable, previously-validated survey questions. (See Table 2)

Table 2 – Social-Psychological models and survey measures used in the project

Model	Reference	Variables
Theory of Planned Behavior	[23]	Attitude towards the technology

Technology Acceptance Model	[24]	Perceived usefulness Perceived ease of use
Norm Activation Model	[25]	Personal norms (moral obligations)
Sustainable Energy Technology Acceptance (SETA)	[26]	Trust in technology providers Knowledge Perceived risk to privacy Problem perception (awareness of consequences)

These survey measures will be supplemented with dependent, demographic variables such as age, gender, occupation, education level, perceived material status and building characteristics and retrofit. Additional dependent measures such as support for SM technology, intention to adopt SM and continued SM use in the future will also be utilized.

This forthcoming part of the project will be split into three rounds of data collection with three different categories of participants:

1. Building operators in public buildings where SM technology is not yet installed.
2. Assigned “sustainability champions” in smart buildings and potentially users who interacted with SM in their buildings.
3. Residential households with recently-installed SM.

3. Preliminary Results

3.1. Data quality check

At the present stage of this project, three common error types were found and defined. These errors will be the basis of automatic data filtering procedures.

- Type A: the sampling time is longer than a user defined value in one or more points.
- Type B: no usable data is available (the meter did not record any data, or the change in the data is almost zero –probably the building was not used).
- Type C: small or large breaks in the time series.

One example for type A errors can be seen in Fig. 3.

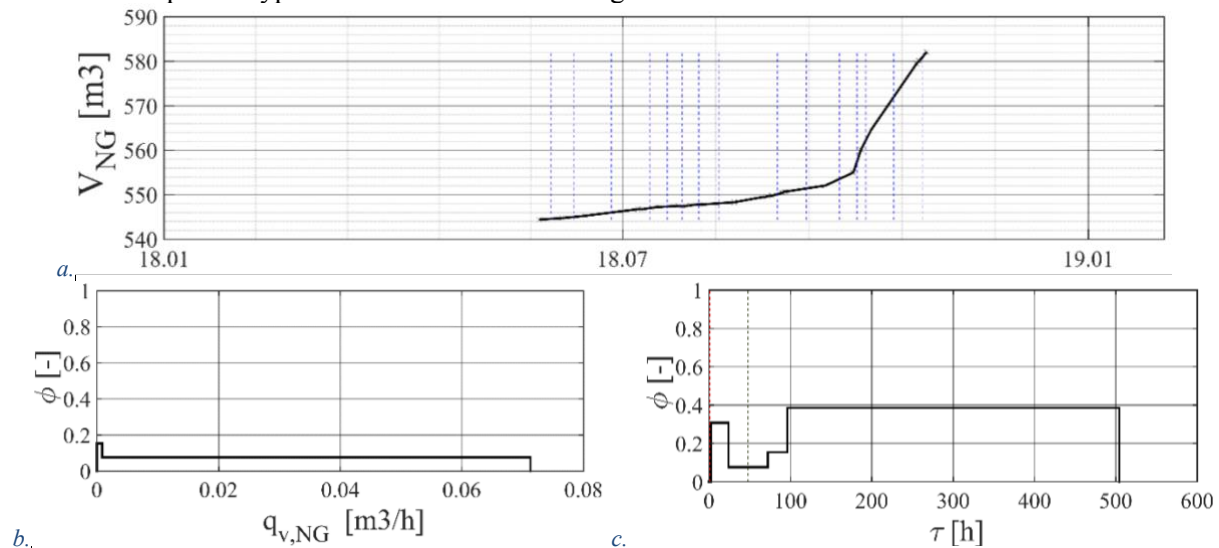


Figure 3., a.: time series, b.: histogram of $q_{v,NG}$, c.: histogram of τ . for the location code named as C00023827.

V_{NG} the incremental gas volume flow through the meter, $q_{v,NG}$ is the mean flow rate between two adjacent samplings, ϕ is the relative probability density, τ is the sampling time (the time between two adjacent points). The criteria for sampling time was 48h in this case, and at the locations where actual

sampling time was higher than this value, vertical blue dashed lines were drawn at the middle between the two adjacent points (Fig. 3.a).

Fig. 3.b shows a histogram created by using the Eq. 1. $q_{v,NG,i}$ is the mean flow rate between the data point i and $i+1$, $V_{NG,i+1}$ and $V_{NG,i}$ are the incremental gas volumes flown through the meter at the i^{th} and $(i+1)^{\text{th}}$ measurement points and τ_i is the difference in time between the two points (sampling time).

$$q_{v,NG,i} = \frac{V_{NG,i+1} - V_{NG,i}}{\tau_i} \quad (1)$$

Fig. 3.c shows a histogram of τ . It can be seen, that this time series is not suitable for any further analysis, as many points are missing.

Type B errors can be identified by only using the time series diagram. Fig. 4. show one example, for which data was transmitted, but apparently either no gas was consumed or instead of the correct numbers only zeros were recorded.

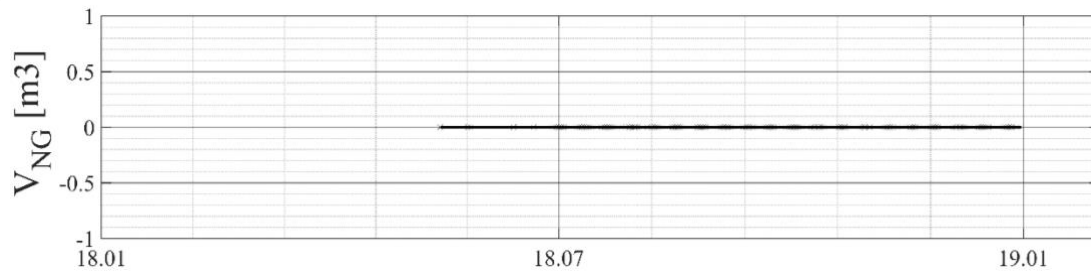


Figure 4., Time series for the location code named as C00023827.

For type C errors Fig. 5. is a good example. In this case the break or jump in the times series data can be the result of meter replacement.

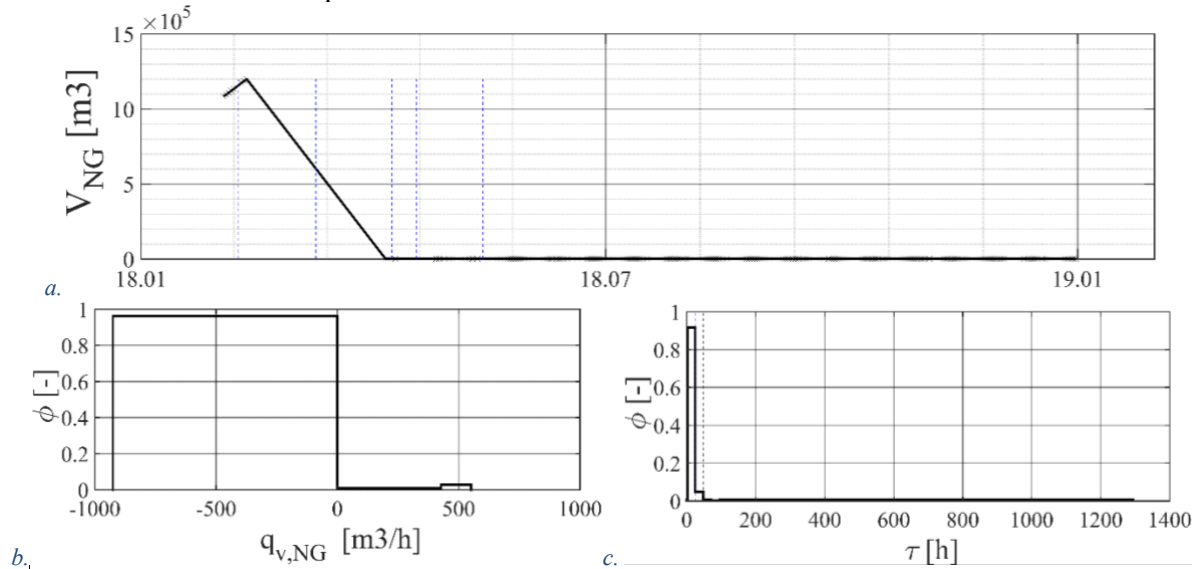


Figure 5., a.: time series, b.: histogram of $q_{v,NG}$, c.: histogram of τ , for the location code named as C00028711.

Type A and C errors can most likely be corrected in some cases, but type B errors make the dataset unusable. The development of correction methods can be the subject of further research.

3.2. Natural Gas

As a preliminary step a basic gas consumption analysis has been carried out for a small selection of buildings. By carefully filtering out the datasets containing errors presented in Section 3.1, it was

possible to examine the monthly natural gas consumption in 11 different locations. Fig. 6 shows locations where no gas was used during the summer season; so, it can be concluded that for cooking and domestic hot water (DHW) production electricity is used. The monthly consumption numbers were divided by the annual consumption ($V_{NG,a}$), so results are presented on a relative scale. It can be observed that the trends are within a narrow range.

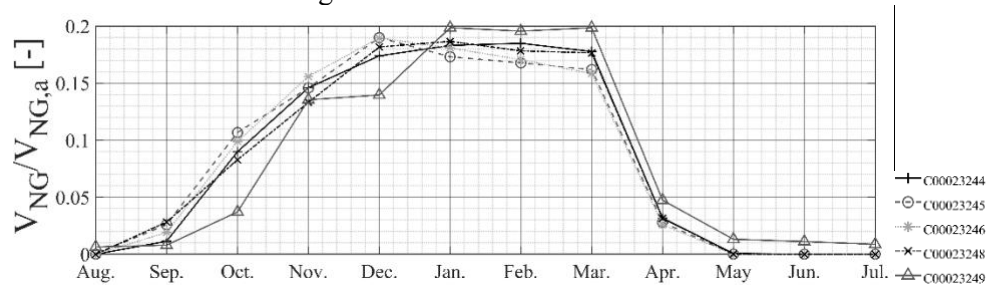


Figure 6., Monthly natural gas consumption for profiles for five different locations with almost zero consumption in the summer.

Fig 7. shows six more locations where DHW production and possibly cooking was also natural gas based, as around 12% percent of the annual gas consumption was used between May and August.

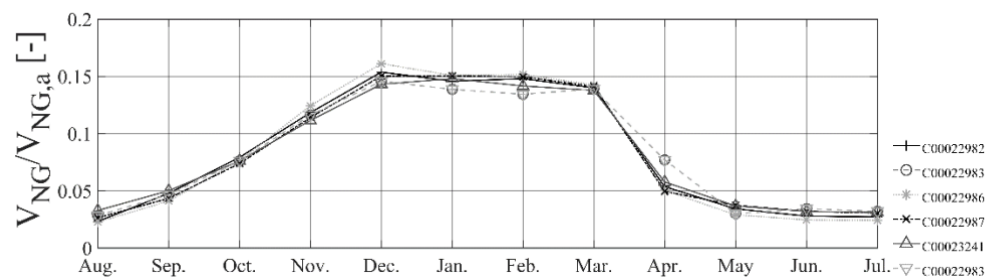


Figure 7., Monthly natural gas consumption for profiles for five different locations with gas based DHW production and cooking.

4. Conclusions and future plans

Statistical methods showed that the large dataset is suitable for selecting a sample from the smart metered buildings that produces representative results for settlement categories and building types, but not for geographical distribution, as most sensors were installed in the South-Eastern part of Hungary. The representative selection can be realized despite data errors in case of a significant number of sensors.

Data are handled with respect towards privacy issues, although GDPR rules makes it challenging to collect qualitative supplementary data about the sample buildings. All results will be anonymised.

The data evaluation process is still in the phase of methodological development and data filtering, although qualitative data collection is ongoing. Results on residential building stock is expected by the end of 2019, then public and other building types will be analyzed. In addition, there is a significant number of large residential buildings where heat cost allocator data are collected, which will be analyzed for a selected smaller number of buildings with a different, more detailed approach in cooperation with housing associations. For public buildings, GDPR is not a problem; thus, more precise supplementary data collection will be possible.

An additional part of the project will be social-psychological research based on questionnaires and interviews focusing on users' habits in approximately 20-30 public buildings in cooperation with Hegyvidék Municipality, 12th district of Budapest.

The project runs until September 2021.

Acknowledgments

Results and the determined trends are being fine-tuned and extended for other building types with a geographic scope of Hungary in another research project entitled “Large Scale Smart Meter Data Assessment for Energy Benchmarking and Occupant Behavior Profile Development of Building Clusters“. Furthermore, methods and approaches developed in the current work are being further developed for large scale data analysis. The project (no. K 128199) has been implemented with the support provided from the National Research, Development and Innovation Fund of Hungary, financed under the K_18 funding scheme.

The monitoring data subject to analysis is being collected within the "Central Smart Grid Pilot Project" by KOM Smart Meter Ltd.

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References

- [1] ÉMI 2015 *National Building Energy Strategy (Nemzeti Épületenergetikai Stratégia, in Hungarian)* (Budapest)
- [2] Csoknyai T, Hrabovszky-Horváth S, Seprődi-Egeresi M and Szendrő G 2014 *National Typology of Residential Buildings in Hungary* (Budapest)
- [3] Csoknyai T, Farkas J, Formanek L and Horváth M 2015 *Building typology report KEOP-7.9.0/12-2013-0019 project (Épülettípológia tanulmány, in Hungarian)* (Budapest)
- [4] Sun Q, Li H, Ma Z, Wang C, Campillo J, Zhang Q, Wallin F and Guo J 2016 A Comprehensive Review of Smart Energy Meters in Intelligent Energy Networks *IEEE Internet Things J.* **3** 464–79
- [5] Smart Energy International 2018 Global trends in smart metering
- [6] The European Parliament and European Council 2009 *DIRECTIVE 2009/72/EC OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL of 13 July 2009 concerning common rules for the internal market in electricity and repealing Directive 2003/54/EC* vol L211
- [7] Bloomberg New Energy Finance 2018 New Energy Outlook 2018.
- [8] Benítez I, Quijano A, Díez J L and Delgado I 2014 Dynamic clustering segmentation applied to load profiles of energy consumption from Spanish customers *Int. J. Electr. Power Energy Syst.* **55** 437–48
- [9] Haben S, Singleton C and Grindrod P 2015 Analysis and Clustering of Residential Customers Energy Behavioral Demand Using Smart Meter Data *IEEE Trans. Smart Grid* **7** 136–44
- [10] Quilumba F L, Lee W J, Huang H, Wang D Y and 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** 911–8
- [11] Tong X, Li R, Li F and Kang C 2016 Cross-domain feature selection and coding for household energy behavior *Energy* **107** 9–16
- [12] Rhodes J D, Cole W J, Upshaw C R, Edgar T F and Webber M E 2014 Clustering analysis of residential electricity demand profiles *Appl. Energy* **135** 461–71
- [13] Gouveia J P and Seixas J 2016 Unraveling electricity consumption profiles in households through clusters: Combining smart meters and door-to-door surveys *Energy Build.* **116** 666–76
- [14] McLoughlin F, Duffy A and Conlon M 2015 A clustering approach to domestic electricity load profile characterisation using smart metering data *Appl. Energy* **141** 190–9
- [15] McKenna E, Richardson I and Thomson M 2012 Smart meter data: Balancing consumer privacy concerns with legitimate applications *Energy Policy* **41** 807–14
- [16] Lisovich M A, Mulligan D K and Wicker S B 2010 Inferring personal information from

- demand-response systems *IEEE Secur. Priv.* **8** 11–20
- [17] Chen C F, Xu X and Arpan L 2017 Between the technology acceptance model and sustainable energy technology acceptance model: Investigating smart meter acceptance in the United States *Energy Res. Soc. Sci.* **25** 93–104
 - [18] The European Parliament and European Council 2010 *DIRECTIVE 2010/31/EU OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL of 19 May 2010 on the energy performance of buildings (recast)* vol L153
 - [19] The European Parliament and European Council 2009 *DIRECTIVE 2009/73/EC OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL of 13 July 2009 concerning common rules for the internal market in natural gas and repealing Directive 2003/55/EC* vol L211
 - [20] E. C 2014 *REPORT FROM THE COMMISSION Benchmarking smart metering deployment in the EU-27 with a focus on electricity/* COM/2014/0356 final */*
 - [21] Hungarian Central Statistical Office (KSH) 2018 Dataset of all places in Hungary
 - [22] Dillman D A . 2000 *Mail and internet surveys: the tailored design method*
 - [23] Ajzen I and Madden T J 1986 Prediction of goal-directed behavior: Attitudes, intentions, and perceived behavioral control *J. Exp. Soc. Psychol.* **22** 453–74
 - [24] Davis FD 1989 Perceived usefulness, perceived ease of use, and user acceptance *MIS Quart* **13** 319–40
 - [25] Schwartz S and Howard J 1981 A normative decision-making model of altruism *Altruism and helping behaviour: social, personality, and developmental perspectives* ed J Rushton and R Sorrentine (Hillsdale, NJ: Lawrence Erlbaum) pp 189–211
 - [26] Huijts, Molin and Steg 2012 Psychological factors influencing sustainable energy technology acceptance: A review-based comprehensive framework *Renew. Sustain. Energy Rev.* **16** 525–31