Method for development and segmentation of load profiles for different final customers and appliances

Andrei Z. Morch
SINTEF Energy Research
NO-7465 Trondheim
Norway
andrei.morch@sintef.no

Nicolai Feilberg
SINTEF Energy Research
NO-7465 Trondheim
Norway
nicolai.feilberg@sintef.no

Hanne Sæle
SINTEF Energy Research
NO-7465 Trondheim
Norway
hanne.saele@sintef.no

Karen Byskov Lindberg
The Norwegian Water Resources and Energy Directorate (NVE)
NO-0301 OSLO
Norway
kli@nve.no

Keywords

consumption dynamics, modelling, smart metering, evaluation methods, load research, segmenting load profiles

Abstract

Implementation of smart metering in Europe creates new opportunities for studying electricity consumption patterns. Measurement of end-uses on appliance level remains however to be very time consuming and expensive, so the possibility to model segmented end-use demand based on metering of total electricity consumption is essential.

The paper presents results from a Norwegian Research project "Electricity Demand Knowledge – ElDeK" (2009–2012). A total of 75 Norwegian households from four electricity Distribution System Operators (DSOs) participated in the study. The project collected hourly time series of total electricity consumption from the households, and additional high-resolution (one minute) metered data of more than 500 different appliance-specific loads as water heaters, washing machines, television sets etc.

The collected data were validated and analysed by use of a software tool called Useload. Based on metered data of the total electricity consumption for the household, the project has developed a statistical method for segmenting the hourly metered consumption data into weather dependent (for example space heating) and weather independent loads. Additionally the weather-independent load has been further segmented into demands from appliances as lighting, refrigeration, water heating etc. Demand patterns of several households have been analysed, resulting in typical group- and household-specific demand profiles.

The new approach provides cost efficient and rapid statistical methods for development of detailed load profiles based essentially on metered data with resolution one hour or higher, collected by smart meters. It allows identifying a potential for goal-oriented energy efficiency actions and later verifying impacts of these. Division of the load between weather-dependent and independent segments identifies potential flexibility in consumption (Demand Response) and creates basis for load forecasts.

Introduction

Residential customers are major users of electric energy in Norway, and in 2010 the residential sector accounted for 40 % of Norway's total electricity consumption [11]. Space heating accounts for approximately 60 % of the residential electricity consumption, and water heating accounts for around 15 % [6]. Since space heating and water heating can be provided by other energy carriers than electricity, electric heating is considered as a target for demand response actions and the facilitation of time-of-use (TOU) pricing [9]. A cost effective and reliable method for estimating the share of heat demand is necessary to account for how the use of TOU and demand response targeting electrical heating could contribute to balancing intermittent electricity production (as wind power and photo voltaic) in the electricity market.

Segmentation of residential electricity demand can be explained as methods to detect the proportion of the electricity demand that is used for specified purposes as appliances, refrigeration, heating and air-conditioning. Traditionally end use segmentation is performed by direct metering of each end-use,

[6]. The share of space heating can also be found by subtraction of appliance specific metered load from the total metered load of the building – i.e. finding the residual.

The implementation of smart metering in Europe creates new opportunities for studies of electricity consumption patterns. Use of smart metering is promising, but has some disadvantages concerning low quality of data which occurs because of missing data during periods, and sometimes unsynchronized data due to "daylight saving times" conversion [2]. These problems can be solved by filtering erroneous data to remove data that are out of predefined limits [2]. Measurement of end-uses on appliance level remains however to be very time consuming and expensive, so the possibility to model segmented end-use demand based on metering of total electricity consumption is important [7].

The paper presents results from a Norwegian Research project "Electricity Demand Knowledge – ElDeK" (2009–2012). The project was a part of the national research program RENERGI and was financed by the Research Council of Norway, Norwegian Water Resources and Energy Directorate (NVE) and Enova SF. The study refers to the existing conditions in Norway for climate and consumption patterns, but the method itself can be adjusted and applied to other countries. The study was initially inspired by an analysis of EPRI [1], but the developed method differs substantially from EPRI's approach.

Data Sample

The present study is based on primary data from 75 household customers, which was collected and verified within the ElDeK project. Using smart metering technology, the project collected the total hourly electricity consumption during a period of one year from each customer. In addition, high-resolution (1 minute) metered data of more than 500 different appliance-specific loads as water heaters, washing machines and stoves for a shorter time period of 4–5 weeks was collected. Figure 1 shows daily average energy consumption profiles for groups of customers. The chart shows groups of less than 7,500 kWh/year up to more than 30,000 kWh/year along the Y axis, and according to the hour of peak (High night, high day, high evening) and special low or high energy factor (Low Power – High Power) along the X axis. Figure 1 shows that all customers are peaking during hours 09–17 or during hours 17–23, except some customers that have a low load factor since they are found in the High Power group.

Sociological data about the individual households was also collected, describing different properties as for example floor space, building's year of construction, number of persons living in the household, income, general space heating patterns etc. for each participating household. Useload offers possibility of filtering data according to the sociological properties of each household for stratification purposes [3]. The filtering is used to assign each household into different customer strata, to improve the resulting statistical analysis. In this paper the number of persons living in each household was the only sociological variable that was used, since this has resulted in only three customer groups or strata. As the number of metered customers is as low as 75, only three strata could be applied in this project so that each stratum would contain a significant number of customers.

Questionnaires from each household are obtained, and the answers in the questionnaires contain data that places the household into one of the following three strata:

- Stratum 1: Households of young singles or couples without children (one–two inhabitants).
- Stratum 2: Households with more than two inhabitants – families with children.
- Stratum 3: Households with retired one–two inhabitants.

The only secondary data used in the project are daily averages of outdoor temperatures, collected by the Norwegian Meteorological Institute (DNMI). Daily averages of temperatures were used because hourly data is less available. Earlier experience has shown that daily averages of temperatures are sufficient for modelling of a building's energy demand, when the energy demand is modelled for each hour separately [2].

Prior to analysing the data for weather dependency, the data series were quality assured to avoid erroneous data as part of the analysis. Erroneous data are the result of problems like meter errors, recorder failure, data transmission problems and human failure. Metered data from smart metering and from end-use metering contains data quality information, and this has been used for filtering: Values that have low quality or have been estimated by the DSO are then removed from the data prior to analysis. Suspicious data as extreme low or zero values are not removed if the quality indicator indicates good data. Other filtering methods can be selected by the user as for example filtering out data based on pre-set limits.

Estimation of Weather Dependent Load

The weather dependent load is defined as electricity used for space heating and air conditioning. However, the electricity demand of the weather dependent load (i.e. the heating) is not directly proportionate to the outdoor temperature. An example of this is that two consecutive cold days do not result in the same demand, since the second day will require more heating power due to aggregation of coldness in the building's structure. In the mathematical model for electricity demand the load is described to be dependent on the temperature of the current day and on the previous day. The weight of current and previous daily temperature for each hour of the day is determined by using stepwise regression to find the best fit showing lowest regression error. Although only daily averages of temperature are used, the demand of each hour is regressed separately, so the intra-day hourly distribution is based on metered data.

MODEL OF EXPECTED HOURLY ENERGY DEMAND

The mathematical model developed for the expected hourly energy demand of a building has two main components; one which specifies how the electricity load is dependent on outdoor temperature for space heating and cooling, and a second that reflects electricity consumption for appliances. The standard deviation of the energy demand is modelled separately to determine the coincident peak demand. The model of the expected demand is specified in Equation 1, where the factors a_h, a_c and b are estimated by regression based on the measured electricity consumption and the belonging temperatures, t_{nh} and t_{nc}. The model is estimated for each of the three household

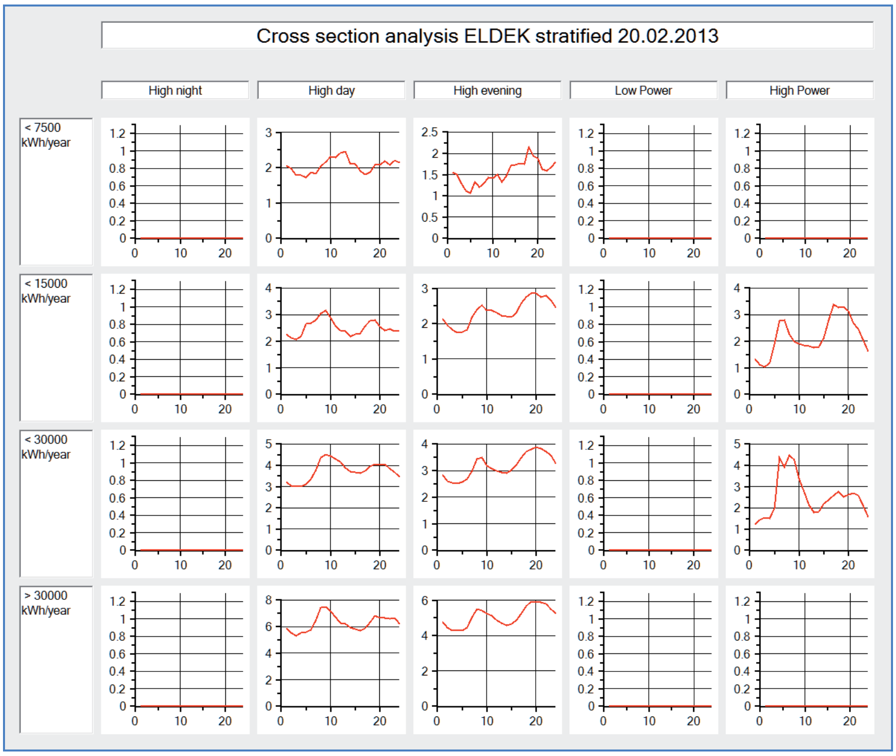

Figure 1. Cross sectional analysis of customer daily averages of total energy demand for 75 customers participating in the ElDeK project. The figure is produced using the Useload software, [3].

groups described in Section Data Sample. The estimated factors are then used to make hourly electricity consumption profiles for each of the specified household groups.

The new method detects the weather dependency factors such as a_h and a_c of Equation 1, and also how the outdoor temperature should be normalized in order to model thermostat settings and saturation effects. Saturation in this context means that the output from the heating or cooling system has reached the maximal limit dependent of the hour of day i.e. the maximum installed capacity. Equation 1 is set up for each hour and for each day-type and season, and models how heating, cooling and appliances are dependent on the outdoor temperature:

$$P = a_h \cdot t_{nh} + b + a_c \cdot t_{nc} \qquad \textit{Equation 1}$$

Where:

P: Total Power consumption of the building

a_h: Factor for current day's temperature corrected for the heating system

t_{nh}: Temperature corrected for the heating system, weighted value of current and yesterdays outdoor temperature

b: Constant – energy use of end-use appliances (data per hour – season and day-type)

a_c: Factor for current day's temperature corrected for the cooling system (i.e. air conditioning)

t_{nc}: Temperature corrected for the cooling system, weighted value of current and yesterdays outdoor temperature

Equation 1 specifies that the hourly energy demand P is linearly dependent on the normalized outdoor temperature for space heating t_{nh}, and similar temperature t_{nc} for cooling/air conditioning. The demand of appliances is governed by a constant (hour, day type and season dependent) b. Section Analytical Results describes how appliance load is further segmented into separate end-uses by use of Equation 1, but with separate data for each appliance.

NORMALIZED TEMPERATURE FOR HEATING AND AIR CONDITIONING

The electricity consumption of buildings does not immediately respond to the outdoor temperature, since much heat is stored in the building's structure. As it was mentioned earlier, when the temperature changes to colder weather, the temperature of the material in the construction is slowly reduced, and after a certain time the indoor temperature is reduced, so that the thermostat turns the heating on. The method incorporated in Useload now identifies the thermal inertia of the heating and cooling systems, and composes normalized temperatures to model this, based on time constants for heating w_h and air conditioning w_c.

Space heating is proportionate to the normalized outdoor temperature for a given hour. An example of this is illustrated in Figure 2: when the saturation temperature (t_{sh}) is reached (-20 °C in the example), the electricity used for heating will not increase further. At temperatures greater than (t_{th}) (or +15 °C in the example), the heating system is turned off, setting the heat demand to zero.

The normalized temperature curve for heating is determined by the saturation set point t_{sh} and the thermostat setting t_{th}. The values of t_{sh} and t_{th} are determined within Useload based on the time series of electricity demand and temperature in a stepwise regression analysis, where all "possible" values of t_{sh} and t_{th} are tried in the regression analysis in turn, and where the "best" tries are recorded. To decide on the "best" values the "sum of

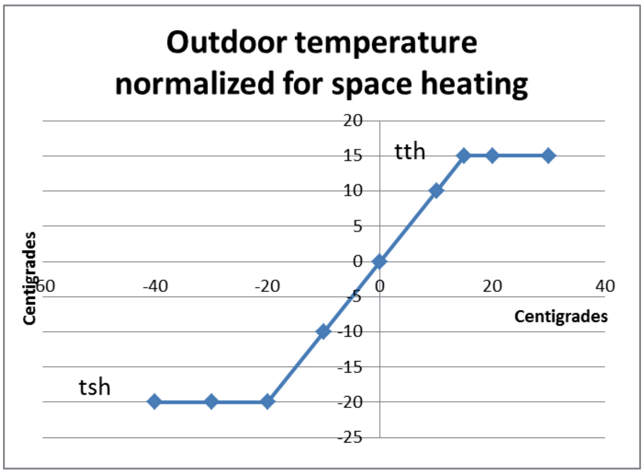

Figure 2. Example of normalized temperature for heating.

squares" (SSD) value of the regression is used. The SSD value indicates how well the normalized temperature series apply to the recorded demand. The same principle applies for definition of the normalized temperatures for cooling/air-conditioning.

WEIGHTING CURRENT AND YESTERDAY'S TEMPERATURE

As mentioned previously, the building's electricity demand depends both on the current and previous day's temperature due to the slow response on temperature change of the building. This behaviour is dependent on the material of the building. Concrete buildings will e.g. response slower on temperature changes and will have a greater dependency on "yesterday's" temperature.

The following equation is used to estimate the weighted temperature consisting of the current and previous day's outdoor temperature. The weight factors are modelled separately for heating (w_h) and cooling (w_c), and are identified from analysing the metered demand regressed on the outdoor temperature.

$$\boldsymbol{t = w \cdot t_c + (1 - w) t_y} \qquad \textit{Equation 2}$$

Where

t: Weighted temperature

t_c: Outdoor temperature of current day

t_y: Outdoor temperature of day before current day

w: Weight factor – 60 % to 100 %. Different weight factors exist for cooling (w_c) and heating (w_h).

All factors in Equation 2 are estimated and stored in the database for each hour, day type (work day or weekend) and season. Similarly, the saturation temperature and the thermostat temperature (Figure 2) for heating (t_{sh} and t_{th}) and cooling (t_{sc} and t_{tc}) are also estimated. In addition to the factors described, the standard deviation of the hourly energy demand is estimated based on metered load and stored in the database.

ESTIMATION OF FACTORS FOR THE HEATING SYSTEM

For a given building, the optimal heating system factors for an hour, season and day type are estimated with the following method:

Useload identifies different day types that indicate a season e.g. "winter months" and whether it is a working day or a weekend/holiday. Within each day type, each hour is modelled separately. Thus, during estimation of the best model fit each given day type and each hour interval during the day (hour) is considered in turn. The program then circulates through all possible combinations of model settings for t_{sh}, t_{th} and w_h. When a model description is set, the initial data set of each building, consisting of pairs of hourly electricity demand and outdoor temperature, is altered according to the settings as follows:

- First, the w_h is set. Possible values are from 0 to 1.
- Second, the weighted temperature dependent on temperatures for current and previous day and the w_h (see Equation 2) is formed.
- Third, the temperature is then altered according to the settings of t_{th} and t_{sh} to form the normalised temperature according to Figure 2.

The initial data set is at this point altered to suit the current setting of the model. In the next step the data is analysed by regression to find the least squares estimates. After looping through all possible combinations (limits to each factor can be set by the user) of the model set points, the combinations that result in the lowermost value of SSD ("sum of squares") is identified, and the best regression line is found. For air conditioning a similar method will be used, but the normalization of the outdoor temperature will simulate air conditioning thermostat settings and saturation levels.

FINAL CALCULATION

Finally, averages and standard deviations are calculated for each customer group (the three stratum groups defined). The total standard deviation for each hour, typical for one customer belonging to the group of customers, is found by adding up the squares of the standard deviations for the metered households, and then use the formula in Equation 3:

$$\boldsymbol{\sigma_t = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\sigma_{it}^2}} \qquad \textit{Equation 3}$$

Where

σ_{it}: Standard deviation of each metered customer, i, for each hour, t.

σ_t: Standard deviation used to model the behaviour of one customer from a group of customers

N: The number of metered customers within each customer group.

The generated sets of estimated values are stored in a database along with an ID that uniquely identifies the profile values. The sets consist of values for a 24 hour profile, for each day-type and season.

Estimation of Weather Independent load

When the weather dependent share of the customer's electricity consumption is analysed, we are left with a residual share of the total load that is assumed to cover demand from appliances and static heating (heating that is not directly connected to the outdoor temperature such as hot tap water). We call this part of the demand the weather independent part, which is defined by the constant value *b* in the load profile for the total demand (ref. Equation 1). Each appliance for a customer group is modelled separately based on metered data.

APPLIANCE MODELLING

The modelling of end-use appliances for a given customer group is based on measurements of four weeks of metered demand with one minute intervals separated on different types of appliances. The measurements are analysed by a regression against outdoor temperature, and dependency of temperature is found along with the constant demand and the standard deviation of the demand. We found that the temperature dependency of most appliances is negligible, and consequently in the ElDeK Project it was decided to neglect the temperature dependency of end-use appliances. The analysis determines a profile for the appliance with separate values for each hour, for different seasons and day-types. The standard deviation of the hourly demand is transformed from the basis of one minute intervals to hourly demand by Equation 4:

$$\sigma_t = \sqrt{\frac{1}{60}\sum_{m=1}^{60}\sigma_{mt}^2} \qquad \textit{Equation 4}$$

Where

σ_{mt}: Standard deviation of each minute, *m*, during a specific hour, *t*.

σ_t: Standard deviation that models the behaviour during an hour, *t*.

When applying Equation 4 one assumes that there is no significant correlation of the demand from one minute interval to the demand of other intervals. The effect of cross-correlations among minute intervals has, however, not been studied. By disregarding the effect of correlation, the hourly standard deviation will be less than the real value.

An example of appliance model is presented in Figure 3, where WORK/HIGL means Workday/High Load period and WEND/HIGHL means Weekend/High Load period.

END-USE SEGMENTATION OF AN AVERAGE HOUSEHOLD'S DEMAND

Useload generates electricity demand for all appliance groups identified in the data sample, and scale the demand according to the typical number of appliances that is owned and used by a household. The data describing the number of appliances owned by each household are based on a customer survey in REMODECE project [6]. If the predicted electricity consumption for an hour, including appliances and weather dependent demand, is less than the metered total – the remaining demand is considered to be the result of non metered appliances, i.e. the residual. The residual may also be negative, meaning that the sum of appliance and weather dependent load is greater than the total simulated demand, in such cases the appliance specific load may be automatically reduced by Useload to fit with the metered total load.

Analytical Results

Using the top-down methods described in this paper, an analysis of the total hourly demand of all customers that have participated in the ElDeK project has been carried out. The analysis of the customers demonstrates how the new methods apply, and also functions as a quality assurance measure for the ElDeK project.

Each stratum group contains different number of customers, but the number of customers is sufficient to give statistically significant results for all strata. By using stratified random sampling [10] in the sample design, the results of the analyses are altered so that the proportion of each stratum in the total population of Norway is obtained.

AVERAGE ELECTRICITY CONSUMPTION

The average metered annual electricity consumption of each of the 75 households that have participated in the metering campaign is found to be 20,138 kWh, and the average maximal coincident hourly electricity demand is found to be 6,254 W. This gives a load factor of 40 % – which is quite high, but considered that the estimated peak is the average/coincident demand referencing a big number of households – the value is reasonable.

Figure 4 shows simulated average electricity consumption during workdays based on measurements from the ElDeK project. The consumption is segmented into typical end-use demand groups. The total demand shown in the figure is found by scaling of the total load, to the average consumption for Norwegian households in general (16,500 kWh/year). The scaling does not affect the end-use demand, so the distribution of the hourly residual then indicates the quality of the model. As can be seen the residual is greatest during night and early hours during day-time. The reason for this is that the metered households have a larger energy demand than the average norwegian household, so that the heating demand will be higher than normal. The residual is low during evening when the use of computers and entertainment appliances is high, so the residual is most probably not due to this type of appliances. Figure 5 shows the distribution of the annual electricity consumption of end-use appliances based on the ElDeK data. 45 % of the electricity demand is due to space heating. The rest of the electricity consumption is divided into residual 19 %, hot water 12 %, lighting 5 % and other appliances (residual) 19 %.

The buildings' consumption shows a significant consistence with the outdoor temperature, and approx. 45 % of the demand is identified as being weather dependent. A residual of approx. 19 % of the total consumption is found in our analysis. The residual is the part of the demand that is not allocated to any end-use appliance. Much of this residual is most probably due to space heating, although it is not weather dependent. Consumption of some space heating appliances as electric floor heating cables will be more or less constant since the purpose is to raise the temperature of the floor to a comfort level, and the thermostat often functions poorly due to slow thermal response of the floor. The residual's magnitude and distribution during day signalises that it most probably is not due to electric lighting, since the highest volume appears during late

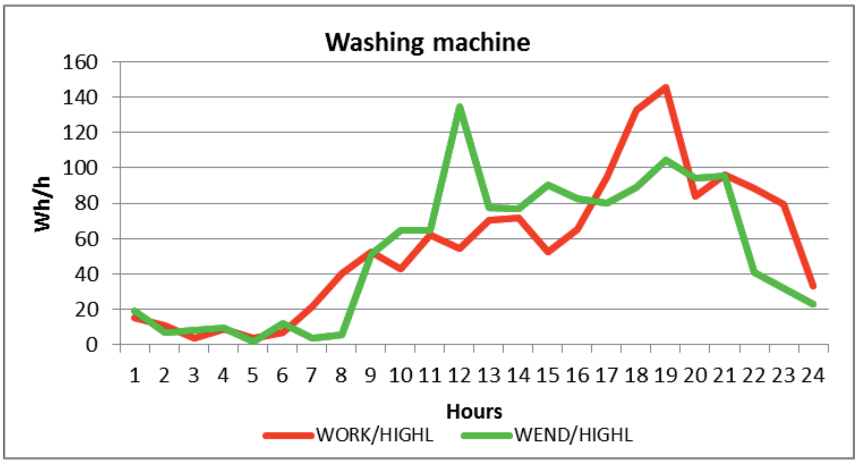

Figure 3. Example of appliance model.

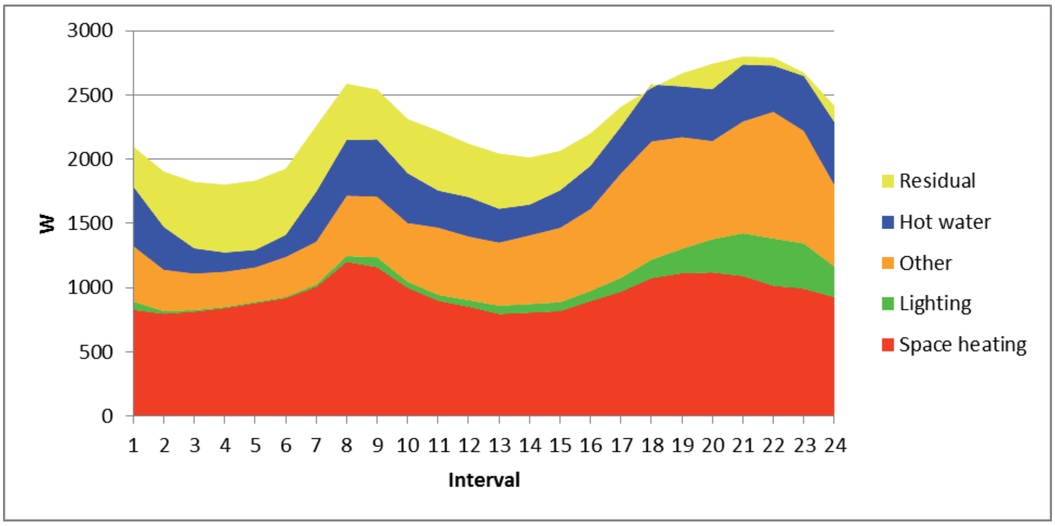

Figure 4. Estimated yearly average demand during workdays segmented into main end-use groups.

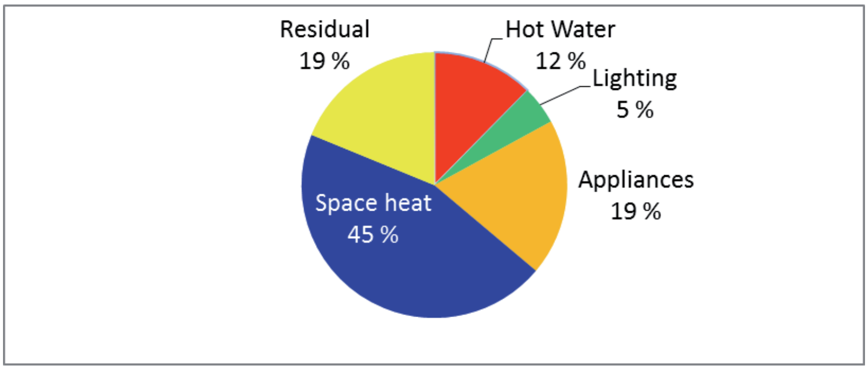

Figure 5. Distribution of annual electricity consumption.

night until early afternoon, when use of lighting is expected to be low.

The electricity shares of Figure 4 comply very well with the results of the REMODECE project [6] what contributes to validation of the new method of estimating the weather dependent load – "Space heat". In REMODECE the Space heat was found as the residual – the sum of all metered end-use subtracted from the total load. Using the new method for detecting space heating gives approximately equal results if we assume that the "residual" also goes to space heating.

Conclusions

This paper describes how weather dependency and end-use segmentation can be determined based on hourly metering of the total consumption of smart metered customers. Knowledge of the dependency on weather of the demand can have great interest for production planning, and also for the development of the total energy production system – since space heating can be accomplished by other energy carriers such as bio energy, oil/gas and district heating. The fact that space heat has a flexibility regarding energy carrier and considerable thermal inertia enables space heating and hot water heating as a potential Demand Response Resource (DRR).

It will be possible to use the methods described in this paper to systematically divide the user demand into weather dependent load and appliance load, resulting in segmented time series with hourly resolution for each separate customer. The residential customer (under a spot price contract and/or Time of Use transmission contract) will earn information that enables planning of how the use of different appliances during the day could reduce the electricity bill. Examples are to avoid the peak hours with high electricity prices to do household tasks as dishwashing and clothes washing and drying etc. Such conduct would also lead to reduced demand during peak hours which in turn would off-load the distribution grid.

The described method can also be applied to aggregated sets of customers, as for example all residential customers in a specific region or all residential customers in a country. The benefit for the Distribution System Operator (DSO) would be e.g. a tool for better forecasting load distribution during the day, or to determine which user appliances are in use at a specific moment – which is helpful for reducing bottleneck situations locally in the distribution grid – or in general to support energy efficiency measures.

Bibliography

[1] "Residential End-Use Load-Shape Estimation." Volume 1: Methodology and Results of Statistical Disaggregation from Whole-House Metered Loads", EPRI (Electric Power Research Institute), EM-4, Volume 1, Project 214, Final Report, May 1986.

[2] Graabak et al., "Results of monitoring of AMR systems in Norway: analyse of metered data and definition of the performance parameters", CIRED June 2009.

[3] Feilberg. "Useload Version 6.5.2 User Manual", TR F5682, SINTEF June 2002, ISBN NO: 82-549-2346-4.

[4] B.J. Birt et al., "Disaggregating categories of electrical energy end-use from whole-house hourly data", Energy and Buildings 50 (2012) 93–102.

[5] http://www.regjeringen.no/nb/dep/fin/dok/nouer/2004/nou-2004-8/5.html?id=385877.

[6] Grinden, Feilberg, "Analysis of Monitoring Campaign in Norway", REMODECE project report. Intelligent Energy – Europe (IEE), EIE/05/124/S12.419657 (2008).

[7] A. de Almeida, P. Fonseca, B. Schlomann, N. Feilberg, "Characterization of the household electricity consumption in the EU, potential energy savings and specific policy recommendations", Energy and Buildings 43 (2011) 1884–1894.

[8] BBC, "UK energy smart meter roll-out is outlined", 2009 http://news.bbc.co.uk/2/hi/business/8389880.stm.

[9] G.R. Newsham, B.G. Bowker, "The effect of utility time-varying pricing and load control strategies on residential summer peak electricity use": a review Energy Policy 38 (7) (2010) 3289–3296. [11] M. Zeifman, K. Roth.

[10] Russel Langley "Practical Statistics", Pan books Ltd, London 1968.

[11] Statistics Norway (SSB) www.ssb.no.