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Application-oriented modelling of domestic energy demand

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Abstract

Detailed residential energy consumption data can be used to offer advanced services and provide new business opportunities to all participants in the energy supply chain, including utilities, distributors and customers. The increasing interest in the residential consumption data is behind the roll-out of smart meters in large areas and led to intensified research efforts in new data acquisition technologies for the energy sector. This paper introduces a novel model for generation of residential energy consumption profiles based on the energy demand contribution of each household appliance and calculated by using a probabilistic approach. The model takes into consideration a wide range of household appliances and its modular structure provides a high degree of flexibility. Residential consumption data generated by the proposed model are suitable for development of new services and applications such as residential real-time pricing schemes or tools for energy demand prediction. To demonstrate the main features of the model, an individual household consumption was created and the effects of a possible change in the user behaviour and the appliance configuration presented. In order to show the flexibility offered in creation of the aggregated demand, the detailed simulation results of an energy demand management algorithm applied to an aggregated user group are used.

Keywords: domestic energy consumption, energy demand model, load profile generation, demand side management

1. Introduction

In recent years the research in the field of residential energy consumption has been intensified both by the scientific community and the industrial sector. This interest is a result of several factors, including the massive integration of intermittent renewable energy sources, the continuously increasing energy demand of the residential sector [1, 2] in combination with the limitations of the current infrastructure for energy production and distribution as well as the idea to create new services with an added value for companies and customers. The availability of affordable smart meters and the establishment of appropriate legal frameworks in many countries enforced the deployment of smart meters in large areas. These smart meters collect measurements of the electric and gas consumption with a relatively low sampling time and give a good idea on the demand of a household.

Detailed smart meter data can be used to offer a wide range of applications and services such as demand optimisation, fault detection and network management. Possible positive effects range from higher economic profits to technical improvements including better power quality and grid stability in electric networks and optimised infrastructure for the gas supply. Both customers and companies from the energy sector benefit from the implementation of advanced services based on residential energy consumption data. However, unresolved privacy issues and quality problems of the collected measurements complicate or even impede the development and validation of new services and applications. These adverse conditions when dealing with residential energy consumption data can be avoided, at least to some extent, by using artificial data generated with the help of mathematical models. Consequently, suitable consumer energy demand models for the generation of realistic domestic energy demand data play an important role in the design of value-added services for the energy sector.

1.1. Research aim

The main objective of this paper is the development of an appropriate consumer energy demand model for the generation of detailed energy demand profiles. In the case of a deficiency or a complete lack of useful measurements, synthetic residential consumption data can be used in the design of advanced services for customers, utilities, network operators and retailers. With the objective to employ the artificial data in the development of a wide range of different applications such a consumer energy demand model has to provide a high degree of flexibility. An application-oriented model needs to allow the generation the generation of consumption data of one or several households over a freely selectable period of time with reasonable detail. Besides, such a model has to offer the possibility to consider local or regional peculiarities, e.g. more frequent use of heating devices in colder climates. It is important to emphasise that the development of a high precision model, e.g for dynamic thermal simulation, material testing or building design optimisation, is not in the scope of this work.

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Another aim of this work is the analysis of typical applications based on detailed residential consumption data and the resulting benefits for utilities, network operators, retailers and customers. The importance of a suitable consumer energy demand model is underlines with the help of several application examples.

1.2. Paper overview

This paper proposes a consumer energy demand model based on the contribution of a wide range of common household appliances and under consideration of photovoltaic installations. The artificial consumption data generated by this model allow the development of new services and applications for customers and companies. The paper is organised at follows: Section 2 reviews different modelling approaches for residential energy consumption and provides the general research background of this paper. A description of possible services and applications based on residential energy consumption data is given in Section 3. Section 4 proposes an application-oriented model for the generation of artificial domestic energy demand data. Then, Section 5 presents simulation results of the applications based on the consumption data generated with the proposed model. Finally, in Section 6 the most important conclusions are drawn.

2. Research background

In the last years, energy consumption modelling gains an increasing interest from the industry and the scientific community. Special attention is paid to the modelling of the residential sector due to the high ratio of primary energy consumption. The understanding of the consumption and prediction of the future demand provides the opportunity to solve, at least partially, energy related problems such as power supply, environmental issues and economic questions. Generally, residential energy consumption models describe the energy needs in function of a certain set of parameters.

The review presented in [3] divides the different modelling techniques for the residential sector in top-down and bottom-up approaches. In the case of top-down models, the residential energy sector is regarded in its entirety without considering the energy consumption of individual customers. This type of model is especially useful to estimate price and income elasticities of the energy demand [4] and to study long-term macroeconomic trends [5]. In contrast, bottom-up models work on a disaggregated level with detailed data of energy end-uses like heating and lighting [6]. The bottom-up models for the energy consumption of the residential sector are frequently classified into two main categories: statistical methods and engineering techniques [3].

2.1. Statistical methods

Statistical methods are based on historical data and regression techniques which determine the relation between the end-uses and the energy consumption. This type of model takes into account the influence of different sets of socio-economic and environmental indicators such as dwelling type, location,

family size and type, earnings, social class and appliance ownership. The common statistical methods in residential energy consumption modelling are regression techniques, conditional demand analysis and neural networks [3]. One of the most important benefits of statistical models is the ability to perceive the effect of occupant behaviour. Besides, these models can be developed without detailed consumption data and without a deep knowledge of the underlying processes. The fundamental disadvantages include the often low significance of the estimated parameters, the required large samples, the low flexibility and the common regression problems such as multicollinearity, heteroscedasticity and autocorrelation. An overview of the benefits and limitations of statistical models can be found in [5].

Statistical methods have been employed in [7] to develop linear regression models for the yearly and monthly household energy consumption using setpoint temperature, electricity usage of appliances and lighting, airflow gains and occupant sensible heat gains as independent variables. A regression analysis was carried out in [8] in order to quantify the influence of window opening, lighting, heating and solar shading on occupant behaviour. The model proposed in [9] estimates the building sector energy end-use intensity for New York City as a function of the ZIP codes.

2.2. Engineering techniques

Engineering techniques use physical principles to determine the residential energy consumption on building level or for sub-level components [10]. Models based on engineering techniques can be developed without historical data and the scope ranges from very simple designs to extremely complex structures. A common approach makes use of appliance ownership, use, rating and efficiency as well as cycle lengths to compute the residential energy consumption [3]. The possibility to consider physical concepts such as heat and mass transfer, thermodynamics and fluid mechanics allows the development of highly precise models. However, the required parameters for such a model are often unavailable or hard to obtain leading to a less accurate estimation of the residential energy consumption. Other disadvantages of engineering techniques are the nearly impossible integration of the effect of macroeconomic changes and the difficulty to consider user behaviour. In contrast, models based on engineering techniques can be easily modified to include technological progress and use physically measurable data. Further information of advantages and drawbacks of engineering techniques for residential energy consumption modelling is given in [5].

An example for engineering techniques is the model for the electric demand in an individual household presented in [11] which combines the active occupancy and daily activity profiles of the occupants to determine the residential energy consumption. The model proposed in [12] considers both appliance characteristics (e.g. operation mode, appliance penetration, power consumption, frequency of use and turn-on times) and socially influenced factors such as number of residents, occupancy pattern and customer classification. The prediction method in [13] uses a dynamic thermal model to determine domestic space heating profiles. The detailed dynamic simulation

models of different types of dwellings developed in [14] can be used for a sensitivity analysis of different variables with respect to the thermal demand. Other models developed with engineering techniques are used for the computation of load profiles of a residential area [15], testing of a residential cogeneration system [16] or validation of demand side management (DSM) strategies [17].

3. Applications and requirements

The recent deployment of smart meters will provide companies from the energy sector technical access[1] to detailed residential energy consumption data. Utilities, network operators, retailers and companies not necessarily related to the field of energy generation and distribution already expressed their interest in the mentioned end-user data. If suitable smart measurements data are unavailable, synthetic consumption data generated by a mathematical model can be used in the development of the value-added services and applications described in the following paragraphs.

3.1. Demand optimisation

One of the principal problems in the energy sector is the domestic demand variation with significant peak loads in the morning and the afternoon/night. Integration of renewable energy sources with their intermittent generation, mainly wind turbines and photovoltaic panels, increase the effects resulting from the difference between generation and demand. The incapability of the mentioned renewable energy sources for up-regulation may cause possible deficiencies and failures in energy supply and distribution systems. Optimisation of the domestic energy demand offers a possibility of reducing the impact of load variations and intermittent generation [20, 21].

A common objective of demand optimisation is the flattening of the daily load curve by shifting energy consuming activities from peak to off-peak periods. In the case of the residential demand, optimisation approaches normally act upon appliances with significant energy consumption and certain flexibility of the customer for the time of use, e.g. washing machines and dishwashers. It is important to underline that most demand optimisation strategies consider a larger number of households to increase the effect on the aggregated load and the related peak-to-average ratio.

3.2. Real-time pricing

The diurnal and seasonal fluctuations in the energy demand and the intermittent generation by some renewable energy sources lead to wholesale price variations. However, electricity is commonly charged to the residential end-users at a fixed rate, i.e. changes in the wholesale prices are not passed down to the customer. Detailed residential energy consumption data can

be used in real-time pricing schemes to establish a link between the wholesale and the retail market [22, 23, 24].

Real-time pricing provides utilities, network operators and retailers an option of passing on the actual costs of generation, transmission and distribution to the consumer. Dynamic pricing schemes incentivize customers to reduce consumption during peak-time and shift the use of energy intensive appliances to periods with low demand. Real-time pricing schemes give customers with an opportunity to cut down the energy costs by modifying their usage habits and provide companies from the energy sector with a tool for influencing the demand.

3.3. Customer services

In recent years, changes in customer needs, increased environmental awareness and liberalised markets forced the energy sector to reconsider the traditional business model. Personalised services with an added value for the customer play an important role in the diversification of the involved companies. Detailed data of residential energy consumption provide an opportunity to develop and offer individualised services which improve customer loyalty and open new sources of income.

Possible additional services for the customers include a comparison of energy tariffs and recommendation of the most suitable ones, remote control of household appliances for increased consumer convenience, prediction of the future energy consumption and the associated costs as well as the detection of inefficient devices to improve household energy efficiency [25, 26]. Besides, the consumption data can be used to demonstrate the effects of a modified user behaviour and analyse the resulting opportunities for the customer. Finally, detailed consumption data could be used in smart appliance programs intended for customer participation in demand optimisation.

3.4. Network management techniques

A continuous supervision and control of transmission networks guarantees a reliable and uninterrupted service. In contrast, the less common monitoring on the distribution network level complicates or even impedes an efficient regulation of the most important grid variables. Residential energy consumption data can be used in the development of state observers to overcome the lack of information and apply advanced network management techniques [27, 28, 29].

Consumption data of high granularity collected by domestic smart meters can be aggregated to determine the total demand of all customers connected to a substation in the distribution network. These data can be employed to detect network errors, enhance load balancing and improve power quality and energy supply. Suitable models allow the dynamic estimation of the operational state of distribution networks and provide valuable information for monitoring and control purposes.

3.5. Promotion of alternative energy sources

In the last years, affordable systems based on sustainable microgeneration, renewable energy sources and residential energy storage have become an interesting alternative for customers. These systems are suitable for distributed generation concepts

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[1]This paper deals only with the technical opportunities related to the residential energy consumption data without considering non-technical restrictions resulting from unresolved legal issues. For information on national regulations and data security see [18, 19].
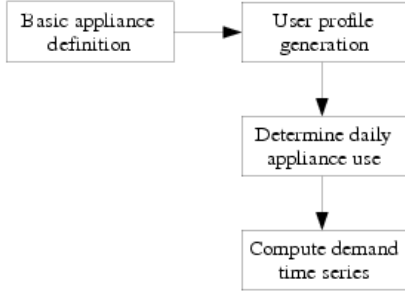
Figure 1: General structure of the consumer demand model used for the generation of artificial consumptions data.

and offer customers an option of increasing energy efficiency while simultaneously reducing costs. Companies with access to residential energy consumption data could promote and offer custom-tailored home generation and storage solutions [26, 30].

Small-scale renewable energy sources are capable of contributing to the energy supply of single households or a reduced number of customers in a small geographic area. The optimal dimension of the system, considering energy efficiency and economic criteria, is determined using the residential energy consumption data of the considered households. The effects of such a system on the necessary amount of external energy can be simulated with the smart meter data and used to promote alternative energy sources and distributed generation.

4. Consumer energy model

Modern smart meter technology provides the opportunity to collect detailed residential energy consumption data for an entire dwelling or separately for each appliance in a household. This data can be exploited in a variety of services and applications (see Section 3) with different objectives such as increased grid stability or added customer value. The problems related to legal issues and the lack of enough high-quality measurements when dealing with smart meter data can be avoided using synthetic consumption data.

This section describes in detail a new consumer demand model for the generation of artificial consumption data, both for a single household and an entire neighbourhood. The general model structure, explained in the following paragraphs, uses some basic appliance definitions to generate the synthetic consumption data in three main steps (see Fig. 1).

4.1. Appliance definition

The developed energy demand model uses some basic information to define the main characteristics of each appliance to be considered in the generation of the artificial consumption data. These definitions contain both technical specifications (e.g. power level during operation or in standby) and socioeconomic data (e.g. average number of appliances per household or seasonal effect on the appliance use). The most common household appliances can be classified according to a reduced number of simplified power level patterns. In the proposed model three different power level patterns for the approximation

of the demand curve have been considered. Pattern 1 represents continuously running appliances with a constant power level[2] such as fridges or freezers, see Fig. 2(a). Pattern 2 allows the approximation of occasionally operated appliances with a possible non-zero energy consumption in standby operation such as washing machines or TVs, see Fig. 2(b). Finally, pattern 3 is used to approximate the power curve of continuously running appliances with a frequently changing power level such as lighting, see Fig. 2(c).

The three simplified power level patterns were used in the development of a classification scheme based on different usage types. These usage types take account of factors such as frequency, duration and time of use of the considered appliances and allow a classification closely related to the customer habits. The nine usage types, initially defined in [31], are the following ones:

- Type A: continuously running appliances, never switched off, based on power level pattern 1.

- Type B: appliances used nearly every day, never more than once a day, long usage duration (more than 12 hours), power level pattern 2.

- Type C: appliances used several times a week, never more than once a day, mainly in the afternoon, long usage duration (between 2 and 12 hours), power level pattern 2.

- Type D: appliances used several times a week, mainly in the morning and afternoon, short to intermediate periods (between 0.5 and 3 hours), power level pattern 2.

- Type E: appliances with non-homogeneous usage frequency, short duration (between 0.1 and 1 hour), mainly around meal preparation times, power level pattern 2.

- Type F: appliances with variable power consumption, based on power level pattern 3.

- Type G: appliances used once a day, long durations, variable time of day, power level pattern 2.

- Type H: appliances used once a day, always at the same time of the day, long durations, power level pattern 2.

- Type I: appliances not represented by other consumer usage types, power level pattern 2.

The appliance definition in the consumer demand model has to provide some basic information used in the generation of synthetic consumption data. An important part of the mentioned basic information, including data on the annual energy consumption, the average number of devices per household, the average number of cycles per day, the daily average load curves

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[2]Note that some appliances based on pattern 1 can show significant short-term variations in the power level, but the average power over the period remains at a constant level.
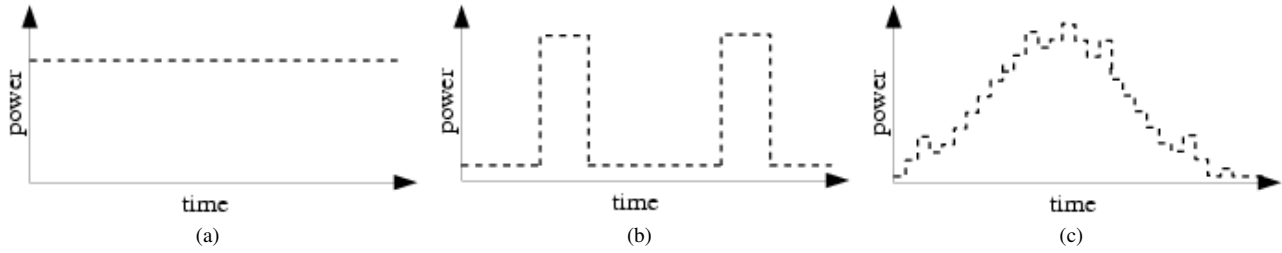
Figure 2: Simplified power level patterns used for household appliance classification.

Type	Appliance
A	**cold app.:** refrigerator, fridge-freezer, upright freezer, chest freezer **computer:** fax/printer **others:** door bell, smoke detector
B	**audiovisual:** set top box, speakers **computer:** modem, router, multifunction printer
C	**audiovisual:** television (CRT, LCD, plasma), hi-fi, DVD recorder, home cinema, VCR, games consoles (PS3, Xbox 360, Wii, box), DVD player, radio, CD player, blu-ray player **computer:** desktop, monitor, laptop, printer, scanner
D	**washing:** washing machine, washer-dryer, clothes dryer, dishwasher **cooking:** bread maker, yoghurt maker **space heat.:** electric space heating, additional space heating **water heat.:** electric water heating, additional water heating **others:** iron, vacuum cleaner, trouser press, sewing machine
E	**cooking:** oven, cooker, hob, microwave, kettle, food steamer, fryer, coffee machine, bottle warmer, toaster, grill, extractor hood, food mixer **others:** steriliser
F	lighting, photovoltaic panel
G	**others:** charger, cordless phone
H	**others:** dehumidifier, aquarium, pond pump, house alarm, vivarium, fan, clock radio, digital picture frame, baby monitor
I	**others:** organ, hair straightener, paper shredder, sun bed, electric blanket

Table 1: Classification of household appliances considered in the proposed consumer energy demand model.

for workdays and holidays[3] as well as the seasonal effect on the daily appliance usage, was extracted from [32]. Further data such as power level during operation, power level in standby mode and duration of operation cycle was gathered from freely available technical specifications. Besides, each appliance was classified according to the usage type and the appliance definition was completed with the estimated ratio of devices switched to standby mode after usage with respect to the total number of devices. Table 1 shows the classification for the 85 common household appliances, including photovoltaic panels where the generation is represented by a negative energy consumption, considered in the proposed consumer demand model.

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[3]On the one hand, the daily average load curves for workdays and holidays can be easily transformed into the time of use (TOU) probabilities by means of a simple normalisation procedure. On the other hand, the ratio between the sums of the two average load curves represents the distribution of the appliance use regarding workdays and holidays.

4.2. Household configuration

The consumer demand model configures in a first step the households to be used in the generation of consumption data. For most appliance types, the number of devices per household is determined by means of a probabilistic approach. However, in the case of a few specific appliances exceptions in the household configuration have been considered.

The probabilistic approach used to calculate the number of devices in a household is based on the binomial distribution given by $B(\eta, \rho)$ where η denotes the maximum number of devices of a certain appliance type per household. The parameter ρ is defined as the average number υ of devices per household divided by η, i.e. $\rho = \upsilon/\eta$. The binomial distribution has been chosen due to the possibility to generate discrete, non-negative numbers around a desired mean value υ. Furthermore, the associated variance $\eta\rho(1 - \rho)$ leads to a suitable dispersion when dealing with the ownership of household appliances.

The most important exception deals with the assumption that every household possesses electric lighting because of being such an essential appliance. The mutual exclusion of gas fuelled and electric devices for one and the same appliance type in a household is another exception and applies to ovens and hobs. Furthermore, the sum of electric and gas space heaters as well as the sum of electric and gas water heaters has been limited to one device per household.

In the last step of the configuration procedure a probabilistic approach is used to define for each appliance in a household the operational state in non-use periods, i.e. if a device is just switched off after use or set to standby mode, and the corresponding energy demand. The chosen approach is based on the Bernoulli distribution $B(\rho)$ where the probability parameter ρ corresponds to the ratio ψ of devices switched to standby mode after use with respect to the total number of devices, i.e. $\rho = \psi$. Depending on this initial configuration, an appliance is always switched off or always switched to standby.

It is important to mention that the consumer energy demand model offers the possibility to manually define the number of appliances in the households if a specific set of households has to be simulated. This procedure allows the generation of consumption data for predefined households without any variance in the appliance ownership.

4.3. Daily appliance use

In a second step, the consumer energy demand model determines the daily usage for each appliance in a household, i.e.

whether and how often a device is used on a particular day. With a few exceptions, the daily use of the considered appliances is computed with discrete probability distributions.

For most appliances the chosen probabilistic approach is based on the binomial distribution $B(\eta, \rho)$ where the parameter η denotes the maximum number of daily operation cycles. The parameter ρ is defined as the average number of cycles per day ν divided by η, i.e. the parameter is given by $\rho = \nu/\eta$. The use of this distribution generates integer numbers between 0 and η with a mean value of ν. For a few appliances with considerably long duty cycles, mainly audiovisual and computer devices, the daily use is computed taking into account an upper limit of one cycle per day. This limitation is easily included using $\eta = 1$ and leads to a reduction of the used binomial distribution to the Bernoulli distribution $B(\rho)$.

One of the exceptions considered in the consumer demand model assumes that some appliances are used exactly once per day. These devices are frequently used in combination with timers and include, amongst others, aquariums, pond pumps and fans. Another exception deals with the group of appliances that are operated 24 hours a day and almost never switched off. This exception mainly applies to cold appliances, but also to devices such as smoke detectors and faxes. Note that lighting and photovoltaic panels have been included in the group of continuously running appliances where the power demand and energy generation vary in a large range throughout the day.

Seasonal variations in the frequency of use can be observed in a not insignificant number of appliances including devices for space and water heating, washing, cooking. The consumer demand model considers the mentioned seasonal effects by means of a variable average number of cycles per day $\nu_\kappa(n)$. This variable is given by $\nu_\kappa(n) = \kappa(n)\,\nu$ where $\kappa(n)$ denotes a seasonal factor and ν is the nominal average number of cycles per day, i.e. the seasonal influence is considered as a scaling of the nominal number of daily uses. The seasonal factor $\kappa(n)$ is a quadratic function which can be written as:

$$\kappa(n) = \max\left\{\alpha + \beta \cdot x(n) + \gamma \cdot x(n)^2, 0\right\} \qquad (1)$$

where α, β and γ are parameters. The function $x(n) = (2n - 366)/364$ depends on the variable n which denotes the n-th day of the year. Starting with a value of $x(1) = -1$ (1st January), the value of the function growths linearly to $x(365) = 1$ (31st December). The parameters α, β and γ depend strongly on the seasonal influence and can vary in a wide interval. For a constant appliance use over the entire year values of $\alpha = 1$, $\beta = 0$ and $\gamma = 0$ are used. In the case of a significant seasonal influence, these parameters have to be adjusted to consider the variations over the year, e.g. space heating can be expressed with $\alpha = -0.8$, $\beta = 0$ and $\gamma = 3.08$. Finally, the variable average number of cycles per day $\nu_\kappa(n)$ is used in the binomial distribution $B(\eta, \rho)$ with $\rho = \nu_\kappa(n)/\eta$ and leads to a variation in the daily cycles during the year[4].

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[4]Note that the variable average number of cycles per day $\nu_\kappa(n)$ is not used for appliances which are used exactly once or for devices with an upper limit of one cycle per day. For these appliances the seasonal effect is included in the duration of the operation cycles, see Section 4.4.

4.4. Energy demand time series

In the last step, the consumer demand model determines the time of use for each appliance in a household. For the proposed model, a sampling time of 15 minutes has been chosen. This sampling time represents a trade-off between the precision of the power curve and the resulting amount of data. It was proven that sampling times of 1 minute or shorter are suitable to capture the fine details of household load patterns [33]. In contrast, most of the currently installed smart meters log the consumption data hourly, half-hourly or at 15 minutes intervals [19]. Furthermore, a sampling time of 15 minutes for the aggregate residential consumption data is adequate for its use in network management based on economic dispatch as energy markets commonly operate with intervals of 30 minutes or longer. However, the sampling time in the proposed consumer energy demand model can be easily changed if more precise data is required.

The exact time of use is computed for most appliances with the aid of a general discrete distribution based on the time of use probability of the considered device. The general discrete distribution, which can be easily generated comparing a random variable u from the continuous uniform distribution $U(0, 1)$ with the cumulative time of use probability [34], provides the exact starting sample of the appliance operation. Note that the normalised daily average load curve, which is part of the basic appliance definition (see Section 4.1), corresponds to the time of use probability. During the determined starting sample and the following samples, where the number of samples depends on the cycle duration, the appliance is in use and its power demand corresponds to the power level during operation given by the initial appliance definition. In the case that an appliance is used more than once a day, the procedure is repeated several times taking into account that operation cycles must not overlap.

One of the exceptions considered in the generation of the energy demand time series deals with appliances operated at the same time every day. The operation times for these appliances are computed only once for workdays and once for holidays using the previously described probabilistic approach based on the cumulative time of use probabilities. The obtained operation times are then extended to all days of the considered period and guarantee that these appliances are always used at the same time. For lighting and photovoltaic panels, which are supposed to be in permanent operation, the power demand in each sample is given by the corresponding element of the daily average load multiplied with the factor λ. The generation of the mentioned factor is done using the log-normal distribution $\Lambda(\mu, \sigma^2)$ with $\sigma = 0.2$ and $\mu = -\sigma^2/2$ [35]. The log-normal distribution generates non-negative, continuous random numbers around the mean value $e^{\mu + 0.5\,\sigma^2}$, i.e. with the given σ and μ a mean value of one has been used. In the case of the other continuously running appliances a constant power level throughout the entire day has been assumed.

Furthermore, the seasonal variation in the cycle duration of some appliances has been included in the consumer energy demand model. Under consideration of the seasonal effects, the
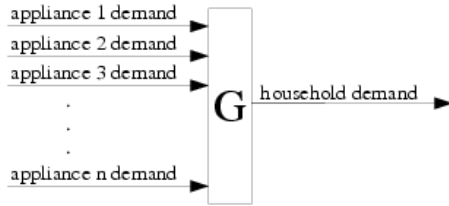
Figure 3: Schematic scheme of the individual appliance demands and the resulting overall household demand.

Figure 4: Daily average demand resulting from different electric lighting types in an example household.

variable cycle duration is given by $\tau_\kappa(n) = \kappa(n)\,\tau$ where $\kappa(n)$ represents a seasonal factor (1) and τ denotes the nominal cycle duration. Note that the seasonal variation in the cycle duration is applied only to appliances used exactly once or with an upper limit of one cycle per day. For all other appliances seasonal effects have been already considered by means of a variable average number of cycles per day $\nu_\kappa(n)$ (see Section 4.3). Finally, the overall household demand is the sum of the individual demands generated by the appliances in a household (see Fig. 3).

Note that consumer energy demand model does not consider the effect of appliance degradation over time. Nevertheless, the model can be easily extended to include the influence of such a degradation on residential energy consumption.

4.5. Model implementation

The developed consumer demand model was implemented in Matlab using the general structure shown in Fig. 1 and the previously mentioned sampling time of $t_s = 15$ min. The program uses the basic appliance definitions given in Section 4.1 and is based on the steps described in Sections 4.2, 4.3 and 4.4. The parameters of the appliances, taken from [32], are read from an external spread sheet at the beginning of the program execution. New appliances to be considered by the consumer demand model can be added easily including their basic information in the mentioned spread sheet. The implemented program provides a large flexibility in the data generation with respect to the number of households and the observation period.

5. Application examples

The proposed consumer demand model has been developed with an intention of providing a new tool for creation and validation of new services and applications offered to either energy end-users or energy providers. A customer service demonstrating effects of modified user behaviour and an aggregated demand optimisation algorithm have been selected as two possible illustrations of the application development process based on the model and will be presented in this section.

5.1. Effects of a modified user behaviour

Detailed insight into the appliance use in a household and the related customer behaviour can be gathered from residential consumption data. The possible effects of changes in the user behaviour or the appliance configuration can be simulated with the developed consumer demand model introducing parametric modifications in the basic appliance definitions.
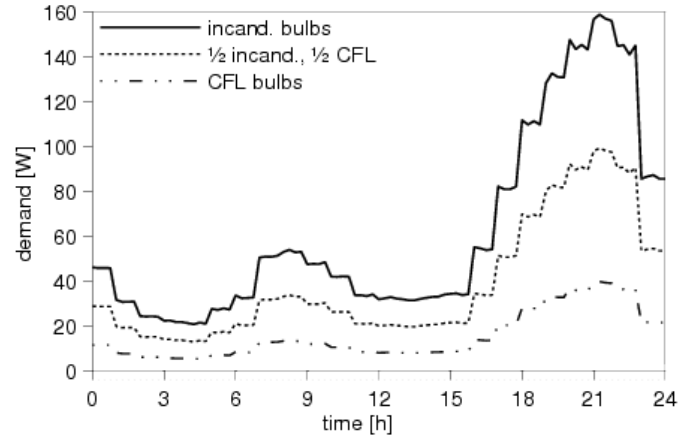
Residential consumption data allows analysing the demand of each appliance or group of appliances in a household such as cold, washing or cooking appliances. Additional information provided by the customer (e.g. appliance type and daily use) as well as data from households with similar configurations give an idea about the efficiency of the appliances used in a certain household. A service to demonstrate to customers the effect of replacing inefficient appliances by new devices which comply with current industrial standards has been developed by using the proposed model. The mentioned effect can be simulated easily by modifying the annual energy consumption and the power level during the appliance operation (and standby) and by introducing the basic appliance definitions of the consumer demand model (see Section 4.1). In order to give an illustrative example, the power consumption of different lighting types has been analysed for an example household (see Fig. 4). The results generated with the customer service based on the consumer demand model compare the daily average demand for three cases: only incandescent light bulbs, only compact fluorescent light (CFL) bulbs and an intermediate scenario (50 % incandescent light bulbs, 50 % CFL bulbs). For the considered example household a replacement of the traditional bulbs by compact fluorescent lamps reduces the annual energy consumption of electric lighting from 544 kWh to 136 kWh. Although the intermediate scenario is not the optimal case, the partial replacement of the incandescent light bulbs leads to an annual energy consumption of 340 kWh. This customer service, based on the proposed consumer demand model, provides the opportunity to illustrate the effect of replacing obsolete appliances in order to achieve an increased household energy efficiency.

Residential energy demand usually shows significant variations over a day due to increased use of some appliances at certain hours, e.g. lighting in the evening and cooking appliances around meal times. The local energy production of photovoltaic panels can lead to an additional mismatch between the consumption and the generation and, as a consequence, reinforce the variations in the resulting residential demand. Here, the proposed consumer demand model has been used to develop an application to show the direct influence of the customer be-
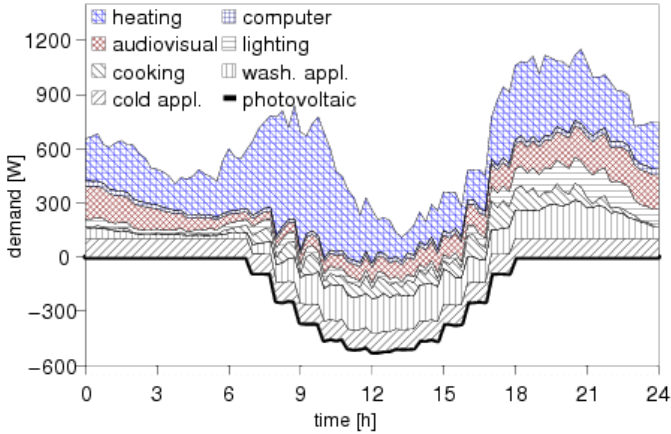
Figure 5: Daily average demand created by the proposed consumer demand model for an example household with PV installation.
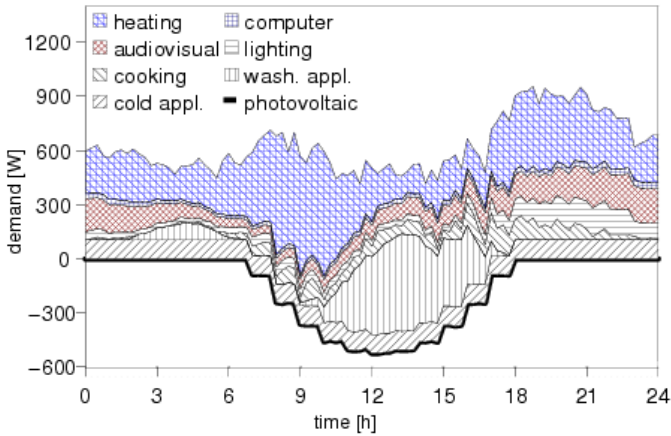

Figure 6: Daily average demand for an example household after a change in the customer behaviour related to the use of washing appliances.

haviour on the residential load. In this application, the effects of changes in the customer behaviour can be simulated modifying the time of use (TOU) probabilities in the basic appliance definitions of the proposed model. These modifications in the customer behaviour related to the usage of household appliances provide us with an opportunity to achieve certain demand curve shaping, especially a demand flattening. As an application example the possible changes in the daily average demand of a household with PV installation has been studied. The original demand of this household, where the power production of the photovoltaic panel has been considered as a negative consumption, shows a very low level at midday and a generally high variation throughout the day (see Fig. 5). For the same example household the usage of washing appliances was limited to periods from 2 am to 4.45 am and from 9 am to 3.45 pm. In the obtained results, given in Fig. 6, it can be observed that the changed user behaviour considerably reduced the demand variations during the day. The application developed on top of the consumer demand model can be further used by end-users or energy companies to analyse the effect of possible modifications in the customer habits.

The proposed consumer demand model allows a better development and validation of new services and applications for the different participants in the energy market. In the presented examples, the model was used to demonstrate the effects of modifications in the appliance configuration (replacement of light bulbs) and the customer behaviour (use of the washing appliances only at certain hours). The obtained results underline the opportunities provided by the model and the significance of detailed consumption data for the improvement of energy efficiency in the residential sector.

5.2. Aggregated demand optimisation

This section demonstrates an application of the proposed consumer demand model in the quantitative evaluation of the benefits of aggregated demand optimisation to the energy provider and customer. The used demand management is based on a distributed real-time optimisation approach. The algorithm solves in each sample a multi-objective optimisation problem which includes both user and energy provider objectives expressed by economic cost functions.

We consider a smart power network comprising a set of users served by an energy provider who participates in the wholesale energy market. Each user is equipped with a smart meter capable of scheduling energy consumption of appliances, and smart meters are connected to the energy provider via a communication link. It is assumed that each user operates a set of appliances including photovoltaic installations over a finite scheduling horizon. In the demonstration of the aggregate demand optimisation, a horizon of 24 hours divided into timeslots of 15 minutes is used. Each appliance requires a predetermined amount of energy during the scheduling horizon, and can operate between a minimum and maximum power level at every timeslot.

By using the established communication links the energy providers are in position to create and apply more personalised tariffs for either individual users or an aggregated group of users. In this particular case, the real-time (dynamic) pricing is assumed to be applied to the group of customers in this example. The tariffs are used as an incentive offered to the customers to minimise their own electricity costs that will at the same time help the energy provider to reduce its own cost of purchasing the electricity in the market at peak times. In other words, to minimise their own costs the energy provider will incentivise the customer (by using tariffs) to consider shifting their load out of the peak times.

Fig. 7 shows a schematic diagram of the interconnections between the consumer demand model and the demand optimisation. After determining the daily appliance use, i.e. how many times an appliance is used, the exact time of use of the controllable appliances is computed by using the demand optimisation algorithm. For all the other appliances (non-controllable appliances) the time of use is calculated with the probabilistic approach of the consumer demand model. Finally, the consumer demand model computes the energy demand time series for both controllable and non-controllable appliances and the resulting household demand.
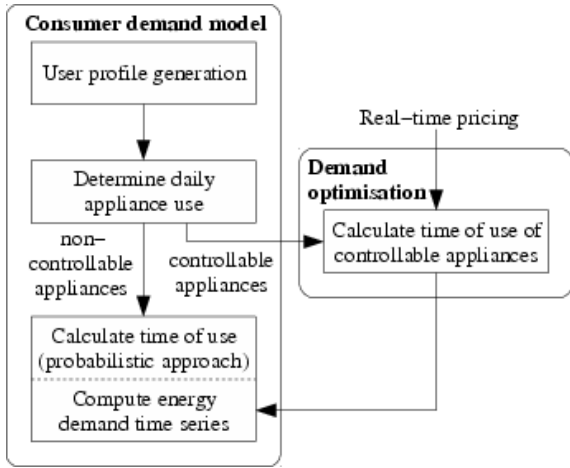
8

Figure 7: Structure of the connection between consumer demand model and optimisation algorithm.
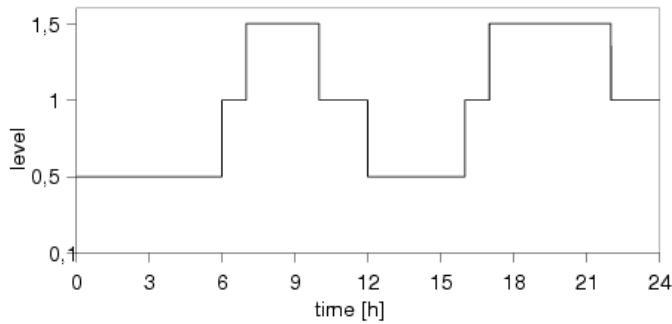

Figure 8: Time-dependent electricity tariff with three different price levels: low (l), medium (m) and high (h).
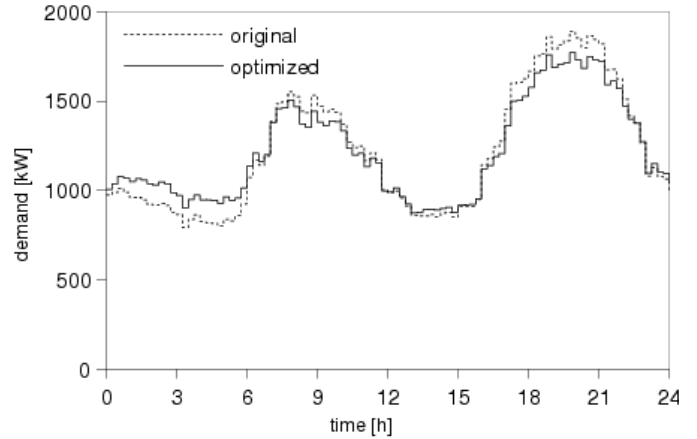

Figure 9: Comparison of the aggregated load of 1000 domestic users for one day before (dotted line) and after demand optimisation (solid line).
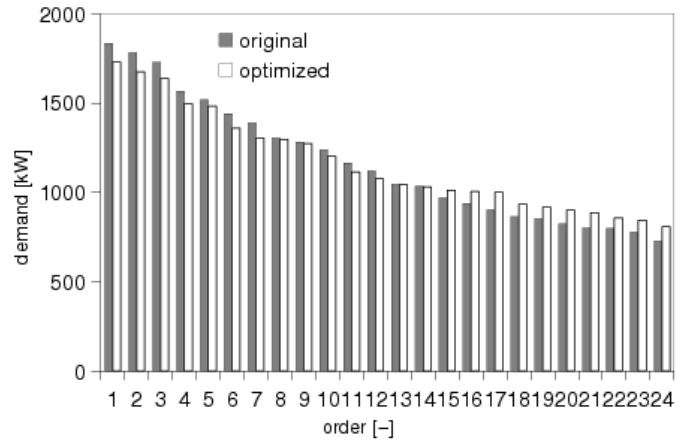

Figure 10: Aggregated load of 1000 domestic users for one day before and after demand optimisation sorted in descending order of hourly average values.

Fig. 8 shows the time-based pricing scheme for electricity used in the optimisation of the aggregated demand of 1000 domestic users. The tariff has three different price levels (low, medium, high) for off-peak, mid-peak and peak periods. The daily distribution of the different levels is 41.7 %, 25 % and 33.3 % for off-peak, mid-peak and peak periods, respectively.

A comparison of the aggregated demand of 1000 users with and without demand optimisation is given in Fig. 9. In both cases, the results have been obtained with the same set of households and for the same day. It can be observed that the optimisation algorithm shifts the demand from on-peak to off-peak periods leading to a higher demand in low price periods and a lower demand during high price periods. During the demand optimisation, washing devices (washing machine, clothes dryer, washer dryer and dish washer) have been considered as controllable appliances (fully shiftable in time). The used optimization algorithm can shift the operation of these appliances within the same day, i.e. the daily energy demand of the controllable appliances is not modified. Furthermore, the power level for the cold devices (refrigerator, fridge freezer, upright freezer and chest freezer) has been varied between 90 % and 110 % of the nominal value.

In Fig. 10 the hourly average of the aggregated load of 1000 domestic users has been sorted in descending order. It can be observed that the optimisation approach reduced the maximum value at peak hours (from 1834.1 kW to 1728.4 kW, i.e. a reduction of 5.8 %) and increased the minimum value at off-peak hours (from 725.9 kW to 807.5 kW, i.e. an increase of 11.2 %).

The peak-to-average ratio for the shown aggregated results has been reduced about 5.1 %. This is an important reduction as it directly contributes to reduced marginal costs of energy at the peak times in the electricity markets. This in turn brings additional disproportionate cost savings to the energy providers and indirectly the consumers involved in the scheme.

6. Conclusions

Availability of detailed residential energy consumption data incentivises the creation of novel services and applications offered to all the participants in the energy market: utilities, distributors and end-users. Although deployment of smart meters is carried out in many areas, unresolved legal and technical questions have a negative effect on the access to the measurements and consequently the development of new services. An alternative solution to avoid these problems is to use an

application-oriented demand model for the generation of detailed residential consumption data that has been developed and presented in this paper. The proposed energy demand model is based on a probabilistic approach and takes into consideration the contributions of a wide range of common household appliances. The data generation process uses 15 minutes sampling time intervals and can be carried out for a single household or for an entire neighbourhood. The synthetic data generated by the model are suitable for creation and validation of value-added services for the energy sector. In order to keep the complexity as low as possible, the effects of appliance degradation, inter-dependency of appliances and vacation periods were not included. Besides, the consumer energy demand model does not consider any influence of external factors such as ambient temperature.

The flexibility offered in generation of the energy consumption data (from single households to entire neighbourhoods) and the level of detail (considering a large number of appliances) distinguishes the proposed model from any other models available in the scientific literature. These features allow generation of consumption data suitable for the development and validation of value-added services for end-users and companies and have been demonstrated by using two test examples.

The first example focused on the effects of the user behaviour in a single household and a possible service offered to the final customer. In this application it has been demonstrated how the model can be used to identify the cost savings opportunities. In the second example, the benefits for both the energy provider and a customer group of an application of the real-time pricing scheme were examined. The model was used along with an demand optimisation tool and the flexibility of modifying the time of use and controlling the appliances were demonstrated. All the obtained results indicated that the prosed model and the generated residential consumption data are suitable for the creation of new services and applications with advanced functionality.

Acknowledgement

[1] J. Iwaro, A. Mwasha, A review of building energy regulation and policy for energy conservation in developing countries, Energy Policy 38 (12) (2010) 7744–7755.

[2] A. H. C. dos Santos, M. T. W. Fagá, E. M. dos Santos, The risks of an energy efficiency policy for buildings based solely on the consumption evaluation of final energy, International Journal of Electrical Power & Energy Systems 44 (1) (2013) 70–77.

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

[4] D. Wiesmann, I. L. Azevedo, P. Ferrão, J. E. Fernández, Residential electricity consumption in Portugal: Findings from top-down and bottom-up models, Energy Policy 39 (5) (2011) 2772–2779.

[5] M. Kavgic, A. Mavrogianni, D. Mumovic, A. Summerfield, Z. Stevanovic, M. Djurovic-Petrovic, A review of bottom-up building stock models for energy consumption in the residential sector, Building and Environment 45 (7) (2010) 1683–1697.

[6] T. Fleiter, E. Worrell, W. Eichhammer, Barriers to energy efficiency in industrial bottom-up energy demand models - A review, Renewable and Sustainable Energy Reviews 15 (6) (2011) 3099–3111.

[7] T. S. Blight, D. A. Coley, Sensitivity analysis of the effect of occupant behaviour on the energy consumption of passive house dwellings, Energy and Buildings 66 (2013) 183–192.

[8] R. V. Andersen, J. Toftum, K. K. Andersen, B. W. Olesen, Survey of occupant behaviour and control of indoor environment in Danish dwellings, Energy and Buildings 41 (1) (2009) 11–16.

[9] B. Howard, L. Parshall, J. Thompson, S. Hammer, J. Dickinson, V. Modi, Spatial distribution of urban building energy consumption by end use, Energy and Buildings 45 (12) (2012) 141–151.

[10] H. x. Zhao, F. Magoulès, A review on the prediction of building energy consumption, Renewable and Sustainable Energy Reviews 16 (6) (2012) 3586–3592.

[11] I. Richardson, M. Thomson, D. Infield, C. Clifford, Domestic electricity use: A high-resolution energy demand model, Energy and Buildings 42 (10) (2010) 1878–1887.

[12] J. Dickert, P. Schegner, A time series probabilistic synthetic load curve model for residential customers, in: Proceedings of the 2011 IEEE Trondheim PowerTech, Trondheim, Norway, 2011, pp. 1–6.

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

[14] E. Ampatzi, I. Knight, Modelling the effect of realistic domestic energy demand profiles and internal gains on the predicted performance of solar thermal systems, Energy and Buildings 55 (2012) 285–298.

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

[16] M. M. Armstrong, M. C. Swinton, H. Ribberink, I. Beausoleil-Morrison, J. Millette, Synthetically Derived Profiles for Representing Occupant-Driven Electric Loads in Canadian Housing, Journal of Building Performance Simulation 2 (1) (2009) 15–30.

[17] J. V. Paatero, P. D. Lund, A model for generating household electricity load profiles, International Journal of Energy Research 30 (5) (2006) 273–290.

[18] J. Vasconcelos, Survey of Regulatory and Technological Developments Concerning Smart Metering in the European Union Electricity Market, Tech. rep., Robert Schuman Centre for Advanced Studies - European University Institute, Fiesole, Italy (2008).

[19] E. McKenna, I. Richardson, M. Thomson, Smart meterdata: Balancing consumer privacy concerns with legitimate applications, Energy Policy 41 (2012) 807–814.

[20] P. S. Moura, A. T. de Almeida, The role of demand-side management in the grid integration of wind power, Applied Energy 87 (8) (2010) 2581–2588.

[21] P. Finn, M. O'Connell, C. Fitzpatrick, Demand side management of a domestic dishwasher: Wind energy gains, financial savings and peak-time load reduction, Applied Energy 101 (2013) 678–685.

[22] S. Tiptipakorn, W.-J. Lee, A residential consumer-centered load control strategy in real-time electricity pricing environment, in: Proceedings of the 39th North American Power Symposium (NAPS '07), Las Cruces, NM, 2007, pp. 505–510.

[23] A.-H. Mohsenian-Rad, A. Leon-Garcia, Optimal Residential Load Control With Price Prediction in Real-Time Electricity Pricing Environments, IEEE Transactions on Smart Grid 1 (2) (2010) 120–133.

[24] A.-H. Mohsenian-Rad, V. W. S. Wong, J. Jatskevich, R. Schober, A. Leon-Garcia, Autonomous demand-side management based on game-theoretic energy consumption scheduling for the future smart grid, IEEE Transactions on Smart Grid 1 (3) (2010) 320–331.

[25] K. C. Armel, A. Gupta, G. Shrimali, A. Albert, Is disaggregation the holy grail of energy efficiency? The case of electricity, Energy Policy 52 (2010) 213–234.

[26] S. S. S. R. Depuru, L. Wang, V. Devabhaktuni, Smart meters for power grid: Challenges, issues, advantages and status, Renewable and Sustainable Energy Reviews 15 (6) (2011) 2736–2742.

[27] P. Järventausta, S. Repo, A. Rautiainen, J. Partanen, Smart grid power system control in distributed generation environment, Annual Reviews in Control 34 (2) (2010) 277–286.

[28] V. Bassilious, C. S. Özveren, A. P. Birch, Using Smart Metering for Load

Aggregation: Towards an Integrated Smart Grid/Active Network Management Framework, in: Proceedings of 2011 46th International Universities' Power Engineering Conference (UPEC), Soest, Germany, 2011, pp. 1–6.

[29] G. A. Taylor, C. J. Axon, M. R. Irving, Scalable high performance information and communications technology for smart distribution network operation, in: Proceedings of the 2012 IEEE Power and Energy Society General Meeting, San Diego, CA, 2012, pp. 1–8.

[30] B. Römer, P. Reichhart, J. Kranz, A. Picot, The role of smart metering and decentralized electricity storage for smart grids: The importance of positive externalities, Energy Policy 50 (2012) 486–495.

[31] J. K. Gruber, M. Prodanovic, Residential Energy Load Profile Generation Using a Probabilistic Approach, in: Proceedings of the 2012 Sixth UKSim/AMSS European Symposium on Computer Modeling and Simulation (EMS), Valletta, Malta, 2012, pp. 317 –322.

[32] J.-P. Zimmermann, M. Evans, J. Griggs, N. King, L. Harding, P. Roberts, C. Evans, Household Electricity Survey: A study of domestic electrical product usage, Tech. rep., Department for Environment, Food and Rural Affairs - Department of Energy and Climate Change – Energy Saving Trust, Milton Keynes, UK (2012).

[33] A. Wright, S. Firth, The nature of domestic electricity-loads and effects of time averaging on statistics and on-site generation calculations, Applied Energy 84 (4) (2007) 389–403.

[34] J. F. Monahan, Numerical Methods of Statistics, 2nd Edition, Cambridge University Press, New York, NY, 2011.

[35] E. L. Crow, K. Shimizu, Lognormal Distributions: Theory and Applications, Marcel Dekker Incorporated, New York, NY, 1988.