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Domestic electricity use: A high-resolution energy demand model

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ABSTRACT

The pattern of electricity use in an individual domestic dwelling is highly dependent upon the activities of the occupants and their associated use of electrical appliances. This paper presents a high-resolution model of domestic electricity use that is based upon a combination of patterns of active occupancy (i.e. when people are at home and awake), and daily activity profiles that characterise how people spend their time performing certain activities. One-min resolution synthetic electricity demand data is created through the simulation of appliance use; the model covers all major appliances commonly found in the domestic environment. In order to validate the model, electricity demand was recorded over the period of a year within 22 dwellings in the East Midlands, UK. A thorough quantitative comparison is made between the synthetic and measured data sets, showing them to have similar statistical characteristics. A freely downloadable example of the model is made available and may be configured to the particular requirements of users or incorporated into other models.

1. Introduction

Domestic low-carbon strategies and technologies, such as demand side management (DSM) and micro-generation, will change the nature of the residential dwelling within the traditional design and operation of electrical power systems. In particular, these low-carbon measures will significantly alter the characteristic shape of the domestic electricity demand profile, whilst at the same time providing much greater local control over it. The flexible demand aspect of DSM, for example, will introduce the capability to time-shift electricity use, by bringing forward or delaying the use of appliances, which in the future will include heat pumps and the charging of electric vehicles. Domestic micro-generation, including solar photovoltaics (PV) and micro-combined heat and power (micro-CHP) will also alter net demand profiles as seen by the supplier, with the micro-CHP potentially providing a further degree of control.

In anticipation of the wide-scale uptake of some or all of the above low-carbon measures, it is essential to model and quantify their potential impacts and benefits from the perspective of the power system. Our particular interest is in the operation of local distribution networks and, in order to successfully model this, it is important to have a demand model that adequately represents the variability of individual dwelling demands, which may be significant, rapid and largely random. For effective network modelling, large numbers of dwellings must be considered at once and the demand model must appropriately represent the time-coincident demand between different dwellings. It must model existing load use in detail and with sufficient versatility to allow future modified energy use patterns to be incorporated.

This paper describes a high-resolution domestic electricity demand model that has been designed to address the above requirements and which may also be useful in other domains. The concepts used in its construction are outlined below and build on those used by the same authors in the construction of a domestic lighting model [1]. The lighting model, which additionally takes into account the level of natural daylight, is now incorporated as a component within the full dwelling model for electricity use presented here.

1.1. Appliances

The model uses the appliance as the basic building block, where “appliance” refers to any individual domestic electricity load, such as a television, washing machine or vacuum cleaner. It is therefore a “bottom-up” model, in common with those developed by Paatero and Lund [2], Capasso et al. [3], Yao and Steemers [4], Stokes [5] and Armstrong et al. [6]. An important feature of the new model is in its approach to represent time-correlated appliance use.

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The appliances in the model are configured using statistics describing their mean total annual energy demand and associated power use characteristics, including steady-state consumption or typical use cycles as appropriate. The next stage of model development considers when the specific appliances are likely to be used.

1.2. Active occupancy

Appliance use within a dwelling is naturally related to the number of people who are at home and awake. This time is referred to as "active occupancy" and it is represented for each dwelling within the model, as an integer that varies throughout the day in a pseudo random fashion, reflecting the natural behaviour of real people going about their daily lives. A previously developed approach [7], is used to create active occupancy data for large numbers of dwellings. It is based upon data derived from the UK 2000 Time Use Survey (TUS) [8], a comprehensive survey of how people spend their time in the UK, based on many thousands of 1-day diaries recorded at a 10-min resolution. The model of active occupancy requires an input of the total number of residents (one to five) for each simulated dwelling. This value is stochastically assigned according to UK statistical data [9].

The representation of active occupancy within the model provides the primary mechanism for creating electricity demand data with appropriate aggregate daily profiles (low use during the night; increasing during the early morning, etc.). Moreover, it provides a basis on which to model the time-correlated use of electricity both within and between dwellings.

1.3. Occupant activity and appliance use

In order to refine the modelling of the timing of electricity demand, a second mechanism, based on the occupants' activities, is used. Again, the TUS data is used to create profiles, but in this case they are "activity profiles", which show, to take an obvious example, that people tend to do cooking activities around meal times. Similarly, they are most likely to watch television in the evening. Other activities each have their own daily profiles.

The next step is to link these activities to appliances. For example, watching television will obviously require a television to be in use; cooking may involve the use of an electric oven and a laundry activity may lead to use of a washing machine. By assigning an activity profile to each appliance in the model, the varying likelihood of the appliance being used throughout the day can be taken into account in a stochastic simulation, which is a key element of the model presented in this paper.

The above steps ensure that the appliances in the model are activated at appropriate times of day without need for detailed appliance usage statistics. Moreover, creating a relationship between energy use and occupant activity is particularly important in the study of demand side management, including flexible demand.

Time-use data was applied in this manner in recent models by Prudenzi et al. [10] and Widén and Wäckelgård [11]. The latter constructs a Markov-chain based occupant activity simulation based on time-use data, where each activity is mapped to an appliance group end-use. In contrast, a different approach is taken here, using static activity profiles, with the main variable being the number of active occupants. This provides a different mechanism to represent the likelihood that more than one appliance is used at the same time.

1.4. Sharing of appliances

Appliances may of course be used by more than one occupant at the same time. For example, if a second occupant arrives at a dwelling where a first occupant is already cooking, only an incremental increase in demand is likely to occur. Using active occupancy as the basis for the modelling enables this sharing of appliances to be taken into account: the modelled likelihood of an appliance being used is increased non-linearly with respect to the number of active occupants.

1.5. Correlated use of appliances

Simultaneous use of both lighting and a television would be likely within a dwelling that had active occupants on a winter evening. Again, the use of active occupancy within the model provides a basis for determining such correlated appliance use.

1.6. Temporal resolution

A 1-min time resolution was chosen as a balance between data volume and demand curve smoothing. At this resolution, a 365-day simulation yields 525 600 data points per dwelling. Wright and Firth (2007) [12] discuss how "...averaging data over periods longer than a minute is shown to under-estimate the proportions of both [electricity] export and import." Their comparison, of 1-min and 30-min demand data, clearly shows how a considerable amount of detail is hidden regarding the "high-frequency variations" of loads. For detailed modelling of local distribution networks, it is considered important that this detail is not lost.

1.7. Reactive power consumption

Basing the model on individual appliances also provides a straightforward means of representing reactive power consumption, which is important for example in network load-flow studies. The model represents the reactive power demands of each appliance through the assignment of an appropriate power factor.

1.8. Validation of the model with measured data

Electricity demand data was recorded at 22 domestic dwellings around the town of Loughborough in the East Midlands, UK. The data was recorded at a 1-min interval throughout 2008.

The construction of the model, outlined above and described in detail in Section 2 of this paper, was completely independent of this measured data set. In Section 4, the measured Loughborough data is used extensively to validate the model by way of a comprehensive comparison of the statistical characteristics of the synthetic and measured data.

1.9. Model implementation

An example implementation of the model is made available [13] for free download as a Microsoft Excel work book. The data and Visual Basic macros are included to provide a self-contained 1-day simulation for a single dwelling. This may be user-configured or incorporated into other models as required. For the purpose of creating very large data sets, the model was also implemented in C#.

2. Structure of the model

The structure of the model is presented in Fig. 1. On the left of the diagram, there are a set of daily activity profiles, which represent the likelihood of people performing different activities at different times of the day; these profiles are the same for all dwellings. To the right of the diagram, dwellings are represented by the outer square block. Each dwelling is assigned an active occupancy data series and a set of installed appliances. Each appliance is mapped to one of