

PAPER • OPEN ACCESS

Characterization of heat load profiles in buildings and their impact on demand side flexibility

To cite this article: H T Walnum *et al* 2019 *IOP Conf. Ser.: Mater. Sci. Eng.* **609** 052035

View the [article online](#) for updates and enhancements.

Characterization of heat load profiles in buildings and their impact on demand side flexibility

H T Walnum^{1,*}, M Justo Alonso² and J Clauß² and K Lindberg¹

¹ SINTEF Building and Infrastructure, Oslo, Norway

² SINTEF Building and Infrastructure, Trondheim, Norway

* harald.walnum@sintef.no

Abstract. A data set of heat load measurements for 197 buildings from different building categories (apartment blocks, hotels, nursing homes, offices and schools), have been analysed to evaluate the potential for peak shaving. A moving average filter is applied to investigate how smoothening of the load profiles can reduce the peak loads. It is shown that for short term peak shaving, apartment blocks and hotels have the highest potential (around 8% for a two hour period), while for longer term peak shaving, the results are more even for all the building categories. Schools stand out, with a large difference in heat consumption between inside and outside opening hours, leading to a large flexibility potential on daily basis, but this would require a large amount of stored energy. As it is difficult to control, and thereby reduce the peaks for unknown loads, a prediction model is applied to the data, to analyse the predictability. It is shown that the peak shaving potential is reduced 90-30 % when analysing only the predictable loads. The biggest difference is in the short-term potential for apartment blocks and hotels, while difference is smaller in the long-term (24-hour) peak shaving potential.

1. Introduction

The Clean Energy Package of the European Union highlights the importance of utilizing demand side flexibility to support the de-carbonisation of the energy system [1]. In Norway, about 80 % of the building sectors' heating demand is met by electricity either with heat pumps or direct electric heating [2,3]. In addition, fossil oil as heating source is to be phased out by (2020), which will further increase the need for electricity as a heating source. Hence, shifting the heating use of buildings comprises a large flexibility potential for the electrical system. Regarding the power grids in European countries, the main reason for the utilization of building energy flexibility is to adjust the load to the availability of renewable energy, while in Norway, the main goal is to reduce the maximum peak load and thereby to reduce the strain on the distribution grid. Regarding district heating networks, demand side flexibility is of interest because it can reduce the need for costly energy sources typically applied during peak hours. Flattening electricity and heat load profiles is thus beneficial for reducing the installed peak capacity as well as for the operation of individual energy systems [4]. Energy-efficient heat supply systems, such as ground source heat pumps (GSHP), are usually installed as base load units, whereas the peak load is covered by a less energy-efficient unit, e.g. an electric boiler [5]. Reducing both peak power and energy demands during peak periods, will lead to an increased utilization of the base load system and decrease the total operation cost of the system [6]. To enable a flexible operation, thermal energy storage is required, examples are water storage tanks for domestic hot water (DHW) or the utilization of the thermal inertia of buildings [7–10]. With the implementation of automatic metering systems (AMS) the availability of data will increase drastically. The data can be used to estimate the buildings flexibility potential. This works seeks to find a simplified way of doing this.



This work aims at investigating the flexibility potential for several building categories by analysing hourly heating demand measurements of 197 buildings. A Linear regression model has been fitted on the data for each building. The main focus is on peak load reduction, and therefore, the emphasis is put on prediction of the winter season. The available information is restricted to the heat load profile, the building category and the location of the buildings. The measurement data has been studied with regards to daily load variations and capacity to forecast the loads based on available parameters.

2. Description of dataset

Heat load measurements have been collected from district heating substations for a range of buildings, including 120 apartment blocks, 31 office buildings, 16 hotels, 15 nursing homes and 15 schools, located in a Nordic climate. For each building, the dataset contains hourly measurements of the heat consumed by the building for a period of one year (2017).

There are large variations in the quality of the measured data samples resulting from the limited information on the datasets. This entails several challenges:

- (1) The resolution of energy metering with regards to district heating measurements. Often, energy meters accumulate to a given threshold before the signal is logged. Commonly-used thresholds are 1, 10 or 100 kWh. If this threshold is too high relative to the energy consumption of the building, the hourly measurements may be inaccurate, also affecting the flexibility potential.
- (2) It is unknown, whether additional energy sources, other than district heating, are applied in the buildings. In that case, the measured energy consumption and load profile will not be representative for the energy needs of the building.
- (3) The lack of information on the building size (heated floor area) and year of construction can make it difficult to draw conclusions with certainty.

3. Methodology

The data analysis is split into two parts. First, the theoretical peak shaving potential for each building in each category is investigated by smoothening the load profiles. Secondly, we fit a linear regression model to the measurements for each building.

3.1. Theoretical peak shaving potential

Local storages can be applied to reduce the peak loads by smoothening the profile (seen by the distribution grid). To investigate the theoretical potential for smoothening the load profile, a Simple Moving Average (SMA) function is applied. SMA is an arithmetic average of the n previous values. The flexibility potential is evaluated by calculating the ratio between the maximum peak load of the filtered load profile ($Q_{MA(n)}$) and the measured hourly profile (Q_{meas}), as shown in equation 1. This ratio will always be equal or smaller than 1 and represent by how much it is possible to reduce the overall peak.

$$P_{flex} = 1 - \frac{\max(Q_{MA(n)})}{\max(Q_{Meas})} \quad (1)$$

3.2. Regression analysis

Several linear regression models with the limited number of explanatory variables was tested. The linear regression model shown in equation 2 and 3 was selected and has been fitted to each building. The dataset is split into three seasons: winter (des-feb), shoulder (mar-may+sept-nov) and summer (jun-aug). Workdays and weekends are separated. This results in 6 models for each building.

$$P_t^h = f(t_{day}) + \beta_1 TLP_t^o + \varepsilon_t \quad (2)$$

$$TLP_t^o = \alpha TLP_{t-1}^o + (1 - \alpha) * T_t^o \quad (3)$$

The regression model is shown in equation 2, where the explanatory variables in the model are time of day (t_{day}) and outdoor temperature (T^o). $f(t_{day})$ is a spline function to describe the diurnal profile. $TLP^o(t)$ (equation 3) is the filtered ambient temperature after application of a first order low pass filter with the smoothening factor α . The lowpass filter enables the model to include the dynamic effects of the

building (due to thermal inertia and insulation). During the model fitting, α is optimized for each building by minimizing the RMSE of the models. α is equal for all the 6 models describing one building. β describes the slope of the temperature dependency curve and is equal for all hours within each model, even though this has shown not to be the most accurate solution [11]. ε is the error term.

4. Results and discussion

4.1. Theoretical peak shaving potential

Figure 1 shows the resulting flexibility potential from smoothing the load profiles with different averaging periods. The histogram shows the share of buildings with the respective flexibility potential (P_{flex}) for each building category and for 2-, 6- and 24-hour moving averaging periods. $P_{flex}=0$ means no potential for peak load reduction, while $P_{flex}=0.5$ means a potential for 50% peak load reduction. From the results, it can be seen that about there is a potential for peak shaving by load shifting (smoothing the load in the peak hour out) over a period of only two hours for about 60 % of the apartment blocks. The potential ranges from 5-15 %. A similar tendency is can also be seen for hotels. Both these building categories have short term peaks, typically driven by DHW consumption in the morning and/or temperature increase in the morning after night set-back periods. For longer averaging periods, high short-term peaks are less influential and the differences between the building categories evens out. For the 24-hour averaging period, schools stands out with a high peak shaving potential. As shown in Figure 2, this is mainly due to the large difference in energy consumption between operating and non-operating hours. One could expect similar results for offices, however it is dependent on how well the HVAC system is controlled. A longer averaging periods would also imply the need for larger available thermal energy storages. Table 1 (a) summarizes the results by showing the mean P_{flex} -value, and the range within each building category.

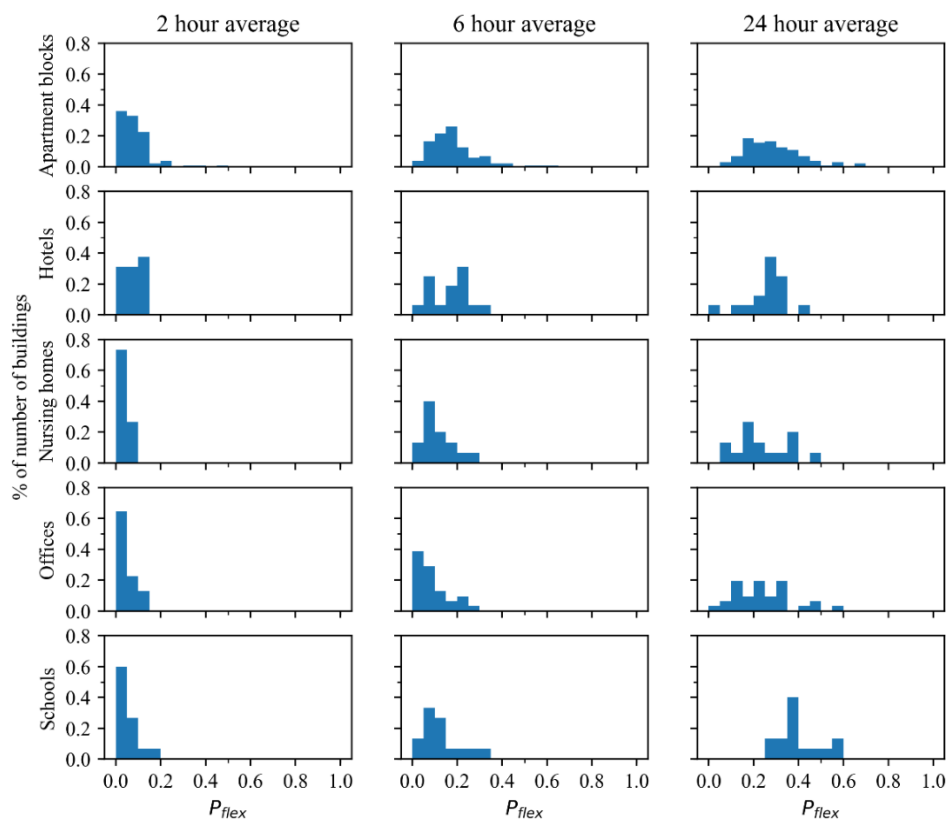


Figure 1. Histograms of resulting P_{flex} from smoothing the load profiles with different averaging periods.

4.2 Heat load prediction

Figure 2 shows examples of predicted daily heat demand profiles, normalized by the total daily consumption, for one selected building per building category with constant outdoor temperature of -15°C (left) and 0°C (right). Both figures are generated for working days using the winter model. Here, the relative daily variation, and thereby the relative flexibility potential, is reduced with reduced outdoor temperature. Thus, the relative potential for peak shaving is larger on warmer days. However, the absolute potential for peak reduction might be similar. Figure 2 also shows that schools have very clearly defined opening hours, and in most cases the indoor temperature is reduced, and the ventilation is reduced or turned off outside opening hours followed by a peak demand before opening, connected to the start of ventilation. Figure 2 shows just one selected building from each category. There are large variations in the profiles within each building category, but the selected buildings are representative for the buildings with high quality measurement data.

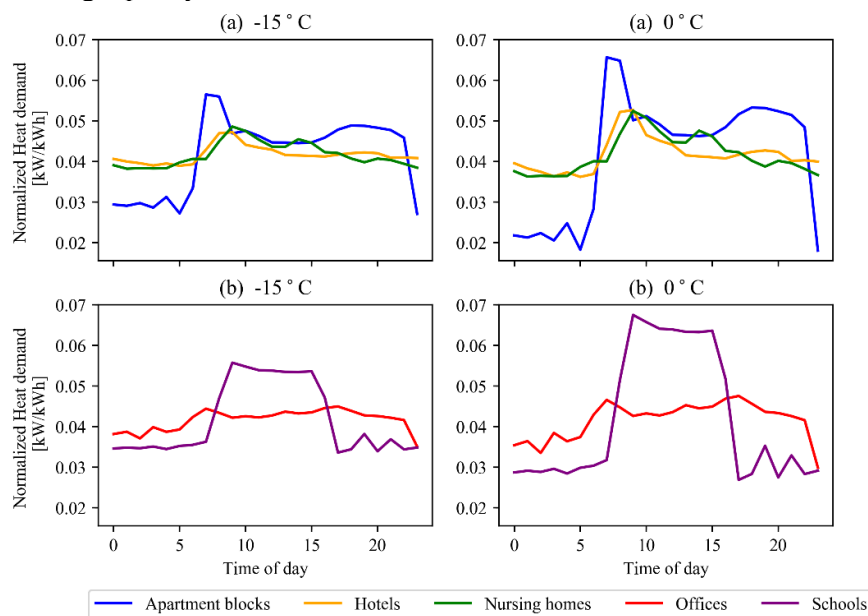


Figure 2. Normalized heat load profile for a day with outdoor temperature at -15°C (a) and 0°C (b) for selected buildings.

Figure 3 shows the predicted load profiles for two days around the peak load hour for the same buildings as in Figure 2. It shows that the ability of the models to predict the peaks are variable. In general, the models are not able to predict the maximum peaks, probably due to occasional effects. For hotels, the predicted peak load is much lower than the measured values. This is probably due to the fact that data on the number of guests are not available for the model. With this model, the peak shaving potential is low, but for a model designed for peak shaving at a selected hotel, predicted guest data would be available from the booking system. The buildings shown in Figure 3 have above average R^2 -values. For the total dataset the average R^2 -value is 0.63, and the median is 0.70.

4.3. Flexibility potential

Table 1 shows the flexibility potential for different types of buildings and time frame. There are several reasons why it is challenging to exploit the full flexibility potential shown in Table 1 (a). The flexibility potential is calculated based on the measured load profiles, where the maximum peaks normally are caused by occasional user-behavior-driven effects (especially for apartments and hotels), in addition to the outdoor temperature and the diurnal routines. These maximum peaks are difficult to predict (as shown in Figure 3, and thereby also difficult to shave. Peaks are very dependent on how the building is controlled. Additionally, flexibility means different use of the existing systems but it maybe the need

for storage that may or not be previously in the building. Storage means investment, but also higher energy use which may not be interesting unless peak power is priced.

Table 1 (b) shows the theoretical peak shaving potential performed on the *predicted values* for the same year. It is shown that the peak shaving potential by smoothing the load profiles is significantly lower for the predicted load profiles. This is partly due to the smaller peaks, as mentioned above. The results for the predicted load profiles will be less affected by potential outliers in the data set.

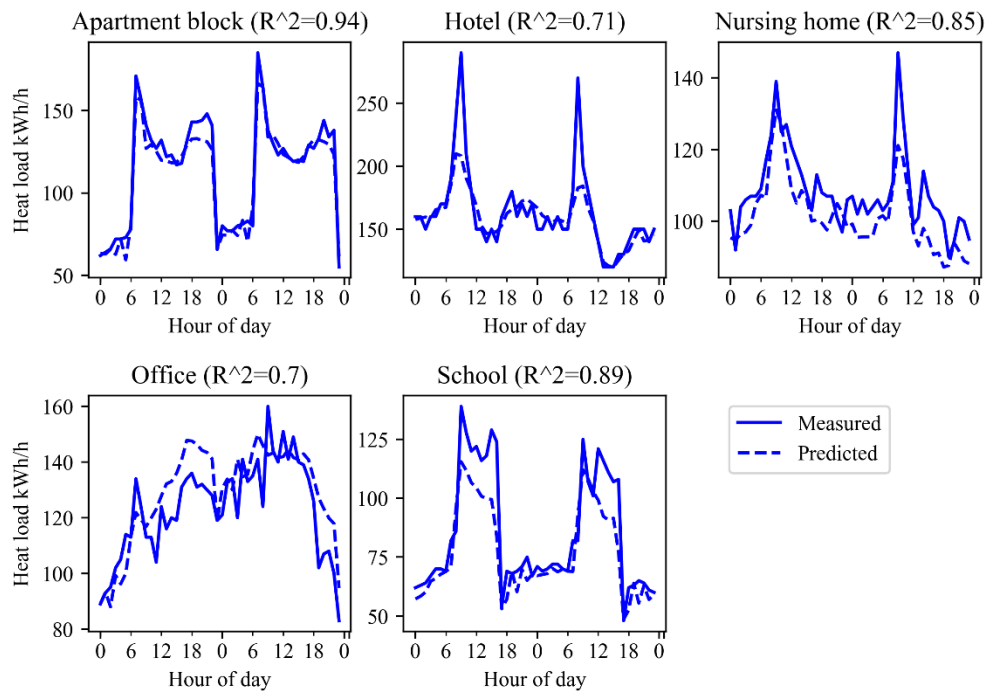


Figure 3. Predicted vs. measured values for 2 days around yearly peak for selected buildings.

Table 1. Theoretical peak shaving potential (Pflex) from (a) moving average test on measured values and from (b) moving average test on predicted values (Range is defined by the 20% and 80% quantiles to disregard the abnormal buildings).

Building category	# buildings	Short term (2 hour MA)		Medium term (6 hour MA)		Long term (24 hour MA)	
		Mean	Range	Mean	Range	Mean	Range
(a) Moving average of measured values							
Apartment blocks	120	8 %	3-12 %	19 %	10-24 %	29 %	18-38 %
Hotels	16	8 %	4-13 %	17 %	9-23 %	26 %	22-30 %
Nursing homes	15	3 %	1-5 %	11 %	5-17 %	24 %	15-36 %
Offices	31	4 %	1-7 %	9 %	3-14 %	24 %	12-33 %
Schools	15	5 %	1-8 %	12 %	5-17 %	40 %	34-49 %
(b) Moving average of predicted values							
Apartment blocks	120	1 %	0-2 %	7 %	3-9 %	15 %	10-19 %
Hotels	16	2 %	0-3 %	8 %	5-10 %	16 %	12-19 %
Nursing homes	15	2 %	1-3 %	6 %	3-8 %	13 %	8-16 %
Offices	31	1 %	0-2 %	4 %	2-7 %	16 %	8-25 %
Schools	15	2 %	1-2 %	6 %	3-8 %	26 %	21-29 %

5. Conclusions

The presented work has analyzed a large data set of heat load measurements from different building categories, to evaluate the theoretical potential for peak shaving. It is shown that for short term peak

shaving, apartment blocks and hotels have the highest potential, with an average of 8 %. For longer term peak shaving, the results are more similar for all the building categories, with a higher potential, but a wide variance between individual buildings (from 12-39 %). Schools stand out, with a large difference in heat consumption between inside and outside opening hours, leading to a large flexibility potential on daily basis, but this would require a large amount of stored energy.

As it is difficult to control, and thereby reduce the peaks for unknown loads, a prediction model is applied to the data, to analyze the predictability. As a prediction model will not predict the maximum peaks, the peak shaving potential is reduced when analyzing the predicted values. This is clearly seen when the moving average analysis is performed on the predicted heat load. For example, the average peak load shaving potential for apartment blocks is reduced from 8 % to 1%. For more long-term peak shaving, the difference is less significant. This difference might be reduced by improving the prediction model, either by adding more parameters, or improving the data quality (fault detection and installing new meters).

The results can further be utilized to investigate how the building flexibility can reduce investment and operational costs in the grid, and how the flexibility can be harvested by thermal energy storage systems.

Acknowledgement

This article has been written within the research project "RockStore - develop, demonstrate and monitor the next generation BTES systems". The authors gratefully acknowledge the support from the Research Council of Norway (ENERGIX-programme) and the project partners.

References

- [1] European Commission. Clean Energy for All Europeans - The Winter Package. [Internet]. 2018 [cited 2018 Nov 26]. Available from: <https://ec.europa.eu/energy/en/topics/energy-strategy-and-energy-union/clean-energy-all-europeans>
- [2] Lindberg KB, Magnussen IH. Reducing GHG emissions from the Norwegian building stock - Measures and policies. Report no.4/2010 (In Norwegian: "Tiltak og virkemidler for redusert utslipp av klimagasser fra norske bygninger"). NVE; 2010.
- [3] Bøeng AC. Energy consumption in households from 1930 - 2004, and by type of household [Internet]. SSB Report 2005/41. Oslo-Kongsvinger; 2005. Available from: https://www.ssb.no/a/publikasjoner/pdf/rapp_200541/rapp_200541.pdf
- [4] v. d. Hoeven M. Linking Heat and Electricity Systems: Co-generation and District Heating and Cooling Solutions for a Clean Energy Future. 2014.
- [5] Angelino L, Dumas P, Garabetian T, Pinzuti V. 2016 EGEC GEOTHERMAL MARKET REPORT. 2017.
- [6] IEA. Technology Roadmap - Energy Storage. 2014.
- [7] Fischer D, Bernhardt J, Madani H, Wittwer C. Comparison of control approaches for variable speed air source heat pumps considering time variable electricity prices and PV. *Appl Energy*. 2017 Oct;204:93–105.
- [8] Clauß J, Stinner S, Sartori I, Georges L. Predictive rule-based control to activate the energy flexibility of Norwegian residential buildings: Case of an air-source heat pump and direct electric heating. *Appl Energy*. 2019 Mar;237:500–18.
- [9] Johnsen T, Taksdal K, Clauß J, Georges L. Influence of thermal zoning and electric radiator control on the energy flexibility potential of Norwegian detached houses. In: Accepted at CLIMA 2019 Conference. Bucharest, Romania; 2019.
- [10] Pedersen TH, Hedegaard RE, Petersen S. Space heating demand response potential of retrofitted residential apartment blocks. *Energy Build*. 2017 Apr;141:158–66.
- [11] Lindberg KB, Doorman G. Hourly load modelling of non-residential building stock. In: 2013 IEEE Grenoble Conference PowerTech, POWERTECH 2013. Grenoble: IEEE; 2013. p. 1–6.