Energy and Buildings 112 (2016) 121–129

Contents lists available at ScienceDirect

Energy and Buildings

journal homepage: www.elsevier.com/locate/enbuild

Bottom-up Markov Chain Monte Carlo approach for scenario based residential load modelling with publicly available data

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ARTICLE INFO

Article history:
Received 25 May 2015
Received in revised form 23 October 2015
Accepted 4 December 2015
Available online 9 December 2015

Keywords:
Residential energy consumption modelling
Electricity consumption
Occupancy
Household appliance
Markov Chain
Load curves

ABSTRACT

In the residential sector, with the introduction of electric vehicles and photovoltaics, developments are taking place which have an impact on residential load curves. In order to assess the integration of these new types of technologies on both the generation and load side, as well as to develop mitigation strategies like demand side management, detailed information is required about the load curve of a household. To gain knowledge about this load curve a residential load model is developed based on publicly available data. The model utilises a Markov Chain Monte Carlo method to model the occupancy in a household based on time use surveys, which together with weather variables, neighbourhood characteristics and behavioural data are used to model the switching pattern of appliances. The modelling approach described in this paper is applied for the situation in the Netherlands. The resulting load curve probability distributions are validated with smart meter measurements for 100 Dutch households for a week. The validation shows that the model presented in this paper can be employed for further studies on demand side management approaches and integration issues of new appliances in distribution grids.

1. Introduction

The energy transition is changing the loading of the distribution grid especially in residential areas. With distributed generation consumers are becoming producers and the electrification of heat and transportation shifts the energy demand from fossil fuels to electricity. The current practices of grid development employed by network operators needs to be adjusted to ensure efficient integration of new loads and generation technologies and to reap the benefits of demand side management. However the current modelling of residential loads is not accurate enough to assess these problems and opportunities [1], as the energy transition and demand side management alter the diversity and stochastic characteristics of the household load curve. With the installation of smart meters more opportunities arise to validate a residential load modelling approach, while the need for modelling remains present from the perspective of forecasting, long-term planning and due to privacy concerns about smart meter data.

In the literature models have been presented for the estimation of the residential load curve. These models can be divided into roughly two basic categories: Top-down models; which focus on the loading of MV/LV transformers and generate load curves based on this aggregation level [2] and bottom-up methods which employ statistical energy usage data or time use data to construct load profiles. There are many different approaches when it comes to building the bottom-up models. These bottom-up models can be combined with the top-down models through smart meter data [3,4]. Machine learning approaches are applied to model household load curves based on smart meter data measurements [5,6]. The residential load curve can also only be modelled at the peak times [7,8]. The modelling of household load over multiple decades requires an adjusted modelling approach, for instance based on how typiclose all cal households, behaviour and appliances change over scenarios [9]. More in-depth reviews of these different household load curve models have been performed [10,11].

The integration of distributed generation creates a voltage rise which is the main problem in distribution grids [12]. To assess the level of the voltage a more in depth assessment than just the peak load is required. The bottom-up time series approach is the most adequate for the modelling of residential load curves in order to assess the integration of distributed generation. To be able to assess the impacts of DSM, information on the appliance level needs to be known. The changes in the loading because of the shift in appliance usage depend on the actual appliances which is shifted. Demand side management approaches are generally based on information on the appliance level (e.g. [13,14]). A bottom-up household load

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http://dx.doi.org/10.1016/j.enbuild.2015.12.004
0378-7788/

Nomenclature

$\mathbb{A}$	set of appliances used in model
$\mathbb{A}_H$	set of appliances present in household
A	appliance
$f_{t,A}$	fraction of time appliance A is on
f_A	fraction of households with appliance A
hr	hour
$I(t)$	irradiance
L_A	average lifetime of appliance A
l_A	remaining lifetime of appliance A
O	occupancy
$P_H(t)$	household power use
$P_A(t)$	power used by appliance A
$P_{R,A}(t_A)$	power of appliance A while running during time t_A
$P_{S,A}$	stand-by power of appliance A
r_h	household size adjustment factor
r_w	household wealth adjustment factor
t	time
t_0	initial time shift
t_A	time after which the appliance A became active
T_w	wind speed adjusted temperature
$t_{A,m}$	minimum run time of appliance A
$t_{A,r}$	average run time of appliance A
$T_{h/c}$	heating/cooling temperature
$n[\mu, \sigma]$	random variable from normal distribution $\mathcal{N}(\mu, \sigma)$
$u[a, b]$	random variable from uniform distribution over interval [a, b]
$x[\lambda]$	random variable from exponential distribution $exp(\lambda)$

modelling approach is therefore a logical choice for the assessment of demand side management (since the bottom-up approach allows for the shifting of individual appliances). Different value propositions exist for demand side management of residential loads, based on the self-consumption, electricity price or network loading. Therefore the residential load curve should be adaptable for many different scenarios, for the model to be usable when assessing future possibilities for demand side management. The bottom-up time series approach may be found in a number of references [15–20], however these approaches either focus on a limited aspect of the residential load, use private data or do not allow for the inclusion of scenarios.

The approach shown in [16] is based on a large database of measurements of appliances in a household and as this information is usually not publicly available, this approach cannot be taken. The approach described in [17] focuses on the heating load, which is appropriate for areas with electric heating, however as the Netherlands has a fairly small percentage of electric heating loads, these kind of approaches lack the required level of detail for the non-heating loads. The approach described in [19], is not designed for load modelling over multiple decades and is therefore hard to use in grid development. With the approach used in [18] assumptions have to be made on the switching behaviour of loads. This is not necessary in the approach described in this paper since statistical data from time use surveys are available in many countries [21].

The paper is organised as follows: Section 2 describes the modelling approach, followed by the modelling of the occupancy of a household and the modelling of the appliances in the household. In Section 3 the results of the model for a typical neighbourhood in the Netherlands are presented and the model is validated using smart meter measurements. Conclusions are given in Section 4.

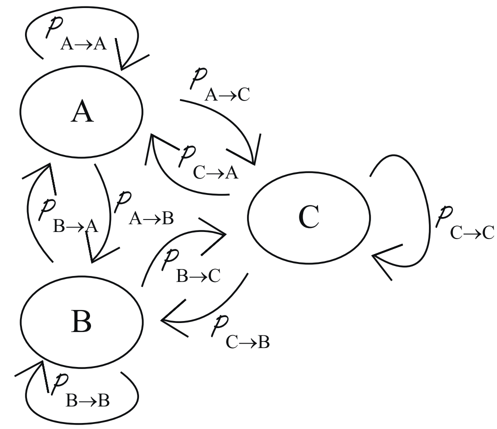

Fig. 1. General schematic of a Markov Chain model with three states.

2. Modelling approach

The proposed modelling approach is based on the occupancy of the household, and to a lesser extent the behaviour of the members of the household. This approach is taken as occupancy is a driving factor for energy usage [22] and the changes in occupancy play an important role in the changes in energy consumption. The occupancy is modelled based on a Markov Chain Monte Carlo method (an explanation on Markov Chain Monte Carlo modelling is given in [23]). In Fig. 1 a schematic of a generic Markov Chain model is given with probabilities $\mathcal{P}$ of changing from one state to the other. At each time instance depending on the current state and the associated probabilities the model switches to another state or remains in the current state.

Next to the occupancy of a household the set of electrical appliances in a household and their energy use need to be modelled. This is done by creating a model for the distribution of appliances over the household based on statistical data on appliance ownership and the level of wealth in the neighbourhood and size of the dwelling. These were identified as key drivers for the degree of appliance ownership within a household [24,25].

After the occupancy of a household has been established and appliances assigned to the household the simulation of the electricity usage patterns for the appliances can be performed. This is done by simulating the switching on/off of each appliance individually using another Markov Chain based on the time of day and the weather conditions.

A flow chart of the model is presented in Fig. 2 to illustrate the computation of the load curves. The flow chart starts on the left with the inputs of the model, where the ellipses are national/state-wide inputs and the rounded rectangles are local inputs. In the following subsections the steps are explained in more detail.

2.1. Occupancy modelling

To get a better understanding of the occupancy, the occupancy profile as reported in a time use survey (2042 respondents, reporting their behaviour at a 15 min time interval, available from the Dutch national statistics agency: Statistics Netherlands) has been plotted in Fig. 3 for two consecutive days for three individual persons of different households. From this figure the large differences between the behaviour of the three persons becomes apparent. These differences will translate into differences in energy use, therefore it is important that the variation present in the occupancy is also incorporated into the model.

The first step in creating the occupancy model is determining the characteristics of a reported occupancy time series. As residents can be either active (at home and not sleeping) or inactive