Modeling hourly energy consumption in Norwegian buildings

Modellering av energiforbruk på timesnivå i norske bygninger

Philosophiae Doctor (PhD) Thesis

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ABSTRACT

Growing world population, unabated use of fossil fuels, and economies aiming at continuous growth exhaust the planet's natural resources and add to an augmented greenhouse effect. Besides limiting population growth in less developed regions, reducing per capita energy consumption in more developed regions, substituting fossil and nuclear fuels by renewable energy carriers is considered a major step towards a sustainable development. The integration of renewable energy sources into the energy system can reduce pollutants and greenhouse gas emissions connected to energy conversion processes and ensure energy supply also in a long-term perspective. However, the varying supply of renewable energy supply implies challenges to existing energy systems, where traditionally supply used to follow demand. In order to plan, design, and manage modern energy systems sound estimates on regional energy demand with high temporal and spacial resolutions are needed. Due to the area-wide installation of smart energy meters time series of individual hourly or sub-hourly energy consumption data become available. In combination with cross-sectional information, such as household characteristics or building physics, valuable data sets can be formed, allowing the development of detailed consumption models.

In this thesis the key factors for energy consumption in Norwegian buildings are analyzed, and a simple approach for modeling hourly energy consumption in different consumer groups within household and service sector is presented. The models are based on panel data sets consisting of hourly meter data combined with cross-sectional data, weather data, and calendric information. The individual impacts of different heating systems on hourly electricity consumption in households are assessed, yielding for example insights about average reductions in hourly consumption in case air-to-air heat pumps or wood stoves are used. Moreover, the impacts of further household- or dwelling-specific variables, such as number of residents or dwelling type, are discussed, and a simple method for disaggregating modeled hourly electricity consumption into a temperature-independent and a temperature-dependent component is applied. Comparing goodness of fit of two regression models based on hourly and daily

mean values of local outdoor temperature yields that daily mean values are sufficient for modeling hourly electricity consumption, which facilitates the input data requirements. The modeling approach is further applied to both hourly electricity and hourly district heat consumption in office buildings and schools. A comparison of modeled total energy consumption in buildings with electric and district heating, correspondingly, indicates that in office buildings with district heating heat consumption in the morning starts earlier than in buildings with electric heating, and that schools with district heating on average apply less indoor temperature reduction during night-time, weekends, and school holidays than schools with electric space heating. Finally the method is used to model historic aggregate electricity consumption in households and service sector in each Norwegian county, and to generate rough forecasts on hourly electricity consumption in Oslo in 2040. Temperature forecasts for 2040 imply increased temperatures during the entire year, and three different scenarios on population development assume low, medium, and high population growth. The forecasts indicate increased electricity consumption from 2013 to 2040 for all three population scenarios, which is mainly due to an increase in modeled consumption for electric appliances and tap water heating. Modeled electricity consumption for space heating purposes decreases in the low population scenario, slightly increases in the medium scenario, and only exhibits a considerable increase under the assumption of high population growth. The overall results of this study indicate that modeling aggregate energy consumption in households and service sector based on a bottom-up regression model approach is useful, but that the availability of building stock related input data is a prerequisite for achieving meaningful results, both for modeling historic consumption and forecasting. Moreover, important factors like thermal building standard or building age were not considered in most of the models, so that the effects of a building stock renewal could not be assessed. Larger samples of meter data and cross-sectional information, covering all Norwegian regions and sectors would enable developing further, more reliable models which could be used to perform forecasts on hourly energy consumption in all counties.

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PAPERS

The thesis is based on the following papers, which are found in Part II:

- Paper I: A. Kipping, E. Trømborg, Hourly electricity consumption in Norwegian households – Assessing the impacts of different heating systems,
  Energy 93, Part 1 (2015) 655 – 671
- Paper II: A. Kipping, E. Trømborg, Modeling and disaggregating hourly electricity consumption in Norwegian dwellings based on smart meter data,
  Energy and Buildings 118 (2016) 350 – 369
- Paper III: A. Kipping, E. Trømborg, Modeling hourly consumption of electricity and district heat in non-residential buildings,
  submitted to Energy
- Paper IV: A. Kipping, E. Trømborg, Modeling and forecasting regional hourly electricity consumption in buildings,
  manuscript

Contents

Part I

SYNOPSIS

1 INTRODUCTION

1.1 Background

A high share of global energy demand is covered by fossil fuels implying carbon dioxide (CO_2)-emissions during combustion. The OECD[1]-member countries, representing only 18 % of world population, accounted for more than one third of global emissions of CO_2 in 2011, and covered more than 80 % of their energy demand by fossil fuels [1]. With conventional economies aiming at economic growth, implying ever increasing production and consumption, global per capita energy demand is unlikely to decrease significantly. The increased frequency of smog emergencies, extreme weather events like floods, droughts, heat waves, during recent years have given a glimpse of what might be the consequences of taking no actions to limit pollution, deforestation, and greenhouse gases emissions. In order to reach sustainable consumption levels on a global level especially the most developed countries need to reduce per capita energy consumption and at the same time reduce CO_2-emissions by substituting fossil fuels with renewable energy carriers, that can be transformed to heat, electrical energy, or motion without combustion processes. According to the International Energy Agency worldwide energy consumption will increase by one third by 2040 compared to consumption in 2013, however, mainly due to increased consumption in non-OECD countries, while energy consumption in the European Union (EU) is expected to decrease [2].

In order to reduce emissions the EU aims to reach an overall share of renewable energy in total energy consumption of at least 20 % by 2020, and a share of 27 % by 2030 [3]. In 2014, the renewable share in the EU was 16 % [4]. Since electricity generation in Norway relies almost exclusively on hydro power, and electricity covers a large part of total energy consumption, the ”renewable-share” in Norway is considerably higher than the EU-average. Norway’s goal for 2020 is a share of 67.5 % renewables [5], which was met for the first time in 2014 [4]. Moreover, both Norway and the EU aim

[1] Organisation for Economic Co-operation and Development

at a renewable share of 10 % within the transport sector within 2020. The corresponding shares in 2014 were 5 % (Norway) and 6 % (EU) [4].

1.2 Energy consumption in Norway

Due to the availability of hydro power and comparably low electricity prices electrical energy has been the most important energy carrier in Norway during the last decades. Energy consumption[2] in Norway from 1976 to 2014, divided according to different energy carriers, is shown in Figure 1. In the late 1970s oil and gas still accounted for

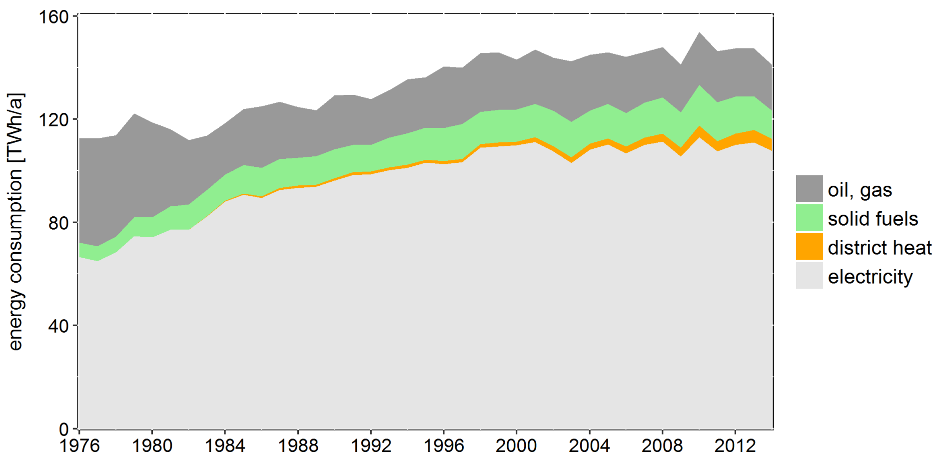


Fig. 1: Energy consumption in Norway, 1976 – 2014 [6]

about one third of consumption, but as a consequence of the oil crisis this share was reduced dramatically during the early 1980s. The use of solid fuels has increased continuously from about 5 % in 1976 to about 13 % in 2014. The share of total energy demand covered by district heat has been comparably small, however, it exhibited a considerable increase from 1.0 % in 2000 to over 3.3 % in 2014. Total energy consumption has been increasing until around 2000 when it started to flatten despite of continuing population growth. Milder winters, higher prices, smaller dwellings, increased use of heat pumps, increased energy efficiency in the industries, stricter building codes with respect to energy consumption, and shutting down factories within the energy-intensive industries are possible reasons for an almost stagnating consumption

[2]Energy consumption in transport sector and energy sector as well as energy carriers consumed as raw materials is not considered in this section.

during the past 15 years, and are discussed e.g. in [7, 8]. The kink in energy consumption in 2009 can be explained by reduced production within the energy-intensive industries, such as aluminium and ferro-alloys production and wood processing, due to the international financial crisis [7]. The consumption peak in 2010 can be explained by an extraordinary cold winter, while low consumption in 2014 can analogously be explained by an unusually warm winter. Thus, both macroeconomic factors, such as price shocks or financial crises, outdoor temperature, and different building stock related factors have had impacts on aggregate energy consumption.

In contrast to most EU countries, where electricity is still mainly generated in thermal power plants and electricity prices are comparably high, electrical energy in Norway is broadly used for space and domestic water heating, which explains typically high electricity shares in total consumption especially in households and service sector. In recent years the use of heat pumps for space heating purposes has increased significantly. While in 2004 heat pumps were installed in only 4 % of dwellings, the share was 27 % – and even 44 % in single family houses – in 2012 [9]. In residential buildings without hot water heating systems air-to-air heat pumps are common, typically using outside air as heat source. Air-to-water or liquid-to-water heat pumps, e.g. using geothermal heat as heat source, require a hot water heating system and are less common. About 10 % of Norway's energy consumption for heating and cooling in 2014 was estimated to be generated by heat pumps [4]. Throughout all dwelling types the use of wood stoves for space heating is common, however, less frequent in apartment buildings. Especially in farm houses heating energy demand is often mainly covered by wood burning, while electric heaters or heat pumps might only be installed in single rooms. Energy consumption in households, services, and industries in 2013 is shown in Figure 2. In household and service sector about 80 % of total energy consumption was electrical energy, compared to only 62 % in the industries. While in the service sector the remainder was mainly district heat and liquid fuels, e.g. heating oil, it was mainly firewood as well as some liquid fuels and district heat in households. Coal and gases covered about 25 % of total industrial consumption, but negligible shares in households and services, indicating that these fuels are mainly used in industrial processes.

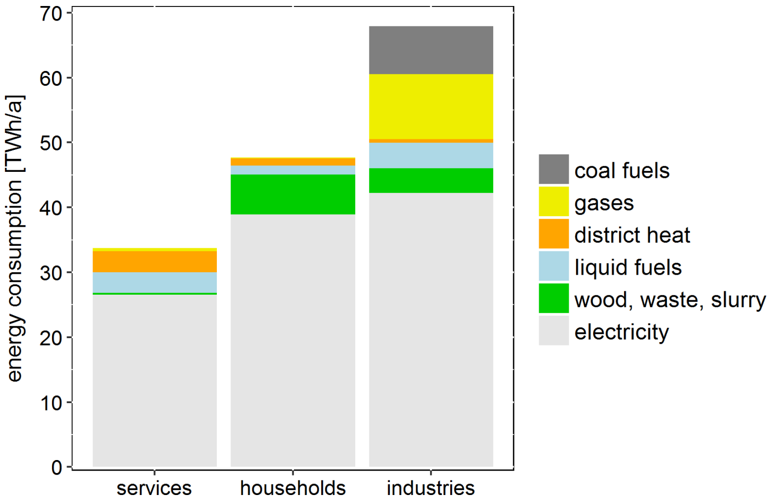


Fig. 2: Energy consumption in services, households, industries, 2013 [10]

1.3 The need for energy consumption models

In order to ensure security of supply also in a long-term perspective, and at the same time avoid CO_2-emissions, energy systems need to integrate variable renewable energy (VRE) sources like wind and solar power, that provide large amounts of energy each year. However, an efficient *use* of this energy provided, e.g. transforming it to heat or electrical energy, implies certain challenges, since the potential and actual occurrence of VRE varies both locally and temporally. This variability in energy supply is in stark contrast to conventional energy systems where production traditionally used to follow demand. Power production in thermal power plants driven by fossil fuels can be controlled so that power demand is met at all times. Integrating VRE into the energy system implies that the energy supply is no longer entirely predictable, and a high supply with heat or power from VRE might not coincide with high heat or electricity demand.

In Norway hydro power accounted for 96 % of total electricity production in 2014, while thermal and wind power plants produced 2.5 % and 1.6 %, respectively [11]. Due to increasing power generation in run-of-river plants that are usually not controllable, higher shares of wind and solar power, as well as a stronger integration into the European power system Norway's energy system needs to implement flexibility measures.

Differences between supply and demand need to be levelled out by flexibility measures, such as storing or converting excess energy, trading energy with other countries, or by influencing the system's demand side. Lund et al. [12] describe and assess various energy system flexibility options. Possible consumers of excess energy could be district heating systems supplied by various heat sources, such as electric boilers or heat pumps [13–16], or individual heating equipment in private households [17]. Demand side management includes various measures that support the synchronization of energy supply and demand on different time perspectives. A simple option is energy conservation, meaning avoiding or reducing energy consumption in general. Another option to reduce the consumption of a specific energy carrier is fuel substitution, meaning another energy carrier is used to cover demand. Petrol can be substituted by electricity in transport, firewood or district heat can substitute electricity for heating purposes. The purpose of load management is changing diurnal load patterns by e.g. reducing load during peak periods, increasing load during off-peak periods, or shifting load from peak to off-peak periods [18]. Since heat and power networks are designed according to an expected maximum load, the reduction of peak loads, that might only occur for short time periods, can avoid grid extensions or even the construction of new power or heating plants. Load management can be implemented by indirect programs, where consumers are motivated by vouchers or lower electricity tariffs to schedule energy consumption according to the patterns preferred by the system operators, or by direct programs, implying that the operators can disconnect and reconnect single consumer appliances according to their preferences. Albadi and El-Sadaany [19] present an overview of demand response options in electricity systems. In order to communicate with individual consumers, e.g. sending price information or control signals, and receiving meter data, most load management options require advanced metering and communication technology. By 2020 more than 70 % of consumers in the EU are expected to be equipped with *smart* electricity meters [20], which in contrast to conventional meters log meter values in intervals between 15 and 60 minutes, and enable two-way-communication between consumers and system operators. In Norway, all electricity consumers are planned to be equipped with smart meters by 2019 [21]. Consumption data transmitted by smart meters yields an enormous potential for developing new tariffs and pricing methods, analysing demand side management options, and for energy-related research.

Forecasts on energy consumption represent valuable information for energy system planning. The required temporal, spacial, and sectoral resolutions depend on the scope of application. For designing power or heating plants, power grids or district heating networks estimates on future maximum loads, e.g. in a city, are needed, while for rough estimates on how much firewood will be needed during a future year, forecasts on annual heating energy consumption are sufficient. Historically there has been a strong correlation between energy consumption, population, and economic indicators, such as gross domestic product (GDP). Rough energy consumption forecasts on annual energy consumption can e.g. make assumptions on quotients like GDP per capita, and energy consumption per GDP, also known as *energy intensity*, and can thus estimate energy consumption based on assumed future population. Rosenberg et al. [22] develop long term projections of energy demand in different Norwegian sectors by identifying important drivers for energy consumption within each sector, calculating energy consumption per driver (intensities) for a base year, and calculate projected energy demand based on assumed changes in intensities and drivers. More detailed forecasting methods rely on models that can take into account changes in multiple factors. In a comparably cold country like Norway, energy consumption is negatively correlated with outdoor temperature during large parts of the year. Climate change is expected to lead to higher outdoor temperatures all year, implying milder winters, but also warmer summers. Seljom et al. [23] identify the effects of climate change both on wind and hydro power production, as well as on annual energy demand for heating and cooling in Norway in 2050. Several studies discuss the effects of reduced heat demand and lower temperature levels, due to higher outdoor temperatures and increased thermal building standards, on district heating systems [24–29]. For more detailed energy system planning and evaluating load management options forecasts with higher temporal resolutions are useful. Andersen et al. [30, 31] identify hourly profiles of electricity consumption within different consumer categories in Denmark. Weights indicating the corresponding impacts of each category on aggregate hourly electricity consumption in different Danish regions are calculated, and based on national projections on electricity consumption in each category forecasts on hourly electricity consumption on a regional level are made.

1.4 Objectives and thesis outline

In order to reduce greenhouse gas emissions renewable energy carriers need to be integrated into the energy system and substitute fossil fuels. Although Norway's energy system heavily relies on hydro power and covers about two thirds of total energy demand by renewable energy, increasing shares of variable power supply by wind, solar, and run-of-river hydro power plants require more system flexibility. Converting

excess power to heat in electric boilers or heat pumps, serving as heat sources to district heating systems, or implementing demand side management measures can help synchronizing supply and demand, and ensuring security of supply. Reliable energy consumption models with high temporal, spacial, and sectoral resolutions are vital for designing, planning, and operating modern energy systems. For example, in order to design power lines forecasts on maximum electric loads are needed, while forecasts on maximum thermal loads are required for planning district heating networks. Different factors affect energy consumption, and their isolated impacts might have different signs and values. Regarded in isolation, i.e. all other factors constant, increasing outdoor temperatures due to climate change imply reduced energy demand for space heating purposes, but an increased energy demand for space cooling. On the one hand population growth might imply increasing energy demand due to more electric appliances and an increase in heated dwelling floor space. On the other hand increased energy efficiency and stricter building codes in theory imply reduced consumption. Thus, energy consumption models need to take into account individual impacts of different factors so that useful forecasts can be produced.
The main objectives of this thesis are to analyse important factors for hourly energy consumption in Norwegian buildings, as well as to assess how regional hourly energy consumption in different consumer groups can be modeled, taking into account changes in the key factors. Moreover, the sub-objectives are as follows:

- Developing a method to model hourly electricity consumption in Norwegian households based on smart meter data and survey response data
- Assessing how different heating systems affect hourly electricity consumption in Norwegian households
- Describing a disaggregation method to estimate how much electricity is consumed for electric space heating and for other purposes correspondingly
- Developing models for hourly consumption of electricity and district heat in non-residential buildings and assessing similarities and differences in consumption patterns
- Developing a method for modeling hourly energy consumption in buildings on a regional level that can be used for forecasting

The remainder of the thesis is organized as follows. Chapter 2 provides theoretic background regarding energy consumption in buildings. In Chapter 3 common approaches for modeling aggregate energy consumption in a building stock are briefly described and discussed. Moreover, a method for modeling hourly energy consumption in buildings based on panel data is described in detail. Chapter 4 reports and discusses the main findings of Papers I–IV, and Chapter 5 concludes the thesis.

2 ENERGY CONSUMPTION IN BUILDINGS

2.1 Energy carriers and energy efficiency

The expressions *energy demand* and *energy consumption* are often used synonymously, although meanings actually differ. Demand can be interpreted as the need or request for some good, while consumption describes how much of the good is actually consumed. Consumption can be metered, while demand often remains unknown. Energy consumption might be considerably lower than the actual energy demand, e.g. due to the unavailability of energy carriers or equipment, but also more energy can be consumed than actually needed, e.g. by wasting energy due to lacking awareness. Assuming that demand is covered at all times, and consumption does not exceed demand, the terms can be used interchangeably.
Primary energy carriers, e.g. wind energy or crude oil, are usually not used in their original form, but transformed into *secondary energy* carriers in conversion processes (Figure 3). Every energy conversion process implies energy losses. Wind energy is usually first transformed into mechanical energy and then into electrical energy using a wind turbine and a generator. Crude oil needs to be cleaned and processed in refineries, where different petrol products are extracted. Petrol, kerosine, diesel, or heating oil are examples for secondary energy carriers derived from crude oil. Secondary energy carriers are usually transported to the end-users, e.g. the consumers of electricity or heating oil, who receive *end-use energy* E_{end}, i.e. secondary energy minus transportation losses, and transform it to *useful energy* E_{useful}, e.g. light or useful heat, in different end-use applications. Typically end-use energy is the amount of delivered energy the consumer is charged for, e.g. in electricity bills. How much of this end-use energy is actually converted into useful energy, e.g. net heating energy, depends on the efficiency of the corresponding end-use appliances, e.g. the heating system.

End-use energy efficiency can be defined as the ratio between useful energy output and end-use energy input (Equation 1).

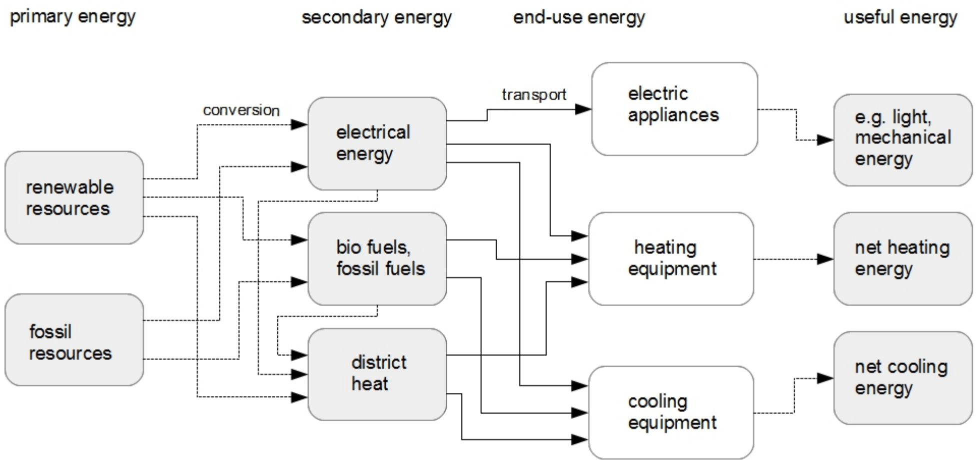


Fig. 3: Schematic conversion from primary energy to useful energy consumed in buildings (simplified and incomplete)

$$\eta_{end} = \frac{E_{useful}}{E_{end}} = \frac{E_{end} - E_{loss}}{E_{end}} \tag{1}$$

In this thesis we focus on end-use energy consumption in buildings within household and service sector. However, with the increasing use of electric vehicles that are often charged at home or at work, i.e. at outlets connected to residential or non-residential buildings, it might become more difficult to identify how much energy is used for transportation and building-related purposes, correspondingly.

2.2 Electricity-bound energy consumption

Energy consumption by white goods (e.g. washing machines, freezers), brown goods (e.g. computers, TVs), electric tools, lamps, and building equipment, e.g. pumps, elevators, fans, motors, is called electricity-bound energy consumption in this thesis, assuming that only electrical energy can be used for these purposes. Different types of electric devices for the same purpose might exhibit very different end-use efficiencies. In the EU average energy efficiency of large electric devices like freezers, washing machines, dish washers, baking ovens, increased by about 12–14 % from 2000 to 2012 [32], mainly due to the replacement of older appliances by new, more efficient ones. Average efficiency of lighting equipment increased by about 17 % [32] in the same period, which can be explained by the replacement of incandescent light bulbs by fluorescent lamps. Roughly speaking, electricity-bound energy consumption depends on the number of electric devices used, corresponding electric loads and efficiencies, and the frequency and duration of grid-connected use or charging. The number of electric appliances in a building often depends on the number of people living or working in it. The number of people is usually positively correlated with building size, or floor space, i. e. the more people, the larger the building. The general building type, e.g. residential building, office building, school, often implies the use of specific appliances. In residential buildings, white goods and kitchen tools often are predominating with respect to electric load and use frequency, while in office buildings, computers, monitors, servers, lamps, and building-related equipment like elevators or ventilation systems might be more important. Additional factors like number and age of residents in a household, employment status, time spent at home, personal interests, routines, individual choices and attitudes largely affect the variety, number, and diurnal use patterns of appliances in residential buildings. The decision to use or not to use an appliance with comparably high electric load, e.g. a baking oven for making dinner, can have a considerable impact on hourly electricity consumption in the corresponding household on the corresponding day, but it is hard to predict. In larger non-residential buildings some large appliances like illumination, ventilation system, or servers, are often either running continuously, or are controlled by a central control system, so that diurnal profiles of total electricity-bound consumption exhibit less variations. However, both in residential and non-residential buildings diurnal consumption patterns depend on day-types, such as working and non-working day, and vary from month to month.

2.3 Energy consumption for heating and cooling

Across all sectors heating energy is needed for covering the demand for space and water heating in the building stock. Heating energy demand can be covered by a variety of energy carriers that can be transformed to heat at the desired temperature level. In Central Europe, heating systems are commonly based on fossil fuels, while in Norway a combination of electric and biomass heating, in single-family houses often supported by air-to-air heat pumps, is usual. Domestic hot water, i.e. hot tap water, can be prepared in instantaneous heaters or in hot water tanks, and both heater types are available electrically driven or combined with a central heating system. Since heating energy for domestic water heating needs to be provided at high temperatures to ensure a certain water temperature for hygienic reasons, the electric or thermal load of domestic water heaters during operation is comparably high. Domestic water heaters are typically designed according to the number of residents, or the number of hot tap water installations, e.g. sinks, showers, in a dwelling or building. In Norway, electrically heated 200-litres tanks are common in single-family houses. As hot water is tapped from the top of the tank, the tank is refilled with cold water at the bottom. As soon as water temperature falls below a lower temperature threshold, re-heating starts until water temperature reaches an upper temperature threshold.

Cooling energy is a common expression for the amount of heat removed from a system, i.e. a room or a refrigerator. Cooling energy demand, e.g. for space cooling or refrigeration, can be covered by compression chillers driven by electrical energy, or by sorption chillers enabling the use of heat for cooling purposes. In Central and Northern Europe space cooling in non-residential buildings like office buildings, shopping centres, hospitals, or hotels is common, but it is usually not provided in residential buildings.

Space heating and cooling load in a building largely depend on the temperature difference between inside and outside environment, the size of the building, and building envelope characteristics. Heat transport from or to the outside environment occurs due to heat transmission through building elements like roofs, walls, floors, through small openings in the building shell, e.g. between windows and wall elements, and through manual or mechanical ventilation. Heat is also transported within a building, e.g. from areas with higher temperatures to areas with lower temperatures. Heat transported out of the building or room can be called heat loss, while heat transported into the building or room represents a heat gain. Moreover, heat gains occur e.g. through body heat of people living or working in the building, waste heat from electric appliances, or solar irradiation.

Heat transmission often accounts for the largest amounts of heat transport between inside and outside environment, so that building codes used to focus on limiting the *thermal transmittances*, or *U-values*, of certain building elements. The U-value of an element U_e mainly consists of the reciprocal of the aggregate *heat transmission resistance* of the element's different layers[1]. Heat transmission resistance is defined as the quotient of the layer's thickness and *thermal conductivity* so that the lower each layer's thermal conductivity and the thicker each layer, the lower the element's U-value.

Heat transmission rate $\dot{Q}_{T,e}$ through an element, e.g. an outside wall, can be described as the product of the element's U-value U_e and surface A_e, and the temperature differ-

[1] neglecting the effects of convection and radiation on the wall's in- and outside

ence between inside and outside. In case inside air temperature t_{in} is above outside air temperature t_{out} heat is transported out of the building, i.e. heat losses occur, typically in winter. In case $t_{out} > t_{in}$ heat is transported into the building, representing another type of heat gains that typically occur in summer.

$$\dot{Q}_{T,e} = U_e \cdot A_e \cdot (t_{in} - t_{out}) \tag{2}$$

Neglecting the thermal storage capacity of the building heating and cooling loads can be defined as difference between heat losses and heat gains. When heat losses exceed heat gains, indoor temperature drops, so that in order to maintain a desired indoor temperature the building needs to be supplied with an adequate amount of heating energy that equalizes all heat losses that can not be outweighed by heat gains. Analogously, heat needs to be removed from the building in case heat gains exceed heat losses and indoor temperature is intended to remain constant. Heating and cooling loads can be modeled and simulated in detail using dedicated software, e.g. IDA ICE [33].
The sum of heat losses $\dot{Q}_{loss}$ can be described as the product of a building specific *heat loss coefficient* H_{loss} and the driving temperature difference $t_{in} - t_{out}$ while internal heat gains $\dot{Q}_{gain}$ are assumed to be temperature-independent (Equation 3). Due to heat gains space heating is first required when outdoor temperature drops below a threshold, called base temperature t_b, so that the impact of heat gains can be approximated by Equation 4. Due to lower heat loss coefficients base temperatures in newer buildings are typically lower than in older buildings.

$$\dot{Q}_H = \dot{Q}_{loss} - \dot{Q}_{gain} = H_{loss} \cdot (t_{in} - t_{out}) - \dot{Q}_{gain} \tag{3}$$

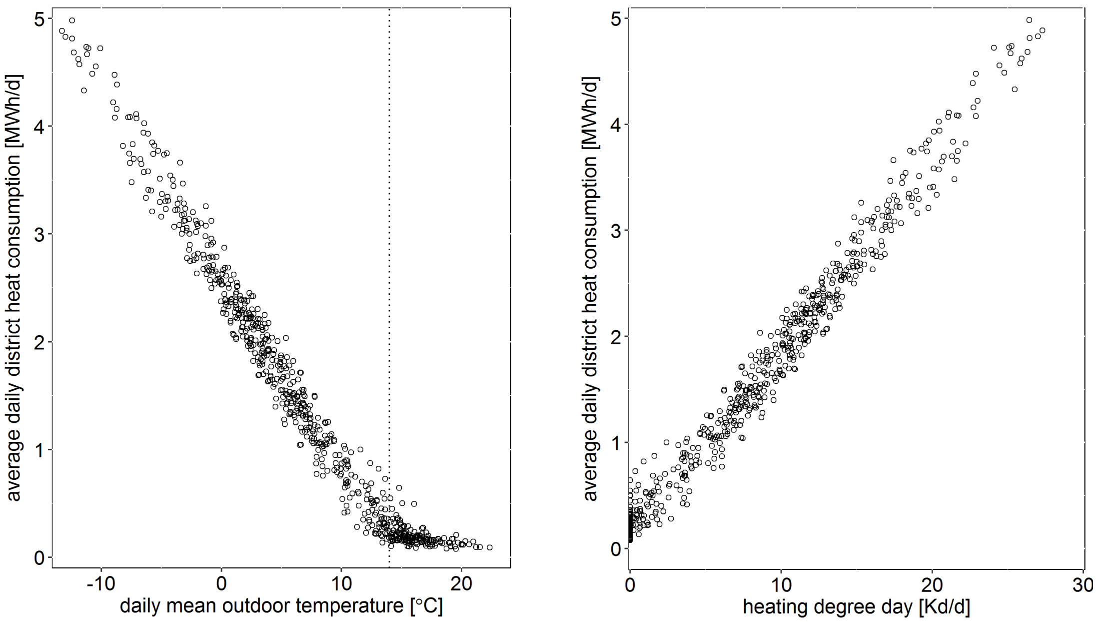
$$\dot{Q}_H \approx H_{loss} \cdot (t_b - t_{out}) \tag{4}$$

Integrating heating load $\dot{Q}_H$ over time yields heating energy Q_H. Neglecting hourly variations in outdoor temperature daily heating energy consumption can be estimated as the product of heat loss rate and the difference between base temperature t_b and daily mean outdoor $\bar{t}_{out,d}$, which describes a common *degree day* practice.

$$Q_{H,d} \approx H_{loss} \cdot (t_b - \bar{t}_{out,d}) = H_{loss} \cdot HDD_d \tag{5}$$

A *heating degree day* HDD_d[2] is defined as the positive difference between a chosen base temperature t_b and daily mean outdoor temperature $\bar{t}_{out,d}$, and it is zero when $\bar{t}_{out,d} \geq t_b$.

Average daily district heat consumption in a sample of office buildings as a function of daily mean outdoor temperature is shown in Figure 4a. Since consumption exhibits a kink around $\bar{t}_{out,d}$=14°C a base temperature of 14°C is used for calculating *HDD* in this example. Average consumption as a function of heating degree day is shown in Figure 4b. While district heat consumption is negatively correlated with outdoor temperature it is positively correlated with *HDD* and the slope in Figure 4b can be interpreted as the sample's average heat loss coefficient. Obviously, using a common t_b for all consumers and the choice of t_b based on visual judgement implies a certain error. Methods for approximating t_b are e.g. described in [34, 35]



(a) Consumption over temperature **(b)** Consumption over *HDD*

Fig. 4: Daily mean district heat consumption in office buildings (workdays) over daily mean outdoor temperature and heating degree days

In order to compare annual energy consumption in different periods, e.g. years, the sums of daily *HDD* during the corresponding periods are calculated. For calculating *HDD* in Norway usually t_b=17°C is chosen. In theory, heat consumption at outdoor temperatures larger than or equal to base temperature represents heat consumption

[2] Index d is dropped in the following.

for tap water heating, which is often negligible in office buildings but substantial in residential buildings. Moreover, space heating consumption only exhibits a clear temperature dependency if the heating system is feed back controlled, i.e. heating energy is only consumed until e.g. a desired indoor temperature is reached. In case heaters are turned off and on manually, or run continuously almost all year, e.g. electric floor heating in bathrooms, heat consumption and outdoor temperature or HDD are less correlated.

Cooling load and cooling energy demand for space cooling can calculated analogously, using cooling degree days CDD. A cooling degree day is defined as the positive difference between $\bar{t}_{out,d}$ and t_b, i.e. $CDD = 0$ as long as $\bar{t}_{out,d} \leq t_b$. When heat gains exceed heat losses, and indoor temperature rises above an upper threshold, heat needs to be removed from the building. Especially office buildings, with often high shares of window area and high heat gains from electric appliances like computers, copy machines, elevators, artificial lighting, as well as from body heat of people working in the building, require space cooling during summer. Space cooling is usually implemented through chillers connected to the central air conditioning unit or by individual chillers placed in the rooms that need to be cooled. Compression chillers and heat pumps utilize the same thermodynamic process, the only difference lies in the application. Using a heat pump the desired energy output is high-temperature heat at the condenser, while the desired effect of a compression chiller is the intake of low temperature heat at the evaporator. A big disadvantage of compression chillers is the comparably large amount of heat of condensation, which is typically discharged as waste heat to the environment by re-coolers placed on the buildings' roofs.

Different heating systems imply different shares of energy losses and thus different end-use efficiencies. Direct electric heating, e.g. using electric ovens directly heating the air, is often assigned an efficiency of $\eta_{end} \approx 1.0$, while a hot water heating system, i.e. central heating, implies some energy losses and thus lower efficiencies. A building connected to a district heating network is usually equipped with a hot water heating system, where a heat exchanger supplied by district heat serves as heat source. Heat losses occur at the heat exchanger and in the central heating system. Similarly heating and cooling via a central air conditioning system implies different kinds of energy losses, however, the systems often implement energy recovery, e.g. using heat exchangers. Heating systems implying a combustion process, e.g. by burning heating oil or fire wood, can be realised by a central furnace and a hot water heating system, or by heating units placed directly in the rooms to be heated. Since during combustion energy is usually lost via the exhaust gas, end-use efficiencies of conventional furnaces are lower than in case of electric or district heating. However, modern systems, e.g. incorporating exhaust gas energy recovery, yield considerably reduced energy losses and thus higher efficiencies. Heat pumps utilize a low temperature heat source that is usually freely available, e.g. outside air, exhaust air, geothermal heat. Since electrical energy is normally the only end-use energy metered and billed, end-use energy efficiencies larger than 1.0 are achieved.

Based on to this theoretical background heat loss rate, base temperature, type of heating or cooling equipment, as well as outdoor temperatures, represented by heating and cooling degree days, are assumed to be important factors for modeling end-use energy consumption for space heating and cooling in buildings.

3 METHODOLOGY

3.1 Approaches for modeling aggregate energy consumption in the building stock

As outlined in Chapter 2 energy consumption in a building consists of different components representing different end-use appliances. Aggregate energy consumption in a multitude of buildings, e.g. a regional buildings stock, represents the sum of energy consumptions by the individual buildings. Mathematical energy consumption models can be roughly divided into *bottom-up* and *top-down* models.
Assuming the goal is modeling aggregate energy consumption in a building stock top-down models usually rely on historic values of aggregate consumption and macroeconomic variables like gross domestic product, prices, population, and weather variables such as *HDD*. Trotter et al. [36] describe a top-down approach for modeling daily electricity consumption in Brazil and use the model for forecasting electricity demand considering different forecasts on weather related input data with respect to climate change. The multiple linear regression model includes *HDD*, *CDD*, and daily sun hours, gross domestic product (GDP), population, as well as calendric information. Dependent variable, GDP, and population are included as log-transformed variables. Bentzen and Engsted [37] use autoregressive distributed lag (ARDL) models that includes a lagged dependent variable, i.e. energy consumption in a preceding period. Top-down models are often used to evaluate economic factors, e.g. income or price elasticities [38], or for long-term projections. Typically top-down models only need few and easily available input variables, however, changes in disaggregate consumption, e.g. regarding the use of different electric appliances or heating equipment, cannot be implemented.
Bottom-up models for aggregate energy consumption typically model energy consumption of individual buildings or end-use appliances, or corresponding archetypes, first and then aggregate consumption over the entire building stock. Typical input variables for bottom-up models are consumer-specific variables, such as building type,

dwelling or building size, building age, information on different appliances and heating equipment, as well as weather variables, e.g. outdoor temperatures or sun hours. Bottom-up models can further be divided into statistical models and engineering models [39]. Bottom-up engineering models are developed based on consumption characteristics of single end-use appliances combined with detailed information on e.g. building physics, occupancy patters, and number of different appliances [40–43]. In theory, no historical consumption data is necessary to develop engineering models, and the effects of new technologies can be implemented and assessed. Disadvantages of engineering models are that consumer behaviour is often based on assumptions, and that developing and applying the models often requires high expertise [39].
Statistical bottom-up models for residential consumption are developed based on historic consumption data of a sample of representative buildings and additional variables describing the individual buildings. Common statistical bottom-up modeling techniques are regression and artificial neural networks (ANN). The latter represent a more sophisticated, data-driven form of mathematical models used for modeling and forecasting energy demand and has become increasingly common during the past 15 years [44–49]. Strongly simplified an ANN consists of input and output nodes that are interconnected by a network of hidden nodes performing calculations and passing on the corresponding results. By comparing output values with desired output values, e.g. meter data, and feeding this error back to the network the ANN can be trained and improved in order to minimize the error. In contrast to regression models ANN do not produce coefficients with a practical interpretation and the method usually requires high developer skills and powerful computer resources.
Conditional demand analysis (CDA) requires a dataset containing meter data from a sample of consumers and detailed information on the appliances used by the individual consumers. Multiple linear regression is applied to model total energy consumption as a function of the numbers of appliances used, and the resulting coefficients represent estimates on energy consumption of each appliance. Parti and Parti [50] applied the method to disaggregate monthly electricity consumption according to different end-use appliances. Larsen and Nesbakken [51] compared modeled annual disaggregate electricity consumption from a CDA model with the results from an engineering model (ERÅD). The CDA model is based on annual electricity consumption and survey data from Norwegian households and yields $R^2 \approx 0.5$. However, insignificant CDA results for appliances that are used within most households result in a high share of miscellaneous consumption, and the shares of modelled end-use energy consumption for space

heating and domestic water heating resulting from the engineering model exceed the CDA-results largely. The high level of detail in required input data is reported to be a major drawback of the engineering model.
Many bottom-up regression models for energy demand modeling rely on the Princeton Scorekeeping Method (PRISM) [34], whose original purpose was to determine the weather-normalized energy savings achieved through retro-fit measures. The model describes the fundamental correlation between outdoor temperature and heating energy consumption, and calculates individual values for base temperature t_b, temperature-independent consumption β_0, and heat loss coefficient β_1 for each consumer, mainly based on monthly billing data of gas heated houses. An iterative procedure is used for finding the base temperature that implies a maximum coefficient of determination R^2 for the straight-line fit of energy consumption $E_{m,i}$ versus average heating degree day $HDD_{m,i}(t_{b,i})$, which is a function of individual base temperature.

$$E_{m,i} = \beta_{0,i} + \beta_{1,i} \cdot HDD_{m,i}(t_{b,i}) \tag{6}$$

With the three main parameters $t_{b,i}$, $\beta_{0,i}$, $\beta_{1,i}$ weather-normalized energy consumption before and after the retro-fit actions can be obtained using the number of heating degree days in a normal year as input variable, thus allowing the calculation of weather-normalized annual energy savings.
Hirst et al. [52] extend the PRISM method in order to categorize households according to their use of other heating fuels, based on electricity meter data. A sample of households is divided into different categories indicating whether only electricity is used for space heating, other fuels are used supplementary, or no electricity is used for space heating, and weather-normalized annual consumption in two subsequent billing periods is calculated. The effects of switching from only electric heating to supplementary or completely heating with other energy carriers from one period to the other, and other household characteristics collected by a telephone survey, are discussed. Moreover, the paper addresses typical issues regarding meter failures and outlier detection.
Pedersen et al. [35] describe prediction models for hourly heat and electricity demand in different residential and non-residential building types with district heating in Norway. For each building base temperature is determined, and temperature-dependent heat demand is modeled using linear regression models for each hour of the day and each day-type, using daily mean outdoor temperature as independent variable. Aver-

age daily design load is calculated as the mean value of the 24 hourly heat loads at design outdoor temperature, and relative design load profiles are generated by dividing each hourly load with average daily design load. Thus, generalized hourly consumption profiles for different building archetypes and daytypes are generated.
Kavousian et al. [53] use a large sample of smart meter data with a 10-minutes metering interval combined with survey response data to evaluate the impacts of different factors on daily minimum and maximum load, respectively. Due to comparably many cross-sectional variables factor analysis to deal with collinearity, i.e. high correlation between explanatory variables, and a stepwise selection method for selecting the included variables are applied. According to [53] weather variables and building physics are the most important factors for residential electricity consumption. Djuric and Novakovic [54] use multivariate analysis to identify the key variables affecting energy consumption in low-energy office buildings based on detailed building energy management data and energy consumption data. Energy consumption is modeled based on Principal Component Analysis and Partial Least Squares. The results indicate that heating energy consumption is more affected by operational parameters than by outdoor temperature, and that occupancy levels, indoor temperature, and single air-conditioning signals are the most important factors for modeling total electricity consumption.
In the following section a bottom-up approach for modeling aggregate hourly energy consumption in a regional building stock is described.

3.2 Multiple linear regression using panel data

Due the implementation of hourly metering, time series of electricity and district heat consumption are stored by the system operators. Cross-sectional data can be collected by performing surveys among different consumer groups, e.g. households and service sector customers. Combining time series and cross sectional data by a consumer identification code *(ID)*, results in *panel data*.
A simplified example of a panel data set based on hourly meter data is shown in Table 1. Since hourly energy consumption in each hour of the day, E_1 through E_{24}, is included in form of separate columns the time-series interval is 1 day, indicated by $date$ in the first column. The second column includes the individual *ID* of each consumer. Calendric variables, such as *month* and *daytype*, and weather data *HDD* vary from day to day, but are constant for all hours of the day. Cross-sectional variables, such as *floor*

space, *adults*, *children*, are constant within each individual time-series.

Tab. 1: Illustration of the panel data structure

date	*ID*	*floor space*	*adults*	*children*	*daytype*	*month*	*HDD*	E_1	...	E_{24}
03-11-2013	M0001	170	2	2	Sun/holiday	11	15.3	3.21	...	3.30
04-11-2013	M0001	170	2	2	workday	11	14.8	3.08	...	3.25
...	...	...	...	...	...	...	...	...	...	...
03-11-2013	M0500	100	1	0	Sun/holiday	11	15.3	2.81	...	2.91
04-11-2013	M0500	100	1	0	workday	11	14.8	2.80	...	2.88

For model development throughout this thesis the method of *Ordinary Least Squares (OLS)* is applied to panel data. Since observations are pooled across time the method is called *pooled OLS* [55].

Explained in terms of energy consumption data, for each consumer i and each date 24 meter data entries are available. The model set for hourly energy consumption is based on multiple linear regression, as illustrated by Equation 7, where $E_{h,i}$ represents energy consumption in hour h and observation i, $\beta_{0,h}$ is the intercept parameter, $\beta_{k,h}$ the slope parameters, and ε_i the unobserved error term. Explanatory variables $x_{k,i}$ represent cross-sectional, weather, and calendric data, and a common model set up is used to estimate separate coefficients for all 24 hours.

$$E_{h,i} = \beta_{0,h} + \sum_{k=1}^{k} \beta_{k,h} \cdot x_{k,i} + \varepsilon_i \tag{7}$$

The modeled values of hourly consumption $\hat{E}_{h,i}$ are calculated based on the corresponding parameter estimates $\hat{\beta}_{0,h}$ and $\hat{\beta}_{k,h}$ (Equation 8). The residuals $\hat{\varepsilon}_i$ represent the difference between modeled and metered consumption values.

$$\hat{E}_{h,i} = \hat{\beta}_{0,h} + \sum_{k=1}^{k} \hat{\beta}_{k,h} \cdot x_{k,i} = E_{h,i} - \hat{\varepsilon}_i \tag{8}$$

Advantages of an hourly energy consumption model based on pooled OLS are its simplicity and the straightforward interpretation of regression coefficients β_0 and $\hat{\beta}_{k,h}$. An analysis of variance (ANOVA) yields the contribution of each explanatory variable to total explained variance for each hour of the day, facilitating an assessment of different factors. Since modeled consumption consists of several individual components, i.e. $\hat{\beta}_0$ and $\hat{\beta}_k \cdot x_k$, it can be broken down accordingly to analyse how much different factors actually contribute to modeled consumption. An example illustrating modeled electricity consumption in all 24 hours, divided into different components, is shown in Figure 5.

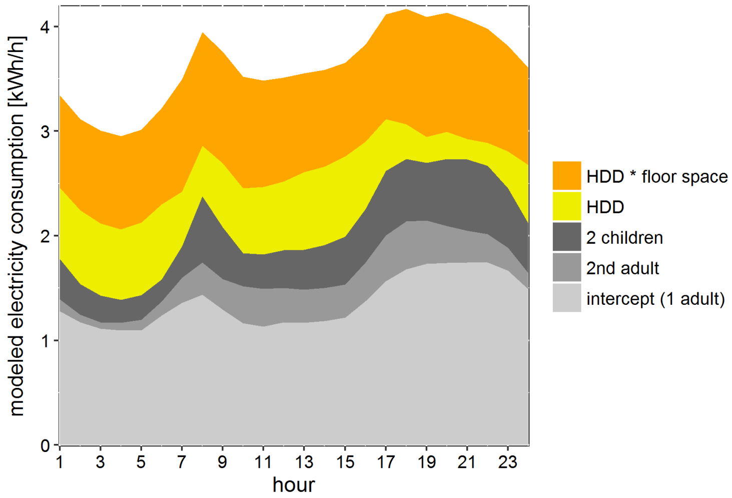


Fig. 5: Illustration of different components forming modeled consumption

In this case the intercept $\hat{\beta}_0$ represents modeled average consumption of a one-person household on a workday in January. The two dark and medium grey components illustrate how much more electricity is consumed on average if a second adult and two children reside in the dwelling as well. The yellow and orange areas represent the contributions of *HDD* and *HDD* in interaction with *floor space*, respectively, for defined input values (in this example *HDD*=20, *floor space*=100). Moreover, components including *HDD* can be interpreted as modeled energy consumption for space heating, assuming that only space heating energy demand is *HDD*-dependent. Components including *CDD* could be interpreted as modeled energy consumption for space cooling, accordingly.

Due to the simple model structure without any transformed variables modeling *time-aggregate*, e.g. individual daily consumption, and *sample-aggregate* consumption, i.e. hourly consumption of several consumers, or a combination of both is easily performed. In order to model aggregate hourly energy consumption in a regional residential building stock the total number of dwellings, aggregate floor space, as well as the relative frequencies of all cross-sectional explanatory variables are required.

The method also implies some drawbacks. As parameter estimates only represent average effects of different variables, samples need to be representative in order to apply the models to an entire building stock. Depending on the number of explanatory variables comparably large samples are required. Roughly speaking, with longer meter data time series available the impacts of weather and calendric variables, such as

HDD, *month*, *daytype*, can be modeled more accurately, while meter data from more individual consumers, i.e. an extended cross-sectional component, yields more reliable estimates on variables such as floor space, or number of adults or children. The method is sensitive to outliers, which can easily be caused by erroneous meter or survey response data. Detecting and evaluating outliers in large panel data sets can be difficult and time consuming.

4 RESULTS AND DISCUSSION

In papers I–IV the methodology described in Section 3.2 is applied and the key factors for hourly energy consumption are analyzed accordingly. The sub-objectives of this thesis are fulfilled by the results of the individual papers.

4.1 Hourly electricity consumption in households

Hourly electricity consumption in Norwegian households is analyzed in Paper I and Paper II. By combining hourly electricity meter data and survey response data from two samples of households located in Norwegian counties Buskerud and Telemark two panel data sets were available. The datasets were completed with outdoor temperature data metered at corresponding weather stations as well as with calendric information.

4.1.1 Assessing the impacts of different heating systems

In Paper I hourly electricity consumption in detached houses included in one of the samples (Buskerud) during the main heating period is modeled using pooled OLS. Two model sets, one for households with direct electric space heating, and one for households with central heating systems are developed, and modeled hourly electricity consumption in an average households using different heating equipment is compared. An interesting result lies in the survey data itself, revealing that households using air-to-air heat pumps as a supplement to direct electric space heating on average use less wood burning than households with direct electric space heating. Wood burning is widely used in Norwegian households, however, with varying intensities. Compared to direct electric heaters air-to-air heat pumps consume less electrical energy when providing the same amount of useful heat. When households partly substitute wood burning by air-to-air heat pumps energy savings by using the heat-pumps may thus not necessarily result in reduced electricity consumption, but rather in reduced wood consumption.

In order to isolate the impacts of using different heating systems and equipment, the developed regression models include corresponding dummy variables, mainly in interaction with *HDD*. Achieved goodness of fit for both model sets is in the same range ($R^2 \approx 0.35 - 0.4$), while the importance of different variables differs. For households with direct electric space heating heating degree day – as stand-alone variable and in interaction with floor space is the most important explanatory variable, and explains about half of total explained variance. For households with central heating *HDD* in interaction with type of heat source, i.e. electric boiler, oil boiler, or liquid-to-water heat pump, *HDD* alone, a dummy variable indicating whether domestic hot water tanks were electrically heated, and floor space were the most important variables. Moreover, in both model sets resident variables, mainly the number of adults and children, were important variables. The results of Paper I indicate that both using air-to-air heat pumps and wood burning, divided into two intensity levels, imply reduced electricity consumption during all hours of the day, however, non-electric central heating implies the largest reductions. A rough scenario analysis on the sample's aggregate hourly electricity consumption on a cold January day compares possible reductions in hourly consumption in case of area-wide changes in heating methods. Assuming all households with direct electric heating would use air-to-air heat pumps, and leave firewood consumption unchanged, the results indicate comparably small reductions of 2–5 % over the course of the day. Assuming the households would in addition use intensive wood burning, reductions in modeled aggregate consumption are 10–12 %. Assuming that all households would switch to non-electric central heating, including domestic water heating, modeled reductions are between 45 % during afternoon and evening, and 60 % during morning.

4.1.2 Modeling and disaggregating hourly electricity consumption and evaluating the use of hourly temperature data

Paper II analyzes electricity consumption in households with direct electric space heating, situated in Buskerud, and includes also attached dwellings, such as terraced and semi-detached houses or apartments. However, the majority of households represent detached houses. Analyzed metering period spans about ten months, missing June and July. In order to evaluate whether including hourly meter values of local outdoor temperature in the corresponding hourly models yields more accurate models two hourly model sets are developed: One model includes heating degree *day*, that is constant for all 24 hours of the day, while the second model includes heating degree *hour*, HDH, that varies from hour to hour. Each model set includes a 1st differences variable, representing the difference in *HDD* from one day to the next, and the difference in HDH from one hour to the next, respectively. Comparing goodness of fit achieved by both models indicates that – with the described model set up – models based on HDH do not perform better than models based on *HDD*, which leads to the conclusion that using the described modeling approach *daily* mean temperature values are sufficient for modeling *hourly* heating energy consumption. Based on the *HDD*-based model set a simple method for disaggregating modeled total hourly electricity consumption into a component for electric space heating and a component for all remaining purposes, i.e. electric appliances and domestic water heating (DWH), is described, dividing modeled consumption into temperature-dependent and temperature-independent elements. In order to properly validate the disaggregation method data from sub-metering electric heating equipment is necessary, which was not available in this study. In order to at least roughly check the results modeled electricity consumption for electric appliances and DWH are compared with modeled electricity consumption in households with non-electric central heating, based on the models presented in Paper I, which indicated useful – albeit uncertain – results. Disaggregate modeled consumption indicates that the characteristic *shape* of hourly electricity consumption in households, e.g. morning peak and evening top, is mainly influenced by temperature-independent components, such as DWH, white goods, lighting, while the *level* of consumption is mainly influenced by temperature-dependent components, i.e. modeled heating energy consumption. In order to test the applicability of the model based on data from Buskerud to other Norwegian regions hourly electricity consumption in the second sample (Telemark) is modeled. In both samples the majority of households using direct electric heating resided in detached houses and average dwelling sizes were in the same range. Both on individual household level as well as on sample-aggregate level achieved goodness of fit were similar to the values achieved for the original data set, indicating that the method is well applicable to other Norwegian regions with a similar structure.

4.2 Hourly consumption of electricity and district heat in non-residential buildings

The analyses performed in Paper III are based on hourly meter data of electricity and district heat in samples of schools and office buildings located in Oslo. Meter data is combined with cross-sectional data from the Norwegian energy label database, temperature data, and calendric information. As opposed to the data used in Papers I and II the resulting panel data sets contain only few observations and few cross-sectional variables, however, the meter data time series spans approximately three years. For both building types three regression models are developed each: one model for hourly consumption of district heat, and one for hourly electricity consumption in case of electric heating and non-electric heating, correspondingly. Due to the limited availability of cross-sectional variables and the low number of observations only *floor space* is included as cross-sectional variable in the electricity consumption models, while the models for district heat in addition include a dummy variable indicating *old* buildings. Although the number of explanatory variables is low the resulting models on average achieve higher shares of explained variance than the electricity consumption models for households, described in Papers I and II. This can be explained by more regular diurnal consumption patterns in non-residential buildings, that are mainly influenced by calendric variables, such as dummy variables indicating workdays or non-workdays, and by the longer meter data time series available. Comparing modeled total hourly energy consumption in buildings with electric heating (only electrical energy) with corresponding values for buildings with district heating (the sum of electrical energy and district heat) indicates that the shape of total consumption is similar, but that there are larger differences between night- and daytime consumption in buildings with electric heating. In office buildings with district heating total consumption in the morning is on average higher than in office buildings with electric heating, while it is lower during the main office hours. This can be explained by the hot water based central heating systems on average requiring more time to deliver heat to the corresponding rooms, compared to e.g. direct electric heaters, and thus starting earlier. Moreover, the comparison indicates that in schools with district heating less indoor temperature reduction during night-time, weekends, and school holidays is used compared to schools with electric space heating. A possible explanation for this result might be that school buildings and sports halls might be used for other purposes beyond the school days. Comparing the annual shares of modeled disaggregate consumption, i.e. modeled consumption for space heating and other purposes, respectively, indicates that buildings using district heat on average consume higher shares of heating energy compared to buildings with electric heating. Since modeled district heat consumption is assumed to include also energy consumption for tap water heating, which is not included in modeled space heating energy consumption in case of electric heating, higher shares of heat in case of district heating are feasible. However, low sample sizes for buildings with electric heating, simplifications connected to the disaggregation method, as well as differences in building age that are not sufficiently accounted for in the models, might lead to differences in modeled shares of disaggregate consumption. Comparing modeled annual heat shares for schools and office buildings indicates that a higher share of total annual energy consumption in schools is used for heating purposes, which can be explained by higher indoor temperatures and less periods with temperature reduction, less internal heat gains, higher consumption of hot tap water, and on average older buildings. Correspondingly a higher share of modeled temperature-independent energy consumption in offices can be explained by more electric appliances used and the use of space cooling during summer.

Although the general model results are feasible the samples, especially for buildings with electric heating, are too small to obtain reliable models.

4.3 Modeling and forecasting regional hourly electricity consumption in buildings

In Paper IV regression models for hourly electricity consumption in different consumer groups within household and service sector are developed based on the data and findings described in Papers I–III. In order to test the applicability of the models historic electricity consumption in the two sectors for each Norwegian county is modeled as aggregate consumption in the building stock connected to the corresponding sectors and compared with metered annual and hourly consumption data. The required input data is based on official building stock statistics as far as available, on household survey results from Buskerud, on the Norwegian energy label database, as well as on a number of assumptions. Average floor space values for each building category are only available for Oslo county. However, being the capital, Oslo on average exhibits more employees per building than other counties, so that average floor space for all other counties is estimated based on a adjustment factor. A comparison of modeled and metered annual electricity consumption in 2012 per sector and county yields relative

errors of less than $\pm 8\,\%$ for most counties. However, the household model overestimates metered consumption in three counties by more than 10 % and underestimates it in the most Northern county by 20 %, which can be explained by weak assumptions regarding main space heating system and wood burning intensity, by not choosing representative weather stations or base temperatures for calculating HDD, or simply by regional differences in consumption that cannot be reproduced by a model based on data from only one county. For example, less daylight and thus higher energy consumption for lighting and less solar gains during winter in northern counties cannot be accounted for in the existing models, that are exclusively based on data from a southern county. Since metered hourly electricity consumption is not available on county level, but only aggregated according to Nord Pool[56] regions, assessing the quality of modeled hourly consumption is more difficult. However, the results show that the shape, i.e. the hourly profile, of modeled aggregate hourly consumption in households and service sector is very similar to the shape of total consumption, both on national level as well as in the largest Nord Pool region, so that the corresponding difference, in theory representing consumption in industries, transport, and agriculture, as well as the modeling error, exhibits relatively small hourly variations.
Based on official forecasts on population development and future outdoor temperatures forecasts on hourly electricity consumption in Oslo in 2040 are performed considering three scenarios of low, medium, or high population growth, respectively. Forecasts on outdoor temperatures imply a reduction in HDD, and an increase in cooling degree days. Since the service sector models do not include variables indicating building age or thermal building standard modeled electricity consumption for space heating purposes is reduced by an arbitrary reduction factor. Assuming low or medium population growth modeled electricity consumption for space heating purposes in 2040 remains approximately on 2013-level, while modeled electricity consumption for electric appliances increases approximately according to population growth in all three scenarios. Only a high population growth scenario implies a noticeable increase in electricity consumption for space heating purposes, indicating that the increase in heated floor space outweighs the effect of reduced HDD, i.e. higher temperatures, and building stock renewal. Building-stock related input data for these simple forecasts were calculated very roughly, not considering changes in factors like average floor space, average number of people per household, average number of employees per building, or shares of employed people in each services category. Thus, the estimated number of future dwellings and buildings is approximately increasing propor-

tionally to population growth assumed in the different scenarios. Since, moreover, the developed models do not take into account future changes regarding number, loads, or energy-efficiency of electric appliances, temperature-independent consumption is approximately increasing proportionally to the number of buildings and dwellings.
The results of Paper IV indicate that the presented method enables modeling and forecasting regional hourly electricity consumption in households and service sector, however, that the availability of building stock related input data is a prerequisite for achieving meaningful results.

4.4 Discussion and further work

Top-down approaches for modeling and forecasting aggregate energy consumption in regional building stocks often mainly rely on macroeconomic variables, so that changes in building-stock related factors usually are not taken into account sufficiently. In contrast, detailed bottom-up engineering models often consider a variety of building specific variables and can take into account factors like energy efficiency improvements. However, engineering models usually require detailed input data, powerful computers, and both developers and users need high expertise.
In this thesis a bottom-up approach based on panel data, consisting of hourly meter data, cross-sectional data, weather data and calendric information is presented. The method enables straightforward assessment of the impacts of different factors on hourly energy consumption as well as the decomposition into different components, e.g. for estimating how much energy is consumed for electric appliances or space heating equipment, correspondingly. All models yield meaningful parameter estimates and acceptable values for goodness of fit. Sample-aggregate consumption can be modeled with considerably higher accuracy, since individual modeling errors are leveled out. Based on the data available the type of heating system, outdoor temperature transformed to heating degree day, floor space, and number of residents are the most important factors for modeling hourly electricity consumption in Norwegian dwellings. For modeling hourly electricity consumption in non-residential buildings building category, heating system, floor space, and daytype, e.g. indicating workdays or non-workdays, are identified as useful variables, however, more cross-sectional data available might reveal other important factors. The identification of the key factors implies that in order to apply the developed models for modeling or forecasting energy consumption in any Norwegian region these factors represent the input data required

to generate useful input data.
Hourly or sub-hourly metering of electricity and district heat consumption yields enormous amounts of individual meter data, and the time series available becomes continuously longer. Standardized and continuously improved customer surveys performed by the system operators can gather cross sectional data that can be unambiguously connected to the corresponding consumption data. Panel data sets with a reliable cross sectional component and a long time series component with little missing or erroneous data enable detailed energy consumption analysis and the development of improved consumption models, that e.g. are able to take into account increased energy efficiency or stricter building codes with respect to heat losses. Panel data from all Norwegian counties, containing the same variables, would allow analyses on regional differences in hourly energy consumption. Moreover, nation-wide surveys on building stock characteristics that are not covered by official statistics, such as heating systems or average floor space, would yield necessary input data to the models, so that useful scenarios for consumption forecasts can be developed.
As the building stock is renewed base temperatures are expected to decrease for both residential and non-residential buildings so that the calculation of *HDD* and *CDD* needs to be adapted. Base temperatures vary across consumers and are not only dependent on building physics and standards, but also highly dependent on behaviour and individual preferences, e.g. regarding indoor temperatures. Moreover, the impacts of different cross sectional or other weather related factors, such as sun hours and solar gains, that are often implemented in low-energy buildings, could be examined in order to obtain estimates on today's and future base temperatures useful for different consumer groups.

5 CONCLUSION

Hourly energy meter data combined with cross-sectional information, weather data, and calendric information can be used to develop models for hourly energy consumption in buildings. The method of pooled OLS enables a straightforward assessment of the importance of each variable for energy consumption in each hour of the day and facilitates the disaggregation of modeled consumption into different components. However, size and quality of the underlying panel data are essential for developing useful and representative models. With more data available the existing models can be refined by including further important variables so that the approach keeps the simplicity of a statistical model but at the same time accounts for important building related variables, such as base temperature or thermal building standard.

Main heating method, i.e. electric or non-electric heating, type of heating system, i.e. direct or central, as well as supplementary heating equipment, e.g. wood stoves or air-to-air heat pumps, largely affect hourly energy consumption in buildings. Moreover, evident key factors are outdoor temperature and building or dwelling floor space. The number and age of residents as well as dummy variables indicating the use of electricity-intensive appliances are further important factors for electricity consumption in households, while calendric variables are important factors for hourly consumption of both electrical energy and district heat in non-residential buildings.

The method described in this thesis yields important information for energy system planning and management. Forecasts on hourly consumption of both electrical energy and district heat on different levels of spacial aggregation are important for designing power grids and district heating networks. Estimates on how much electrical energy is used for space heating and could thus be replaced by e.g. district heat, as well as the involved changes in hourly and seasonal heat consumption patterns, yield valuable data for fuel substitution and load management evaluations. With refined models and improved building-stock- and weather-related input data, forecasts on electricity consumption in all Norwegian counties, e.g. in 2040, can be performed and serve as input data to energy system models. For example, different scenarios regarding area-wide changes in heating methods, such as introducing central heating systems supplied by modern district heating systems, could be analyzed with respect to economic and technological consequences.

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Part II

PAPERS

6 PAPER I

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Hourly electricity consumption in Norwegian households – Assessing the impacts of different heating systems

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ABSTRACT

This paper analyzes how different heating systems affect hourly electricity consumption in detached houses in Norway. Hourly electricity meter data, weather data, and response data from a household survey are merged into a large panel data set, and multiple regression models are applied to isolate the impacts of different heating systems for each hour of the day during the heating period. The results show that compared to direct electric heating, the additional use of air-to-air heat pumps, wood burning stoves, and oil stoves leads to relatively constant reductions in hourly electricity consumption over the course of the day while largest reductions – especially during hours of morning peak consumption – are achieved by using non-electric central heating systems. The presented method can be applied to other energy carriers, metering intervals and consumer groups and – depending on the data available – be used to model individual and aggregate regional energy demand with a high temporal resolution as well as to analyze how area-wide changes in climatic factors and important consumer characteristics will affect consumption of different energy carriers in smart energy systems.

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1. Introduction

While in conventional energy systems production used to follow demand, increasing power generation from variable renewable energy sources like wind and photovoltaics, as well as growing interconnections to other countries require more flexibility and storage capacity in today's and future energy systems. Accurate consumption models with a high temporal resolution are crucial in evaluating and implementing flexibility measures and help ensuring system stability and efficient operation. Due to the introduction of smart metering, hourly consumption data is available on micro level, and may be utilized to improve our understanding of electricity and heat consumption, including important dynamic features, differences between consumer categories, and differences associated with other important variables, e.g. heating systems.

In combination with competitive storage technologies for heat and electricity, demand side management measures like increased energy efficiency, fuel substitution and load management can help synchronizing energy demand and production in modern energy systems. Hedegaard and Balyk [1] report that a flexible operation of individual fluid-to-water heat pumps combined with in-house heat storages benefits the integration of wind power and is able to reduce peak loads. Modern district heating systems supplied by several different heat sources represent an important infrastructure for balancing energy systems with high shares of variable renewable supply, as illustrated by Lund et al. [2]. Lund et al. [3] present and discuss different flexibility measures forwarding energy systems with high levels of renewable electricity. According to their review, treating thermal and electrical system as one can be an important measure forwarding the integration of renewable power production [3]. The importance of combining thermal and electricity grids and increasing flexibility in 100% renewable energy systems are further illustrated by Lund [4], Lund et al. [2,5], and by Mathiesen et al. [6].

Aggregate and individual hourly electricity consumption data combined with cross-sectional data is analyzed by a number of studies. Average hourly profiles of different consumer groups or economic sectors in Norway and Denmark have been analyzed by Ericson and Halvorsen [7] and Andersen et al. [8] respectively. While workdays and non-workdays as well as different seasons are distinguished, the studies do not reveal differences in individual hourly consumption connected to different household characteristics, as e.g. heating systems. Kavousian et al. [9] present regression

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models for daily average, minimum, maximum and range of hourly electricity consumption based on meter data (10-min resolution) for a period from February to October 2010. Dwelling size (floor space) and cooling degree days are reported to be the most important factors explaining the different response variables. Yohanis et al. [10] examine average consumption profiles of different dwelling types in Northern Ireland on annual, monthly and hourly levels. Average profiles – absolute or specific (i.e. divided by dwelling floor space) – are generated according to different household characteristics, as e.g. number of residents, dwelling type and income. McLoughlin et al. [11] examine the influence of dwelling and occupant socio-economic variables on total electricity consumption over a six-months period and estimate maximum demand, load factor, and time of use of maximum electricity demand based on smart meter data from about 4200 Irish dwellings. Sandelds et al. [12] model hourly load profiles for Swedish detached houses with direct electric heating based on meter data from a substation in Stockholm, i.e. aggregate hourly consumption data. Paatero and Lund [13] use hourly electricity meter data from Finnish apartment buildings to generate hourly load profiles of individual households, not including larger electric heating loads. Pedersen et al. [14] describe prediction models for heat and electricity load in different building types in Norway. Hourly heat demand profiles are estimated using load factors, representing relative load referring to average daily design load. Hourly electricity demand – containing no heat demand – is based on probability distributions. In a recent study, Rhodes et al. [15] use smart electricity meter data combined with survey response data of 28 households in Texas in order to test the effect of different retrofit measures on daily electricity consumption using fixed effects panel regression. Further, a multiple regression model on total annual energy consumption of 41 homes is presented, reporting year of construction, dwelling size, number of adults as well as knowledge on energy and water use to be important explanatory variables. In another recent study, Fan et al. [16] identify the driving factors of residential energy demand in Australia. Though based on hourly electricity meter data, only daily electricity consumption is modeled both on individual and aggregate level.

To our knowledge, no study estimating the effects of different variables on individual hourly electricity consumption in households is available.

The goal of this paper is to quantify the impacts of different electric and non-electric heating systems on hourly electricity consumption in Norwegian detached houses, enabling systematic analyses on possible changes in individual and aggregate regional electricity consumption in case of area-wide changes in heating systems. To do so, hourly meter data of about 600 households is combined with weather data and data from a household survey into a large panel data set. The study documents a simple method for modeling hourly energy consumption that can easily be applied to other regions, dwelling types, energy carriers (e.g. district heat), and consumer groups (e.g. non-residential customers) in order to establish a complete picture of hourly regional energy demand.

2. Climate goals, regulations and heating systems in Norway

Due to climate and topography, Norway is able to cover about 96% [17] of its domestic power production by hydro power, and electricity covers about 50% [18] of domestic energy consumption. 35% of Norway's total electricity consumption in 2012 was consumed by households [19].

Although not a member of the EU (European Union), Norway is an important part of the European energy system – exporting oil, gas, power to EU countries – as well as an important part of the Nordic power system. Norway aims at being carbon-neutral by 2050 [20], covering 67.5% of its energy consumption in 2020 by renewable energy sources [20], and reducing greenhouse gas emissions according to the EU goals[1] [22]. The use of heating oil and paraffin for heating purposes is planned to be phased out by 2020 [23].

Today's building code defines that about 50%[2] of heating energy demand of new buildings need to be covered by alternative energy carriers, i.e. others than fossil fuels or pure electricity. Dwellings with a calculated heat demand of less than 15 MWh per year do not need to fulfill these minimum shares but can alternatively be equipped with a chimney and a fireplace for biofuels (e.g. firewood). Passive houses and dwellings not larger than 50 m^2 are excluded from all heating equipment requirements. In new buildings, central oil boilers as main heating source are no longer allowed and hot water heating systems need to be installed when located in concession areas of district heating networks [24].

The most common type of space heating in existing single-family houses in Norway is direct electric space heating in combination with wood burning. Electrically heated storage tanks are mainly used for DWH (domestic water heating). Hot water based central heating systems are relatively rare and mainly based on central electric boilers, central oil boilers, or central fluid-to-water (or air-to-water) heat pumps. In some Norwegian cities, district heating networks are established and cover the heating energy demand of connected consumers which today are mainly multi-family houses and non-residential buildings. Dwellings with central hot water heating systems do not necessarily use domestic hot water tanks supplied by the central heating system. Using electrically heated hot water tanks instead allows the central boiler (e.g. oil boiler) to be turned off outside the heating period.

During the last decade there has been a significant increase in the use of air-to-air heat pumps in Norway. In 2012, air-to-air heat pumps were installed in 27% of Norwegian households, and in even 44% of Norwegian detached houses [25]. An increased use of heat pumps[3] was expected to reduce average household electricity consumption. However, Halvorsen and Larsen [26] find that, on average, households using heat pumps do not consume less electrical energy per year compared to other households. Moreover, households using heat pumps might exhibit an even higher annual electricity consumption, indicating a certain rebound effect. Higher indoor temperatures, less consumption of alternative fuels and less commitment in energy-saving behavior are named as possible reasons [26].

3. Data

A web based survey on household specific data was carried out among electricity customers of system operator Ringerikskraft Nett AS in Hønefoss (Ringerike municipality) in southern Norway in October 2013. Only customers that had hourly metering systems installed in their homes were invited to participate. Invitations were sent to 9379 available customers, of which 1550 (response rate 16.5%) answered the questionnaire containing about 30 different items, mainly on technical information (e.g. floor space, dwelling age, number of household members, heating systems).[4]

[1] The European Union's latest targets regarding climate change and energy sustainability for all member states are a reduction of greenhouse gas emissions by at least 40% (with reference to 1990 level), a share of 27% of energy consumption from renewable energy sources and an increase in energy efficiency by 27% by the year 2030 [21].

[2] 40% for buildings $\leq$500 m^2 and 60% for buildings >500 m^2.

[3] If not otherwise indicated, *heat pump* refers to air-to-air heat pumps in this paper.

[4] Not all questions are answered by all 1550 respondents.

Outdoor temperature data metered at Hønefoss Høyby weather station is provided by the Norwegian Meteorological Insititute [27].

3.1. Survey response data

Altogether 608 useful responses represent permanently occupied, detached houses with usable electricity meter data during the defined heating period from 2 October 2013 to 30 April 2014. 508 observations use direct electric space heating, partly supplemented by air-to-air heat pumps, wood stoves, or oil stoves,[5] while 100 households use central heating systems.[6] All directly electrically heated dwellings use electric DWH, while some dwellings with central heating use hot water tanks supplied by the central heating unit. Thus, in the sample data, direct electric space heating is the clearly dominating heating method, being used in about 84% of households while only 16% of households use central heating systems, which is in good accordance with the results from Statistics Norway, reporting a share of about 13% hot water heating systems in Ringerike municipality in 2001 [28]. In our sample of centrally heated homes, oil boilers (45%) and electric boilers (35%) were the most frequent central heating units while central heat pumps were used by about 20% of households with central heating.

According to Statistics Norway [28], most households used a combination of heating appliances, i.e. at least one heating unit in addition to direct electric or central heating in Ringerike in 2001. In our sample data, wood stoves are used in 96% of electrically heated homes and in 90% of dwellings with central heating systems. Moreover, wood stoves are approximately equally used in old and new dwellings. In electrically heated homes, the share of households using air-to-air heat pumps is about 50% while the share in dwellings with central heating is only 16%. Oil or gas stoves on average are used in 9% of households with direct electric heating and in 13% of households with central heating. About 50% of households with central heating systems claim to use some electric heaters in addition to the central heating systems.

Average floor space of dwellings with direct electric heating without air-to-air heat pumps is 154 m^2, while it is 162 m^2 for dwellings with heat pumps. Average floor space of dwellings with central heating and electric DWH is around 203 m^2, while it is 182 m^2 for purely centrally heated homes. Thus, dwellings with hot water heating systems on average are larger than dwellings with direct electric heating, and directly electrically heated dwellings with air-to-air heat pumps are on average larger than those without heat pumps.

The survey participants were asked to rate their wood burning customs choosing one out of four intensity levels: 1) *no*, 2) *only for cozyness*, 3) *supplementary*, and 4) *mainly*. In addition, the participants were asked to estimate their annual firewood consumption.[7] Frequency shares of different wood burning customs over different heating systems are shown in Fig. A.1. About 60% of households not using heat pumps report to use firewood as the main heating source, 30% use it supplementary, less than 10% use wood burning for cozyness and less than 5% claim to use no firewood at all. Only 30% of households using air-to-air heat pumps report to use firewood as main heating source, while 56% use it supplementary. Households using heat pumps on average consuming firewood less frequently is in accordance with Halvorsen and Larsen [26]. Compared to directly electrically heated homes, a large share of households with central heating systems reports to use wood burning only for cozyness (nearly 30%) or not at all (nearly 10%). The share of households using firewood as main heating source is only 25%.

Median annual firewood consumption of households using wood burning only for cozyness, supplementary, and mainly is 1.0 m^3/a, 2.4 m^3/a, 5.0 m^3/a respectively and approximately equal across heating system groups. Thus, self-reported wood consumption is consistent with wood burning intensity, i.e. consumption is increasing with intensity. However, actual consumption of firewood during a given time period is hard to measure and conversion into a common unit (cubic meters) does not take into account differences in delivery form, stacking, wood billet size, wood type, water content, as well as types and efficiencies of the wood stoves used. Thus, the amount of useful energy per cubic meter firewood might vary largely from household to household so that annual firewood consumption can at best serve as a rough indicator.

3.2. Electricity meter data

Meter data is provided as a data set of hourly meter readings.[8] Hourly consumption of hour h is calculated as difference between meter reading of hour h and meter reading of hour h-1.

All included households are located in the city of Hønefoss or its suburbs. The installation of smart meters followed a predefined schedule, starting automatic meter readings in different areas at different points in time. Usable meter data of all 608 included households is available for the period of 2 October 2013 to 30 April 2014, in the following called metering period or heating period. The term *usable* means that realistic meter data is available, but does not imply that there are no missing or erroneous values at all. During some shorter periods general meter failures occurred resulting in missing meter data for a large part of the sample. In addition, metered hourly consumption of zero as well as constant consumption over several hours is excluded from further analysis.[9]

Average hourly electricity consumption of households with direct electric heating, with and without heat pumps, and non-electric central heating, on workdays and weekends, during the period 22 January – 11 February 2014, is shown in Fig. A.2.

On workdays, directly electrically heated dwellings without heat pumps exhibit a peak in average hourly consumption during morning hour 8, i.e. between 7 and 8 a.m., and a consumption top around evening hours 18 and 19. On weekends, the morning peak is shaped more flatly and occurs first around hour 11. Day-time consumption is considerably higher, evening peaks only slightly higher than on workdays. Average consumption after 7 p.m. is similar on workdays and weekends, however, on workdays, there is a relatively steep decline in consumption between hour 24 and hour 1 which is missing on weekends. Though similarly shaped, average hourly consumption of households using heat pumps is lower than consumption of households not using heat pumps. On workdays, the difference in average consumption is highest (−0.5 kWh/h) during morning hour 8.

[5] includes stoves fueled by heating oil, gas, or paraffin.

[6] In this paper, *central heating system* is used as a synonym for *hot water heating system*, meaning a central heating unit supplies heaters (e.g. radiators or floor heating) in different parts of the dwelling by distributing heated water through a piping network. The central heating unit may e.g. be an oil-fired or electrically heated boiler, a fluid-to-water or air-to-water heat pump, or a heat exchanger supplied by a district heating network.

[7] Respondents could fill in consumption in liters, 60-L-bags, fathoms or cubic meters. 1 Norwegian fathom ≈ 2.4 m^3.

[8] Only meter data of customers that have answered the questionnaire is provided by the system operator.

[9] it is assumed that in all households at least one electric appliance is running constantly during the day. Meter data was logged hourly with two digits so that consumptions as low as 0.01 kWh could be logged. Meter values of zero can of course be caused by switching off all devices, by blackouts or removed fuses, but are treated as meter failures in the analysis.

Households with non-electric central heating systems on average exhibit considerably lower hourly electricity consumption than electrically heated dwellings, with two consumption tops in the morning and evening, but without the characteristic morning peak. During the arbitrarily chosen winter period, average hourly consumption during hour 8 is about 1.5 kWh/h lower than average consumption of electrically heated homes without heat pumps.

Morning peak consumption of electrically heated homes is probably caused by electric appliances, electric hot water tanks and electric space heating units, operating at the same time (or at least during the same hour). As electric heaters often operate in night-setback mode from late evening to early morning, a relatively large heating load occurs when the dwelling needs to be reheated (reaching comfort indoor temperature) during morning hours. A more efficient use of electrical energy for space heating can explain the reduced morning peak consumption of households with heat pumps, compared to only electrically heated homes. Moreover, heat pumps might be running more continuously, i.e. maintaining a constant indoor temperature throughout the day, without any night-setback. Thus, possibly less reheating energy is needed in the morning, which reduces peak consumption.

Since households with non-electric central heating systems consume less or no electrical energy for space heating or DWH, average hourly electricity consumption differs from consumption of electrically heated homes. Largest difference in average consumption during morning hours can be explained by less electric reheating energy in centrally heated homes.

However, differences in average hourly consumption can also occur due to differences in variables like e. g. dwelling size and age, number and age of residents, as well as due to behavioral differences between the consumer groups. In order to isolate the impacts of different heating systems, differences in other important variables need to be corrected for.

4. Methods

4.1. Panel data regression

Combining time series (meter data) and cross sectional data (survey response) results in a large panel data set. Multiple linear regression is applied to model electricity consumption on household level for each hour of the day. For each hourly model, a maximum time period of $T = 211$ days and N observations are available ($N = 508$ for direct electric heating, $N = 100$ for central heating).[10] Due to the relatively large number of time periods and variables, applying the method of OLS (ordinary least squares) to panel data[11] is preferred to other panel data methods such as FE (Fixed Effects) or RE (Random Effects) estimators in this study.

Outdoor temperature is transformed into variable *heating degree day HDD*[12] defined as the difference between 17° C and diurnal mean outdoor temperature (mean value of 24 hourly meterings) $\bar{t}_{o,d}$. *HDD* is zero in case $\bar{t}_{o,d} \geq 17°$ C (Equation (1)).

$$HDD_d = \begin{cases} 17 - \bar{t}_{o,d}, & \text{for } \bar{t}_{o,d} < 17 \\ 0, & \text{else} \end{cases} \tag{1}$$

The difference in heating degree days between any day d and the day before $(d-1)$ is called *first differences in heating degree days HDD1st* (Equation (2)). Thus, a positive value of *HDD1st* implies that mean outdoor temperature during day d is lower compared to the day before.

$$HDD1st_d = HDD_d - HDD_{d-1} \tag{2}$$

For both directly electrically heated dwellings and dwellings with central heating systems a separate set of 24 hourly models is estimated. The included explanatory variables $x_{k,i}$ for both model sets are briefly described in Tables A.7 and A.8. Within both dwelling groups, each of the 24 linear models contain the same explanatory variables, of which some are included in interaction with heating degree day *HDD*. However, not all variables that were significant in the hourly model sets for directly electrically heated dwellings (Table A.7) were significant and meaningful in the model sets for dwellings with central heating systems (Tables A.8), which can be explained by a considerably lower number of observations for centrally heated homes, as well as by substantial differences between the two groups.

The hourly model sets are determined by the formula for ordinary least squares regression (Equation (3)) where $E_{i,h}$ represents hourly electricity consumption of hour h and observation i.

$$E_{h=1,\dots,24,i} = \beta_{0,h} + \sum_{k=1}^{k} \beta_{k,h} \cdot x_{k,i} + \varepsilon_{h,i} \tag{3}$$

4.2. Explanatory variables for dwellings with direct electric heating

Explanatory variables included in the hourly models for directly electrically heated homes are listed in Table A.7. After merging the two least frequent wood burning groups, wood burning customs are now divided into three intensity levels: 1) *no wood burning or only for cozyness*, 2) *supplementary wood burning*, and 3) *mainly wood burning*. Since the corresponding impacts of dwelling size and different heating systems are assumed to vary with outdoor temperature, *floor space* and variables describing wood burning customs and the use of oil stoves are included as interaction terms with *HDD*. However, the dummy variable describing the use of air-to-air heat pumps is only included as stand-alone variable. Interaction term *HDD•heat pump* is significant but only explains a negligible share of total variance. This indicates that reductions in hourly electricity consumption achieved by using heat pumps are approximately independent from outdoor temperature during the examined heating period. A possible explanation can be found in Section 5.1.2.

Since number of residents and dwelling floor space are positively correlated, *floor space* is not included as stand-alone variable but only in interaction with *HDD,* in order to avoid issues with collinearity.

The different starting dates of hourly metering – named after the month hourly metering started – are used as proxies for different residential areas within the municipality (*area 1,...,10*). Areas 1 to 4 are merged into one area representing the reference group. Assuming differences in outdoor temperature between the different areas within the municipality to be negligible, variable *HDD•area* is included to correct for possible differences in unobserved variables (as for example employment rate and local temperatures) between the different areas.

4.3. Explanatory variables for dwellings with central heating

As indicated above, a smaller number of explanatory variables is significant and thus included in the hourly regression models for centrally heated dwellings (Table A.8). Heating system variables, describing which type of central heating system and whether an

[10] Since not all observations contain meter data for all hours of the 211 days, the panel data set is *unbalanced*.

[11] also called pooled OLS, see for example Wooldridge [29], chapter 13.

[12] For simplicity, index d is dropped in the text and *HDD* is used without physical unit.

air-to-air heat pump is used, are included in interaction with *HDD*. While redundant in the models for directly electrically heated dwellings, *HDD•heat pump* is preferred to stand-alone variable *heat pump* in the models for centrally heated homes.

4.4. Modeling aggregate consumption across time and observations

Due to the simple structure of the hourly models, individual daily electricity consumption can easily be modeled by using the summarized hourly coefficients for each variable (Equation (4)) and applying Equation (3).

$$\beta_{k,d} = \sum_{h=1}^{24} \beta_{k,h} \quad (4)$$

Aggregate hourly electricity consumption of each consumer group (direct electric and central heating) can be modeled directly by using the sample's overall characteristics, i.e. total number of households, summarized floor space, etc., as cross-sectional input data. The time series component is the same as for the individual models and consists of *HDD* and *HDD*1*st* for each day *d* as well as variables describing the type of day, i.e. variables x_{11} through x_{14} in Table A.7.

5. Results

5.1. Individual hourly electricity consumption

Parameter estimates, p-values and percent shares of explained variance of all explanatory variables are listed in Appendix A. The F-statistics of all 24 models yield extremely low p-values, indicating overall significance of the included variables. Residuals seem independent from the most important explanatory variables and are approximately normally distributed. Though square-root transforming the response variable yields more normally distributed residuals, the non-transformed response is preferred in order to obtain a simple model with estimates easy to interpret. Slightly positive skew and kurtosis are assumed not to cause larger issues. Durbin–Watson test indicates no autocorrelated residuals. Breusch–Pagan test indicates slightly heteroskedastic residuals. In order to correct for heteroskedasticity, robust standard errors are used.

5.1.1. Explained variance

For electrically heated homes, total explained variance – represented by adjusted coefficient of determination R^2 – varies from 0.34 during night-time to 0.39 during morning and late afternoon. For detached houses with central heating R^2 lies between 0.34 during mid-day and night-time and 0.42 during morning. Percent shares of total variance explained by the explanatory variables in both model sets are listed in Tables A.5 and A.6 in Appendix A, and a graphical presentation is shown in Fig. A.3.

While some important variables are plotted separately, the remaining variables are grouped into *appliances*, *day-type variables* and *resident variables*. *Day-type variables* represent the three dummy variables describing whether day *d* either is a Saturday, a Sunday or a holiday, or within school holidays. *Appliances* include variables describing the use of electricity-intensive appliances such as cold storages, clothes dryers, solariums or saunas, and other appliances. *Resident variables* include number of adults and children as well as dummy variables indicating the presence of senior citizens, residents that are at home nearly all day, and residents that are only present on weekends or holidays.

Model results for directly electrically heated dwellings identify *HDD* as the most important explanatory variable throughout all 24 h, explaining about 10–13% of the variance in hourly electricity consumption (Fig. A.3a). The interaction term of heating degree day and floor space *HDD•floor space* contributes with nearly 10% during all hours of the day. Variables *HDD•wood burning* and *HDD•area* explain about 1–2% each, while the contribution of *heat pump* is about 0.5–1% during day-time and less than 0.5% during night-time. *HDD•oil stove* explains less than 0.5% during all hours of the day. The contribution of first differences in heating degree days, *HDD*1*st*, is largest during the first hours of the day and decreasing over the rest of the day.

In dwellings with central heating systems, the variance in hourly electricity consumption is mainly explained by the type of heating system in interaction with *HDD*, by *HDD* as stand-alone variable, as well as by DWH technology *(electric DWH)* and *resident variables* (Fig. A.3b). The relatively large share of variance explained by *HDD* indicates that even households with non-electric central heating (i.e. in this sample mainly central oil boilers) to a certain extent use electric heaters, e.g. placed in garages or workshops or in the form of electric floor heating in bathrooms. Interaction term *HDD•heat pump* indicating the use of air-to-air heat pumps in addition to a central heating system explains about 3% and is thus more important than for electrically heated homes (where it is included as stand-alone variable).

5.1.2. Parameter estimates

Parameter estimates are listed in Tables A.3 and A.4. Within both model sets, variables *HDD* and *floor space* exhibit positive estimates, resulting in increased modeled electricity consumption with increasing heating degree day (i.e. decreasing outdoor temperature) and dwellings size. Moreover, modeled electricity consumption increases with the number of residents and in case electric appliances are used, which is feasible. Estimates for 1st differences in *HDD*, i.e. the difference between heating degree days of day *d* and $d-1$, yield largest (negative) estimates during the first hours of the day which are continuously decreasing in absolute value over the course of the day. Thus a positive jump in *HDD* from one day to the next, i.e. a drop in daily mean outdoor temperature, is absorbed by negative estimates for *HDD*1*st*. For directly electrically heated dwellings, heating system variables *HDD•supplementary wood burning*, *HDD•mainly wood burning*, *HDD•oil stoves*, and *heat pump* exhibit negative estimates, implying reduced electricity consumption during all hours of the day, compared to only direct electric heating. While modeled reductions achieved by the use of oil stoves or wood burning increase with *HDD*, i.e. with decreasing mean outdoor temperature, modeled reductions by using air-to-air heat pumps are temperature-independent during the examined period. With decreasing outdoor temperatures space heating demand increases while heat pump efficiency decreases,[13] leading to a higher electricity consumption by the heat pump itself. These two effects leveling out each other could be an explanation for temperature-independent reductions achieved by using air-to-air heat pumps in directly electrically heated dwellings during the examined period.

Within the model set for centrally heated dwellings, the reference group is represented by dwellings with central oil boilers (i.e. non-electric central heating) that also supply the domestic hot water tanks. Estimates for variables *electric DWH*, *HDD•central electric boiler*, *HDD•central heat pump*, and *HDD•heat pump* are positive for all hours of the day, indicating a higher hourly electricity consumption in case the corresponding heating equipment

[13] Usually, coefficient of performance decreases with increasing temperature difference between heat source (outdoor temperature) and heat sink (indoor temperature).

is used. Representing a form of electric heating, the use of air-to-air heat pumps included as interaction term *HDD*•*heat pump* implies increased electricity consumption when referring to a non-electric central heating system and moreover an increasing elevation in consumption as outdoor temperature decreases.

5.1.3. Individual consumption profiles with respect to different heating systems

In the following example, eleven different heating systems are considered in an average household consisting of two adult residents and one child living in a detached house with 150 m^2 of floor space. Hourly electricity consumption on a workday in January with a daily mean outdoor temperature of -2.5° C is modeled and displayed in Fig. A.4a. Differences in modeled hourly consumptions – referring to the reference case of direct electric heating with no or only little wood burning – represent the modeled impacts of each different heating system compared to the reference case and are shown in Fig. A.4b.

Highest hourly consumptions are modeled for the case the household uses a central electric boiler, which can be explained by energy losses in the hot water heating system. There is a consumption peak in hour 8 and a consumption top during evening (hours 17–22). Compared to direct electric space heating without noticeable wood burning (reference case), modeled consumption is considerably increased, especially during morning hours 3–8. In case of direct electric heating plus supplementary wood burning, modeled hourly consumption over the course of the day is approximately 0.3 kWh/h lower than in the reference case, but with similarly shaped peaks in the morning, afternoon, and evening. Except for night hours 23-5, the use of air-to-air heat pumps without wood burning yields slightly lower modeled hourly consumption than supplementary wood burning. Using direct electric heating supplemented by an oil or gas stove yields a modeled consumption similar to that modeled for using an air-to-air heat pump, however, with slightly higher consumption, mainly during night-time and morning peak. Using both air-to-air heat pump and supplementary wood burning generates a diurnal profile similar to using direct electric heating plus mainly firewood. In case the household uses an air-to-air heat pump plus mainly wood burning, modeled hourly consumption is more than 1 kWh/h lower compared to the reference case. During hours 9 to 24, modeled consumption is approximately equal to modeled consumption for the case of central heating with a central heat pump, while during night-time and morning hours, modeled consumption for the centrally heated home is considerably higher. While modeled reductions achieved by using an air-to-air heat pump are independent from outdoor temperature, modeled differences by using wood burning, an oil stove, or a central heating system increase with *HDD*, i.e. will be larger when outdoor temperature is below 2.5° C and vice versa. Lowest modeled consumption profiles are achieved by using a non-electric central heating system. Compared to the reference case, maximum reductions of almost 2.5 kWh/h are modeled for morning hours 8 and 9. In case electric hot water tanks are used in combination with a non-electric central heating system, modeled hourly consumption is about 0.4 kWh/h higher compared to purely non-electric central heating.

5.2. Aggregate hourly electricity consumption

5.2.1. Goodness of fit

Referring to the whole metering period, aggregate hourly electricity consumption can be modeled with $R^2 = 0.95$ for households with direct electric heating and $R^2 = 0.92$ for households with central heating systems. A comparison of metered and modeled aggregate hourly electricity consumption of households with direct electric heating and central heating during the winter period 22 January – 11 February 2014 is shown in Fig. A.5. While the models in general seem to reproduce metered consumption quite well, consumption peaks and troughs as well as day-time consumption on weekends are often underestimated by the models.

5.2.2. Scenarios for aggregate hourly electricity consumption on a cold day

In this section, the impacts of area-wide changes in heating methods on aggregate hourly electricity consumption are briefly evaluated considering four different scenarios, as described in Table A.9. The sample's heating characteristics as recorded by the survey in 2013 represent the base case, where 84% of households uses direct electric heating, partly supplemented by wood burning, oil stoves, and air-to-air heat pumps, and only 16% use hot water heating systems. Scenarios 1 and 2 only imply changes in heating methods of directly electrically heated homes while the subsample of households with central heating remains as in the base case. Scenarios 3 and 4 imply that all households switch to non-electric central heating, so that there are no households using direct or central electric space heating.

In order to illustrate possible changes in aggregate consumption during periods of typically high demand for electrical heating energy, aggregate hourly electricity consumption is modeled for the coldest day during the metering period, which was a workday during January with a mean outdoor temperature of about -13° C, i.e. $HDD = 30$. Modeled aggregate consumption in the base case as well as the four scenarios is shown in Fig. A.6.

In the base case, modeled hourly consumption is highest, varying from 2350 kWh/h during night-time and 2900 kWh/h during evening. Morning peak consumption is about 2800 kWh/h.

In case all directly electrically heated homes used air-to-air heat pumps (scenario 1), modeled aggregate consumption is reduced by about 2–5% over the course of the day, but with a similarly shaped diurnal profile. Since air-to-air heat pumps represent a more efficient kind of electric heating, scenario 1 implies no increased consumption of substituting fuels.

In case all electrically heated homes used air-to-air heat pumps *and* mainly wood burning (scenario 2), modeled aggregate consumption is relatively evenly reduced by 10–12% during all 24 h of the coldest day, while the overall shape of diurnal consumption is retained. In this scenario, the modeled reduction in electricity consumption needs to be partly substituted by an increased firewood consumption.

In case all households switched to non-electric central heating plus electric DWH and would not use any air-to-air heat pumps (scenario 3), modeled aggregate consumption is reduced by about 40% during early evening and 50% during morning. In the case of all households using exclusively non-electric central heating (scenario 4), modeled reductions are between 45% during afternoon and evening and about 60% during morning. Considering that modeled electricity consumption in scenarios 3 and 4 still contains some electric space heating energy (compare Sections 3.1 and 5.1.1), aggregate consumption could presumably be reduced even more, if no electric heaters were used at all. In these two scenarios, modeled reductions in electricity consumption need to be covered by other energy carriers supplying the central heating systems (e.g. district heat, biomass, solar heat). Although wood burning customs are not considered in the model for centrally heated homes, aggregate firewood consumption in scenarios 3 and 4 is assumed to decrease compared to the base case, since centrally heated homes on average use wood burning less frequently than households with direct electrical heating (see Fig. A.1 in Chapter 3.1).

Assuming electricity consumption for non-heating purposes to be independent from heating systems, modeled reductions in aggregate hourly electricity consumption in the different scenarios represent the modeled amount of electric heating energy that is saved by different heating techniques, as e.g. air-to-air heat pumps, wood burning and non-electric central heating. However, since different heating systems might also imply differences in hourly *heat* consumption – on which no meter data is available in this study – hourly demand for substituting energy carriers (e.g. firewood or district heat) cannot be derived from the presented models.

6. Discussion

6.1. Regression model results

Though electricity consumption is modeled independently for each hour of the day, relatively smooth hourly profiles are generated. Parameter estimates are consistent and exhibit meaningful values. On individual household level, coefficients of determination are comparatively low which might be due to omitted variables, as e.g. detailed information on the residents' diurnal routines regarding indoor temperatures, thermostat settings, and firewood consumption.

The use of *HDD* as explanatory variable implies a simplification, as reference temperature 17° C is not the true space heating limit temperature for all households. Moreover, some households might use electric space heating all year (e.g. electric floor heating in bathrooms) while others might turn electric heaters on and off manually and not exactly as soon as outdoor temperature has reached a certain reference temperature. The general assumption of linear relationship between electricity consumption and *HDD* is a possible error source in the models, as consumption is flattening once certain (individual) lower and upper temperature limits are passed.

Due to the relatively small number of observations with central heating systems, combinations of heating equipment, as e.g. central electric boiler or central heat pump *plus* air-to-air heat pump, are not considered in the models, although the effect of using air-to-air heat pumps is assumed to be different for the different central heating systems. Moreover, due to some correlation between DWH technology and heating equipment no variable indicating the use of electric heaters is included. If a larger sample would be provided, separate models for electric and non-electric central heating systems, including more explanatory variables, could possibly yield more reliable models.

Though highly significant, including wind speed as explanatory variable does not lead to a considerably increased goodness of fit. Further weather data such as sun hours and cloud cover, probably affecting electricity demand for space heating and artificial lighting, are not available for Hønefoss weather station and are therefore not included.

The metering period altogether includes ten public holidays and five weeks of school breaks when electricity consumption of some households is considerably higher compared to workdays, probably because residents spend more time at home using electrical appliances and space heating. Other households, however, consume considerably less electrical energy during these periods, since the residents are not at home at all. The same applies to weekends where people might choose to stay at home or travel. Households without school children might choose to take a holiday outside the school breaks. Thus, modeling electricity consumption without detailed information on presence or absence of the residents, implies further uncertainties and possible error sources.

Considering the simplicity of the models, achieved goodness of fit seems sufficient. Aggregate hourly electricity consumption can be easily modeled by using overall sample characteristics as input and yields a relatively high accuracy. However, extreme consumption values (peaks and troughs) as well as day-time consumption during weekends are often underestimated by the model, which indicates that e.g. the impacts of day-type and other dummy variables are not constant throughout the metering period. Examining these effects more thoroughly, e.g. based on a dataset with a longer metering period, could help improving the models significantly.

6.2. Possible issues regarding self-selection and measurement errors

As in most surveys with voluntary participation, self-selection might be present. On the one hand, consumers especially interested in energy saving might be over-represented in the response data. On the other hand, since the survey invitation was sent out via e-mail and the questionnaire was answered electronically, some consumers groups, as e.g. senior citizens, might be under-represented in the sample. Regarding some observed factors, e.g. heating systems, our sample seems representative (see Chapter 3.1). However, differences in unobserved factors – possibly affecting electricity consumption (e.g. attitudes towards surveys, smart metering, or energy saving) – between participants and non-participants can make our results less applicable to the population, e.g. all detached houses in the municipality. If also meter data of non-participants would be provided, consumption characteristics of participants and non-participants could be compared and possible differences identified.

Using heating degree day based on the daily mean value of outdoor temperature instead of heating degree hours based on hourly temperature values implies some measurement error. As confirmed by plausible regression results, including 1st differences in heating degree days, *HDD1st*, as explanatory variable seems to sufficiently correct for this simplification. The share of explained variance by *HDD1st* as well as its absolute parameter estimate is continuously decreasing over the course of the day, representing a declining impact of yesterday's mean temperature on today's electricity consumption. Including heating degree hours *HDH* instead of *HDD* as explanatory variables for estimating hourly consumption does not lead to a higher goodness of fit.[14] This supports the assumption that the variance in hourly electricity consumption *within* a single day is mainly caused by observation-specific patterns, e.g. the residents' daily routines. Thus, including *HDD* and *HDD1st* as explanatory variables for estimating hourly electricity consumption seems sufficient and at the same time simplifies the model.[15]

6.2.1. Estimated savings in electricity consumption compared to self-reported firewood consumption

Reductions in electrical energy consumption during any time period of at least one day, achieved by e.g. using firewood supplementary or mainly in directly electrically heated dwellings, can be

[14] Model results can be obtained by contacting the corresponding author.

[15] Variations in hourly outdoor temperature most probably *do* affect hourly electricity consumption, but with some attenuation due to the thermal storage capacity of the dwelling's mass. Further, outdoor temperature is often lowest during night-time when night-setback of electric heaters is active so that the dwelling is first re-heated during the morning hours. Since detailed information on dwelling characteristics, indoor temperature and thermostat settings would be required, the temperature-effect on hourly electricity consumption is not evaluated in detail in this paper.

estimated by multiplying the corresponding daily parameter estimate by the number of heating degree days during the examined time period. For example, assuming wood burning is used as main heating source and $HDD = 30$, i.e. a mean outdoor temperature of -13° C, modeled reduction in electricity consumption on that day would be $\sum_{h=1}^{24}\hat{\beta}_{31} \cdot HDD = -26.8$ kWh. The number of heating degree days over the whole metering period is $\sum HDD = 3092$, so that households using firewood mainly (or supplementary) on average consume 2762 kWh (1250 kWh) less electrical energy compared to households using only direct electric heating. Median[16] self-reported firewood consumption of households using firewood mainly and supplementary is 5.0 m^3 and 2.4 m^3 respectively, yielding approximately 5410 kWh and 2600 kWh of useful heating energy.[17] Thus approximately consumed firewood energy is about twice as high as modeled reductions in electricity consumption over the entire heating period. Although these figures are only very rough estimations they indicate that the amount of useful firewood energy consumed is larger than the amount of electrical energy saved over the course of the heating period. Apart from the large uncertainties regarding energy content, wood burning efficiencies, self-reported consumption, and modeling accuracy, there are several possible explanations for this result: First of all, average *annual* firewood consumption is reported by the survey participants, so that wood burning might also take place outside the defined heating period from 2 October to 30 April. Depending on weather conditions – households may start wood burning already in September and stop during May or June. Secondly, the examined metering period does not represent a normal but a relatively mild winter, resulting in a lower number of heating degree days, while reported firewood consumption rather refers to an average year. For comparison, the sum of heating degree days in Hønefoss from October to April in a normal[18] year is $\sum HDD = 4041$ [27] and thus about 30% higher than during the examined period in 2013/2014. Thirdly, since wood burning stoves are mainly running continuously for several hours and can only be roughly regulated, households using wood burning are assumed to maintain relatively high indoor temperatures while the wood stoves are in use, so that more useful heating energy may be consumed than in only directly electrically heated homes, that are probably maintaining lower indoor temperatures.

Thus, modeled reductions in electrical energy consumption by using firewood or other energy carriers as a supplement to direct electric heating do not necessarily represent the amount of heat provided by the supplementary energy carriers.

6.3. Scenario analysis and policy implications

A simple scenario analysis based on a sample of existing detached houses reveals modeled reductions in aggregate hourly electricity consumption, assuming area-wide changes in heating systems. In case all directly electrically heated homes used air-to-air heat pumps, no substituting energy carriers are needed, but modeled reductions are comparatively small. Assuming a sustainable production and supply of firewood, a combination of air-to-air heat pumps and wood burning stoves that are intensively used, represents a relatively simple solution for reducing aggregate electricity consumption during all hours of the day, during the heating period. Since nearly all electrically heated dwellings are already equipped with wood stoves, and air-to-air heat pumps are relatively easily installed, this scenario does not imply extensive installation efforts.

In case of all households using non-electric central heating systems largest reductions in aggregate hourly electricity consumption are modeled. Hot water based heating systems enable heat supply by various different energy carriers and can be supplied by either individual equipment or district heating networks. Assuming central heating systems to be connected to district heating networks that can be supplied by different heating sources, an area-wide use of hot water heating systems could forward higher shares and a more efficient use of renewable energy sources and at the same time reduce unwanted consumption peaks in the power system caused by individual electric heating.

However, retro-fitting hot water heating systems to existing dwellings is relatively costly and with comparatively low electricity prices it is often not economically feasible in Norway today. The installation of hot water heating systems in passive houses will probably be relatively expensive, referring to the annual amount of heating energy consumed, and compared to other heating systems, as e.g. wood stoves or ventilation systems. However, domestic hot water tanks are expected to cause considerable heating loads in both new and existing dwellings. Results from an updated model, based on an extended dataset, could be used as input data to energy system models, that take into account numerous economic and technological aspects, and thus help identifying the most feasible heating solutions for different time horizons.

7. Conclusion

The paper presents a simple method for analyzing hourly electricity consumption data from smart meters in combination with survey response data. The results show which variables are most important for consumption during each hour of the day and the presented regression models can be used for modeling and forecasting individual and aggregate hourly electricity consumption. A rough scenario analysis shows that air-to-air heat pumps and wood burning stoves that are intensively used, represent relatively simple solutions for reducing aggregate hourly electricity consumption during the heating period, however, yielding comparably small reductions of about 2–12% on a cold day. In case all households used non-electric central heating, the morning peak of the sample's modeled aggregate electricity consumption on a cold day is reduced by about 60%. An increased share of dwellings equipped with hot water heating systems – for example supplied by flexible district heating networks – can forward an efficient integration of heat and electricity provided by renewable energy sources, while at the same time unwanted peak loads in electricity supply caused by individual electric space heating could be reduced.

The presented method can be used to model regional energy demand with a high temporal resolution, taking into account changes in outdoor temperature, heating systems, and other dwelling and population characteristics.

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Appendix A. Regression results

[16] Due to a skewed distribution and several outliers the median value is preferred to the arithmetic mean here.

[17] Theoretical useful energy content is estimated by multiplying wood consumption by an average heating value of 1804 kWh/m^3 [31,30] and an average wood burning efficiency of 60% [32], assuming mainly birch and pine in 30 cm-billets with 17% moisture content are burned.

[18] referring to the period 1961–1990.

Table A.1
p-values for each variable and hour, households with direct electric heating.

	h 1	h 2	h 3	h 4	h 5	h 6	h 7	h 8	h 9	h 10	h 11	h 12	h 13	h 14	h 15	h 16	h 17	h 18	h 19	h 20	h 21	h 22	h 23	h 24
intercept	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
HDD	0.000	0.000	0.000	0.000	0.000	0.000	0.005	0.018	0.004	0.003	0.002	0.002	0.000	0.000	0.000	0.002	0.027	0.190	0.353	0.271	0.362	0.284	0.075	0.004
HDD1st	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
adults = 2	0.157	0.345	0.399	0.331	0.200	0.110	0.004	0.001	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.002	0.012	0.066
adults = 3	0.001	0.019	0.086	0.134	0.093	0.081	0.005	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
adults = >3	0.001	0.007	0.022	0.037	0.032	0.045	0.021	0.001	0.003	0.007	0.003	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
kids = 1	0.337	0.473	0.495	0.501	0.497	0.846	0.267	0.011	0.042	0.140	0.139	0.140	0.183	0.163	0.111	0.123	0.058	0.063	0.048	0.020	0.013	0.018	0.040	0.193
kids = 2	0.000	0.004	0.010	0.024	0.017	0.032	0.006	0.000	0.000	0.007	0.004	0.002	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
kids = >2	0.176	0.257	0.231	0.175	0.176	0.147	0.059	0.019	0.014	0.026	0.022	0.016	0.018	0.018	0.010	0.003	0.001	0.004	0.011	0.004	0.002	0.004	0.027	0.116
adults >65 yrs	0.009	0.013	0.011	0.009	0.010	0.110	0.623	0.148	0.000	0.000	0.000	0.000	0.001	0.001	0.001	0.002	0.017	0.122	0.226	0.458	0.379	0.209	0.057	0.011
resident >20 h at home	0.295	0.317	0.231	0.292	0.352	0.862	0.875	0.488	0.222	0.114	0.054	0.119	0.208	0.195	0.171	0.075	0.144	0.305	0.330	0.372	0.343	0.280	0.146	0.187
weekend res., workday	0.003	0.013	0.019	0.031	0.034	0.108	0.144	0.001	0.000	0.001	0.000	0.001	0.001	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001
Saturday	0.000	0.000	0.011	0.265	0.070	0.000	0.000	0.000	0.003	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.131	0.236	0.004	0.483	0.000	0.000	0.000	0.425
Sunday/holiday	0.000	0.000	0.000	0.002	0.828	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.146	0.906	0.348	0.092	0.001	0.000	0.008
school break	0.000	0.000	0.017	0.002	0.516	0.011	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.128	0.237	0.175	0.314	0.003	0.000	0.000	0.333
cold storage	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
dryer	0.518	0.529	0.418	0.343	0.413	0.652	0.272	0.348	0.357	0.181	0.054	0.027	0.036	0.037	0.039	0.050	0.068	0.079	0.128	0.121	0.230	0.337	0.372	0.494
solarium/sauna	0.178	0.172	0.121	0.101	0.081	0.033	0.020	0.037	0.061	0.059	0.064	0.057	0.033	0.035	0.025	0.039	0.046	0.028	0.026	0.034	0.029	0.039	0.087	0.144
other el.-intensive	0.014	0.020	0.021	0.015	0.012	0.018	0.027	0.044	0.029	0.022	0.031	0.024	0.023	0.025	0.017	0.006	0.005	0.012	0.015	0.021	0.015	0.013	0.012	0.010
heat pump	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
month = Feb	0.000	0.000	0.005	0.033	0.358	0.779	0.004	0.000	0.000	0.042	0.944	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.107	0.118	0.264	0.098	0.000	0.000
month = Mar	0.000	0.000	0.000	0.000	0.000	0.004	0.885	0.776	0.048	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
month = Apr	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
month = Oct	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
month = Nov	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
month = Dec	0.127	0.670	0.083	0.179	0.298	0.143	0.183	0.069	0.000	0.000	0.000	0.008	0.105	0.868	0.168	0.091	0.301	0.392	0.073	0.309	0.923	0.341	0.519	0.380
HDD: floor space	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
HDD: oil stove	0.197	0.159	0.150	0.169	0.087	0.019	0.007	0.041	0.038	0.028	0.011	0.008	0.006	0.006	0.004	0.001	0.004	0.002	0.007	0.009	0.009	0.033	0.162	0.319
HDD: mainly wood b.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
HDD: suppl. wood b.	0.002	0.007	0.011	0.014	0.026	0.040	0.053	0.036	0.017	0.017	0.024	0.021	0.017	0.021	0.038	0.098	0.099	0.089	0.049	0.039	0.040	0.024	0.006	0.002
HDD: 1980–1989	0.081	0.074	0.079	0.101	0.142	0.181	0.197	0.541	0.530	0.290	0.243	0.208	0.149	0.117	0.219	0.411	0.381	0.341	0.312	0.220	0.254	0.352	0.337	0.143
HDD: 1990–1999	0.006	0.004	0.006	0.021	0.023	0.100	0.149	0.733	0.200	0.398	0.324	0.141	0.135	0.164	0.226	0.363	0.374	0.530	0.448	0.165	0.042	0.036	0.013	0.007
HDD: 1999<	0.000	0.000	0.000	0.001	0.003	0.011	0.088	0.060	0.005	0.001	0.001	0.000	0.001	0.001	0.000	0.001	0.002	0.007	0.006	0.008	0.016	0.009	0.002	0.001
HDD: area 6	0.234	0.098	0.049	0.027	0.014	0.008	0.015	0.017	0.026	0.024	0.028	0.032	0.064	0.065	0.072	0.111	0.038	0.027	0.008	0.013	0.003	0.005	0.033	0.168
HDD: area 8	0.003	0.004	0.004	0.003	0.002	0.004	0.005	0.004	0.009	0.009	0.008	0.011	0.010	0.011	0.013	0.026	0.018	0.005	0.002	0.003	0.002	0.002	0.002	0.003
HDD: area 9	0.079	0.029	0.013	0.012	0.027	0.090	0.155	0.195	0.267	0.276	0.081	0.107	0.089	0.080	0.090	0.059	0.016	0.029	0.034	0.026	0.033	0.043	0.078	0.138
HDD: area 10	0.035	0.039	0.025	0.014	0.007	0.004	0.032	0.017	0.021	0.020	0.014	0.015	0.018	0.029	0.019	0.027	0.021	0.017	0.018	0.016	0.010	0.009	0.021	0.051

Table A.2
p-values for each variable and hour, households with central heating.

	h 1	h 2	h 3	h 4	h 5	h 6	h 7	h 8	h 9	h 10	h 11	h 12	h 13	h 14	h 15	h 16	h 17	h 18	h 19	h 20	h 21	h 22	h 23	h 24
intercept	0.969	0.761	0.545	0.483	0.500	0.660	0.824	0.425	0.976	0.944	0.791	0.600	0.738	0.565	0.562	0.343	0.133	0.224	0.231	0.247	0.228	0.134	0.235	0.347
HDD	0.094	0.065	0.077	0.040	0.050	0.094	0.154	0.303	0.037	0.010	0.006	0.008	0.003	0.004	0.006	0.017	0.192	0.136	0.093	0.106	0.203	0.559	0.565	0.647
HDD1st	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.028	0.148	0.183	0.025	0.018	0.008	0.003	0.006	0.001
floor space	0.002	0.001	0.001	0.001	0.003	0.004	0.013	0.011	0.005	0.006	0.008	0.007	0.006	0.010	0.005	0.006	0.002	0.001	0.002	0.002	0.002	0.004	0.004	0.004
adults = 2	0.819	0.793	0.542	0.349	0.216	0.160	0.103	0.454	0.449	0.412	0.512	0.587	0.533	0.495	0.316	0.182	0.126	0.116	0.132	0.158	0.230	0.366	0.704	0.996
adults = >2	0.078	0.117	0.054	0.027	0.014	0.022	0.011	0.013	0.017	0.012	0.009	0.008	0.007	0.005	0.002	0.001	0.000	0.001	0.002	0.002	0.003	0.006	0.016	0.040
kids = >1	0.493	0.533	0.428	0.409	0.450	0.809	0.374	0.393	0.835	0.940	0.884	0.604	0.343	0.336	0.407	1.000	0.492	0.692	0.760	0.467	0.507	0.791	0.857	0.481
adults >65 yrs	0.430	0.381	0.363	0.463	0.570	0.732	0.972	0.679	0.222	0.168	0.141	0.147	0.163	0.141	0.136	0.172	0.196	0.225	0.360	0.566	0.443	0.381	0.368	0.389
resident >20 h at home	0.329	0.327	0.325	0.412	0.395	0.356	0.771	0.617	0.332	0.159	0.094	0.101	0.084	0.095	0.090	0.085	0.130	0.204	0.384	0.617	0.722	0.752	0.598	0.417
Saturday	0.000	0.009	0.782	0.239	0.052	0.000	0.000	0.000	0.445	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.367	0.920	0.189	0.405	0.000	0.000	0.007	0.743
Sunday/holiday	0.000	0.002	0.001	0.471	0.611	0.004	0.000	0.000	0.044	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.190	0.233	0.068	0.553	0.711	0.543	0.971
school break	0.061	0.959	0.297	0.860	0.770	0.303	0.000	0.000	0.372	0.040	0.000	0.000	0.000	0.000	0.000	0.036	0.800	0.014	0.010	0.008	0.005	0.001	0.018	0.274
cold storage	0.758	0.628	0.684	0.698	0.647	0.691	0.494	0.486	0.371	0.416	0.362	0.396	0.555	0.510	0.533	0.517	0.577	0.690	0.463	0.425	0.561	0.545	0.601	0.692
electric DWH	0.125	0.144	0.087	0.053	0.052	0.103	0.163	0.220	0.115	0.131	0.142	0.119	0.070	0.116	0.092	0.173	0.323	0.251	0.340	0.414	0.387	0.466	0.419	0.298
month = Feb	0.001	0.173	0.713	0.281	0.764	0.421	0.083	0.005	0.060	0.812	0.175	0.006	0.010	0.011	0.000	0.000	0.000	0.005	0.738	0.644	0.890	0.318	0.098	0.018
month = Mar	0.000	0.000	0.009	0.177	0.277	0.976	0.648	0.676	0.262	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
month = Apr	0.000	0.000	0.000	0.000	0.000	0.006	0.002	0.008	0.004	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
month = Oct	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
month = Nov	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
HDD: central heat pump	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
HDD: central electric b.	0.002	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.001	0.002	0.002	0.002	0.003	0.003	0.006	0.002	0.003	0.007	0.008	0.007	0.008	0.005	0.003
HDD: air-to-air heat p.	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.002	0.002	0.002	0.001	0.002	0.003	0.002	0.005	0.001	0.004	0.006	0.005	0.003	0.002	0.001	0.000

Table A.3
Estimates for each variable and hour, households with direct electric heating.

	h 1	h 2	h 3	h 4	h 5	h 6	h 7	h 8	h 9	h 10	h 11	h 12	h 13	h 14	h 15	h 16	h 17	h 18	h 19	h 20	h 21	h 22	h 23	h 24
intercept	1.24	1.14	1.06	1.04	1.07	1.23	1.35	1.44	1.32	1.20	1.17	1.21	1.19	1.21	1.24	1.40	1.62	1.74	1.79	1.78	1.76	1.76	1.67	1.47
HDD	0.04	0.04	0.04	0.04	0.04	0.04	0.03	0.03	0.03	0.03	0.03	0.03	0.04	0.04	0.04	0.03	0.02	0.01	0.01	0.01	0.01	0.01	0.02	0.03
HDD1st	−0.06	−0.06	−0.06	−0.06	−0.06	−0.06	−0.05	−0.05	−0.05	−0.04	−0.04	−0.04	−0.04	−0.04	−0.03	−0.02	−0.02	−0.02	−0.02	−0.02	−0.02	−0.02	−0.02	−0.02
adults = 2	0.12	0.08	0.07	0.09	0.11	0.14	0.24	0.31	0.30	0.35	0.36	0.33	0.32	0.32	0.32	0.37	0.44	0.45	0.42	0.36	0.31	0.28	0.23	0.17
adults = 3	0.41	0.28	0.21	0.18	0.20	0.21	0.35	0.52	0.50	0.51	0.58	0.59	0.63	0.64	0.70	0.82	0.93	0.91	0.88	0.82	0.79	0.76	0.69	0.55
adults = >3	0.90	0.68	0.55	0.49	0.51	0.48	0.58	0.87	0.84	0.74	0.78	0.85	0.94	0.98	1.04	1.14	1.34	1.32	1.24	1.19	1.20	1.23	1.22	1.08
kids = 1	0.12	0.09	0.08	0.08	0.08	0.02	0.13	0.32	0.29	0.20	0.19	0.18	0.17	0.17	0.19	0.19	0.23	0.24	0.26	0.30	0.34	0.33	0.29	0.18
kids = 2	0.40	0.31	0.27	0.24	0.25	0.23	0.32	0.64	0.51	0.34	0.35	0.38	0.40	0.42	0.47	0.52	0.63	0.61	0.56	0.65	0.69	0.66	0.58	0.49
kids = >2	0.54	0.41	0.44	0.50	0.50	0.54	0.89	1.35	1.31	1.11	1.01	0.98	0.93	0.87	0.91	1.08	1.19	1.14	0.96	1.07	1.18	1.05	0.86	0.68
adults >65 yrs	0.27	0.24	0.24	0.24	0.23	0.15	0.05	0.15	0.39	0.44	0.43	0.39	0.34	0.32	0.32	0.32	0.25	0.17	0.13	0.08	0.10	0.14	0.21	0.27
resident >20 h at home	0.12	0.12	0.14	0.12	0.11	0.02	0.02	0.10	0.16	0.19	0.23	0.18	0.14	0.14	0.14	0.18	0.16	0.11	0.11	0.10	0.11	0.12	0.16	0.15
weekend res., workday	−0.53	−0.42	−0.39	−0.35	−0.35	−0.31	−0.30	−0.61	−0.69	−0.64	−0.64	−0.59	−0.59	−0.58	−0.67	−0.75	−0.76	−0.76	−0.74	−0.78	−0.76	−0.75	−0.69	−0.61
Saturday	0.08	0.05	0.03	0.01	−0.02	−0.10	−0.32	−0.44	−0.07	0.20	0.32	0.35	0.30	0.26	0.22	0.15	0.03	0.02	0.05	0.01	−0.11	−0.15	−0.12	−0.01
Sunday/holiday	0.13	0.11	0.07	0.03	−0.00	−0.10	−0.33	−0.46	−0.18	0.13	0.33	0.40	0.38	0.35	0.33	0.25	0.10	0.02	0.00	−0.02	−0.03	−0.04	−0.05	−0.04
school break	0.05	0.04	0.02	0.03	0.01	−0.03	−0.13	−0.23	−0.07	0.06	0.12	0.15	0.17	0.14	0.12	0.10	0.02	−0.02	−0.02	−0.01	−0.04	−0.06	−0.05	−0.01
cold storage	0.45	0.49	0.51	0.51	0.53	0.54	0.59	0.62	0.52	0.48	0.45	0.44	0.44	0.43	0.40	0.38	0.45	0.47	0.48	0.51	0.53	0.52	0.50	0.46
dryer	0.05	0.05	0.06	0.07	0.06	0.03	0.09	0.08	0.08	0.11	0.15	0.17	0.16	0.15	0.15	0.14	0.14	0.14	0.12	0.12	0.09	0.07	0.07	0.05
solarium/sauna	0.23	0.22	0.25	0.26	0.27	0.35	0.39	0.38	0.35	0.33	0.31	0.32	0.35	0.34	0.36	0.35	0.33	0.37	0.37	0.35	0.37	0.35	0.30	0.26
other el-int.	0.44	0.42	0.41	0.42	0.44	0.45	0.39	0.35	0.38	0.41	0.40	0.41	0.41	0.40	0.40	0.45	0.47	0.43	0.42	0.40	0.42	0.42	0.42	0.45
heat pump	−0.30	−0.29	−0.31	−0.31	−0.35	−0.43	−0.46	−0.52	−0.50	−0.48	−0.48	−0.49	−0.49	−0.48	−0.48	−0.48	−0.47	−0.48	−0.47	−0.46	−0.45	−0.42	−0.37	−0.33
month = Feb	−0.11	−0.05	−0.04	−0.03	−0.01	0.00	0.05	0.08	0.07	0.03	0.00	−0.07	−0.10	−0.10	−0.10	−0.15	−0.18	−0.08	−0.03	−0.03	−0.02	−0.03	−0.06	−0.09
month = Mar	−0.22	−0.15	−0.12	−0.09	−0.08	−0.05	0.00	−0.01	−0.04	−0.11	−0.22	−0.29	−0.32	−0.37	−0.40	−0.49	−0.57	−0.55	−0.41	−0.28	−0.23	−0.20	−0.22	−0.24
month = Apr	−0.46	−0.40	−0.35	−0.33	−0.31	−0.29	−0.25	−0.28	−0.30	−0.35	−0.46	−0.54	−0.59	−0.62	−0.67	−0.78	−0.89	−0.94	−0.89	−0.82	−0.66	−0.55	−0.50	−0.46
month = Oct	−0.58	−0.52	−0.49	−0.47	−0.46	−0.45	−0.39	−0.38	−0.42	−0.44	−0.51	−0.59	−0.63	−0.67	−0.70	−0.78	−0.85	−0.81	−0.69	−0.57	−0.54	−0.55	−0.57	−0.58
month = Nov	−0.36	−0.34	−0.30	−0.28	−0.27	−0.26	−0.21	−0.21	−0.22	−0.24	−0.28	−0.36	−0.39	−0.41	−0.40	−0.41	−0.35	−0.34	−0.33	−0.31	−0.30	−0.32	−0.33	−0.34
month = Dec	0.02	0.01	0.03	0.02	0.01	0.02	0.02	0.03	0.06	0.08	0.09	0.05	0.03	0.00	0.02	0.03	0.02	−0.02	−0.03	−0.02	0.00	−0.02	−0.01	0.01
HDD: floor space/100 m^2	0.04	0.04	0.04	0.04	0.04	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.04	0.05	0.05	0.05	0.06	0.06	0.06	0.05	0.05	0.05
HDD: oil stove	−0.01	−0.01	−0.01	−0.01	−0.01	−0.02	−0.02	−0.02	−0.02	−0.02	−0.02	−0.02	−0.02	−0.02	−0.02	−0.02	−0.02	−0.02	−0.02	−0.02	−0.02	−0.02	−0.01	−0.01
HDD: mainly wood b.	−0.04	−0.04	−0.04	−0.04	−0.04	−0.04	−0.04	−0.04	−0.04	−0.04	−0.04	−0.04	−0.04	−0.04	−0.04	−0.03	−0.03	−0.03	−0.03	−0.04	−0.04	−0.04	−0.04	−0.04
HDD: suppl. wood b.	−0.02	−0.02	−0.02	−0.02	−0.02	−0.02	−0.01	−0.02	−0.02	−0.02	−0.02	−0.02	−0.02	−0.02	−0.01	−0.01	−0.01	−0.01	−0.02	−0.02	−0.02	−0.02	−0.02	−0.02
HDD: 1980–1989	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.00	−0.00	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.00	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01
HDD: 1990–1999	−0.02	−0.02	−0.02	−0.02	−0.02	−0.01	−0.01	−0.00	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.02	−0.02	−0.02	−0.02
HDD: 1999<	−0.03	−0.03	−0.03	−0.03	−0.02	−0.02	−0.02	−0.02	−0.03	−0.03	−0.03	−0.03	−0.03	−0.03	−0.03	−0.03	−0.03	−0.02	−0.02	−0.02	−0.02	−0.02	−0.03	−0.03
HDD: area 6	0.01	0.02	0.02	0.02	0.02	0.02	0.02	0.03	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.03	0.02	0.03	0.03	0.02	0.01
HDD: area 8	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.02	0.02	0.02	0.02	0.02
HDD: area 9	−0.01	−0.01	−0.02	−0.02	−0.02	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.02	−0.02	−0.02	−0.02	−0.02	−0.02	−0.01	−0.01
HDD: area 10	0.02	0.01	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02

Table A.4
Estimates for each variable and hour, households with central heating.

	h 1	h 2	h 3	h 4	h 5	h 6	h 7	h 8	h 9	h 10	h 11	h 12	h 13	h 14	h 15	h 16	h 17	h 18	h 19	h 20	h 21	h 22	h 23	h 24
intercept	0.02	−0.13	−0.26	−0.30	−0.29	−0.19	0.10	0.37	−0.01	−0.03	0.11	0.22	0.14	0.23	0.22	0.37	0.58	0.48	0.49	0.48	0.50	0.65	0.55	0.44
HDD	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.01	0.02	0.03	0.03	0.03	0.03	0.03	0.03	0.02	0.01	0.02	0.02	0.02	0.01	0.01	0.01	0.01
HDD1st	−0.05	−0.05	−0.05	−0.05	−0.04	−0.04	−0.04	−0.03	−0.03	−0.03	−0.02	−0.02	−0.03	−0.03	−0.02	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01
floor space/100 m^2	0.53	0.53	0.52	0.49	0.47	0.46	0.43	0.50	0.52	0.48	0.44	0.42	0.41	0.38	0.39	0.41	0.45	0.54	0.54	0.55	0.54	0.52	0.54	0.54
adults = 2	0.08	0.09	0.19	0.28	0.36	0.40	0.48	0.24	0.26	0.26	0.20	0.16	0.18	0.19	0.28	0.37	0.43	0.47	0.46	0.43	0.37	0.29	0.13	0.00
adults = >2	0.76	0.65	0.75	0.82	0.90	0.84	1.01	1.15	1.12	1.12	1.06	1.02	1.00	1.02	1.11	1.24	1.36	1.36	1.32	1.27	1.27	1.23	1.14	0.95
kids = >1	−0.24	−0.22	−0.27	−0.26	−0.23	−0.08	0.29	0.27	0.06	0.02	−0.04	−0.13	−0.24	−0.23	−0.19	0.00	0.15	0.09	0.07	0.17	0.16	0.08	−0.06	−0.24
adults > 65 yrs	0.23	0.25	0.25	0.21	0.17	0.10	−0.01	0.15	0.42	0.47	0.49	0.45	0.41	0.42	0.42	0.40	0.38	0.37	0.28	0.17	0.22	0.26	0.28	0.26
resident >20 h at home	0.36	0.36	0.36	0.29	0.30	0.32	0.10	0.16	0.29	0.40	0.47	0.47	0.50	0.49	0.51	0.51	0.46	0.37	0.25	0.15	0.11	0.11	0.19	0.30
Saturday	0.10	0.06	0.01	−0.03	−0.05	−0.10	−0.35	−0.52	−0.04	0.29	0.40	0.39	0.31	0.27	0.22	0.16	0.04	0.00	0.05	−0.03	−0.15	−0.20	−0.11	0.01
Sunday/holiday	0.13	0.08	0.07	0.01	−0.01	−0.08	−0.35	−0.58	−0.13	0.20	0.39	0.44	0.43	0.42	0.36	0.29	0.16	0.05	0.04	0.05	0.02	−0.01	−0.02	−0.00
school break	0.05	0.00	0.03	−0.00	0.01	−0.02	−0.24	−0.34	−0.04	0.08	0.16	0.15	0.17	0.16	0.10	0.07	0.01	−0.12	−0.09	−0.09	−0.11	−0.13	−0.09	−0.03
cold storage	0.11	0.16	0.14	0.14	0.17	0.15	0.28	0.31	0.37	0.32	0.34	0.30	0.20	0.22	0.21	0.22	0.19	0.15	0.29	0.32	0.24	0.25	0.23	0.16
electric DWH	0.40	0.35	0.39	0.44	0.44	0.38	0.35	0.34	0.42	0.38	0.34	0.34	0.39	0.34	0.37	0.32	0.23	0.29	0.25	0.21	0.23	0.20	0.23	0.29
month = Feb	−0.11	−0.05	−0.01	0.04	0.01	0.03	0.08	0.13	0.08	0.01	−0.06	−0.11	−0.11	−0.11	−0.16	−0.25	−0.27	−0.12	−0.01	0.02	−0.01	−0.05	−0.08	−0.10
month = Mar	−0.25	−0.16	−0.13	−0.07	−0.05	0.00	0.03	0.02	−0.06	−0.21	−0.35	−0.44	−0.40	−0.46	−0.50	−0.65	−0.73	−0.69	−0.49	−0.27	−0.23	−0.25	−0.26	−0.28
month = Apr	−0.38	−0.32	−0.32	−0.25	−0.24	−0.18	−0.21	−0.19	−0.23	−0.34	−0.46	−0.55	−0.53	−0.59	−0.69	−0.86	−1.02	−1.02	−0.97	−0.90	−0.74	−0.60	−0.48	−0.45
month = Oct	−0.44	−0.37	−0.36	−0.30	−0.32	−0.31	−0.27	−0.23	−0.28	−0.33	−0.45	−0.52	−0.51	−0.61	−0.68	−0.81	−0.89	−0.79	−0.58	−0.40	−0.38	−0.39	−0.42	−0.48
month = Nov	−0.32	−0.29	−0.27	−0.24	−0.23	−0.22	−0.24	−0.19	−0.23	−0.25	−0.35	−0.41	−0.36	−0.39	−0.38	−0.43	−0.36	−0.31	−0.29	−0.23	−0.24	−0.28	−0.28	−0.31
HDD: central heat pump	0.10	0.11	0.11	0.11	0.12	0.12	0.14	0.15	0.12	0.11	0.11	0.11	0.10	0.10	0.10	0.10	0.11	0.12	0.11	0.11	0.12	0.12	0.12	0.11
HDD: central electric b.	0.06	0.06	0.07	0.07	0.07	0.07	0.07	0.08	0.07	0.06	0.05	0.05	0.05	0.05	0.05	0.05	0.06	0.06	0.06	0.06	0.06	0.06	0.07	0.07
HDD: air-to-air heat p.	0.05	0.05	0.06	0.05	0.05	0.06	0.05	0.05	0.05	0.05	0.05	0.05	0.04	0.04	0.04	0.04	0.05	0.04	0.04	0.04	0.05	0.05	0.05	0.06

Table A.5
Share of explained variance for each variable and hour, households with direct electric heating.

	h 1	h 2	h 3	h 4	h 5	h 6	h 7	h 8	h 9	h 10	h 11	h 12	h 13	h 14	h 15	h 16	h 17	h 18	h 19	h 20	h 21	h 22	h 23	h 24
HDD	10.95	11.83	12.48	13.13	13.16	12.78	11.61	10.55	10.53	10.53	10.68	10.89	11.58	12.11	12.76	12.86	13.14	12.70	11.74	10.95	10.09	9.77	10.16	11.15
HDD1st	2.13	2.11	2.21	1.98	1.83	1.55	1.02	0.71	0.85	0.89	0.93	0.93	1.00	1.01	0.90	0.68	0.50	0.47	0.38	0.34	0.31	0.32	0.29	0.35
adults	3.47	2.58	2.09	1.95	2.05	2.00	2.73	3.40	2.95	2.84	3.00	3.20	3.54	3.78	3.94	4.39	5.53	5.46	5.21	5.01	5.14	5.39	5.27	4.27
kids	0.73	0.49	0.54	0.63	0.65	0.77	1.64	3.20	2.29	1.53	1.38	1.37	1.32	1.30	1.39	1.79	2.27	2.24	1.86	2.52	2.95	2.55	1.80	1.08
adults >65 yrs	0.42	0.38	0.38	0.42	0.40	0.18	0.01	0.11	0.78	0.97	0.87	0.73	0.58	0.52	0.49	0.42	0.22	0.09	0.05	0.01	0.03	0.07	0.19	0.38
resident >20 h at home	0.03	0.04	0.02	0.04	0.07	0.24	0.27	0.12	0.04	0.01	0.00	0.02	0.04	0.04	0.04	0.01	0.03	0.08	0.09	0.11	0.10	0.08	0.02	0.01
weekend res., workday	0.51	0.35	0.31	0.25	0.23	0.13	0.06	0.25	0.49	0.56	0.66	0.59	0.58	0.55	0.67	0.73	0.65	0.59	0.58	0.65	0.63	0.64	0.59	0.52
Saturday	0.01	0.00	0.00	0.00	0.01	0.04	0.33	0.51	0.01	0.13	0.26	0.27	0.17	0.12	0.07	0.02	0.00	0.00	0.01	0.00	0.05	0.11	0.07	0.00
Sunday/holiday	0.21	0.16	0.10	0.03	0.01	0.03	0.56	0.95	0.11	0.15	0.75	1.05	0.97	0.89	0.81	0.49	0.13	0.03	0.01	0.00	0.00	0.00	0.00	0.00
school break	0.04	0.03	0.02	0.02	0.01	0.00	0.03	0.09	0.00	0.04	0.11	0.14	0.16	0.14	0.12	0.10	0.03	0.02	0.01	0.00	0.00	0.00	0.00	0.01
cold storage	2.46	2.94	3.36	3.54	3.80	3.90	4.08	4.17	3.25	2.95	2.64	2.52	2.43	2.38	2.24	2.05	2.31	2.48	2.53	2.74	2.88	2.97	2.81	2.39
dryer	0.25	0.25	0.32	0.37	0.34	0.23	0.43	0.35	0.35	0.47	0.63	0.72	0.64	0.61	0.58	0.53	0.48	0.49	0.45	0.47	0.40	0.34	0.33	0.26
solarium/sauna	1.18	1.23	1.47	1.59	1.68	2.06	2.05	1.86	1.70	1.57	1.45	1.44	1.54	1.47	1.55	1.44	1.33	1.51	1.56	1.55	1.71	1.74	1.54	1.29
other el-int.	0.45	0.45	0.44	0.48	0.54	0.52	0.32	0.21	0.26	0.30	0.28	0.31	0.32	0.31	0.31	0.39	0.40	0.30	0.29	0.26	0.32	0.34	0.35	0.42
heat pump	0.16	0.16	0.22	0.25	0.37	0.68	0.71	0.96	0.83	0.69	0.70	0.79	0.81	0.80	0.77	0.73	0.63	0.62	0.58	0.57	0.54	0.49	0.39	0.23
month	1.60	1.53	1.39	1.32	1.28	1.21	0.89	0.82	0.96	0.99	1.27	1.46	1.63	1.78	1.99	2.32	2.55	2.51	2.17	1.86	1.46	1.30	1.30	1.42
HDD: floor space	6.17	6.55	7.12	7.35	7.33	7.15	7.99	7.25	7.13	7.02	6.42	6.13	5.67	5.49	5.17	5.17	5.58	6.31	6.88	6.97	7.32	7.28	6.83	6.20
HDD: oil stove	0.01	0.01	0.02	0.02	0.06	0.15	0.26	0.17	0.14	0.15	0.20	0.19	0.19	0.19	0.21	0.26	0.22	0.26	0.21	0.19	0.18	0.11	0.03	0.00
HDD: wood burning	1.49	1.56	1.47	1.56	1.69	1.97	1.55	1.36	1.55	1.43	1.41	1.34	1.33	1.33	1.29	1.16	1.00	0.89	0.87	0.96	1.04	1.08	1.17	1.41
HDD: age	0.87	0.93	0.88	0.65	0.57	0.38	0.22	0.13	0.36	0.40	0.42	0.48	0.48	0.47	0.44	0.36	0.27	0.19	0.21	0.25	0.29	0.33	0.55	0.78
HDD: area	1.19	1.34	1.57	1.73	1.77	1.68	1.22	1.20	0.96	0.92	1.10	1.02	0.97	0.93	0.89	0.80	1.01	1.11	1.25	1.27	1.39	1.42	1.26	1.06
R^2	34.31	34.91	36.42	37.34	37.85	37.65	37.98	38.38	35.54	34.52	35.15	35.59	35.96	36.21	36.65	36.70	38.28	38.33	36.91	36.68	36.83	36.34	34.96	33.23

Table A.6
Share of explained variance for each variable and hour, households with central heating.

	h 1	h 2	h 3	h 4	h 5	h 6	h 7	h 8	h 9	h 10	h 11	h 12	h 13	h 14	h 15	h 16	h 17	h 18	h 19	h 20	h 21	h 22	h 23	h 24
HDD	6.07	6.64	6.89	6.87	6.89	6.66	6.13	5.45	5.82	6.48	6.87	7.13	7.52	8.00	8.77	9.21	9.34	9.33	8.36	7.43	6.72	5.75	5.60	5.63
HDD1st	0.92	0.83	0.82	0.68	0.56	0.46	0.27	0.14	0.23	0.29	0.33	0.32	0.42	0.49	0.36	0.25	0.21	0.19	0.18	0.16	0.13	0.11	0.09	0.12
floor space	4.94	4.68	4.57	4.07	3.73	3.42	2.85	3.43	4.07	3.62	3.16	3.05	2.97	2.70	2.87	2.91	3.25	4.16	4.31	4.68	4.76	4.43	4.75	4.93
adults = 2	1.93	1.33	1.19	0.99	0.89	0.58	0.71	2.29	1.91	1.87	2.00	2.10	2.05	2.04	1.94	1.80	1.90	1.65	1.47	1.56	1.98	2.27	3.08	3.18
adults = > 2	1.42	1.17	1.48	1.69	1.97	1.83	2.41	2.61	2.70	2.80	2.59	2.35	2.21	2.38	2.72	3.26	3.81	3.53	3.44	3.52	3.59	3.47	2.95	2.05
kids = >1	0.24	0.31	0.30	0.33	0.42	0.95	2.55	2.17	1.09	0.86	0.60	0.37	0.20	0.17	0.25	0.67	1.26	1.04	0.88	1.22	1.34	1.01	0.60	0.23
adults >65 yrs	0.51	0.57	0.74	0.96	1.20	1.59	2.25	1.25	0.21	0.09	0.05	0.09	0.17	0.11	0.12	0.14	0.21	0.24	0.36	0.63	0.55	0.41	0.32	0.37
resident >20 h at home	0.35	0.40	0.38	0.24	0.25	0.29	0.04	0.08	0.23	0.42	0.59	0.59	0.68	0.67	0.69	0.68	0.53	0.32	0.18	0.09	0.05	0.05	0.11	0.25
Saturday	0.01	0.00	0.00	0.01	0.01	0.03	0.22	0.36	0.00	0.17	0.28	0.25	0.14	0.08	0.05	0.02	0.00	0.00	0.00	0.01	0.08	0.12	0.04	0.00
Sunday/holiday	0.13	0.06	0.04	0.01	0.00	0.02	0.34	0.87	0.04	0.17	0.64	0.88	0.87	0.88	0.69	0.47	0.18	0.04	0.02	0.02	0.01	0.00	0.00	0.01
school break	0.03	0.01	0.01	0.00	0.00	0.00	0.07	0.12	0.00	0.04	0.11	0.11	0.12	0.13	0.08	0.05	0.02	0.00	0.00	0.00	0.01	0.01	0.00	0.00
cold storage	0.03	0.07	0.04	0.04	0.07	0.05	0.16	0.17	0.31	0.25	0.29	0.21	0.08	0.11	0.10	0.10	0.06	0.03	0.18	0.23	0.12	0.14	0.13	0.07
electric DWH	6.52	6.88	8.15	8.92	9.07	8.31	8.25	7.30	7.53	6.82	6.42	6.52	7.00	6.43	6.57	5.68	5.12	5.44	4.95	4.76	5.36	5.11	4.86	5.12
month	0.59	0.50	0.50	0.40	0.40	0.42	0.40	0.30	0.33	0.38	0.65	0.89	0.84	1.11	1.35	1.83	2.18	2.07	1.74	1.56	1.08	0.73	0.54	0.61
HDD: heating system	7.89	9.41	10.95	10.79	11.22	12.01	12.86	12.27	9.53	8.59	7.95	7.85	7.85	7.68	7.25	7.07	8.40	8.35	7.91	8.22	9.10	9.29	8.80	8.53
HDD: air-to-air heat p.	2.65	2.89	2.89	2.63	2.63	2.88	1.97	1.60	1.72	1.75	1.75	1.80	1.58	1.64	1.63	1.34	1.55	1.29	1.31	1.42	1.68	1.99	2.28	2.74
R^2	34.24	35.76	38.96	38.62	39.33	39.49	41.50	40.42	35.72	34.59	34.27	34.54	34.70	34.62	35.45	35.49	38.03	37.68	35.29	35.51	36.56	34.90	34.15	33.83

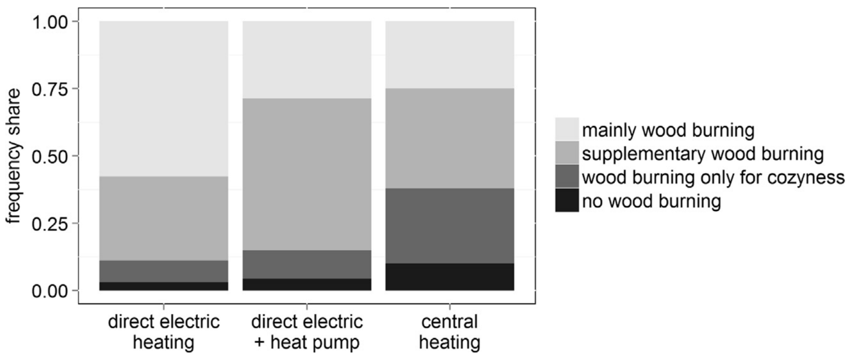


Fig. A.1. Wood burning customs of households using different heating systems.

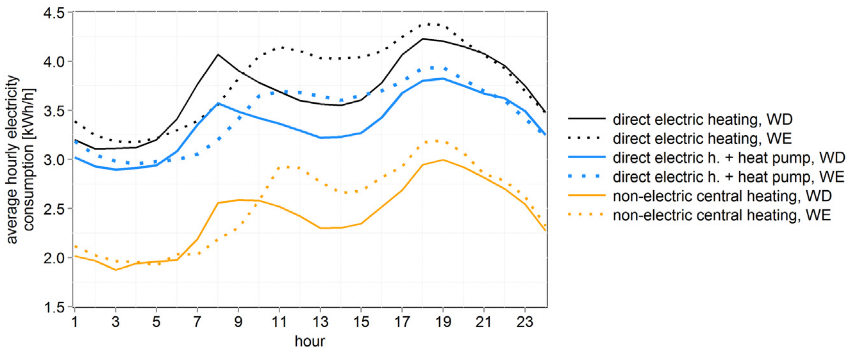


Fig. A.2. Average hourly electricity consumption of households with different heating systems, workdays (WD) and weekends (WE), January/February 2014.

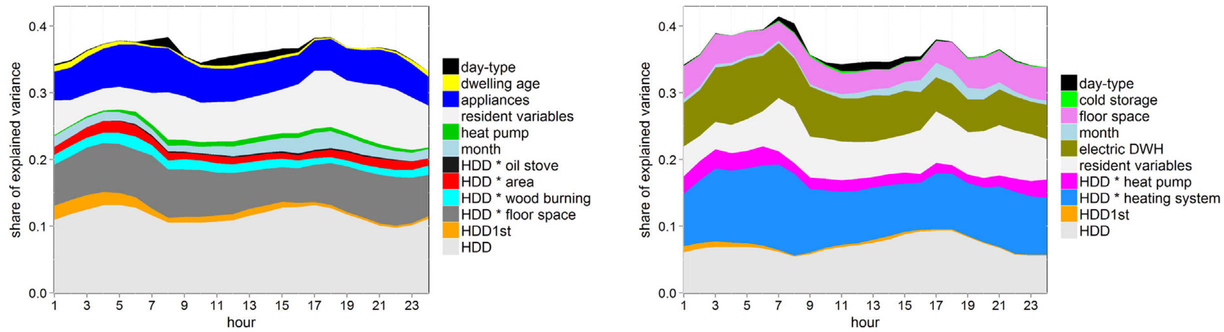
Table A.7
Explanatory variables, direct electric heating.

Variable	Description	Type	Reference group
x_1	heating degree day *HDD*	continuous	–
x_2	1st differences in *HDD*	continuous	–
$x_{3,\ldots,5}$	number of adults = 2, 3, >3	dummy	1
$x_{6,\ldots,8}$	number of children[a] = 1, 2, >2	dummy	0
x_9	resident older than 65 years	dummy	no
x_{10}	resident more than 20 h at home, but no residents older than 65	dummy	no
x_{11}	*d* is workday & there is a weekend resident	dummy	no
x_{12}	*d* is a Saturday but no holiday	dummy	no
x_{13}	*d* is a Sunday or holiday	dummy	no
x_{14}	*d* is within school holidays but no weekend or holiday	dummy	no
x_{15}	cold storage used	dummy	no
x_{16}	clothes dryer used	dummy	no
x_{17}	solarium/sauna used	dummy	no
x_{18}	other electricity-intensive appliances used	dummy	no
x_{19}	air-to-air heat pump used	continuous	–
$x_{20,\ldots,25}$	month = 2, 3, 4, 10, 11, 12	dummy	1
x_{26}	*HDD*· floor space	continuous	–
x_{27}	*HDD*· oil/gas/paraffine oven used	cont./dummy	no
x_{28}	*HDD*· dwelling age = 1980–89	cont./dummy	<1980
x_{29}	*HDD*· dwelling age = 1990–99	cont./dummy	<1980
x_{30}	*HDD*· dwelling age = >1999	cont./dummy	<1980
x_{31}	*HDD*· wood burning mainly	cont./dummy	no or for cozyness
x_{32}	*HDD*· wood burning supplementary	cont./dummy	no or for cozyness
$x_{33,\ldots,36}$	*HDD*· area = 6, 8, 9, 10	cont./dummy	1,2,3,4

[a] younger than 16 years.

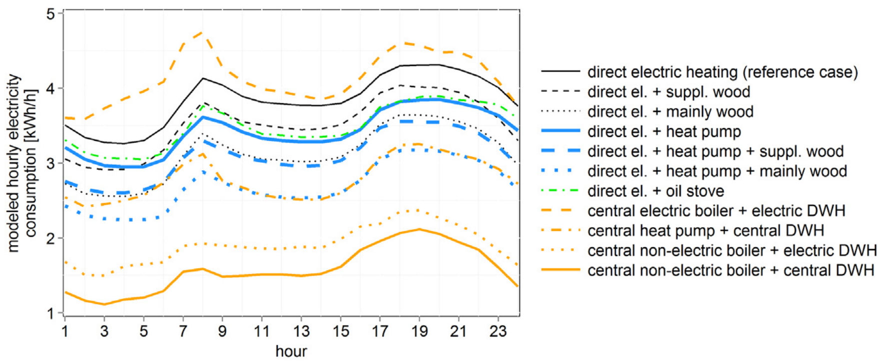
Table A.8
Explanatory variables, central heating.

Variable	Description	Type	Reference group
x_1	heating degree day *HDD*	continuous	–
x_2	1st differences in *HDD*	continuous	–
x_3	floor space	continuous	–
x_4	number of adults = 2	dummy	1
x_5	number of adults = >2	dummy	1
x_6	number of children = >1	dummy	0
x_7	resident older than 65 years	dummy	no
x_8	resident more than 20 h at home, but no residents older than 65	dummy	no
x_9	*d* is a Saturday but no holiday	dummy	no
x_{10}	*d* is a Sunday or holiday	dummy	no
x_{11}	*d* is within school holidays but no weekend or holiday	dummy	no
x_{12}	cold storage used	dummy	no
x_{13}	electric DWH	dummy	non-electric DWH
$x_{14,...,18}$	month = 2, 3, 4, 10, 11	dummy	12 or 1
x_{19}	*HDD*· central heat pump used	cont./dummy	oil boiler used
x_{20}	*HDD*· central electric boiler used	cont./dummy	oil boiler used
x_{21}	*HDD*· air-to-air heat pump used	cont./dummy	no

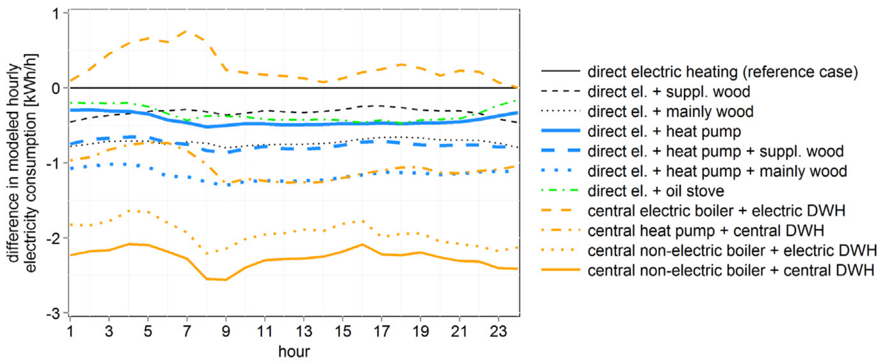


(a) Direct electric heating **(b)** Central heating

Fig. A.3. Shares of explained variance in hourly electricity consumption.

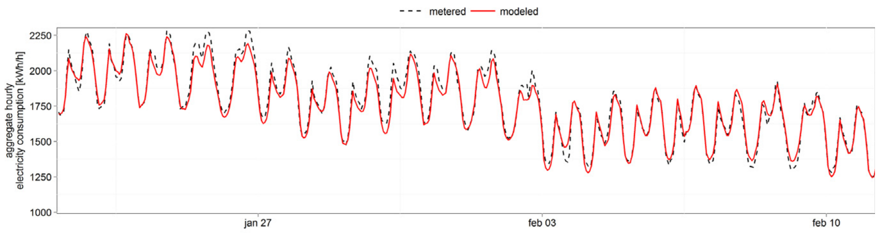


(a) Modeled hourly consumption

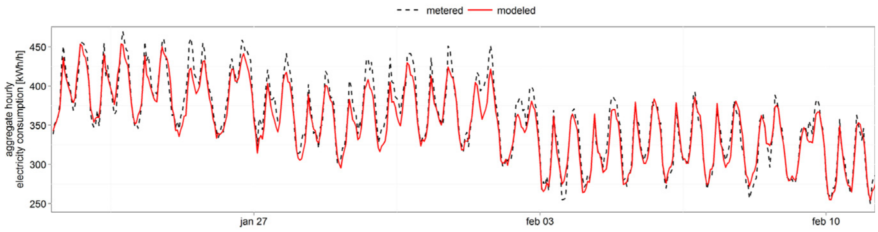


(b) Differences in modeled hourly consumption compared to the reference case

Fig. A.4. Modeled hourly electricity consumption of an average household using different heating methods.



(a) Aggregate hourly consumption, directly electrically heated dwellings



(b) Aggregate consumption, dwellings with central heating systems

Fig. A.5. Metered and modeled aggregate hourly electricity consumption during winter period.

Table. A.9
Scenarios.

Scenario	name	Changes referring to the base case
0	base case	–
1	heat pumps	all electrically heated homes use air-to-air heat pumps
2	heat pumps + mainly firewood	all electrically heated homes use air-to-air heat pumps and mainly wood burning
3	central heating + electric DWH	all households switch to non-electric central heating and electric DWH
4	central heating + central DWH	all households switch to non-electric central heating and central DWH

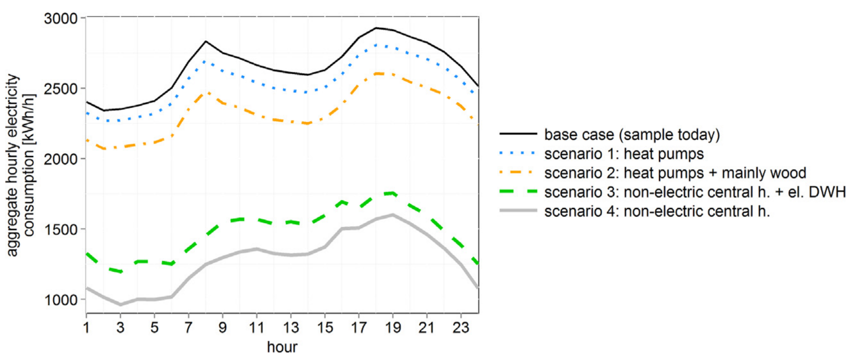


Fig. A.6. Modeled aggregate hourly electricity consumption with $HDD = 30$ in base case and scenarios 1–4.

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7 PAPER II

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Modeling and disaggregating hourly electricity consumption in Norwegian dwellings based on smart meter data

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ABSTRACT

By area-wide implementation of smart metering, large amounts of individual electricity consumption data with a high temporal resolution become available. We use multiple regression models for hourly electricity consumption in Norwegian dwellings, based on panel data consisting of hourly smart meter data, weather data, and response data from a household survey. Two models based on daily and hourly mean values of outdoor temperature, respectively, are compared and discussed. Our results indicate that daily mean outdoor temperature – represented by heating degree day – can serve as weather-related input variable for modeling aggregate hourly electricity consumption. The regression models are further used to break down hourly electricity consumption into two components, representing modeled consumption for space heating and other electric appliances, respectively. Thus, without submetering electric heating equipment an estimate for heating energy consumption is available, and can be used for evaluating different demand side management options, e.g. fuel substitution or load control. Moreover, the models can be used for forecasting aggregate regional electricity consumption in the Norwegian household sector with a high temporal resolution, as e.g. changes in regional climatic conditions, dwelling structure, and demographic factors can be taken into account.

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1. Introduction

1.1. Climate goals and smart metering in Norway

According to the European Union's climate goals [1], by 2030, greenhouse gas emissions should be reduced by at least 40%, and energy efficiency should be improved by at least 27%, referring to 1990 levels. Moreover, at least 27% of energy demand should be covered by renewable energy sources in 2030. In order to approach these goals the integration of variable renewable energy sources (VRE) is forwarded, implying challenges to existing European energy systems. While power generation by thermal power plants based on conventional fuels can be controlled by the system operators, power supply by VRE needs to be utilized at occurrence, even when it is not coinciding with demand. Besides competitive storage technologies, demand side management (DSM) includes various measures to help synchronizing energy supply and demand. Energy conservation, fuel substitution, load building, and load management are examples for DSM options [2]. Load management options are intended to change the load patterns generated by the consumers, by e.g. reducing load during peak periods, increasing load during off-peak periods, or shifting load from peak to off-peak periods. In order to communicate with individual consumers, e.g. sending price information or control signals, and receiving meter data, advanced metering and communication technology (*smart metering*) is required. Both Norway and the EU forward the roll-out of *smart* electricity meters, and by January 2019, all consumers in Norway should be equipped with the new metering technology [3,4]. The local grid companies are responsible for installation, and metering intervals should be between 15 and 60 min [5].

Load management can broadly be categorized into *direct* and *indirect* load control. In indirect load control programs customers are usually offered vouchers or lower electricity tariffs as incentives for participating and scheduling own consumption according to the patterns preferred by the grid companies. Indirect load control programs are already implemented by several electricity companies, e.g. in North America and France, and achieve considerable load reductions during peak periods [6]. Direct load control implies that the grid companies are able to directly control certain appliances of participating customers. Ericson [7] describes a study about direct load control of residential water heaters in Norway and points out that by disconnecting water heaters during a period with high demand, the original consumption top can be reduced,

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but a new top may occur when re-connecting all water heaters simultaneously (*pay-back effect*).

The introduction of area-wide smart metering yields enormous amounts of highly resolved micro-level electricity consumption data which – in combination with weather data and cross sectional data (e.g. collected by customer surveys) – can be utilized to develop more precise prediction models and detailed analyses on the drivers of electricity consumption. While whole-house smart meter data for some regions is already available today, data from submetering campaigns, i.e. metering different electric appliances separately, is relatively rare, so that we have little knowledge on how different electric devices contribute to household electricity consumption over the course of the day. Efficient methods to model electricity consumption by the most important appliances with a high temporal resolution can forward the development and implementation of load management programs that can help synchronizing demand and supply in energy systems with high shares of VRE.

1.2. Previous work

Aggregate and individual hourly electricity consumption data combined with cross-sectional data, as well as disaggregating whole-house consumption is subject to a number of studies. Several models for aggregate hourly electricity consumption take into account climatic conditions – as e.g. outdoor temperature represented by heating or cooling degree day – but without including dwelling stock and household variables (e.g. Psiloglou et al. [8], Beccali et al. [9]). Sandelds et al. [10] model hourly load profiles for a population of Swedish detached houses with electric heating. Their model is based on aggregate hourly electricity consumption data of a substation in Stockholm and breaks down total consumption into domestic water heating, electric appliances, and space heating consumption. Paatero and Lund [11] use hourly electricity meter data from Finnish apartment buildings without electric heating to generate hourly load profiles of individual households. Pedersen et al. [12] describe prediction models for heat and electricity load in different building types. Hourly heat demand profiles are estimated using load factors, i.e. relative loads referring to average daily design loads. Modeled hourly electricity demand for electric appliances, excluding electric heating equipment, is based on probability distributions. In a previous paper [13] we use smart meter data combined with survey response and weather data to investigate the impacts of different space heating systems on hourly electricity consumption in detached houses in Norway. Separate regression models for hourly electricity consumption of households with conventional direct electric heating and central heating systems during the heating period are presented.

Birt et al. [14] propose a method for disaggregating hourly electricity consumption of Canadian dwellings into base load and activity load. The model is based on samples with hourly and minutely metered whole-house electricity consumption and a sample with minutely submetering of heating and cooling equipment consumption. Temperature dependence is considered during both heating and cooling period. Perez et al. [15] present a disaggregation method for residential air-conditioning load based on smart meter data with a 1-min metering interval from 88 households in Texas. Submeter data from A/C loads in 19 households is used to train the A/C load model. Iyer et al. [16] describe a method for disaggregating hourly energy consumption in supermarkets into a weather-dependent and a weather-independent component, based on hourly meter data from 94 stores. Besides weather data, design loads for each store are used as input data to the model. Sæle et al. [17] summarize the findings of the first part of the ElDeK project [18], during which electricity consumption of 32 participating Norwegian households was metered in detail. Whole-house consumption was metered every hour for at least one year, while individual consumption of several electric appliances was metered every minute for a period of approximately four weeks. All participating customers reside in single-family houses and provide further household information via a questionnaire. During the examined four-weeks metering period the typical consumption profile exhibits two peaks during morning and evening which are mainly caused by lighting in the living room. Maximum consumption of electric water heating coincides with the morning peak, and space heating equipment is reported to be the largest consumer during all hours of the day [17]. Unfortunately, no detailed results of the project have been published to date.

To the best of our knowledge, previous studies have not compared the impacts of hourly and daily mean outdoor temperature values on hourly electricity consumption, or described a simple disaggregation method based on whole-house meter data.

1.3. Goals of the study

In this study, hourly electricity meter data of 470 household customers in south-eastern Norway is combined with cross sectional data which was collected by a web-based survey among the customers. The resulting panel data set is further merged with weather data and calendric information referring to the metering period.

The overall objective of this paper is to examine the impacts of outdoor temperature and different household characteristics on hourly electricity consumption in Norwegian dwellings. We evaluate whether *daily* mean values of outdoor temperature are sufficient to model *hourly* electricity consumption by comparing the results from two models, one based on daily and one based on hourly mean temperatures. Moreover, we develop a simple method for disaggregating modeled whole-house electricity consumption into two components, representing modeled consumption for electric space heating and other electric appliances, respectively. Estimates on how much electrical energy is consumed for space heating and other purposes facilitates the evaluation of different load management options.

2. Data

2.1. Typical dwelling characteristics in Norway

About 50% of Norwegian dwellings are detached houses, apartments account for about 25%, and about 20% are represented by semi-detached houses and terraced houses [19]. However, in larger cities (e.g. Oslo) apartments reach considerably higher shares. The most common space heating method in Norway is direct electric space heating, which is often used in combination with wood burning stoves and air-to-air heat pumps. In most households electrically heated storage tanks are used for domestic water heating. In most Norwegian regions hot water based central heating systems are relatively rare, and often supplied by electric boilers or oil boilers. However, district heating networks are established e.g. in Oslo, Trondheim, and Bergen, and the use of oil boilers will be abandoned by 2020.

2.2. Sample data

A web based survey on household-specific data was carried out among electricity customers of system operators *Ringerikskraft Nett AS*[1] and *Skagerak Nett AS*[2] in October 2013. Meter data from

[1] Supplying Ringerike municipality, Buskerud county.
[2] Supplying several municipalities in Telemark and Vestfold county.

Table 1
Number of observations and average floor space for each dwelling type and group, training data.

Dwelling type/group	Observations	Average floor space
Ordinary detached houses	353	157 m^2
Detached houses with secondary suites	33	212 m^2
Detached dwellings	**386**	**161 m^2**
Semi-detached houses	30	105 m^2
Terraced houses	24	106 m^2
Apartments	30	85 m^2
Attached dwellings	**84**	**98 m^2**

Skagerak Nett is available for the period June 2009–May 2010, so that about four years lie between metering period and survey. Thus, the data is only used as test data for cross validation in Section 4.5. Meter data and survey response data from Ringerikskraft Nett constitutes the training data set in this study and is described in detail in the following.

Invitations were sent to 9379 available customers with hourly metering systems installed in their homes, and 1550 customers answered the questionnaire (response rate 16.5%). The questionnaire contained about 30 different items, mainly on technical data (e.g. floor space, dwelling age, number of household members, heating systems).[3] All items are listed in Tables A.4–A.6 in the Appendix. Since hourly metering in different areas started at different points in time between December 2012 and February 2014, the length of available meter data time series varies across customers. While the starting date of hourly metering varies, the time series ended in May 2014 for all observations. If a period of one year was to be examined only relatively few observations would be available. In case the examined period was reduced to e.g. the winter months only, considerably more observations, but a shorter time series would be available. In order to find a trade-off between length of metering period and number of available observations a period from August to May is chosen.

2.2.1. Survey response data

Due to a low number of participating households with central heating systems, only households using direct electric space heating, supplemented by air-to-air heat pumps, wood stoves, or paraffin stoves, and using electrically heated hot water tanks are included in the sample. Furthermore, only the five most frequent dwelling types are included, namely ordinary detached houses, detached houses with secondary suites,[4] vertically separated semi-detached houses, terraced houses, and apartments. After these limitations, a sample of 470 households remains.

In the questionnaire (see item 6 in Table A.4), respondents were free to type in three of the different values that are typically used to describe a dwelling's floor space in Norway: *gross floor space*, *primary floor space*,[5] and *heated floor space*. Since some unfeasible, reported data indicates misunderstandings regarding the different floor space definitions, the variable *dwelling floor space* used in this study is the mean value of largest and smallest floor space value reported by each respondent. Frequencies of dwelling types and average floor space per dwelling type are shown in Table 1.

In the sample, the large majority of included households reside in ordinary detached houses (75%) while the other dwelling types account for only 5–7% each. Therefore, we group the five dwelling types into only two *dwelling groups*, which are *detached* and *attached* dwellings. Thus, *attached dwellings* represent all dwellings that share at least one common wall with a neighboring dwelling, while *detached dwellings* are isolated. Mean floor space is 161 m^2 for detached dwellings, and 98 m^2 for attached dwellings (Table 1).

Relative frequencies of different household sizes, construction periods, and wood burning habits, in both dwelling groups, are shown in Fig. 1. In detached dwellings, two-person households are most common (50%), while households with only one person are comparatively rare (13%) (Fig. 1a). In attached dwellings one-person households are most common (43%), followed by two-person households (30%). The corresponding shares of households with three or four persons are slightly higher in detached dwellings, while households with more than four persons are least frequent (6%) within both dwelling groups.

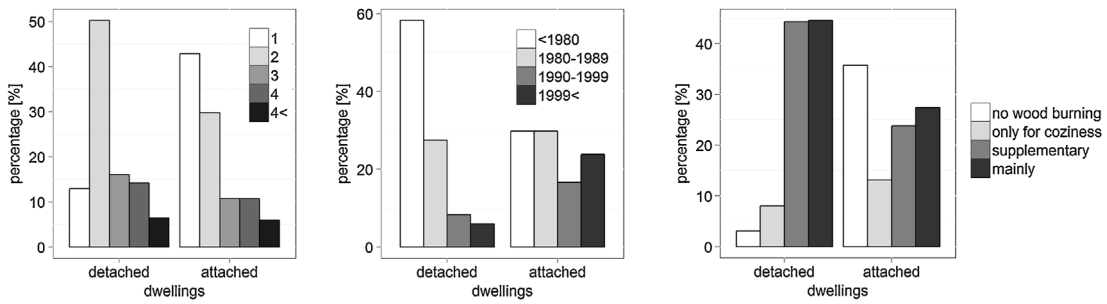
58% of detached dwellings were built before 1980, about 27% were built during the 1980s, and 8% during the 1990s (Fig. 1b). Buildings built after 1999 represent the smallest share (6%). In contrast, 30% of attached dwellings were built before 1980 and during the 1980s, respectively, and 25% represent dwellings built after 1999. Thus, in our sample, attached dwellings on average are newer than detached dwellings.

Survey participants were asked to rate their wood burning habits according to the following scale (item 19, Table A.6): (1) *no wood burning*, (2) *only for coziness*, (3) *supplementary*, and (4) *mainly*. *Supplementary wood burning* means, that wood burning is used when electric heating is not sufficient to maintain the desired indoor temperature, while *mainly wood burning* means that wood burning is a major heating method and practically used during the entire heating period. In detached dwellings about 90% of households use wood burning either supplementary or as a major heating source, while only 8% report to use wood burning only for coziness and 3% use no wood burning at all (Fig. 1c). In contrast, more than one third of households residing in attached dwellings use no wood burning at all, while about 50% use it supplementary or mainly, and 13% only for coziness. The survey participants were further asked to estimate their average annual firewood consumption (item 20, Table A.6). Respondents reported consumption in litres, 60-litres-bags, fathoms,[6] or cubic meters. Average annual firewood consumption of households using wood burning *only for coziness*, *supplementary*, and *mainly* is approximately 1 m^3/a, 3 m^3/a, 6 m^3/a, respectively, and is thus consistent with wood burning intensity, i.e. average consumption is increasing with intensity. However, since the amount of useful energy per cubic meter firewood might vary largely, self-reported annual firewood consumption is not used as explanatory variable in our analyses.

2.2.2. Meter data

Hourly outdoor temperature data – metered at Hønefoss Høyby weather station – is provided by the Norwegian Meteorological Institute [21]. Electricity meter data is given as a data set of hourly meter readings.[7] Hours 1–24 are defined as followed: Hour 1 refers to the time period between midnight and 1:00 a.m., hour 2 refers to the period between 1:00 a.m. and 2:00 a.m., etc., and hour 24 represents the period between 11:00 p.m. and midnight. Thus, electricity consumption during one hour is calculated as the difference between the meter readings enclosing the corresponding hour. All included households are located in the city of Hønefoss or its suburbs. Usable meter data of all 470 included households is available for the period of 3 August 2013 to 21 May 2014 – called metering period in the following. The term *usable* means that realistic meter data is available, but that some missing or erroneous values might be included. During some shorter periods general meter

[3] Not all questions are answered by all respondents.
[4] Representing two households when the secondary suite is inhabited.
[5] Excluding garages, storages, technical rooms, etc.
[6] 1 Norwegian fathom ≈ 2.4 m^3.
[7] Only meter data of customers that have answered the questionnaire is provided by the system operator.



(a) Number of residents (b) Year of construction (c) Wood burning customs

Fig. 1. Number of residents (a), year of construction (b), wood burning habits (c) in detached and attached dwellings.

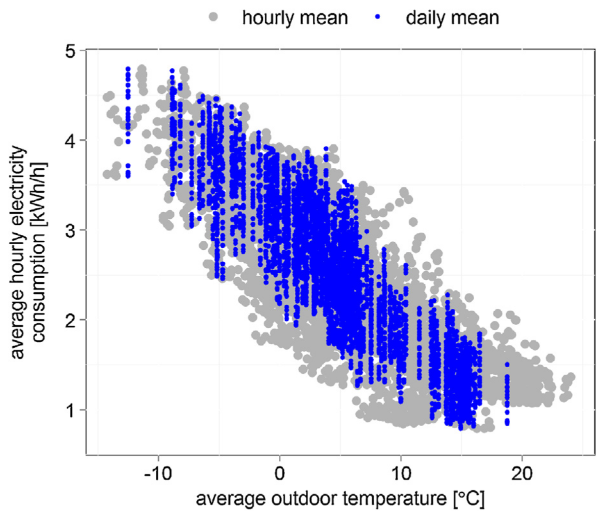


Fig. 2. Average hourly electricity consumption over average outdoor temperature (detached dwellings, working days).

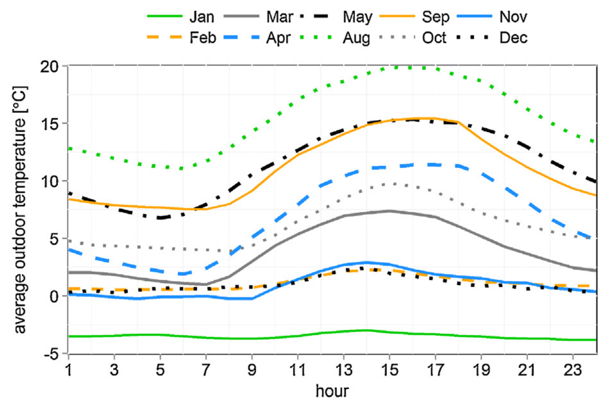


Fig. 3. Average hourly outdoor temperature per month, August 2013–May 2014.

failures occurred resulting in missing meter data or constant values for a large part of the sample. Though a calculation routine was established to remove most erroneous data (especially interpolated values), it is assumed that some spurious values remained in the data set.

Due to electric space heating there is a strong negative correlation between electricity consumption and outdoor temperature. Average hourly electricity consumption in detached dwellings as a function of both hourly and daily mean outdoor temperature is shown in Fig. 2. Hourly mean temperature $\bar{t}_{o,h}$ represents the mean value of the two hourly measurements in the beginning and end of hour h,[8] while daily mean temperature $\bar{t}_{o,d}$ represents the mean value of 24 hourly measurements during day d. The correlation coefficient between hourly consumption and hourly mean temperature is $R = 0.81$, while hourly consumption and daily mean temperature yield $R = 0.88$. Also when focusing on the main heating period (October to April) there is a stronger linear correlation between hourly consumption and daily mean temperature than between hourly consumption and hourly temperature.

Average hourly outdoor temperature during each month within the metering period is shown in Fig. 3. On average, hourly temperature values are lowest during early morning and highest during afternoon. Length of night- and day-time, temperature level, and range between the lowest and the highest temperatures during the day correspond to seasonal differences. Average hourly electricity consumption in detached dwellings in September 2013 and January 2014 is shown in Fig. 4. At first glance, average hourly consumption seems relatively independent from average hourly temperature values during the corresponding month (Fig. 3). Average hourly consumption in January is higher than in September, and there are noticeable differences between working days and non-working days, especially during day-time. However, apart from some differences during afternoon and evening, average profiles in January and September are shaped similarly. On working days, a morning peak occurs during hour 8, and an evening top around hours 18 and 19 in January and around hours 21 and 22 in September. On non-working days, a morning top occurs around hours 11 or 12,

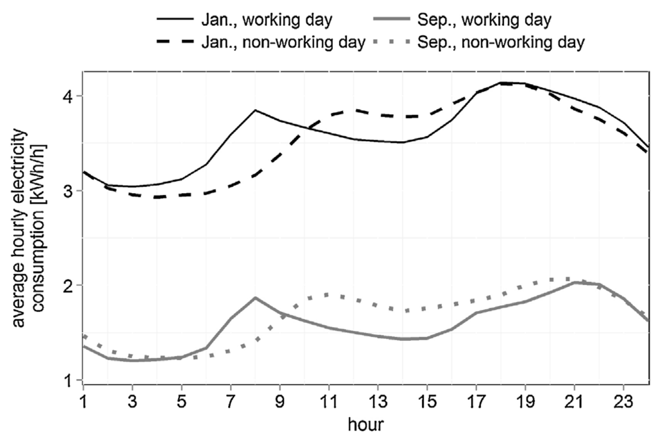


Fig. 4. Average hourly electricity consumption in detached dwellings per month (September, January)

[8] See Section 3.2.1.

Table 2
Illustration of the panel data structure.

date	*ID*	*group*	*floor space*	*adults*	*children*	*heat pump*	*daytype*	*month*	*HDD*	*HDD1st*	E_1	...	E_{24}
03-11-2013	M0001	detached	170	2	2	yes	Sun/holiday	11	15.3	−0.2	3.21	...	3.30
04-11-2013	M0001	detached	170	2	2	yes	workday	11	14.8	−0.5	3.08	...	3.25
...	...	...	...	...	...	...	...	...	...	...	...	...	...
03-11-2013	M0500	attached	100	1	0	no	Sun/holiday	11	15.3	−0.2	2.81	...	2.91
04-11-2013	M0500	attached	100	1	0	no	workday	11	14.8	−0.5	2.80	...	2.88

and day-time consumption is considerably higher than on working days.

3. Methods

Combining time series (meter data) and cross sectional data (survey response) results in a large panel data set. An example illustrating the structure of the data set – containing only some variables – is shown in Table 2. For each observation (*ID*) and each day (*date*) a set of 24 hourly electricity meter values ($E_1, E_2, \ldots, E_{24}$), as well as cross sectional data (*dwelling group, floor space*,...) is available. Temperature data (*HDD, HDD1st*) and calendric data (*daytype, month*) represent time series components that may change from day to day but are constant across observations, since all dwellings are located in the same region.

3.1. Panel data regression

All statistical analysis in this study is performed using *R* [22]. We model electricity consumption on household level for each hour of the day using the *plm*-package [23], which enables different panel data regression methods. We apply the method of pooled OLS (ordinary least squares)[9] to a panel data set containing hourly consumption data from $N = 470$ households over a time period of $T = 292$ days. For each hour of the day a separate model is estimated based on about $N \cdot T$ observations[10], resulting in a set of 24 hourly models. The hourly model set is based on multiple linear regression, as illustrated by Eq. (1), where $E_{h,i}$ represents hourly electricity consumption of hour h and observation i, $\beta_{0,h}$ is the intercept parameter, $\beta_{k,h}$ are the slope parameters, and ϵ_i is the unobserved error term. The included explanatory variables x_k are described in the next subsection.

$$E_{h,i} = \beta_{0,h} + \sum_{k=1}^{k} \beta_{k,h} \cdot x_{k,i} + \epsilon_i \tag{1}$$

The modeled value of hourly consumption $\hat{E}_{h,i}$ is calculated based on the corresponding parameter estimates $\hat{\beta}_{0,h}$ and $\hat{\beta}_{k,h}$ (Eq. (2)). The residuals $\hat{\epsilon}_i$ represent the differences between modeled and metered consumption values.

$$\hat{E}_{h,i} = \hat{\beta}_{0,h} + \sum_{k=1}^{k} \hat{\beta}_{k,h} \cdot x_{k,i} = E_{h,i} - \hat{\epsilon}_i \tag{2}$$

3.2. Explanatory variables

3.2.1. Heating degree day and heating degree hour

Daily mean outdoor temperature $\bar{t}_{o,d}$ of day d is represented by the arithmetic mean value of 24 hourly temperature values, metered during day d. Based on the assumption, that temperature-dependent electricity consumption only takes place at temperatures below 17 °C *(heating limit temperature)*, outdoor temperature is transformed into *heating degree day HDD*,[11] defined as the difference between 17 °C and daily mean outdoor temperature $\bar{t}_{o,d}$. *HDD* is zero in case $\bar{t}_{o,d} \geq 17$ °C (Eq. (3)).

$$HDD_d = \begin{cases} 17 - \bar{t}_{o,d}, & \text{for } \bar{t}_{o,d} < 17 \\ 0, & \text{else} \end{cases} \tag{3}$$

The difference in heating degree days between any day d and the day before ($d - 1$) is called *first differences in heating degree days HDD1st* (Eq. (4)). Thus, a positive value of *HDD1st* implies that mean outdoor temperature during day d is lower compared to the day before.

$$HDD1st_d = HDD_d - HDD_{d-1} \tag{4}$$

In order to establish a model set based on *hourly* outdoor temperature meter data, a variable called *heating degree hour HDH* is defined analogously to *HDD* (Equation (5)). While *HDD* represents daily mean outdoor temperature, *HDH* represent the mean value $\bar{t}_{o,h}$ of the two hourly measurements enclosing hour h, e.g. $\bar{t}_{o,h=3} = 0.5 \cdot (t_{o,3:00\,a.m.} + t_{o,2:00\,a.m.})$.

$$HDH_h = \begin{cases} 17 - \bar{t}_{o,h}, & \text{for } \bar{t}_{o,h} < 17 \\ 0, & \text{else} \end{cases} \tag{5}$$

The difference in heating degree hours between hour h and hour $h - 1$ is called *first differences in heating degree hours HDH1st* (Eq. (6)). Correspondingly, a positive value of *HDH1st* indicates a temperature drop from $h - 1$ to hour h.

$$HDH1st = HDH_h - HDH_{h-1} \tag{6}$$

3.2.2. Description of the explanatory variables

In order to compare the influence of heating degree day and heating degree hour on hourly electricity consumption, two model sets – consisting of 24 models each – are estimated and correspondingly called *HDD*-models and *HDH*-models. Within both model sets, each of the 24 linear models contain the same explanatory variables, of which some are included in interaction with heating degree day *HDD* or heating degree hour *HDH*. All explanatory variables for the *HDD*-model set are listed in Table 3. Variables are chosen according to statistical significance and share of total variance explained. Since not all respondents answered all survey items, some possibly important variables are not included. For each categorical variable the corresponding reference group is reported. The *HDH*-model set contains the same explanatory variables, with the only difference, that *HDD* is replaced by *HDH*, and *HDD1st* is replaced by *HDH1st*. Wood burning customs are divided into three intensity levels, namely *no wood burning or only for coziness, supplementary wood burning*, and *mainly wood burning*. *Dwelling age* is divided into only two levels representing the period of construction, which are *<1980* and *1980≤*. Since temperature-dependent

[9] see e.g. Wooldridge [24], chapter 13
[10] Not all households exhibit meter data for all hours during the metering period.
[11] For simplicity, index d is dropped in the text and *HDD* is used without physical unit.

Table 3
Explanatory variables, *HDD*-model set.

Variable	Description	Type	Reference group
x_1	Dwelling group = attached	Dummy	Dwelling group = detached
$x_{2,\ldots,4}$	Number of adults (incl. children ≥16 years) = 2, 3, >3	Dummy	Adults = 1
$x_{5,\ldots,7}$	Number of children (<16 years) = 1, 2, >2	Dummy	Children = 0
x_8	Senior resident (>65 years) = yes · daytype = workday	Dummy	Senior residents = no
x_9	Resident more than 20 h at home (no senior residents) = yes · daytype = workday	Dummy	Residents home >20 h = no
x_{10}	Weekend resident = yes · daytype = workday	Dummy	Weekend residents = no
$x_{11,\ldots,13}$	Daytype = Saturday but no holiday, Sunday or holiday, workday within school breaks	Dummy	Daytype = workday
x_{14}	Cold storage = yes	Dummy	Cold storage = no
x_{15}	Other electricity-intensive appliances = yes	Dummy	Appliances = no
$x_{16,\ldots,24}$	Month = 2, 3, 4, 5, 8, 9, 10, 11, 12	Dummy	Month = 1 (January)
x_{25}	*HDD*	Continuous	–
x_{26}	*HDD1st*	Continuous	–
x_{27}	*HDD* · floor space	Continuous	–
x_{28}	*HDD* · dwelling group = attached	Cont./dummy	Dwelling group = detached
x_{29}	Heat pump = yes · dwelling group = detached · *HDD* > 0	Dummy	Heat pump = no
x_{30}	Heat pump = yes · dwelling group = attached · *HDD* > 0	Dummy	Heat pump = no
x_{31}	*HDD* · age = 1980≤ · dwelling group = detached	Cont./dummy	Age = <1980
x_{32}	*HDD* · age = 1980≤ · dwelling group = attached	Cont./dummy	Age = <1980
x_{33}	*HDD* · wood burning = supplementary · dwelling group = detached	Cont./dummy	Wood burning = no or only for coziness
x_{34}	*HDD* · wood burning = supplementary · dwelling group = attached	Cont./dummy	Wood burning = no or only for coziness
x_{35}	*HDD* · wood burning = mainly · dwelling group = detached	Cont./dummy	Wood burning = no or only for cosiness
x_{36}	*HDD* · wood burning = mainly · dwelling group = attached	Cont./dummy	Wood burning = no or only for cosiness

electricity consumption is assumed to differ between detached and attached dwellings we include variables *dwelling age*, and *wood burning* in interaction with both *HDD* and *dwelling group*. Variable *heat pump*, indicating the use of air-to-air heat pumps, is only considered if *HDD* > 0 and is included in interaction with *dwelling group*. Thus, we assume that reductions achieved by using an air-to-air heat pump are temperature-independent, but only occur during days with space heating demand.

3.3. *Disaggregation into basic and space heating consumption*

By including temperature variables *HDD* and *HDD1st* (or *HDH* and *HDH1st*) modeled consumption can be broken down into a temperature-independent and a temperature-dependent component. The temperature-independent part can be interpreted as consumption for electric appliances including electrically heated hot water tanks (*basic* consumption, Eq. (7)), while the temperature-dependent part can be interpreted as *space heating* consumption (Eq. (8)). Since categorical variable *month* takes into account seasonal differences in temperature-independent consumption (e.g. higher electricity consumption for illumination during winter) the assumption of a temperature-dependent component mainly representing space heating energy seems reasonable. However, estimated space heating consumption does not necessarily include all space heating appliances, but only those with temperature-dependent behavior, i.e. increasing consumption with decreasing outdoor temperature.

$$\hat{E}_{basic,h,i} = \hat{\beta}_{0,h} + \sum_{k=1}^{24} \hat{\beta}_{k,h} \cdot x_{k,i} \tag{7}$$

$$\hat{E}_{spheat,h,i} = \sum_{k=25}^{36} \hat{\beta}_{k,h} \cdot x_{k,i} \tag{8}$$

3.4. *Modeling aggregate consumption*

3.4.1. Time-aggregate *consumption*

Due to the simple structure of the hourly models, individual daily electricity consumption can be modeled by using the summed hourly coefficients for each variable (Eq. (9) and (10)) and applying Eq. (11).

$$\hat{\beta}_{0,d} = \sum_{h=1}^{24} \hat{\beta}_{0,h} \tag{9}$$

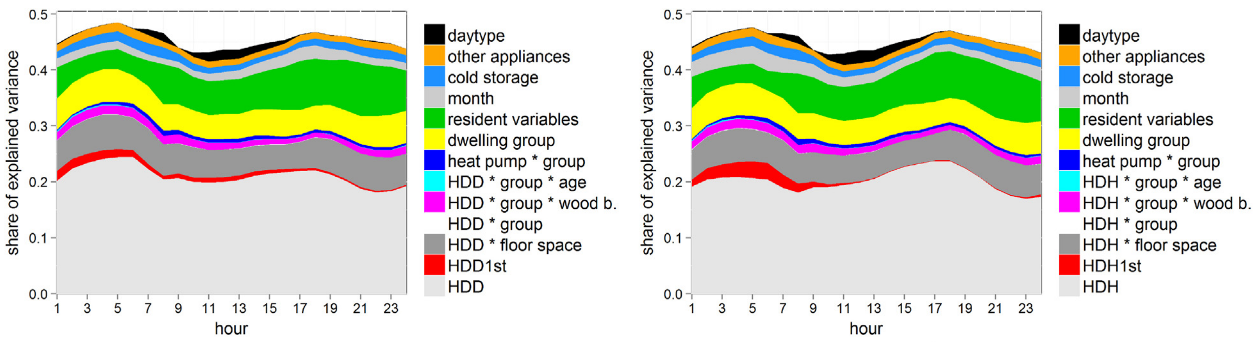
$$\hat{\beta}_{k,d} = \sum_{h=1}^{24} \hat{\beta}_{k,h} \tag{10}$$

$$\hat{E}_{d,i} = \hat{\beta}_{0,d} + \sum_{k=1}^{k} \hat{\beta}_{k,d} \cdot x_{k,i} \tag{11}$$

For modeling daily consumption temperature data and calendric information for each day *d* during the examined period are identical to the corresponding data used in the individual hourly consumption model set. For modeling consumption per week, month, or any other time period, temperature and calendric variables that are not constant during the examined period need to be considered in summarized form in the corresponding model components (e.g. $\sum HDD$ instead of *HDD*, total number of days within each *daytype* or *month* category), and the intercept estimate needs to be multiplied by the total number of days.

3.4.2. Sample-aggregate *consumption*

Aggregate hourly electricity consumption, i.e. summed consumption of all observations in the sample, can be modeled directly by using the sample's overall characteristics, i.e. total number of households, summed floor space, etc., as cross-sectional input data. Temperature data and calendric information for each day *d* during the examined period are identical to the corresponding data for modeling individual hourly consumption.



(a) *HDD*-model set (b) *HDH*-model set

Fig. 5. Shares of explained variance in hourly electricity consumption.

4. Results

4.1. Regression results

A Breusch-Godfrey test indicates autocorrelated residuals ($p <$ 0.0001), i.e. correlation between residuals and lagged residuals, and a Breusch-Pagan test indicates heteroskedastic residuals ($p <$ 0.0001), i.e. non-constant residual variance. In order to yield reliable p-values for all variables, heteroskedasticity- and autocorrelation-consistent (HAC) standard errors are used. p-values for all explanatory variables of both model sets (*HDD* and *HDH* model) are listed in Tables B.7 and B.10 in Appendix B. F-statistics for all 48 models yield p-values below 0.0001, indicating overall significance of the included variables. The residuals seem independent from explanatory variables and are approximately normally distributed. Though square-root transforming response variable E_h yields more normally distributed residuals, the non-transformed response is preferred in order to retain simple models with easily interpretable estimates which, moreover, allow efficient modeling of aggregate hourly consumption using summed input data (see Section 3.4).

4.1.1. Explained variance and goodness of fit

Percent shares of total variance explained by the explanatory variables are listed in Tables B.9 and B.12 in Appendix B. Graphical presentations of explained variance are given in Fig. 5. Total explained variance in hourly consumption – represented by adjusted coefficient of determination R^2 – varies from 0.43 to 0.49 for the hourly models based on *HDD*. Total explained variance for the *HDH*-model set is very similarly shaped and exhibits slightly lower values, except during afternoon. The results identify heating degree day (heating degree hour in the *HDH*-model) as the most important explanatory variable throughout all 24 h, explaining about 20% of the variance in hourly consumption. While *HDD* contributes most during early morning, the contribution of *HDH* is highest during late afternoon. Contribution of first differences in heating degree days, *HDD1st*, is largest during the first hours of the day and continuously decreases over the course of the day, which seems feasible, as *HDD*1*st* represents the impact of the temperature difference between the examined day and the day before. First differences in heating degree hours, *HDH1st*, represent the temperature difference between the examined hour and the hour before. Its contribution to R^2 is also highest during early morning hours, when both total consumption and outdoor temperature on average are lowest. A possible explanation is, that during night-time and early morning a high proportion of total electricity consumption is used for space heating, and that changes in outdoor temperature from one hour to the next are attenuated by the thermal storage capacity of the dwelling's mass.

Apart from *HDD* (*HDH* correspondingly), variables *HDD·floor space* (*HDH·floor space*), *dwelling group*, and *resident variables* are the most important explanatory variables, explaining about 5-10% of total variance in both model sets. *Resident variables* include explanatory variables $x_{2,...,10}$ (Table 3), i.e. number of adults and children, and dummy variables indicating whether there are senior or weekend residents, or residents that spend most of the day at home. Compared to most other variables, the contribution of *resident variables* varies more clearly over the course of the day, with a minimum during night-time and early morning and a maximum during evening. Assuming that the residents use electric appliances, as e.g. white goods, mostly during afternoon and evening and are asleep during night-time, these results seem feasible. While during early morning *HDD* and *HDD*1*st* explain slightly more variance than *HDH* and *HDH*1*st*, the latter two explain a slightly higher share during afternoon. Categorical variable *month* seems to outweigh these differences, by contributing slightly more during afternoon in the *HDD*-models and during morning in the *HDH*-models. *Daytype* contributes most during morning and mid-day, while the interaction terms *HDD·dwelling group·dwelling age* and *HDD·dwelling group* only explain negligible shares.

4.1.2. Hourly parameter estimates

Parameter estimates for both model sets are listed in Tables B.8 and B.11 in Appendix B. Only estimates resulting from the *HDD*-model set are briefly described in the following.

Intercept estimates depict consumption troughs during night-time and mid-day, a distinct peak during hour 8, and maximum consumption during an evening top, approximately lasting from hour 18 to hour 22. Parameter estimates for *HDD* are positive all day, with lowest values during evening. Estimates for *HDD*1*st* are negative all day, so that a jump in *HDD*, i.e. a temperature drop between yesterday and today, is attenuated. The estimate's absolute value is largest in hour 1 and continuously decreases over the course of the day, which is feasible, since the impact of yesterday's temperature is likely to decrease over the course of the day. In general, additional adults or children imply higher consumption, i.e. positive estimates. Especially morning and evening consumption are increased compared to a household with only one adult person and no children. However, estimates for *number of children = 1* are slightly negative during night-time and around zero during the rest of the day. This can be explained by other variables already taking into account differences between households with no children and those with one child, e.g. the presence of more than one adult or larger floor space. Another possible explanation might be that households with one child consume less electrical energy during night-time (e.g. residents go to bed earlier) while the child does not cause increased electricity consumption during these hours. *Dwelling group = attached* exhibits

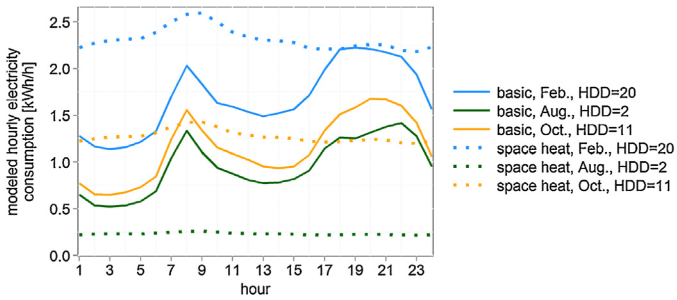


Fig. 6. Modeled components for different months and outdoor temperatures (workdays).

negative estimates for all 24 h, with maximum absolute values during morning and late evening. *Daytype* categories (Saturday, Sunday/holiday, school break) exhibit distinct negative estimates during morning peak hour 8 and positive estimates during daytime, which can be explained by residents getting up later and then spending more time at home. *Month* exhibits almost exclusively negative estimates, implying a reduced consumption compared to the reference month January. Estimates for March through October indicate distinct reductions during afternoon and evening, which can be explained by e.g. reduced electricity consumption for lighting – and temperature-independent heating – during these months. Variables *cold storage*, indicating the use of cold storage rooms or very large fridges, and *other appliances* exhibit positive estimates all day, while *heat pump·dwelling group* exhibits only negative estimates. Estimates for detached dwellings using air-to-air heat pumps are larger in absolute values (compared to attached dwellings) with a distinct maximum in hour 8. *Floor space* in interaction with *HDD* yields positive estimates with highest values during morning peak and evening top. *HDD·dwelling group = attached* exhibits negative estimates during all hours, indicating lower temperature-dependent electricity consumption, which can be explained by lower heat losses to the outside environment due to less outside wall area. *Dwelling age* in interaction with *HDD* and *dwelling group* yields similar negative estimates for both dwelling groups, however, with largely differing values during morning hours, when absolute values for attached dwellings are considerably smaller. High *p*-values (see Table B.7) indicate that *dwelling age = 1980≤* is not significant for attached dwellings during these hours. Also *HDD·wood burning·dwelling group* exhibits negative estimates and thus implies reduced temperature-dependent consumption compared to households using no wood burning.[12] Absolute estimates for *detached dwellings* are larger than absolute estimates for *attached dwellings*, and estimates for *mainly wood burning* are larger than estimates for *supplementary wood burning* within both dwelling groups.

4.2. Disaggregation of individual hourly electricity consumption

The results reported in this section as well as in the following are based on the *HDD*-model set. Modeled *basic* and *space heating consumptions* in an arbitrarily defined household[13] for three different months and outdoor temperatures are shown in Fig. 6. On a working day in February (*HDD* = 20), modeled space heating consumption is larger than modeled basic consumption during most hours of the day and exhibits a maximum in hour 9. Highest space heating consumption during morning can be explained by energy demand for reheating after night-setback or by electric heaters that are switched-on manually in the morning. Modeled basic consumption exhibits a distinct peak in hour 8, a consumption top during evening hours 18–22, and troughs during mid-day and night-time and is thus shaped similarly to the intercept estimate. In October (*HDD* = 11), both modeled basic and space heating consumption are shaped similarly to the February case but on lower levels. Assuming a mean outdoor temperature of 15 °C (*HDD* = 2), modeled space heating consumption in August is very low and approximately constant over the course of the day, while modeled basic consumption is only 0.2–0.4 kWh/h lower compared to the October case. For all three cases, modeled basic consumption exhibits a characteristic shape with morning peak and evening top, while modeled space heating consumption only exhibits a slight morning top which becomes more distinct as *HDD* increases. Modeled disaggregation of total hourly electricity consumption on a cold January day (−13 °C) is shown in Fig. 7. Stacking the modeled components illustrates that space heating consumption is clearly larger than basic consumption throughout the day, yet only contributes little to the hourly variations in modeled whole-house consumption (Fig. 7).

While total modeled consumption can easily be compared with total metered consumption ($R^2 = 0.47$), the estimated basic and space heating components cannot be validated by meter data. In order to at least roughly validate estimated basic consumption, we compare it with modeled total electricity consumption of a comparable household using non-electric central heating, by applying the model proposed by Kipping and Trømborg [13]. In theory, total electricity consumption of households that exclusively use non-electric central heating, but still use electric hot water tanks, should match modeled basic electricity consumption. Unfortunately, non-electric central heating systems, as e.g. central oil boilers, are rarely used without being supplemented with electric heating, at least to some extent, so that corresponding electricity meter data mostly includes a certain share of electric space heating energy. Thus, hourly electricity consumption of households using non-electric central heating modeled according to [13] is correlated with *HDD*, while modeled basic consumption is temperature-independent. Despite these relatively large uncertainties, we compare modeled basic consumption of an arbitrarily defined household at average outdoor temperatures in February, March, and April with modeled whole-house electricity consumption of a corresponding household using non-electric central heating and electric (domestic) water heating (Fig. 8). For March and April modeled hourly consumption profiles in both cases are similar in shape and level, however, with relatively large deviations during night-time and early morning. For February conditions, modeled consumption in case of non-electric central heating is higher than modeled basic consumption also during day-time and evening top. The deviations between modeled basic consumption in case of electric space heating and modeled whole-house consumption in case of non-electric

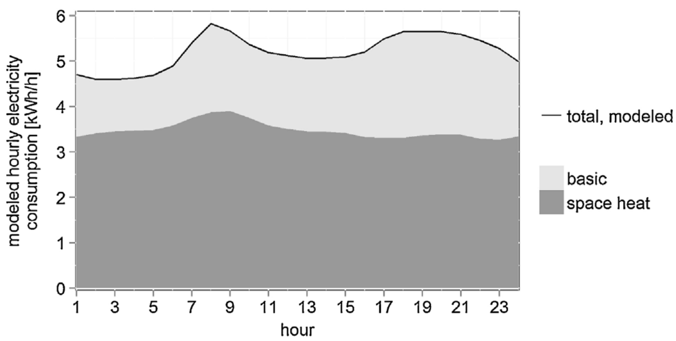


Fig. 7. Stacked modeled components for a cold day in January (workday).

[12] The detailed impacts of different space heating equipment are discussed in [13]

[13] detached dwelling, 150 m^2, two adults, one child

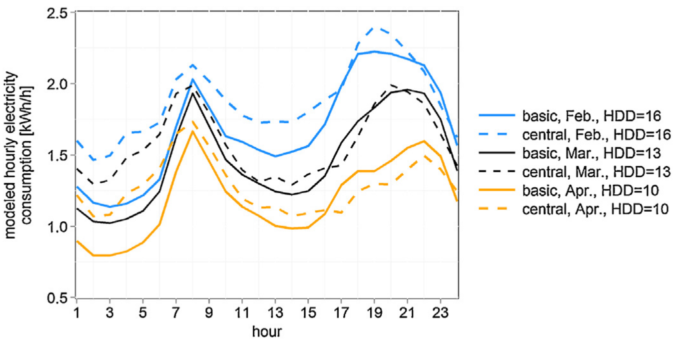


Fig. 8. Modeled basic consumption in case of electric heating (continuous lines) and modeled whole-house consumption in case of non-electric heating (dashed lines).

central heating can be explained by electrical energy consumed for space heating in households using non-electric central heating.

4.3. Sample-aggregate hourly electricity consumption

The sample's aggregate hourly electricity consumption can be modeled with $R^2 = 0.98$. Aggregate metered and modeled hourly consumption during three short periods in September, January, and May, are shown in Fig. 9. On several days during the chosen period in September, modeled consumption overestimates metered consumption, especially during mid-day and afternoon, which might indicate that not all included households have started the heating season yet (Fig. 9a). A feasible explanation for these deviations is, that households do not necessarily start heating exactly as soon as daily mean outdoor temperature falls below heating limit temperature (17 °C), but with some attenuation, and that in general heating limit temperatures vary across households. In the beginning and end of the heating period, the assumption of linear relationship between electricity consumption and outdoor temperature (heating degree day) might not hold and might lead to some deviations. In January, aggregate consumption on weekends is slightly underestimated by the model, which indicates, that the impact of *daytype* is not constant throughout the year, but also exhibits a certain seasonality or temperature-dependence (Fig. 9b). During morning hours of May 17, the Norwegian national holiday, the model underestimates metered consumption largely, indicating that the impacts of different holidays might vary and, also differ from normal Sundays (Fig. 9c). Consumption on May 16 is also considerably higher than modeled consumption, which might be related to preparations for the upcoming holiday. Moreover, outdoor temperature was considerably increasing from May 15 to May 16 and remained on this higher level, so that underestimated metered consumption on both May 16 and May 17, can also be explained by an attenuated fading of space heating during spring, which might not be sufficiently considered by the model.

4.4. Aggregating electricity consumption over time

As illustrated in Section 3.4, daily electricity consumption can be modeled using the summarized hourly parameter estimates as parameters in a corresponding daily consumption model. On individual household level, daily electricity consumption during the entire metering period can be modeled with a goodness of fit of $R^2 = 0.61$, while the sample's aggregate daily electricity consumption can be modeled with $R^2 = 0.99$.

4.5. Cross validation

In order to validate the hourly whole-house consumption model set, the models are applied to 173 observations from *Skagerak Nett*. Also in the test data set, the large majority of surveyed households (almost 80%) reside in detached dwellings, and average floor space of detached and attached dwellings are similar to the corresponding mean values in the training data.

On individual household level, cross validation yields a goodness of fit of $R^2 = 0.47$ which is as high as for the training data. Also on aggregate level, achieved goodness of fit is comparatively high ($R^2 = 0.92$). Modeled consumption mostly underestimates metered consumption slightly, which can be explained by some uncertainties connected to the test data set. For example, it is unlikely, that all households reporting to use air-to-air heat pumps in the end of 2013 were already using heat pumps during the metering period in 2009/2010. Setting dummy variable *heat pump* to zero, i.e. assuming that no heat pumps were used during the metering period, yields an increased model accuracy of $R^2 = 0.49$ for individual hourly consumption and $R^2 = 0.95$ for aggregate hourly consumption.

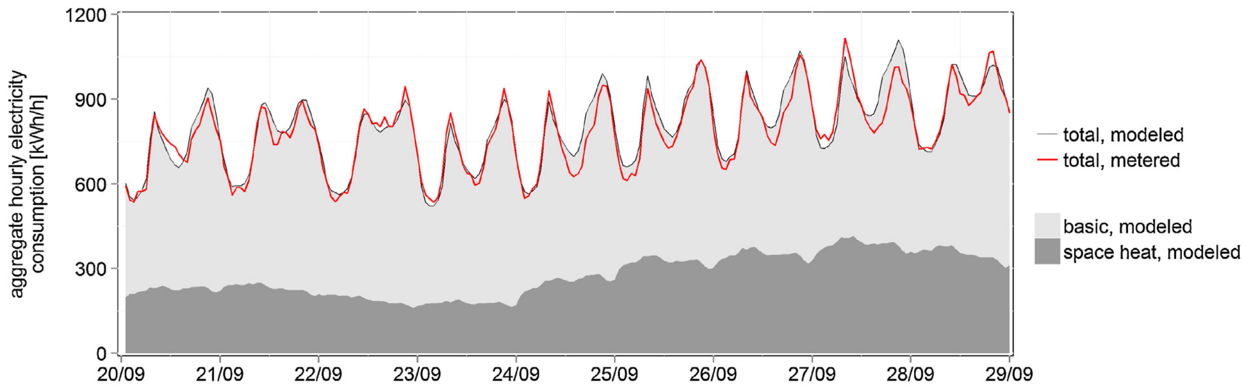
5. Discussion

5.1. Regression results

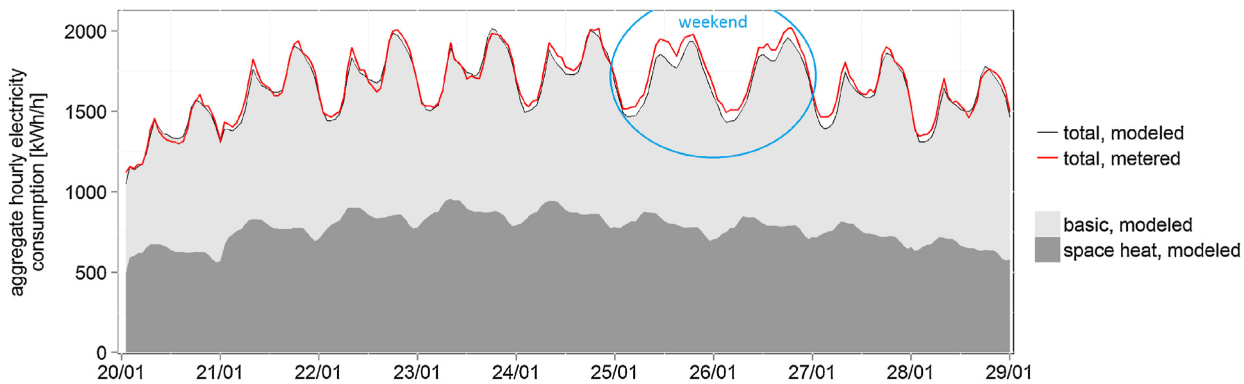
On individual household level, coefficients of determination are comparatively low which might be due to omitted variables (e.g. detailed information on the residents' diurnal routines regarding indoor temperatures, thermostat settings, and firewood consumption). The use of *HDD* or *HDH* as explanatory variables implies a simplification, as reference temperature 17 °C is not the true space heating limit temperature for all households. Moreover, some households might use electric space heating all year (e.g. electric floor heating in bathrooms) while others might turn electric heaters on and off manually and not exactly as soon as outdoor temperature has reached a certain reference temperature. Especially the definition of *HDH* made in this paper might be too simple since it e.g. yields positive values during periods with an hourly outdoor temperature varying between values above and below heating limit temperature, which typically occur during the summer months.

Aggregate hourly electricity consumption of the training data set can be modeled with a relatively high accuracy using the *HDD*-model. However, as deviations between modeled and metered aggregate consumption indicate, the impacts of weekends and holidays could be examined in more detail. Moreover, during transition periods in the beginning and end of the heating period the linear relationship between modeled electricity consumption and *HDD* seems to cause some deviations which could possibly be fixed by e.g. including month variables in interaction with *HDD* or by evaluating alternative definitions of *HDD*, e.g. choosing different heating limit temperatures.

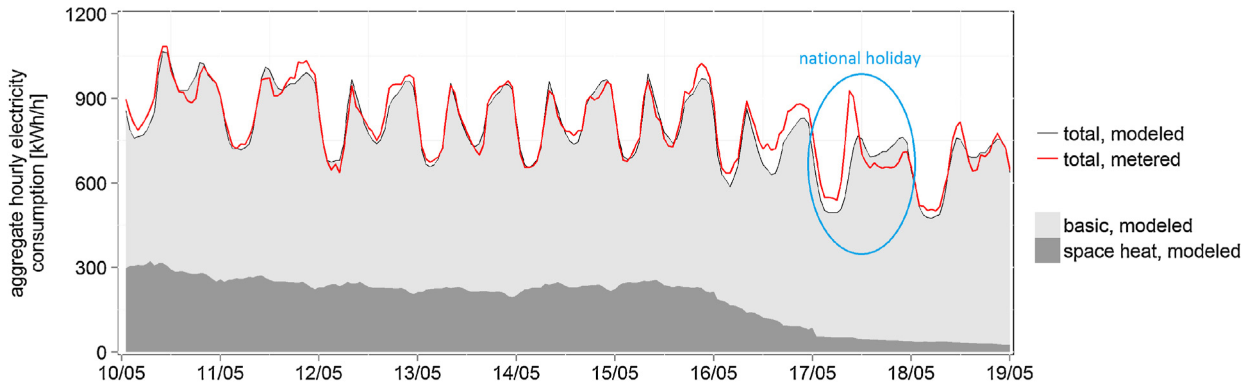
Cross-validation indicates that the *HDD*-model is applicable to other regions in south-eastern Norway. Both on individual household level and on sample-aggregate level hourly electricity consumption can be modeled with a relatively high accuracy, although validity of the test data set is limited due to a large time-lag between metering period and survey period. On average, the model slightly underestimates metered consumption, which can be explained by two factors. As explained in Section 4.5, not all households reporting to use air-to-air heat pumps in 2013 were necessarily already using them in 2009/2010. Moreover, firewood consumption for space heating purposes seems to differ between training and test data set. In the training data, average self-reported annual consumption of firewood is 1.1 m^3, 2.9 m^3, and 5.5 m^3 for households using wood burning *only for coziness*, *supplementary*, or *mainly*, respectively. In the test data, however, average firewood consumption is considerably lower (0.7 m^3, 1.4 m^3, and 1.7 m^3, respectively), so that on average less heating energy is provided



(a) Aggregate hourly consumption, September 2013



(b) Aggregate hourly consumption, January 2014



(c) Aggregate hourly consumption, May 2014

Fig. 9. Aggregate hourly consumption and disaggregation.

by wood burning compared to the training data, especially in households using wood burning *supplementary* or *mainly*. If more detailed information about wood burning habits was available, the model could be further improved and thus correct for regional differences.

5.2. Heating degree day versus heating degree hour

Using heating degree day *HDD* based on the daily mean value of outdoor temperature implies a certain measurement error. Especially consumption during the first hours of the day seems unlikely to be influenced by a mean value, that is based on 24 hourly meter values during the day that has just started. However, as confirmed by plausible regression results, including first differences in heating degree days, *HDD1st*, as explanatory variable seems to sufficiently correct for the simplification connected to *HDD*. The share of explained variance by *HDD1st* as well as its absolute parameter estimate is continuously decreasing over the course of the day, representing a declining impact of yesterday's mean temperature on today's electricity consumption.

Including heating degree hour *HDH* and *HDH1st* instead of *HDD* and *HDD1st* as explanatory variables for estimating hourly consumption does not lead to a higher goodness of fit, as illustrated in Fig. 5. This supports the assumption that the variance in hourly electricity consumption *within* a single day is mainly caused by household-specific patterns, e.g. the residents' daily routines (see Figs. 3 and 4). Moreover, hourly variations in outdoor temperature, and thus the difference between *HDD* and *HDH*, are smallest during the coldest periods of the year, when electricity consumption is highest (compare Fig. 3). Thus, including *HDD* and *HDD1st* as explanatory variables for estimating hourly electricity consumption seems sufficient, and – compared to the *HDH*-model set – input data requirement is considerably reduced (daily instead of hourly mean temperature values), which makes the *HDD*-models more useful for long-term forecasts.

In reality, variations in hourly outdoor temperature might have an impact on hourly electricity consumption, however, this impact is probably attenuated due to the thermal storage capacity of the dwelling and depending on building envelope characteristics (e.g. thermal transmittance (*U*-values) and airtightness). Moreover, outdoor temperature is mostly lowest during night-time when night-setback of electric heaters is active so that the dwelling is first reheated during the morning hours. Thus, electricity consumption of hour *h* might not necessarily be influenced the most by mean outdoor temperature during hour *h*, but might be more affected by temperature values of previous hours ($\bar{t}_{o,h-1}$, $\bar{t}_{o,h-2}$, etc.). Determining which lag to use for estimating hourly electricity consumption more precisely could be an interesting subject to a future study, however, since detailed information on building envelope, indoor temperatures, and thermostat settings is not available, the detailed impact of hourly outdoor temperature values on hourly electricity consumption is not analyzed in this paper.

5.3. Disaggregation method

According to our results, modeled basic consumption mainly influences the overall shape of hourly electricity consumption over the course of the day which seems feasible. Sæle et al. [17] report that during their metering campaign the morning peak was mainly generated by lighting and hot water tanks, and that the evening peak was mainly caused by lighting. However, without corresponding data from submetering space heating equipment and other electric appliances, modeled hourly components, i.e. the disaggregation method, cannot be validated. Comparing modeled basic consumption with modeled total consumption of households using non-electric central heating shows that shape and level of modeled hourly electricity consumption over the course of the day are similar, but also exhibit larger differences, especially during night-time and during the winter months. Apart from general model shortcomings, a possible explanation for these differences is, that households using non-electric central heating systems often use electric heating as a constant or occasional supplement. The seasonal use of electric and central heating equipment or hot water tanks are not covered sufficiently in the survey and would yield important data in a revised version of the questionnaire. Modeled basic consumption might also include some space heating consumption, e.g. caused by electric floor heating in bathrooms, which is often used without thermostats and even during summer, i.e. when *HDD* = 0. Including specific survey items about floor heating or other constantly running heaters could yield more reliable estimates for basic and space heating components.

In its current version the model yields some negative values for space heating consumption of individual households during periods with low positive values of *HDD* and for smaller dwellings, in combination with variables that on average imply a reduced consumption (e.g. *heat pump* = *yes*, *dwelling age* = *1980*≤, *wood burning* = *mainly*). Separate models for different dwelling types, considering different heating limit temperatures, or defining a heating period with attenuated start-up and fading could help reducing the occurrence of negative values.

5.4. Further work

Additional meter and survey response data could help to further validate, improve, and adjust the presented models in order to make them more applicable to other Norwegian regions. If a larger sample would be provided, separate models for different dwelling types and heating systems could possibly yield better models. Several samples from different geographical regions would enable the identification of regional differences in household variables and electricity consumption. A longer time series, i.e. metering periods covering at least one year, would allow models that also include the summer month June and July, which are missing in the training-data set for this study. The survey could be significantly improved, e.g. regarding items on heating equipment and its seasonal usage, as well as on thermostat settings, indoor temperatures, detailed wood burning habits, and diurnal routines. Regarding detached houses with secondary suites it needs to be clearly inquired whether the secondary suite is connected to the main electricity meter or is metered separately.

A submetering campaign, e.g. metering hourly consumption by electric heating equipment in addition to whole-house consumption in a subsample of participating households would yield valuable data for validating the presented disaggregation method.

As in most surveys with voluntary participation, self-selection might be present. If also meter data of a sample of non-participants would be provided, possible differences in household and consumption characteristics of participants and non-participants could be identified.

6. Conclusion

According to our results, outdoor temperature, dwelling group, floor space, and number of residents are the most important variables required for modeling hourly electricity consumption in Norwegian dwellings with electric heating. In order to evaluate whether daily mean temperature can be used to model hourly electricity consumption, we compared two multiple regression model sets using heating degree day (*HDD*) and heating degree hour (*HDH*), respectively. In general, the models based on *HDD* achieve a slightly higher goodness of fit compared to the models based on *HDH*. On sample-aggregate level, hourly electricity consumption can be modeled with relatively high accuracy. Thus, only the daily mean value of outdoor temperature is needed as weather-related input data for modeling aggregate hourly electricity consumption in a certain region, which makes the model useful for long-term forecasts and scenario analyses. Cross-validation also indicates that the presented models are applicable for modeling regional hourly electricity consumption in the Norwegian household sector.

Our results from a simple disaggregation method based on the *HDD*-models indicate that the shape of hourly electricity consumption over the course of the day is mainly influenced by electricity consumption for electric appliances and domestic water heating, while electricity consumption for space heating purposes is shaped relatively evenly throughout the day. Thus, substituting electric space heating by other energy carriers is assumed to reduce the *level* of hourly electricity consumption, while load control of other electric appliances, e.g. domestic water heaters, white goods, and lighting, is assumed to affect the *shape*, i.e. peaks and troughs, of hourly consumption patterns. Though modeled values of *basic* and *space heating consumption* seem feasible, they should be validated by results from submetering campaigns.

By providing models for aggregate hourly electricity consumption, which simultaneously estimate how much electricity is used for space heating purposes, the presented methods can yield valuable data for energy system management and policies. Implications for future aggregate hourly electricity consumption can be simulated considering e.g. a phase-out of individual electric space heating and an increased use of district heating, as well as changes in important factors, as e.g. dwelling structure, resident variables, wood burning habits, and outdoor temperature, on regional level.

Forecasts on hourly consumption under different scenarios can be useful for grid design and for evaluating impacts of short-term demand side management options, as e.g. substituting electric heating during periods of peak consumption.

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Appendix A. Questionnaire items

Table A.4
Questionnaire items 1–8.

Question	Answers
1. Number of residents per age group	5 years or younger 6–15 years 16–25 years 26–45 years 46–65 years 66 years or older
2. Number of residents per time spent at home	Only on weekends Less than 12 hours per day 12–20 hours per day More than 20 hours per day
3. Are the residents owners or tenants	Owners Shareholders Tenants Others, please specify: *free text*
4. Dwelling type	Detached house Detached house + secondary suite Semi-detached h., horiz. separated Semi-detached h., vertic. separated Four-family house House in rows Terraced house Cabin Other house
5. Year of construction	Before 1900 1900–1924 1925–1949 1950–1959 1960–1969 1970–1979 1980–1989 1990–1999 2000–2009 2010 or later
6. Dwelling floor space	Gross floor space: ____ Primary floor space: ____ Heated floor space: ____
7. Has the dwelling been extended?	Yes/no
7a. If yes, when has the dwelling been extended?	*free text*
8. Which materials does the dwelling mainly consist of?	Wood Concrete, LECA Bricks Glass Other, specify: *free text*

Table A.5
Questionnaire items 9–14.

Question	Answers
9. Has the dwelling been rehabilitated?	Yes/no
9a. If yes, which measures have been undertaken?	Insulation (large parts of walls, floor, roof) New heating equipment New hot water tank New windows/outside doors Other, specify: *free text*
9b. If yes, when have the measures been undertaken?	Before 1900 1900–1924 1925–1949 1950–1959 1960–1969 1970–1979 1980–1989 1990–1999 2000–2009 2010 or later
10. Is the dwelling inhabited all year?	All year Partly during summer and winter Partly, mainly during summer (May–Oct) Partly, mainly during winter (Nov–Apr)
11. Has the dwelling been empty during the last years?	Yes/no
12. Does the dwelling have a central heating system?	No Yes, district heat Yes, oil or gas boiler Yes, electric boiler Yes, pellets/biomass boiler Yes, ventilation system Yes, other, specify: *free text*
12a. If yes, does the heating system supply several dwellings or housing units?	Yes/no
13. Which space heating equipment is used in the dwelling?	Radiators, convectors, floor heat (hot water supplied) Oil, gas, paraffine stoves Wood stoves Air-to-air heat pumps Other heat pump Other, specify: *free text*
14. What kind of domestic water heater is installed in the dwelling?	Own tank, electrically heated Own tank, centrally heated Shared tank, electrically heated Shared tank, centrally heated Other, specify: *free text*

Table A.6
Questionnaire items 15–28.

Question	Answers
15. What is the average indoor temperature in the dwelling during the heating period?	<18 $^\circ$C 18–19 $^\circ$C 20–21 $^\circ$C 22–23 $^\circ$C 24–25 $^\circ$C >25 $^\circ$C Don't know
16. Are there thermostats connected to heating equipment (radiators, electric heaters,*ldots*)?	No Yes, in some rooms Yes, in all or almost all rooms
17. Is night-setback or time-control implemented with the heating equipment?	No Yes, in some rooms Yes, in all or almost all rooms
18. Is there a central control system for heating and lighting installed in the dwelling?	Yes/no
19. Is wood burning used in the dwelling	No *(no wood burning)* Yes, for coziness *(wood burning only for coziness)* Yes, when it is not warm enough *(supplementary wood burning)* Yes, during the entire heating period *(mainly wood burning)*
20. How much firewood is on average consumed during the wood burning period?	____ litres ____ 60-litres bags ____ cubic meters ____ fathoms
21. What white goods are used in the dwelling	Washing machine Clothes dryer Dishwasher Fridge Freezer Oven Micro-wave oven Other, specify: *free text*
22. Are there other electricity-intensive appliances connected to the electricity meter?	Heated pool Solarium, sauna Greenhouse with heating or lighting Cold storage room, freezer room Heat pump used for cooling Outdoor floor heating Water bed Other electricity-intensive appliances, specify: *free text*
23. Are there electric vehicles charged at the dwellings connection?	No Yes, one electric vehicle Yes, more than one electric vehicle
24. Compared to other households you know, how do you rate your own household?	We use less energy Average We use more energy
25. What could motivate you to make your home more energy-efficient?	Higher electricity/energy prices Financial support Practical support or counseling Better technical solutions If it was easier to find craftsmen Other
26. Compared to other households you know, how warm is it in your house during winter?	Colder Average Warmer
27. What is your main motivation for saving energy?	Environment, climate, sustainable energy consumption Saving money I am not very motivated Other
28. Comments	*free text*

Appendix B. Regression results

B.1. *Hourly model using* HDD

Table B.7
p-Values for each variable and hour (* $p <$ .0005), *HDD* model

		h 1	h 2	h 3	h 4	h 5	h 6	h 7	h 8	h 9	h 10	h 11	h 12	h 13	h 14	h 15	h 16	h 17	h 18	h 19	h 20	h 21	h 22	h 23	h 24
	Intercept	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
x_1	Dwelling group = attached	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
x_2	Adults = 2	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
x_3	Adults = 3	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
x_4	Adults = >3	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
x_5	Kids = 1	*	*	*	*	*	*	*	*	.006	*	*	*	*	*	.012	.007	.983	.394	.022	.003	*	.751	.001	*
x_6	Kids = 2	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
x_7	Kids = >2	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
x_8	Senior resident, workday	*	*	*	*	*	.001	*	*	*	*	*	*	*	*	*	*	*	.232	.001	*	*	*	.323	*
x_9	Resident home >20 h, workday	.007	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	.001	.025	.002	*	*
x_{10}	Weekend resident, workday	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
x_{11}	Daytype = Saturday, no holiday	*	*	*	.019	.410	*	*	*	.155	*	*	*	*	*	*	*	.007	.049	*	.095	*	*	*	.863
x_{12}	Daytype = Sunday or holiday	*	*	*	*	.424	*	*	*	*	*	*	*	*	*	*	*	*	.002	.189	.008	*	*	*	.003
x_{13}	Daytype = school break, workday	.004	.013	.074	.029	.668	.002	*	*	*	.001	*	*	*	*	*	*	.206	*	.002	.001	*	*	*	.013
x_{14}	Cold storage = yes	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
x_{15}	Other appliances = yes	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
x_{16}	Month = Feb	*	.181	.399	.805	.582	.141	.001	*	*	.386	.438	*	*	*	*	*	*	*	.001	.006	.037	.029	*	*
x_{17}	Month = Mar	*	*	*	*	*	*	.112	.080	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
x_{18}	Month = Apr	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
x_{19}	Month = May	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
x_{20}	Month = Aug	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
x_{21}	Month = Sep	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
x_{22}	Month = Oct	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
x_{23}	Month = Nov	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
x_{24}	Month = Dec	.027	.019	.004	.003	.002	.072	.227	.841	.074	*	*	.033	.920	.369	.306	.387	.566	.099	.002	.009	.167	.057	.068	.321
x_{25}	HDD	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
x_{26}	HDD1st	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
x_{27}	HDD: floor space/100 m^2	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
x_{28}	HDD: attached	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
x_{29}	Heat pump: detached: HDD >0	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
x_{30}	Heat pump: attached: HDD >0	*	.002	.279	.344	*	*	*	*	*	.001	*	*	*	*	*	*	*	*	*	*	*	*	*	*
x_{31}	HDD: detached: age = 1980≤	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
x_{32}	HDD: attached: age = 1980≤	*	*	*	*	*	.004	.040	.350	.057	.001	*	*	*	*	*	*	*	*	*	*	.001	*	*	*
x_{33}	HDD: detached: wood b. = supp.	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
x_{34}	HDD: attached: wood b. = supp.	.001	*	*	.013	.387	.047	.016	.193	.002	.756	.506	.169	.015	.003	.032	.030	.027	*	*	*	*	*	*	*
x_{35}	HDD: detached: wood b. = main.	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
x_{36}	HDD: attached: wood b. = main.	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*

Table B.8
Estimates for each variable and hour, *HDD* model.

		h 1	h 2	h 3	h 4	h 5	h 6	h 7	h 8	h 9	h 10	h 11	h 12	h 13	h 14	h 15	h 16	h 17	h 18	h 19	h 20	h 21	h 22	h 23	h 24
	Intercept	1.43	1.30	1.26	1.25	1.27	1.37	1.54	1.62	1.46	1.32	1.28	1.31	1.34	1.35	1.37	1.51	1.72	1.86	1.89	1.86	1.86	1.87	1.79	1.61
x_1	Dwelling group = attached	−0.29	−0.28	−0.30	−0.31	−0.32	−0.32	−0.35	−0.33	−0.31	−0.28	−0.24	−0.26	−0.24	−0.24	−0.22	−0.22	−0.19	−0.22	−0.25	−0.30	−0.32	−0.34	−0.36	−0.34
x_2	Adults = 2	0.13	0.08	0.06	0.07	0.09	0.11	0.22	0.29	0.29	0.34	0.37	0.35	0.33	0.32	0.33	0.38	0.46	0.46	0.43	0.37	0.32	0.29	0.24	0.18
x_3	Adults = 3	0.44	0.31	0.22	0.19	0.19	0.23	0.37	0.51	0.51	0.55	0.63	0.64	0.64	0.63	0.68	0.81	0.92	0.91	0.88	0.83	0.79	0.77	0.73	0.58
x_4	Adults = >3	0.78	0.58	0.48	0.46	0.54	0.57	0.75	0.98	0.88	0.85	0.90	0.92	0.97	1.01	1.11	1.22	1.33	1.30	1.27	1.29	1.26	1.21	1.14	0.98
x_5	Kids = 1	−0.19	−0.20	−0.18	−0.16	−0.15	−0.17	−0.10	0.05	0.02	−0.04	−0.04	−0.05	−0.06	−0.05	−0.03	−0.03	−0.00	0.01	−0.02	0.03	0.04	0.00	−0.03	−0.15
x_6	Kids = 2	0.17	0.08	0.07	0.06	0.07	0.05	0.11	0.43	0.31	0.17	0.19	0.20	0.21	0.23	0.25	0.28	0.38	0.38	0.35	0.45	0.48	0.42	0.35	0.28
x_7	Kids = >2	0.44	0.31	0.29	0.32	0.32	0.31	0.43	0.86	0.92	0.82	0.79	0.76	0.71	0.66	0.66	0.74	0.82	0.72	0.62	0.77	0.82	0.69	0.64	0.57
x_8	Senior resident, workday	0.04	0.04	0.06	0.06	0.05	−0.03	−0.16	−0.11	0.21	0.38	0.40	0.34	0.28	0.25	0.24	0.19	0.07	−0.01	−0.03	−0.09	−0.10	−0.06	0.01	0.05
x_9	Resident home >20 h, workday	0.03	0.04	0.06	0.07	0.06	−0.04	−0.07	0.05	0.07	0.16	0.20	0.17	0.15	0.14	0.13	0.15	0.13	0.06	0.06	0.04	0.03	0.04	0.07	0.04
x_{10}	Weekend resident, workday	−0.47	−0.38	−0.33	−0.29	−0.26	−0.27	−0.29	−0.56	−0.60	−0.54	−0.51	−0.47	−0.41	−0.39	−0.47	−0.58	−0.57	−0.53	−0.62	−0.71	−0.72	−0.72	−0.67	−0.58
x_{11}	Daytype = Saturday, no holiday	0.08	0.05	0.03	0.02	−0.01	−0.12	−0.38	−0.46	−0.01	0.34	0.46	0.45	0.38	0.33	0.29	0.20	0.03	0.02	0.06	−0.02	−0.13	−0.18	−0.11	0.00
x_{12}	Daytype = Sunday or holiday	0.12	0.10	0.07	0.04	0.01	−0.12	−0.39	−0.51	−0.11	0.25	0.46	0.50	0.46	0.42	0.38	0.29	0.11	0.03	0.01	−0.03	−0.04	−0.06	−0.04	−0.03
x_{13}	Daytype = school break, workday	0.03	0.03	0.02	0.02	−0.00	−0.03	−0.14	−0.21	−0.06	0.04	0.08	0.11	0.12	0.10	0.07	0.06	−0.02	−0.05	−0.04	−0.04	−0.06	−0.08	−0.06	−0.03
x_{14}	Cold storage = yes	0.39	0.43	0.45	0.44	0.47	0.50	0.56	0.59	0.49	0.46	0.42	0.42	0.40	0.40	0.38	0.40	0.45	0.47	0.49	0.52	0.51	0.52	0.49	0.45
x_{15}	Other appliances = yes	0.27	0.27	0.28	0.29	0.30	0.33	0.32	0.28	0.28	0.30	0.29	0.28	0.28	0.27	0.28	0.30	0.31	0.32	0.30	0.30	0.31	0.31	0.29	0.28
x_{16}	Month = Feb	−0.09	−0.02	−0.01	0.00	0.01	0.02	0.05	0.07	0.06	0.02	−0.01	−0.07	−0.11	−0.10	−0.11	−0.16	−0.19	−0.12	−0.06	−0.05	−0.04	−0.04	−0.07	−0.07
x_{17}	Month = Mar	−0.24	−0.15	−0.12	−0.10	−0.10	−0.06	−0.02	−0.03	−0.07	−0.15	−0.25	−0.31	−0.36	−0.40	−0.43	−0.52	−0.60	−0.60	−0.45	−0.32	−0.25	−0.23	−0.25	−0.25
x_{18}	Month = Apr	−0.47	−0.39	−0.35	−0.33	−0.32	−0.29	−0.26	−0.29	−0.31	−0.37	−0.47	−0.54	−0.60	−0.64	−0.68	−0.78	−0.89	−0.95	−0.90	−0.80	−0.66	−0.57	−0.51	−0.46
x_{19}	Month = May	−0.53	−0.48	−0.45	−0.43	−0.43	−0.42	−0.40	−0.42	−0.42	−0.48	−0.57	−0.64	−0.69	−0.71	−0.73	−0.83	−0.93	−0.98	−0.90	−0.80	−0.70	−0.66	−0.57	−0.52
x_{20}	Month = Aug	−0.72	−0.65	−0.63	−0.62	−0.63	−0.62	−0.60	−0.63	−0.66	−0.68	−0.73	−0.80	−0.83	−0.84	−0.86	−0.96	−1.04	−1.07	−1.04	−0.94	−0.84	−0.75	−0.73	−0.68
x_{21}	Month = Sep	−0.72	−0.67	−0.64	−0.62	−0.63	−0.62	−0.58	−0.60	−0.63	−0.66	−0.73	−0.78	−0.82	−0.85	−0.87	−0.97	−1.07	−1.11	−1.02	−0.87	−0.72	−0.71	−0.74	−0.71
x_{22}	Month = Oct	−0.60	−0.53	−0.50	−0.48	−0.48	−0.46	−0.40	−0.40	−0.43	−0.46	−0.52	−0.59	−0.65	−0.69	−0.72	−0.80	−0.84	−0.82	−0.70	−0.58	−0.54	−0.56	−0.58	−0.58
x_{23}	Month = Nov	−0.37	−0.33	−0.31	−0.29	−0.28	−0.27	−0.24	−0.22	−0.23	−0.24	−0.29	−0.36	−0.41	−0.42	−0.40	−0.41	−0.35	−0.34	−0.34	−0.32	−0.31	−0.32	−0.33	−0.33
x_{24}	Month = Dec	−0.03	−0.03	−0.04	−0.04	−0.04	−0.03	−0.02	−0.00	0.03	0.06	0.08	0.04	0.00	−0.02	0.02	0.02	0.01	−0.03	−0.06	−0.05	−0.03	−0.03	−0.04	−0.02
x_{25}	HDD	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.05	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.03	0.02	0.02	0.02	0.02	0.02	0.03	0.03
x_{26}	HDD1st	−0.06	−0.05	−0.05	−0.05	−0.05	−0.05	−0.05	−0.04	−0.04	−0.04	−0.04	−0.03	−0.03	−0.03	−0.03	−0.03	−0.02	−0.02	−0.02	−0.02	−0.02	−0.02	−0.01	−0.02
x_{27}	HDD: floor space/100 m^2	0.05	0.05	0.05	0.05	0.05	0.05	0.06	0.06	0.06	0.06	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.06	0.06	0.06	0.06	0.06	0.05	0.05
x_{28}	HDD: attached	−0.04	−0.04	−0.04	−0.04	−0.04	−0.04	−0.04	−0.05	−0.05	−0.04	−0.03	−0.03	−0.03	−0.04	−0.04	−0.03	−0.03	−0.03	−0.03	−0.03	−0.03	−0.03	−0.03	−0.03
x_{29}	heat pump: detached: HDD >0	−0.19	−0.19	−0.22	−0.24	−0.27	−0.33	−0.35	−0.40	−0.36	−0.33	−0.32	−0.32	−0.32	−0.32	−0.30	−0.29	−0.29	−0.31	−0.31	−0.30	−0.29	−0.28	−0.26	−0.23
x_{30}	Heat pump: attached: HDD >0	−0.07	−0.03	−0.01	−0.01	−0.05	−0.10	−0.13	−0.27	−0.15	−0.07	−0.21	−0.22	−0.21	−0.18	−0.19	−0.25	−0.28	−0.26	−0.23	−0.12	−0.11	−0.12	−0.10	−0.06
x_{31}	HDD: detached: age = 1980≤	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01
x_{32}	HDD: attached: age = 1980≤	−0.01	−0.01	−0.01	−0.01	−0.01	−0.00	−0.00	0.00	−0.00	−0.00	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.00	−0.00	−0.01	−0.01	−0.01
x_{33}	HDD: detached: wood b. = supp.	−0.03	−0.03	−0.03	−0.03	−0.03	−0.03	−0.03	−0.04	−0.04	−0.03	−0.03	−0.03	−0.03	−0.03	−0.03	−0.02	−0.02	−0.03	−0.03	−0.03	−0.03	−0.03	−0.03	−0.03
x_{34}	HDD: attached: wood b. = supp.	−0.00	−0.00	−0.00	−0.00	0.00	−0.00	0.00	0.00	−0.00	0.00	−0.00	−0.00	−0.00	−0.00	−0.00	−0.00	−0.00	−0.01	−0.01	−0.01	−0.02	−0.01	−0.01	−0.01
x_{35}	HDD: detached: wood b. = main.	−0.04	−0.04	−0.04	−0.04	−0.04	−0.04	−0.05	−0.05	−0.05	−0.05	−0.04	−0.04	−0.04	−0.04	−0.04	−0.04	−0.04	−0.04	−0.04	−0.04	−0.04	−0.04	−0.04	−0.05
x_{36}	HDD: attached: wood b. = main.	−0.01	−0.00	−0.00	−0.01	−0.01	−0.01	−0.02	−0.02	−0.01	−0.01	−0.02	−0.02	−0.01	−0.01	−0.01	−0.02	−0.02	−0.03	−0.03	−0.03	−0.03	−0.03	−0.02	−0.02

Table B.9
Share of explained variance (in %) for each variable and hour, *HDD* model.

		h 1	h 2	h 3	h 4	h 5	h 6	h 7	h 8	h 9	h 10	h 11	h 12	h 13	h 14	h 15	h 16	h 17	h 18	h 19	h 20	h 21	h 22	h 23	h 24
x_1	Dwelling group	5.59	5.66	5.76	5.85	5.85	5.01	5.13	4.67	4.60	4.57	4.34	4.45	4.43	4.68	4.82	4.72	4.35	4.34	4.69	4.83	5.02	5.55	5.82	5.81
$x_{2,\ldots,4}$	Adults	3.58	2.51	2.05	1.96	2.38	2.43	3.48	4.30	3.48	3.31	3.56	3.78	4.12	4.40	4.95	5.50	6.36	6.27	5.97	6.16	6.33	6.24	5.98	4.71
$x_{5,\ldots,7}$	Kids	1.53	1.17	1.10	1.13	1.06	0.99	1.09	2.58	2.22	1.78	1.71	1.69	1.60	1.50	1.46	1.66	2.03	1.80	1.60	2.30	2.66	2.22	1.98	1.89
x_8	Senior resident, workday	0.01	0.01	0.04	0.05	0.05	0.03	0.01	0.06	0.37	0.40	0.25	0.13	0.09	0.07	0.08	0.05	0.01	0.00	0.00	0.01	0.01	0.00	0.02	0.04
x_9	Resident home >20 h, workd.	0.03	0.02	0.00	0.00	0.00	0.02	0.00	0.07	0.00	0.01	0.02	0.04	0.04	0.03	0.03	0.00	0.00	0.01	0.01	0.01	0.00	0.00	0.00	0.00
x_{10}	Weekend resident, workday	0.43	0.28	0.21	0.15	0.10	0.06	0.03	0.17	0.39	0.49	0.54	0.49	0.39	0.34	0.43	0.53	0.40	0.30	0.41	0.54	0.55	0.60	0.57	0.50
$x_{11,\ldots,13}$	Daytype	0.21	0.15	0.09	0.05	0.02	0.09	1.05	1.49	0.03	0.73	1.69	1.90	1.60	1.34	1.08	0.63	0.12	0.03	0.02	0.00	0.06	0.12	0.05	0.00
x_{14}	Cold storage	1.20	1.46	1.63	1.63	1.73	1.79	2.03	2.00	1.45	1.28	1.08	1.10	1.02	1.01	0.91	0.93	1.12	1.19	1.34	1.48	1.51	1.67	1.59	1.39
x_{15}	Other appliances	1.25	1.35	1.49	1.56	1.57	1.66	1.43	1.05	1.05	1.16	1.11	1.05	1.06	1.00	1.02	1.07	1.10	1.15	1.08	1.10	1.22	1.25	1.22	1.18
$x_{16,\ldots,24}$	Month	1.58	1.61	1.51	1.46	1.45	1.38	1.10	1.02	1.13	1.12	1.32	1.45	1.59	1.76	1.93	2.18	2.38	2.40	2.06	1.68	1.36	1.31	1.31	1.36
x_{25}	HDD	20.22	22.36	23.38	24.11	24.43	24.46	22.25	20.43	20.68	19.99	19.89	20.00	20.34	21.05	21.48	21.70	21.97	22.06	21.34	20.20	18.76	18.11	18.31	19.19
x_{26}	HDD1st	1.76	1.73	1.64	1.57	1.44	1.27	0.89	0.65	0.79	0.79	0.84	0.81	0.78	0.78	0.66	0.56	0.39	0.40	0.37	0.32	0.29	0.28	0.24	0.27
x_{27}	HDD: floor space	5.46	5.79	6.21	6.33	6.12	5.78	6.42	5.59	5.40	5.41	4.96	4.98	4.79	4.61	4.45	4.39	4.74	5.51	5.94	5.91	6.04	6.08	5.82	5.56
x_{28}	HDD: dwelling group	0.04	0.05	0.05	0.05	0.05	0.04	0.02	0.02	0.03	0.03	0.03	0.03	0.04	0.06	0.07	0.06	0.04	0.02	0.02	0.02	0.01	0.01	0.01	0.03
$x_{29,30}$	Heat pump: dw. gr.: HDD>0	0.24	0.24	0.33	0.42	0.54	0.78	0.80	1.00	0.76	0.60	0.58	0.63	0.64	0.66	0.56	0.50	0.45	0.51	0.52	0.48	0.47	0.47	0.42	0.33
$x_{31,32}$	HDD: dw. group: age	0.21	0.25	0.26	0.19	0.13	0.09	0.04	0.00	0.02	0.03	0.05	0.08	0.07	0.06	0.05	0.03	0.02	0.02	0.02	0.02	0.03	0.03	0.08	0.16
$x_{33,36}$	HDD: dw. group: wood b.	1.42	1.60	1.62	1.60	1.62	1.65	1.54	1.52	1.61	1.36	1.23	1.11	1.05	1.02	0.96	0.88	0.87	0.82	0.87	1.01	1.14	1.19	1.31	1.41
	R^2	44.75	46.25	47.38	48.10	48.54	47.50	47.30	46.62	44.03	43.06	43.20	43.71	43.64	44.38	44.95	45.38	46.36	46.81	46.25	46.07	45.46	45.14	44.74	43.82

B.2. *Hourly model using* HDH

Table B.10
p-Values for each variable and hour (* $p < .0005$), *HDH* model.

		h 1	h 2	h 3	h 4	h 5	h 6	h 7	h 8	h 9	h 10	h 11	h 12	h 13	h 14	h 15	h 16	h 17	h 18	h 19	h 20	h 21	h 22	h 23	h 24
	Intercept	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
x_1	Dwelling group = attached	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
x_2	Adults = 2	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
x_3	Adults = 3	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
x_4	Adults = >3	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
x_5	Kids = 1	*	*	*	*	*	*	*	*	.004	*	*	*	*	*	.004	.002	.660	.638	.012	.008	*	.767	.001	*
x_6	Kids = 2	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
x_7	Kids = >2	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
x_8	Senior resident, workday	*	*	*	*	*	.001	*	*	*	*	*	*	*	*	*	*	*	.068	*	*	*	*	.314	*
x_9	Resident home >20 h, workday	.007	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	.003	.034	.002	*	*
x_{10}	Weekend resident, workday	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
x_{11}	Daytype = Saturday, no holiday	*	*	*	.009	.651	*	*	*	.816	*	*	*	*	*	*	*	*	*	*	.653	*	*	*	.049
x_{12}	Daytype = Sunday or holiday	*	*	*	*	.808	*	*	*	*	*	*	*	*	*	*	*	*	.014	.960	*	*	*	*	*
x_{13}	Daytype = school break, workday	.010	.004	*	.001	*	*	*	*	*	.051	*	*	*	*	*	*	.612	.003	.027	.024	.010	*	.001	.995
x_{14}	Cold storage = yes	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
x_{15}	Other appliances = yes	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
x_{16}	Month = Feb	*	.001	*	*	*	.008	.675	.271	.246	.369	.109	*	*	*	*	*	*	*	.006	.001	.001	*	*	*
x_{17}	Month = Mar	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
x_{18}	Month = Apr	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
x_{19}	Month = May	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
x_{20}	Month = Aug	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
x_{21}	Month = Sep	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
x_{22}	Month = Oct	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
x_{23}	Month = Nov	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
x_{24}	Month = Dec	*	*	*	*	*	*	*	.008	.655	.176	.024	.207	.254	.157	*	.005	.027	.270	*	*	.002	*	*	*
x_{25}	HDH	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
x_{26}	HDH1st	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
x_{27}	HDH: floor space/100 m^2	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
x_{28}	HDH: attached	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
x_{29}	Heat pump: detached: HDH >0	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
x_{30}	Heat pump: attached: HDH >0	*	.001	.262	.235	*	*	*	*	*	.001	*	*	*	*	*	*	*	*	*	*	*	*	*	*
x_{31}	HDH: detached: age = 1980≤	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
x_{32}	HDH: attached: age = 1980≤	*	*	*	*	*	.021	.170	.187	.109	.001	*	*	*	*	*	*	*	*	*	*	.001	*	*	*
x_{33}	HDH: detached: wood b. = supp.	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
x_{34}	HDH: attached: wood b. = supp.	*	*	*	.027	.186	.206	.010	.064	.003	.857	.491	.156	.010	.002	.029	.023	.017	*	*	*	*	*	*	*
x_{35}	HDH: detached: wood b. = main.	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
x_{36}	HDH: attached: wood b. = main.	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*

Table B.11
Estimates for each variable and hour, *HDH* model.

		h 1	h 2	h 3	h 4	h 5	h 6	h 7	h 8	h 9	h 10	h 11	h 12	h 13	h 14	h 15	h 16	h 17	h 18	h 19	h 20	h 21	h 22	h 23	h 24
	Intercept	1.65	1.52	1.50	1.51	1.54	1.67	1.83	1.90	1.72	1.56	1.53	1.56	1.55	1.51	1.49	1.60	1.77	1.94	1.98	2.00	2.06	2.12	2.06	1.88
x_1	Dwelling group = attached	−0.21	−0.19	−0.20	−0.21	−0.21	−0.22	−0.25	−0.24	−0.26	−0.27	−0.27	−0.31	−0.30	−0.32	−0.32	−0.32	−0.29	−0.31	−0.33	−0.34	−0.35	−0.36	−0.35	−0.30
x_2	Adults = 2	0.13	0.08	0.06	0.07	0.09	0.11	0.22	0.29	0.29	0.34	0.37	0.35	0.33	0.33	0.33	0.39	0.46	0.46	0.43	0.37	0.32	0.29	0.24	0.18
x_3	Adults = 3	0.43	0.30	0.21	0.19	0.19	0.23	0.36	0.51	0.50	0.55	0.63	0.64	0.64	0.65	0.70	0.82	0.93	0.92	0.89	0.84	0.80	0.77	0.73	0.58
x_4	Adults = >3	0.76	0.56	0.47	0.44	0.52	0.55	0.74	0.97	0.87	0.85	0.91	0.94	1.00	1.04	1.14	1.25	1.36	1.33	1.30	1.31	1.27	1.22	1.14	0.97
x_5	Kids = 1	−0.19	−0.20	−0.17	−0.16	−0.15	−0.17	−0.10	0.05	0.02	−0.04	−0.04	−0.05	−0.07	−0.05	−0.03	−0.03	−0.00	0.01	−0.03	0.03	0.04	0.00	−0.03	−0.15
x_6	Kids = 2	0.17	0.07	0.07	0.05	0.06	0.05	0.11	0.42	0.31	0.17	0.19	0.21	0.21	0.24	0.26	0.29	0.39	0.39	0.35	0.46	0.49	0.42	0.35	0.27
x_7	Kids = >2	0.43	0.29	0.28	0.31	0.31	0.30	0.42	0.85	0.91	0.82	0.80	0.77	0.73	0.69	0.69	0.77	0.85	0.75	0.65	0.79	0.83	0.70	0.63	0.56
x_8	Senior resident, workday	0.04	0.04	0.06	0.06	0.05	−0.03	−0.16	−0.11	0.22	0.38	0.39	0.34	0.28	0.25	0.24	0.19	0.06	−0.02	−0.04	−0.09	−0.10	−0.06	0.01	0.05
x_9	Resident home >20 h, workday	0.03	0.05	0.06	0.07	0.06	−0.04	−0.07	0.06	0.07	0.16	0.20	0.17	0.15	0.13	0.12	0.15	0.12	0.05	0.06	0.03	0.03	0.04	0.07	0.04
x_{10}	Weekend resident, workday	−0.47	−0.38	−0.33	−0.29	−0.26	−0.26	−0.29	−0.56	−0.60	−0.54	−0.51	−0.47	−0.42	−0.39	−0.47	−0.58	−0.58	−0.53	−0.62	−0.71	−0.72	−0.72	−0.67	−0.58
x_{11}	Daytype = Saturday, no holiday	0.08	0.06	0.04	0.02	−0.00	−0.11	−0.37	−0.45	0.00	0.36	0.48	0.47	0.42	0.36	0.31	0.22	0.05	0.04	0.07	−0.00	−0.11	−0.15	−0.10	0.02
x_{12}	Daytype = Sunday or holiday	0.12	0.10	0.08	0.04	0.00	−0.12	−0.39	−0.50	−0.10	0.27	0.48	0.53	0.49	0.45	0.40	0.31	0.12	0.02	0.00	−0.04	−0.06	−0.08	−0.07	−0.06
x_{13}	Daytype = school break, workday	−0.03	−0.03	−0.04	−0.03	−0.05	−0.08	−0.18	−0.24	−0.08	0.03	0.06	0.09	0.12	0.10	0.08	0.07	−0.01	−0.04	−0.03	−0.03	−0.04	−0.07	−0.04	0.00
x_{14}	Cold storage = yes	0.39	0.42	0.44	0.44	0.46	0.50	0.55	0.58	0.48	0.46	0.43	0.43	0.42	0.41	0.40	0.41	0.47	0.49	0.51	0.53	0.52	0.53	0.49	0.44
x_{15}	Other appliances = yes	0.27	0.27	0.28	0.28	0.29	0.33	0.31	0.28	0.28	0.30	0.30	0.29	0.29	0.28	0.29	0.31	0.33	0.33	0.31	0.31	0.32	0.31	0.29	0.27
x_{16}	Month = Feb	−0.12	−0.05	−0.05	−0.05	−0.05	−0.04	−0.01	0.02	0.02	−0.02	−0.03	−0.08	−0.10	−0.06	−0.06	−0.10	−0.15	−0.10	−0.05	−0.06	−0.06	−0.08	−0.11	−0.12
x_{17}	Month = Mar	−0.37	−0.28	−0.27	−0.28	−0.30	−0.30	−0.27	−0.25	−0.22	−0.21	−0.24	−0.25	−0.24	−0.23	−0.21	−0.29	−0.36	−0.41	−0.34	−0.29	−0.30	−0.33	−0.39	−0.40
x_{18}	Month = Apr	−0.59	−0.54	−0.54	−0.56	−0.59	−0.60	−0.58	−0.57	−0.50	−0.48	−0.50	−0.48	−0.46	−0.44	−0.44	−0.52	−0.59	−0.64	−0.64	−0.64	−0.60	−0.61	−0.64	−0.63
x_{19}	Month = May	−0.68	−0.65	−0.67	−0.69	−0.72	−0.74	−0.70	−0.65	−0.56	−0.56	−0.61	−0.65	−0.64	−0.60	−0.58	−0.66	−0.73	−0.80	−0.75	−0.73	−0.71	−0.74	−0.71	−0.70
x_{20}	Month = Aug	−0.95	−0.90	−0.92	−0.96	−1.00	−1.04	−1.03	−1.01	−0.96	−0.89	−0.91	−1.00	−0.98	−0.95	−0.92	−1.00	−1.03	−1.09	−1.08	−1.04	−0.99	−0.96	−1.01	−1.01
x_{21}	Month = Sep	−0.94	−0.90	−0.90	−0.90	−0.93	−0.96	−0.93	−0.94	−0.92	−0.85	−0.84	−0.84	−0.82	−0.78	−0.73	−0.79	−0.85	−0.91	−0.88	−0.84	−0.79	−0.88	−0.97	−0.97
x_{22}	Month = Oct	−0.72	−0.67	−0.66	−0.66	−0.67	−0.68	−0.63	−0.63	−0.65	−0.63	−0.62	−0.62	−0.62	−0.56	−0.52	−0.56	−0.61	−0.65	−0.61	−0.58	−0.61	−0.68	−0.72	−0.74
x_{23}	Month = Nov	−0.43	−0.39	−0.38	−0.38	−0.38	−0.36	−0.32	−0.31	−0.33	−0.31	−0.31	−0.34	−0.35	−0.33	−0.29	−0.31	−0.27	−0.29	−0.30	−0.31	−0.32	−0.36	−0.39	−0.40
x_{24}	Month = Dec	−0.08	−0.08	−0.09	−0.10	−0.09	−0.07	−0.07	−0.04	−0.01	0.02	0.04	0.02	0.02	0.03	0.06	0.05	0.04	−0.02	−0.07	−0.07	−0.06	−0.07	−0.08	−0.08
x_{25}	HDH	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.04	0.03	0.03	0.02	0.02	0.03	0.03	0.03	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.02
x_{26}	HDH1st	−0.14	−0.18	−0.18	−0.19	−0.19	−0.19	−0.18	−0.15	−0.13	−0.10	−0.08	−0.06	−0.06	−0.06	−0.05	−0.05	−0.05	−0.06	−0.06	−0.04	−0.05	−0.04	−0.04	−0.05
x_{27}	HDH: floor space/100 m^2	0.04	0.04	0.04	0.04	0.04	0.04	0.05	0.05	0.05	0.05	0.05	0.06	0.06	0.06	0.05	0.06	0.06	0.06	0.07	0.06	0.06	0.06	0.05	0.05
x_{28}	HDH: attached	−0.04	−0.04	−0.04	−0.04	−0.04	−0.04	−0.04	−0.05	−0.05	−0.04	−0.03	−0.03	−0.03	−0.04	−0.04	−0.03	−0.03	−0.02	−0.02	−0.02	−0.02	−0.03	−0.03	−0.03
x_{29}	heat pump: detached: HDH >0	−0.19	−0.20	−0.22	−0.24	−0.28	−0.34	−0.36	−0.40	−0.37	−0.33	−0.33	−0.33	−0.32	−0.33	−0.31	−0.30	−0.30	−0.32	−0.32	−0.31	−0.29	−0.28	−0.26	−0.23
x_{30}	Heat pump: attached: HDH >0	−0.07	−0.04	−0.01	−0.02	−0.05	−0.10	−0.14	−0.28	−0.15	−0.07	−0.21	−0.23	−0.21	−0.20	−0.21	−0.27	−0.29	−0.27	−0.25	−0.12	−0.11	−0.11	−0.10	−0.06
x_{31}	HDH: detached: age = 1980≤	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.00	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01
x_{32}	HDH: attached: age = 1980≤	−0.01	−0.01	−0.01	−0.01	−0.01	−0.00	−0.00	0.00	−0.00	−0.00	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.00	−0.00	−0.01	−0.01	−0.01
x_{33}	HDH: detached: wood b. = supp.	−0.03	−0.03	−0.03	−0.03	−0.02	−0.02	−0.03	−0.03	−0.03	−0.03	−0.03	−0.03	−0.03	−0.03	−0.03	−0.03	−0.03	−0.03	−0.03	−0.03	−0.03	−0.03	−0.03	−0.03
x_{34}	HDH: attached: wood b. = supp.	−0.00	−0.00	−0.00	−0.00	0.00	−0.00	0.00	0.00	−0.00	0.00	−0.00	−0.00	−0.00	−0.00	−0.00	−0.00	−0.00	−0.01	−0.01	−0.02	−0.02	−0.01	−0.01	−0.01
x_{35}	HDH: detached: wood b. = main.	−0.04	−0.04	−0.04	−0.04	−0.04	−0.04	−0.04	−0.05	−0.05	−0.05	−0.04	−0.04	−0.04	−0.05	−0.04	−0.04	−0.04	−0.04	−0.04	−0.04	−0.04	−0.04	−0.04	−0.04
x_{36}	HDH: attached: wood b. = main.	−0.01	−0.00	−0.00	−0.01	−0.00	−0.01	−0.01	−0.02	−0.01	−0.01	−0.02	−0.02	−0.01	−0.01	−0.02	−0.02	−0.03	−0.03	−0.03	−0.03	−0.03	−0.03	−0.02	−0.01

Table B.12
Share of explained variance (in %) for each variable and hour, *HDH* model.

		h 1	h 2	h 3	h 4	h 5	h 6	h 7	h 8	h 9	h 10	h 11	h 12	h 13	h 14	h 15	h 16	h 17	h 18	h 19	h 20	h 21	h 22	h 23	h 24
x_1	Dwelling group	5.57	5.64	5.74	5.82	5.81	4.98	5.10	4.65	4.58	4.55	4.33	4.43	4.41	4.66	4.80	4.71	4.35	4.34	4.68	4.83	5.01	5.53	5.79	5.78
$x_{2,\ldots,4}$	Adults	3.56	2.49	2.04	1.95	2.36	2.41	3.46	4.28	3.46	3.29	3.53	3.75	4.09	4.36	4.91	5.46	6.33	6.23	5.94	6.13	6.31	6.22	5.95	4.68
$x_{5,\ldots,7}$	Kids	1.53	1.17	1.10	1.12	1.06	0.98	1.09	2.58	2.22	1.78	1.70	1.68	1.60	1.49	1.46	1.66	2.02	1.80	1.59	2.29	2.65	2.22	1.98	1.89
x_8	Senior resident, workday	0.01	0.01	0.03	0.04	0.04	0.02	0.00	0.04	0.32	0.35	0.20	0.10	0.06	0.05	0.06	0.04	0.01	0.00	0.00	0.02	0.01	0.00	0.02	0.04
x_9	Resident home >20 h, workd.	0.04	0.02	0.01	0.00	0.00	0.03	0.00	0.06	0.00	0.02	0.03	0.06	0.06	0.05	0.04	0.01	0.00	0.01	0.01	0.01	0.01	0.00	0.00	0.00
x_{10}	Weekend resident, workday	0.43	0.29	0.22	0.15	0.11	0.07	0.03	0.18	0.41	0.52	0.57	0.52	0.41	0.36	0.45	0.55	0.41	0.31	0.42	0.55	0.56	0.60	0.57	0.49
$x_{11,\ldots,13}$	Daytype	0.23	0.19	0.15	0.08	0.05	0.11	1.00	1.37	0.04	0.95	2.07	2.27	1.93	1.62	1.25	0.72	0.15	0.04	0.04	0.01	0.03	0.07	0.02	0.02
x_{14}	Cold storage	1.20	1.46	1.62	1.62	1.73	1.78	2.02	2.00	1.45	1.27	1.08	1.10	1.01	1.01	0.91	0.92	1.12	1.18	1.34	1.48	1.51	1.67	1.59	1.38
x_{15}	Other appliances	1.25	1.35	1.49	1.56	1.57	1.66	1.43	1.05	1.05	1.16	1.11	1.05	1.06	1.00	1.02	1.08	1.10	1.15	1.08	1.10	1.22	1.25	1.22	1.18
$x_{16,\ldots,24}$	Month	2.67	2.82	2.86	3.02	3.17	3.18	2.59	2.28	2.32	1.94	1.74	1.72	1.73	1.62	1.45	1.38	1.28	1.31	1.29	1.31	1.36	1.71	2.19	2.51
x_{25}	HDH	19.17	20.41	20.75	20.87	20.65	20.41	18.87	18.06	19.01	19.04	19.41	19.84	20.53	21.76	22.71	23.21	23.73	23.66	22.44	20.69	18.68	17.46	16.95	17.30
x_{26}	HDH1st	1.24	2.00	2.37	2.67	2.96	2.95	2.40	1.59	1.02	0.54	0.38	0.22	0.16	0.12	0.09	0.09	0.08	0.12	0.11	0.10	0.14	0.19	0.29	0.44
x_{27}	HDH: floor space	5.37	5.63	5.97	6.06	5.80	5.43	6.14	5.37	5.24	5.32	4.92	4.94	4.78	4.65	4.56	4.52	4.83	5.55	5.94	5.90	5.99	6.03	5.72	5.43
x_{28}	HDH: dwelling group	0.06	0.08	0.08	0.08	0.08	0.06	0.04	0.03	0.04	0.03	0.02	0.01	0.02	0.02	0.03	0.02	0.01	0.00	0.00	0.00	0.00	0.01	0.01	0.03
$x_{29,30}$	Heat pump: dw. gr.: HDD>0	0.24	0.24	0.34	0.43	0.55	0.79	0.82	1.02	0.78	0.60	0.59	0.61	0.60	0.63	0.54	0.48	0.45	0.50	0.50	0.47	0.47	0.47	0.43	0.34
$x_{31,32}$	HDH: dw. group: age	0.21	0.24	0.25	0.18	0.12	0.08	0.03	0.00	0.02	0.03	0.05	0.08	0.08	0.07	0.06	0.03	0.02	0.02	0.02	0.02	0.03	0.03	0.07	0.15
$x_{33,36}$	HDH: dw. group: wood b.	1.40	1.58	1.60	1.58	1.61	1.65	1.55	1.53	1.62	1.36	1.23	1.11	1.05	1.02	0.96	0.90	0.89	0.85	0.89	1.02	1.13	1.18	1.29	1.39
	R^2	44.17	45.63	46.62	47.24	47.68	46.59	46.58	46.10	43.59	42.76	42.96	43.49	43.56	44.50	45.29	45.76	46.77	47.07	46.30	45.91	45.11	44.64	44.09	43.07

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8 PAPER III

Modeling hourly consumption of electricity and district heat in non-residential buildings

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Abstract

Models for hourly consumption of heat and electricity in different consumer groups on a regional level can yield important data for energy system planning and management. In this study we use hourly meter data combined with cross-sectional data from the Norwegian energy label database to model hourly consumption of both district heat and electrical energy in office buildings and schools using either electric or district heating. We compare modeled total energy consumption as well as modeled energy consumption for space heating and other purposes in buildings with electric heating with corresponding model results for buildings with district heating. Our results show that modeled hourly total consumption in comparable buildings with electric heating and district heating is generally similar in shape, but that office buildings using district heating consume more energy in the morning and less during mid-day, compared to corresponding buildings with electric heating. The results indicate further, that schools using district heat tend to use less indoor temperature reduction during nighttime, weekends, and school holidays, compared to schools with electric heating. Although based on small samples our regression results indicate that the presented method could be used for forecasting regional hourly energy consumption, but also that larger samples and additional cross-sectional information could yield improved models and more reliable results.

Keywords: energy systems, smart meter data, hourly electricity consumption, district heat, panel data

1. Introduction

1.1. Background

In the light of ambitious goals for reducing climate gas emissions and energy consumption the integration of variable renewable energy carriers (VRE) into the energy system has become a major focus in energy research. Norway is not a member of the European Union (EU), but plays an important role in the European energy system and joins the EU-goals regarding greenhouse gas emissions [1]. While the EU wants to cover 20 % of total energy consumption by

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renewable energy sources in 2020 [2] Norway aims at a share of 67.5 % [3], which was met for the first time in 2014 [4]. The use of heating oil and paraffin for heating purposes in Norway is planned to be phased out by 2020 [5].

The service sector accounted for 21 % of Norway's total energy consumption and 24 % of the country's electricity consumption in 2013 [6] (Fig. 1)[1]. Total energy consumption in Norway's service sector has been increasing from 25.5 TWh/a in 1990 to 34 TWh/a in 2013, and constantly about 80 % have been covered by electrical energy [7] (Figure 2). Comparably low energy consumption in 2014 can be explained by a mild winter, while relatively high consumption in 2010 can be explained by an unusually cold winter, i.e. a higher energy consumption for space heating. The contribution of district heat to total energy consumption in the service sector was negligible until the late 1990s, when it started to increase slowly but steadily. From 1997 to 2014 the share of district heat increased from 3 % to 10 %, while the common share of heating oil, paraffin, and other fossil fuels decreased from 19 % to 12 % during the same period [7].

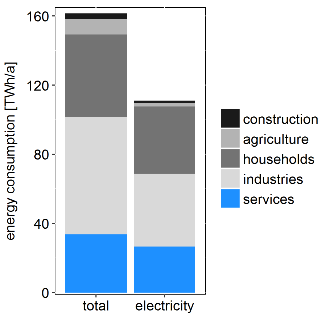


Fig. 1: Energy consumption per sector, Norway, 2013 [6]

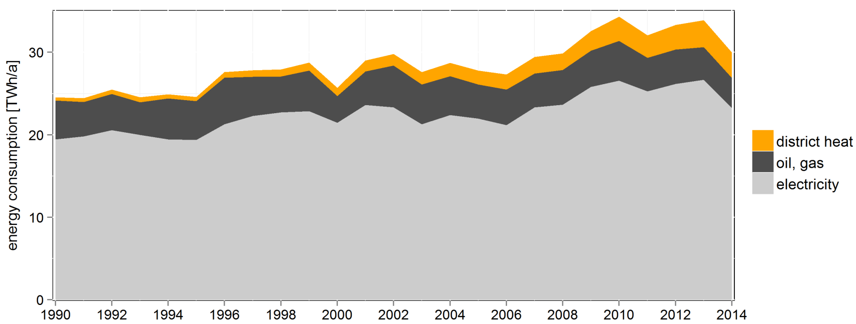


Fig. 2: Energy consumption in the service sector, per energy carrier, Norway, 1990–2014 [7]

With the phase-out of oil boilers, district heat and electrical energy will probably be the two most important energy carriers in the Norwegian service sector in the next decades. District heating networks are to date mainly established in larger cities, e.g. in Oslo, Trondheim, and Bergen. In 2014, total district heat production in Norway was about 5 TWh, of which about 1.5 TWh were produced in Oslo. 56 % of district heat production in Oslo came from garbage combustion plants and 27 % from flexibly operating electric boilers [8].

1.2. Energy system flexibility

While in conventional energy systems production usually follows demand, increasing production shares from VRE require more flexibility and storage capacity in modern energy systems. According to Lund et al. [9] combining heat and power systems is a major step to forward the integration of VRE. Lund et al. [10] describe modern district heating systems supplied by different independent heat sources, including large scale heat pumps and electric boilers that can

[1] In this section total energy and electricity consumption excludes consumption in transport sector and energy industries

transform excess energy supplied by VRE into thermal energy. During summer periods with a high supply with solar thermal energy large scale sorption chillers could contribute to cover the space cooling energy demand.

Demand side flexibility is another important component of modern, *smart* energy systems. In many European countries, including Norway, the roll-out of smart meters has started. While in Norway smart meters to date are merely used to deliver meter data to the system operators, the devices are intended to be utilized for implementing demand side management options such as direct or indirect load control in the future. In combination with competitive storage technologies for heat and electricity demand side management measures, e.g. fuel substitution and load management, can help synchronizing energy supply and demand in modern energy systems.

1.3. Building stock within the Norwegian service sector

The total number of buildings within the service sector in Norway has been steadily increasing from about 123,000 in 2001 to about 140,000 in 2016 [11]. Buildings within education and culture (including schools, universities, museums, churches, etc.) represented the largest group that also exhibited the strongest growth during the past 15 years. The next largest group are office and commercial (e.g. stores or shopping centers) buildings, which did not exhibit a considerable growth. The corresponding shares of different building categories in Norway and Oslo in 2016 are shown in Figure 3. In Oslo, there were about 6,700 buildings within the service sector in the beginning of 2016, which is about 5 % of the national figures [11]. Compared to whole Norway, the share of buildings within education in Oslo is about twice as high, and the share of office buildings is even three times as high. Correspondingly, the shares of cultural, commercial, as well as hotel and restaurant buildings is lower. Since office buildings and buildings connected to education (i.e. schools, kindergartens, universities) represent more than 50 % of buildings within the service sector in Oslo, we assume that a significant share of energy consumption within the service sector in Oslo is consumed in these building categories[2], and that corresponding energy consumption models would be useful for energy system analysis, planning, and management.

1.4. Previous work

Milder winters, stricter energy standards in building codes, and retro-fitting of existing buildings are assumed to lead to reduced heat demand in buildings in the future. Several studies discuss the effects of reduced heat demand and lower temperature levels in district heating systems [12–17]. A number of studies have used hourly meter data to establish models or profiles for heat or electricity consumption in buildings [18–24]. Iyer et al. [25] describe a method for disaggregating hourly energy consumption in supermarkets into a weather-dependent and a weather-independent component, based on hourly meter data of 94 stores from a supermarket chain. Besides weather data, design loads for each store are used as input data to the model. Birt et al. [26] disaggregate hourly electricity consumption of Canadian dwellings into base load and activity load, based on samples with hourly and minutely whole-house electricity

[2] Offical figures on energy consumption per *building category* and region are unfortunately not available.

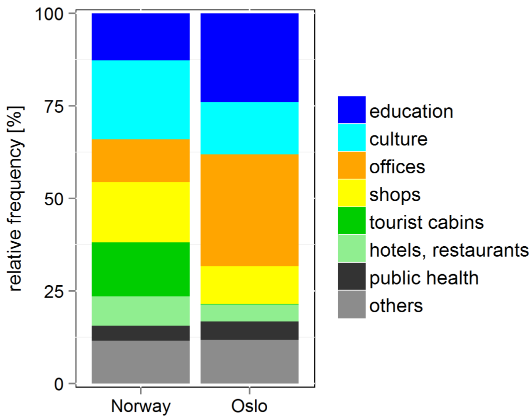


Fig. 3: Share of building categories in Norway and Oslo, 2016 [11]

consumption data and a sample with minutely sub-meter data of heating and cooling equipment. In our previous work [27, 28] we use smart meter data combined with survey response and weather data to investigate the impacts of different variables on hourly electricity consumption in Norwegian households by applying multiple regression. Moreover, we disaggregate total modeled hourly consumption into two components, representing temperature-independent and temperature-dependent consumption. The Norwegian Water Resources and Energy Directorate (NVE) recently published a report [29] about annual energy consumption in Norwegian non-residential buildings where representative distributions of energy consumption for different purposes, such as lighting, space heating, domestic water heating, space cooling, electric appliances, are calculated. For each building category electricity sub-meters were installed in five buildings, and based on the corresponding meter data average shares of total energy consumption for each purpose were calculated.

1.5. Objectives

While smart metering yields huge amounts of highly resolved consumption meter data the obligatory energy labeling of buildings yields large databases of cross-sectional consumer specific information. Both data sources imply a large potential for data mining and data analysis, and may be utilized to develop energy consumption models. Consumption models with high temporal resolution are crucial in evaluating and implementing flexibility measures and help ensuring system stability and efficient operation. Models that can be used for forecasting hourly heat and electricity consumption with respect to different time horizons and scenarios, taking into account changes in important factors, such as outdoor temperature and building stock characteristics, can provide estimates for electric or thermal *loads* which are crucial for designing power lines or district heating networks.

The overall objective of this study is to model hourly consumption of district heat and electrical energy in Norwegian buildings within the service sector. We combine information provided by the Norwegian energy label database with hourly meter data of a sample of about 50 schools and office buildings located in Oslo. By modeling hourly consumption of both heat and electrical energy in buildings with and without electric heating we can determine differences in total hourly energy consumption, and our results can help evaluating the effects of substituting electric space heating by district heating. The method presented in this paper describes how an existing cross-sectional dataset, containing building stock information, combined with a sample of highly resolved meter data can be used to model consumption of heat and electricity on a regional level. The models can be used for scenario-based forecasts that take into account changes in building stock, heating methods, and outdoor temperature and thus help to design future energy systems.

2. Data

2.1. The Norwegian energy label database

Since July 1st 2010 an EU directive has regulated energy labeling also in Norway [30]. Energy labels rate specific annual energy demand, while heating labels indicate to what extent heating energy demand can be covered by other energy sources than fossil fuels or electrical energy. Energy and heating labels are mandatory for all residential and non-residential buildings[3] that are either newly built or to be sold or rented, as well as for all non-residential buildings larger than 1.000 m^2. In order to assign energy label characters *delivered energy* – a theoretical value calculated according to the Norwegian code NS 3031[4] – is used to calculate specific energy consumption, requiring a number of building-specific variables, as e.g. floor space, building category and type, year of construction, construction material, and location. However, not all variables are available and reported for all buildings in the database. By January 2016 the energy label dataset contained about 3,100 non-residential consumers that were located on about 1,700 different plots in Oslo. One plot may include several buildings, and one building may include several consumers, as many non-residential buildings are used by different consumer groups, e.g. a shop on the first floor and offices on the above floors. Thus, different parts of a building can be included separately in the database. Office buildings account for 40% of included consumers, while commercial buildings and buildings within education represent 18 % and 17 % respectively. The most common heating methods among the non-residential buildings located in Oslo and included in the data base were direct electric heating (used in 63 % of buildings), district heating (39 %), and oil boilers (13 %), which are often used in various combinations. Heat pumps are used in 8 % of included buildings, and are most common in kindergartens and schools.

2.2. Panel data

In this study we combine cross-sectional data from the Norwegian energy label data base with hourly meter data (time series). Meter data is provided by Hafslund Nett AS (electricity) and Hafslund Varme AS (district heat) and spans

[3] larger than 50 m^2
[4] NS 3031:2007 Beregninger av bygningers energiytelse, Metode og data

a period from 1 January 2013 to 29 February 2016. Especially schools often consist of several buildings located on a common plot, e.g. a sports hall and a main building. In the following, the expressions *office building* and *school building* (or simply *school*) refer to plots with only office or only school buildings, but not necessarily to only one single building. In other words, we treat all consumers located on a common plot as one consumer.

Meter data and cross-sectional data are merged by the plot ID. As mentioned above, one plot might include several buildings, which in turn can include several consumers as defined in the energy label data base. Moreover, several electricity meters might be located on one plot, while there is only one meter for district heat consumption per plot. In order to link the data sets correctly, we *aggregate* both meter data and cross-sectional data that is assigned to each plot. Aggregate electricity meter data is the sum of hourly meter data recorded by all electricity meters installed on one plot, while aggregate cross-sectional data represents summarized floor space and average age of all buildings on the plot. In case different consumer types are located on one plot (e.g. offices, shops, and storages), mixed building types occur. For example, an office and a storage building located on one plot yield a mixed building type, and we cannot assign data from the individual electricity meters to neither the office nor the storage building. Since we focus on more or less *pure* office buildings and schools the number of useful observations in each subset is relatively low. Although the time series spans a period of approximately three years, not all consumers include useful meter data throughout the whole metering period (e.g. due to metering failures, late installation of the meter, or due to periods during which the building has not been in use), which further reduces the number of useful observations.

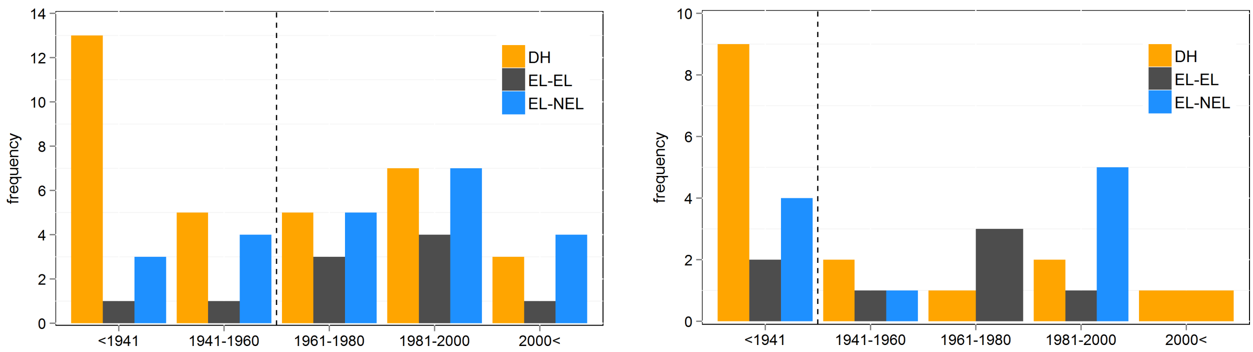
Electricity and district heat meter data are combined with the *aggregate* cross-sectional data using the plot ID, and further combined with outdoor temperature data recorded at *Oslo Blindern* weather station [31] and some calendric information (e.g. weekday, month, school holidays), resulting in separate panel data sets containing electricity (EL) and district heat (DH) meter data. We further divide the EL-set into two sets, according to whether electric heating is used or not. The dataset describing buildings using electric heating is called EL-EL, while observations with non-electric heating form dataset EL-NEL. Thus we get three panel data sets (DH, EL-EL, EL-NEL) which are further divided according to building category. In this study, we only focus on office and school buildings, so that we end up with six subsets.

Number of observations and mean floor space in each subset is shown in Table 1. Buildings consuming district heat also consume electrical energy and can in theory be included both in dataset DH as well as in dataset EL-NEL. Dataset EL-NEL includes buildings with non-electric heating in general, i.e. also buildings with e.g. central oil or pellets boilers. In this study we treat both datasets as independent from each other. The DH set includes most observations, and average floor space of office buildings and schools is in the same range (around 6,500 m^2). Datasets EL-EL and EL-NEL consist of comparably few observations and mean floor space in offices is about 2,000 m^2 higher than in schools. On average, both office buildings and schools with electric heating (EL-EL) exhibit larger floor space than corresponding buildings with non-electric heating.

Tab. 1: Number of observations and average floor space for each building category and energy carrier

	district heat DH		**electricity, non-el. heating EL-NEL**		**electricity, el. heating EL-EL**	
	offices	schools	offices	schools	offices	schools
observations	33	15	23	10	10	7
mean floor space [m^2]	6,390	6,750	7,260	5,435	9,310	7,100

Frequencies of different years (decades) of construction in the different samples are shown in Figure 4. Most office and school buildings with district heating (DH) have been built before 1941. Most offices with electric heating (EL-EL) have been built after 1960, and office observations within non-electric heating (EL-NEL) are relatively evenly distributed over the different age groups. In our subsequent analyses concerning district heat consumption, we distinguish between "old" and "new" buildings, indicated by the dashed lines in Fig. 4. *Old* office buildings are arbitrarily defined as being from before 1961, whereas *old* schools are defined as being from before 1941.



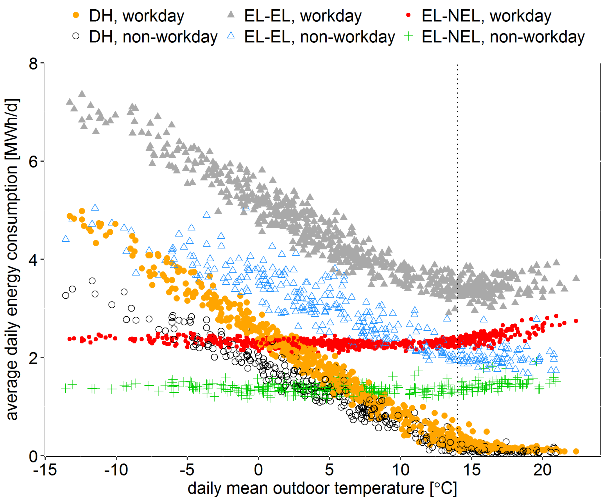
(a) Year of construction, offices

(b) Year of construction, schools

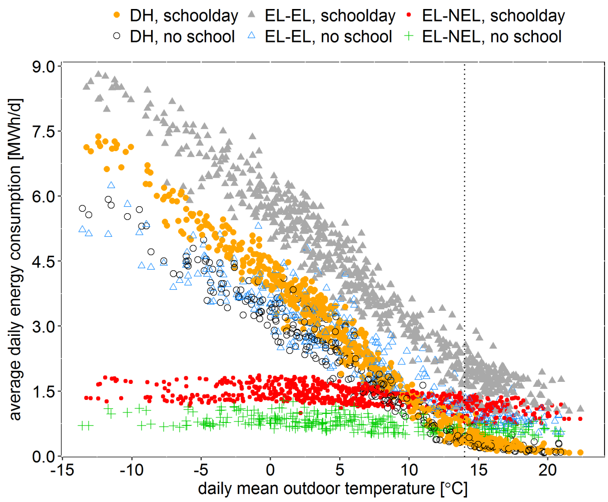
Fig. 4: Frequency of different years of construction

2.3. *Correlation between daily energy consumption and outdoor temperature*

Average daily consumption of district heat and electricity as a function of daily mean outdoor temperature is shown in Figure 5. Since district heat is mainly used for space heating there is a strong negative correlation between the daily mean values of district heat consumption (DH) and mean outdoor temperatures below approximately 14°C (threshold or base temperature) in office buildings (Fig. 5a) and schools (Fig. 5b). Average daily electricity consumption in offices and schools with electric heating (EL-EL) is also negatively correlated with daily mean outdoor temperature, however, the average base temperature for schools is around 17°C. Moreover, electricity consumption (EL-EL and EL-NEL) on workdays in office buildings exhibit a slight positive slope at mean temperatures above approximately 14°C, indicating space cooling. At outdoor temperatures below about 5°C average daily electricity consumption in NEL-schools is on an approximately constant level, but slightly decreasing at higher mean temperatures. This might be explained by direct electric heating that is used to partly cover the heating demand at moderate outdoor temperatures. Since both in schools with and without electric heating there is no positive correlation between average electricity consumption and outdoor temperature, the average school in our sample does not use space cooling. Average electricity consumption on non-workdays (non-schooldays) is lower than on workdays (schooldays) and temperature-dependent consumption (DH, EL-EL) is less increasing with falling outdoor temperatures.



(a) Office buildings



(b) School buildings

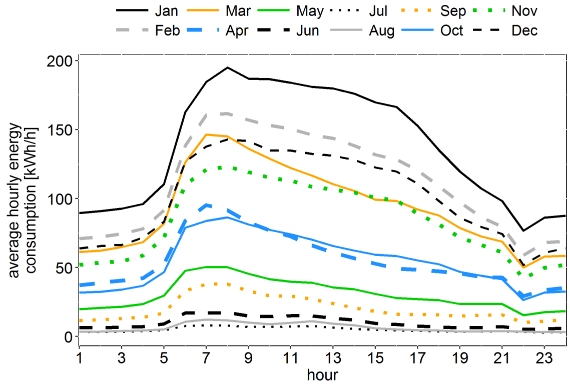
Fig. 5: Average daily consumption of district heat and electricity as a function of mean outdoor temperature

2.4. Average hourly consumption of electricity and district heat

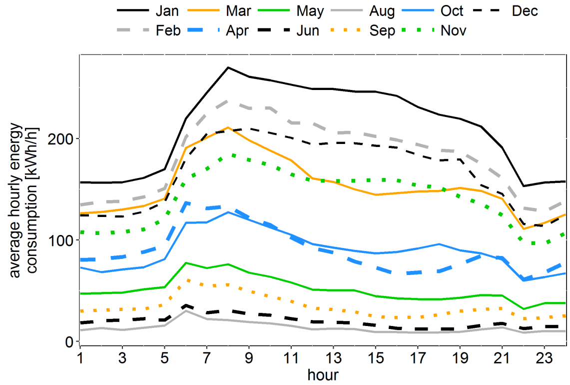
Average hourly consumption of electricity and district heat on workdays (offices) and schooldays (schools) are shown in Figure 6. Since there are no school days in July, this month is missing in the corresponding figures. District heat consumption exhibits strong seasonal variations, resulting in highest average consumption in January, when outdoor temperatures are lowest, and lowest average consumption during summer, when outdoor temperatures are highest, and district heat is mainly consumed for water heating purposes. During the winter months average DH consumption exhibits a small peak in hour 8 and decreases over the course of the day. In offices (Fig. 6a) the decrease becomes stronger after hour 16, while consumption in schools (Fig. 6b) first decreases more sharply after hour 20. From March to October average DH consumption in schools exhibits a slight trough during afternoon, and a slight increase during evening, which indicates that the buildings are used for other purposes after the actual school day. We have to date no explanation for the kink at hour 22. Since the kink occurs in several buildings, and both in office buildings and schools, it might be caused by some automatised routines, e.g. revision processes in the HVAC system that imply an interruption in district heat consumption for several minutes.

Average hourly electricity consumption in buildings with electric space heating (EL-EL) also varies strongly from month to month, however, while in school buildings (Fig. 6d) average consumption during summer is clearly lowest, there are smaller differences between spring, summer, and fall in office buildings (Fig. 6c). Increased average consumption during afternoon hours in the summer months June through September indicates electricity consumption for space cooling in offices. In schools with electric heating, average electricity consumption in the evening does not decrease as continuously as in office buildings, but exhibits a bump, indicating that the buildings might be used for other purposes after the actual school day.

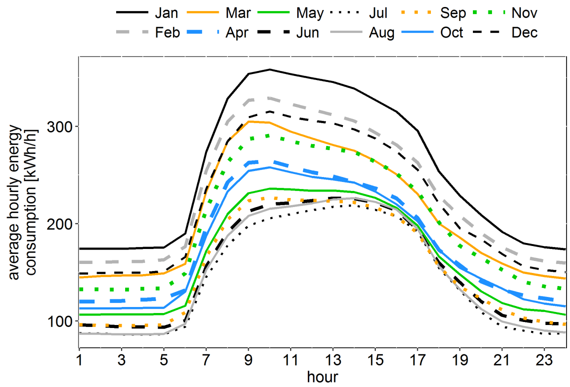
Average hourly consumption of electrical energy in office buildings with non-electric heating (EL-NEL) (Fig. 6e) varies only little from month to month. Average hourly consumption is highest in June and August, and increasing consumption in the afternoon again indicates space cooling. Since July is in the middle of the Norwegian summer holidays, average consumption in this month is lower than in August or June. In schools with non-electric heating (Fig. 6f), there are much higher differences in average hourly consumption from month to month, which indicates that some electrical energy is used for space heating.



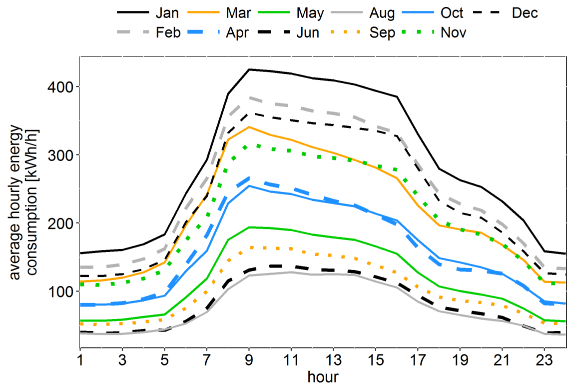
(a) District heat, offices



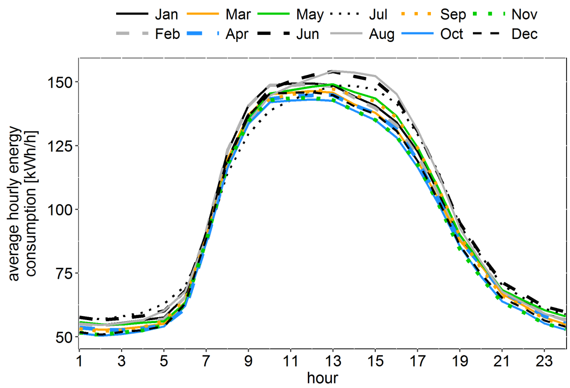
(b) District heat, schools



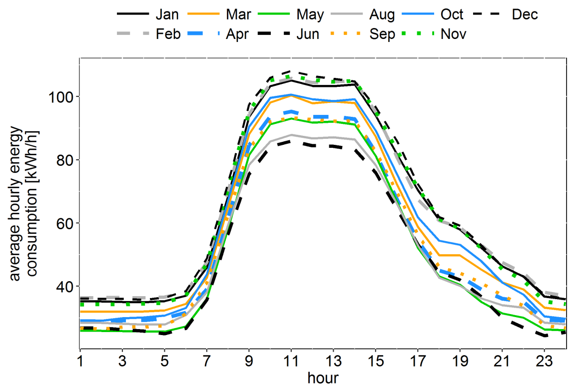
(c) Electricity, electric heating, offices



(d) Electricity, electric heating, schools



(e) Electricity, non-electric heating, offices



(f) Electricity, non-electric heating, schools

Fig. 6: Average hourly consumption of district heat and electricity grouped after month, only workdays/schooldays

3. Methods

3.1. Heating degree days and cooling degree days

Base temperature t_b indicates at which value of daily mean outdoor temperature a building consumes energy for space heating purposes. Base temperatures might vary across consumers and consumer groups, and can change from year to year, largely depending on how the heating system is controlled. Heating degree days HDD are defined as the sum of positive differences between t_b and daily mean outdoor temperature $\bar{t}_{o,d}$ during a certain period, e.g. one year. Usually a base temperature of $t_b = 17°\mathrm{C}$ is chosen to define HDD in Norway, which is most appropriate for the existing residential building stock. Due to higher internal heat gains, e.g. caused by electric appliances and lighting, and lower indoor temperatures, t_b in office buildings might be lower, as indicated by Fig. 5a. For EL-EL consumption in office buildings and DH consumption in both office buildings and schools $t_b = 14°\mathrm{C}$ could roughly serve as an average base temperature for our samples. Based on visual judgement $t_b = 17°\mathrm{C}$ seems be most appropriate for describing temperature-dependent EL-EL consumption in schools in our sample (Fig. 5b). However, for simplicity, we use common base temperatures for office buildings and schools, and thus treat EL-EL consumption at outdoor temperatures between 14°C and "true" base temperature as temperature-independent.

In order to model the linear relationship of cooling energy consumption and outdoor temperature *cooling degree day* CDD is defined as the difference between daily mean outdoor temperature $\bar{t}_{o,d}$ and 14°C. The calculation of heating and cooling degree days as well as the first differences variable $HDD1st$ is explained in Appendix A.

3.2. Modeling hourly consumption of district heat and electrical energy

The method we apply is documented in detail in our previous work [28] and we only explain the most important differences in this subsection.

Combining time series (meter data) and cross sectional data (survey response) results in a large panel data set. For each observation (ID) a time series of hourly electricity meter values (DH_1, DH_2, ..., DH_{24} for district heat, EL_1, EL_2, ..., EL_{24} for electricity) as well as building floor space and building age as cross sectional data are available. Temperature data (HDD, CDD, ...) as well as day-type information (weekday, holiday, month, ...) for each day are constant across observations, since all buildings are located in the same region (Oslo). For each hour of the day a separate model *(pooled OLS)* is estimated, resulting in a set of 24 hourly models.[5] The hourly model set is determined by the formula for ordinary least squares regression (Equation 1) where $E_{i,h}$ represents hourly electricity consumption of hour h and observation i.

$$E_{h=1,...,24,i} = \beta_{0,h} + \sum_{k=1}^{k} \beta_{k,h} \cdot x_{k,i} + \varepsilon_{h,i} \tag{1}$$

[5]We use the *plm*-package [32] in *R*.

We estimate models for hourly district heat and hourly electricity consumption based on the six datasets described in the data section. All six models are set up according to Equation 1 but the explanatory variables $x_{k,i}$ differ.

Floor space is the only cross sectional variable included in all six models. Due to the comparably low number of observations building age is only considered in the district heat models for office and school buildings. A corresponding dummy variable indicates whether a building was built before 1961 (office buildings) or before 1941 (schools). Heating degree days (HDD, $HDD1st$) are included in all models except for the NEL-model in office buildings. Cooling degree days CDD are only included in the EL- and NEL-models for offices. The remaining explanatory variables represent calendric information: *free* indicates a non-working day, *school holidays* indicates whether a workday lies within school holidays, and *month* represents the current month.

Modeled DH and EL-EL consumption is broken down into a HDD-independent and a HDD-dependent component[6]. The HDD-dependent component is the the sum of all elements containing HDD or $HDD1st$ and can be interpreted as *space heating* consumption. The HDD-independent part is the sum of all remaining elements and can be interpreted as consumption for electric appliances including electrically heated hot water tanks and space cooling equipment (*basic* consumption).

Tab. 2: Explanatory variables, offices

description	type	reference group	DH	NEL	EL
floor space	continuous	-	yes	yes	yes
free=TRUE	dummy	free=FALSE	yes	yes	yes
heating degree day HDD	continuous	-	yes	no	yes
1st differences $HDD1st$	continuous	-	yes	no	yes
month = 2, ..., 12	dummy	month=1 (January)	yes	yes	no
floor space · month = 2, ..., 12	dummy	month=1 (January)	no	no	yes
floor space · free=TRUE	dummy	free=FALSE	no	yes	yes
floor space · school holidays=TRUE & free=FALSE	dummy	school holiday=FALSE	no	yes	yes
HDD · floor space	continuous	-	yes	no	yes
HDD · floor space · age="'≤1960"'	continuous	age="'>1960"'	yes	no	no
HDD · floor space · free=TRUE	continuous	free=FALSE	yes	no	yes
CDD · floor space	continuous	-	no	yes	yes
CDD · floor space · free=TRUE	continuous	free=FALSE	no	yes	yes

Tab. 3: Explanatory variables, schools

description	type	reference group	DH	NEL	EL
floor space	continuous	-	yes	yes	yes
free=TRUE	dummy	free=FALSE	yes	yes	yes
heating degree day HDD	continuous	-	yes	no	yes
1st differences $HDD1st$	continuous	-	yes	no	yes
month = 2, ..., 12	dummy	month=1 (January)	yes	yes	no
floor space · month = 2, ..., 12	dummy	month=1 (January)	no	no	yes
floor space · free=TRUE	dummy	free=FALSE	no	yes	no
floor space · school holidays=TRUE & free=FALSE	dummy	school holiday=FALSE	no	yes	yes
HDD · floor space	continuous	-	yes	no	yes
HDD · floor space · age="'≤1940"'	continuous	age="'>1940"'	yes	no	no
HDD · floor space · free=TRUE	continuous	free=FALSE	yes	no	yes
HDD · floor space · school holidays=TRUE & free=FALSE	continuous	school holidays=FALSE	yes	no	yes

[6]See [28] for a detailed description of the decomposition method.

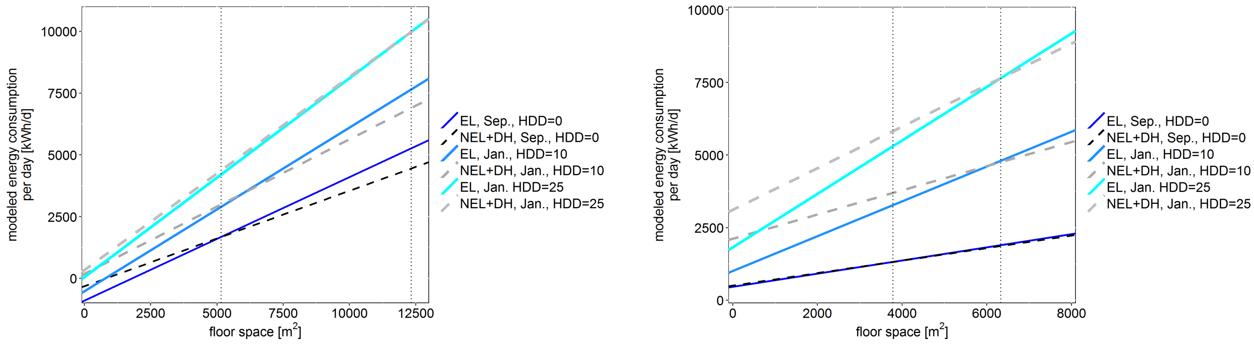
4. Results and discussion

4.1. General regression results

Adjusted coefficients of determination R^2 for the hourly regression models are in the range of 0.70–0.86 for EL and 0.58–0.74 for DH. The NEL-model for office buildings achieves R^2=0.77–0.84, while the NEL-model for schools exhibits values ranging between 0.37 during late evening and 0.79 in hour 11. Comparably high coefficients of determination for EL-EL-models can be explained by the strong correlation between hourly energy consumption and *HDD*. Floor space and heating degree day explain the majority of explained variance in both EL-EL- and DH-models. Lower R^2 for DH-models can partly be explained by larger samples with more diverse hourly and seasonal consumption patterns. Electricity consumption in NEL-buildings is modeled as *HDD*-independent, so only floor space and calendric variables are included, which explains the lower R^2 in NEL-schools. Moreover, average NEL-consumption in schools (see Figure 5b) indicates that some electric heating equipment is used at moderate temperatures during the heating period, but including *HDD* as defined in Appendix A might not be sufficient. In order to achieve a more accurate model, a *HDD* variable could be defined that is constant below a lower outdoor temperature limit and zero above an upper limit. However, due to the small sample size it is uncertain whether this behaviour is typical for schools with non-electric heating, and therefore keep the model in its simple version.

Although the sample size in our six different datasets is comparably low and there is some uncertainty connected to the cross-sectional information in the panel data, our regression results seem feasible. However, a number of other variables that were not included in our dataset are likely to have an impact on energy consumption (e.g. number and electric and thermal loads of electric appliances, U-values of building components facing the outside environment, indoor temperatures, space cooling and air conditioning equipment), and might represent omitted variables. Year of construction is often used as a proxy for the building's insulation and tightness standard, however, due to the small number of observations we include building age only in our DH-models, and only in a very simplified way, by distinguishing between *old* and *new* buildings.

In order to illustrate some general differences in modeled energy consumption in buildings with electric (EL) and district heating (NEL+DH), correspondingly, we compare modeled energy consumption per day as a function of floor space considering three different cases: a) A September day with 14°C outdoor temperature, so that both *HDD*=0 and *CDD*=0, b) a January day with *HDD*=10, and c) a January day with *HDD*=25. The corresponding regression lines are shown in Fig. 7. In all three cases the intercept in EL-buildings is smaller than in NEL+DH-buildings, while the slope is larger. Thus the corresponding regression lines exhibit an intersection at positive floor space values. This implies that for all floor spaces smaller than the intersection modeled consumption in a building with district heating would be larger, while for all floor spaces larger than the intersection, modeled consumption would be smaller than in a building with electric heating. Moreover, the intersection-floor space increases with *HDD*. Considering *HDD* ranges between 0 and 25, for smaller buildings ($<5000\,\mathrm{m}^2$ for offices, $<4000\,\mathrm{m}^2$ for schools) modeled total consumption in case of EL+DH will always be higher than in case of EL, while for larger buildings (> 12000 m^2 for offices, > 600 m^2 for schools) modeled EL-consumption will always be larger than modeled NEL+DH consumption.



(a) Office building (DH: > 1960)

(b) School building (DH: > 1940)

Fig. 7: Modeled energy consumption per day as a function of floor space, EL and NEL+DH

Our regression models are based on only few observations per subset, and only some single observations represent very small or very large buildings, so that parameter estimates are relatively uncertain. Moreover, the relationship between energy consumption and floor space might not be perfectly linear so that the regression model might not exhibit an appropriate functional form. However, higher energy consumption per square meter floor space in case of district heating in smaller buildings, and lower specific consumption in larger buildings – compared to buildings with electric heating – could be explained by larger heat losses in the central heating system referring to building size, which might decrease with increasing building size. Larger samples with a better distribution of different building sizes could yield more reliable estimates and allow a more detailed discussion of this behaviour.

Although we briefly compare modeled total consumption in buildings with electric and district heating in the following, we focus on describing differences in the shape of diurnal profiles and seasonal variations.

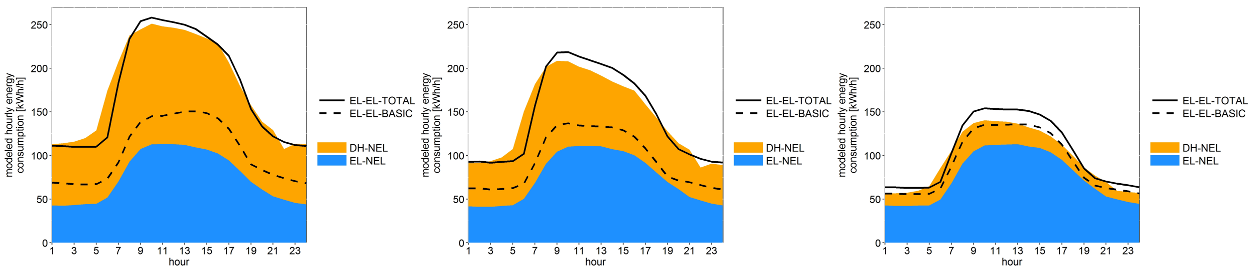
4.2. Comparison of hourly energy consumption in buildings with electric heating and district heating

In order to compare the shape of total hourly energy consumption in buildings with electric and district heating, modeled hourly consumption of district heat and electrical energy in case of district heating is stacked (NEL+DH) and compared with modeled hourly consumption of electrical energy in case of electric heating (EL).

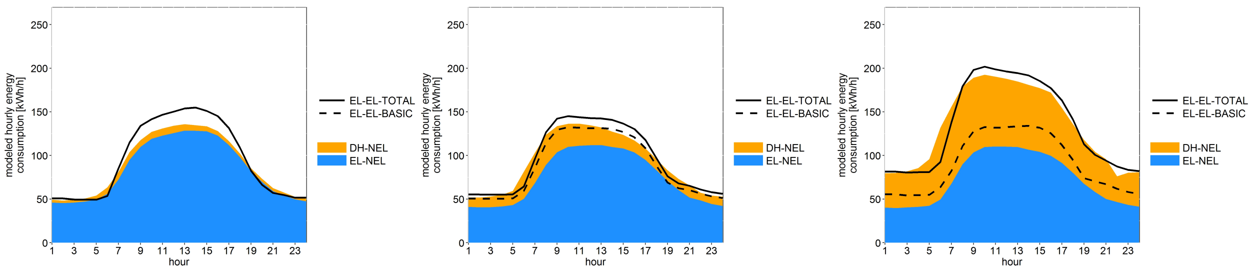
Modeled hourly energy consumption in a building with 6,000 m^2 floor space for six different months and outdoor conditions is shown in Figures 8 (office building) and 9 (school). Modeled total energy consumption in buildings using district heat is the upper limit of the stacked blue and orange areas, depicting modeled consumption of electrical energy and district heat, respectively. The solid black line shows modeled electricity consumption in buildings with electric heating (EL-EL TOTAL), which equals total energy consumption assuming that no other energy carriers are used. The dashed black line represents modeled basic consumption (EL-EL BASIC).

4.2.1. *Office building*

In all six cases, during the main office hours 8–17, EL-EL-TOTAL exceeds modeled total energy consumption in a corresponding NEL+DH building, and the difference becomes smaller with increasing *HDD* (Fig. 8). Especially cases January, March, and November indicate that space heating in a NEL+DH office building starts some hours earlier than in a comparable EL-building, which can be explained by a hot water based central heating system supplied by district heat usually requiring more time to distribute heat within the building, compared to e.g. electric heaters placed directly in the corresponding rooms. Modeled basic electricity consumption EL-EL-BASIC in an EL-office building is higher than modeled NEL-consumption in a corresponding NEL+DH-building, where electricity is assumed not to be used for space heating. This difference is highest in January and lowest during summer, which can be partly explained by electricity consumption for domestic water heating which is covered by electricity in EL-buildings and by district heat in NEL+DH-buildings. Since *month* is correlated with daily mean outdoor temperature, and the corresponding model component is assiged to basic consumption, modeled EL-EL-BASIC consumption is might contain some electricity consumption for space heating purposes.



(a) January, $\bar{t}_{o,d}$=-4°C, *HDD*=18 **(b)** March, $\bar{t}_{o,d}$=+1°C, *HDD*=13 **(c)** May, $\bar{t}_{o,d}$=+11°C, *HDD*=3

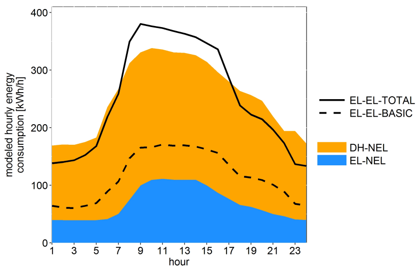


(d) July, $\bar{t}_{o,d}$=+19°C, *CDD*=5 **(e)** September, $\bar{t}_{o,d}$=+12°C, *HDD*=2 **(f)** November, $\bar{t}_{o,d}$=+3°C, *HDD*=11

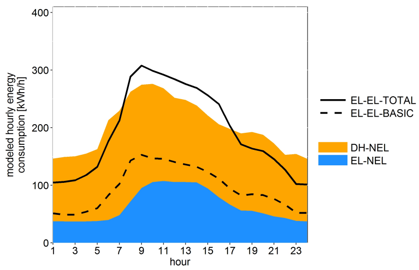
Fig. 8: Modeled hourly consumption of district heat and electricity, office building, 6,000 m^2, (DH: > 1960), workday

4.2.2. *School building*

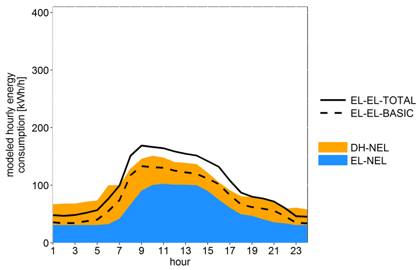
During the main school hours modeled total energy consumption in an EL-school is higher than in a comparable NEL+DH-school, however, the difference vanishes during summer and increases with *HDD* (Fig. 9). From about hour 17 to hour 7 during the heating period modeled total consumption in a NEL+DH-school exceeds modeled total consumption in an equally large EL-school. A possible explanation for this result might be that schools using district heat implement less night-setback, i.e. do not lower the indoor temperature set-point during night-time (i.e. outside the school hours) as much as schools with electric heating do. Thus, more heat is consumed during night-time and less re-heating energy is needed during the day. Schools with electric heating might let the indoor temperature drop to a lower set-point, and thus need less energy during night-time and more re-heating energy during day-time. As in a comparable office building modeled basic electricity consumption in a school with electric heating is higher than modeled NEL-consumption in a NEL+DH-school. The difference is approximately zero in the July case and increases with *HDD*. Again, this might be explained by electricity consumption for tap water heating as well as by temperature-independent electricity consumption for space heating purposes being included in modeled basic consumption.



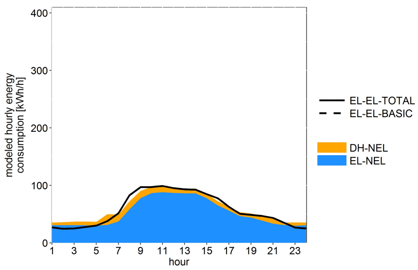
(a) January, $\bar{t}_{o,d}$=-4°C, *HDD*=18



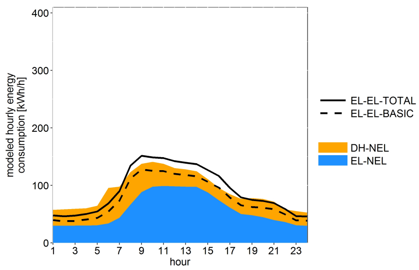
(b) March, $\bar{t}_{o,d}$=+1°C, *HDD*=13



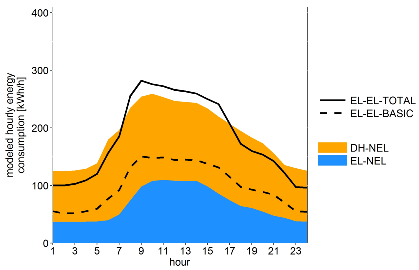
(c) May, $\bar{t}_{o,d}$=+11°C, *HDD*=3



(d) July, $\bar{t}_{o,d}$=+19°C, *CDD*=5



(e) September, $\bar{t}_{o,d}$=+12°C, *HDD*=2



(f) November, $\bar{t}_{o,d}$=+3°C, *HDD*=11

Fig. 9: Modeled hourly consumption of district heat and electricity, school, 6,000 m^2, (DH: > 1940), school day

4.3. *Daily energy consumption*

To a certain extent differences in *hourly* energy consumption, e.g. caused by different set-point temperatures, night-setback, and reheating periods, are leveled out by aggregating hourly consumption over time. In the following, we compare modeled *daily* energy consumption of heat and electricity in an office building and a school with electric and district heating, correspondingly, over the course of one year (2012, Fig. 10). With a chosen floor space of 6,000 m^2 modeled daily energy consumption on workdays in an office building with electric heating is higher than modeled consumption in case of district heating during summer, but slightly lower during the coldest days (Fig. 10a). Modeled consumption on non-workdays, indicated e.g. by the troughs in the end of each week, is approximately equal most of the year.

Modeled consumption in a school with electric heating is slightly lower than in a school with district heating, both on school days as well as during holiday periods (see Easter and Christmas holidays in April and December, respectively) and weekends during the heating period (Fig. 10b). This indicates that on average not only night-setback but also a temperature set-back on non-school days is less common in schools using district heat, or that schools with district heating are more often used for other purposes during weekends and holidays (e.g. the sports hall).

Outside the heating period, consumption in case of electric and district heating is approximately equal, however with a slightly higher consumption in NEL+DH-schools during summer holidays.

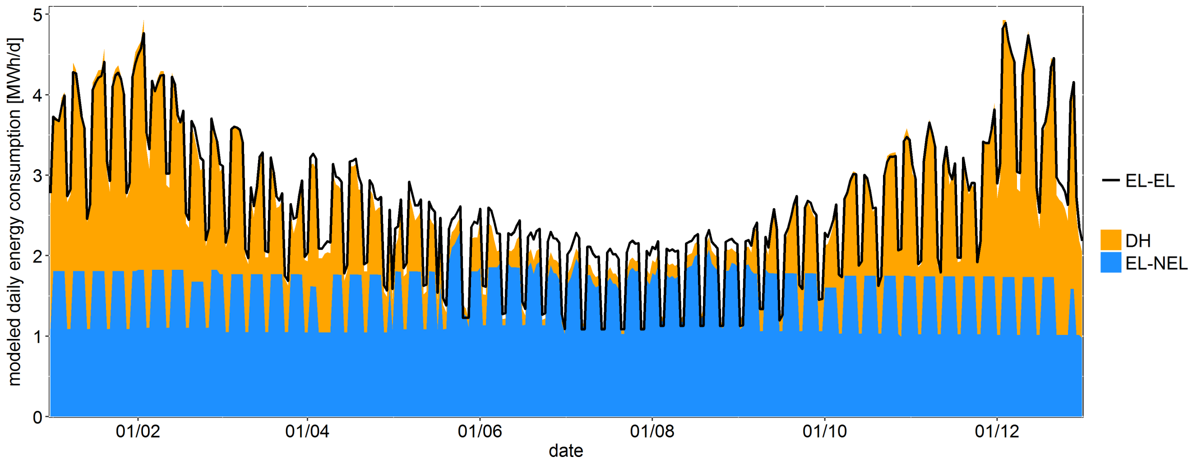
Irrespective from heating systems, during summer modeled total consumption in an office building is higher than in an equally large school, which can be explained by the summer holidays, and by the fact that usually space cooling takes place in office buildings, but not in schools. During the rest of the year, however, modeled total energy consumption in a school is higher than in an office building, which can be mainly explained by a higher heating energy consumption. In our samples schools are on average older than office buildings, which is not sufficiently accounted for in the models. Moreover, in schools indoor temperatures might be higher and there might be less internal heat gains caused by electric appliances, compared to office buildings.

4.4. Energy consumption shares in a normal year

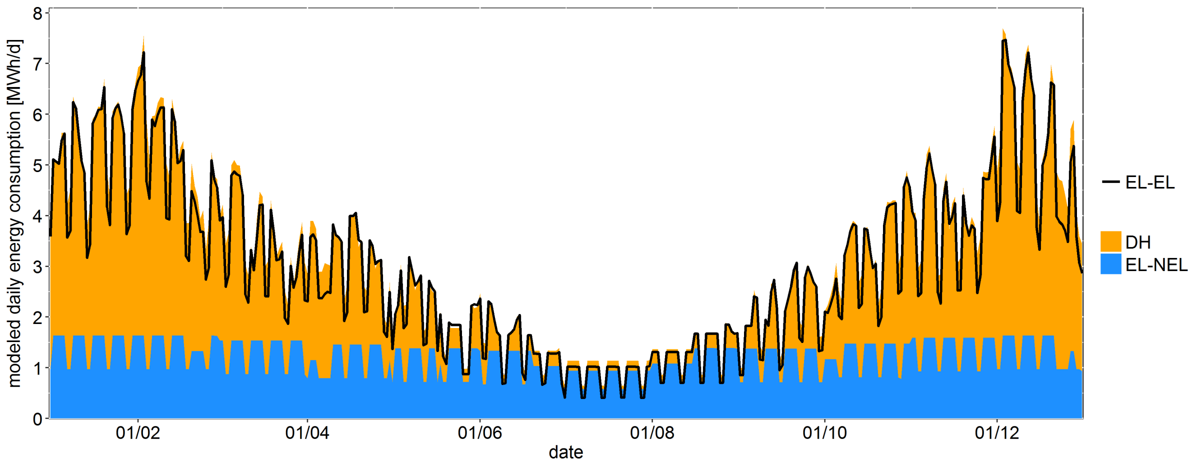
Relative energy consumption for heating and other purposes in both building categories over the course of a *normal* year[7] is shown in Fig. 11. Since energy consumption for heating purposes in buildings with electric heating is not metered, but only estimated by disaggregating consumption into a HDD-dependent and -independent component, energy consumption shares in buildings with electric heating and district heating cannot be directly compared. In case of electric heating domestic water heating is mainly included in modeled basic consumption (dark-grey bars), since it is assumed not to be correlated with outdoor temperature. In case of district heating energy consumption for domestic water heating is assumed to be included in district heat consumption. According to our results about 39 % of total energy consumption in an office building (Fig. 11a) with district heating are spent for space and water heating, which is approximately in accordance with the report from NVE [30], reporting 36 % – 31 % for space heating and 5 % for water heating – in a representative office building. The share of modeled space heating consumption in a corresponding building with electric heating is 27 % which is slightly lower than figures reported by NVE (31 %).

For a school building (Fig. 11b) our model results yield 62 % district heat consumption, which meets NVE's results (59 % space heating + 3 % water heating) very well. However, modeled space heating consumption in schools with electric heating is only 42 % and thus considerably lower than the representative share of 59 % [30]. Since the sample

[7] We calculate HDD and CDD based on the normal daily mean temperatures in Oslo for the normal period 1961-1990. Normal temperatures are provided by [31]



(a) Office building (DH: > 1960)

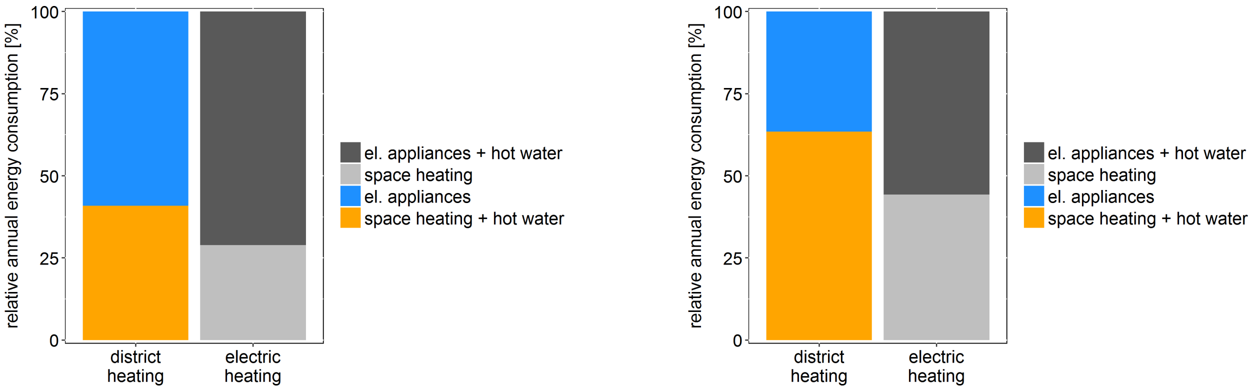


(b) School (DH: > 1940)

Fig. 10: Modeled daily energy consumption in office building and school, 6,000 m^2, 2012

size for schools with electric heating is very small (only 7 observations) model results are quite uncertain. Moreover, a higher temperature-independent consumption in schools with electric heating, which might also include some electric heaters that e.g. are not switched off during summer, is a possible explanation for the comparably low share of modeled space heating energy. As indicated by modeled daily consumption for 2012 (Fig. 10b), modeled consumption in schools with electric heating during weekends and holidays is lower than in schools with district heating, which might also contribute to the comparably low share of modeled heating energy.

Higher indoor temperatures, less indoor temperature reduction beyond school days, on average older buildings, and less internal heat gains caused by electric appliances might explain higher modeled heat shares in schools compared to offices. Correspondingly, higher shares of basic consumption in office buildings can be explained by more electric appliances and the use of space cooling.



(a) Office building (DH: > 1960)

(b) School (DH: > 1940)

Fig. 11: Relative energy consumption in office building and school, 6,000 m^2, normal year

5. Model shortcomings and further work

The use of heating and cooling degree days, based on average base temperatures, simplifies the models but also implies some modeling error. In reality base temperatures vary across consumers, and a linear relationship between energy consumption and *HDD* or *CDD* is only valid within a certain range. Moreover, using the same base temperature to define *HDD* and *CDD* implies that office buildings directly switch from heating to cooling at a daily mean outdoor temperature of 14°C, while most buildings probably exhibit some temperature range when neither heating nor cooling takes place. Moreover, average daily temperatures might not be able to explain temperature-dependent variations in energy consumption from one hour to the next. In our hourly models we include first differences in heating degree days *(HDD1st)* in order to correct for abrupt drops in daily mean temperature from one day to another. Since during winter hourly variations in outdoor temperature values are relatively small, hourly models for heating energy consumption based on daily mean temperatures seem to yield sufficient results, as indicated by a previous study [28].

For modeling space cooling demand, however, the use of *CDD* might imply a larger error. During summer, there are relatively large temperature differences between day-time and night-time and high maximum temperatures – mostly occurring during afternoon – are likely to affect space cooling demand during the corresponding and adjacent hours. Since apparently not all buildings in our sample used space cooling, and due to relatively cool Norwegian summers, the number of operating hours of space cooling equipment was probably comparatively low during the examined metering period. Although the use of *CDD* for estimating hourly electricity consumption implies a great simplification, regression results seem feasible. In the light of expected temperature increases due to climate change, Norway might face considerably hotter summers in the future so that models for hourly space cooling demand should be improved accordingly.

Unfeasible data (both meter data and cross-sectional data) and an insufficient method for linking meter data and cross-sectional data based on plot ID resulted in very small, not necessarily representative samples. If each electricity and district heat consumer had an individual ID that would be stored both in the customer data as well as in the energy label database, a much larger sample would be available, allowing much more detailed and reliable analyses. As an alternative to the energy label database, a brief survey among the included non-residential customers, containing few questions on floor space, building type, business line, and e.g. heating and cooling equipment, as well as year of construction and rehabilitation measures, would yield valuable information that could be used to improve the presented models.

A similar sample from another Norwegian region, e.g. Trondheim or Bergen, could be used to test the applicability of the presented Oslo-based models to other regions. Moreover, while in this study only two building types were examined, similar studies on other residential and non-residential building types, such as apartment buildings, shopping centres, stores, hotels, industrial buildings, would enable useful models for Norway's stationary energy demand.

Our samples include mainly buildings where either direct electric heating or district heating is used, while in reality electric heating is often used in combination with a non-electric central heating system (district heat, oil boiler). Consumers might e.g. use electric heating to cover the base heating load, and only use the non-electric heating system to cover the top load during winter. Alternatively, electric heaters might be used to supplement the central heating system locally. These variations are not considered in our work but would be an interesting subject for further studies.

6. Conclusion

Comparing modeled total hourly energy consumption in buildings with electric heating with modeled consumption in buildings with district heating indicates that office buildings using district heat start space heating some hours earlier than buildings with electric heating which can be explained by direct electric heaters distributing heat faster than hot water based central heating systems. Moreover, the comparison indicates that schools using district heat use less night-setback and less temperature setback during weekends and school holidays, which can be explained by school buildings being used for other purposes during these periods, or by less advanced control systems. Although the applied method for disaggregating electricity consumption in buildings with electric heating yields only rough estimates on energy consumption for the two components representing electric appliances and water heating, and electric space heating, respectively, a comparison of disaggregate energy consumption indicates that similar shares of annual energy consumption are used for heating purposes in buildings with electric heating and buildings with district heating. Annual heat shares of modeled total energy consumption in schools are higher than in offices which can be explained by on average older buildings, higher indoor temperatures, and less internal heat gains caused by electric appliances. Moreover, as opposed to schools, office buildings included in our samples apparently consumed electrical energy for space cooling, which contributes to higher shares of modeled energy consumption for electric appliances. Regression results indicate that the applied method can be used for developing models for hourly consumption of district heat and electrical energy, but that the samples available in this study might be too small to achieve reliable results. For smaller buildings modeled consumption in case of district heating exceeds modeled consumption in case of electric heating, while the opposite is the case for larger buildings. An analysis based on a larger covering a wider range of building sizes, and possibly including further cross-sectional variables, could show whether this behaviour is feasible or rather caused by the low number of observations in our data or by the functional form of the regression model.

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Appendix A. Heating and cooling degree days

Daily mean outdoor temperature $\bar{t}_{o,d}$ of day d is represented by the arithmetic mean value of 24 hourly temperature values, metered during day d. A heating degree day HDD[8] is defined as the positive difference between HDD-base

[8]For simplicity, index d is dropped in the text and HDD is used without physical unit.

temperature $t_{b,HDD}$ and daily mean outdoor temperature $\bar{t}_{o,d}$ (Equ. A.1).

$$HDD_d = \begin{cases} t_{b,HDD} - \bar{t}_{o,d}, & \text{for } \bar{t}_{o,d} < t_{b,HDD} \\ 0, & \text{else} \end{cases} \tag{A.1}$$

The difference in heating degree days between any day d and the day before $(d-1)$ is called *first differences in heating degree days* $HDD1st$ in this study (Equ. A.2).

$$HDD1st_d = HDD_d - HDD_{d-1} \tag{A.2}$$

Cooling degree day CDD is calculated as the positive difference between $\bar{t}_{o,d}$ and CDD-base temperature $t_{b,CDD}$ (Equ. A.3).

$$CDD_d = \begin{cases} \bar{t}_{o,d} - t_{b,CDD}, & \text{for } \bar{t}_{o,d} > t_{b,CDD} \\ 0, & \text{else} \end{cases} \tag{A.3}$$

9 PAPER IV

Modeling and forecasting regional hourly electricity consumption in buildings

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Abstract

Sound estimates on future heat and electricity demand with a high temporal and spacial resolution are needed for energy system planning and management, grid design, and evaluating demand side management options. In this study we develop regression models for hourly electricity consumption in different consumer categories within the household and service sector, and disaggregate modeled consumption into an electricity-bound and a space heating component. In order to validate the developed models we use official building stock statistics as input data and compare the resulting model output with historical regional aggregate consumption data in both sectors. In the next step we use existing forecasts on population growth and outdoor temperature to model hourly electricity consumption in Oslo county in 2040. According to our results and assuming medium population growth net heat consumption will be approximately on today's level, meaning a milder winter and building stock renewal outweigh an increase in heated floor space due to population growth. In contrast, electricity-bound energy consumption increases approximately according to population growth, which can be explained by strongly simplified assumptions regarding future number of buildings, dwellings, and average floor space, and by not taking into account changes in use and energy efficiency of electric appliances. Our results indicate that the presented method can be useful for modeling and forecasting energy consumption on a regional level, but also that the quality of the model output highly depends on the quality and availability of both the panel data for developing the models as well as the building stock data used as input data.
Keywords: energy systems, smart meter data, hourly electricity consumption, forecasting, panel data, climate change

1. Introduction

1.1. Background

Energy consumption in Norway has been steadily increasing over the last quarter of the 20th century, and due to the availability of hydro power electricity has been the most important energy carrier (Fig. 1).[1] However, especially electricity consumption has flattened since the year 2000. Shutting down factories within the energy-intensive industries,

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[1]Energy and electricity consumption described in this section excludes consumption in transport sector and energy industries.

higher energy prices, stricter building codes with respect to energy demand, reduced heat demand due to a milder climate, more energy-efficient electric appliances, and the increased use of heat pumps are possible reasons for this development. The industrial sector, including energy-intensive branches like aluminium and ferro-alloys production and wood processing, represents the largest electricity consumer, but its consumption exhibited a significant reduction in 2009 (Fig. 2), which can be explained by a reduced demand for products like steel and aluminium due to the international financial crisis [1]. From 1990 to 2008 consumption in household and service sector accounted for about 52–54 % of total electricity consumption, while the share has been 57–59 % since 2009 [2]. Due to comparably low electricity prices electrical energy is largely used for space and domestic water heating, so that electricity consumption is strongly correlated with outdoor temperature. Thus, the consumption peak in 2010 and the consumption low in 2014 can be explained by 2010 and 2014 exhibiting unusually cold and warm heating periods.

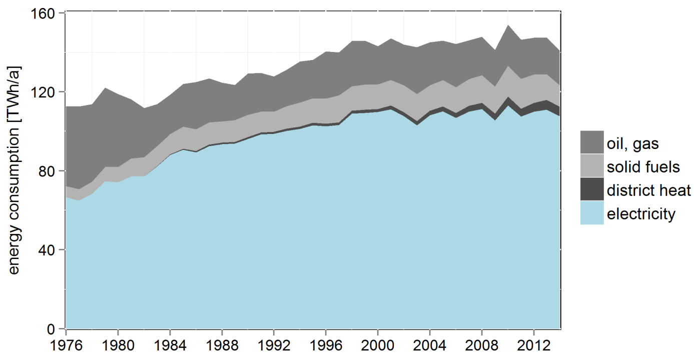


Fig. 1: Total energy consumption, excl. transport and energy industries, per energy carrier, Norway, 1976–2014 [3]

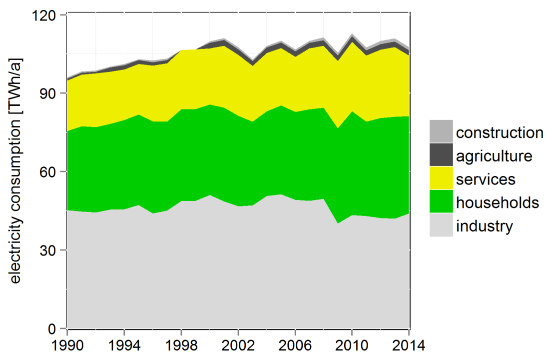


Fig. 2: Electricity consumption, excl. transport and energy industries, per sector, Norway, 1990–2014 [2]

Milder winters, stricter energy standards in building codes, and retro-fitting of existing buildings might contribute to reduced heat demand in buildings in the future, whereas higher temperatures during summer may lead to increased cooling energy demand. Moreover, population growth implies a growing residential and non-residential building stock and thus increased energy consumption for electric appliances as well as space heating and cooling, while increased energy-efficiency of electric appliances contributes to reduced electricity-bound consumption. Ideally, models that are used for energy demand forecasting should be able to take into account these factors. Consumption models with comparably high temporal and spacial resolutions are useful tools in evaluating and implementing demand side management measures that can forward the integration of renewable energy carriers into the energy system. Moreover, forecasts on regional hourly energy consumption can provide estimates for electric or thermal *loads* which are crucial for designing power lines, district heating networks, or decentralized generators of heat and power.

1.2. Modeling approaches

Typical modeling approaches for energy consumption are top-down and bottom-up models. Top-down models usually model a country's aggregate energy consumption directly, mainly based on macroeconomic indicators like population, gross domestic product, or employment rate, and climate variables like outdoor temperature. Bottom-up models first describe consumption of comparably small consumers or consumer groups, e.g. single households or appliance groups, and then aggregate consumption. Swan and Ugursal [4] further divide bottom-up models into statistical and engineering models. Engineering models primarily rely on building physics and technical characteristics of different end-use appliances, so that in theory energy consumption can be modeled without any historical consumption data. Engineering models for residential electricity consumption are e.g. described in [5–8]. An advantage of engineering models is the implementation of changes in consumer behaviour or energy efficiency. However, the models often require detailed input data. Statistical bottom-up models for energy consumption are developed based on historic consumption data of a sample of representative consumers and additional variables describing the individual consumers. Common statistical bottom-up modeling techniques are regression and artificial neural networks (ANN). The use of ANN for modeling and forecasting energy consumption has become increasingly common after the year 2000, see e.g. [9–14]. An ANN can be trained, i.e. it learns from errors and is thus continuously improved. Artificial neural networks usually require high developer proficiency as well as comparably powerful computers, and – as opposed to e.g. regression coefficients – the model coefficients are not easily interpretable with respect to practical implications. Based on the strong correlation of outdoor temperature and energy consumption for space heating and cooling regression models describing this correlation have been developed, e.g. the Princeton Scorekeeping Method (PRISM). Fels [15] gives a detailed introduction to PRISM, including comprehensive explanations of the underlying physical principles and interpretations of temperature-dependent and temperature-independent energy consumption. Seljom et al. [16] model the changes in annual heating and cooling energy demand in Norway from 2005 to 2050 under different outdoor temperature scenarios, using a degree-day approach as well as a more sophisticated bottom-up building physics model for one of the scenarios. Energy demand for heating is estimated to decrease by 9–17 % depending on the corresponding scenarios, while cooling energy demand is estimated to slightly increase [16]. Pedersen et al. [17] describe how generalized profiles for hourly heat and electricity demand in different residential and non-residential building archetypes can be used for energy system planning. Temperature-dependent heat demand of each building is modeled using linear regression models for each hour of the day and each day-type, with daily mean outdoor temperature as independent variable. Daily design load is calculated as the mean value of the 24 hourly heat loads at design outdoor temperature, and relative load profiles for each archetype are generated. Andersen et al. [18, 19] identify hourly electricity consumption profiles for different consumer categories in Denmark and estimate weights indicating the impact of each category on aggregate hourly electricity consumption in different Danish regions. The method is used for forecasting hourly electricity consumption on a regional level based on national projections on electricity consumption in each category. In our previous work [20, 21] we use smart meter data combined with survey response data, weather data, and calendric information to investigate the impacts of different variables on hourly electricity consumption in Norwegian households. We develop panel data regression models that enable disaggregating total modeled hourly consumption into two components, representing temperature-independent and temperature-dependent consumption.

In this study we apply the method described in [20, 21] to develop models for regional hourly electricity consumption in different consumer groups within household and service sector in Norway. We model aggregate electricity consumption, broken down into an electricity-bound and an electric space heating component, in each consumer group and each Norwegian county, and compare the results with historic annual and hourly consumption data. Moreover, we illustrate how historic statistics combined with population and temperature forecasts can be used to obtain input data for energy consumption forecasts, and perform simplified forecasts on electricity-bound and heating energy consumption in Oslo in 2040.

2. Drivers of electricity consumption in Norwegian buildings

2.1. *Number and size of buildings and dwellings*

The models used in this study (see Sec. 3) calculate electricity consumption per dwelling (residential sector) or building (service sector). In order to estimate aggregate regional consumption we need sound estimates on the number of dwellings and non-residential buildings per region. Continental Norway is divided into 19 counties that differ in population, economic structure, and climate. A list of all counties with county number and name is included in Tab. A.5. The number of dwellings is strongly correlated with the number of people *living* in each county, while the number of non-residential buildings is mainly determined by the number of people *working* in the corresponding counties. Besides the number of buildings and dwellings, their actual sizes are important factors affecting energy consumption. In general the number of electric appliances and installations (e.g. light sources) is increasing with building and dwelling size. Moreover, heat losses to the environment are correlated to the total area of outside walls, roofs, floors, so that in general absolute heating energy consumption in a larger building is higher than in a smaller building, assuming comparable building standards. Total floor space is often used as a proxy for building size and heating energy demand is often given in kWh per m^2 floor space and year. Relatively detailed statistics and historical data are available for mean floor space of different dwellings types in each county, so that we can use these as input data to our household consumption model. For non-residential buildings, i.e. the service sector, no official statistics on floor space are available, so that we make assumptions based on the Norwegian energy label database. The database includes technical information on all buildings that have been assigned an official energy label [22], which is mandatory for almost all non-residential buildings. Since the database mainly includes buildings located in Oslo, we estimate building floor space for the remaining 18 counties using an adjustment factor (see Sec. 4.2).

2.2. *Outdoor temperature*

Outdoor temperature is a main driver of heating and cooling energy consumption in buildings, since heat transfer through walls is proportional to the temperature difference between inside and outside environment. Heat is transferred out of the building in case indoor temperature is above outdoor temperature, and into the building in case outdoor temperature is above indoor temperature. In order to maintain a desired indoor temperature, this heat transfer has to be equalized by supplying the building with heating or cooling energy.[2] Due to its Northern situation Norway exhibits relatively cold winters, and moderate summers. Space cooling is not common in households, yet in some non-residential buildings such as office buildings, shopping centres, or hospitals. Space cooling energy demand is mostly covered by electrical energy, e.g. using compression chillers, while space heating demand may be covered by electrical energy or other energy carriers, e.g. firewood, heating oil, or district heat.

2.3. Building standard

A building's energy standard, partly represented by the thermal transmittances (U-values) of different elements (windows, walls, roofs, etc.), has a large impact on heating and cooling energy consumption. Lower U-values and higher air-tightness lead to reduced heat transport out of (or into) the building and thus less heating (cooling) energy consumption compared to a similar building with a lower energy standard. Year of construction is often used as a proxy for energy standard, since building codes have become gradually stricter over the course of the last decades. However, buildings are often renovated and rehabilitated after some decades, e.g. windows might be replaced by new ones with lower U-values and better seals, roofs and walls might be retro-fitted with insulation, which makes year of construction a less suitable proxy. Building standard is only roughly considered in our regression models for residential electricity consumption, and not included in our models for electricity consumption in the service sector. However, we will consider an improved building standard and thus lower heat losses in our 2040-scenarios by assuming a reduction in modeled heating energy consumption (Sec. 4, Appendix A.4).

2.4. Heating systems

Heating equipment and heating energy carriers are important factors for modeling electricity consumption in Norway. In case of non-electric heating, e.g. oil boilers or district heating, in theory no electrical energy is used for space heating purposes. However, electric heaters – at least in some rooms – are widely used, also in buildings with a non-electric central heating system. In Norwegian households non-electric heating using a central heating system is mainly used in regions with district heating as well as in apartment buildings. In single-family houses direct electric heating, often combined with air-to-air heat pumps or wood burning, is most common. On average, the supplementary use of air-to-air heat pumps and wood stoves implies reductions in electric heating energy consumption, compared to only direct electric heating [20].

Few official statistics regarding energy carriers and heating systems used in both residential and non-residential buildings are available, so that we have to make a number of assumptions. In our consumption models for the service sector we only distinguish between electric and non-electric heating and assume different shares of non-electric heating for

[2] Adding *cooling energy* actually means transporting heat out of the building.

each county and consumer category, ranging between 0.6 and 0.8. For the household sector we combine official statistics on heating equipment from 2001 with own assumptions as well as survey results from a previous study [20].

3. Regression models

Our regression models are based on panel data, consisting of hourly electricity meter data, calendric and weather data, as well as cross sectional data, providing information on the individual electricity consumers. The household model is based on meter data from household customers in Buskerud county, and the corresponding cross-sectional data was gathered by a survey. The models for electricity consumption in the service sector are based on meter data from consumers located in Oslo, combined with cross-sectional data from the Norwegian energy label database[3]. The principle structure of the regression models is explained in detail in [21], and we give a brief overview of the method in Appendix A. All models, both for households and different service sector categories, are set up according to Equ. A.1 while the explanatory variables $x_{k,i}$ differ from model to model. Heating degree day *HDD* and cooling degree day *CDD* are the only weather-related variables in our models and are defined in Appendix A.2. In our study, we use different base temperatures for *HDD* in household model ($t_{b,res,HDD}$=17°C) and service sector models ($t_{b,ser,HDD}$=14°C). *CDD* is only included in the service sector models for office buildings and shops, and we choose a base temperature of $t_{b,ser,CDD}$=14°C. We choose $t_{b,ser,HDD}$ and $t_{b,ser,CDD}$ based on visual judgement of average temperature dependence of the corresponding samples, and 14°C seems to be appropriate for both *HDD* and *CDD*. However, equal base temperatures imply that only if $\bar{t}_{d,out}$=$t_{b,ser}$ neither space heating nor space cooling takes place, while in reality there may a temperature band, i.e. $t_{b,ser,HDD} < t_{b,ser,CDD}$.

Due to the low number of observations floor space is the only cross sectional variable in our service sector models, while the household model includes several household-specific variables, e.g. number of adults and children, and dummy variables indicating the use of electric appliances and different space heating equipment. The remaining explanatory variables represent calendric information, e.g. dummy *free* indicates a non-working day. All explanatory variables are listed in Tab. A.2 and A.4. A more detailed table showing which variables are included in the different models for each service sector category can be found in Tab. A.3.

We use separate models for different building categories, namely dwellings, office buildings, schools and universities, kindergartens, shops and stores, nursing homes, and a category representing hotels, restaurants, and cultural buildings. Each building category represents a consumer category, i.e. dwellings represent households, office buildings represent all services that are office-based, schools, universities, kindergartens represent education, shopping centres and grocery stores represent trade, and nursing homes represent health-related services. Hotels and museums represent services within hotel, catering, and partly culture. For office buildings as well as school and university buildings

[3]We describe the non-residential dataset in detail in a paper currently under review. The manuscript can be obtained from the corresponding author.

we use separate models for buildings with and without electric heating, while for the remaining categories, due to limited meter data, only one model is available, respectively. Electricity consumption in buildings or dwellings with non-electric heating is calculated by setting HDD-dependent component, i.e. modeled consumption for electric space heating, to zero. An overview of the different models for building and consumer categories is given in Tab. 1.

Tab. 1: Model overview

sector	consumer category	building category (meter data)	separate models for electric/non-electric heating
households	households	dwellings	no
services	offices	office buildings	yes
services	education	schools, universities	yes
services	education	kindergartens	no
services	trade	shops, stores	no
services	health	nursing homes	no
services	others	hotels, museums	no

Each model calculates hourly electricity consumption for an individual consumer, e.g. a household, a school, or an office building. In order to calculate aggregate hourly electricity consumption in a whole building category, e.g. all residential buildings, schools, office buildings in a specific county and time period, we perform the following steps as illustrated in Fig. 3 and Fig. 4. We assume that all buildings and dwellings in each region are ”in use”, i.e. not empty or abandoned. For the household sector (Fig. 3) we directly model aggregate hourly electricity consumption by using aggregate input data, e.g. total number and aggregate floor space of all dwellings in a specific region, calculated based on official Norwegian statistics [23]. Different dummy variables, e.g. indicating the number of residents or the use of electric appliances and heating equipment, are given as percent shares, and are mainly based on survey response data from Buskerud county.[4]

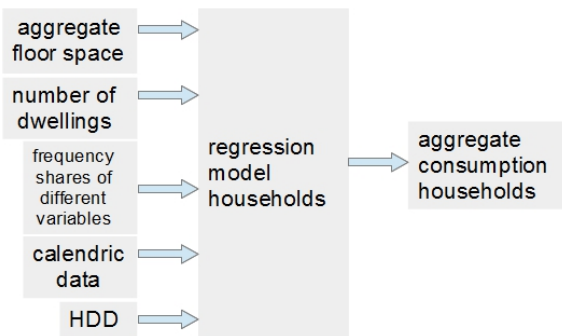


Fig. 3: Modeling aggregate hourly electricity consumption in the household sector

For the service sector (Fig. 4) we model hourly electricity consumption in an average building within each category and multiply the result with the total number of buildings. Average floor space of different non-residential buildings is calculated based on the mean values obtained from the Norwegian energy label database (Equ. 6).

[4]Survey items are included in [21]. Chosen input data for each county can be obtained from the corresponding author.

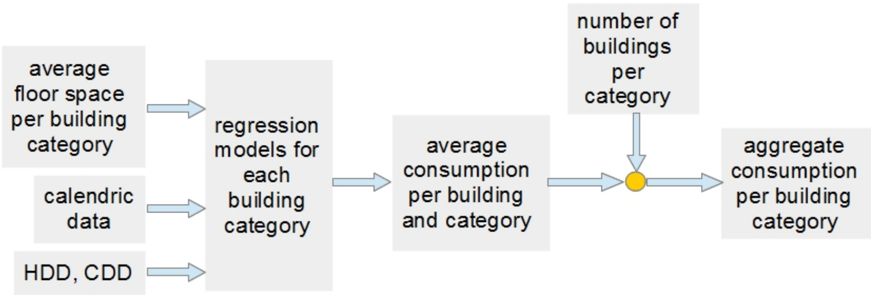


Fig. 4: Modeling aggregate hourly electricity consumption in different service sector categories

Acronyms and Symbols

$\bar{A}$	average floor space
$\bar{t}_{o,d}$	daily mean outdoor temperature
β_k	regression coefficient for the *k-th* explanatory variable
ε	error term
$\hat{\beta}_k$	estimated coefficient for the *k-th* explanatory variable
φ	relative share
$build$	buildings
cat	building category
CDD	cooling degree day
cty	county number
E_h	electricity consumption in hour h
eb	electricity-bound
emp	employees
epb	employees per building
epp	employees per population
f	epb-adjustment factor
HDD	heating degree day
$HDD1st$	first differences in heating degree days
hs	heating system
i	count variable for individual observations
n	count, absolute number
pop	population
r	reduction factor
res	residential/household sector
ser	services sector
sh	space heating
t_b	base temperature
x_k	the *k-th* explanatory variable
ANN	artificial neural network
RCP	Representative Concentration Pathway

4. Input data for model validation and forecasts

4.1. Number of dwellings

The number of people living in each county, grouped according to dwelling type, is shown in Fig. 5. Oslo (county 3) and Akershus (county 2, Oslo surroundings) exhibit the highest population number, followed by counties Rogaland

(11, Stavanger region) and Hordaland (12, Bergen region). While in most counties detached houses are the most common dwelling type, apartments are prevailing in Oslo.

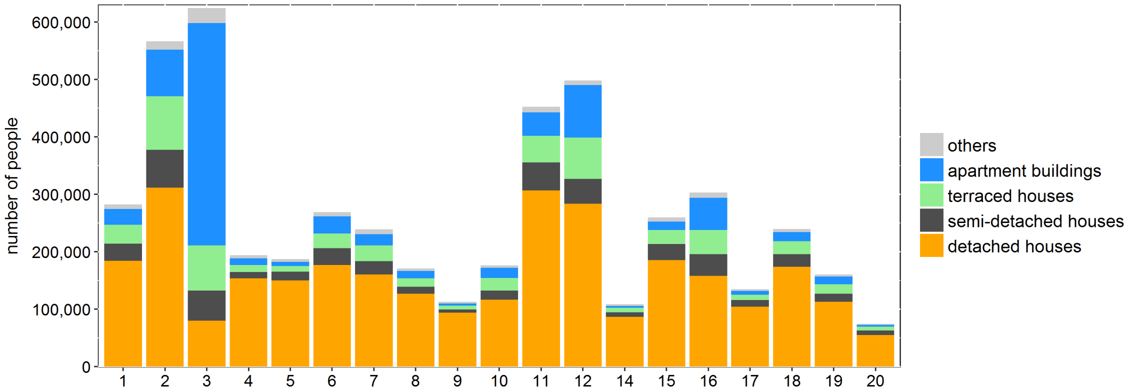


Fig. 5: Population per dwelling type and county (number), 2013 [24, 25]

The number of households is approximately proportional to the number of people living in each county (Fig. 6). The average number of people per household *(pph)* varies between 2.2 and 2.4 for most counties, while it is only 1.9 for Oslo, which can be explained by the large share of apartments, that are typically smaller than other dwellings. In this study, we assume the number of households to be equal to the number of dwellings, meaning one household per dwelling. Historical values for average number of residents per dwelling pph combined with forecasts on total population n_{pop} yield simple estimates for the future number of dwellings n_{dw} per county, which is an important input variable to our models.

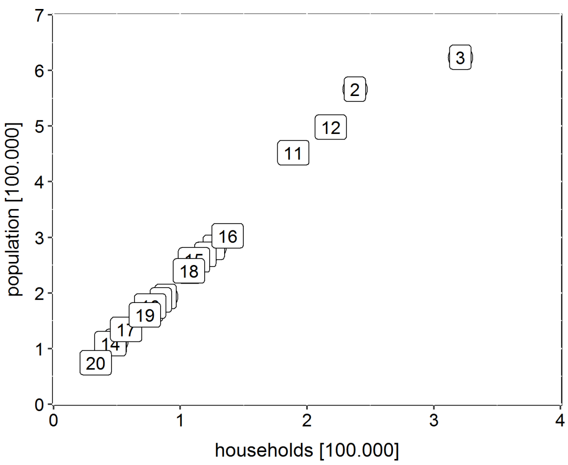


Fig. 6: Population over number of dwellings in each county, 2013 [24, 26]

$$pph_{cty} = \frac{n_{pop,cty}}{n_{dw,cty}} \tag{1}$$

Statistics Norway has published population forecasts for each county until 2040 and distinguishes three main scenarios: *high* (high levels of fertility, life expectancy, immigration, respectively), *medium* (medium levels), and *low* (low levels). Historical development and forecasts of the population in Oslo are shown in Fig. 7. Compared to population in 2013 the three scenarios *high*, *medium*, *low* imply a population growth of 52 %, 37 %, 26 %, respectively, towards 2040.

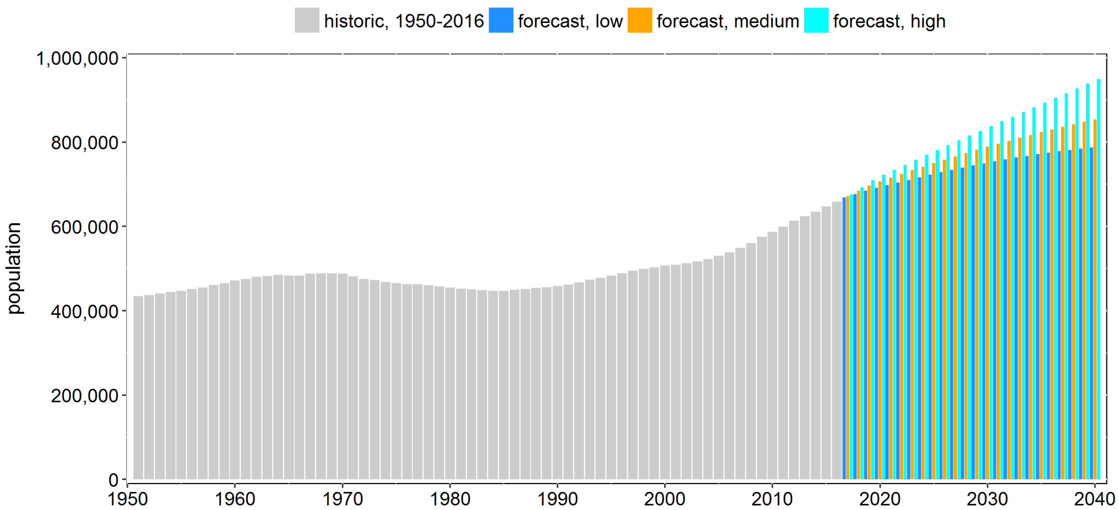


Fig. 7: Population, Oslo county, historical (1950-2016) and forecasts [24, 27]

The number of dwellings, i.e. households, for each county in 2040 is estimated by multiplying the official population forecasts with the a chosen *pph*-value (Fig. 8). The number of dwellings within each dwelling type (detached, semi-detached, terraced houses, apartments, others), divided according to space heating system (electric or non-electric) is calculated using the corresponding shares φ_{typ} and $\varphi_{typ,hs}$ for each county. In our forecasts for Oslo county in this paper we simply use the latest available values for pph, φ_{typ}, $\varphi_{typ,hs}$, and average floor space, i.e. we assume no changes in these factors.

$$\varphi_{typ,cty} = \frac{n_{dw,typ,cty}}{n_{dw,cty}} \tag{2}$$

$$\varphi_{typ,hs,cty} = \frac{n_{dw,typ,hs,cty}}{n_{dw,typ,cty}} \tag{3}$$

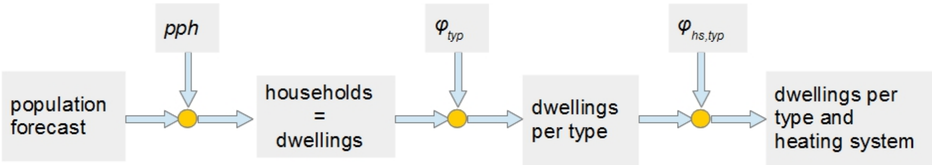


Fig. 8: Estimation of future number of residential buildings per county

4.2. *Number of non-residential buildings*

The number of employees per county, i.e. people working but not necessarily living in the corresponding county, grouped according to business line is shown in Fig. 9. Oslo exhibits the highest number of employees, and a large percentage is working in office-related fields (commercial services, finance & insurance, technical & real estate services, information & communication). In many other regions, the share of people working in health, education, or trade is larger, while the share of office-related branches is smaller.

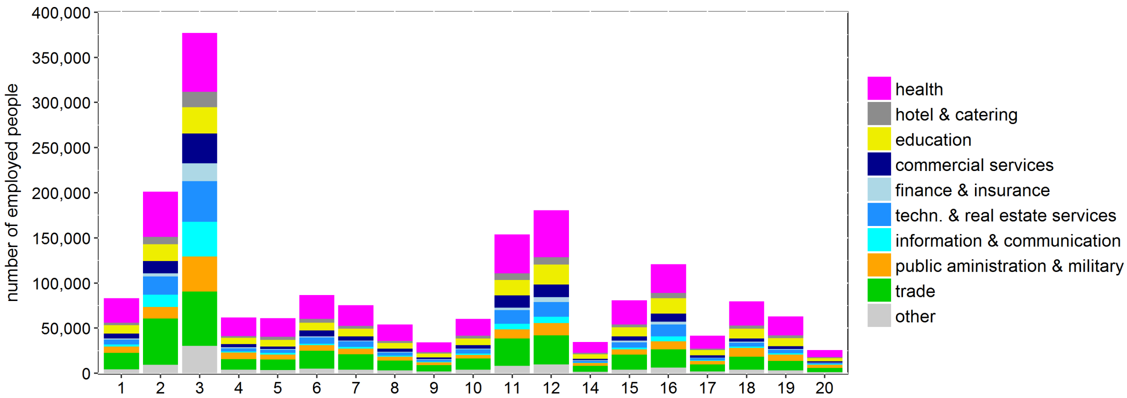


Fig. 9: Employed people per category (service sector), 2013 [28]

As described in Sec. 3 we use separate regression models for six different building categories, and number of buildings and average floor space are needed as cross-sectional input variables in each model. The number of non-residential buildings n_{build} is positively correlated with the number of employees n_{emp} (Fig. 10), however, while Oslo clearly exhibits the highest number of employees the absolute number of non-residential buildings in Oslo is comparably low. This leads to the assumption that non-residential buildings in Oslo on average are larger compared to buildings in other counties, since there are on average more employees per building.

Since our regression models are based on meter data from Oslo buildings, and we only have average floor space values for non-residential buildings in Oslo, we define *employees per building (epb)* (Equ. 4) and an adjustment factor f, relating the *epb* for each county to *epb* in Oslo (Equ. 5).

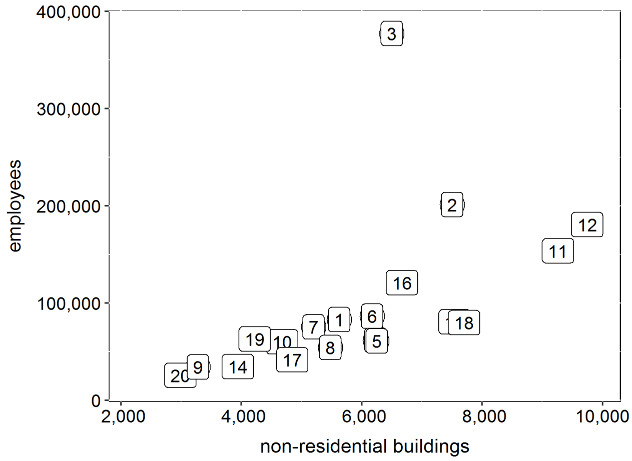


Fig. 10: Number of employees over number of buildings per county (numbers), 2013 [28, 29]

$$epb_{cat,cty} = \frac{n_{emp,cat,cty}}{n_{build,cat,cty}} \tag{4}$$

$$f_{cat,cty} = \frac{epb_{cat,cty}}{epb_{cty=3,cat}} \tag{5}$$

The resulting values for f in each county and category are shown in Fig. 11, and according to the definitions made $f = 1$ for Oslo. Adjustment factors are smallest for trade, hotel & catering, and other services, while highest for education. In the Trondheim area (county 16) the number of employees per building within education is almost as high as in Oslo (3), which can be explained by Norway's second largest university being located in this county.

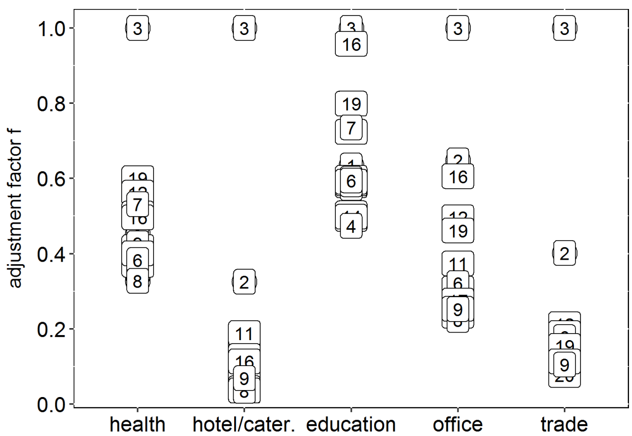


Fig. 11: Adjustment factors f for each county and category, 2013

Average building floor space in each building category $\bar{A}_{cat,cty}$ in the remaining 18 counties is estimated by multiplying the average floor space in Oslo $\bar{A}_{cty=3,cat}$ by factor f (Equ. 6).

$$\bar{A}_{cat,cty} = f_{cat,cty} \cdot \bar{A}_{cty=3,cat} \tag{6}$$

In order to estimate the number of buildings within each category and county, e.g. in 2040, the official population forecasts (Fig. 7) are multiplied with chosen values of employees per population φ_{epp} (Equ. 7), yielding first an estimate for the number of employees, which is further multiplied with shares of the different service sector categories φ_{cat} (Equ. 8), and *epb*-values (Fig. 12). Multiplied with the corresponding shares $\varphi_{hs,cat}$ (Equ. 9) we obtain estimates for the future number of buildings using electric and non-electric heating for each county and building category. For our forecasts for electricity consumption in Oslo in 2040 we simply use historic mean values, i.e. over the last five years, for φ_{epp}, φ_{cat}, $\varphi_{hs,cat}$, i.e. we assume no changes in employment rate, employees per building, and distribution of different service sector branches and heating systems. Moreover, we assume average floor space per building type to be unchanged.

$$\varphi_{epp,cty} = \frac{n_{emp,cty}}{n_{pop,cty}} \tag{7}$$

$$\varphi_{cat,cty} = \frac{n_{emp,cat,cty}}{n_{emp,cty}} \tag{8}$$

$$\varphi_{hs,cat,cty} = \frac{n_{hs,build,cat,cty}}{n_{build,cat,cty}} \tag{9}$$

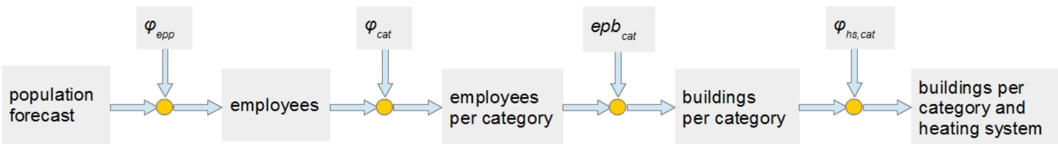


Fig. 12: Estimation of future number of non-residential buildings per county

4.3. Outdoor temperature, heating and cooling degree days

The Intergovernmental Panel on Climate Change (IPCC) defined several *Representative Concentration Pathways (RCP)*, considering different levels of reduction in future climate gas emissions . The Norwegian Climate Service Center published modeled temperature increases in case of two different RCPs [30]. RCP4.5 assumes stable or slightly increasing emissions until 2040 and reduced emissions after 2040. RCP8.5 assumes continuously increasing emissions ("business as usual"). Daily mean outdoor temperature during normal period 1971–2000 as well as temperature forecasts for 2040 and 2100 for RCP4.5 and RCP8.5 in Oslo are shown in Fig. 13. Temperature forecasts are based on modeled temperature differences referring to the 1971–2000-normal temperature, and are only available per season, i.e. 3-months-period. Thus temperature forecasts exhibit kinks at the transitions between February and March, May and June, etc.. Since RCP4.5 implies no emissions reductions until 2040 modeled temperatures for both RCPs in 2040 are similar. However, temperature forecasts for 2100 imply a large difference between RCP8.5 and RCP4.5, and RCP8.5 implies a considerable increase compared to the 2040-figures.

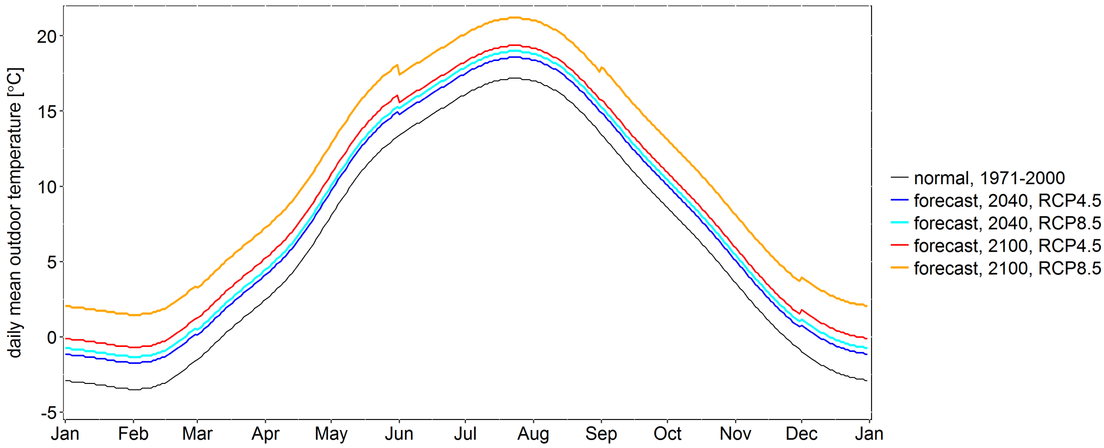


Fig. 13: Daily mean outdoor temperature, Oslo county, historical mean values and forecasts for 2040 [30, 31]

Historical and forecast heating and cooling degree days (base temperature t_b=14°C for both) are shown in Fig. 14 and Fig. 15. Historical number of heating degree days *HDD* per year has been decreasing since about 1970, and both RCPs imply a further decrease in *HDD*, i.e. higher temperatures during the heating period. Under RCP8.5 the decrease in *HDD* is stronger compared to RCP4.5, but the difference between both RCPs first becomes apparent after about 2045. Historical number of cooling degree days *CDD* per year has been increasing since the 1950s, and both RCPs imply a further increase in *CDD*, i.e. more daily mean temperatures above base temperature. From about 2030 the increase in *CDD* under RCP8.5 is considerably stronger compared to RCP4.5.

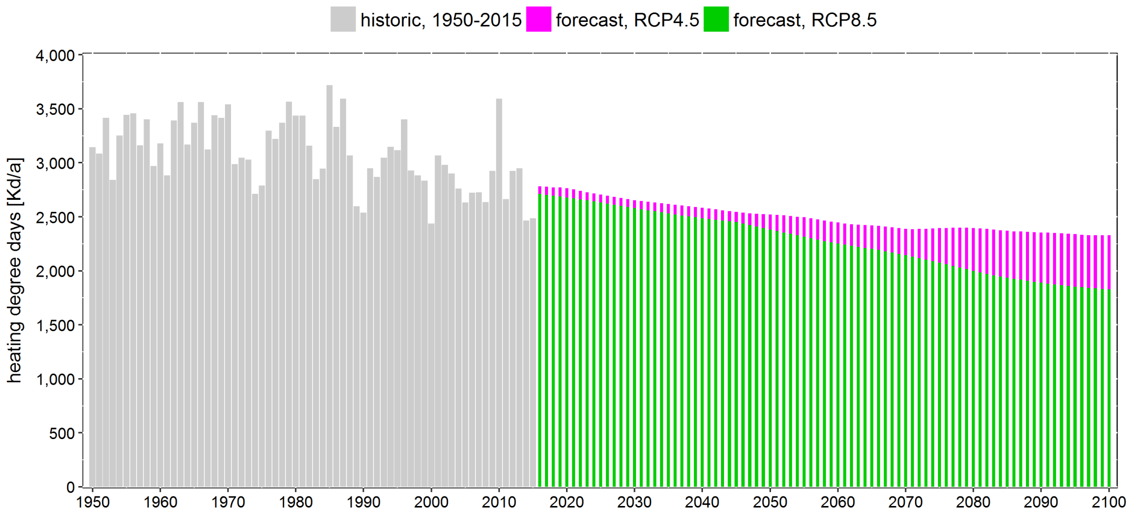


Fig. 14: Number of heating degree days per year, Oslo county, historical (1950-2015) and forecasts [30, 31]

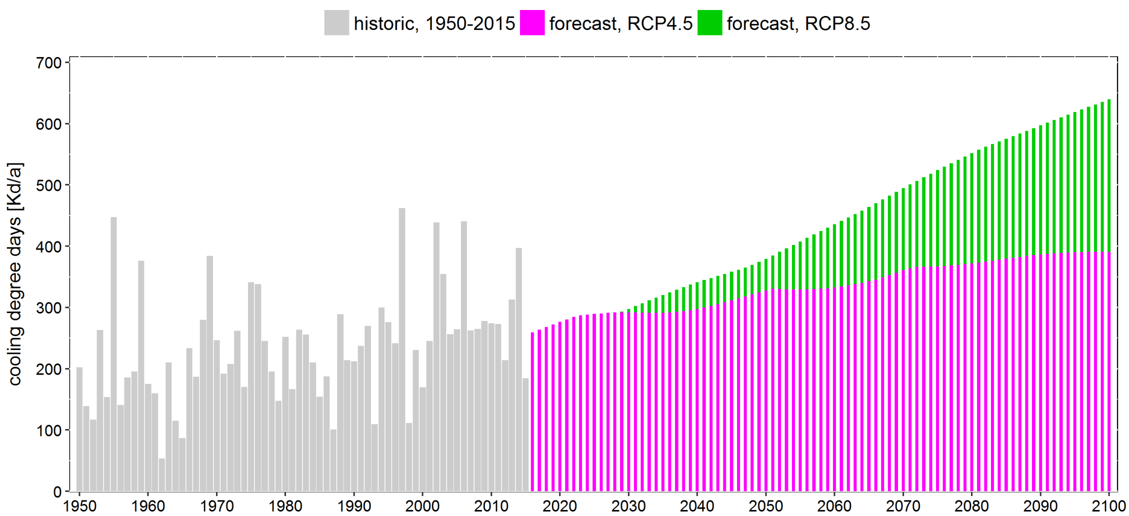


Fig. 15: Number of cooling degree days per year, Oslo county, historical (1950-2015) and forecasts [30, 31]

4.4. Assumptions regarding future energy efficiency and building stock renewal

Due to limited cross-sectional data available the impacts of different building standards with respect to heating energy consumption are not considered in our service sector models. The household model includes dummy variable *new* in interaction with *HDD* allowing estimates on reductions in *HDD*-dependent consumption due to a renewed building stock, i.e. an increased share of new buildings. Percent shares of dwellings built after 2000 in Oslo, from 2010 to 2014, are shown in Fig. 16. By assuming a linear increase of about 0.7 %-points/a that continues until 2040 we estimate the share of new dwellings in 2040 $\varphi_{new,2040}$ to be approximately 30 %. With $\varphi_{new,2040} \approx 0.3$ compared to $\varphi_{new,2014} \approx 0.12$ and all other factors constant the reduction in aggregate modeled space heating electricity consumption due to a renewed building stock in Oslo from 2014 to 2040 would be about 10 %.

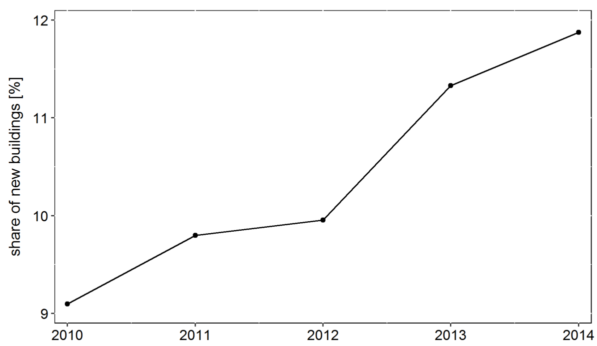


Fig. 16: Historic percent shares of new dwellings (built after 2000) in Oslo, 2010–2014 [32]

Usually a building stock is renewed by continuously removing mainly old buildings, constructing new, and rehabilitating and retro-fitting some existing buildings, so that both *old* and *new* buildings (built before and after 2000) on average become ”newer”. Building codes in Norway have become continuously stricter, and today’s requirements are near low-energy standard. Assuming that future building codes demand and achieve today’s energy standard requirements for new buildings, additional reductions in space heating energy demand can be expected, but are not implemented in the current household model.

Since building age or standard is not included in the service sector models, and no data on years of construction of the non-residential building stock is available, we assume an arbitrary reduction in modeled space heating energy consumption by 15 % (r_{sh}=0.15, see Appendix A.4) in non-residential buildings in 2040 compared to the metering period (2013–2016) of the original data set that was used to develop the models. We assume a higher reduction compared to what was estimated for residential buildings (10 %) can partly take into account stricter future requirements in building standards for new and existing buildings.

5. Results

5.1. Model validation with historical data

5.1.1. Electricity consumption per county, sector, and year

In order to validate our models we first compare annual electricity consumption in households and services in each county in 2012 (Fig. 17). For most counties electricity consumption in both sectors is modeled with a relative error less than 8 %. Consumption within the household sector is overestimated by more than 10 % in counties 1, 4, and 17, which can be explained by different space heating habits, e.g. more intensive wood burning. In county 20, an especially cold region, household consumption is largely underestimated, which might also be due to wrong assumptions regarding space heating systems, or by an insufficient estimation of heating degree days, e.g. by not choosing representative weather stations. Deviations between modeled and metered consumption in the service sector can be explained by the large uncertainty regarding category *others*, that includes hotel and catering, culture, and all other service branches, for which we do not have appropriate consumption models. Moreover, assumptions made on the share of non-residential buildings with non-electric heating might be insufficient.

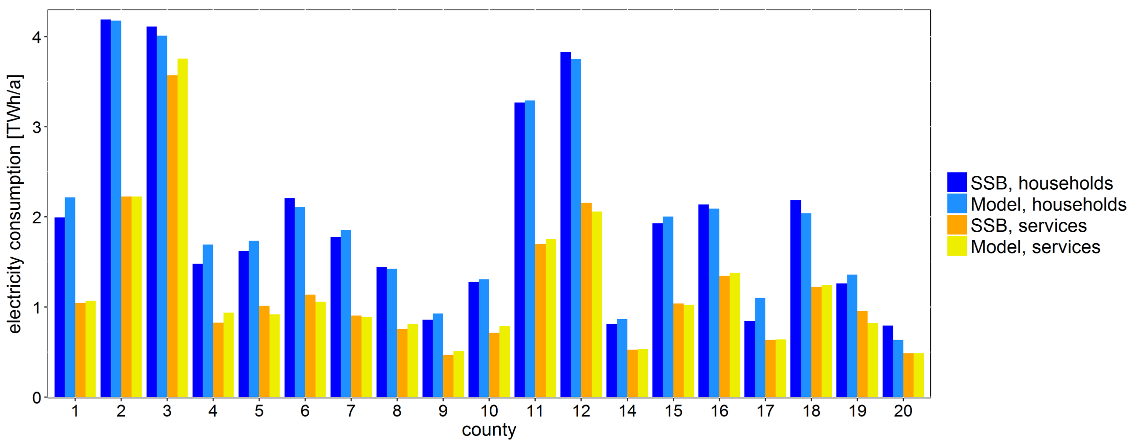
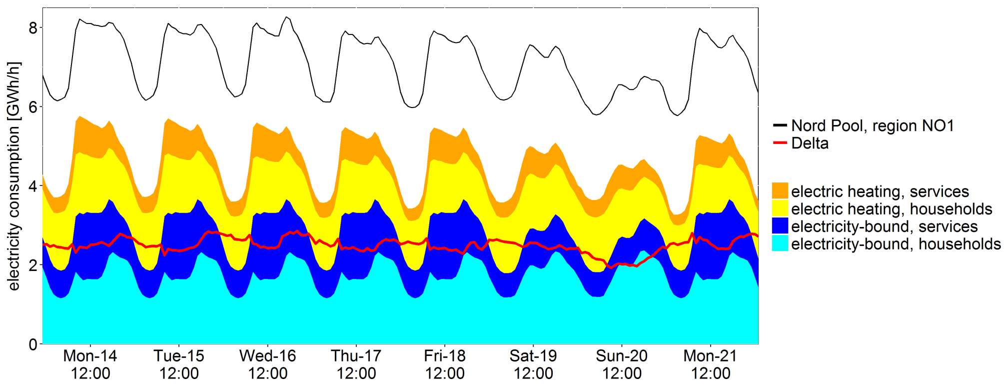


Fig. 17: Modeled and metered [33, 34] electricity consumption in household and service sector per county, 2012

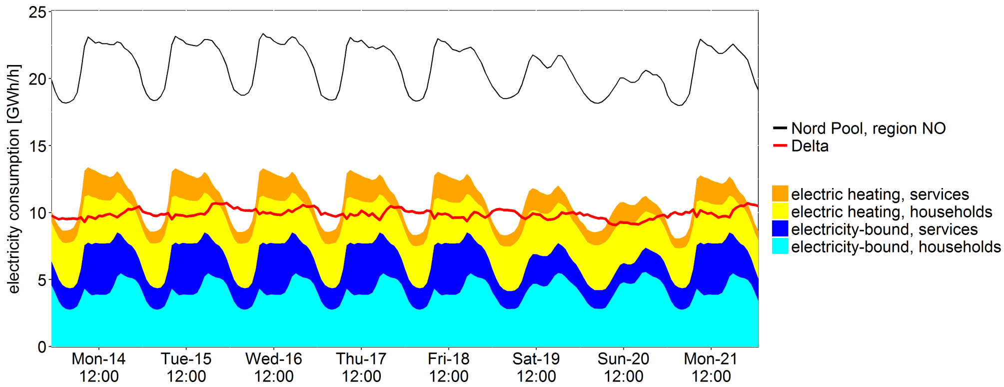
5.1.2. Hourly electricity consumption per sector and Nord Pool-region

In a second step we compare modeled hourly consumption with hourly consumption data from Nord Pool, the Nordic power market [35] (Fig. 18). Nord Pool divides Norway *(NO)* into five regions, called *NO1* through *NO5*. Region *NO1* approximately spans counties 1–6 and exhibits the highest consumption among the five regions. During a January week in 2013 aggregate modeled consumption both for region *NO1* (Fig. 18a) and for the whole country *NO* (Fig. 18b) fits the shape of metered consumption relatively well. The difference between metered and modeled consumption is called *Delta* in the following, and represents in theory consumption in agriculture, industries, construction, transport, as well as the modeling error. During the depicted period *Delta* exhibits relatively little hourly variations, except a slightly higher consumption during evening and night-time and a slightly lower consumption during mid-day as well as on Sunday, which can be explained by reduced production in the industrial sector.

Due to our simple disaggregation method *electricity-bound* consumption includes energy consumption for domestic water heating, while component *electric heating* only refers to space heating.



(a) South-East Norway (region *NO1*)

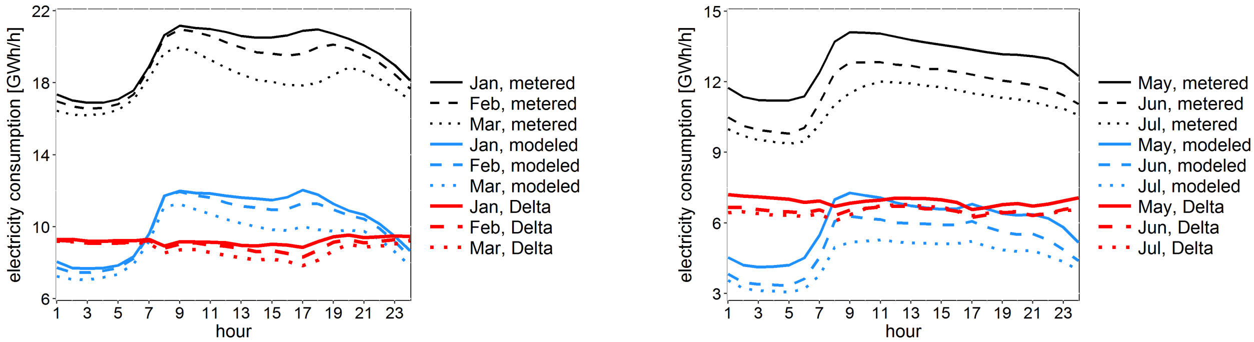


(b) Whole country (region *NO*)

Fig. 18: Modeled electricity consumption in household and service sector, metered total consumption, and *Delta*, January 2013

5.1.3. Average hourly profiles per month

Average hourly consumption in Norway on workdays in different months in 2013 is shown in Fig. 19. Both during the winter months January, February, March, and during the warmer months May, June, July average modeled and metered hourly consumptions are similar in shape, and the resulting average *Delta*s are relatively constant during all 24 hours. While during winter *Delta* is approximately 9 GWh/h, it is only about 7 GWh/h during summer. Thus in theory, assuming that no consumers included in residual consumption *Delta* (e.g. factories) shut down or use space cooling during summer, about 20 % of *Delta* were on average used for space heating purposes in January 2013.



(a) January, February, March

(b) May, June, July

Fig. 19: Average hourly consumption in different months, 2013, metered (Nord Pool, *NO*), modeled, and *Delta*

5.2. Forecasts on energy consumption in Oslo in 2040

5.2.1. Consumption of heat and electrical energy per year

Historic and forecast modeled annual electricity consumption in Oslo, divided into electricity-bound and space heating consumption, as well as modeled non-electric net space heating energy consumption are shown in Fig. 20. Since we assume that large share of consumers in Oslo county uses non-electric space heating, the share of modeled electric space heating energy is comparably low. Non-electric net space heating energy, e.g. covered by district heating or heating oil, is modeled by calculating *HDD*-dependent electricity consumption in buildings and dwellings with non-electric heating and only represents a very rough estimate.

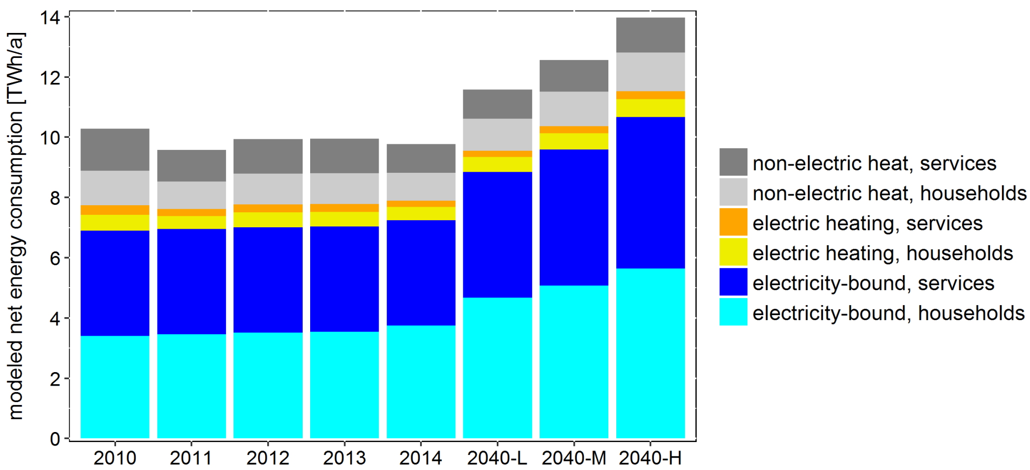


Fig. 20: Modeled net energy consumption per sector and purpose, Oslo, 2010-2014 and 2040

The three bars on the right-hand side in Fig. 20 represent modeled energy consumption under the three different scenarios on population growth, where L, M, H indicate low, medium, high population growth, respectively. Since there are only slight differences in heating degree days under RCP4.5 and RCP8.5 for 2040, we only display consumption forecasts for RCP8.5. Assuming scenarios L–M–H, implying 26–37–52 % population growth from 2013 to 2040, the increase in total modeled electricity consumption is 23–33–48 %. In households electricity-bound consumption increases by 32–43–59 %, electric space heating consumption increases by 1–10–22 %, and non-electric net heating energy consumption increases by 4–13–25 %. In the service sector electricity-bound consumption increases by 19–30–44 %, while both electric and non-electric space heating consumption decrease by 16 and 8 % in scenarios L and M, and increase by 2 % in scenario H.

The relative changes of modeled annual energy consumption, population, *HDD*, and *CDD* between 2013 and 2040 are shown in Fig. 21. In all three scenarios the increase in modeled electricity consumption is slightly lower than population growth. The number of cooling degree days increases by about 8 % while the number of heating degree days decreases by about 15 %. In scenario L electricity consumption for space heating purposes is reduced by about 5 %, and in scenario M it increases by about 3 %. A considerable increase of 12 % is only estimated for scenario H, implying that the impact of an increase in number of buildings and heated floor space outweighs the impact of a decrease in heating degree days and estimated building stock renewal.

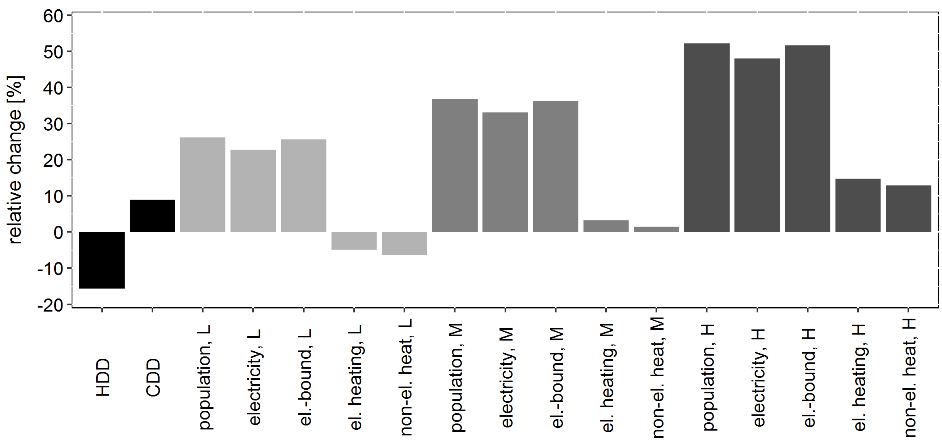
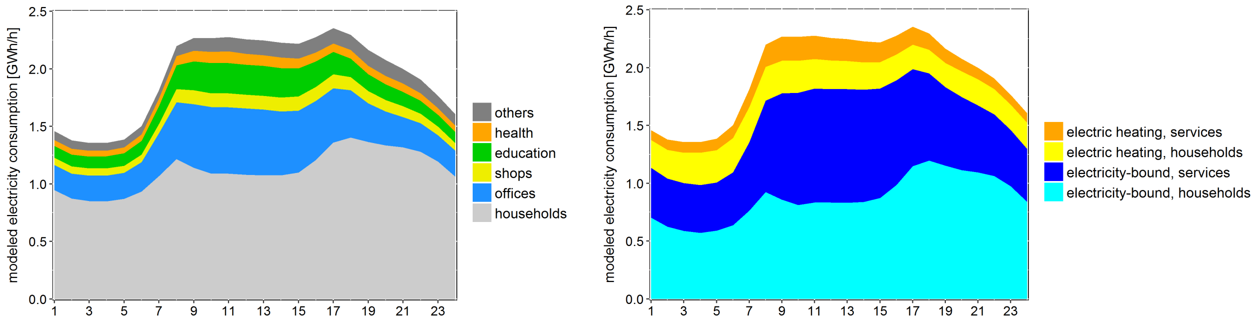


Fig. 21: Relative change in modeled energy consumption, population, *HDD*, and *CDD*, from 2013 to 2040, Oslo

5.2.2. Hourly electricity consumption on a cold day and on a hot day

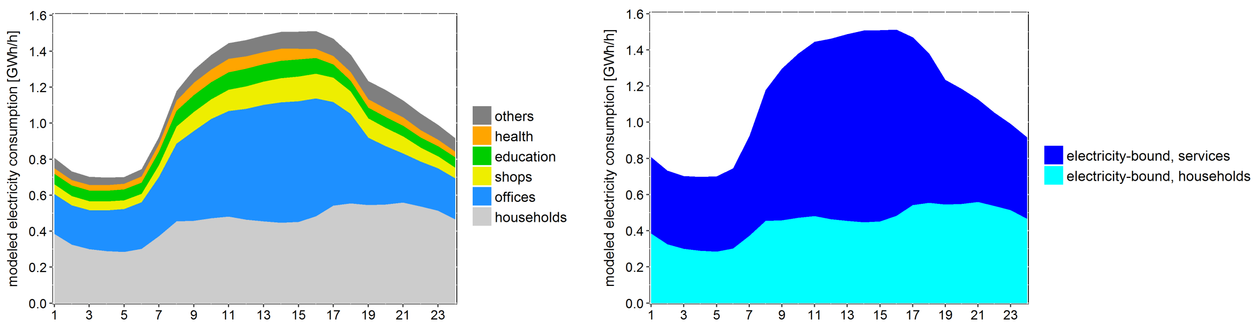
Although mean outdoor temperatures during winter, and thus the average number of heating degree days are assumed to decrease towards 2040, very cold (or hot) days might still occur. In order to estimate extreme values of hourly consumption, we model electricity consumption on a cold and a hot day in 2040, assuming the *high* population scenario. Aggregate modeled hourly consumption in Oslo on a cold January day ($\bar{t}_{o,d}$=-16°C) in 2040 is shown in Fig. 22. Households account for nearly 50 % of modeled consumption during day time and for about two thirds during night time (Fig. 22a). Maximum aggregate modeled consumption og about 2.4 GWh/h occurs in hour 17. Modeled space heating electricity consumption represents about one fourth of total modeled consumption during early morning, and about one fifth during the rest of the day (Fig. 22b). Aggregate modeled hourly consumption in Oslo on a hot day ($\bar{t}_{o,d}$=28°C) in July 2040 is shown in Fig. 23. Maximum consumption of about 1.5 GWh/h occurs in hour 16. The consumption share of households is considerably lower than on a cold day, and the distinct morning peak in household consumption in hour 8 is missing. A higher share of electricity consumption in the service sector on a hot day can be explained by cooling energy consumption that is not considered to take place in households. Moreover, the summer holidays during July contribute to a lower consumption in households, while consumption in the service sector is less affected by school holidays.



(a) Electricity consumption per consumer category

(b) Electricity-bound and electric space heating consumption

Fig. 22: Forecast electricity consumption on a workday in January 2040, Oslo, $\bar{t}_{o,d}$=-16°C



(a) Electricity consumption per consumer category

(b) Electricity-bound and electric space heating consumption

Fig. 23: Forecast electricity consumption on a workday in July 2040, Oslo, $\bar{t}_{o,d}$=28°C

A comparison of modeled hourly electricity consumption on a cold day and on a hot day in 2014 and 2040 (scenario H, 52 % population growth) are shown in Fig. 24. According to our results, maximum hourly consumption on a cold winter day (hour 17) increases by about 44 % while maximum hourly consumption on a hot summer day (hour 16) increase by about 45 % from 2014 to 2040.

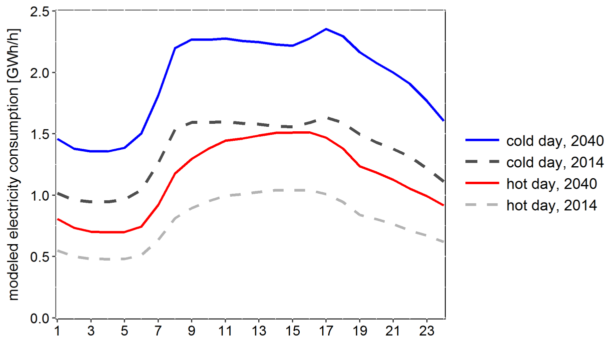


Fig. 24: Modeled aggregate electricity consumption on a cold and hot day in Oslo in 2014 and 2040

6. Discussion

6.1. Uncertainties regarding regression models and input data

6.1.1. Household sector electricity consumption model

A number of statistics on different household and dwelling characteristics, often on county level, are provided by official statistics so that relatively detailed input data is available for modeling historic consumption in the household sector. However, the shares of households using electric and non-electric heating, heat pumps, or wood stoves, per county need to be assumed, which leads to an increased uncertainty. Moreover, the applied household model is based on a sample of consumers located in county 6 (Buskerud) that mainly consisted of detached houses, while other dwelling types were poorly represented. For counties like Oslo, where apartments are the predominating dwelling type, our household model results might be less accurate than for a region with mainly detached houses. Energy and insulation standard is only considered very roughly in our household model by including the dummy variable *new*, being true if the dwelling was built in 2000 or later, in interaction with *HDD*. Since the reductions in modeled hourly electricity consumption in a new dwelling compared to an old one also depend on other variables like dwelling size or heating system, our simplified models are not able to sufficiently estimate the impact of different energy standards or dwelling ages. Electricity consumption in dwellings with non-electric heating is modeled by setting the *HDD*-dependent consumption to zero. Since modeled electricity-bound (*HDD*-independent) consumption usually includes some heat consumption, e.g. for electric water heating or space heating equipment that is used also during summer, modeled consumption in households with non-electric heating might be slightly overestimated. However, since most

Norwegian households use some kind of electric heating equipment, and electric water heaters are common even in households with non-electric space heating, we assume the method to be acceptable. Model validation on annual electricity consumption per county indicates that the model produces useful results. However, separate regression models for different dwelling types, divided into electric and non-electric heating, would yield more reliable results.

6.1.2. Service sector electricity consumption models

Official statistics on non-residential buildings in Norway are rare. We have information on the absolute number of buildings per category and county, but no information on important factors such as floor spaces, heating systems, years of construction, is available. The calculation of average floor space per category in Oslo based on the energy label data base, and using a self-defined adjustment factor, that accounts for – on average – larger buildings and more employees per building in the capital city, can only yield rough estimates that are not necessarily representative. Our regression models for different building categories within the service sector are based on a relatively small sample of buildings, all located in Oslo, over a period of approximately three years, and floor space is the only cross-sectional variable. For many counties average floor space values estimated using the adjustment factor are considerably lower than those estimated for Oslo, and would in some cases lead to meaningless model outputs. Thus, to be able to use the Oslo-based models for all counties we need to assign lower floor space limits.

The shares of buildings using electric or non-electric heating is based on assumptions, and mixed heating systems, e.g. combined electric and district heating, or the use of heat pumps, are not considered. For most categories electricity consumption in buildings with non-electric heating is modeled by setting the *HDD*-dependent consumption to zero, implying some error. Due to the low number of observations the impact of different energy standards, or building age as a proxy, is not considered in our models. Since better insulation standard and air-tightness, and thus lower heat losses, in theory imply a reduction in *HDD*-dependent consumption, we can roughly account for improved energy standards in our forecasts using a reduction factor r. The value of r is very uncertain and only serves as a rough approximation. A reduction in cooling energy demand can be estimated using factor r as well, however, we leave the *CDD*-dependent component unchanged in our forecasts in this paper. Our models for category *others*, representing hotels, restaurants, and museums, are based on very few observations and merge three building groups that might exhibit quite different hourly consumption profiles. Although there is an error connected to category *others* we find it useful to include it in order to be able to model consumption in the entire service sector.

6.1.3. Forecasts

According to our forecasts the increase in electricity consumption for electricity-bound purposes in Oslo from 2013 to 2040 is similar to the increase in population in all scenarios, which can be explained by simplified input variables, implying that the number of buildings and households increases proportionally to population. Moreover, no energy-efficiency improvements, or changes with respect to average floor space, number of residents per household, or the use of electric appliances were implemented in the forecasts, so that temperature-independent consumption is merely scaled up. Assuming e.g. unchanged values for *epb* (employees per building), average floor spaces, and share of employed people per category (Fig. 12) implies that the number of non-residential buildings and thus modeled electricity-bound consumption increases similarly to total population. Especially in metropolitan areas like Oslo, where construction ground might be limited, both the number of employees per building as well as average floor space per building are likely to increase to a certain extent as population increases. Similarly, leaving household-describing factors like *pph* (persons per household) and shares of detached and attached dwellings constant (Fig. 8), also modeled electricity-bound consumption in the household sector exhibits a similar relative increase as population. All input factors can be adjusted when feasible estimates are available. However, the purpose of this study was to merely present the methodology and make simple forecasts for 2040.

6.2. Further work

While we practically only could validate our models with annual electricity consumption data in this study, more disaggregated hourly data, e.g. per sector and county or Nord Pool region, would enable model validation also on an hourly level.

Larger samples of reliable meter data and cross-sectional data would enable refined models for both residential and non-residential consumers. Detailed surveys among different consumer groups could collect important cross-sectional information needed for building specific models, and as input data for model validation and forecasts on a regional level. Especially the impacts of different building standards with respect to energy demand, or comparably new appliances like electric vehicles need to be implemented in more reliable models. While we only include forecasts for electricity consumption in Oslo in this paper, forecasts for each county or municipality could be performed, yielding consumption forecasts per region that could e.g. be aggregated according to Nord Pool regions.

Base temperature t_b varies across consumers and is not only dependent on building physics and standards but also on behaviour and individual preferences, e.g. regarding indoor temperature and thermostat usage. As the building stock is renewed base temperature is expected to decrease for both residential and non-residential buildings so that the calculation of *HDD* and *CDD* needs to be adapted. The impact of different cross sectional or other weather related factors (e.g. wind, solar irradiation) on t_b could be examined in order to obtain estimates on today's and future base temperatures useful for different consumer groups. Space cooling is expected to become more important assuming an increase in outdoor temperatures, also outside the heating period. Today, space cooling in Norway is mainly used in non-residential buildings, e.g. office buildings, however, improved models used for forecasting should be able to consider space cooling also in other non-residential and residential building types.

7. Conclusion

We developed separate regression models for household consumers and different consumer categories within the service sector, and divided modeled consumption into an electricity-bound and an electric space heating component. Moreover, we estimated non-electric net heating energy covered by other energy carriers on an annual level. Model validation indicates that the models are able to reproduce historic annual electricity consumption data in households and service sector on county level with acceptable results. The overall shape of total hourly electricity consumption in South-East Norway and in Norway as a whole is reproduced well by the models, indicating that mainly household and service sector cause hourly variations in total regional electricity consumption. However, important input data, especially regarding the non-residential building stock, is largely based on assumptions and the models lack some important explanatory variables, e.g. building age or energy standard. The applicability of the models for forecasting was briefly tested by modeling electricity consumption in Oslo in 2040, based on existing forecasts on outdoor temperature and population. Leaving most input factors constant leads to the number of buildings and dwellings and thus electricity-bound consumption increasing roughly according to population growth. In contrast, assuming low or medium population growth, modeled energy consumption for space heating exhibits only small changes, indicating that a reduction in heating degree days and the renewal of the building stock counterbalances an increase in the number of heated buildings and dwellings. The presented method can be refined and – with more detailed input data available – applied to any other Norwegian region and can thus produce estimates on regional electricity consumption on an hourly level.

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Appendix A. Regression models for hourly electricity consumption

Appendix A.1. Panel data regression

Combining time series (meter data) and cross sectional data (e.g. survey response data) from a sample of consumers results in panel data. For each consumer (household or non-residential building) a time series of hourly electricity meter values (E_1, E_2, ..., E_{24}) is available, that is combined with cross-sectional data, temperature data, as well as calendric information (weekday, holiday, month, ...) for each day. The *plm*-package [36] in *R* enables different panel data regression methods. We apply the method of pooled ordinary least squares *(pooled OLS)* to our panel data sets, estimating separate models for each hour of the day, so that a model set consist of 24 single models. The hourly model set is determined by the formula for ordinary least squares regression (Equ. A.1) where $E_{i,h}$ represents hourly electricity consumption of observation i in hour h, $\beta_{0,h}$ is the intercept parameter, $\beta_{k,h}$ the slope parameters, and ε_i the unobserved error term. The included explanatory variables x_k are described in Appendix A.3.

$$E_{h=1,\ldots,24,i} = \beta_{0,h} + \sum_{k=1}^{k} \beta_{k,h} \cdot x_{k,i} + \varepsilon_{h,i} \tag{A.1}$$

Appendix A.2. Definition of heating and cooling degree days

Heating and cooling degree day are defined as the differences between daily mean outdoor temperature and chosen base temperatures $t_{b,HDD}$ and $t_{b,CDD}$. Daily mean outdoor temperature $\bar{t}_{o,d}$ is represented by the arithmetic mean value of 24 hourly temperature values, metered during day d, e.g. at local weather stations. For each county we calculate $\bar{t}_{o,d}$ based on mean values of hourly meter data from at least one weather station located near the most densely populated area(s) (Tab. A.5). Based on the assumption that no temperature-dependent heating energy consumption takes place during the summer season, heating degree day HDD is zero in case $\bar{t}_{o,d} \geq t_{b,HDD}$ (Equ. A.2).

$$HDD_d = \begin{cases} t_{b,HDD} - \bar{t}_{o,d}, & \text{for } \bar{t}_{o,d} < t_{b,HDD} \\ 0, & \text{else} \end{cases} \tag{A.2}$$

We define *first differences in heating degree days* $HDD1st$ as the difference in heating degree days between any day d and the day before $(d-1)$ (Equ. A.3). A positive value of $HDD1st$ implies that mean outdoor temperature during day d is lower compared to the day before.

$$HDD1st_d = HDD_d - HDD_{d-1} \tag{A.3}$$

In order to model the linear relationship of cooling energy consumption and outdoor temperature *cooling degree day* CDD is defined as the positive difference between daily mean outdoor temperature $\bar{t}_{o,d}$ and $t_{b,CDD}$ (Equ. A.4).

$$CDD_d = \begin{cases} \bar{t}_{o,d} - t_b, & \text{for } \bar{t}_{o,d} > t_b \\ 0, & \text{else} \end{cases} \tag{A.4}$$

Appendix A.3. Explanatory variables

Tab. A.2: Explanatory variables for service sector models

variable	symbol	description	type	reference group
x_1	A	avg. floor space	continuous	-
x_2	HDD	heating degree day	continuous	-
x_3	$HDD1st$	1st differences in HDD	continuous	-
x_4	CDD	cooling degree days	continuous	-
$x_{5,...,15}$	$month$	month = 2, ..., 12	dummy	1 (January)
x_{16}	$free$	d is a non-workday day	dummy	no
x_{17}	Sat	d is a Saturday but no holiday	dummy	no
x_{18}	Sun	d is a Sunday or holiday	dummy	no
x_{19}	$schoolholidays$	d is within school holidays but no weekend or holiday	dummy	no

Tab. A.3: Explanatory variables in each service sector models

variable	offices, el.	offices, non-el.	schools, el.	schools, non-el.	kindergartens	shops	health	others
A	x	x	x	x	x	x	x	x
HDD	x	-	x	-	x	x	x	x
$HDD1st$	x	-	x	-	x	x	x	x
$month$	-	x	-	-	-	-	-	-
$free$	x	x	x	x	x	-	-	-
$schoolholidays$	-	-	x	x	x	-	-	-
Sat	-	-	-	-	-	x	-	-
Sun	-	-	-	-	-	x	-	-
$A \cdot month$	x	-	x	x	x	x	x	x
$A \cdot free$	x	x	x	x	x	-	x	x
$A \cdot schoolholidays$	x	x	-	-	-	-	-	-
$A \cdot HDD$	x	-	x	-	x	x	x	x
$A \cdot Sat$	-	-	-	-	-	x	-	-
$A \cdot Sun$	-	-	-	-	-	x	-	-
$A \cdot HDD \cdot free$	x	-	x	-	x	-	-	-
$A \cdot CDD \cdot free$	x	x	-	-	-	-	-	-
$A \cdot HDD \cdot Sun$	-	-	-	-	-	x	-	-
$A \cdot CDD \cdot Sun$	-	-	-	-	-	x	-	-

Tab. A.4: Explanatory variables, households

variable	description	type	reference group
x_1	dwelling group = attached	dummy	dwelling group = detached
$x_{2,...,4}$	number of adults (incl. children $\geq$ 16 years) = 2, 3, >3	dummy	adults = 1
$x_{5,...,7}$	number of children (< 16 years) = 1, 2, >2	dummy	children = 0
x_8	senior resident (> 65 years) = yes · daytype = workday	dummy	senior residents = no
x_9	resident more than 20h at home (no senior residents) = yes · daytype = workday	dummy	residents home all day = no
x_{10}	weekend resident = yes · daytype = workday	dummy	weekend residents = no
$x_{11,...,13}$	daytype = Saturday but no holiday, Sunday or holiday, workday within school holidays	dummy	daytype = workday
x_{14}	cold storage = yes	dummy	cold storage = no
x_{15}	other electricity-intensive appliances = yes	dummy	appliances = no
$x_{16,...,24}$	month = 2, 3, 4, 5, 8, 9, 10, 11, 12	dummy	month = 1 (January)
x_{25}	HDD	continuous	-
x_{26}	$HDD1st$	continuous	-
x_{27}	HDD · floor space	continuous	-
x_{28}	HDD · dwelling group = attached	cont./dummy	dwelling group = detached
x_{29}	HDD · heat pump = yes	cont./dummy	heat pump = no
x_{30}	HDD · central electric boiler = yes	cont./dummy	central electric boiler = no
x_{31}	HDD · central heat pump = yes	cont./dummy	central heat pump = no
x_{32}	HDD · age = $\geq$ 2000	cont./dummy	age = < 2000
x_{33}	HDD · wood burning = supplementary	cont./dummy	wood burning = no or only for coziness
x_{34}	HDD · wood burning = mainly	cont./dummy	wood burning = no or only for coziness

Appendix A.4. Decomposition method and estimating reduced heat losses

By including temperature variables *HDD* and *HDD1st*, modeled consumption can be broken down into a *HDD*-independent and a *HDD*-dependent component[5]. The *HDD*-dependent component is the the sum of all elements containing *HDD* or *HDD1st* and can be interpreted as *electric space heating* consumption $\hat{E}_{h,sh}$. The *HDD*-independent part is the sum of all remaining elements and can be interpreted as consumption for electric appliances including electrically heated hot water tanks and space cooling equipment, i.e. *electricity-bound* consumption $\hat{E}_{h,eb}$. Since categorical variable *month* takes into account seasonal differences in *HDD*-independent consumption (e.g. higher electricity consumption for illumination during winter) the assumption of a *HDD*-dependent component representing mainly space heating energy seems reasonable. However, estimated space heating consumption does not necessarily include all space heating appliances, but only those with *HDD*-dependent behavior, i.e. increasing consumption with decreasing outdoor temperature.

Since the building stock is continuously renewed, i.e. mainly older buildings are removed and new buildings are built, so that the share of newer buildings – with in general higher energy standards – increases. Since different energy standards are not considered in our service sector models, we estimate a reduction in heat losses – needed for our 2040-forecasts – by multiplying temperature-dependent consumption $\hat{E}^*_{h,sh}$ by an arbitrarily chosen reduction factor r_{sh}. A reduction in cooling energy demand, i.e. *CDD*-dependent consumption, due to a higher energy standard can be estimated analogously.

$$\hat{E}^*_{h,sh} = \hat{E}_{h,sh} \cdot (1 - r_{sh}) \tag{A.5}$$

[5] See [21] for a more detailed description of the decomposition method.

Appendix A.5. Weather stations per county

Tab. A.5: Weather stations per county

station no	station	location	county	county no
3190	SARPSBORG	Sarpsborg	Østfold	1
3290	RAKKESTAD	Rakkestad	Østfold	1
2650	AURSKOG II	Aurskog Høland	Akershus	2
4780	GARDERMOEN	Ullensaker	Akershus	2
17850	ÅS	Ås	Akershus	2
18700	Oslo Blindern	Oslo	Oslo	3
180	TRYSIL VEGSTASJON	Trysil	Hedmark	4
12320	HAMAR - STAVSBERG	Hamar	Hedmark	4
12680	LILLEHAMMER - SÆTHERENGEN	Lillehammer	Oppland	5
16560	DOMBÅS - NORDIGARD	Dombås	Oppland	5
20301	HØNEFOSS - HØYBY	Hønefoss	Buskerud	6
26990	SANDE - GALLEBERG	Sande	Vestfold	7
27450	MELSOM	Stokke	Vestfold	7
27500	FÆRDER FYR	Tjøme	Vestfold	7
30420	SKIEN - GEITERYGGEN	Skien	Telemark	8
30650	NOTODDEN FLYPLASS	Notodden	Telemark	8
36200	TORUNGEN FYR	Arendal	Aust-Agder	9
38140	LANDVIK	Grimstad	Aust-Agder	9
40880	HOVDEN - LUNDANE	Bykle	Aust-Agder	9
39040	KJEVIK	Kristiansand	Vest-Agder	10
41090	MANDAL III	Mandal	Vest-Agder	10
44640	STAVANGER - VÅLAND	Stavanger	Rogaland	11
47350	RØVÆR	Haugesund	Rogaland	11
50500	FLESLAND	Bergen	Hordaland	12
51530	VOSSEVANGEN	Voss	Hordaland	12
55700	SOGNDAL LUFTHAVN	Sogndal	Sogn Og Fjordane	14
57420	FØRDE - TEFRE	Førde	Sogn Og Fjordane	14
57710	FLORØ LUFTHAVN	Flora	Sogn Og Fjordane	14
60945	ÅLESUND IV	Ålesund	Møre Og Romsdal	15
62270	MOLDE LUFTHAVN	Molde	Møre Og Romsdal	15
64330	KRISTIANSUND LUFTHAVN	Kristiansund	Møre Og Romsdal	15
10380	RØROS LUFTHAVN	Røros	Sør-Trøndelag	16
68860	TRONDHEIM - VOLL	Trondheim	Sør-Trøndelag	16
69150	KVITHAMAR	Stjørdal	Nord-Trøndelag	17
71000	STEINKJER - SØNDRE EGGE	Steinkjer	Nord-Trøndelag	17
72580	NAMSOS LUFTHAVN	Namsos	Nord-Trøndelag	17
79600	MO I RANA LUFTHAVN	Rana	Nordland	18
82290	BODØ VI	Bodø	Nordland	18
84700	NARVIK LUFTHAVN	Narvik	Nordland	18
87640	HARSTAD STADION	Harstad	Troms	19
90490	TROMSØ - LANGNES	Tromsø	Troms	19
93140	ALTA LUFTHAVN	Alta	Finnmark	20
94280	HAMMERFEST LUFTHAVN	Hammerfest	Finnmark	20
99370	KIRKENES LUFTHAVN	Sør-Varanger	Finnmark	20