Norwegian University of Life Sciences
Department of Ecology
and Natural Resource Management

Philosophiae Doctor (PhD)
Thesis 2016:91

Modeling hourly energy consumption in Norwegian buildings

Modellering av energiforbruk på timesnivå i norske bygninger

Anna Kipping

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PhD Supervisors:

Erik Trømborg
Professor
Department of Ecology and Natural Resource Management
Norwegian University of Life Sciences

Torjus Folsland Bolkesjø
Professor
Department of Ecology and Natural Resource Management
Norwegian University of Life Sciences

PhD Evaluation Committee:

Frits Møller Andersen
Professor
Department of Management Engineering
Technical University of Denmark

Natasa Nord
Associate Professor
Department of Energy and Process Engineering
Norwegian University of Science and Technology

Per Kristian Rørstad
Researcher
Department of Ecology and Natural Resource Management
Norwegian University of Life Sciences

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 and 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 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 historical 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 historical 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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Jörg, for always believing in me

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

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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 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] Organisation for Economic Co-operation and Development

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 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.

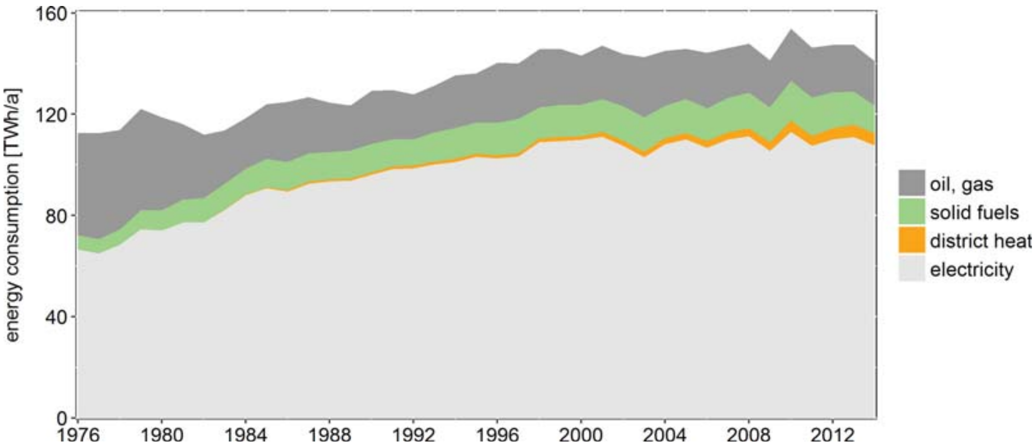


Figure 1: Energy consumption in Norway, 1976 – 2014 [6]

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 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

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

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 outdoor 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 were mainly used in industrial processes.

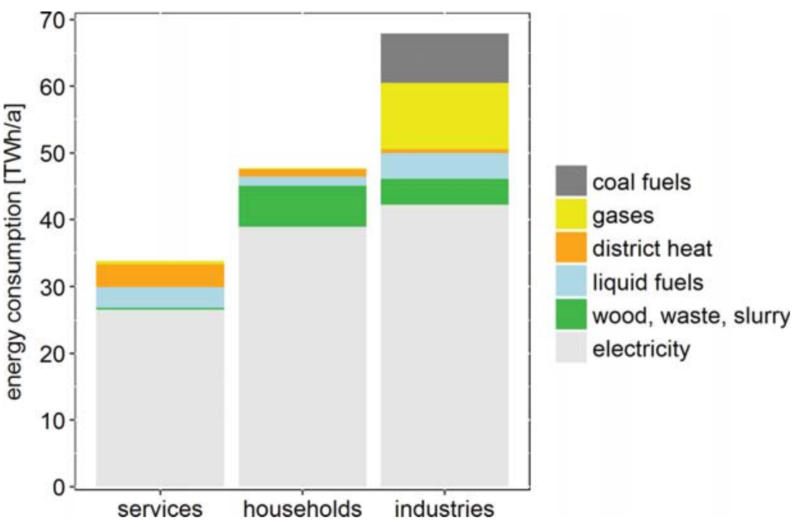


Figure 2: Energy consumption in services, households, industries, 2013 [10]

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, analyzing 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 referred to 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 in 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 analyze 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 theoretical 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 their 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 distributed 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 distribution losses, and convert 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).

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

In this thesis we focus on end-use energy consumption in buildings within household and

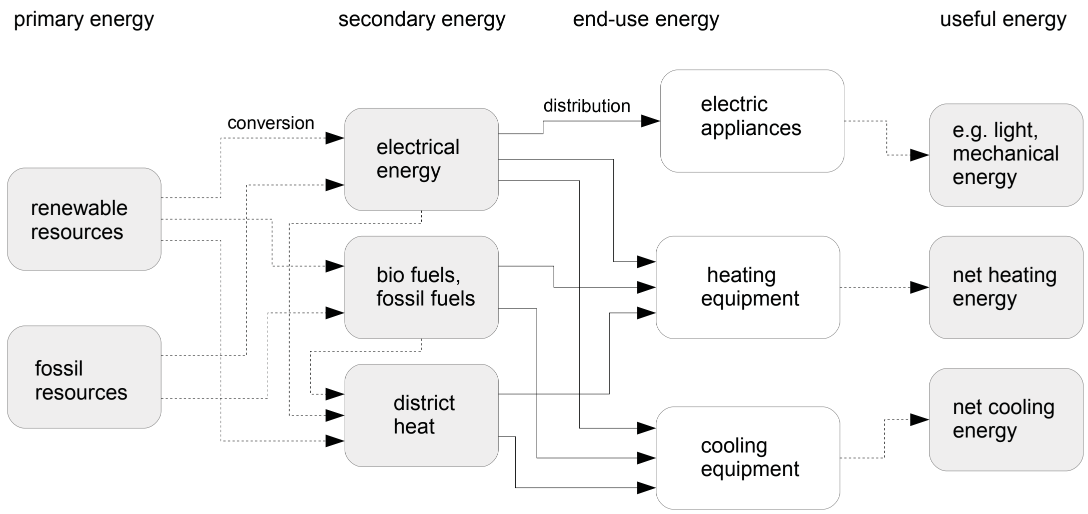


Figure 3: Schematic conversion from primary energy to useful energy consumed in buildings (simplified and incomplete)

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 converted 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 and 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 the 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 indoor and outdoor environment, the size of the building, and building envelope characteristics. Heat transport from or to the outdoor 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 gains.

Heat transmission often accounts for the largest amounts of heat transport, so that building codes used to focus on limiting the overall *thermal transmittances (U-values)* of certain building elements. The U-value of an element 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 external wall, can be described as the product of the element's U-value U_e and surface A_e, and the temperature difference between indoor and outdoor air. In case indoor air temperature t_{in} is above outdoor 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

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

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 temperature $\bar{t}_{out,d}$, which describes a common *degree day* approach.

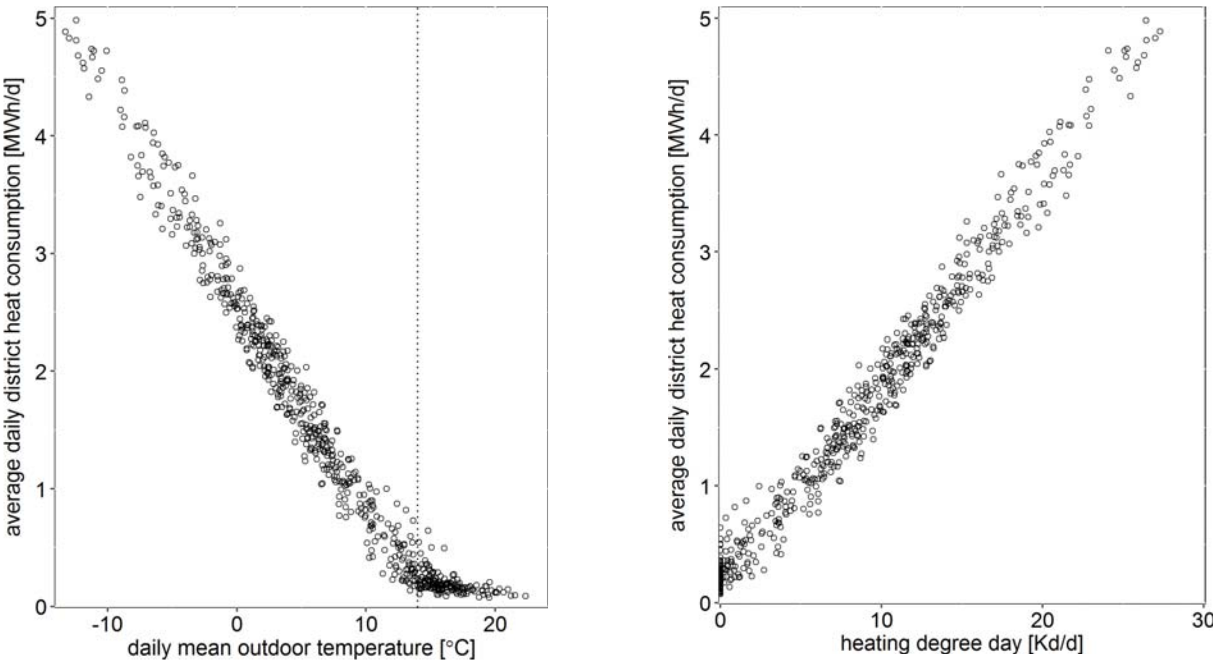
$$Q_{H,d} \approx H_{loss} \cdot (t_b - \bar{t}_{out,d}) = H_{loss} \cdot HDD_d \tag{5}$$

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 $\bar{t}_{out,d}$ 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 HDD is shown in Figure 4b. While district heat consumption is negatively correlated with $\bar{t}_{out,d}$ 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 imply a certain error. Methods for approximating t_b are e.g. described in [34, 35].

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 greater

[2] Index d is dropped in the following.



(a) Consumption over $\bar{t}_{out,d}$

(b) Consumption over HDD

Figure 4: Daily mean district heat consumption in office buildings (workdays) over $\bar{t}_{out,d}$ and HDD

than or equal to base temperature represents heat consumption 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 feedback 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 be calculated analogously, using *cooling degree day 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 buildings, 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. 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 chiller is the intake of low-temperature heat at the evaporator. 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, is a big disadvantage of chillers.

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 realized 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. outdoor air, exhaust air, or geothermal heat. Since electrical energy is normally the only end-use energy metered and billed, end-use energy efficiencies greater 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 temperature, represented by HDD and CDD, 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 historical values of aggregate consumption and macroeconomic variables like GDP, 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, 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 include 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 historical 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 represents 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 a *coefficient of determination* of $R^2 \approx 0.5$. 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 retrofit 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 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 the 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 retrofit actions can be obtained by 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 the base temperature is determined, and temperature-dependent heat demand is modeled using linear regression models for each hour of the day and each daytype, using daily mean outdoor temperature as independent variable. Average daily design load is calculated as the mean value of the 24 hourly heating 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.

Table 1: Illustration of the panel data structure

date	*ID*	*floor space*	*adults*	*children*	*daytype*	*month*	*HDD*	E_1	...	E_{24}
2013-11-03	M0001	170	2	2	Sun/holiday	11	15.3	3.21	...	3.30
2013-11-04	M0001	170	2	2	workday	11	14.8	3.08	...	3.25
...	...	...	...	...	...	...	...	...	...	...
2013-11-03	M0500	100	1	0	Sun/holiday	11	15.3	2.81	...	2.91
2013-11-04	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 *ID* 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 by observation i, $\beta_{0,h}$ is the intercept parameter, $\beta_{k,h}$ are the slope parameters, and ε_i is 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.

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

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.

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

Advantages of an hourly energy consumption model based on pooled OLS are its simplicity and the straightforward interpretation of regression coefficients $\hat{\beta}_{0,h}$ 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. $\hat{\beta}_{0,h}$ and $\hat{\beta}_{k,h} \cdot x_{k,i}$, it can be broken down accordingly to analyze 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. In this case the intercept $\hat{\beta}_{0,h}$ 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 ex-

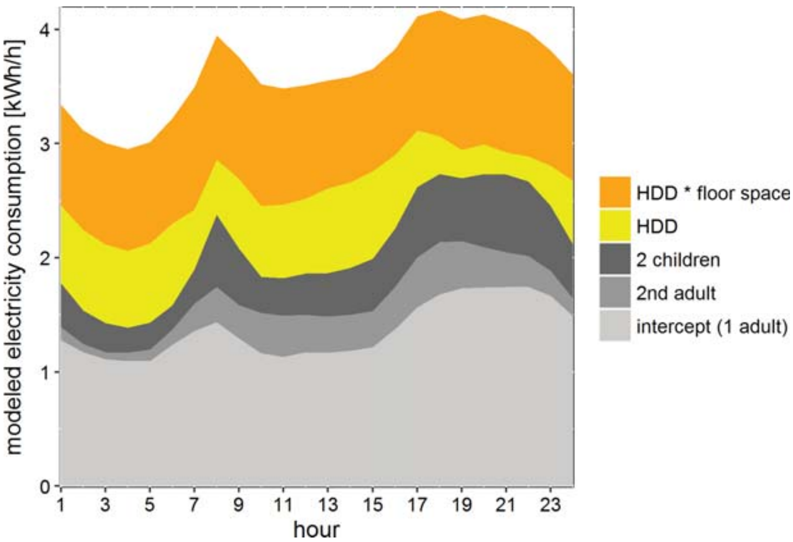


Figure 5: Illustration of different components forming modeled consumption

planatory 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 household 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 only 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 *HDD* – 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. The 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 *HDD*, 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 is 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 of 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 was 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, correspondingly, 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 historical 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 an adjustment factor. A comparison of modeled and metered annual electricity consumption in 2012 per sector and county yields relative errors of less than ± 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 *CDD*. 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 effects 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 proportionally 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 *HDD*, 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 output 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, nationwide 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

Paper I Kipping, A. & Trømborg, E. 2015. Hourly electricity consumption in Norwegian households – Assessing the impacts of different heating systems. - Energy 93(1): 655-671. DOI: 10.1016/j.energy.2015.09.013
Paper II Kipping, A. & Trømborg, E. 2016. Modeling and disaggregating hourly electricity consumption in Norwegian dwellings based on smart meter data. - Energy and Buildings 118: 350-369. DOI: 10.1016/j.enbuild.2016.02.042
Paper III Kipping, A. & Trømborg, E. Modeling hourly consumption of electricity and district heat in non-residential buildings. - Energy. (Submitted)
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Norwegian University
of Life Sciences

Postboks 5003
NO-1432 Ås, Norway
+47 67 23 00 00
www.nmbu.no