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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.

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.