Further development and validation of the "PROFet" energy demand load profiles estimator

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Abstract

Long-term forecasts of the aggregate energy load profiles are crucial for energy system planning. Previous work has developed a load profile model named PROFet to forecast aggregated weather-dependent load profiles. This with an hourly resolution for buildings based on energy measurements from buildings connected to district heating. In this study, further development of the PROFet model is presented, including the extension of measurements in the database, the separation of building categories into three efficiency levels, and the separation of energy load profiles for electric loads, space heating, and domestic hot water heating. Load profiles created with PROFet for apartments have been validated against out-of-sample data (load measurements from buildings with hourly resolutions). This study shows that the out-of-sample datasets are in good agreement with the PROFet prediction. Also, the validation results are satisfactory as they are below the threshold values for the statistical indicators. A lasting contribution is a tool for creating aggregated load forecasts, which provides crucial information in grid planning and modelling. The results also provide typical load profiles that can be used as reference values when evaluating a neighbourhood/area's energy flexibility.

Key Innovations

PROFet is a tool for generating aggregated load forecasts for heating and electric loads in buildings (both residential and non-residential) in a given area, needing only outdoor temperature and floor areas as additional data inputs. The validation of generated load profiles for apartment buildings in the model has been successful.

Practical Implications

The PROFet model utilizes measured energy data from buildings for estimating aggregated loads. Aggregated load forecasts can provide crucial information for grid planning, including estimation of dimensioning peak loads. PROFet can also model future energy demand and loads on a larger scale (regional or national).

Introduction

Forecasting of aggregate energy load profiles is crucial for grid investment decisions and energy system planning. (Daneshi, Shahidehpour, and Chobbari, 2008) (Jinliang *et al.*, 2018). In this paper, the term 'aggregate load profile' refers to the yearly time-series of hourly values of energy demand in buildings on a neighbourhood level to the national level. Traditionally, load forecasts for energy planning have been built by extrapolating future data from historical trends (Boßmann *et al.*, 2013; Carvallo *et al.*, 2018). Future changes in the European energy system calls for methods for forecasting of long-term hourly electricity load that accounts for changes of the building stock, including energy efficiency measures (Sandberg *et al.*, 2016), technology choices (such as more heat pumps and PV(European Commission, 2018)), storage and flexibility options. Recent developments in policy and practice highlight the importance of utilizing end-user flexibility to support the decarbonization of the energy system (European Commission, 2018) (IEA, 2019). In the Norwegian research centre for Zero Emission Neighbourhoods (FME-ZEN, www.fmezen.no), a ZEN definition is being developed. The ZEN definition from FME ZEN states that a ZEN should be able to "respond to signals from the grid and manage its demand, storage and local generation to optimize its response to such signals while satisfying user comfort" (Junker *et al.*, 2018) (Jensen *et al.*, 2017). To evaluate a neighbourhoods performance on this goal, energy flexibility key performance indicators (KPIs) need to be established (Wiik *et al.*, 2019). To establish such KPIs, standard load profiles (i.e., unaware signal profiles) should be used as a reference against which evaluating the flexibility potential.

PROFet (Energy demand load PROFile EsTimator) is a load profile estimation tool that can be used for generating aggregated load forecasts (for heating and electric loads separately) for a given area, needing only outdoor temperature and floor areas as additional data inputs. The tool can be used for planningof the electricity grid, and in energy and climate plans on municipal and national scale.

A previous version, which PROFet is based on of the model was developed using panel data regression models (Bessler *et al.*, 2014) on monitored data with hourly resolution from 100 non-residential buildings (Lindberg, Bakker and Sartori, 2019), and regression models for measured data from apartments and single-family houses (Pedersen, 2007). This paper improves previous work previously performed by expanding the sample of investigation.

This study aims to present further developments of the PROFet and validate the typical load profiles from the PROFet model with out-of-sample datasets. This study will also aim to evaluate how typical profiles generated from PROFet might be used to establish load flexibility KPIs.

Methodologies

The PROFet model

PROFet estimates the typical load profile of an area-based solely on building area input and outdoor temperatures. The model created a specific load profile based on the typical energy signature curves (ESC) for buildings in different groups (building categories and energy efficiency categories). The ESC Figure 1 below shows the relationship between the energy load heat load in an observed building and the outdoor temperature. For a typical building, the ESC for heating consists of two parts, divided by the change point temperature (CPT) – namely the temperature-dependent part and the temperature-independent part.

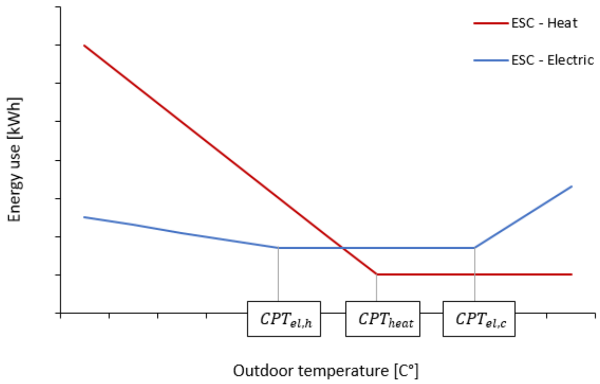


Figure 1: Energy signature curve concept for heating and electric demand various building categories.

The space heat load y_{th} [kWh/m^2] of a building type (building category and efficiency standard) at the time t, depends on the time of day (i) dependent constants; α_i^h and γ_i^h, the variable outdoor temperature, x_t and the 24-h moving average temperature ($x_t^{h,TMA}$) when the outdoor temperature (x_t) is lower than the change point temperature for space heating, CPT_{heat} see Equation 1.

$$y_{th} = \begin{cases} \alpha_i^h + \beta_i^h x_t + \beta_i^{h,TMA} x_t^{h,TMA} + \gamma_i^h & if\ x_t < CPT_{heat} \\ \gamma_i^h & if\ x_t > CPT_{heat} \end{cases}$$

The electric load ESC in PROFet consists of three parts; 1) when the curve is temperature-dependent under a low CPT (which increases the demand for electricity use on cold and dark days) 2) a part which is temperature independent 3) and a part where the outdoor temperature is above a higher CPT, and where the energy use again becomes temperature dependent due to a cooling demand in the building.

The electric load y_{te} [kWh/m^2] at the time t, depends on the time of day (i) dependent constants; α_i^h and γ_i^h, the variable outdoor temperature, x_t, and wheatear this temperature is above the cooling threshold ($CPT_{el,c}$) and below the heating threshold ($CPT_{el,h}$). See Equation 2 below.

$$y_{te} = \begin{cases} \alpha_i^{e,h} + \beta_i^{e,h} x_t & if\ x_t < CPT_{el,h} \\ \gamma_i^h & if\ CPT_{el,h} < x_t < CPT_{el,c} \\ \alpha_i^{e,c} + \beta_i^{e,c} x_t & if\ x_t < CPT_{el,c} \end{cases}$$

Most residential buildings in Norway have not installed cooling systems, and so the typical electrical load ESC for houses and apartments will have flat curve when the temperature is above $CPT_{el,c}$.

The coefficients, α, β, and γ for each of the building categories, energy efficiency categories, and energy purposes have been created using panel data regression models (Bessler et al., 2014) on actual measurement data monitored buildings. In this paper, new sets of coefficients have been generated by the PROFet model concerning the initial work (Bessler *et al.*, 2014).

trEASURE energy measurement database

trEASURE is a measurement database where monitored energy data with hourly resolution from different buildings in Norway has been collected, including the data from the 100 buildings used for the previous development of PROFet (Bessler *et al.*, 2014). trEASURE has now been extended to include more than 300 entries representing ca. 2.4 million m^2 of floor area, subdivided into 11 building categories, both residential and (mostly) non-residential buildings. Most of the entries in the trEASURE had hourly measurements of total energy use for heating based on district heating consumption measurements in the buildings. In previous versions of PROFet, the load profiles were divided into thermal loads (SH and DHW) and electric loads. The heating measurements of each entry in trEASURE have been pre-treated with a decomposition of the heat load measurements into domestic hot water heating (DHW) and space heating (SH) using a hybrid seasonal/energy signature method(Lien, Ivanko and Sartori, no date). This separation of heat load measurements into SH and DHW has made it possible to predict separate SH and DHW load profiles in PROFet. In PROFet. The DHW heat load is assumed to be temperature independent. The DHW profile is solely dependent on the time of day (but varies for each building category and type of day). See Equation 3.

$$y_{i,dhw} = \gamma_i^{dhw} \qquad (3)$$

The building entries' energy efficiency has been inferred by comparing the space heating measurement data's temperature dependency with reference values from building standards. The data entries have been split into 3 different efficiency categories: Very Efficient (E, buildings with typical heat demand profiles for Passive House and Low Energy Buildings), Efficient (T, buildings with typical heat demand profiles for buildings build according to the technical regulations from 2010 or later) and Regular (R, The remaining buildings). The splitting of the building entries into these three efficiency categories has been conducted using a newly proposed method, named the "Self-inferred energy classification/categorization method". This is further described in the results-chapter.

An overview of the available input building area categories and the output load profiles in PROFet are given in Table 1 below.

Table 1: PROFet – categories of input and output.

Input categories		Output	Variations
Building categories	**Efficiency categories**	**Energy purposes**	**Days (types)**
House Apartment Office Shop Hotel Kindergarten School University Culture Sport Nursing home Hospital	Regular Efficient Very efficient	EL SH DHW	Workday Weekday Holiday

By entering a neighbourhood's building area composition, accompanied by an outdoor temperature profile, PROFet can generate a typical hourly load profile for an area, divided into the purpose's electric loads, DHW and SH, for 24 hours more than a full year.

Self-inferred energy categorization

To split the buildings in the treasure database into different efficiency categories (very efficient (E), efficient (T), and regular (R)), a data-driven inference approach has been applied. The method consists of performing a linear regression of the space heating demand in the winter months (January, February, and December) for each building separately. The primary regression is performed with a simple linear regression on the daily energy consumption for space heating (Φ_{SH}) against the daily average outdoor temperature ($\overline{T}_a$) of the same day. See Equation 4 below.

$$\Phi_{SH} = \alpha + \beta\overline{T}_a \qquad (4)$$

The daily energy consumption is calculated by summation of the hourly consumption for each day. Only days with measured values for all hours of the day are included. In further analysis, the data is split according to the building categories applied in NS3031. There are simulation models for apartments and offices meant to represent buildings in both the E and T categories. The calculated α and β for these buildings define the borders for splitting the measured buildings into the different categories. The principle for determining the categories is shown in Figure 2 below.

A line is drawn between the mean of the models for category E and category T. A weighted point on that line is then calculated (70% from E and 30% from T). Then, a line is then drawn from the point to the x-axis, generally to a line between the point and origin. The resulting triangle is mirrored to create an isosceles triangle (the green area on the figure). Buildings with a combination of alpha and beta that falls within this area are marked as "E". The blue area, which categorizes the buildings as "T" is created by extending the triangle legs by 50%.

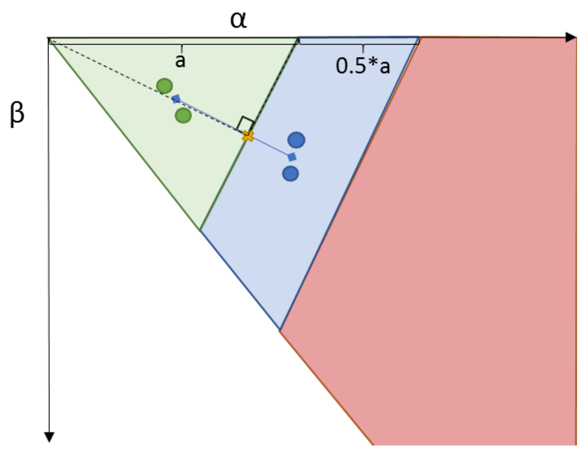


Figure 2: Self-inferred energy categorization methodology.

Further extending the triangle legs creates the red area, which categorizes buildings as "R". The argument for weighting the separation between "E" and "T" towards "T" is that the energy-efficient category is expected to have a more extensive spread and that it is commonly expected that buildings typically perform worse in real life than in simulations. Since simulation models are only available for apartment blocks and office buildings, the categorization areas calculated for offices are applied to all other non-residential buildings.

Out-of-sample datasets

To validate the resulting load profiles from PROFet, load profiles for given locations and dates are compared with out-of-sample (OOS) datasets, i.e., energy measurements that are not included in the trEASURE database. It should be noted that since the PROFet model is meant to generate load profiles valid at an aggregated level, also the out-of-sample datasets need to be conspicuous to have a meaningful comparison.

For the validation of the load profiles from the non-residential building categories, energy measurements from 100 buildings were collected for the out-of-sample dataset. However, due to selection criteria such as 'no heat pump' (as the treasure database consists of buildings with district heating), no significant solar production (photovoltaic or solar collectors), and a need for separate meters for heating and electricity, none of the 100 buildings were adequate to be included as the out-of-sample datasets, and it was not possible to perform an OOS-validation for the non-residential buildings.

For the OOS validation of heat loads from apartments, a data set consisting of district heating measurements from 43 apartment blocks was used. This dataset was not included in the PROFet database (trEASURE) due to missing information about m^2 of heated floor area for any of the buildings. The dataset was collected from the district heating company in the city of Oslo. Table 2 describes the general information about the out-of-sample (OOS) for apartments.

Table 2: General information about out-of-sample (OOS) datasets.

Building type	**Location and year**	**Nr. of out-of-sample files**
Apartment (Apt)	Oslo, 2017	43
		Heated floor area [m²]
		No floor area (m²) available in the datasets. Scaled floor area in avg. file: 8345 m²

As mentioned, no information about the heated floor area (m²) for the OOS apartment files was available. Due to this, the heat load of each of the apartments in the OOS data set was calibrated so that the annual total heat load per year was equal to the annual total heat load of apartments (regular) from the PROFet model. Further, the 43 out-of-sample datasets were then averaged into one file (8760 values with an area of 8345 m²), which was used for the actual validation of the apartment heat load profile from PROFet in the Results section.

The OOS apartments data was collected from buildings in Oslo in 2017. Weather data corresponding to the location (Blindern, 2017) was obtained from the *Norsk Klima Service Senter* website. For the validation of the heat load for regular apartments in PROFet, load profiles were generated using the Oslo climate file from 2017 as input.

Figure 3 below describes a whisker plot (minimum, 25 percentile, median, 75 percentile, and maximum) for the percentage of the average heating power for each of the 43 files.

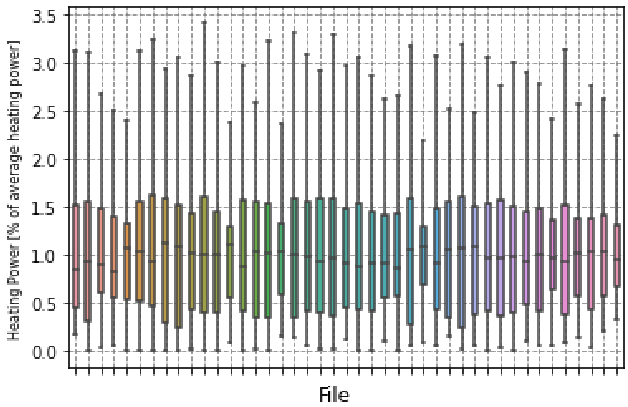


Figure 3: Percentage of average heating power for each of the 43 files.

Statistical indicators for validation

Efforts have been made to improve the validation reliability of building energy models. Several validations and uncertainty studies use statistical functions/metrics such as Mean Bias Error (MBE), Normalized Mean Bias Error (NMBE), and Coefficient of Variance Root Mean Squared Error (CVRMSE) (Ruiz and Bandera, 2017) (Chakraborty and Elzarka, 2018). Especially after the development of ASHRAE guideline 14-2014, where among these statistical functions are presented for applying and validating simulation models (ASHRAE Guideline 14-2014, 2014). Another statistical term frequently used is the Coefficient of Determination, the R^2. However, this term can be expressed in many different ways, and general confusion often arises in comparison studies (Ruiz and Bandera, 2017) (Kvålseth, 1983). In this study, it was chosen to use NMBE, CV(RMSE) and R^2 for validation of the PROFet model.

Equation 5 describes the Normalized Mean Bias Error (NMBE [%]) function (ASHRAE Guideline 14-2014, 2014). The threshold value for a valid model is < 10 % on hourly yearly data, according to ASHRAE Guideline 14-2014.

$$\mathrm{NMBE} = \frac{\sum_{i=1}^{n}(Y_i^o - Y_i^p)}{n} * \frac{100}{\overline{Y^o}} \tag{5}$$

Y_i^o = Out-of-sample data point

Y_i^p = PROFet data point

n = Number of out-of-sample points

$\overline{Y^o}$ = Mean of the out-of-sample data points

Equation 6 describes the Coefficient of Variation Root Mean Squared Error (CV(RMSE)) [%] function (ASHRAE Guideline 14-2014, 2014). The threshold value for a valid model is < 30 % on hourly yearly data according to Ashrae Guideline 14-2014.

$$\mathrm{CV(RMSE)} = \sqrt{\frac{\sum_{i=1}^{n}(Y_i^o - Y_i^p)}{n}} * \frac{100}{\overline{Y^o}} \tag{6}$$

Y_i^o = Out-of-sample data point

Y_i^p = PROFet data point

n = Number of out-of-sample points

$\overline{Y^o}$ = Mean of the out-of-sample data points

Equation 7 describes the Coefficient of Determination (R^2 [-]) and can be calculated by the following steps according to Kvålseth, (1983).

1) Calculating the mean of the data:

$$\overline{y^o} = \frac{1}{n}\sum_{i=1}^{n} y_i^o$$

2) Residual sum of squares of the residuals:

$$SSres = \sum_i (y_i^o - y_i^p)^2 = \sum_i {e_i}^2$$

3) The total sum of squares:

$$SStot = \sum_{i=1}^{n} (y_i^o - \overline{y^o})^2$$

$\overline{y^o}$ = The mean average of the out-of-sample

y_i^o = Out-of-sample data point

n = Number of out-of-sample data points

y_i^p = PROFet data point

e_i = Residuals

$$R^2 = 1 - \frac{SSres}{SStot} \quad (7)$$

Figure 5: Annual heating load Apartments Regular.

Results

Self-inferred energy categorization

As earlier mentioned in the methodology, the self-inferred energy categorization was applied to all buildings in trEASURE. Figure 4 shows the results from the categorization for the Apartment category. The crosses show results from the simulation models, while the circles show the buildings in trEASURE. The two green circles are measurements from buildings known to be built to high energy efficiency standards. Many of the buildings are clustered in the "Efficient" category. This is reasonable as most of the buildings were built between 2010 and 2015.

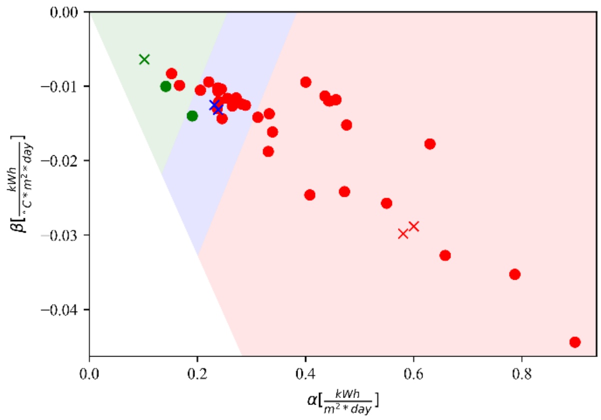


Figure 4: Results from the self-inferred energy categorization applied to the Apartment building category in trEASURE.

Annual heating and electricity use

The total annual heating use consists of Space Heating (SH), ventilation heat, and Domestic Hot Water (DHW). The electricity use consists of plug loads, appliances, and others. However, as mentioned earlier, the electrical total was not available in the OOS datasets, only from the PROFet datasets. Because of this, validation of electrical loads is neglected in this study.

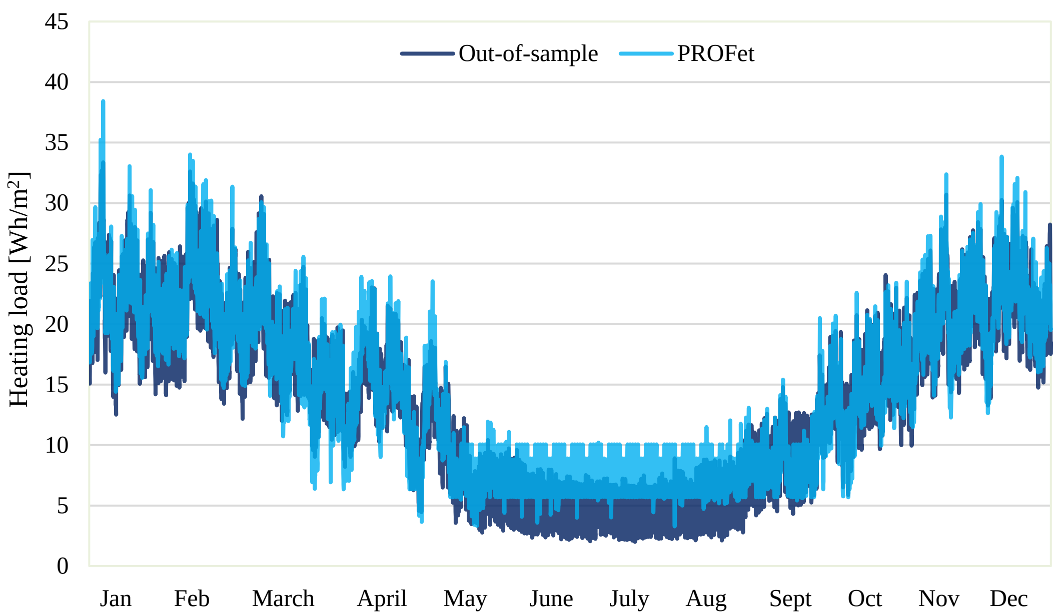
As the results in Table 3 below show, the yearly energy use for heating in PROFet was calculated to 120 kWh/m^2 year using a standard Oslo Climate file. As the building area was not available in the out-of-sample datasets, the OOS dataset were scaled to be equal to the annual heat load from PROFet to find an averaged floor area. The OOS datasets (43 files) were then averaged into one file, which is presented in the Results section.

The peak load deviation from OOS and PROFet was calculated to 5 Wh/m^2.

Table 3: Average for heating and electricity use.

Building type	Out-of-sample		PROFet	
Energy use (heating power, HtTot) (kWh/m^2 year)				
	ElTot	HtTot	ElTot	HtTot
Apartment Regular	-	120 (scaled)	39	120
Peak load (Wh/h/ m^2)				
	ElTot	HtTot	ElTot	HtTot
Apartment Regular	-	33.4 (scaled)	7.8	38.4

Figure 5 below illustrates the yearly heating load for Apartments Regular Oslo year 2017. The 43 out-of-sample data was generated to represent an average file. As one can observe in the figure below, PROFet seems to overestimate the heating use during the summer months. Nevertheless, the average Oslo out-of-sample and PROFet dataset heating use show strong similarities.



Statistical indicators

Statistical indicators, NMBE, CV(RMSE), and R^2 were calculated on the entire time series for each out-of-sample location corresponding to the building category and can be seen in Table 4 below.

Table 4: The entire time series of the averaged OOS file (8670 values) are calculated for NMBE, CV(RMSE), and R^2 for heating loads.

Building type	CV(RMSE) [%]	NMBE [%]	R^2 [-]
Apartment Regular	15	0	0.92

The table above shows that Apartment Regular is valid according to the CV(RMSE) threshold, which is calculated to 15 %. Naturally, the NMBE is calculated to 0 % when the OOS is calibrated to have the same yearly total. In addition, R^2 is calculated to 0.92, which indicates a good fit of the PROFet model. However, the floor area was artificially created, which may have affected the results. This is further discussed in the Discussion section below.

Load duration curve

Figure 6 below illustrates the load duration curve for Apartments Oslo and PROFet. One can observe that the PROFet prediction is in relatively good agreement with the out-of-sample data.

Comparison plot

Figure 7 below illustrates a comparison plot of the out-of-sample as a function of the PROFet. The continuous red line shows where x = y, and the red dotted line is the fitted line of PROFet and out-of-sample data. It can be observed that there is no bias and generally a good fit of the data. However, there is a slight distortion for the lowest and highest values for the PROFet model.

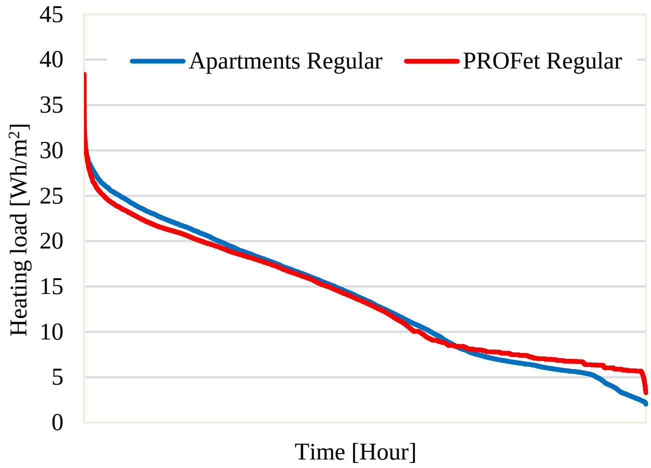


Figure 7: Load duration curve heating loads Apartments Regular.

Typical days

Typical days were created for heating loads (HtTot) for winter (December, January, and February), swing season (average between spring (March, April, and May) and autumn (September, October, and November), and summer (June, July, and August) for both workdays and weekends. Figures 8 and 9 below show the typical day for Apartments Regular out-of-sample and PROFet Regular heating load (HtTot), both for workday and weekend.

As it can be observed for the typical days below, the heating load for all seasons is performing as expected (morning peak due to ventilation, occupants, electricity use or etc.). However, the out-of-sample are to some extent, overestimating the heat loads in the afternoon, especially during the winter and in the swing season, on both workday and weekend.

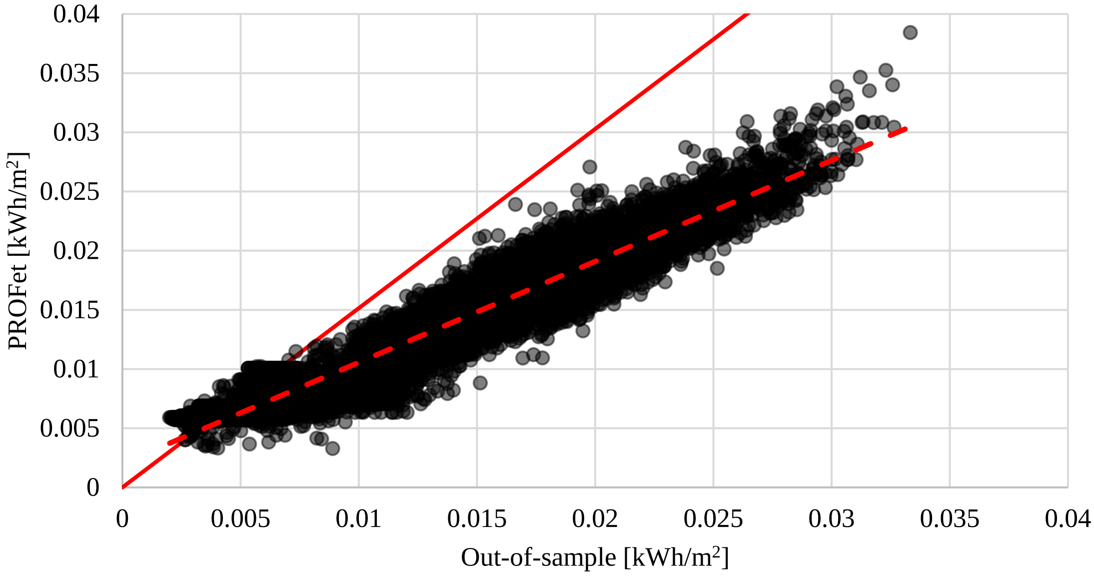


Figure 6: Comparison plot. Out-of-sample as a function of PROFet.

Autocorrelation

Figure 10 below shows the autocorrelation function correlogram of the PROFet model and the out-of-sample datasets. The correlogram shows a repetitive pattern over 24 hours with a week's lag. The reason for this may be due to that PROFet does not take solar radiation into consideration (only dry bulb temperature), the correlation trend may be one of the reasons for this. Further development of PROFet can be found in the Further work section.

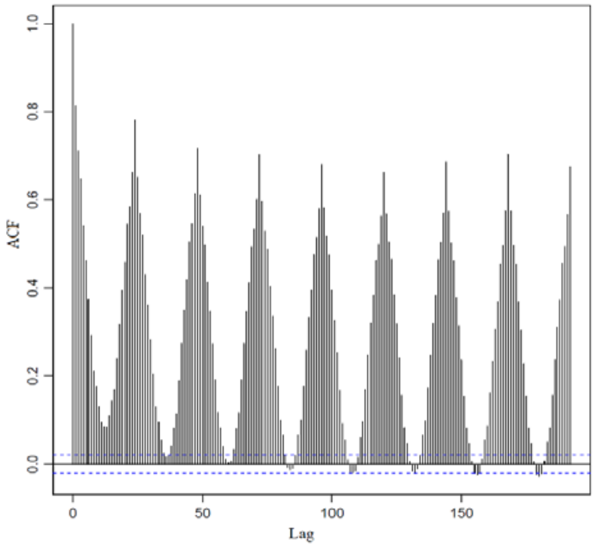


Figure 10: Autocorrelation function correlogram PROFet model and out-of-sample

Discussion

When investigating the annual heating load during the summer season, PROFet overestimates the heating load. In this version of the PROFet model for apartments, holidays are not flagged, which may have influenced the overestimation. However, in the typical days, the out-of-sample heating load is slightly overestimating in the afternoon. This can be due to user behavior such as setpoint, occupant presence, or individual use of apartments.

On one hand, the floor area of the apartments was not known, and therefore calibration of the surface area in the out-of-sample data can be discussed in which this is artificially created to fit the PROFet model. On the other hand, removing the bias allows for deeper focus on the curve shape undisturbed.

Conclusion

This study aimed to present further developments of the PROFet and validate load profiles from the PROFet model with out-of-sample datasets. This paper also evaluated how profiles generated from PROFet might be used to establish load flexibility KPIs in the future.

The further development of PROFet consisted of extending the building categories to 11 (including residential and non-residential building categories), extending the efficiency levels to 3 ('regular', 'efficient' and 'very efficient' and splitting thermal energy demand into energy demand for space heating and heating of domestic hot water.

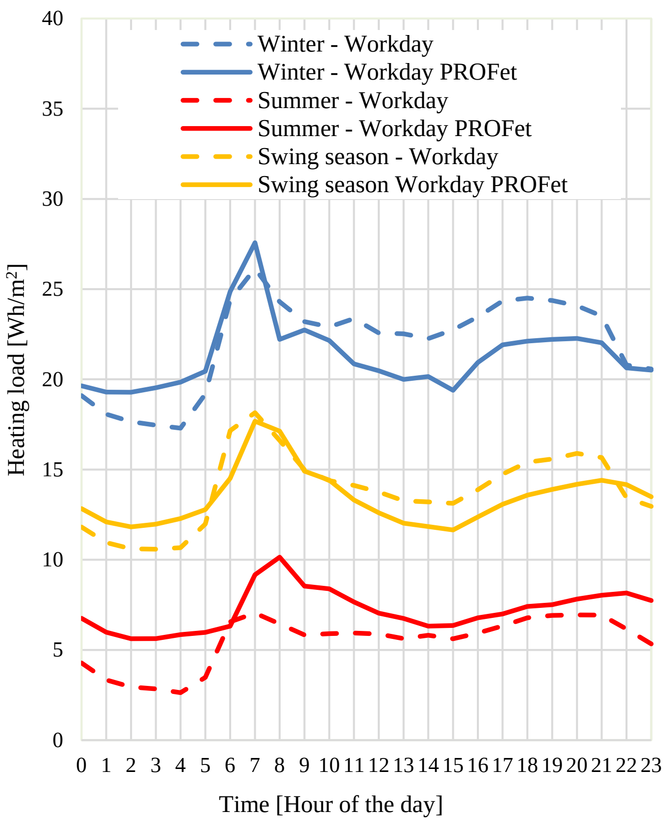


Figure 8: Apartments Regular HtTot Workday.

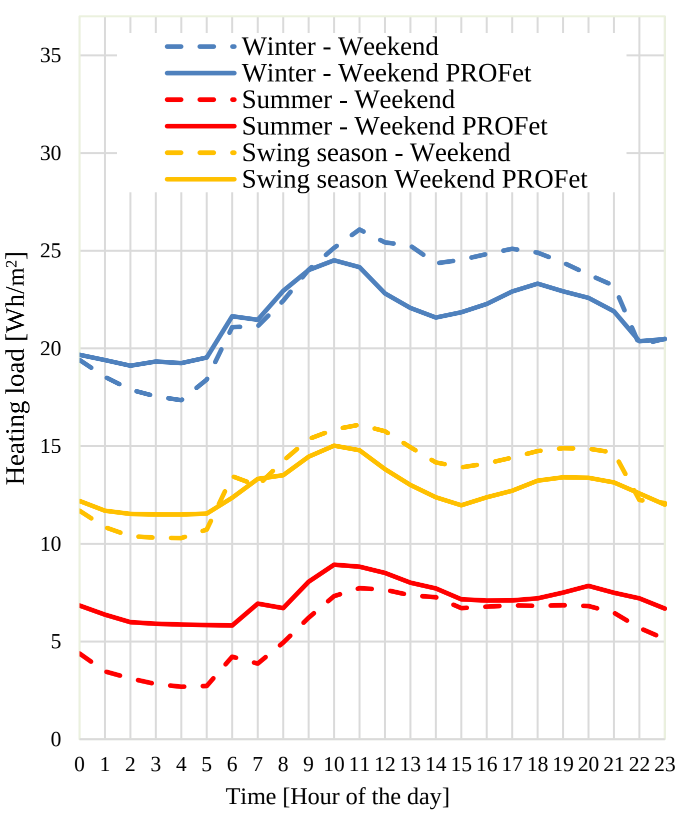


Figure 8: Apartments Regular HtTot Weekend.

The validation of the building categories in PROFet was successful for Apartments according to the statistical indicator NMBE and CV(RMSE) threshold. Nevertheless, further investigation and validation of other out-of-sample building categories are needed in order to provide a comprehensive and reliable validation of PROFet.

The results also provide typical load profiles, which have been successfully validated for apartments. These can be used as reference values when evaluating a neighborhood/area's energy flexibility when energy flexibility KPIs will be developed in future work to use in the Norwegian ZEN definition.

Further work

Further work of PROFet will be developed in three directions (Innovation report FME ZEN, 2020):

1) The statistical method will be improved, introducing season specific profiles, influence of solar and wind, data-driven split between space heating and hot water demand, data-driven evaluation of energy efficiency, weighting of data sources based on data accuracy, evaluation of non-linear modelling

2) Make the tool available as a webtool and maintain it. This will be open source.

3) Make the tool available via API (Application Programming Interface) for integration in other software tools and maintain it. Possibility commercial exploitation of this service/product will be investigated.

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