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On the energy demands of small appliances in homes

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Abstract

Understanding the use of electrical appliances in households is crucial for improving the accuracy of electricity and energy loads forecasts. In particular, bottom-up techniques provide a powerful tool, not only for predicting demands considering socio-demographic characteristics of the occupants, but also to better resolve and implement demand side management strategies in homes.

With this purpose, a study of the temporal energy use of low-load appliances (meaning those whose annual energy share is individually negligible but relevant when considered as a group) has been carried out, with the longer term objective of finding a parsimonious approach to modelling them, and which considers an appropriate aggregation of appliances. In this work, a discrete-time stochastic process has been implemented for a specific classification of low-load appliances. More precisely, a time-inhomogeneous Markov chain has been used to model energy variations over time for four different categories of appliances and its prediction capabilities have been tested and compared.

Keywords: residential energy demand; electrical appliance modelling; stochastic method; Markov;

1. Introduction

In predicting energy demands in buildings, electrical loads caused by the use of appliances play an important role. However, modelling the use of appliances is a complex task, given the diversity of appliances available and the variability of their use from one user to another. Broadly speaking, electrical appliances may be modelled using top-down strategies – modelling their aggregate use, possibly dependent on time – or using bottom-up strategies –

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modelling their time-dependent use, one by one. In this paper, we are interested in the latter, since our longer term objective is not only to predict aggregate temporal power demands considering individual household socio-demographic characteristics, but also to test demand-side management strategies.

Thus far, the bottom-up modelling of electrical appliances has focused on those devices that are commonly owned and used in households and which are individually relevant in terms of their share of annual energy use. Examples include cold appliances, cooking appliances, washing machines and dishwashers. But households also use a diverse range of low-load appliances in their everyday lives. Whilst these may individually use a negligible share of annual energy, their contribution is relevant when considered as a group (or groups), with consequent implications for aggregate power demand profiles.

This paper describes the first from a range of strategies to be employed in order to model the use of low-load appliances, in the search for a parsimonious approach. The strategy implemented thus far is based on a time-inhomogeneous Markov process, for a given aggregation of low-load appliances, which is conceived to dynamically model transitions in fractional energy use: $f \in [0,1]$, where f is the ratio of energy use to the maximum permissible (meaning it is limited by the appliance power rating) during a time step for a given appliance.

As implied above, the work presented here will be followed by the study of other different modelling strategies that consider various aggregations (and aggregation levels) of low-load appliances. This research will supplement previous efforts in modelling the use of high-load appliances and together with appliance ownership modelling, will support improved prediction of buildings' thermal and electrical energy demands as well as the design and control of low voltage networks and the testing of demand side management strategies for those devices that may be (partially) regulated autonomously.

The remainder of the paper is organized as follows: Section 2 presents related work on the topic; the dataset used and the mathematical tools implemented are described in Section 3; it is followed by the results and discussion of other techniques that could be applied; finally, Section 5 concludes with a summary.

2. Background

Many different approaches have been considered in modelling the use of electrical appliances, with applications in several research areas. Focusing on the bottom up techniques, different methodologies have been studied so far. One option is to relate the energy loads due to the use of electrical appliances to socio-economic characteristics, such as that described in [1, 2]. An alternative method was adopted by Page in [3], where the occupancy model developed is linked with the use of appliances. On the other hand, Time Use Survey datasets (TUS) where participants complete diaries of their daily activities have been widely employed to derive occupancy patterns and power use profiles [4]–[7]. Although the modelling of activities can be generated using static patterns [5] or dynamic models [6], usually fixed power conversion schemes are assigned depending on the type of appliance in order to obtain power consumption values.

A more refined methodology is studied by Jaboob et al. [8], where several approaches to model the use of appliances are tested. Apart from considering switch on events, the duration of use while appliances are on is modelled taking into account conditional probability to a related activity. More importantly, this modelling approach differentiates from those presented above in the capability of resolving for dynamic power variations whilst the appliances are being used by implementing Markov processes.

In our quest for parsimony our work is focused on identifying which of the above tasks needs to be modelled explicitly in the case of low-load appliances, finding also a suitable aggregation of appliances to which apply the modelling strategies.

3. Methodology

3.1. Household Electricity Survey dataset

The Household Electricity Survey is an exhaustive monitoring of electricity use carried out by the UK government, in which 250 households were recorded between 2010 and 2011. Twenty-six of those houses were monitored for a whole year with 10-minute energy use data, whereas the rest of households were monitored for one month with 2 minutes resolution. The study covers electricity consumption at appliance level, with a total of 254 different appliances, and a variety of typology and socio-demographic characteristics.

For the following reasons, only the annual data regarding the 26 household monitored for a whole year has been used. Firstly, the monthly data available for the other 224 households was not monitored during the same month of the year, leading to possible seasonal effects on the use of appliances. Secondly, since the use of small appliances is difficult to measure accurately, having ten-minute resolution minimizes the existence of inconsistent entries and outliers. However, the number of different appliances present in the 10-minutes subset of the data is reduced, potentially leading to loss of information. For this reason, future research will involve the consideration of the complete dataset, therefore modelling at a five times higher resolution.

The low-load appliances available to model are classified into four categories of small appliances: audiovisual appliances, computing appliances, kitchen appliances and a miscellaneous of other small appliances. The variety of appliances considered in each category, together with information about their contribution to annual energy is depicted in Figure 1. The height of the bars corresponds to the mean value of annual energy of the corresponding set of grouped appliances; the width is proportional to the number of instances recorded in the 26 houses (e.g. the kettle is a popular appliance present in 26 houses, while the AV receiver was found only in one household).

3.2. Modelling technique

As it was previously indicated, this paper describes one particular strategy for the dynamic modelling of groups of low-load appliances, aggregated as specified above, by means of a time-inhomogeneous Markov chain. It is relevant to mention that the first idea was to model variations in power demand, however, given the resolution and the nature of the data used, containing averaged energy use over ten minutes periods, it was found to be more significant to directly model the energy use variations.

The mathematical techniques adopted during the modelling process are explained below.

3.2.1 Modelling fractional energy demand

Fractional energy refers to the fraction of maximum energy f that is being consumed by a given appliance at certain period of time. This approach allows the comparison of the energy use fluctuations of appliances that may have different maximum rated power and consequently different ten-minute maximum energy use. The data is therefore transformed to temporal profiles of fractional energy, where $f \in [0,1]$.

Energy states result from the discretization of the fractional energy profiles. Eleven states were considered as a first approximation: ten linearly spaced states of 0.1 fractional energy width, plus a state corresponding to an off state of the device (fractional energy equal to zero). The modelling will be focused on the simulation of the

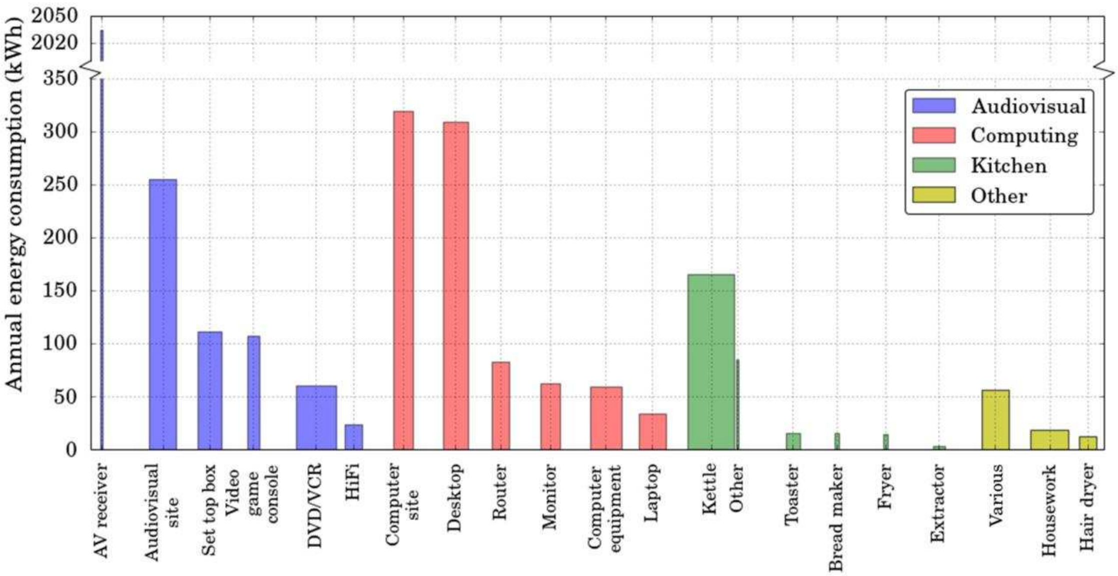

Figure 1. Annual energy use of the types of appliances considered in the modelling, divided in four categories: audiovisual, computing, kitchen and other. The height of the bars corresponds to the mean value of annual energy for the corresponding group, while the width is proportional to the number of times that the appliance was recorded in the dataset.

transitions between these energy states. A time-inhomogeneous Markov process is employed to do this.

In order to be able to obtain values of energy performance, the fractional energy states simulated must be converted first to a fractional energy profile f using the mean fractional power $\tilde{F}_s$ of each state, and second to the energy value using the maximum energy of appliances. Given that we are considering a group of appliances with different maximum rated powers, one simple approach is to multiply by a mean maximum energy $\tilde{M}$.

However, in our case rated power values were not available on the dataset, leading to a low estimation of the maximum energy values and consequently of $\tilde{M}$. For this reason, the capabilities of the model to forecast energy use are diminished, as will be shown below. Nevertheless, in a general case, maximum energy should be accurately known from the rated power of each of the appliances allocated.

3.2.2 Discrete-time Markov process

A Markov process is a memoryless stochastic process that fulfills the Markov property, by which predictions for the future of the process is only based on its present state and not on the previous history: $p_{ij}(t) = p(X(t+1) = j \mid X(t) = i)$. The probability of transition between a present state i to a future state j can be formulated as the ratio of transitions that occur to state j from i and the total number of transitions occurring from state i, as indicated in equation (1).

$$p_{ij}(t) = \frac{n_{ij}(t)}{\sum_j n_{ij}(t)} \tag{1}$$

Therefore, a transition probability matrix is defined as

$$P_{ij}(t) = \begin{pmatrix} p_{11}(t) & p_{12}(t) & \cdots & p_{1m}(t) \\ p_{21}(t) & p_{22}(t) & \cdots & p_{2m}(t) \\ \vdots & \vdots & \ddots & \vdots \\ p_{m1}(t) & p_{m2}(t) & \cdots & p_{mm}(t) \end{pmatrix} \tag{2}$$

for a set of m possible Markov chain states, giving a $m \times m$ dimension of the matrix in the case of a homogeneous Markov process, where transition probabilities does not have dependency with time. Alternatively, inhomogeneous Markov chains can be used to describe dependencies in the probability transitions with time; in this case, the matrix described in equation (2) will require a third axis that contains a number of $m \times m$ matrices equal to the number of time slots desired.

In the case we are concerned with, 11 energy states and 24 temporal states are taken into account, leading to a tensor of dimension $11 \times 11 \times 24$. One of the challenges when using Markov processes is to determine the existence of redundant calculations, when more states are defined than required or hourly matrices do not describe different behaviours. A procedure to deal with this is the use of cluster analysis techniques, in order to find the number of steps and time slots strictly needed for the modelling.

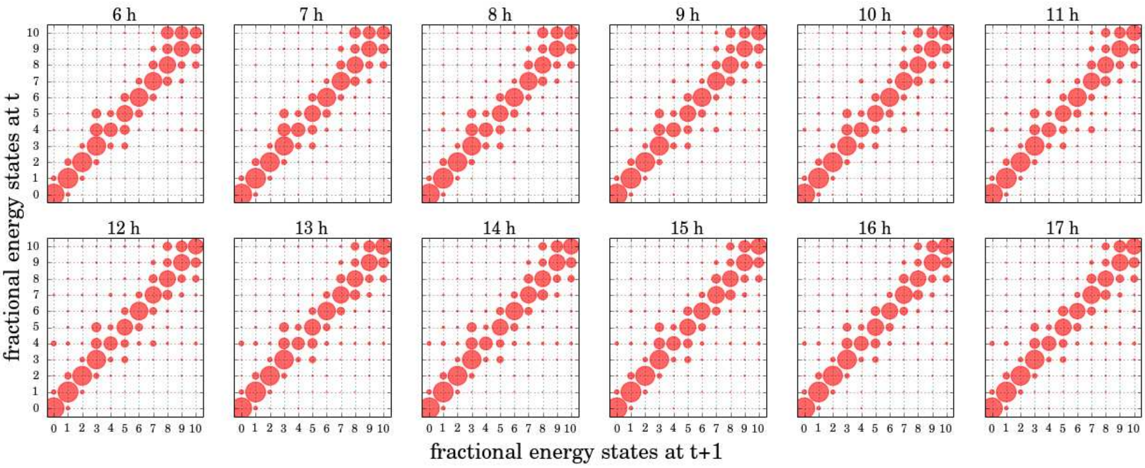

Figure 2. Graphical representation of a inhomogeneous Markov tensor for the category relevant to audiovisual appliances. It shows transitions between eleven energy states at time t and time t+1; the tensor is composed of 12 matrices, one for each hour of half a day.

4. Results and discussion

In this section the main results are presented for the modelling approach explained above. The construction of the model was based on approximately 92% of the available annual data, leaving around an 8% to evaluate the technique, which corresponds to one complete month of validation data.

4.1.1. Time-inhomogeneous Markov matrix

As explained in section 3.2.2, it is possible to extract a tensor such as the one defined in equation (2), when counting the transitions between energy states. In Figure 2, the tensor concerning the category of audiovisual appliances is shown. The graph contains 12 matrices corresponding to each hour of a typical day between 6:00 and 17:00h. Each of those matrices shows transitions between states from time step t to time step $t+1$, represented as points of size proportional to the probability of that transition to occur. From the graphs it is inferred that the dominant transitions are situated along the diagonal, corresponding to those that do not imply variations in energy demand, practically independently from the time of the day. Variations are found outside the diagonal over time, even though they are modest.

In general, the time-inhomogeneous approach in this particular case is not describing large temporal differences on the transition probabilities, taking into account that we are representing a combination of the energy states transitions of a group of appliances; nevertheless, this behavior is not observed when building tensors of the individual appliances. One explanation to this could be that a dominant appliance presenting this transition behaviour is influencing more significantly the overall plot. A further task to refine the modelling then would be to identify those appliances that could have dominant behaviour.

4.1.2. Simulation results

From the information extracted from the annual data and represented as a tensor of transition probabilities, it is possible to generate a sequence of energy states that follow the probability distribution. An inverse cumulative distribution function (CDF) method is employed to do that, where for the relevant time t, a random number from a continuous uniform distribution over the interval (0,1) is drawn and the corresponding interval in the CDF is selected as the state for $t+1$. This process is repeated for every 10 minute step over the validation period.

The result of the simulation is a stochastic sequence of energy states, which can be evaluated by means of performance indicators [10]. In the case of audiovisual appliances, the sensitivity (True Positive Rate, TPR), the specificity (True Negative Rate, TNR) and the model accuracy (ACC) are equal to 0.180, 0.918 and 0.484, respectively, which means that the model is performing reasonably well in the prediction of a sequence energy states.

These values can be complemented with a comparison between the probabilities of simulating and observing each of the energy states. Figure 3 presents the CDF's for both simulated and observed energy states during the

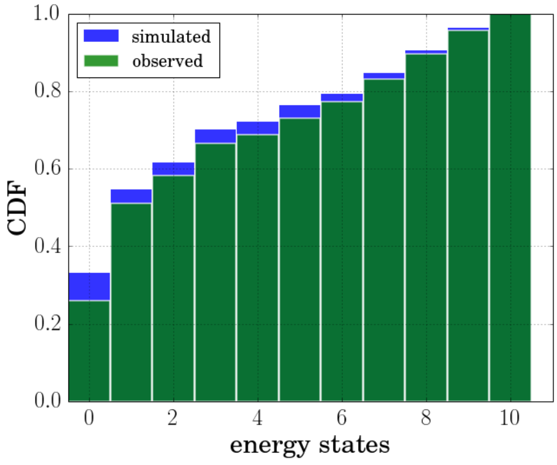

Figure 3. Simulated and observed CDF's of the probabilities of being in each of the energy states during the validation period, for audiovisual equipment.

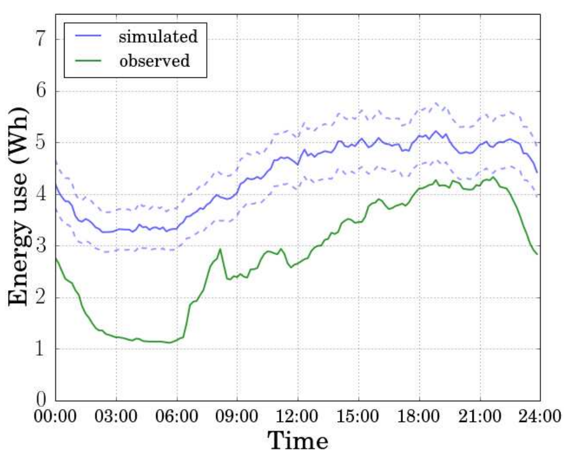

Figure 4. Average day of the validation data for observed and simulated (58 simulations), for audiovisual equipment. Dashed lines show the 90% confidence interval of the simulations.

validation period. In general, the off-state (state 0) is found to be overestimated while the stand by-state (state 1) is underestimated. This fact suggests that the technique could be improved by modelling the switch on events separately, and use the Markov approach only to model energy variations whenever the appliances are being used.

The sequence of energy states can be further used to obtain an energy consumption profile due to low-load appliances of each category by following the methodology described in section 3.2.1; this makes it possible to evaluate the goodness of the prediction of energy use. As discussed above, maximum energy values were poorly estimated due to lack of information on rated power, leading to a relative error of 34% in the prediction of annual energy. Nevertheless, the core formulation of the model is still reliable, assuming that in reality this value should be accurately known from the allocation of appliances. The former can be visualized in Figure 4, where the energy consumption of the average day of the validation data is presented, for both measured and simulated (50 simulations); the overestimation is clear, showing the observed data far away from the 90% confidence interval of the simulations. Different alternatives to address the problem of estimating the maximum energy are currently being investigated, including the use of finer temporal data.

5. Conclusion

In this paper the application of a time-inhomogeneous Markov process to four categories of appliances has been presented, with the purpose of dynamically modelling fractional energy use.

Thus far, results show that Markov processes can be used to perform stochastic simulations of the fractional energy states. However, further study should consider the reduction of energy and temporal states in order to avoid redundant calculations and increase computing efficiency; identification of dominant appliances and cluster analysis techniques are the next steps to take into account in this research. On the other hand, improved estimations of the maximum energy use are required to predict accurate demand profiles.

Also, other candidate strategies such as the probability of switching on an appliance, the duration of use or its conditional probability to be linked to an activity will be further tested and compare, with the objective of finding the most parsimonious approach, and the most suitable aggregation of appliances.

Modelling the low-load appliances, will contribute to improved prediction of buildings' thermal and electrical energy demands, when considering together with previous efforts in modelling the use of high-load appliances and appliance ownership modelling.

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