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Modelling electric and heat load profiles of non-residential buildings for use in long-term aggregate load forecasts

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ABSTRACT

Long-term forecasts of the aggregate electric load profile are crucial for grid investment decisions and energy system planning. With current developments in energy efficiency of new and renovated buildings, and the coupling of heating and electricity demand through heat pumps, the long-term load forecast cannot be based on its historic pattern anymore. This paper presents part of an on-going work aimed at improving forecasts of the electric load profile on a national level, based on a bottom-up approach. The proposed methodology allows to account for energy efficiency measures of buildings and introduction of heat pumps on the aggregated electric load profile. Based on monitored data from over 100 non-residential buildings from all over Norway, with hourly resolution, this paper presents panel data regression models for heat load and electric specific load separately. This distinction is crucial since it allows to consider future energy efficiency measures and substitution of heating technologies. The data set is divided into 7 building types, with two variants: regular and energy efficient. The load is dependent on hour of the day, outer temperature and type of day, such as weekday and weekend. The resulting parameter estimates characterize the energy signature for each building type and variant, normalized per floor area unit (m^2). Hence, it is possible to generate load profiles for typical days, weeks and years, and make aggregated load forecasts for a given area, needing only outdoor temperature and floor areas as additional data inputs.

1. Introduction

Forecasts of the long-term future aggregate electric load are crucial for both power system planning and strategy development of the power market (Daneshi et al., 2008; Zhang et al., 2018). In this paper, the term 'aggregate electric load profile' refers to the yearly time-series of hourly values of electricity demand on a regional or national level. Traditionally, load forecasts are built on mathematical models that extrapolate future trends from historical load data, see e.g. (Boßmann et al., 2013; Carvallo et al., 2018; Chen and Wang, 2012; Goude et al., 2014; Pillai et al., 2014). However, the current architecture of the power sector in Europe (and elsewhere) is evolving towards a system of systems, where centralised and decentralised systems co-exists (ENTSO-E, 2018). In such a system, featuring building integrated photovoltaics (BIPV), distributed batteries and electric vehicles (EV), district heating (DH), heat pumps (HP) and combined heat and power units (CHP) located on-site, along with advanced communication and information technologies, the characteristics of the electricity load will change substantially, not only in the annual magnitude but also in the seasonal and hourly profile (Asare-Bediako et al., 2014; Boßmann and Staffell, 2015; Fischer et al., 2015a). Therefore, long-term load forecasting becomes increasingly challenging when both classical load forecast methods and long-term macroeconomic trends need to be combined (Moral-Carcedo and Pérez-García, 2017). Power system planners and operators must prepare for these changes and update their models and analytic frameworks accordingly. This paper is part of an on-going work on long-term load forecasting, 10–30 years ahead, to be used as input for power systems planning, including transmission and distribution grids.

In Europe, decarbonisation of the heating sector is seen as one of the main solutions for combating greenhouse gas emissions from the buildings stock (Connollyet al., 2013). In practice this means substituting oil and gas boilers with cleaner alternatives, such as heat pumps, bio fuelled boilers and district heating. For the electricity grid, the implementation of heat pumps is especially crucial as the electricity demand will increase substantially (Fischer et al., 2015a; European

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Commission, 2011), and the peak load may increase by as much as 100% for a household (Asare-Bediako et al., 2014). Furthermore, retrofitting buildings will, slowly but steadily, make them more energy efficient (Sandberg et al., 2016). When buildings become more energy efficient their annual energy consumption declines substantially, but also their peak load may be significantly reduced (Lindberg and Doorman, 2013).

The aim of this paper is to support a methodology for forecasting the long-term hourly electricity load, on a regional or national scale, while accounting for changes of the building stock, including energy efficiency measures, technology choices, storage and flexibility options. In this context, this paper contributes to the first of these four, that is, how the hourly demand profiles (i.e. the demand for energy services) are changed as buildings become more energy efficient. For this we analyse hourly energy demand of *heat* (i.e. heat consumed by the waterborne heating system) and *electricity* (i.e. electricity consumed for electric specific demand) of regular buildings compared to energy efficient buildings. Through the separate load prediction of the heat and electric specific demand, it is possible to evaluate the impact of different heating technologies on the hourly electric load profile of buildings. Further, the load profile methodology finds the temperature dependency of the load profiles, and by this it also able to evaluate the impact of future global warming on the electricity demand and peak loads. In this context, this paper provides so-called ‘reference load profiles' which may be used as basis before applying advanced technologies and smart controls. A first, partial version of the methodology has already been published in (Lindberg and Doorman, 2013; Lindberg et al., 2015), and applied in studies of the future Nordic power system (Lindberg et al., 2016) and of the future Scandinavian Energy System (Seljom et al., 2017).This paper presents a refined methodology for the heat and electric specific load profiles of buildings and shows results for all 7 non-residential building types, and discusses it in greater detail.

In this article we define the *electric specific load* of a building as the energy demand that cannot be met by any other energy carrier than electricity, e.g. lighting, appliances, fans and pumps; and the *heat load* as the energy demand required to satisfy the building's space heating and domestic hot water (DHW) needs, regardless of which energy carriers are used to meet it. Energy demand for cooling is commonly provided by electric driven cooling machines and is therefore considered as part of the electric specific load.[1] This segmentation can be seen in Fig. 1.

The parameters that influence the *heat load* of a building are different from those that determine the electric specific load. The electric specific load depends predominantly on factors such as number of persons, their behaviour, number and type of appliances and other technical equipment (e.g. elevators). The DHW part of the heat load too depends mainly on number of persons in the building and their behaviour. On the other hand, space heating depends strongly on shape, size and physical properties of the building, on top of depending on user behaviour and preferences (e.g. choice of indoor temperatures). Hence, to capture the effect of electric heating the heat load of buildings and its hourly profile, need to be analysed and investigated separately.

The choice of focusing on non-residential buildings has two reasons. The first is that despite representing only 27% of the total floor area (Bøhn et al., 2012), non-residential buildings account for about 40% of the stationary energy end-use in buildings in Norway (Statistics Norway, 2011). The second reason is that limited previous work is available on non-residential buildings (cf. Section 2). This paper improves previous work performed on non-residential buildings in Norway (Pedersen et al., 2008), by expanding the sample of investigation and investigating non-linear effects.

[1] Absorption cooling (thermally driven) does not account for any significant fraction of the cooling demand in Europe, either per today or in the 2050 projections of the Energy Roadmap 2050 (European Commission, 2011).

This work analyses hourly measurements from over 100 non-residential buildings from all over Norway and performs panel data analysis for the *heat load* and the *electric specific load* separately, i.e. the blue rectangles in Fig. 1. This distinction is crucial since it allows to consider future energy efficiency measures and substitution of heating technologies. The data set is divided into 7 non-residential building types, with two variants: regular and energy efficient. For each combination we estimate a model that explains load as a function of time (hour of the day, type of day, such as weekdays and weekends, and outdoor temperature. The resulting parameter estimates characterize the average energy signature – a curve describing the temperature dependency of energy use – for each building type and variant, and for each time instance, normalized per floor area unit (m^2).

In such average representative profiles, the short-term stochasticity of individual buildings is evened out and the coincidence factor between different buildings is implicitly accounted for. Hence, it is possible to generate load profiles for typical days, weeks and years, and make aggregated load forecasts for a given area, needing only outdoor temperature and floor areas as additional data inputs.

2. Literature review

This section elaborates on previous work on heat and electric specific load profiles of buildings with hourly or sub-hourly time resolution.

There are several ways of classifying load modelling of buildings. (Fumo, 2014) and (Pedersen, 2007) propose three main categories; statistical, hybrid and engineering models, whereas (Grandjean et al., 2012) classifies load modelling in top-down, bottom-up and combined statistical-engineering models. In this paper, we classify the model approach in *top-down* and *bottom-up* along the vertical axis in Fig. 2, where the hybrid or combined statistical-engineering models lie along the horizontal axis. Since the aim of our work is to develop a load model that can provide predictions on an aggregate level, the vertical axis reflects whether the reference is used to predict the load on a *building level* or a *national level.* The literature is developed for different building types and loads. As seen in the figure, most of them involves load profiles for households (as squares), with main focus on the electricity load (blue colour).

Several of the references start by investigating trends on a building level, and then aggregate the loads to a higher level (national or regional). This is reflected by the dotted arrows in Fig. 2. Both bottom-up and top-down approaches for load profile forecasting of a building can be used to scale up the load based on information on the buildings stock. The challenge is however to link the electric specific demand which relates to the number of appliances or households (in no.), to the heat demand which is dependent on the size of the building stock (in m^2). (Kipping and Trømborg, 2015) and (Livik et al., 1999) predict load profiles in kWh/household, and aggregate the loads using the number of households, whereas (Pedersen et al., 2008) and (Lindberg, 2017) aggregate by using the size of the building stock (in m^2). Fischer et al. (2016a) use a pre-assumed size of various households when determining the heat load, and aggregates according to the number of households when creating the aggregate heat and electric specific load profiles (Fischer et al., 2015a). The heat load input in (Henning and Palzer, 2014) is aggregated according to the size of the building stock (in m^2), whereas the aggregated electric specific load is equal to the measured present electricity demand in the grid. Hedegaard uses an aggregate heat demand profile for households in (Hedegaard et al., 2012). However, in (Hedegaard and Balyk, 2013) the thermal mass of households and its resulting thermal electric load for HPs seems to be calculated on a per m^2 basis. But whether the aggregation procedure is done according to the number household or the size of the building stock is not described.

Several studies have been made on *household's* energy profiles both in Norway (Ericson 2009; Kipping and Trømborg, 2015; Livik et al.

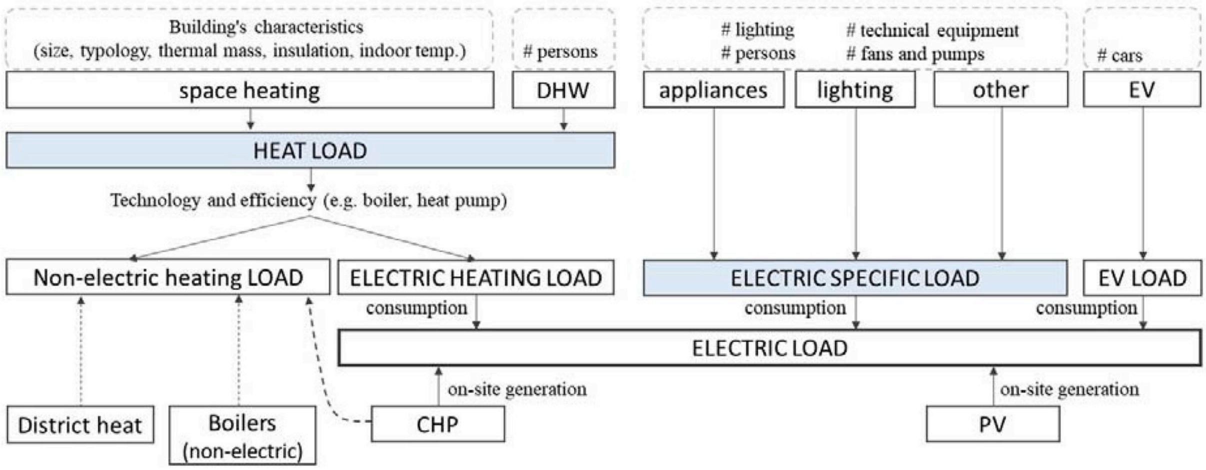


Fig. 1. General structure of the electricity load of buildings, including technologies (EVs, PV, CHP and electric heating) at end-user level that may influence the building's electricity load. Examples of the main influential parameters for each load type are listed in the dotted squares.

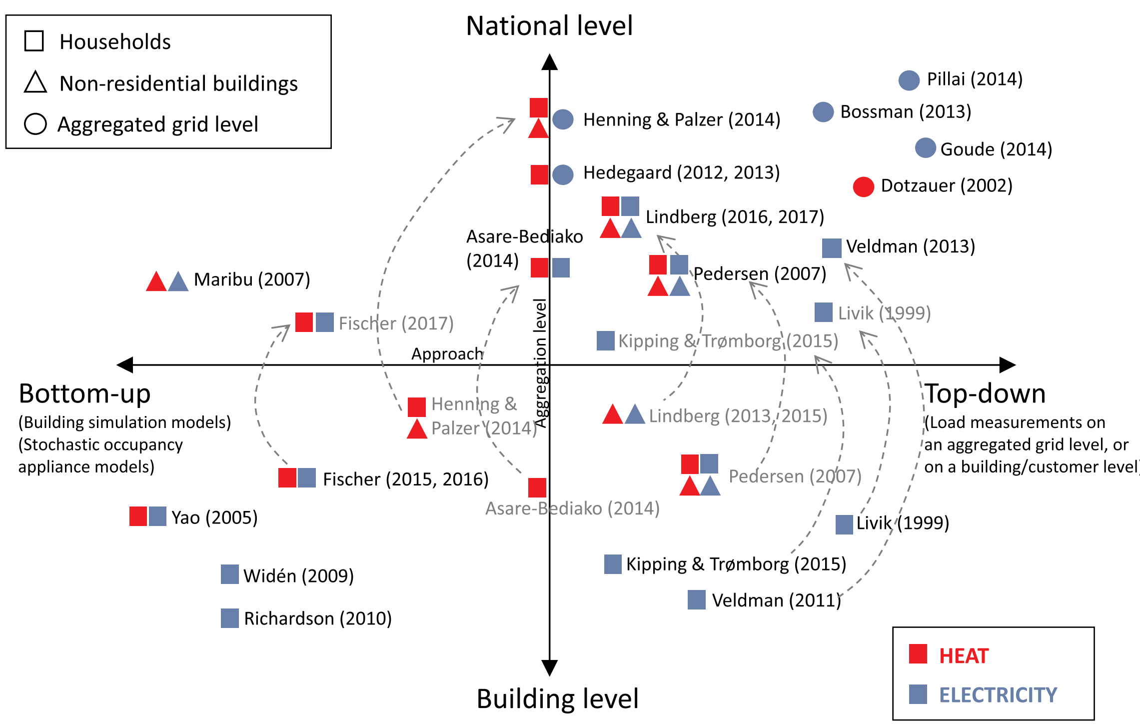


Fig. 2. Graphical representation of the literature review of load modelling methodologies for buildings. Heat load models in red, and electric load models in blue. Load models of households (squares), of service buildings (triangles) and load models based on electricity or heat consumption on an aggregated grid level (circles).

1999, 1993; Morch et al. 2013; Pedersen et al., 2008; Sæle et al., 2010; Stokke et al., 2010), and other countries as in the US (Aigner et al., 1984), Sweden (Widén et al., 2009), the UK (Richardson et al., 2010; Richardson et al., 2008; Yao and Steemers, 2005) and Germany (Fischer et al., 2015b). The four load models in (Fischer et al., 2015b; Richardson et al., 2010; Widén et al., 2009; Yao and Steemers, 2005) all entail single load traces for e.g. lighting or cooking by utilising time-of-use surveys and predict stochastic load profiles for predefined sets of household types, e.g. two-person household, retired couple, or 5-person household. These models are so-called bottom-up models where the load profile of each appliance is linked to the activity of the occupants and summed to the household's electricity consumption on an hourly or sub-hourly scale. However, none of them include heat demand for space heating.

In general, there are two approaches for including electricity for heating in household's electricity load; bottom-up or top-down. In a *bottom-up approach* the building's heat load is either endogenously modelled by a simplified electric equivalent (RC-network) as in e.g. (Asare-Bediako et al., 2014; Fischer et al., 2016a; Aigner et al., 1984; Yao and Steemers, 2005), or it is calculated externally by a detailed building simulation model (e.g. IDA ICE,[2] EnergyPlus[3] or TRNSYS[4]) and used as input in (Hedegaard et al., 2012; Hedegaard and Balyk, 2013; Henning and Palzer, 2014). These references calculate the heat load of the building, based on assumptions on the building's characteristics (cf. Fig. 1), such as typology, thermal mass and/or indoor temperature which might be challenging for a cluster of buildings or even for a region or an entire country. Hence, such bottom-up engineering models

[2] https://www.equa.se/en/ida-ice.
[3] https://energyplus.net/.
[4] http://www.trnsys.com/.

are well suited when investigating load patterns in the design phase of new buildings, or new neighbourhood areas, but less for investigating load patterns of existing building (Fumo, 2014).

The second approach for including electricity for heating is to analyse measurements of electricity consumption including electric heating load, and use a *top-down statistical methodology* to predict the electric load. (Kipping and Trømborg, 2015; Livik et al., 1999; Morch et al., 2013) use a top-down regression model for determining electricity load profiles of Norwegian households based on hourly electricity consumption data. As electricity is vastly used for heating purposes in Norway, the consumption data also includes electricity for heating purposes, although it is not measured separately. They create aggregated load profiles within an area by multiplying with the number of different household types, e.g. 1-person, family or retired couple, but as the methodology do not separate electricity for heating purposes, the models cannot be used for analysing the introduction of new heating technologies, nor the effect of renovation measures of the building stock. Another and a more accurate approach is to analyse electricity consumption for heating purposes only, as done in (Veldman et al., 2011), and afterwards merge it with the electric specific demand to form the electricity load (cf. Fig. 1).

Previous work on modelling load profiles for *non-residential buildings* is less widespread (Maribu et al., 2007). use a building simulation model to create the heat load profiles of service buildings. Likewise (Henning and Palzer, 2014) also use building simulation models for heat load profiles of both residential and service buildings (Pedersen et al., 2008). use a top-down regression model for specific energy consumption, kWh/m,[2] which is applicable for all building types, both residential and non-residential, and is developed for the purpose of aggregating load on district level.

On an aggregate scale (Dotzauer, 2002), analyse the heat consumption of a district heating grid, and compares the simple top-down regression model to more sophisticated time-series models. The authors identify that the forecasts are very similar and concludes that further focus for making better load forecasts should be on "improving the quality of the weather forecasts, rather than on developing advanced load prediction algorithms". Another top-down approach is found in (Moral-Carcedo and Pérez-García, 2017) that forecast the long-term hourly load for Spain while accounting for long-term trends such as economic growth, electricity prices and demographic changes (through number of households). A related study is found in (Wenz et al., 2017) which evaluates the temperature dependency of the aggregate electric load of different countries by a regression approach. Based on projections of future temperature changes, the changes of the electricity demand and peak loads are estimated. However, as both (Moral-Carcedo and Pérez-García, 2017) and (Wenz et al., 2017) rely on historical top-down data, they are not able to account for future changes of the building stock incl. energy efficiency and technology penetration.

Statistical top-down models use historical data to predict the future electric load, and consequently, they are inadequate for analysing solutions that are absent in the existing system, such as PV and heat pumps. Bottom-up building engineering models involve details of the thermal building components and indoor temperature but use the electric specific load as input (often provided from statistical models). These engineering models are well suited for analysing new components but is not as well suited to capture the sensitivity of the peak load on external parameters, such as energy prices, weather conditions or occupancy behaviour, as a top-down statistical model might do.

(Fumo, 2014) states that the most suitable model depends on the scope of the analysis and concludes that physical engineering models are well suited for design of *new buildings*, however statistical models are preferred when evaluating *existing buildings*. According to (Richalet et al., 2001), a methodology for load and energy predictions should be based on measured energy data (i.e. statistical models), because the real behaviour of the building can differ significantly from its design due to various operation of the building's energy system (Pedersen, 2007; Turner and Frankel, 2008; Sandberg et al., 2017).

As the electricity grid is designed to handle the actual load of the buildings, measurements from buildings are essential for determining their real heat and electric load. As the current work seeks to forecast the long-term aggregate load in the electricity grid, we use real load measurements of 100 buildings, to capture their impact on the power grid, and use a statistical top-down approach.

3. Data

Hourly measurements of energy consumption were collected for 214 existing buildings over a three-year period. After cleaning the data, 116 buildings were used for the analysis including 27 office buildings, 24 health buildings (nursing homes and hospitals), 36 educational buildings (schools, kindergartens), 22 business & trade buildings, and 7 hotels. This corresponds to approximately 2 628 000 observations, denoted as a 'long and narrow' dataset. Along with the large number of buildings, this makes it a unique data set. The data was retrieved from a company providing energy management services (EMS), which had separate meters for electricity consumption and district heat consumption.

We assume that the measurements of the district heat consumption represent the building's heat load for both space heating and domestic hot water (DHW), given that there is no local heat generation on-site. Hence, the losses of the internal heat distribution system within the building is included in the heat consumption, making the heat load representative for buildings with waterborne heating. Should the data be used for analysing buildings with direct electric heating (electric panel heaters and/or air-source heat pumps), which are the majority in Norway (Sartori et al., 2009), the data should be adjusted. Data on typical distribution losses of different heating system are available for example in (NS 3031, 2007).

Fig. 3 shows the average annual energy consumption for each of the building categories in the sample separated on heat and electricity consumption. To assess the sample's representativeness, the numbers are compared to the Enova's building statistics for 2011 (Enova, 2012), as the measurements were collected in the period of 2009–2011. Although it contains only data on total annual consumption, Enova's building statistics is based on thousands of buildings. Comparing the two, we see that the average annual energy consumption within each category is reasonable, although the sample's consumption in kindergartens is slightly higher, and for hotels is slightly lower. Compared to estimates made by the Norwegian Water Resources and Energy Directorate (NVE) in 2015 (Langseth, 2016), our sample has lower energy consumption for shops & malls and hospitals.

The dataset of the energy efficient buildings contains three non-residential buildings, one school and two office buildings. All three

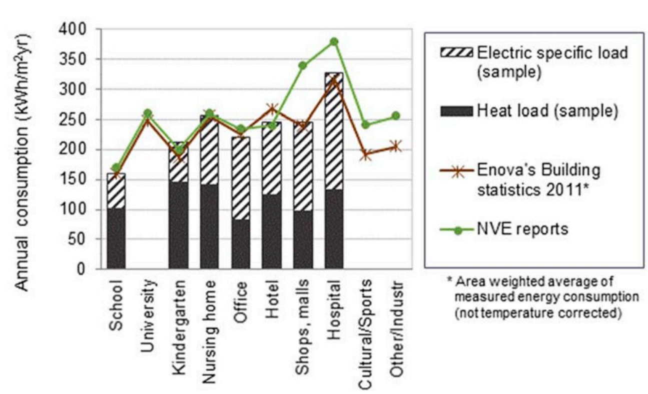


Fig. 3. Average annual energy consumption (kWh/m2yr) of each of the building categories in the sample (bars) compared to the national Enova's Building statistics 2011 (Enova, 2012) and NVE (Langseth, 2016).

buildings have annual energy consumption that corresponds to being a 'passive building' according to the Norwegian technical norm NS 3701:2012 (NS 3701, 2012).

In the following, different variables are investigated that can explain the load pattern of the buildings, among them outdoor temperature. These hourly climatic weather parameters are downloaded from eKlima.no (MET, 2015) for the same time frame of the energy consumption data (2009–2011). As there is a limited amount of weather stations, the nearest situated weather station to the geographical situation of each building was identified.

4. Methodology

This section gives a general presentation of the methodological framework for the heat and electricity regression models developed for 7 non-residential buildings. The methodology builds on previous work on load models for schools and office buildings developed in (Lindberg and Doorman, 2013; Lindberg et al., 2015). In this previous work, the influence of other climatic variables than outdoor temperature was tested, namely solar radiation and wind. The conclusion was that, on the available dataset, adding these explanatory variables did not improve the fit of the regression models or only marginally improved it, thus not justifying the additional complexity and the consequent limitations in the applicability of the models. Indeed, wind speed and (mostly) solar radiation are not so easily retrievable from meteorological databases. Furthermore, this outcome is reasonable because the data set is composed of several buildings, representing a varied sample of building physics properties and geographical distribution. For a single building, wind might be a significant explanatory variable for its heat load in the case the building has poor air-tightness and is wind exposed (e.g. isolated rather than in tight urban context). Similarly, for a building with large windows area and good solar exposition (again, isolated rather than in tight urban context) solar radiation might be a significant explanatory variable. However, when taking the average effect over several buildings these effects did not show statistical significance. This paper improves the methodology of previous work by correcting for autocorrelation in the error terms.

4.1. Fixed effects regression model for panel data

Panel data is a multidimensional dataset which contains data observed over T time periods and N individuals. Let $\mathscr{B} = \{1,...,N\}$, indexed by i, consist of all individuals (or buildings) and $\mathscr{T} = \{1,..., T\}$, indexed by t, of all time instances.

A general model formulation for a panel data regression model is shown in Eq. (1). The dependent variable y_{it} (e.g. electricity or heat consumption of each building) depends on a constant term α, independent of both individual and time, a fixed effect α_i for each individual, a $1 \times K$ vector of observable explanatory variables $\boldsymbol{x}_{it}$ (with corresponding $K \times 1$ vector of coefficients $\boldsymbol{\beta}$) and an error term ε_{it}.

$$y_{it} = \alpha + \alpha_i + \beta \boldsymbol{x}_{it} + \varepsilon_{it}, \quad i \in \mathscr{B},\ t \in \mathscr{T} \tag{1}$$

Here, $\boldsymbol{x}_{it}$ may vary by individuals, by time and by both time and individuals. Moreover, α_i is usually referred to as the fixed or unobserved effect in panel data analysis. Finally, we have to make the exogeneity assumption that $E[\varepsilon_{it}|\boldsymbol{x}_{it}, \alpha_i] = 0$ for all. t.

The regression model thus investigates the relationship between energy consumption and climatic variables, taking into account that each building has individual characteristics that may influence the buildings' energy demand (such as age, no of storeys and U-values). However, we note that the individual effect variables might be hard to collect, or even are unobservable. By investigating measurements of electricity (or heat) consumption, y_{it}, and the explanatory variables $\boldsymbol{x}_{it}$, the model parameters can be estimated using a fixed effect (FE) framework (Wooldridge, 2010). This estimation method transforms Equation (1) to eliminate the unobservable effect α_i and allows for estimation of the parameter vector $\boldsymbol{\beta}$ corresponding to the time-varying variables $\boldsymbol{x}_{it}$. In addition, it allows the fixed effects to be correlated with the explanatory variables. As an example, outdoor temperature varies from hour to hour, but also depends on the location of the building. Therefore, temperature is dependent on both time, t, and individual i. However, we would like the temperature effect to be independent of individuals, as we are interested in the temperature effect of the whole building stock. Therefore, we assume that the individual effect is captured by α_i, and the temperature effect is reflected in the β-parameters, which are the same for all individuals. Because β-parameters are similar for all the buildings, by this model formulation we obtain a general (or average) shape of the load profile for all the measured buildings. Nevertheless, the level of the load profile, or the intercept, will be different for each individual building reflected in the building specific α_i term. So, when predicting load profiles for each building category, the average of all α_i-s within the same category, denoted as α^* is used (cf. Section 4.5).

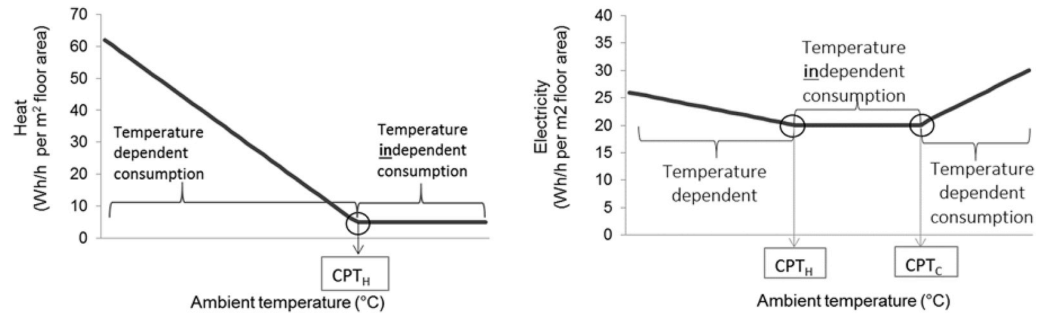
4.2. Autocorrelation

Previous work on prediction of electricity consumption has indicated that auto correlation (serial correlation) might be present in the residuals of the fixed effects regression, e.g. (Ericson, 2009). In panel data models, unlike normal regression or time-series models, testing the errors for autocorrelation is challenging. The key-point is that we cannot estimate the residuals due to the time demeaning transformation in the fixed-effect estimation procedure. We therefore test our estimated models for first-order autocorrelation, making use of the autocorrelation test suitable for fixed effect panel data models as given in (Wooldridge, 2010). Under several assumptions, the resulting test-statistic for testing the null hypothesis of no autocorrelation can be shown to be asymptotically normally distributed. When signs of autocorrelation are present, we instead estimate the model using a Cochrane-Orcutt transformation procedure, specifying a first-order autoregressive structure for the residuals. That is, in the model formulation we prescribe that $\varepsilon_{it} = \rho\varepsilon_{i(t-1)} + e_{it}$, where ρ is the correlation coefficient and $\{e_{it}\}$ is now an independent and identically distributed sequence of random variables with zero mean.

4.3. Energy signature curve

The energy signature is a graphic tool used by building operators to map its energy performance. By plotting the measured energy consumption data against outdoor temperature as in Fig. 4, temperature dependent and temperature independent areas are defined. These areas are separated by changing point temperatures, CPTs. Fig. 4a shows that the heat consumption increases as temperature decreases, creating one changing point temperature denoted as CPT_H. Fig. 7b shows the electric specific demand as a function of outdoor temperature. The experimental data indicates that the electricity consumption increase both at low temperatures (due to electric heating) and at high temperatures (due to electric cooling machines), as shown in Fig. 4b. It therefore has two changing point temperatures; CPT_H and CPT_C, for heating and cooling respectively. Although a heating effect in the electric specific demand is in itself contradictory, we include it in the general model formulation to be able to check for this effect when estimating the model. The CPTs of both heat load and electric specific load are identified for each hour and each building category such that the model gives the best fit.

Based on the energy signature curves of the observations in the sample, the load models are defined for different temperature regimes, denoted by $\mathscr{R}$, where $\mathscr{R} = \{heat, indep, cool\}$ in the case of electric demand and $\mathscr{R} = \{heat, indep\}$ in the case of heat demand. Each regime corresponds to a certain temperature range, given by $[L_r, U_r]$. For example, in the case of electrical load, for the cooling range (i.e. $r = cool$),



a) Heat demand b) Electric specific demand

Fig. 4. Concept of the energy signature of a building, showing the heat load (left) and the electricity load (right), and their respective changing point temperatures (CPT).

we have that $L_r = \mathrm{CPT}_C$ and $U_r = \infty$. Now, if the temperature at a particular time instance t for a specific building i, denoted by x_{it}^{TEMP}, is within a certain range, that is $L_r \le x_{it}^{TEMP} < U_r$ for some $r \in \mathscr{R}$. Then, the electrical or heat demand can be described as follows:

$$y_{it} = \alpha_i + \alpha_r + \beta_r x_{it}^{TEMP} + \varepsilon_{it}, \quad i \in \mathscr{B}, \; t \in \mathscr{T} \tag{2}$$

Note that for $r = indep$, we enforce that $\beta_r = 0$, such that α_r represents the temperature independent consumption of electricity. Additionally, as can be seen from Fig. 4, we expect that $\beta_{heating} < 0$ and $\beta_{cooling} > 0$.

4.4. Basic model structure

By use of a dummy variable approach, Equation (2) is applied for each hour of the day and for each type of day (weekday, weekend and holiday) separately. This enables the model to capture the hourly consumption pattern throughout the year. Furthermore, we extend the model by allowing for different day types, monthly and daylight effects.

Let $\mathscr{D} = \{weekday, weekend, Saturday, Sunday, holiday\}$ denote the set consisting of different types of days and $\mathscr{H} = \{1,2,\ldots,24\}$ consists of the hours under consideration. Moreover, let $\mathscr{M} = \{January,\ldots,December\}$ consist of all months. Now, we define the dummy variable D_{dhrit} for all $d \in \mathscr{D}, \; h \in \mathscr{H}, \; r \in \mathscr{R}, \; i \in \mathscr{B}$ and $t \in \mathscr{T}$. It equals one if time instance t represents hour h, is of day type d and x_{it}^{TEMP} belongs to temperature regime r, and zero otherwise. In addition, we define dummy variables D_{dt}^{DAY}, D_{mt}^{MON}, and D_t^L, which equal one if the time instance t is of day type d, falls within month m, or occurs during daylight.

Equation (3) presents the model in its most general form. Besides the direct temperature effect through x_{it}^{TEMP}, we also include a 24-h moving average temperature (TMA) effect, which is captured in x_{it}^{TMA}. For ease of interpretation, we choose not to make use of superscripts to distinguish between the electrical and heat load model.

For the model to be used for load prediction purposes, first, the parameters of Equation (3) have to be estimated for each configuration of interest. That is, any combination of building type, electricity specific or heat load, and energy class. In addition, as α_i is different for each individual building in the sample, the average of all α_i-s within the same category, denoted as α^* is used. We assume that the expectation of the error term, given the variables equals zero, i.e. $E[\varepsilon_{it}|\boldsymbol{x}_{it}, \alpha_i] = 0$. Hence, to get a prediction of the electricity or heat consumption for some average building i and future time period t, denoted by $\hat{y}_{it}$, we only need to have forecasts for future outdoor temperatures, which depend on the location of the building. Moreover, the values of the day, month and daylight dummy variables are easily constructed. We would like to note that since the load predictions are made in Wh/h per m^2 of each building type, that with assumptions on the future building stock in a certain area, regional load profiles can be constructed for electric specific load and heat load (See more on future work in Section 6.).

5. Results

Section 5.1 and 5.2 discuss all the estimated heat load profiles and electric specific load profiles. For *regular* buildings this is done for all 7 non-residential building categories and for *energy efficient* buildings this is done for schools and offices. To get the best model fits, different configurations of variables where tested for each model. To select the best models, we used amongst others the R-squared value as a goodness of fit measure. (Please consult (Lindberg and Doorman, 2013; Lindberg et al., 2015) that present this procedure in more detail.) In this work we focus more on the results after model selection has taken place. The estimated model parameters are shown as graphics in Appendix C, and in tables[5] which also include significance results for all 16 models. The majority of these model estimates are significant at 1% significance level.

$$\begin{aligned} y_{it} = \; & \alpha_i + \textstyle\sum_{d\in\mathscr{D}} \sum_{h\in\mathscr{H}} \sum_{r\in\mathscr{R}} [D_{dhrit}(\alpha_{dhr} + \beta_{dhr}^{TEMP} x_{it}^{TEMP} + \beta_{dhr}^{TMA} x_{it}^{TMA})] \\ & + \textstyle\sum_{d\in\mathscr{D}} D_{dt}^{DAY} \beta_d^{DAY} + \sum_{m\in\mathscr{M}} D_{mt}^{MON} \beta_m^{MON} + D_t^L \beta^L + \varepsilon_{it}, \quad i \in \mathscr{B}, \; t \in \mathscr{T} \end{aligned} \tag{3}$$

Equation (3) prescribes a relation between the load (either electrical or heat), and the following terms: a building specific fixed effect (α_i), a temperature independent (α_{dhr}) and temperature dependent ($\beta_{\mathrm{dhr}}^{\mathrm{TEMP}}$ and $\beta_{\mathrm{dhr}}^{\mathrm{TMA}}$) effect that both are dependent on the regime, day type, month and daylight. The models for heat and electrical load will differ in which explanatory variables are accounted for and for what subsets we apply the resulting equation (e.g. only a certain set of hours $\mathscr{H} \subseteq \{H\}$). Note that, when estimating this model, we have to remove one element from each set in the summations, to account for the dummy trap (multicollinearity). Load prediction.

5.1. Heat load models

This section presents the heat load profiles of 7 non-residential building categories.

5.1.1. Regular buildings

The first step of developing the heat regression models, is to apply

[5] The tables can be accessed in the online resource connected to this paper.

Table 1
Determined heat load model formulation per building category.

Building type		Heat Load Model		P-value auto-correlation test	Number of buildings in the sample
		Significant explanatory variables	Hours where temperature dependency is active		
1	Schools	x^{TEMP}, x^{TMA}	1 to 24/WD,WE,HD	0.0000	27
2	Offices	x^{TEMP}, x^{TMA}	1 to 24/WD,WE,HD	0.0000	27
3	Shops and malls	x^{TEMP}, x^{TMA}	1 to 24/WD,ST,SN	0.0000	18
4	Kindergartens	x^{TEMP}, x^{TMA}	1 to 24/WD,WE,HD	0.0004	9
5	Hotels	x^{TEMP}, x^{TMA}	1 to 24/WD,HD	0.0198	7
6	Nursing Homes	x^{TEMP}, x^{TMA}	1 to 24/WD,WE	0.0000	20
7	Hospitals	x^{TEMP}, x^{TMA}	1 to 24/WD,WE,HD	0.0804	6

Table 2
Determined heat load model formulation for energy efficient school and office buildings.

Building type		Heat Load Model		P-value auto-correlation test	Number of buildings in the sample
		Significant explanatory variables	Hours where temperature dependency is active		
1	Energy efficient Schools	x^{TEMP}, x^{TMA}	1 to 24/WD, WE and HD	–	1
2	Energy efficient Offices	x^{TEMP}, x^{TMA}	1 to 24/WD, WE and HD	0.1005	2

the basic model formulation from Equation (3) to the data set for each of the eight building categories. The second step is to tailor and customize the basic model so that it fits best to the measured values in the data set. The results of the best model formulation for the different building categories are shown in Table 1. We see that the best suitable model formulation for all categories includes the direct outdoor temperature, x^{TEMP}, and the 24 h moving average outdoor temperature x^{TMA}. Whether the α-s and β-s are estimated for working days (WD), weekends (WE), holidays (HD), Saturdays (ST) and/or Sundays (SN) depend on the building category. I.e. schools have different heating load pattern for working days and weekends, whereas stores and shopping malls have a distinct load profile for Saturdays and thus, this building category needs separate estimates for Saturdays and Sundays. The fourth column of Table 1 shows the p-values of the autocorrelation test of (Wooldridge, 2010). In this test, the null hypothesis is that the error term does not exhibit autocorrelation of order 1. When the p-value is lower than the assumed significance level, we have to reject the null hypothesis. For all our models, when using a significance level of 0.1 (10%), we therefore have to reject the null hypothesis of no autocorrelation. So, all the heat load models must be estimated using an error term that follows an AR(1) process (autoregressive process of order 1), as described in Section 4.2. This is achieved by applying the Cochrane-Orcutt estimation procedure. We observe that the parameter estimates, and the corresponding standard errors change significantly when controlling for autocorrelation, in particular when there is strong evidence of autocorrelation (i.e. a small p-value). Please find the values of the estimated α-s and β-s as graphics in Appendix C.1.

5.1.2. Energy efficient buildings

The sample contains three energy efficient buildings; two office buildings and one school building.

Table 2 shows the results of the heat load model for the energy efficient buildings. The best suited model formulation was found to be equal to the model formulation for the regular buildings, with the outdoor temperature and the 24-h moving average of the outdoor temperature as the most significant explanatory variables. Although the model formulation is equal, the values of the estimated parameters are different. Note that for energy efficient schools we only have one building in the sample, and therefore perform a basic time-series regression. For the energy efficient offices we only have two buildings in the sample. Still, the p-value of the auto-correlation test indicates that we might want to estimate the model using AR(1) error terms. The estimates of the coefficients for both models can be found in Appendix C.1.

The aim is to make a load forecast of the entire buildings stock, including all building categories. Hence, we would like to evaluate a general effect of buildings becoming more energy efficient.

Table 3 compares the estimated parameters of the regular buildings to the parameters of the energy efficient buildings, for the school and the office buildings separately. The comparison is done for each parameter, i.e. for all hours and day types. Although the evaluation is done per hour, the table shows the average reduction of all 24 h for each parameter type, i.e. the first value in the table shows the average reduction for $\alpha_{WD,h,heat}$ taken over all hours $h \in \mathscr{H}$. Table 3 shows that, on average, all values are reduced, both the temperature independent terms (α) and temperature dependent terms (β). The reduced alphas lead to a downward shift in the load profile, as the intersection with the y-axis in Fig. 4a is reduced. The reduced betas reflect a reduced temperature dependency of the heat load and leads to a slope of the curve in Fig. 4a that is less steep. This fits well with theory that well insulated energy efficient buildings have less heat demand and react slower to changes in the outdoor temperature.

Table 3
Comparison of estimated parameters of the heat load model for normal vs. energy efficient buildings for schools and offices (%).

Building category		*Parameter reduction (%). Average of hour no.1–24.*			
		$\alpha_{d,h,heat}$ d: WD/ WE/HD	$\alpha_{d,h,indep}$ d: WD/WE/HD	$\beta^{TEMP}_{d,h,heat}$ d: WD/WE/HD	$\beta^{TMA}_{d,h,heat}$ d: WD/WE/HD
1	Normal to energy efficient School	69/79/na	82/80/na	15/51/na	59/63/na
2	Normal to energy efficient Office	57/55/59	48/50/50	36/33/41	59/59/64

Table 4
Determined electricity load model formulation for each building category.

Building type		Electricity Load Profile		P-value auto-correlation test	Number of buildings in the sample
		Significant explanatory variables	Hours where temperature dependency is active		
1	Schools	x^{TEMP}(Heating effect)	1 to 24/WD, WE, HD	0.0000	26
2	Offices	x^{TEMP} (Cooling effect), D_{dt}^{DAY}	7 to 18/WD, HD	0.0000	27
3	Shops and malls	x^{TEMP} (Cooling effect)	10 to 18/WD, ST, SN	0.0000	22
4	Kindergartens	D_{mt}^{MON}	–	0.0000	10
5	Hotels	x^{TEMP} (Cooling effect)	10 to 20/WD	0.0000	7
6	Nursing Homes	D_{mt}^{MON}	–	0.0000	18
7	Hospitals	x^{TEMP} (Cooling effect)	10 to 18/WD	0.0165	6

Table 5
Determined electric specific load model formulation for energy efficient school and office buildings.

Building type	Electricity Load Model		P-value auto-correlation test	Number of buildings in the sample
	Significant explanatory variables	Hours where temperature dependency is active		
Energy efficient School	–	–	–	1
Energy efficient Offices	x^{TEMP} (Cooling effect), D_{dt}^{DAY}	9 to 18/WD	0.2180	2

5.2. Electric specific load models

This section presents the electric specific load profiles of all 7 non-residential building categories.

5.2.1. Regular buildings

To find the best suitable load models for electric specific demand, the basic model formulation from Equation (3) is applied to each of the seven building categories. Table 4 shows the results of the tailored model formulation for the different building categories. We see that a cooling effect is observed in both offices, shops&malls, hotels and hospitals. The cooling effect is present on weekdays and holidays in offices from hour no.7 to 18, on all days in shops&malls between hour no.10–18, and on working days in hotels and hospitals. A heating effect was observed in the electric load profiles of regular schools, which we believe is caused by electric batteries of the ventilation system, although the schools are heated by waterborne heating.

As was the case with the heat load models, the p-values from Table 4 show that all the models should be estimated using error terms with an AR(1) specification. The values of the estimated α-s and β-s are shown as graphics in Appendix C.2.

5.2.2. Energy efficient buildings

Table 5 shows the result of the electric specific load models for the energy efficient buildings. A cooling effect was observed in the office buildings on working days, no cooling effect was observed for the schools. This is reasonable as schools are closed in summer time due to holidays. Further, the heating effect observed for the regular schools was not present in the energy efficient school building. We note again that the number of buildings are very small for both building types. For energy efficient offices, the p-value of the auto-correlation test indicates that we cannot reject the null hypothesis of no autocorrelation of order 1. Hence, in this case, we can use the panel data regression model that does not take into account first order auto-correlation.

Table 6 compares the estimated parameters for the electricity load model for the normal buildings to the parameters of the energy efficient buildings. The table shows the average daily reduction over 24 h for weekdays, weekends and holidays, respectively. As opposed to the heat load model, there are two additional rows that splits the comparison in operating and non-operating hours. For schools on weekdays, the parameter reduction during operating hours is zero, whereas the reduction is 34% during non-operating hours. This indicates that the electric demand for lighting, fans&pumps and appliances during operating hours is little reduced for energy efficient school buildings. However, during non-operating hours the regular school buildings has 30% higher electricity demand than the energy efficient school. This indicates that the heating, ventilation and air-conditioning (HVAC) control system of the regular school buildings might have less functioning control algorithms. During weekends the reduction is more distinct at 30%, and during holidays the demand is increased during operating hours but reduced during non-operating hours. Again, this might reflect the operational mode of the HVAC system, so that public

Table 6
Observed change of model parameters for electricity load for schools and offices (daily average %).

Building category		Parameter reduction (working days/weekends/holidays)		
		$\alpha_{d,h,indep}$ d: *WD*/ *WE*/HD	$\alpha_{d,h,cool}$ d: *WD*/ *WE*/HD	$\beta_{d,h,cool}^{TEMP}$ d: *WD*/ *WE*/HD
1	Normal to energy efficient School	20/30/17 Hour# 7–17: 0/29/−3 Hour# 18–6: 34/32/32	*not applicable* (i.e. no cooling effect observed)	
2	Normal to energy efficient Office (**including** IT-server)	9/3/7 Hour# 7–19: 15/5/12 Hour# 20–6: 2/0/1	24/na/na Hour# 11–14: 18/na/na Hour# 15–18: 30/na/na	−33/na/na Hour# 11–14: 36/na/na Hour# 15–18: 29/na/na
2*	Normal to energy efficient Office (**excluding** IT-server)	26/26/26 Hour# 7–19: 27/28/27 Hour# 20–6: 25/24/25	37/na/na Hour# 11–14: 30/na/na Hour# 15–18: 44/na/na	−41/na/na Hour# 11–14: 46/na/na Hour# 15–18: 36/na/na

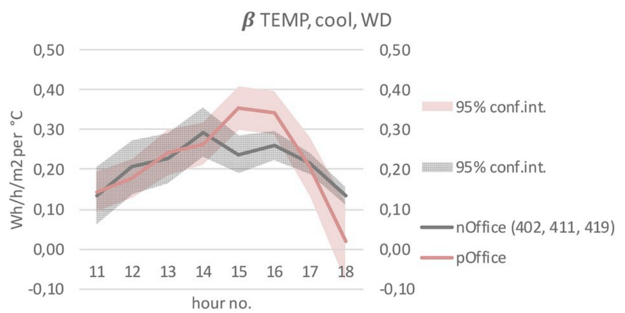


Fig. 5. Results of temperature dependency on weekdays. Comparing results of two energy efficient office buildings to three regular office buildings with cooling.

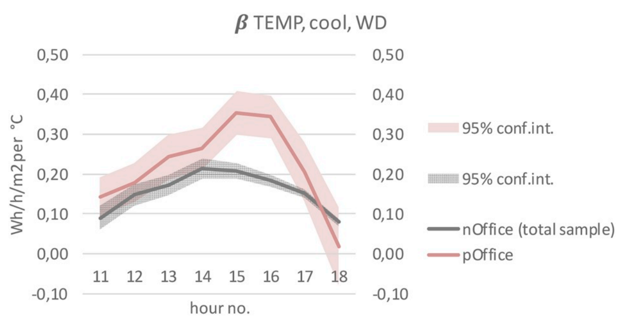


Fig. 6. Results of temperature dependency on weekdays. Comparing results of two energy efficient office buildings to the total sample of 27 regular office buildings.

holidays are defined as weekends in the regular school building, whereas holidays for energy efficient school have an in-between-mode of the HVAC system. Nevertheless, it is the load profiles for weekdays that are of our main interest as it includes the peak load of the building, which is decisive for the capacity of the transmission grid.

For offices, two comparisons have been made. The energy efficient office buildings have separate meters for IT-servers situated within the buildings, showing a flat load profile. As it is likely that the use of IT-servers will increase in future, either within or outside office buildings, we compare the profiles including the electricity consumption of the IT-servers Since the load profile of the IT-servers is flat throughout the day, we observe that it is the level of the load profile that is different in the two cases, and not it's shape, which reflect the effect seen from the grid's perspective (in row number 2). However, we also compare the two without the IT-servers, as this gives a picture of the improvement of the building as such (in row number 2*).

The comparison *excluding* the IT-servers, shows that the reduction is evenly distributed throughout all hours of the day, at 26% for weekdays, weekends and holidays. This indicates a higher efficiency of the HVAC system of energy efficient office buildings. Especially, one of the energy efficient office buildings has alternative ducts for ventilation air that reduces the fan power significantly. This also explains the high reduction during non-operating hours. The cooling effect $\beta_{d,\,h,cool}^{TEMP}$, reflects the electricity demand in Wh/hr/m^2 per °C increased outdoor temperature (β is the slope of the graph of Fig. 4b). The results show that when the temperature increases, the electricity demand of an energy efficient office building increases 41% more than the demand of a regular office building, indicating increased cooling demand.[6]

The comparison *including* the IT-servers show that the average daily consumption is 9% lower during weekdays. However, during non-operating hours the consumption is almost unchanged (at 2% reduction)

[6] This is opposite to what we found in previous work when not correcting for autocorrelation of the error terms, cf. (Lindberg et al., 2015).

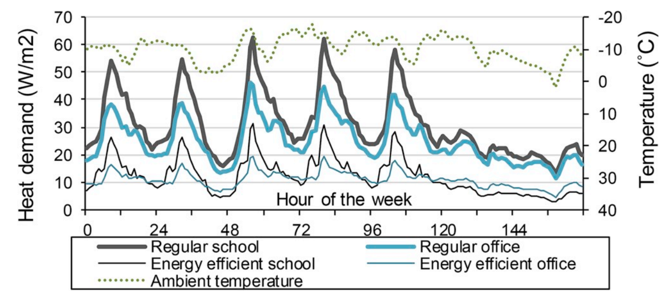


Fig. 7. Predicted heat load profile for a cold week in winter of regular and energy efficient school buildings (black) and office buildings (blue).

as the IT-servers shift the load profile upwards and counteracts the positive effect of the more efficient HVAC system. Table 6 shows that it is mainly during working hours, from hour number 7 to 19, that the electricity load is reduced, at 15% on working days and 12% on holidays.

5.2.3. Cooling demand

To investigate the cooling demand further we did a new regression of three regular office buildings that had cooling detected in their electricity load profiles. The estimated values of $\beta_{d,\,h,cool}^{TEMP}$ for these three buildings (grey) are shown in Fig. 5 and compared to the result of the two energy efficient office buildings (red). We see that the temperature dependency for energy efficient office buildings is higher only in hour number 15 and 16, and otherwise similar to the three regular office buildings. Fig. 6 shows the estimated beta-values when using the total sample of 27 regular office buildings which includes buildings both with and without AC-systems. Here, we see that the regular cooling demand is significantly higher for the passive office buildings in most of the hours. The result is therefore highly dependent on the sample selected and should be used with care.

We conclude that energy efficient office buildings have similar cooling demand as normal existing office buildings with AC-equipment installed. However, the cooling demand of the future stock of office building is assumed to increase as it is likely that old buildings without AC will be demolished and new and/or renovated buildings will install AC. As the intention of this paper is to develop an aggregation methodology for the future buildings stock which uses today's building stock as starting point, we use the findings from Fig. 6 in the load aggregation for future work.

5.3. Load prediction

Once the regression models for heat and electricity loads are established, they can be used to predict generalised average heat and electric demand profiles by using the outdoor temperature of the geographical situation of the buildings. These generalised average load profiles do not show the peak load demands for each individual building analysed, because the latter profiles include the coincidence factor due to the average expected value (Pedersen et al., 2008). Hence, the load profiles reflect the average expected load per building category, and the average building loads may thus be summed without considering the coincidence factor. Fig. 7 show examples of heat load prediction for a week in winter with temperatures reaching down to −16 °C. The peak heat load of the energy efficient school building is approximately 50% lower when compared to peak heat load of the regular school building. The difference for the energy efficient office buildings lies between 57 and 59% at the peak heat load.

Prediction of the electric specific load profile of energy efficient offices is done including IT-server as it is assumed that IT-equipment in future office-buildings will increase. And if not present within the office-building, it is assumed that the server will be placed somewhere nearby (regionally or nationally), and hence it will affect the regional

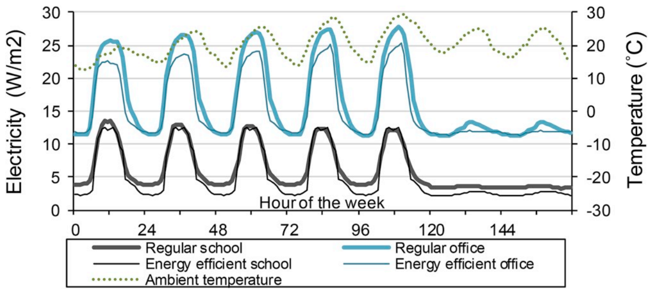


Fig. 8. Predicted electric specific load profile for a warm week in summer of regular and energy efficient school buildings (black), and office buildings (blue).

aggregate electric load regardless of if situated within or outside the building. Examples of prediction of the electric specific load are shown in Fig. 8. The characteristic bell shape of the load profile is similar, however the electric specific peak load for offices is about 10% lower, despite the higher temperature dependency of the efficient office buildings due to cooling demand (cf. Fig. 6).

The total energy demand (sum electric specific and heat) of energy efficient offices and schools is respectively 27% and 55% lower when compared to the regular buildings. The reduction of the electric specific demand is however less obvious, at 6% for offices. A heating effect was detected when analysing the electric specific load profiles of the regular school buildings in Norway, which causes a 29% reduction of the annual electric specific consumption. When removing this heating effect (as it is actually caused by heating needs in the ventilation system), the reduction is approximately 10%, but the peak load is little affected. By this, we may conclude that electricity demand is less affected, compared to heat demand, when buildings become more energy efficient.

6. Conclusions, discussions and further work

This paper is part of an on-going work to generate aggregate load profiles that can be used as input to long-term (10–30 years ahead) power market analyses, while accounting for future changes at the end-user. The contribution of this paper is the evaluation of how the hourly heat and electric specific load profiles are changed as buildings become more energy efficient. Through the separate load prediction of the heat and electric specific demand, it is possible to evaluate the impact of different heating technologies on the aggregate hourly electric load profile. Further, through the temperature dependency of the load profile, it is also possible to evaluate the impact of future global warming on the electricity demand and peak loads. Hence, the load profiles provided in this paper may be used as 'reference load profiles' before applying heat technologies and smart controls.

The paper presents panel data regression models for hourly heat and electric specific load profiles of non-residential buildings. The load profiles are dependent on outdoor temperature, time of day, and type of day. The methodology developed enables to predict hourly load profiles in different regions (due to temperature differences), dependent on type of building, and its energy class. The data set consists of hourly measurements of 114 buildings containing 7 types of non-residential buildings. The proposed methodology provides average profiles for several non-residential building types, treats heat load and electric specific load separately and uses only outdoor temperature as input data. Hence, the load forecasting framework is easy to apply and aggregate. The developed load profiles have the unit Wh/m.[2] Future work will include aggregation of the loads on a regional and national scale by using forecasts of the composition of the future building stock. Further work will also include analysis of load profiles for electric vehicles, and large industrial plants. Although the methodology is developed for Norwegian conditions, with increased use of electricity for heating purposes, e.g. through heat pumps, the proposed methodology will apply for all other countries as well.

From a statistical point of view, the panel data regression models presented in this paper depend only on exogenous explanatory variables and have no autoregressive (AR) or moving average (MA) terms. Moreover, we show that significant serial-correlation is present, and we correct for this by estimating the model using a Cochrane-Orcutt transformation procedure, specifying a first-order autoregressive structure for the residuals. The estimated parameters show good results in terms of significance levels. Examples of predicted load profiles show that renovation measures may reduce the heat peak load by 58% and 50% for office and schools respectively, while the electric specific peak load is less affected, at 10% and 0% respectively. The current paper improves past work by correcting for first term auto-correlation of the error terms of the regression models for each building category.

The consumption data used as basis for this work is collected from buildings connected to a district heating network. This is necessary in order to separate the electric specific demand from the heat demand. However, it implies that buildings have a waterborne heating system, making the sample less representative for Norway, as most buildings have direct electric heating. Using electric radiators, the internal heat distribution losses within the building are avoided, thus lowering the heat load by 2–15% (see Section 3). Thus, the heat load should be duly scaled if applied to building stocks with large share of electric heating, such as in Norway (Sartori et al., 2009) .

The regression models developed for the energy efficient buildings rely on a very small sample. Future work will emphasise to expand the sample with more energy efficient buildings to improve the representativeness and robustness of the energy efficient load profiles. We also suggest to investigate different time ranges of the moving average outdoor temperature. In this paper we have used 24 h moving average, however a shorter or longer time range might improve the model results.

Demand response and demand side management are seen as flexible resources within buildings that may alleviate the peak power load (Strbac, 2008) (Logenthiran et al., 2012). According to (Fischer et al., 2016b), the flexibility potential of electric specific demand might be limited, while (Gils, 2014) identifies substantial theoretical demand response potential in all consumer sectors in Europe. It should be noted that the flexibility offered by heat demand of buildings is based on the utilization of thermal storages that are already in place, e.g. building's thermal mass (Le Dréau and Heiselberg, 2016; Foteinaki et al., 2018), or the DHW tank or a swimming pool (Ottesen and Tomasgard, 2015); hence its potential is large and investment free. By evaluating the measured[7] heat load profiles and electric specific load profiles of buildings separately, the current work forms the basis for evaluating their actual electric flexibility potential, and how to utilise it. Hence, future work will focus on how to incorporate flexibility in the methodology of forecasting the long-term aggregate electricity load.

Acknowledgements

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[7] which is different from the simulated or calculated load.

Appendix A: Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jup.2019.03.004.

Appendix B: Glossary of Notation and Abbreviations

1.1 Sets

$\mathscr{B} = \{1, \ldots, N\}$	Buildings (individuals)
$\mathscr{T} = \{1, \ldots, T\}$	Time Instances
$\mathscr{R} = \{heat, indep, cool\}$	Temperature regimes. Includes heating region, temperature independent region and cooling region
$[L_r, U_r]$	Temperature range for temperature regime r, defined by its lower bound L_r and upper bound U_r
$\mathscr{D} = \{weekday, weekend, Saturday, Sunday, holiday\}$	Day types
$\mathscr{H} = \{1, 2, \ldots, 24\}$	Hour of the day
$\mathscr{M} = \{January, \ldots, December\}$	Months

1.2 Variables

y_{it}	Dependent variable (electricity or heat consumption of each building)
$\boldsymbol{x_{it}}$	Vector of explanatory variables
$\boldsymbol{x_{it}^{TEMP}}$	Temperature at time instance t for building i
$\boldsymbol{x_{it}^{TMA}}$	24-h moving average temperature (TMA)
$\boldsymbol{D_{dhrit}}$	Dummy variable equaling one if time instance $t \in \mathscr{T}$ represents hour $h \in \mathscr{H}$, is of day type $d \in \mathscr{D}$ and x_{it}^{TEMP} belongs to temperature regime $r \in \mathscr{R}$.
$\boldsymbol{D_{dt}^{DAY}}$	Dummy variable equaling one if time instance t is of day type d
$\boldsymbol{D_{mt}^{MON}}$	Dummy variable equaling one if time instance t is within month m
$\boldsymbol{D_t^L}$	Dummy variable equaling one if time instance t occurs within daylight
ε_{it}	Error term
$\boldsymbol{e_{it}}$	Independent and identically distributed random variable with zero mean

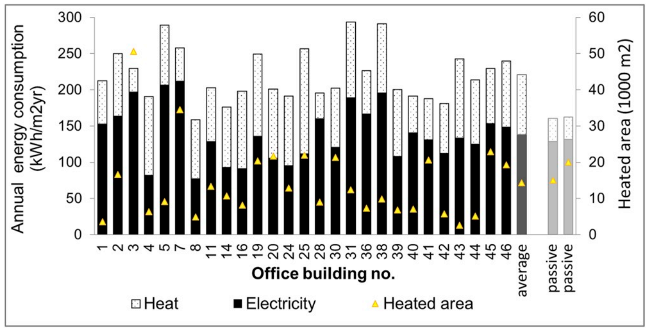
1.3 Parameters

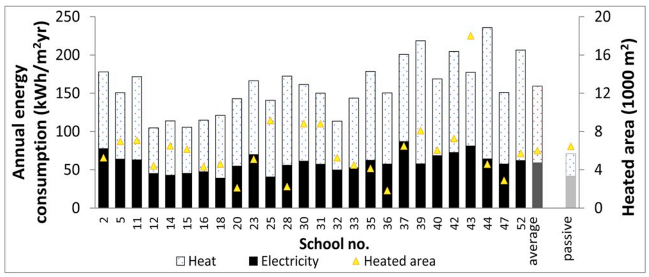
α	Constant term
α_i	Fixed effect
α^*	Average of all fixed effect coefficients α_i
α_{dhr}	Constant term for day type d, hour h and temperature regime r
β	Vector of coefficients
$\beta_{dhr}^{TEMP}, \beta_{dhr}^{TMA}, \beta_d^{DAY}, \beta_m^{MON}, \beta^L$	Coefficients corresponding to the variables defined in A.2
ρ	Correlation coefficient

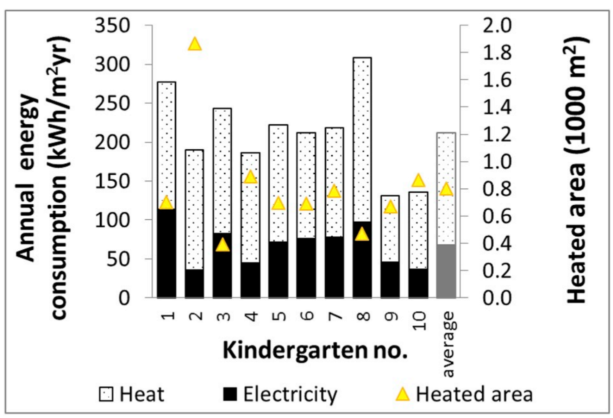
1.4 Abbreviations

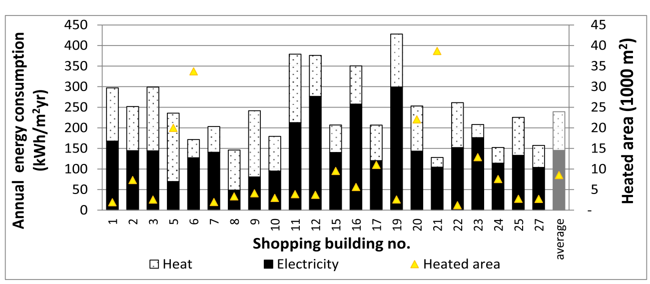
AC	Air-conditioning
AR	Auto regressive
ARMA	Auto regressive moving average
BIPV	Building integrated photo voltaics
CHP	Combined heat and power
CPT	Changing Point Temperature
DHW	Domestic hot water
EnergyPlus	(building simulation tool)
EV	Electric Vehicle
FE	Fixed Effect
HCVAC	Heating, cooling, ventilation and air-conditioning system
HD	Holiday
HP	Heat pump
IDA ICE	IDA Indoor Climate and Energy (building simulation tool)
IT	Information technology
MA	Moving average
NVE	Norges Vassdrags- og Energidirektorat (Norwegian Water Resources and Energy Directorate)
PV	Photo voltaic
RC	Resistance-capacitance (electric circuit representation of thermal properties of a building)
SN	Sunday
ST	Saturday
TMA	24hr moving average temperature
TRNSYS	Transient System Simulation Tool (building simulation tool)
WD	Weekday
WE	Weekend

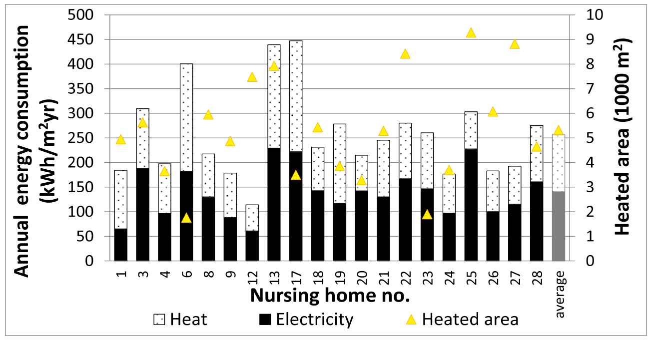
Appendix C: Data set

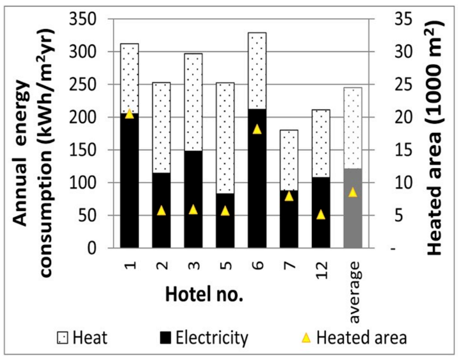


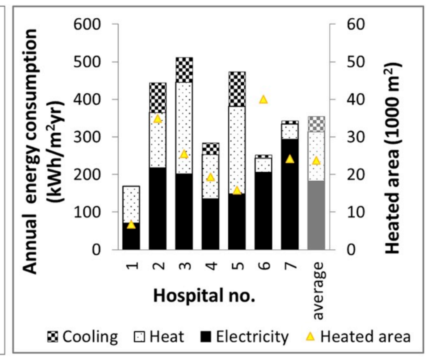










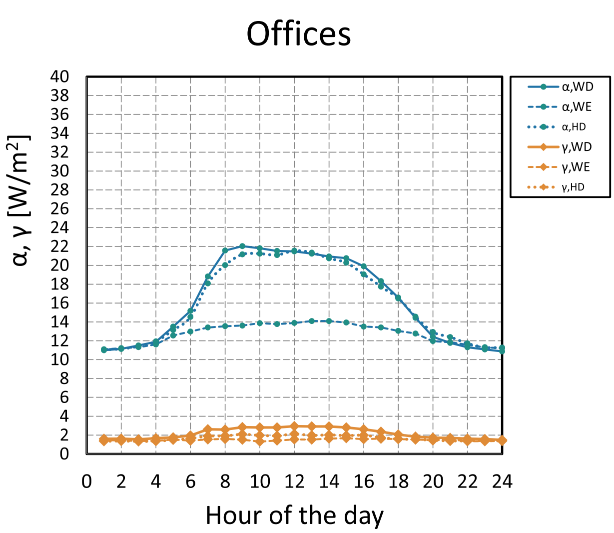


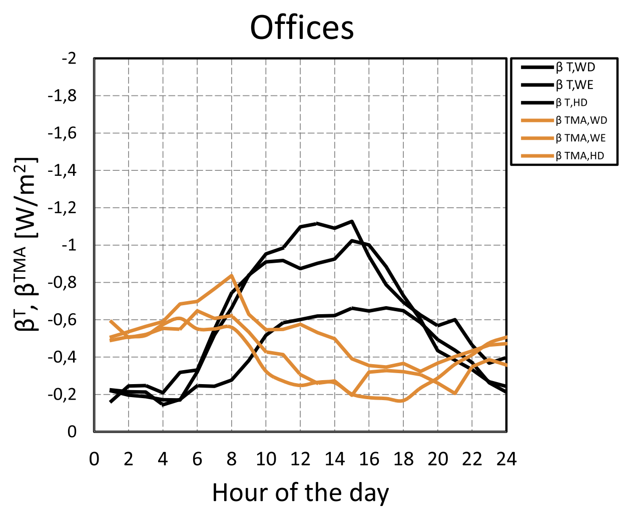
Appendix D: Load profile models

This appendix shows graphs of the estimated parameters of the final load models for both heat and electricity demand for all building categories analysed in this work.

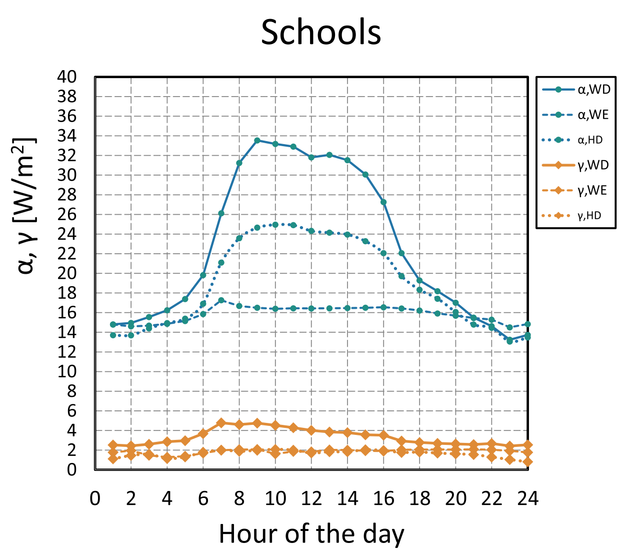
3.1 Heat load coefficients

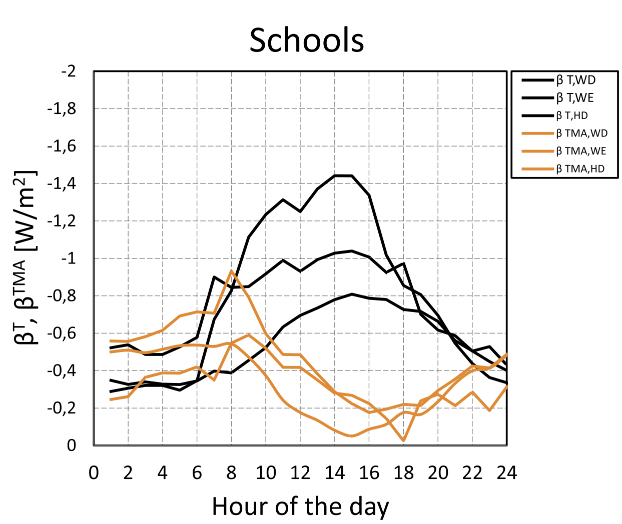
Offices



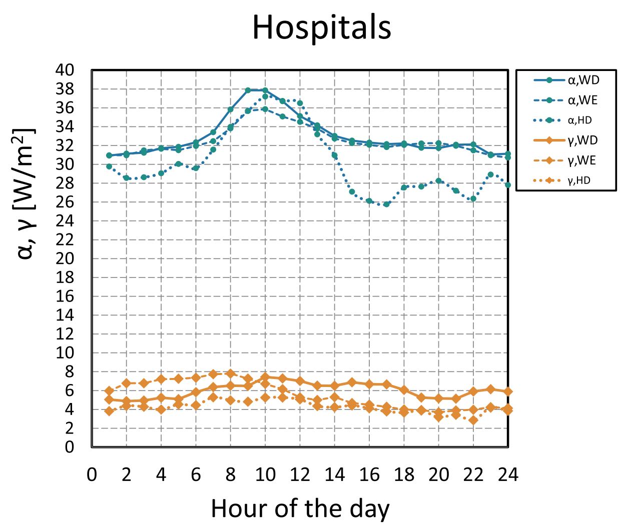

Offices
βT, βTMA [W/m2]
Hour of the day
β T,WD
β T,WE
β T,HD
β TMA,WD
β TMA,WE
β TMA,HD

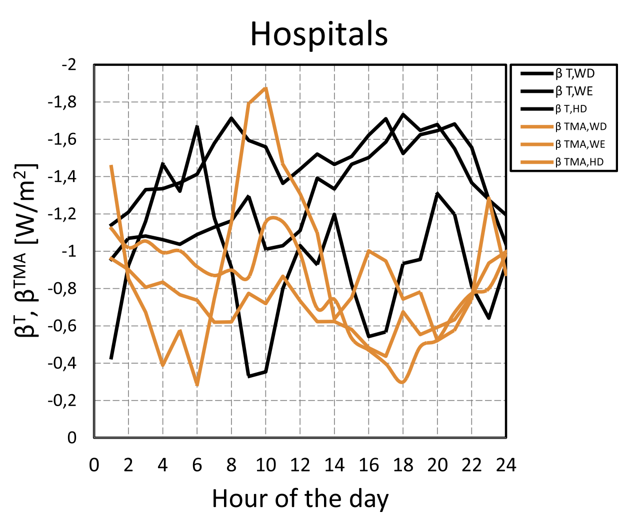
Schools


Schools
α, γ [W/m2]
Hour of the day
α,WD
α,WE
α,HD
γ,WD
γ,WE
γ,HD

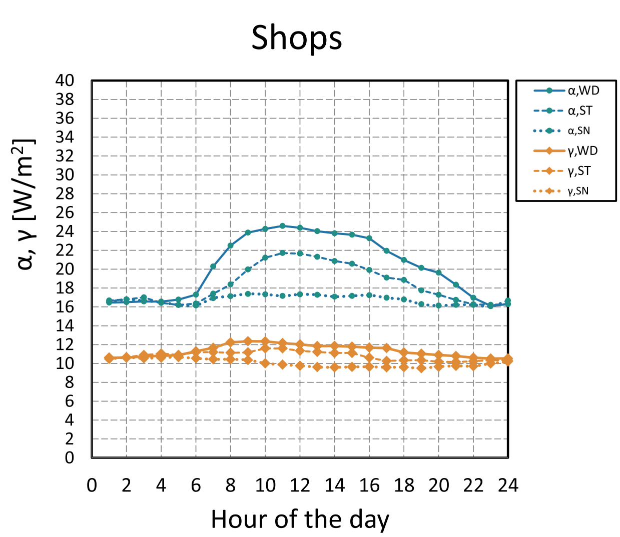

Schools
βT, βTMA [W/m2]
Hour of the day
β T,WD
β T,WE
β T,HD
β TMA,WD
β TMA,WE
β TMA,HD

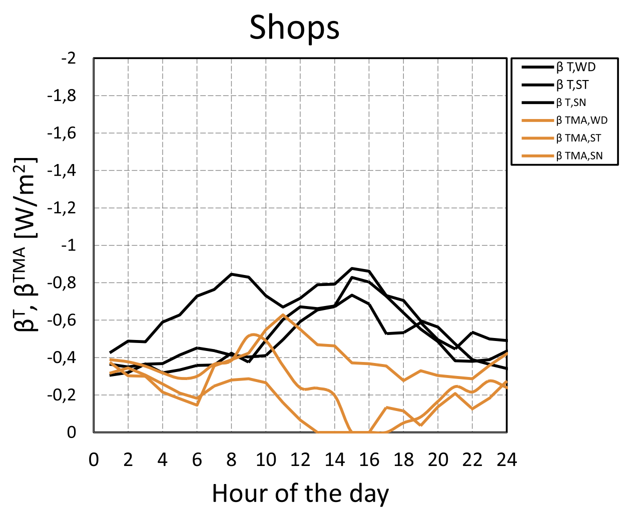
Hospitals



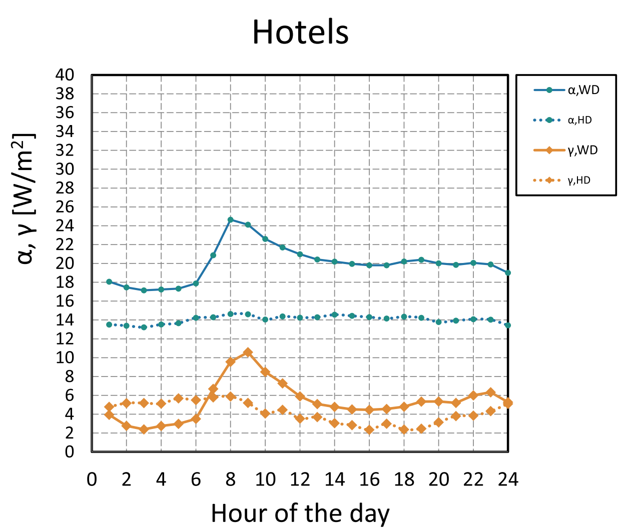


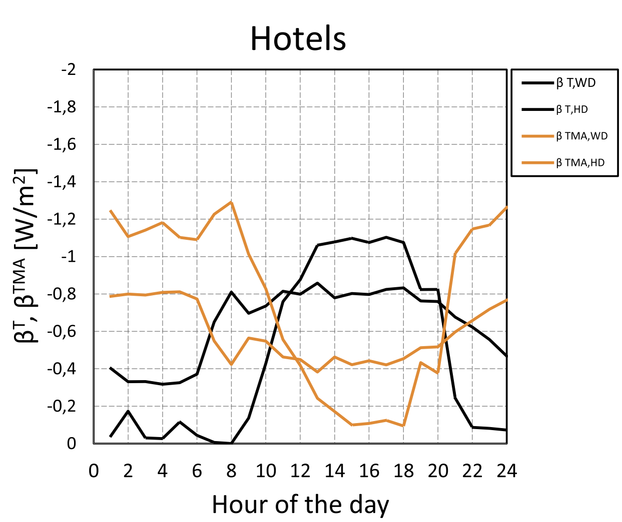
Shops



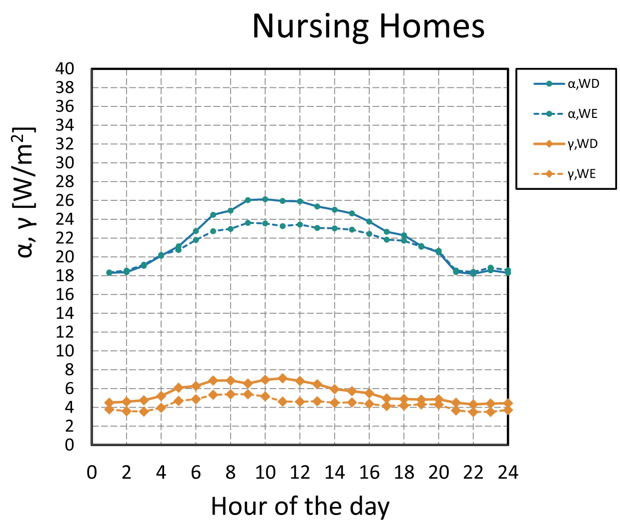

Shops
β T,WD
β T,ST
β T,SN
β TMA,WD
β TMA,ST
β TMA,SN
βT, βTMA [W/m2]
Hour of the day

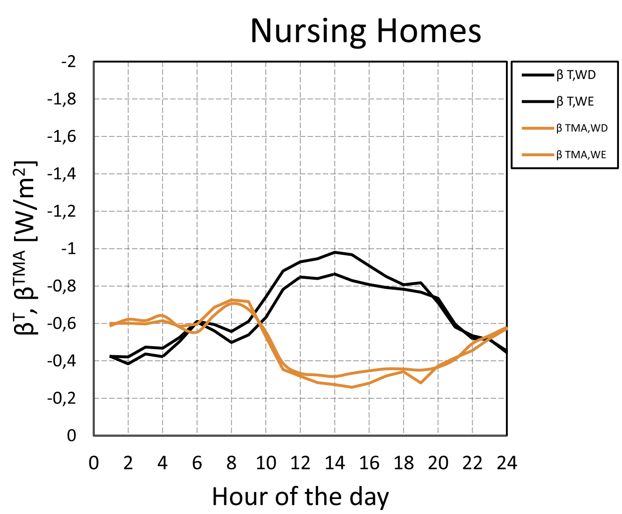
Hotels


Hotels
α,WD
α,HD
γ,WD
γ,HD
α, γ [W/m2]
Hour of the day

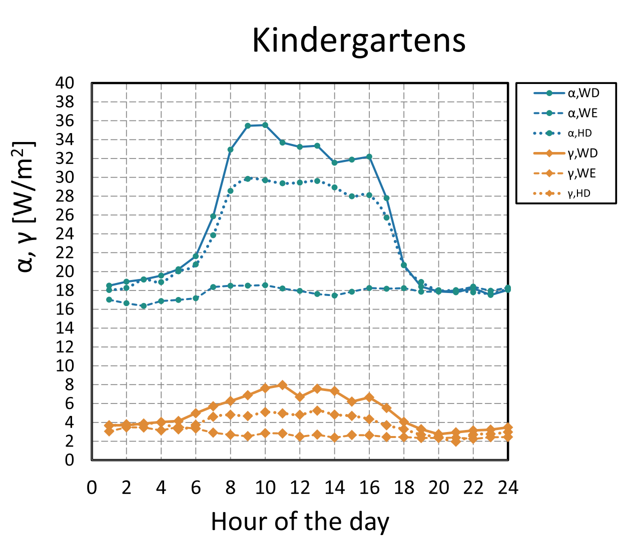

Hotels
β T,WD
β T,HD
β TMA,WD
β TMA,HD
βT, βTMA [W/m2]
Hour of the day

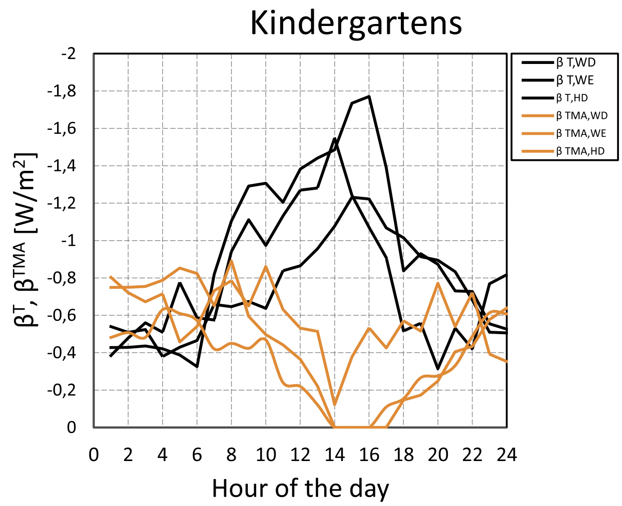
Nursing homes



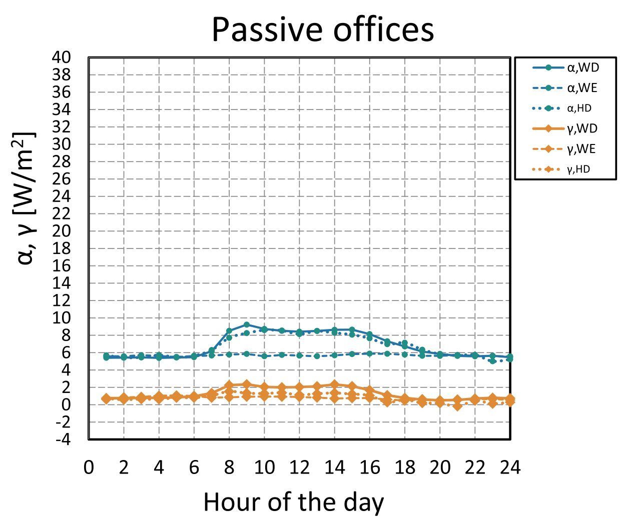


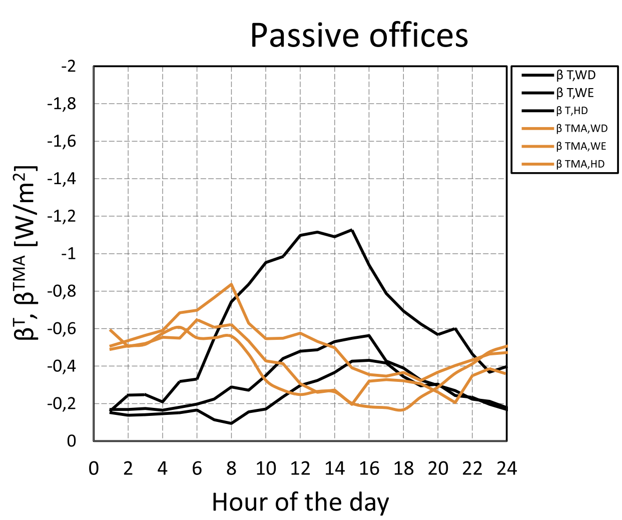
Kindergartens



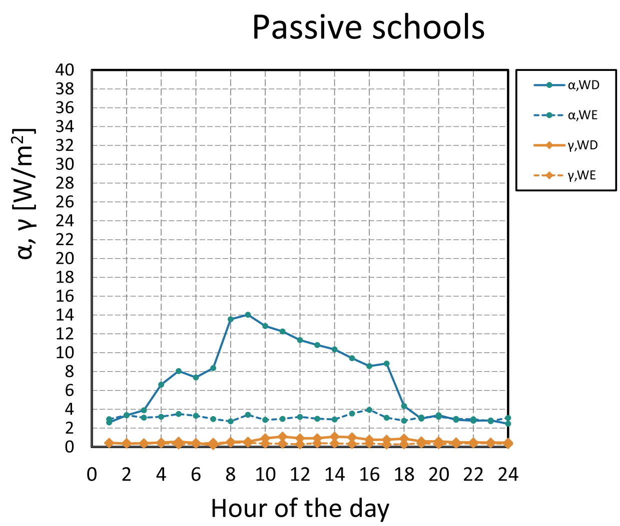


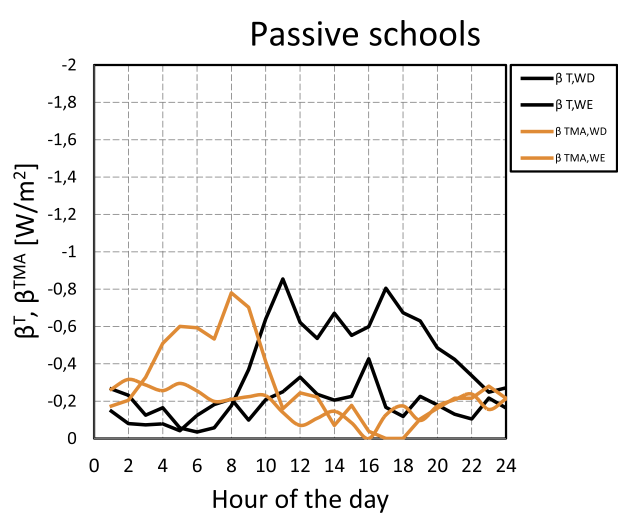
Energy efficient offices





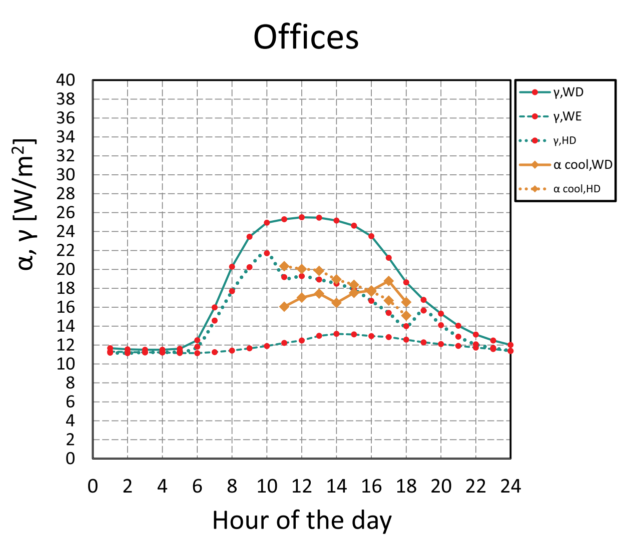
Energy efficient schools

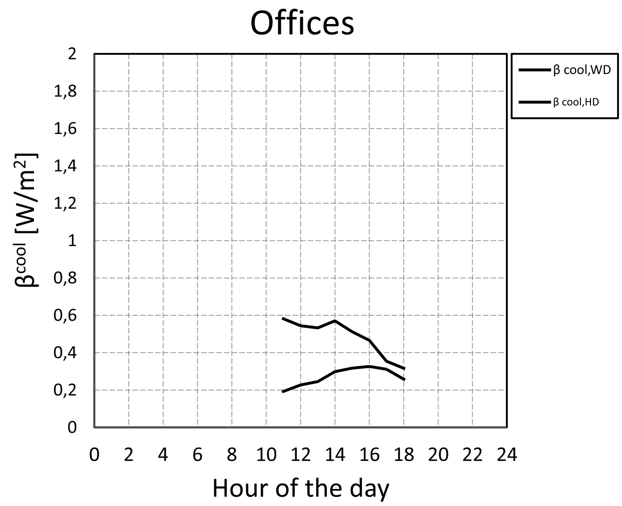




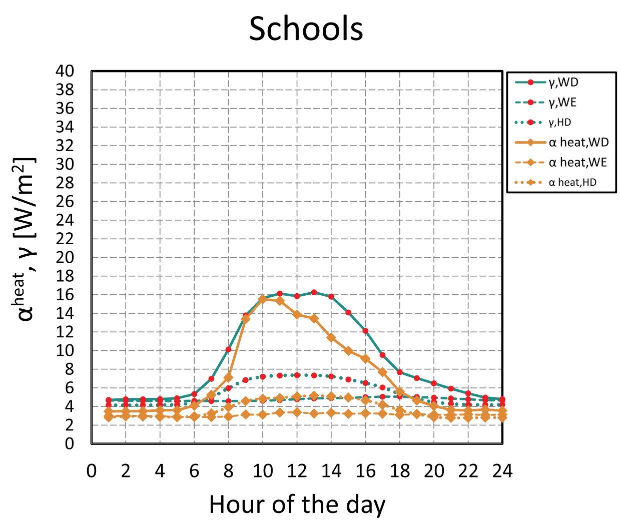
3.2 Electricity load coefficients

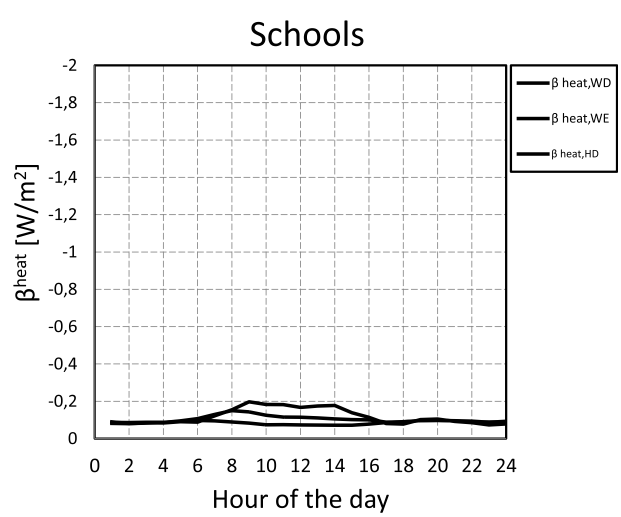
Offices



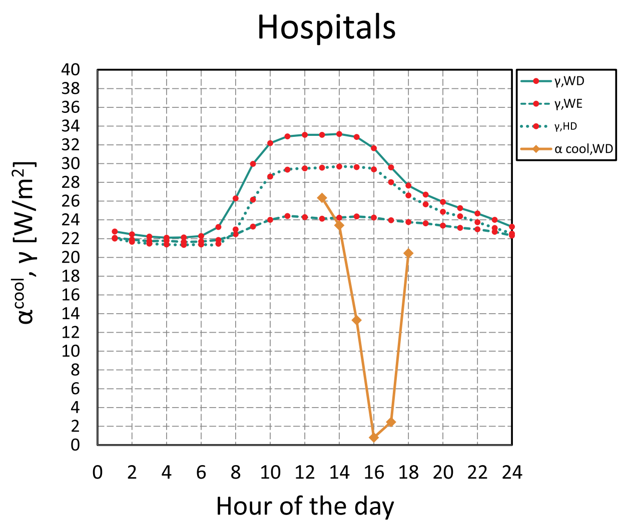

Offices
β cool,WD
β cool,HD
β^cool [W/m²]
Hour of the day

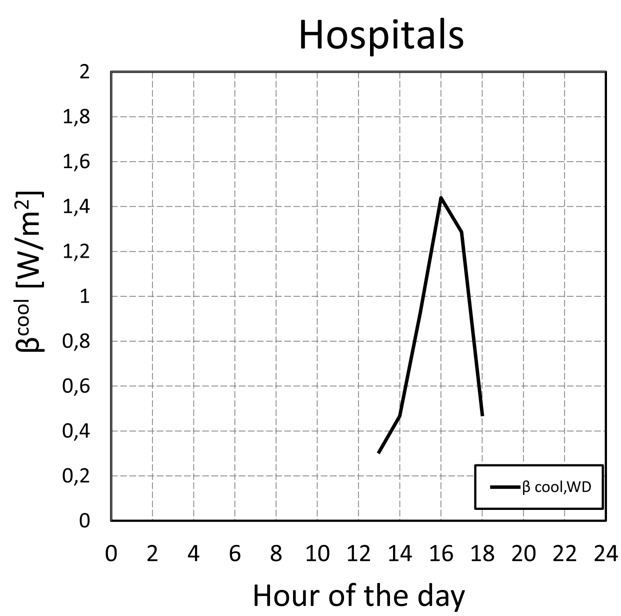
Schools


Schools
γ,WD
γ,WE
γ,HD
α heat,WD
α heat,WE
α heat,HD
α^heat, γ [W/m²]
Hour of the day

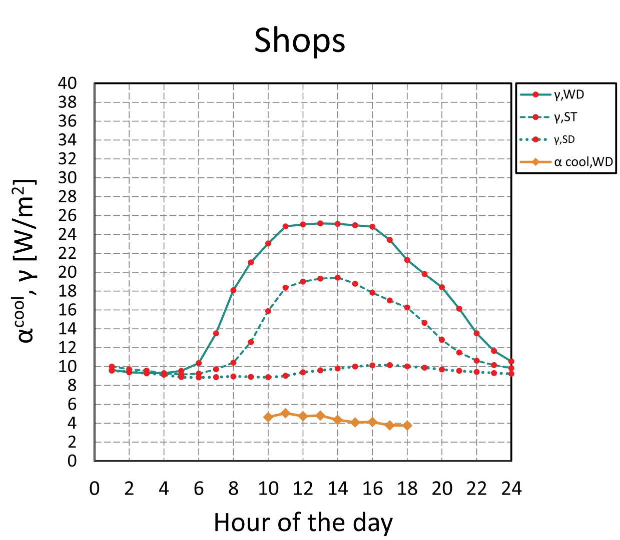

Schools
β heat,WD
β heat,WE
β heat,HD
β^heat [W/m²]
Hour of the day

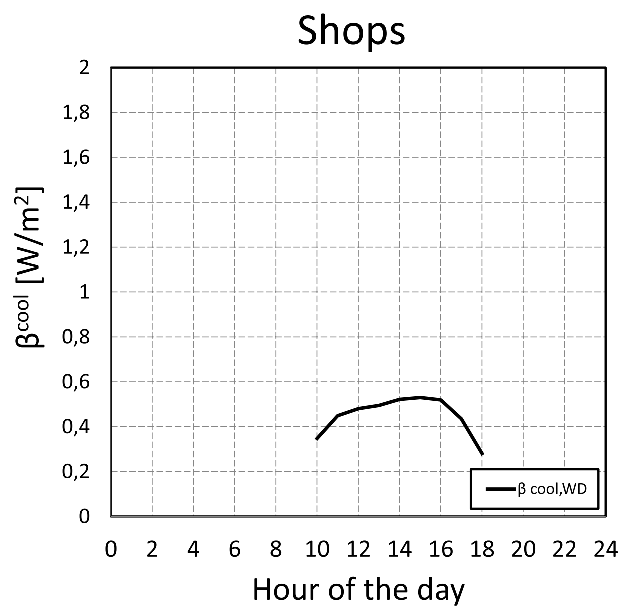
Hospitals



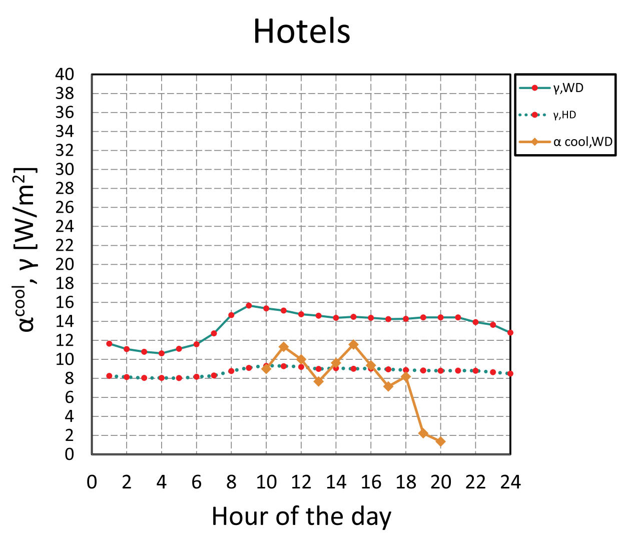


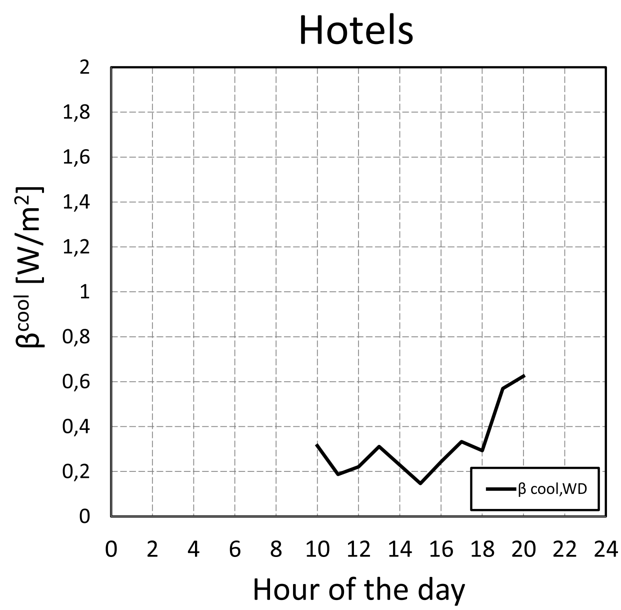
Shops



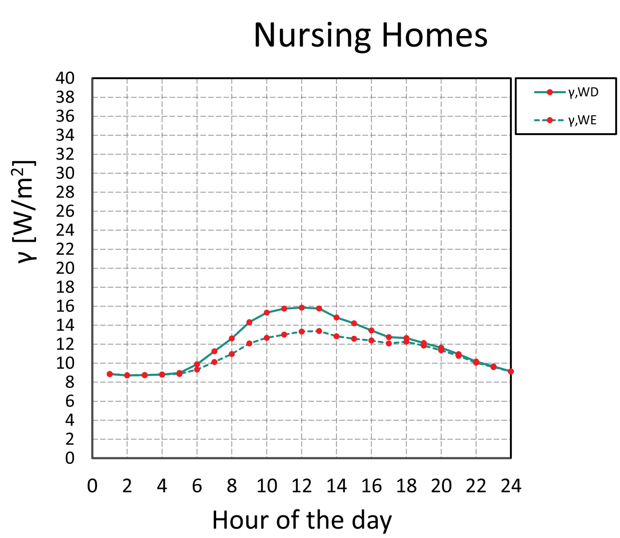

Shops
βcool [W/m2]
2
1,8
1,6
1,4
1,2
1
0,8
0,6
0,4
0,2
0
0 2 4 6 8 10 12 14 16 18 20 22 24
Hour of the day
β cool,WD

Hotels

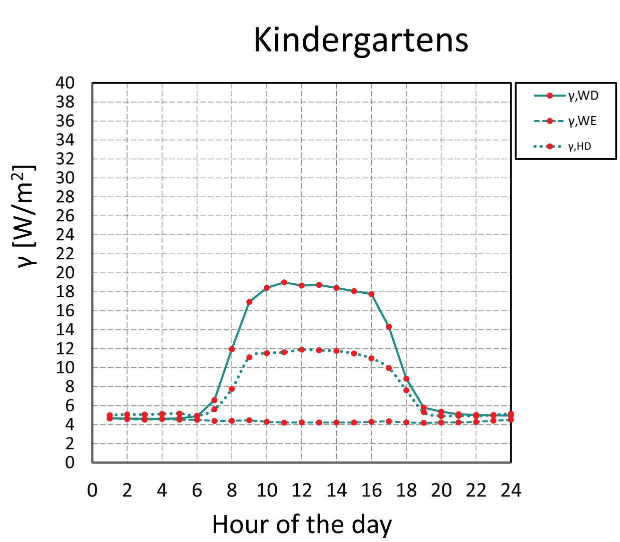

Hotels
αcool, γ [W/m2]
40 38 36 34 32 30 28 26 24 22 20 18 16 14 12 10 8 6 4 2 0
0 2 4 6 8 10 12 14 16 18 20 22 24
Hour of the day
γ,WD
γ,HD
α cool,WD



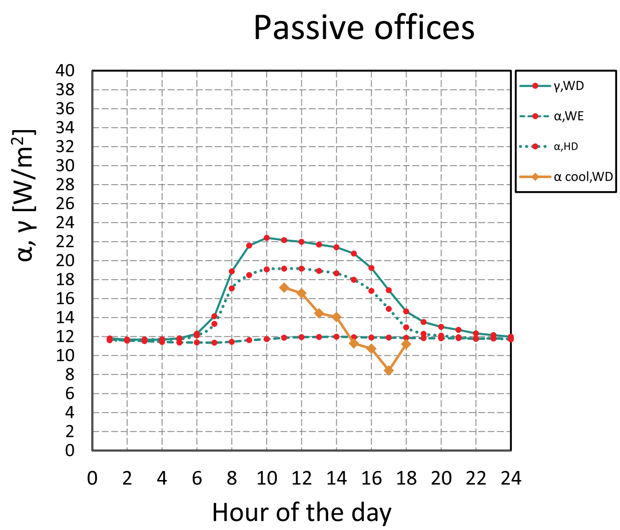
Nursing homes

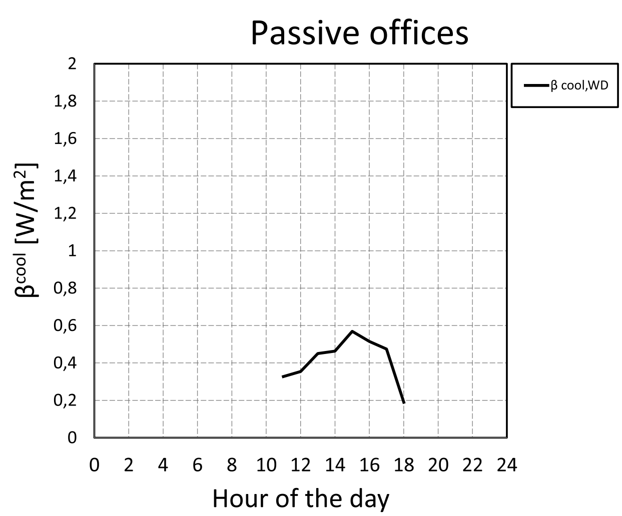


Kindergartens

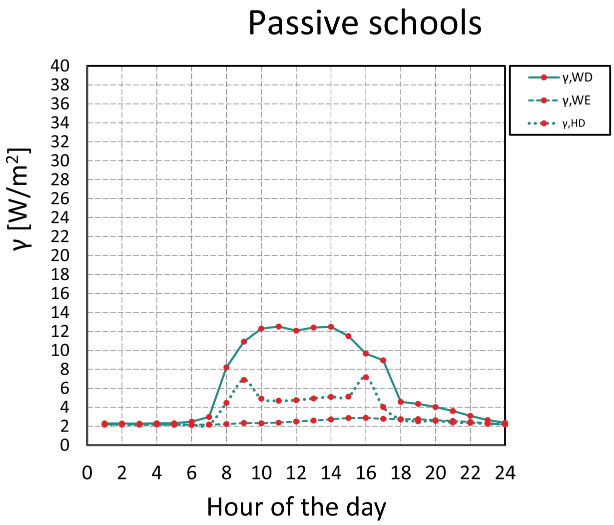


Energy efficient offices





Energy efficient schools



References

Aigner, D.J., Sorooshian, C., Kerwin, P., 1984. Conditional demand analysis for estimating residential end-use load profiles. Energy J. 5 (3), 81–97.

Asare-Bediako, B., Kling, W.L., Ribeiro, P.F., 2014. Future residential load profiles: scenario-based analysis of high penetration of heavy loads and distributed generation. Energy Build. 75, 228–238.

Bøhn, T.I., Palm, L.T., Bakken, L., Nossum, Å., Jordell, H., 2012. Potensial- og barrierestudie: energieffektivisering i norske yrkesbygg. Bakgrunnsrapport. Enova Rep. 2 2012-01.

Boßmann, T., Staffell, I., 2015. The shape of future electricity demand: exploring load curves in 2050s Germany and Britain. Energy 90, 1317–1333.

Boßmann, T., Lickert, F., Elsland, R., Wietschel, M., 2013. "The German load curve in 2050 : structural changes through energy efficiency measures and their impacts on the electricity supply side. In: ECEEE Summer Study Proceedings, pp. 1199–1211.

Carvallo, J.P., Larsen, P.H., Sanstad, A.H., Goldman, C.A., 2018. Long term load forecasting accuracy in electric utility integrated resource planning. Energy Policy 119, 410–422 March.

Chen, T., Wang, Y.-C., 2012. Long-term load forecasting by a collaborative fuzzy-neural approach. Electr. Power Energy Syst. 43, 454–464.

Connolly, D., et al., 2013. Heat Roadmap Europe 2050. Second Pre-study for the EU27.

Daneshi, H., Shahidehpour, M., Choobbari, A.L., 2008. Long-term load forecasting in electricity market. In: 2008 IEEE Int. Conf. Electro/Information Technol. IEEE EIT 2008 Conf. pp. 395–400.

Dotzauer, E., 2002. Simple model for prediction of loads in district-heating systems. Appl. Energy 73 (3–4), 277–284.

Enova, S.F., 2012. Enova's Building Statistics 2011.

ENTSO-E, 2018. Completing the Map - the Ten-Year Network Development Plan (TYNDP) 2018 System Needs Analysis.

Ericson, T., 2009. Direct load control of residential water heaters. Energy Policy 37 (9), 3502–3512.

European Commission, 2011. Energy Roadmap 2050. Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions. *COM*(2011), pp. 885 Final.

Fischer, D., Scherer, J., Flunk, A., Kreifels, N., Lindberg, K.B., 2015a. Impact of HP , CHP , PV and EVs on households ' electric load profiles. In: IEEE Eindhoven PowerTech Conference, Holland, pp. 2–7 29 June - 2 July.

Fischer, D., Härtl, A., Wille-Haussmann, B., 2015b. Model for electric load profiles with high time resolution for German households. Energy Build. 92, 170–179.

Fischer, D., Wolf, T., Scherer, J., Wille-haussmann, B., 2016a. A stochastic bottom-up model for space heating and domestic hot water load profiles for German households. Energy Build. 124, 120–128.

Fischer, D., et al., 2016b. Modelling the effects of variable tariffs on domestic electric load profiles by use of occupant behaviour submodels. IEEE Trans. Smart Grid 8 (6).

Foteinaki, K., Li, R., Heller, A., Rode, C., 2018. Heating system energy flexibility of low-energy residential buildings. Energy Build. 180, 95–108.

Fumo, N., 2014. A review on the basics of building energy estimation. Renew. Sustain. Energy Rev. 31, 53–60.

Gils, H.C., 2014. Assessment of the theoretical demand response potential in Europe. Energy 67, 1–18.

Goude, Y., Nedellec, R., Kong, N., Jan. 2014. Local short and middle term electricity load forecasting with semi-parametric additive models. IEEE Trans. Smart Grid 5 (1), 440–446.

Grandjean, A., Adnot, J., Binet, G., 2012. A review and an analysis of the residential electric load curve models. Renew. Sustain. Energy Rev. 16 (9), 6539–6565.

Hedegaard, K., Balyk, O., 2013. Energy system investment model incorporating heat pumps with thermal storage in buildings and buffer tanks. Energy 63, 356–365.

Hedegaard, K., Mathiesen, B.V., Lund, H., Heiselberg, P., 2012. Wind power integration using individual heat pumps - analysis of different heat storage options. Energy 47 (1), 284–293.

Henning, H.-M., Palzer, A., Feb. 2014. A comprehensive model for the German electricity and heat sector in a future energy system with a dominant contribution from renewable energy technologies—Part I: Methodology. Renew. Sustain. Energy Rev. 30, 1003–1018.

Kipping, A., Trømborg, E., 2015. Hourly electricity consumption in Norwegian households - assessing the impacts of different heating systems. Energy 93, 655–671.

Langseth, B., 2016. *Analyse Av Energibruk I Yrkesbygg*. Oslo, Norway: Norwegian Water Resources and Energy Directorate (NVE). Report no. 04/2016.

Le Dréau, J., Heiselberg, P., 2016. Energy flexibility of residential buildings using short term heat storage in the thermal mass. Energy 111, 991–1002.

Lindberg, K.B., 2017. "Impact of Zero Energy Buildings on the Power System - A Study of Load Profiles , Flexibility and System Investments," Doctoral Thesis. Norwegian University of Science and Technology (NTNU).

Lindberg, K.B., Doorman, G., June, 2013. Hourly load modelling of non-residential building stock. IEEE Grenoble PowerTech Conf. Fr. 16–20.

Lindberg, K.B., Chacon, J.E., Doorman, G.L., Fischer, D., 2015. Hourly electricity load modeling of non-residential passive buildings in a nordic climate. In: IEEE Eindhoven PowerTech Conference, Holland, 29 June - 2 July.

Lindberg, K.B., et al., 2016. Large scale introduction of zero energy buildings in the nordic power system. In: 13th International Conference on the European Energy Market, 6-9 June 2016. Porto, *Portugal*.

Livik, K., Feilberg, N., Foosnes, J.A., 1993. Estimation of annual coincident peak demand and load curves based on statistical analysis and typical load data. In: CIRED 12th International Conference on Electricity Distribution, Birmingham.

Livik, K., Feilberg, N., Morch, A.Z., Larsson, L., 1999. USELOAD - a multipurpose software tool for simulation of end-use loads. Model description and examples of use. In: *DA/DSM DistribuTECH Europe 99 Conference*, Madrid, Spain.

Logenthiran, T., Srinivasan, D., Shun, T.Z., 2012. Demand side management in smart grid using heuristic optimization. IEEE Trans. Smart Grid 3 (3), 1244–1252.

Maribu, K.M., Firestone, R.M., Marnay, C., Siddiqui, A.S., 2007. Distributed energy resources market diffusion model. Energy Policy 35 (9), 4471–4484.

MET, 2015. The Norwegian Meteorological Institute (MET). [Online]. Available: www.eklima.no, Accessed date: 14 March 2015.

Moral-Carcedo, J., Pérez-García, J., 2017. Integrating long-term economic scenarios into peak load forecasting: an application to Spain. Energy 140, 682–695.

Morch, A.Z., Feilberg, N., Sæle, H., Lindberg, K.B., 2013. Method for development and segmentation of load profiles for different final customers and appliances. In: ECEEE Summer Study Proceedings, pp. 1927–1933.

NS 3031, 2007. Norsk Standard: Beregning Av Bygningers Energiytelse. vol.2007 Metode og data.

NS 3701, 2012. Norsk Standard: Kriterier for Passivhus Og Lavenergibygninger. vol.2012 Yrkesbygninger.

Ottesen, S.O., Tomasgard, A., 2015. A stochastic model for scheduling energy flexibility in buildings. Energy 88, 364–376.

Pedersen, L., 2007. Use of different methodologies for thermal load and energy estimations in buildings including meteorological and sociological input parameters. Renew. Sustain. Energy Rev. 11 (5), 998–1007.

Pedersen, L., Stang, J., Ulseth, R., 2008. Load prediction method for heat and electricity demand in buildings for the purpose of planning for mixed energy distribution

systems. Energy Build. 40 (7), 1124–1134.
Pillai, G.G., Putrus, G. a., Pearsall, N.M., 2014. Generation of synthetic benchmark electrical load profiles using publicly available load and weather data. Int. J. Electr. Power Energy Syst. 61, 1–10.
Richalet, V., Neirac, F.P., Tellez, F., Marco, J., Bloem, J.J., 2001. HELP (house energy labeling procedure): methodology and present results. Energy Build. 33, 229–233.
Richardson, I., Thomson, M., Infield, D., 2008. A high-resolution domestic building occupancy model for energy demand simulations. Energy Build. 40 (8), 1560–1566.
Richardson, I., Thomson, M., Infield, D., Clifford, C., 2010. Domestic electricity use: a high-resolution energy demand model. Energy Build. 42 (10), 1878–1887.
Sandberg, N.H., Sartori, I., Vestrum, M.I., Brattebø, H., 2017. Using a segmented dynamic dwelling stock model for scenario analysis of future energy demand: the dwelling stock of Norway 2016–2050. Energy Build. 146, 220–232.
Sandberg, N.H., et al., 2016. Dynamic building stock modelling: application to 11 European countries to support the energy efficiency and retrofit ambitions of the EU. Energy Build. 132, 26–38.
Sartori, I., Wachenfeldt, B.J., Hestnes, A.G., 2009. Energy demand in the Norwegian building stock: scenarios on potential reduction. Energy Policy 37 (5), 1614–1627.
Seljom, P., Lindberg, K.B., Tomasgard, A., Doorman, G.L., Sartori, I., 2017. The impact of zero energy buildings on the scandinavian energy system. Energy 118, 284–296.
Statistics Norway. Norwegian Energy Balance 2013. [Online]. Available: https://www.ssb.no/energi-og-industri/statistikker/energibalanse/aar-endelige, Accessed date: 13 March 2018.
Stokke, A.V., Doorman, G.L., Ericson, T., 2010. An analysis of a demand charge electricity grid tariff in the residential sector. Energy Effic. 3 (3), 267–282.
Strbac, G., 2008. Demand side management: benefits and challenges. Energy Policy 36 (12), 4419–4426.
Sæle, H., Rosenberg, E., Feilberg, N., 2010. State-of-the-art Projects for Estimating the Electricity End-Use Demand. SINTEF Technical Report TR, pp. A6999.
Turner, C., Frankel, M., 2008. Energy Performance of LEED ® for New Construction Buildings. Vancouver, Canada.
Veldman, E., Gibescu, M., Slootweg, J.G., Kling, W.L., 2011. Impact of electrification of residential heating on loading of distribution networks. In: IEEE Trondheim PowerTech, pp. 1–7.
Wenz, L., Levermann, A., Auffhammer, M., 2017. North–south polarization of European electricity consumption under future warming. Proc. Natl. Acad. Sci. Unit. States Am. 114 (38), E7910–E7918.
Widén, J., Lundh, M., Vassileva, I., Dahlquist, E., Ellegård, K., Wäckelgård, E., 2009. Constructing load profiles for household electricity and hot water from time-use data—modelling approach and validation. Energy Build. 41 (7), 753–768.
Wooldridge, J.M., 2010. Econometric Analysis of Cross Section and Panel Data, second ed. MIT Press.
Yao, R., Steemers, K., 2005. A method of formulating energy load profile for domestic buildings in the UK. Energy Build. 37 (6), 663–671.
Zhang, J., Wei, Y.M., Li, D., Tan, Z., Zhou, J., 2018. Short term electricity load forecasting using a hybrid model. Energy 158, 774–781.