Model for Electric Load Profiles With High Time Resolution for German Households

Article *in* Energy and Buildings · February 2015

DOI: 10.1016/j.enbuild.2015.01.058

David Fischer

Fraunhofer Institute for Solar Energy Systems ISE

Model for Electric Load Profiles With High Time Resolution for German Households

David Fischer[a,b,*], Andreas Härtl[a], Bernhard Wille-Haussmann[a]

[a] *Fraunhofer Institute for Solar Energy Systems, Freiburg, Germany*
[b] *KTH Royal Institute of Technology, Stockholm, Sweden*

Abstract

Approximately 27% of the European energy consumption is caused by the domestic sector, where 19% of the end use energy demand is caused by electric devices. To investigate the factors at play, a stochastic bottom-up model for the generation of electric load profiles is introduced in this paper. The model is designed for investigating the effects of occupant behaviour, appliance stock and efficiency on the electric load profile of an individual household. For each activity of a person in the household, an electric appliance is used, and its electricity consumption is linked to measured electric load traces with a time resolution of 10 seconds. Probability distributions are incorporated for when and how often an appliance is operated. Duration of operation is given as probability density conditional on the start time. Shared use of an appliance by multiple persons is included in the model. Seasonal effects are considered by using changing probability sets during the course of the year. For validation, seven subgroups, which reflect typical household configurations, were formed and tested against measured field data from 430 households in 9 different cities across Germany. The results showed an accuracy of 91% and a correlation of up to 0.98.

Keywords: Load Modelling, Demand Side Management, Stochastic Model, Bottom-up Model, Load Profiles, Domestic Electricity Demand

1. Introduction

In this paper a stochastic bottom-up model, referred to as synPRO, for generating synthetic electric load profiles for German households is introduced.

1.1. Motivation

Energy consumption in the domestic sector contributed to about 27% of the final energy consumption in the 28 EU countries in 2012 [1]. Understanding the energy consumption in this sector forms the basis for measures being taken both regarding efficiency and flexibility matters. Load profiles play an important role for the planning and control design of energy systems [2; 3], as they contain information on the energy demand on an hourly or sub-hourly scale. This information is critical for determining the capacity of the energy systems, e.g. the electricity distribution grid, and the way they are operated. When working with the design and operation of domestic energy systems typically three main questions arise:

1. Which energy technology should be used?
2. What is the optimal sizing?
3. Which control strategy should be applied?

The answers to these questions are often highly dependent on the load profiles assumed. Similar questions arise during the process of planning distribution grids. In many cases pre-made standardized load profiles [4; 5] or load profiles based on statistical analysis derived from field measurements [6; 7; 8; 9; 10; 11] are used. The level of the time-resolution plays an important role for the system sizing and controller design of domestic energy systems [12]. Measured data with high time-resolution are first of all hard to retrieve and may suffer from measurement errors or limitation to only a few datasets. The latter can lead to an over-adaptation of the results to the input load profiles. Especially when considering larger living units, like multifamily houses or quarters, the combination of a few available measured load profiles can lead to statistically irrelevant outcomes. Aggregation of a limited number of load profiles will lead to a summation of peaks while neglecting smoothing effects that may occur.

The use of a stochastic model for the generation of load profiles can overcome these drawbacks, since each output load profile will most certainly be different from the ones already generated. However, in addition to the above mentioned lack of data, purely descriptive methods also lack insight into the processes causing the observed values, e.g. the occupancy pattern, appliance stock and the way appliances are being used. This is becoming increasingly important in the future as the electrical load profiles are expected to change due to more efficient appliances and the deployment of distributed generation [13]. Demand response, which targets classical household appliances such as dish washers, washing machines and dryers [14; 15], may automatically shift the load patterns according to the electricity price or grid tariffs. The on-going change of lifestyle towards a situation where families have both parents working full time, could also impact the household load profiles. Urbanisation, the tendency towards lower occupancy levels, and

*Corresponding author. Tel.: +49 761 4588 5429. E-mail-address: David.Fischer@ise.fraunhofer.de

people's income creating a demand for more appliances may cause different consumption patterns than in the past. Therefore, a bottom-up model helps to gain more insight into how user behaviour and the appliance stock influence the electric load profiles. The synPRO model introduced in this work is on a long term perspective intended to cover all aspects of domestic electricity use such as electric appliances, heating, cooling, domestic hot water preparation as well as electric vehicles. Thus helping system engineers at building, district and city level to answer the three questions introduced in the beginning. In the first step, which is described in the following work, focus is on electricity demand caused by the use of electrical appliances in households, used for non-thermal applications. By the use of the synPRO model, high resolution electric load profiles may be derived for the domestic sector while taking into account consumption patterns of the occupants, the stock of technical appliances in different household categories in addition to seasonal effects.

The paper is structured as follows. A brief review of existing models for electrical load profiles is presented in Section 1.2 along with the improvements and differences to the approach developed in this work. A detailed description of the simulation model for synthetic load profiles can be found in Section 2. In Section 3 the synPRO model is calibrated for the German domestic sector and validated against over 430 measured German households. A discussion of the findings and a conclusion will close this paper.

1.2. Modelling domestic electricity demand

In literature two common approaches for modelling domestic electricity demand can be found. These are statistical models and bottom-up models. Statistical models are based on a set of measured load profiles. The models aim to describe and reproduce the characteristics of the input data and intend to partly explain its variance based on selected input parameters such as season, temperature or household-size. Statistical models based on a decomposition of measured data to extract patterns on different time scales, such as seasons and weekdays, can be found at Wang [6]. Pedersen [7] uses regression to model temperature depended energy consumption in households and stochastic processes to describe the temperature independent part. A further regression based approach can be found in [8] where a multiple linear regression model was applied to describe total electricity consumption, maximum demand, load factor and time of use. Socio-economic factors like dwelling type, number of bedrooms, head of household age and household composition where used as model input.
Decomposition based on the frequency domain characteristics of the load profile is described by McLoughlin and Magnano [9; 16]. In [16] an autoregressive moving average is used to describe stochastic processes on a shorter time-scale. A top-down approach based on a reproduction of the cumulated density function of the load profile is presented by Bucher [10]. Stephen [11] uses a Gaussian Mixture Model to cluster measured load profiles and generate synthetic load profiles from the learned clusters. A method for constructing reference load profiles using representative days from measured data are introduced in [5; 4].
The introduced - data driven - models can reproduce the analysed data and help to understand the main influence factors. However, they commonly suffer in explaining and investigating the effects of user behaviour. This drawback is overcome by the use of bottom-up models. This approach is based on modelling occupant behaviour and relates the energy consumption to it. All bottom-up models referred to in the following use a stochastic process for generation of load profiles. The bottom-up models differ in three aspects:

- Level of detail occupant behaviour is modelled
- Level of detail of appliance data used for generating the electric profile
- Stochastic approach used

Capasso [17] introduced a stochastic bottom-up model in 1994 based on time of use survey conducted in Italy. Start and duration of individual activities where modelled and an electric load attached to each activity. In 2005 Yao [18] published a stochastic method for British households based on national energy statistics and people present in the household - for the latter occupation patterns where assumed. In 2006 Paatero and Lund [19] model the starting of individual appliances as random process, depending on season and a social factor. The data used for calibrating the model comes from various statistics. In 2009 Armstrong [20] describes a method to generate 5-minute electrical consumption profiles for single-family detached households. She groups the consumers into low, medium and high consumers all having a different power factor. Based on total energy use statistics and normalized energy use profiles, a simple random process is used to determine the number and the time of a switching event.
From 2008 to 2010 Richardson [21; 22; 23] introduced a model for describing occupancy, light usage and domestic electricity demand. The used concept of active occupancy covers the number of active people in a household. Active occupancy is modelled as Markov-chain and the transition probabilities are constructed using the time of use survey [24] for Britain. In 2009 the concept of active occupancy for lighting was taken over and extended by Widén [25; 26; 27]. He also extended the concept including a Markov-chain process for a set of energy consuming activities and including variable transition probabilities during the day. The model was further extended to cover the consumption of domestic hot water in Swedish households. In 2012 Zeilinger introduces an approach similar to Paatero's and extends the model to cover three-phase electricity characteristics for selected appliances. A comprehensive review on modelling techniques before 2009 can be found in [28].

The synPRO-model introduced in this work seeks to improve the previous models by combining their strengths and extending the methods with new ideas. Specifically, synPRO takes into account:

- Influence of household-specific socio-economic factors:
  As daily routines of the occupants as well as the amount

and types of electrical appliances used in households are influenced by socio-economic factors such as family status or working pattern, the scope of characterizing households is extended by using working pattern (3), age (3), housing type (3) and family situation (2) as socio-economic factors. This forms 14 different household classes of which 4 will be demonstrated in this work. For each class of household, the user behaviour and the appliance stock is modelled separately.

- Distinction of type of day:
  Most of the models introduced in the past account for weekdays and weekends. In this work the model considers three categories: Working days, Saturdays and Sundays as measured data show that Saturdays and Sundays show different behavioural patterns.
- Correlation between duration and start-time of an activity:
  In most former models, the duration of an activity was considered independent of its starting time. In this work the activity duration and start-time are linked by a conditional probability distribution.
- Seasonal user patterns:
  Seasonality highly effects heating and lighting demand as demonstrated in [21]. SynPRO additionally considers that the daily utilisation pattern of all appliances included is also changing with the seasons and thus extends the scope of seasonal effects.
- High time-resoluted sample data:
  Electricity consumption for each appliance is achieved from measurements of 10 seconds [29]. Through this, the resulting electricity load profiles are able to incorporate power peaks occurring on a sub-minute level.

A further distinction is the stochastic approach used to generate the load profiles, which is based on a three step procedure for the number of starts, start times and duration of each activity (see 2.2). All probabilities are based on the information provided in the national time of use survey for Germany[24].
Summed up, synPRO offers a sophisticated approach to generate stochastic electricity load profiles for the domestic sector. In the following, the method for modelling domestic electric energy consumption is explained.

2. Method

SynPRO, a model for synthetic load profiles, is based on the premise that domestic electricity use is caused by the operation of technical appliances. Each appliance has its individual load trace depending on the appliance, the duration, and the intensity of use. The usage frequency and intensity strongly depend on the behaviour of the user. In section 2.1 the main drivers and the most important appliances in domestic electric energy consumption are listed.
The general model approach, based on a separation of the consumption into user driven and user independent, is introduced in section 2.2. This is followed by a detailed description of the model (section 2.2-2.6).

2.1. Drivers of Domestic Energy Consumption

Energy consumption in domestic dwellings can be split into:

1. Thermal energy - energy used to enhance thermal comfort such as heating and cooling of the dwelling as well as the preparation of domestic hot water
2. Electrical energy used for daily activities

The latter is in the focus of this paper. Table 1 depicts the common structure of domestic electricity use in German households, which is directly reflected in the model. Over 92% of the electricity demand in dwellings is caused by 9 principal categories of appliances. Electricity used for heat generation and cooling is not regarded in this work. The use of heating pumps for the circulation of the water in the hydronic system is considered since it is not seen as part of the heat generation and thus energy transformation process but as part of the domestic electric system. The resulting electricity consumption of each appliance for an individual household depends on the energetic standard of the appliance as well as the way and the frequency the appliance is used. The model structure introduced in the following is tailored to reflect these understandings.

Table 1: Share of domestic electricity demand by appliance.

Appliance	**Electricity Demand Share [2] [%]**
Office Equipment	14.5
Entertainment	13.3
Laundry[1]	13.1
Fridge	12.0
Lighting	11.1
Cooking	10.1
Pumps	7.4
Dish washing	5.9
Freezer	5.3
Other	7.4

[1] Includes drying [2] Source: [30], without electrical domestic hot water

2.2. The synPRO Model Structure

Domestic electricity demand is separated in user dependent demand, like cooking and user independent demand, like fridges. Energetic standards and usage intensity of each appliance play an important role when modelling electricity use. The most important steps in the calculation procedure (see Figure 1) are:

1. Each household is characterised by socio-economic indicators. Household size, age of the occupants, working pattern and family status are chosen to classify the persons in the dwelling to a certain household group.
2. Based on the household class the appliance stock is defined for the simulation (see Section 2.3).

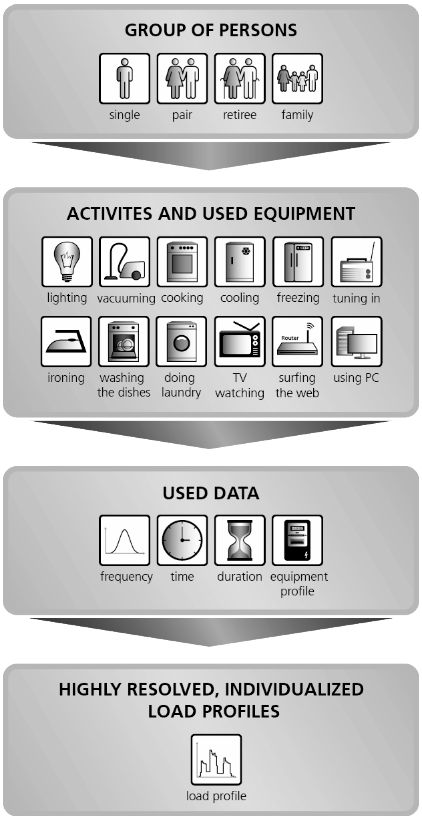


Figure 1: Model structure of synPRO

3. The activity data which contains information of appliance usage in each household group is loaded (see Section 2.4).
4. For each day of the year a usage profile for every appliance is generated. This is based on the daily number of starts, start-times and the corresponding duration of use.
5. An electric load profile for each appliance is generated by linking appliance use to measured load traces of each appliance.
6. The generated load profiles for all appliances are aggregated for the considered household. The result is a specific electric load profile with high time resolution for the individual household.

Each step is explained in more detail in the following.

2.3. *Selection of Socio-economic Factors and Household Appliance Stock*

Socio-economic factors like age, family status and employment have a significant influence of how and when energy is used during the day. This is due to differences in lifestyle of the occupants and the available appliances present in a household. In synPRO the household type is categorised by the following features:

- Number of people in each household (from one to four)
- Family (2 parents + x children)
- Age in years (<30, 30-65, >65)
- Housing-type (SFH: single family house, SDH: semi-detached house, S/B-MFH: small/big multi-family-house)
- Working pattern (F: Full-time, P: Part-time, N: Not employed)

For each category the appliance stock of the dwelling is different. Statistical data presented in [31] is used to select the typical appliance stock depending on the category of the household.

2.4. *Modelling Activity-based Appliance Use*

The main task in generating an electric load profile based on appliance use, is to determine when an appliance is in use. Frequency, start time and duration of use are taken to model appliance use. A stochastic approach based on sampling from probability distributions has been chosen in order to take into account the variability of occupant behaviour during the day, week and year.

2.4.1. *Determination of the Daily Usage*

The daily usage of appliances describes how often an appliance is used by a single person of the household. The number of starts at a given day is sampled from a probability distribution, which is derived from the time of use data [24]. Figure 2 shows this distribution for the number of starts per day for watching TV. Probability distributions are provided for workdays, Saturdays and Sundays to account for differences in daily routines.

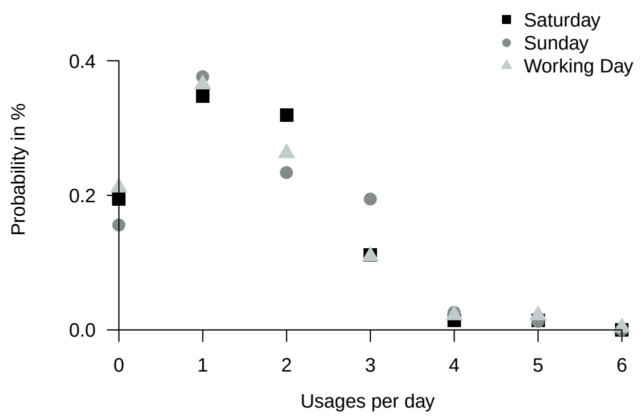


Figure 2: Distribution of daily number of starts for watching TV.

2.4.2. *Determination of the Start Time*

Once knowing the number of starts for each day, the start time of an event is determined. Again a stochastic approach, based on probability distributions is taken. The probability distribution for starting to watch TV on different weekdays is shown in Figure 3. The data are smoothed in this model using Gaussian kernel density estimation (KDE) to reduce noise. A further reason for using KDE is to generate a continuous probability distribution which can be used for sampling on a 10 second time-scale.

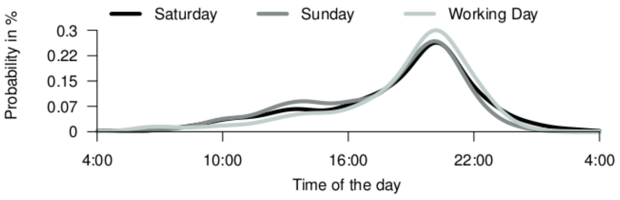


Figure 3: Probability of a start at a given time of day for watching TV.

2.4.3. *Determination of the Duration*

Eventually the duration of operation for each appliance has to be determined. Analysing the time of use data (see Section3.2.1), a correlation of start time with the duration of an activity was observed. This is implemented into the synPRO model, by relating the operation time to the start time of an appliance using a joint probability distribution. The use of this correlation is a distinct feature of the model presented in this paper. A joint probability distribution for watching TV on Saturdays is shown in Figure 4.

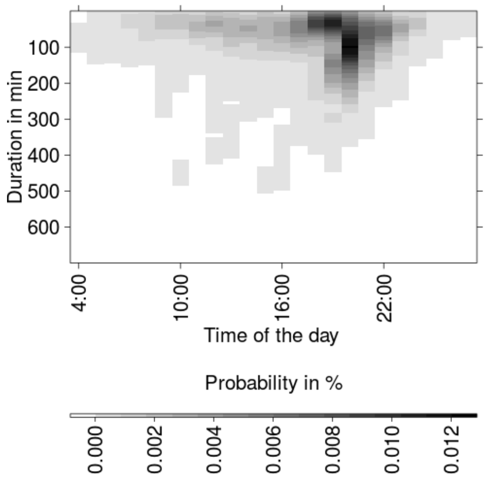


Figure 4: Joint probability of the duration of use and the start time of an activity. TV usage on Saturdays shown as an example.

2.4.4. *Simultaneous and Conflicting Use of Appliances*

Simultaneous use of appliances describes the usage of the same appliance from different people at the same time – like watching TV together. This effect is essential in multi person households since the number of appliances in a dwelling is finite and the probability of more than one person wanting to use the specific appliance is greater than zero. To include shared appliance use in the model a co-use-factor is introduced. This factor states the probability that a appliance is used by multiple persons. The co-use factor is extracted from the time use survey (see Section3.2.1), where information of doing a specific activity together with another person in the household is provided. If an appliance is already in use and an additional person wants to use the same appliance at a given time, binary sampling (True or False) using the co-use-factor decides whether the appliance is shared or the case of conflicting use appears.
Conflicting use of appliances describes the blocking of an appliance if it is already occupied and shared use is not taking place. If despite the introduction of the co-use-factor conflicting use occurs a re-run of the sampling process is started until persons, activities and appliances match.

2.4.5. *Seasonal Effects*

Seasonal effects describe the change in the load profile during the year. Load profiles on a summer day differ from those in winter. It can be seen in [21] that ignoring seasonal effects leads to differences in modelled and measured energy use during the year. Seasonal effects are also considered in the generation process of standardized load profiles for Germany [4]. This is done by having different profiles and by scaling them according to the time of year. In this work seasonal effects are accounted for in three ways, (1) light use, (2) the operation of the heating pump in the hydronic system and (3) the use of appliances. The use of light, described in Section 2.5.1, is dependent on the occupancy of the dwelling as well as on the solar irradiation, which varies during the course of the year. The operation of the heating pump, used for pumping water through the heating circuit depends on the outdoor temperature and has a considerable share of the domestic electricity demand in Germany, listed in Table 1. The heat generation system is defined to be operating if the daily mean outdoor temperature is below at 15°C and is not covered in more detail in this work.
The third component of the seasonality in electricity-use are changes in the daily activity of the household members. An analysis of the time of use survey showed that starting times did not change greatly during the year for most activities. However the number of starts during a day changed depending on the season. This leads to a change in overall daily use of the appliances. Therefore the distribution for the number of starts is modified to account for seasonal differences. The probability distributions of daily use are generated for summer and winter. Linear interpolation is used to derive the distributions for a given day in the year.

2.5. *Modelling Appliance Operation*

The electrical appliances used in synPRO are classified into three main groups:

1. Directly used appliances, which are switched on and used for a certain duration (e.g. TV).
2. Finite state appliances (as suggested in [32; 33]) which undergo a finite set of states depending on the operation mode (e.g. dishwasher).
3. Continuously running appliances – like routers or fridges - which account for most of the base load in the domestic load profiles

2.5.1. Directly Used Appliances

Directly used appliances (like TV) are switched on and are used for a certain time during the exertion of an activity (like watching TV). The usage duration linked to the start time (see section 2.4.3).

Lighting is a special case of a directly used appliance. If a person is in the dwelling, not sleeping and the global irradiation I_g is below a threshold ($I_{g,max}$) lights are switched on. The more people are active at home (n_{active}) and the darker it gets, the more light is used. The light usage value increases linearly between 0 and 1, with decreasing solar irradiation between 30 W/m^2 ($I_{g,min}$) and 60 W/m^2($I_{g,max}$). The electricity used for lighting ($P_{el,l}$) at time t is calculated:

$$P_{el,l}(t) = n_{active} \cdot P_{el,l,pp}(t) \cdot \frac{I_{g,max} - I_g(t)}{I_{g,max} - I_{g,min}} \tag{1}$$

Where $P_{el,l,pp}$ is the individual light use for a person.

2.5.2. Finite State Appliances

Hardt [33] describes the concept of finite state appliances as *"... a model (that) allows for an arbitrary set of discrete states and transitions"*. SynPRO considers washing machines, dishwashers and dryers as such appliances. For this group the duration of use is fixed by the program the appliance is operated. The used program is sampled randomly from a number of predefined programs. Different programs are for example the operation-mode of a washing machine (7 programs) or dishwasher (3 programs).
Tumble driers are modelled as fixed program appliances(7 programs), their starting time is linked to the washing machine, as driers are only needed if laundry is taken out of the washing machine. If a household is in possession of a drier it is running with a certain probability after the washing is finished. The time between the end of a washing operation and the start of the dryer is sampled from a uniform distribution between 10 and 60 minutes.

A special case of finite state appliances is meal preparation. The combination of appliances used for the preparation of a specific dish is included as a single load trace. Electrical load traces have been measured for 11 meals such as boiled eggs or pasta with sauce. These are used to account for the different possibilities of combined appliance use in meal preparation. The selection of meals depends on the sampled duration of the activity L_{S}. The probability P for a specific meal X being prepared depends is:

$$P(X) = \frac{1}{|L_{\mathrm{S}} - L_{\mathrm{X}}|} \tag{2}$$

The sampled activity duration L_{S} and L_{X} the time needed for preparation of meal X are used for meal selection.

2.5.3. Continuous Appliances

Continuous appliances are accounting for the electric base-load in domestic energy consumption. The three main reasons for base-load are stand-by power demand, refrigeration and communication appliances. Fridges and freezers are modelled as pulsing appliances, assuming a discrete power value when the compressor is working. The pulsing character of refrigeration appliances is spread over the simulation period. The duration of On-times and Off-times of the compressor is sampled from a Gaussian distribution.
Communication appliances such as internet routers and house phones are modelled as constantly running base-load throughout the whole simulation period given that dwelling has internet and telephone access.
Even switched-off appliances use a small amount of power when not plugged-off, which is accounted for in the model by a constant power value. An additional power demand is presumed for all other appliances, which are not explicitly modelled. The additional power demand is added as a base-load and determined in the calibration process (see Section 3.2).

2.6. Appliance Load Traces

A database of measured load profiles is used to link appliance usage to an electrical load profile. The load profiles are generated by slicing the measured load profiles taken from [29] into a start-up phase and a steady state phase. The load profile for a given length of operation is assembled by concatenation of the different parts. When an appliance is switched on the start-up part is taken and combined with the steady state load trace, which is repeated so that the profile length equals the length of the time the appliance is in use. Combining the operation schedule for each appliance with its load trace leads to the yearly load profile of each appliance.

3. Validation

For the validation process measured load profiles of 430 households, acquired within the Intelliekon project [34], were used. The load profile data have a one hour resolution and were measured in Germany between December 2009 and November 2010. The data were divided into groups representing different socio-economic features, which are listed in Table 2. To work with a clean dataset outliers and incomplete time series were removed. The validation process contained two steps. First, the model was calibrated using national statistics [30] for an application for German households. Second, selected groups were simulated and the results compared to the measured data. For each group 100 households where simulated for one year.

3.1. Households Selected for Validation

Validation aims to investigate the ability of the model to account for differences in load profiles related to socio-economic factors as described in Section 2.3. Household size and working patterns were selected as group specific features. Table 2 presents the selected groups and the number of clean samples in the validation data. For the validation process only groups with a minimum of 20 clean samples, were selected. Household size varies between one and four inhabitants with at least two fully employed inhabitants (FF). For a 2-person household

Table 2: Groups of households divided by household size and working pattern used for further investigation

Group label	Persons in Household	Working Pattern	Sample Size N
1FF	1	1 full-time	89
2FF	2	2 full-time	78
3FF	3	2 full-time	43
4FF	4	2 full-time	32
2NN	2	2 unemployed	137
2FN	2	1 full-time 1 unemployed	37
2FP	2	1 full-time 1 part-time	20

the working patterns are differentiated into workers (F), non-workers (N) and part-time-workers (P). This results into four groups that are listed in Table 2.

3.2. *Modell Calibration and Input Data*

Before using synPRO, the model has to be calibrated for German households. The following data needs to be provided:

- The activity distributions which are the probability distributions for the daily use, start-time and duration of an event, depending on the starting time
- The appliance stock in the individual households
- Typical energy use of the appliances

3.2.1. *Data Used*

For the activity and appliance stock distributions the German part of the Harmonized European Time Use Survey (G-HETUS), supplied by the German Statistic Office was used [24; 35]. The survey contains activity diaries for around 14,000 individual persons in 5,200 households on two weekdays and one weekend-day in a 10 min resolution. In each diary three questions are asked for each time-slot.

- What were you doing? (Primary activity)
- What else were you doing? (Secondary activity)
- Were you alone or with somebody you know? (Used for calculation of the co-use factor see Section 2.4.4)

For each country an individual list of possible activities is used to cover country-specifics. The activities recorded range from "Going for a walk with the dog" to "Cleaning of the Flat". For the purpose of this work activities, that are connected to the most relevant household appliances listed in Table 1 were selected and evaluated.
Additional to the activity diaries, the survey contains a appliance stock statistic for the interviewed households. These data are used for generating the appliance stock distributions in the simulations. For the use of computers and internet appliances the statistical input data from the G-HETUS from 2002 are used. It was adjusted to accomplish the simulation of computer and internet usage in 2009 and further on. According to [36] the usage duration changed by factor of 1.86 and the daily usage changes from the G-HETUS value of 24.9% to a daily usage of 75.9% for all households [36]. The availability of computer and internet access has also changed per household up to 83.5% and 79.4% respectively [35].

3.2.2. *Calibration to Typical Energy Use of Appliances*

Measured data [29] were used for the appliance load traces and the resulting energy demand. Energy consumption of appliances relating to refrigeration, cooking and lighting strongly depends on the size of the household, . Calibration of the model was done with a survey of the Northrinewestphalian Energy Agency, [30] which contains the typical yearly energy demand for appliance groups and household sizes. The following parts of the model were calibrated to account for the typical appliance energy consumption according to the household size:

- Refrigeration appliances
  The yearly energy demand of refrigeration appliances is mainly determined by their size. The data in [30] show that smaller households have also smaller refrigeration appliances or even fridge-freezers. The refrigeration appliances are scaled to a yearly energy demand depending on the household size in the model.
- Cooking
  Kitchen usage depends on the household size, as the amount groceries are dependent on the amount of people. Energy intensive kitchen appliance profiles are more likely in bigger households than in smaller households, which is taken into account with respect to the total energy consumption for cooking provided in [30].
- Lighting
  The energy demand for lighting is calibrated for active occupancy in the building between one and four persons. The electricity needed for lighting increases by 120 W, 0 W, 85 W and 170 W, for each additional person. The lack of additional lighting demand for the second inhabitant is due to a shared usage of lighting in 2-person households as the data indicates [30].
- Additional power demand
  The calibration of additional power demand including standby use and other appliances which are not exactly distinguished by the model leads to a base-power value of 25 W (see 2.5.3)

After calibrating the model for the German households, synthetic load profiles were generated and compared against the measured profiles. A detailed description of these results is given in the following section.

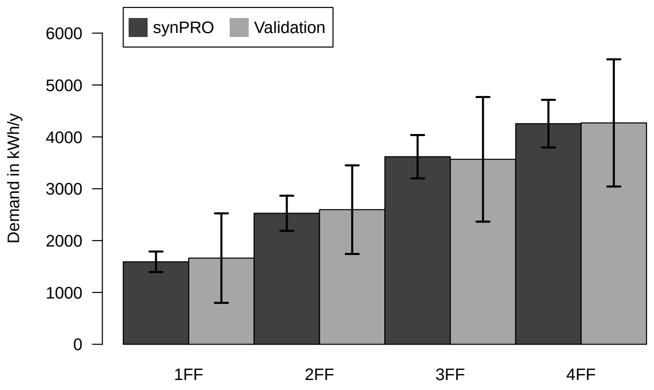


Figure 5: Comparison of yearly energy demand for the selected groups

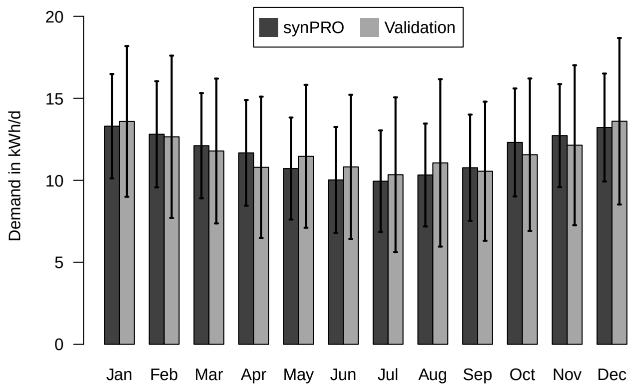


Figure 6: Comparison of the mean daily energy demand per month for group 4FF.

4. Results

In the following measured and simulated load profiles using the synPRO model are compared and the yearly, monthly, daily and hourly electricity demand is analysed.

4.1. Measures of model quality

The quality of the model is described by two indicators: Correlation analysis is used to assess the similarity for all data points N of measured and simulated load curves.
The mean relative error Err, defined as the relative difference at each data point i between measurement y_i and simulation x_i:

$$Err = \frac{1}{N} \sum_{i=1}^{N} \frac{|y_i - x_i|}{y_i} \tag{3}$$

is used to account for the error.

4.2. Annual Demand

The comparison of the yearly electricity demand is shown in Figure 5. It can be seen that within the measured data there is considerable variance in the yearly electricity demand within the selected subgroups. The simulated load data have a similar yearly demand compared to the validation group but shows less intra-group variance . The differences in the yearly mean electricity demand are below 5.2% in all cases.

4.3. Monthly Demand and Seasonal Effects

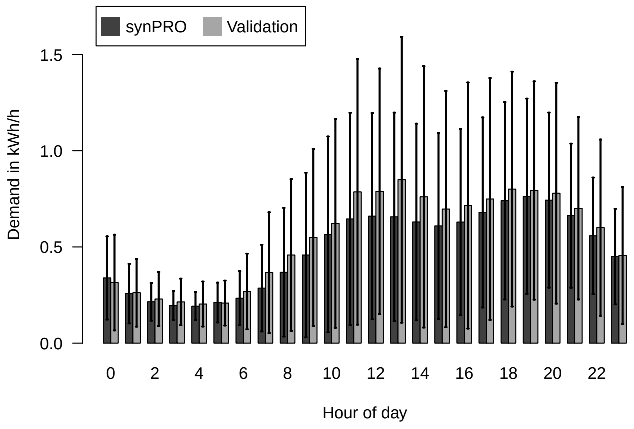
Figure 6 shows the mean daily electricity demand on a monthly basis for group 4FF. The model and the measured data show up to 13.2% variation in daily demand during a month. Spread in the measured data is higher than in the synthetic data. Regarding the mean values the measured data show a seasonal trend, which is also visible in the synthetic load profiles. It can be seen that in summer and winter synPRO is slightly underestimating the used electricity whereas in the changing periods of the year the modelled electricity demand is higher than the measured demand. A comparison of yearly electricity demand (see section 4.2) shows that during the course of the year the errors almost level out. The resulting error for all groups can be found in Table 3. Correlation is mostly above 0.9 which indicates, that synPRO captures the general shape and thus the seasonal pattern. The overall relative error in the mean daily energy demand is below 6%.

Table 3: Model evaluation for mean daily electricity demand per month

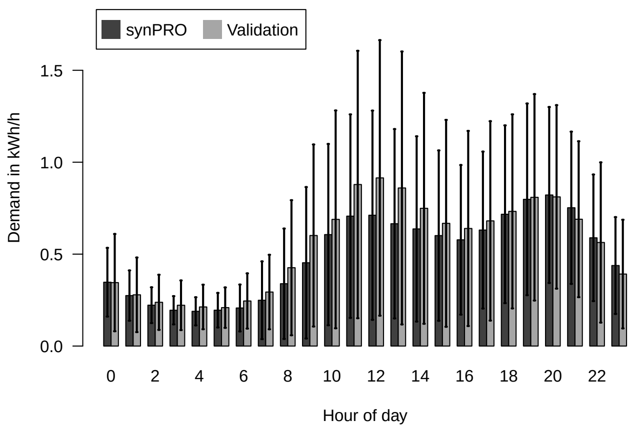
Group	Correlation R	Err [%]
1FF	0.92	4.5
2FF	0.96	2.9
3FF	0.86	4.7
4FF	0.88	4.6
2NN	0.96	3.7
2FN	0.95	4.1
2FP	0.96	5.7

4.4. Daily Demand Profile

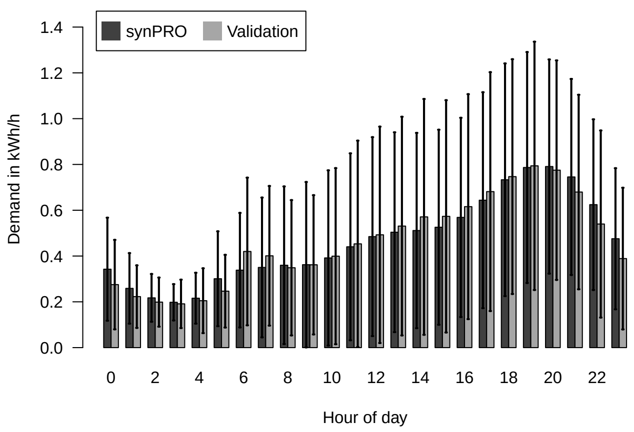
One key interest in developing synPRO is to describe the shape of the daily load profiles in detail. The mean daily energy demand profile is used in many applications from tariff design to the sizing of system components. Figure 7 shows the mean daily load profile and the standard deviation for Working-days, Saturdays and Sundays.
It can be seen that the shape of the measured profiles and the synthetic load profiles is similar. Table 4 contains correlation coefficients and relative errors of the mean daily load profiles. In all cases, correlation is above 0.9 and in the best case 0.98. The relative error is between 8.8% and 16.1%. During working days the synthetic load profile shows a slightly higher load during night times. Generally synPRO matches the characteristics of the measured profile. During Saturdays and Sundays the characteristic shape of the load profile shows a mid-day and an evening peak. Both can be found in the synthetic profiles as



(a) Saturday



(b) Sunday



(c) Working Day

Figure 7: Profile traces of the daily average synthetic and measured data for different weekday categories for 4FF.

Table 4: Key values for model evaluation based on the 24 hour average load profile

Gr-	Correlation R				Err [%]			
oup	Sat.	Sun.	Wd.	All	Sat.	Sun.	Wd.	All
1FF	0.98	0.97	0.95	0.96	6.1	10.7	9.7	8.8
2FF	0.97	0.93	0.90	0.92	7.2	11.5	16.1	12.7
3FF	0.96	0.96	0.96	0.96	8.3	11.2	9.9	9.7
4FF	0.98	0.96	0.97	0.97	8.8	9.3	9.9	9.0
2NN	0.93	0.90	0.96	0.95	10.1	12.3	9.9	9.9
2FN	0.93	0.85	0.91	0.91	10.8	15.9	11.6	10.7
2FP	0.90	0.93	0.96	0.95	11.6	14.9	10.3	10.4

well. During weekends the peak at midday is slightly higher in the measured data than in the simulated load. As indicated by the displayed graphs, the model tends to underestimate the load during the afternoon at weekends.

4.5. Hourly Demand

Figure 8 shows the hourly load duration curve for the synthetic and measured data. Both data series were pre-sorted as load duration curves for a complete year. Afterwards the mean profile and standard deviation were calculated. The duration curve shows that the mean general distribution of loads in the synthetic load profile is almost identical to the one in the measured data, whereas variance is higher in the measured data compared to the synthetic profiles. The extreme values of the measured data are about 5.8% to 16.9% higher than the peak value of the synthesized load. This can also be seen in the carpet plot shown in Figure 9 which shows the hourly load for the measured and the synthetic load profiles for each hour of the year. The peak values of the measured data at certain points are not reflected in the synthetic data. It can also be seen that the general characteristic in terms of weekly patterns, stochasticity, evening peak and seasonal fluctuations are captured by the model. As already seen in the daily load plots the consumption peak at lunchtimes is underestimated in particular at weekends. In Figure 10 a comparison of a single synthetic load profile with a single measured profile is shown. For both profiles it can be seen that the characteristic hours and the values of the peaks are captured. The change in the load profile from one day to another that is reflected in synPRO, can be also observed in the measured data.

4.6. Discussion of Results

A comparison of the synthetic load data with measured data shows that the synPRO model is able to capture the general characteristics of the electric load profiles for German households. The variation of the data visible in the yearly electricity consumption and the daily mean values (Figure 5 and 6) is mostly covered by the model. The reasons why not all variation is covered by the synthetic load profiles are differences in age and type of the technical equipment used in the individual households, and different electricity consumption habits of the residents.

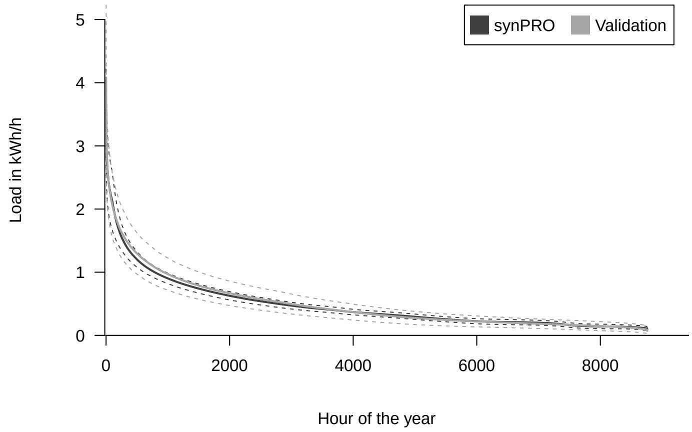


Figure 8: Load duration curve for the synthetic and measured load profiles of group 4FF. The mean values (solid line) and the standard deviation (dashed line) are shown.

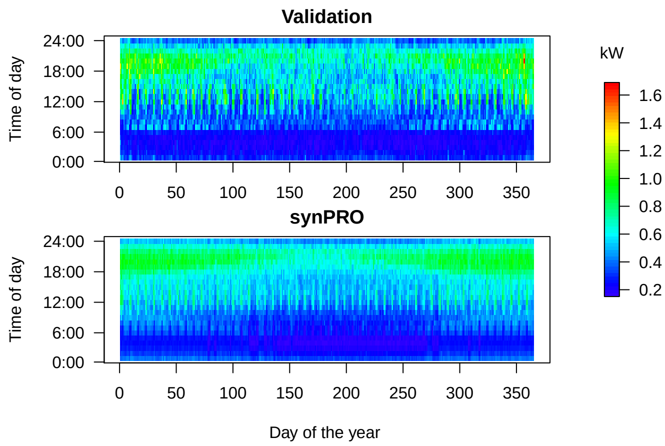


Figure 9: Hourly load values for one year for synthetic and measured load profiles of group 4FF.

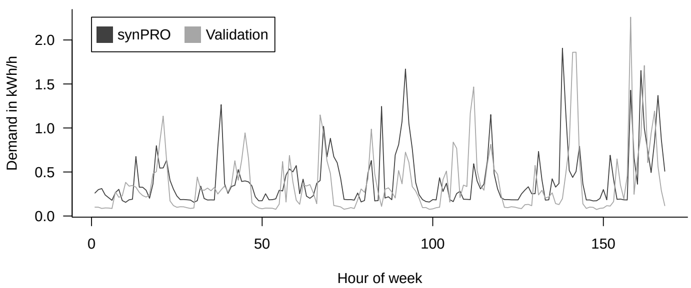


Figure 10: Hourly load values for one week for a single synthetic and a single measured load profile of group 4FF.

The match of the daily load profiles with measured data is summarised in Table 4 and shows correlation values above 0.9 for all groups. It can be seen in Figure 7 that the lunchtime peak is underestimated by the synPRO model. A reason for this could be, that sampling of cooking profiles using the duration of the cooking process leads to a choice of too little energy intensive meals. This may further indicate, that the measured load traces used in the model for cooking are less energy intensive than for a typical cooking process at lunchtime.
In Figure 9 the hourly load values of one year are compared. Overall, the general characteristics are very well reflected in the model. It can be seen, that at some days the peak values are lower in synPRO than in the measured data. This is because the stochasticity assumption in the model overestimates the independence of the load profiles of the different households to each other and leads to a smoothing of aggregated load profiles. Certain events like Christmas show very unique and specific consumption patterns, where many households do the same activity at a specific time. Clearly visible in Figure 9 day 358, almost all households show a similar load profile and a very high intra group correlation at day 358. In the sum of all load profiles such behaviour leads to extreme values in the aggregated load profile. Such extreme events can explain part of the missing peak values and will be included in future versions of the model (see Section 6).

5. Conclusion

In this paper a model to generate individualised, stochastic load profiles was introduced. The model was calibrated for German households by using national statistics about appliance stock, time of use [24], and appliance energy demand [30]. A one year simulation of 100 households for different subgroups was undertaken to generate synthetic load profiles, which were compared to measured data from 430 households. The results show that synPRO reaches an accuracy of 91% for the mean yearly, monthly and daily energy consumption for each group investigated. The intra-group variance of energy demand and the load peak at lunchtime during the weekends can only partly be covered by the model so far. Correlation of the daily measured load profiles with the model results can reach up to 0.98 and the relative mean error lies between 8.8% and 16.1%. Seasonal effects are addressed in synPRO by incorporating behavioural change of the inhabitants, operation of the pumps for heating and light usage. This leads to a change in the load curve during the year, which is consistent with the measured data.
The strength of the model is the fact that stochasticity is covered, individuality of load profiles for different socio-economic groups can be integrated, and that the electric load profile of an household can be explained by the use of appliances. This supports research in a wide range of fields aiming at energy efficiency, demand side management and increased applicability of PV supply. Load-shifting with household appliances and change of the load profile to a price are just some examples of possible applications. The model can also be used for simulating loads in electrical distribution networks.

The synPRO model extends the existing stochastic model approaches and brings a valuable input to the discussion of bottom-up modelling for domestic electricity use, such as incorporating a correlation between duration and start time of an activity, a distinction of weekdays, high resolved measured data and changed behaviour based on seasons.

6. Further work

Since electrical load in the domestic sector is heavily influenced by thermal applications such as electric showers or heat pumps further work will address the influence of thermal-electric heat generation technologies. Electric vehicles will play an increasing role in residential electricity demand and will be included in the model. Further study will be conducted to find ways to include extreme events (like Christmas) into the model to enable a better representation of yearly peak loads in electrical networks. A detailed comparison with standardised load profiles will be undertaken to show the benefits and drawbacks of both approaches.

Acknowledgements

The research leading to these results was developed within the ORIGIN project and has received funding from the European Union Seventh Framework Programme (FP7/2007-2013) under grant agreement N° 314742.

References

[1] Eurostat. Electricity production and supply statistics - Statistics Explained, 2012.

[2] Richard Piwko, Dale Osborn, Robert Gramlich, Gary Jordan, David Hawkins, and Kevin Porter. Transmission Planning and Cometitive Electricity Market Operation. *IEEE Power & Energy Magazine*, 3.6(12):47–56, 2005.

[3] R. Baetens, R. De Coninck, L. Helsen, and D. Saelens. The Impact of Load Profile on the Grid-Interaction of Building Integrated Photovoltaic (BIPV) Systems in Low-Energy Dwellings. *Journal of Green Building*, 5(4):137–147, November 2010.

[4] C. Fünfgeld and R. Tiedemann. Anwendung der Repräsentativen VDEW-Lastprofile step-by-step, 2000.

[5] G. Dubielzig, H. Frey, K. Heikrodt, K. Ksinsik, A. Nunn, W.-H. Scholz, and T. Winkelmann. *Referenzlastprofile von Ein- und Mehrfamilienhäusern für den Einsatz von KWK-Anlagen*. VDI Verlag GmbH, Düsseldorf, 2007.

[6] Chi-hsiang Wang, George Grozev, and Seongwon Seo. Decomposition and statistical analysis for regional electricity demand forecasting. *Energy*, 41(1):313–325, May 2012.

[7] Linda Pedersen. *Load Modelling of Buildings in Mixed Energy Distribution Systems*. Doctoral thesis, Norwegian University of Science and Technology, NTNU, 2007.

[8] Fintan McLoughlin, Aidan Duffy, and Michael Conlon. Characterising domestic electricity consumption patterns by dwelling and occupant socio-economic variables: An Irish case study. *Energy and Buildings*, 48(July 2009):240–248, May 2012.

[9] Fintan McLoughlin, Aidan Duffy, and Michael Conlon. Evaluation of time series techniques to characterise domestic electricity demand. *Energy*, January 2013.

[10] Christof Bucher. Generation of Domestic Load Profiles - an Adaptive Top-Down Approach. In *PAMAPS*, pages 436 – 411, Istanbul, 2012.

[11] Bruce Stephen, Antti J Mutanen, Stuart Galloway, and Graeme Burt. Enhanced Load Profiling for Residential Network Customers. *IEEE Transactions on Power Delivery*, 29(1):88–96, 2014.

[12] Bernhard Wille-Haussmann, Jochen Link, and Andreea Sabo. Photovoltaik Eigenstromnutzung – Fluktuation von Strahlung und Last. In *Tagungsband 27. PV-Symposium*, Berlin, 2012. Ostbayerisches Technologie-Transfer-Institut.

[13] Tobias Bossmann, Fridolin Lickert, Rainer Elsland, and Martin Wietschel. The German load curve in 2050 : structural changes through energy efficiency measures and their impacts on the electricity supply side. In *ECEEE Summer Study Proceedings*, pages 1199–1211, 2013.

[14] Rolf Apel, Thomas Audrup, B.M. Buchholz, Hans Peter Domels, Funke Stephan, and Gesing Thomas. Demand Side Integration - Lastverschiebungspotentiale in Deutschland. Technical report, VDE, Frankfurt, 2012.

[15] Sebastian Gottwalt, Wolfgang Ketter, Carsten Block, John Collins, and Christof Weinhardt. Demand side management—A simulation of household behavior under variable prices. *Energy Policy*, 39(12):8163–8174, December 2011.

[16] L. Magnano and J. Boland. Generation of synthetic sequences of electricity demand: Application in South Australia. *Energy*, 32(11):2230–2243, November 2007.

[17] A. Capasso, W. Grattieri, R. Lamedica, and A. Prudenzi. A bottom-up approach to residential load modeling. *IEEE Transactions on Power Systems*, 9(2):957–964, May 1994.

[18] R. Yao and K. Steemers, Runming Yao, and Koen Steemers. A method of formulating energy load profile for domestic buildings in the UK. *Energy and Buildings*, 37(6):663–671, June 2005.

[19] Jukka V. Paatero and Peter D. Lund. A model for generating household electricity load profiles. *International Journal of Energy Research*, 30(5):273–290, April 2006.

[20] Marianne M. Armstrong, Mike C. Swinton, Hajo Ribberink, Ian Beausoleil-Morrison, and Jocelyn Millette. Synthetically derived profiles for representing occupant-driven electric loads in Canadian housing. *Journal of Building Performance Simulation*, 2:15–30, 2009.

[21] Ian Richardson, Murray Thomson, David Infield, and Conor Clifford. Domestic electricity use: A high-resolution energy demand model. *Energy and Buildings*, 42(10):1878–1887, October 2010.

[22] Ian Richardson, Murray Thomson, David Infield, and Alice Delahunty. Domestic lighting: A high-resolution energy demand model. *Energy and Buildings*, 41(7):781–789, July 2009.

[23] Ian Richardson, Murray Thomson, and David Infield. A high-resolution domestic building occupancy model for energy demand simulations. *Energy and Buildings*, 40(8):1560–1566, January 2008.

[24] Eurostat. Harmonized European Time Of Use Survey, 2000.

[25] Joakim Widén, Annica M. Nilsson, and Ewa Wäckelgå rd. A combined Markov-chain and bottom-up approach to modelling of domestic lighting demand. *Energy and Buildings*, 41(10):1001–1012, October 2009.

[26] Joakim Widén, Magdalena Lundh, Iana Vassileva, Erik Dahlquist, Kajsa Ellegå rd, and Ewa Wäckelgå rd. Constructing load profiles for household electricity and hot water from time-use data—Modelling approach and validation. *Energy and Buildings*, 41(7):753–768, July 2009.

[27] Joakim Widén and Ewa Wäckelgå rd. A high-resolution stochastic model of domestic activity patterns and electricity demand. *Applied Energy*, 87(6):1880–1892, June 2010.

[28] Lukas G. Swan and V. Ismet Ugursal. Modeling of end-use energy consumption in the residential sector: A review of modeling techniques. *Renewable and Sustainable Energy Reviews*, 13(8):1819–1835, October 2009.

[29] TU Darmstadt. High-Resolution Power Consumption Traces, 2012.

[30] Energieagentur Nordrhein-Westfalen. Erhebung: Wo im Haushalt bleibt der Strom?, April 2011.

[31] Destatis. Ausstattungsgrad und Ausstattungsbestand von Haushalten (Laufende Wirtschaftsrechnungen) Deutschland, 2011.

[32] European Parliament, Council. Directive 2009/28/EC of the European Parliament and of the Council of 23 April 2009 on the promotion of the use of energy from renewable sources and amending subsequently repealing Directives 2001/77/EC and 2003/30/EC.

[33] GW W Hart. Nonintrusive appliance load monitoring. *Proceedings of the IEEE*, 80(12):1870–1891, 1992.

[34] Intelliekon Project Consortium. Nachhaltiger Energiekonsum von Haushalten durch intelligente Zähler-, Kommunikations- und Tarifsysteme Ergebnisbericht. Technical Report November, Fraunhofer Institute For Solar Energy Systems ISE, Freiburg, 2011.

[35] Destatis. Zeitbudgets - Tabellenband I, 2001.
[36] Media Perspektiven. Basisdaten - Daten zur Mediensituation in Deutschland. Technical report, Media Perspektiven, Frankfurt am Main, 2013.