Energy consumption characteristics based on monitored data: a school case study

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Abstract. This study is an initial step for a creation of smart platform for schools in Estonia which will model, analyze, and evaluate the real energy performance of school buildings. Energy meters provide electricity consumption data which can be used to understand energy usage patterns and finally improve building energy management. First, data preparation is made. On the following step hierarchical clustering is applied to identify the outliers of weekly electricity load profiles. Finally, daily electrical load patters are clustered and similar profiles are grouped using K-means centroids.

Keywords. Electricity consumption, school building, occupants' behavior, COVID, energy efficiency analysis, profiling.
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1. Introduction

The building sector is crucial for achieving the EU's energy and environmental goals. In general, buildings are responsible for approximately 40% of final energy consumption [1]. The first step towards sustainable transformations is understanding of the underlying factors influencing energy demand. Beside formal information above mentioned documents do not provide information how to support a sustainable change in the end-user behavior. Influence of occupants' behavior on energy consumption is getting more and more significant as the overall energy demand of the new or renovated buildings is substantially decreasing [2]. Development of the smart technologies and metering devices together with a concept of Industry 4.0 has opened new perspectives in monitoring occupants' behavior. Obtained data can be used for different purposes such as end-user behavioral modelling, fine tuning of certain values or load forecasting. Moreover, clear understanding of energy consumption is the key for timely decisions to reduce energy consumption. In addition, improvement of energy efficiency of public buildings promotes significance of culture of energy efficiency to the local society [3], [4].

Several studies related to energy consumption and efficiency of school buildings have been conducted [5]–[7]. Advanced metering infrastructure measures and collects electricity consumption data. Readings help to understand the characteristics of energy use behaviors and potentially prevent energy waste. Energy consumption of the buildings can be influenced by the various parameters: building characteristics, energy use profile and occupants' behavior. Energy use includes space heating/cooling, lighting, ventilation and plug loads. Occupants' behavior consists of turning off the lights, air conditioners and other equipment then not in use.

The aim of this work is to find out what is the occupants' behavior and what are the consumption profiles of air handling units. This is preliminary step for creation of a smart platform for schools which further will automatically classify current consumption and forecast it based on already known. The difficulties for the automation of the profiles clustering based on available data caused by the fact that non-classical behavior during so-called COVID-19 periods should be considered. Pattern differences are caused by the fact that legislation for handling ventilation units has been changed. Secondly, occupation of the schools during those times is changing drastically [8], [9].

2. Methodology and data

2.1 The case study building

Metered data was retrieved from one of the schools in Tartu, Estonia, which renovation have been finished by August 2020.

2.2 Data preparation

The data is gathered from the following measurement points: kitchen, air-conditioning and main meter. The school facility management collects energy data with hourly resolution. Non-air-conditioning loads (plugs and lighting) were found by subtracting sum of all HVAC systems from the readings of main meter.

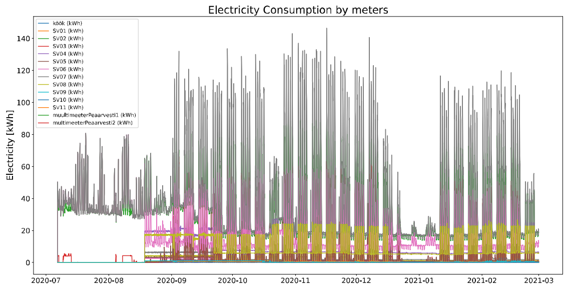

Fig. 1 - General consumption of the school: air-conditioning plus plugs and lighting consumptions

First, electricity meter data was transformed into the electricity consumption time series, shown in Fig. 1. Additional data engineering and analysis are needed, since smart meter data from buildings can be very noisy with gaps of missing values and typically contains outliers. In general case, where a lot of different objects are studied, obtained values should be normalized since we mostly interested in capturing of temporal variation rather than absolute values of magnitudes [10]. Here we are focused on a single building and therefore normalization step can be skipped.

We reshape raw time series to be used by data segmentation. To identify Typical Electricity Load Patterns (TELPs) available data was segmented using weekly cycles. Tracking changes in energy performance by week may help to understand is there some specifics in days-of-the-week and how does the electricity usage behavior differ during weekends [11].

Consumption calculated from the readings of the "Main meter" is shown in Fig. 2. Consequent weeks have close colors, after one-year colors repeat. Such an approach gives possibility to see common patterns of the subsequent weeks and observe if behavior repeats at the same week in the next year. Additionally, this helps during validation stage when clusters found with machine learning techniques are approved. Fig. 2 shows that several behavioral patterns can be extracted from the obtained results.

For better understanding of the energy use and its correlation with occupants' behavior, the following analysis is made separately for air-conditioning and non-air-conditioning units.

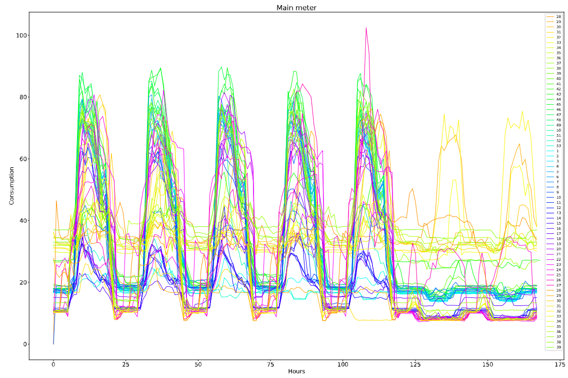

Fig. 2 - Main meter with weekly segmentation

2.3 Extraction of typical electricity patterns

To find typical electricity patterns hierarchical clustering was applied. Namely, Agglomerative Clustering with bottom-up approach, where separate clusters are merge using the minimization of the maximum distance between all observations of pairs of clusters with Euclidian metrics.

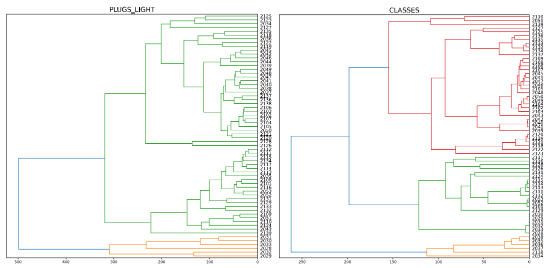

Fig. 3 - Dendrograms, where numbers on the right site represent 'yyww': week ('w') of a year ('y'). Left plot shows all plugs and lighting consumption at school. Right plot represents ventilation units of all classes

Fig. 3 illustrates that in every case weeks 28-33 from the year 2020 are separated to independent cluster and considered as outliers: baseline of those signals is higher than others. Additionally, there is a high consumption at the weekends (see Fig. 2 yellow and orange lines after 125 hours). On the other hand, lines of the same color which represent exactly the same time period from the next year, have different pattern. This is caused by the fact that data obtained during first six weeks should be removed from further analysis since ventilation worked in a test or special mode caused by the completion of repair works and school preparation for a new academic year.

On the next step Nearest Centroid or K-Means Clustering proposes centroids for each group of clusters and typical representatives of behavioral patterns are found (see Fig. 4). First, it is seen that there is no difference in ventilation behavior during the working days. It is working according to the schedule and does not depend on the occupancy of the room, in other words, ventilation is not controlled by CO_2 level measurements.

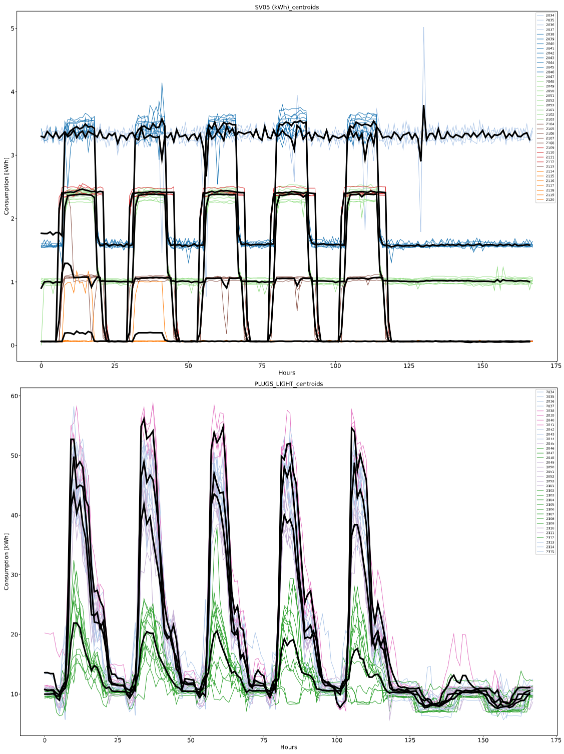

Fig. 4 - Weekly Clustering of a) a typical ventilation unit on example of "Teachers' room" and b) "Plugs and Lighting" for the whole period

Moreover, through the year behavior of the system has changed a lot. Some patterns were valid for a longer period, others – not. Additionally, it is set that clusters having less than three weeks are not taken into account. In general, clustering procedure should be automated, thus other additional parameters and conditions should be considered.

First, unlike other (for example office) buildings on business days schools may have vacations. At those times some patterns are close to non-working days, but since school workers are visiting buildings, have meetings, consultations with some students, etc. those patterns make separate class. Occupancy of the building is lower, that should as well decrease the consumption and ventilation loads.

All above mentioned leads to the conclusion that Daily Electricity Load Patterns (DELPs) can be studied. Initially data was split into three periods: business days, business days on vacations and weekends with holidays. Unfortunately, behavioral patterns during business days differ too much and automatic clustering procedure cannot guarantee satisfying result. Thus, it was suggested to split working days into two categories: normal working days then school has original occupational load and so-called COVID period, where occupation can vary from fully closed, occupied by some personnel, elementary school and graduation students. In addition, other legislation procedures were applied to control of ventilation units (working hours and loads). This explains why there are several base lines for electricity consumption.

Finally, four different time periods were studied for clustering: normal working days (see Fig. 5, Fig. 9), vacations working days (see Fig. 6 and Fig. 10), weekends plus holidays (Fig. 7 and Fig. 11) and COVID-19 working days (Fig. 7 and Fig. 12).

3. Results

Once profiles are set the following analysis was made. At the beginning of a school year rooms are ventilated with high constant air flow ("light blue line" in Fig. 5).

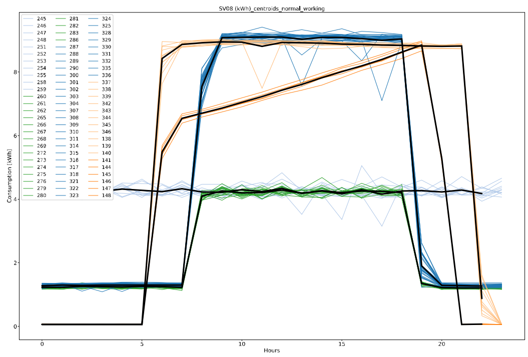

Fig. 5 - DELPs of ventilation unit for A-building Westside classes in normal working conditions

After that scheduled technique is applied: all air units are starting from 7.00 and reaching its highest load by 8.00. At 18.00 ventilation is turned off and reaches its base line after one hour. In some classes after beginning of the heating season high load was increased (see "green and blue lines" in Fig. 5). Rise of the top load mostly depends on the fact if this part of the building belongs to "sunny side" or not.

At the beginning of December 2020 COVID situation in Estonia became worser, thus ventilation schedule was changed from 5.00 till 21.00. In second part of May 2021 when all students returned to schools, gradual increase of the ventilation load was applied. Such an approach was used only in this part of the building and, most probably, caused by the fact that it belongs to the "sunny side" where through the day temperature increases drastically.

During weekends common situation can be described as: preparation for a new academic year, low season base line, high season base line.

In general, ventilation levels are set to minimal during the vacations, but during hot summer of 2021 it was working on high load from 5.00-20.00 (Fig. 6).

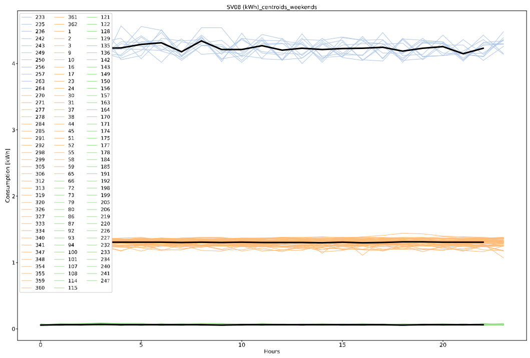

Fig. 6 - DELPs of ventilation unit for A-building Westside classes on weekends and holidays

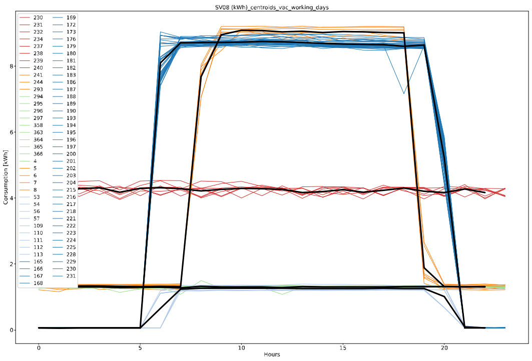

Fig. 7 - DELPs of ventilation unit for A-building Westside classes during vacations (working days only).

On 14.12.2020 schools were closed for all students; thus, ventilation was switched back for shorter working hours ("light blue line" Fig. 8). Then only elementary school studied, or building was closed, ventilation worked at minimum level. When graduation classes returned, ventilation worked with maximum load 5.00-21.00.

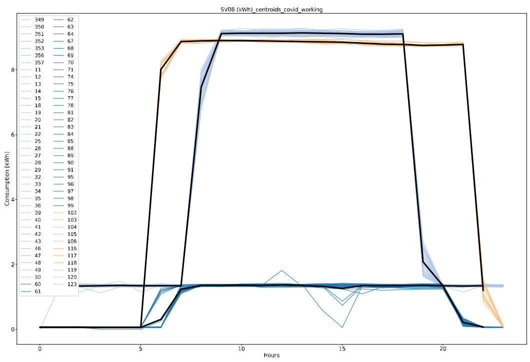

Fig. 8 - DELPs of ventilation unit for A-building Westside classes under COVID-19 working conditions

Plug and Lighting consumption strictly corresponds to the occupancy of the school and daylight period. This can be seen from most of the figures: during high season outside lighting works for a longer period and then electricity consumption drops to a lower level. This can be explicitly seen during weekends and holidays in Fig. 11. During normal working days level drops near by 5 o'clock in the morning before people come to school and after that plugs loads drastically rise. It can be observed in Fig. 9.

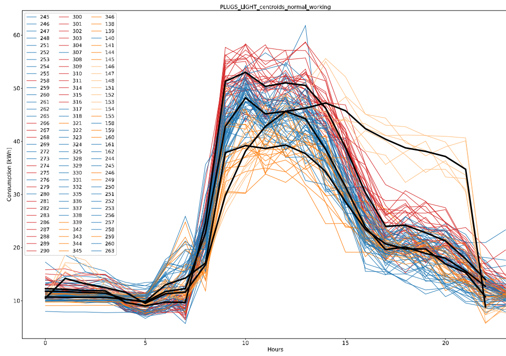

Fig. 9 - DELPs of Plugs and Lighting in normal working conditions

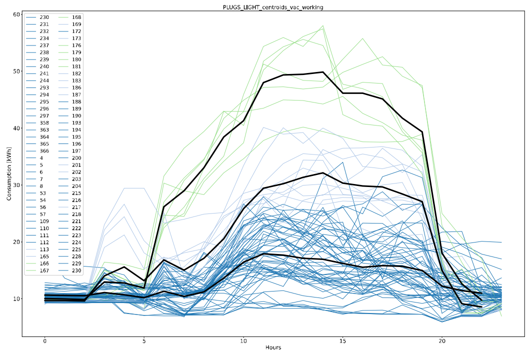

Fig. 10 - DELPs of Plugs and Lighting during vacations (working days)

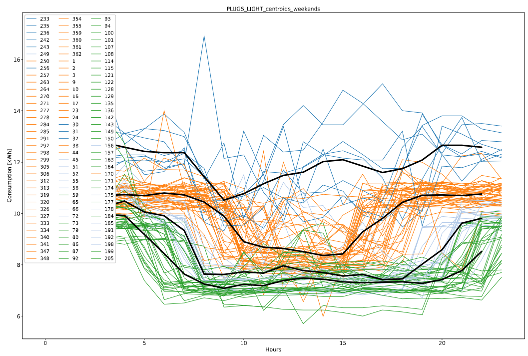

Fig. 11 - DELPs of Plugs and Lighting weekends and holidays

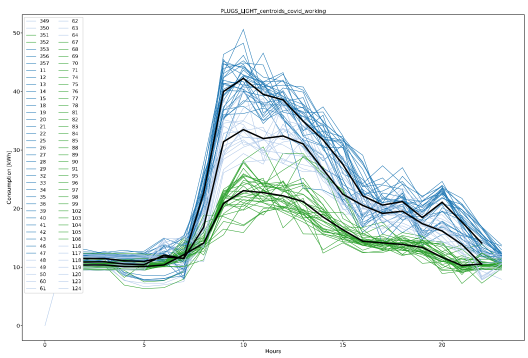

Fig. 12 - DELPs of Plugs and Lighting under COVID-19 working conditions

Occupancy of the building during COVID period can be derived from patterns presented in Fig. 12. By comparing with Fig. *9* one can observe a significant decrease of occupancy level of the building during this period.

Another point that should be mentioned, starting from 02.04.20 (with amendments on 29.11.20) ventilation with normal occupancy of the building must be turned on full power 2 hours before occupational hours and turned off 2 hours after those (if occupancy is less than 50%, then with the above-mentioned timing ventilation load allowed to be 50% of full power).

In Fig. 13 Plug and lighting profiles, which are presented by red lines, are overlaid on ventilation profiles. Assuming that plug loads to some extend represent occupancy of the building, it can be observed from timing comparison that sometimes air handling units' schedules were not set according to the new standards.

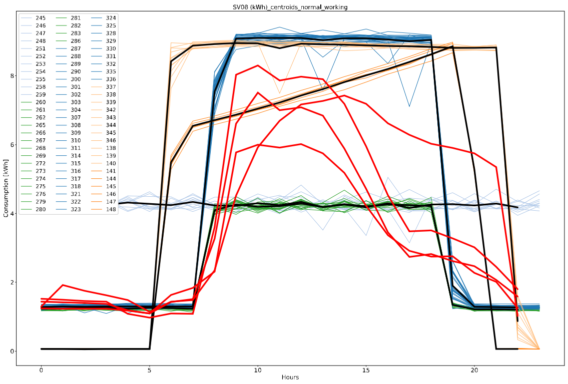

Fig. 13 – Plug and Lighting profiles correspondence to ventilation schedules in normal working period

4. Conclusions

Initial step for creation of smart platform for schools has been made. Automatic finding DELPs at schools differs from other buildings profiles. Instead of business days and weekends for high and low seasons, school vacations should be considered as well. Additionally, COVID-19 brought variety of settings for air handling units' schedules. The effectiveness was demonstrated by comparison of found clusters and timing of events happened in Estonia.

5. Acknowledgement

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6. References

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