Simulation of high-resolution domestic electricity demand based on a building occupancy model and its applicability to the study of demand side management

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Abstract

Alongside the well understood need to reduce overall electricity consumption, there is an increasing need to provide demand response: the ability to time shift electrical demand in accordance with available low-carbon generation including wind, marine and solar power. Many domestic loads can readily be employed to provide time shifting demand response in the range of minutes to hours and this concept is already the subject of numerous demonstrations worldwide. The modelling presented in this paper provides a basis for the quantification of the availability and impact of demand response in the domestic sector. In particular, this paper describes the development of a domestic electricity demand model capable of providing data with a one-minute time resolution and with which the operation of demand response may be assessed. The electricity demand model is constructed at the level of individual household appliances and their usage is based on surveyed time-use data. This provides for appropriate temporal diversity of energy use between simulated dwellings. Occupancy data allows the correlated usage of appliances to be represented within an actively occupied dwelling, as well as representing the sharing of appliances, such as lighting, in dwellings with multiple occupants. This paper summarises previously developed occupancy and lighting models and explains how the lighting model can be extended to create an integrated appliance model.

Introduction

Demand response is considered to provide benefits to both electricity market operation and technical system efficiency [1],[2]. It is of particular interest in electricity generation systems that comprise time variable generation sources such as renewable technologies because demand can be scheduled to coincide with generation availability.

The time of operation of many domestic loads may be shifted without undue inconvenience to the dwelling's occupants. An example is in the cold appliances category, where thermal storage provides scope to advance or delay a cooling cycle of a fridge [3]. A further example, in the wet appliance category, is a washing machine, where the delay of operation by several hours may have minimal impact on the household. When aggregated to include many thousands of dwellings (and hence appliance units), there is clearly significant potential for demand rescheduling in response to market or technical balancing considerations.

This work is concerned with the development of a model of domestic demand at sufficient time resolution (initially one-minute) to support studies of demand response. Because effective demand response is dependent on having sufficient quantities of appliances to time shift, it is essential that any such modelling takes properly into account demand diversity between dwellings, as well as, appropriate correlation of appliance use within a dwelling that is actively occupied. It is acknowledged that a one-minute time resolution is more suitable for local studies, rather than an electricity market. This resolution does however provide a basis for assessing fast demand response.

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The appliance model presented in this paper uses high-resolution domestic occupancy patterns as an input. These patterns detail when people are active within a dwelling and hence likely to use electrical appliances. The model simulates the use of the main types of electrical devices found in domestic dwellings in order to provide high-resolution synthetic electricity demand profiles.

The occupancy model [4] and the domestic lighting [5] aspects of the model have both been completed and the results published. Excel Worksheet examples of the models are available for free download [6],[7].

Architecture of the Appliance Model

The architecture of the integrated appliance model is presented in Fig. 1. The core of the model is the simulation of active occupancy, which is provided as one of a number of common data inputs to the individual appliance models. The use over time of domestic appliances is stochastically simulated. The simulation uses a set of physical input factors, such active occupancy and the level of natural light which are both used to determine the demand for lighting.

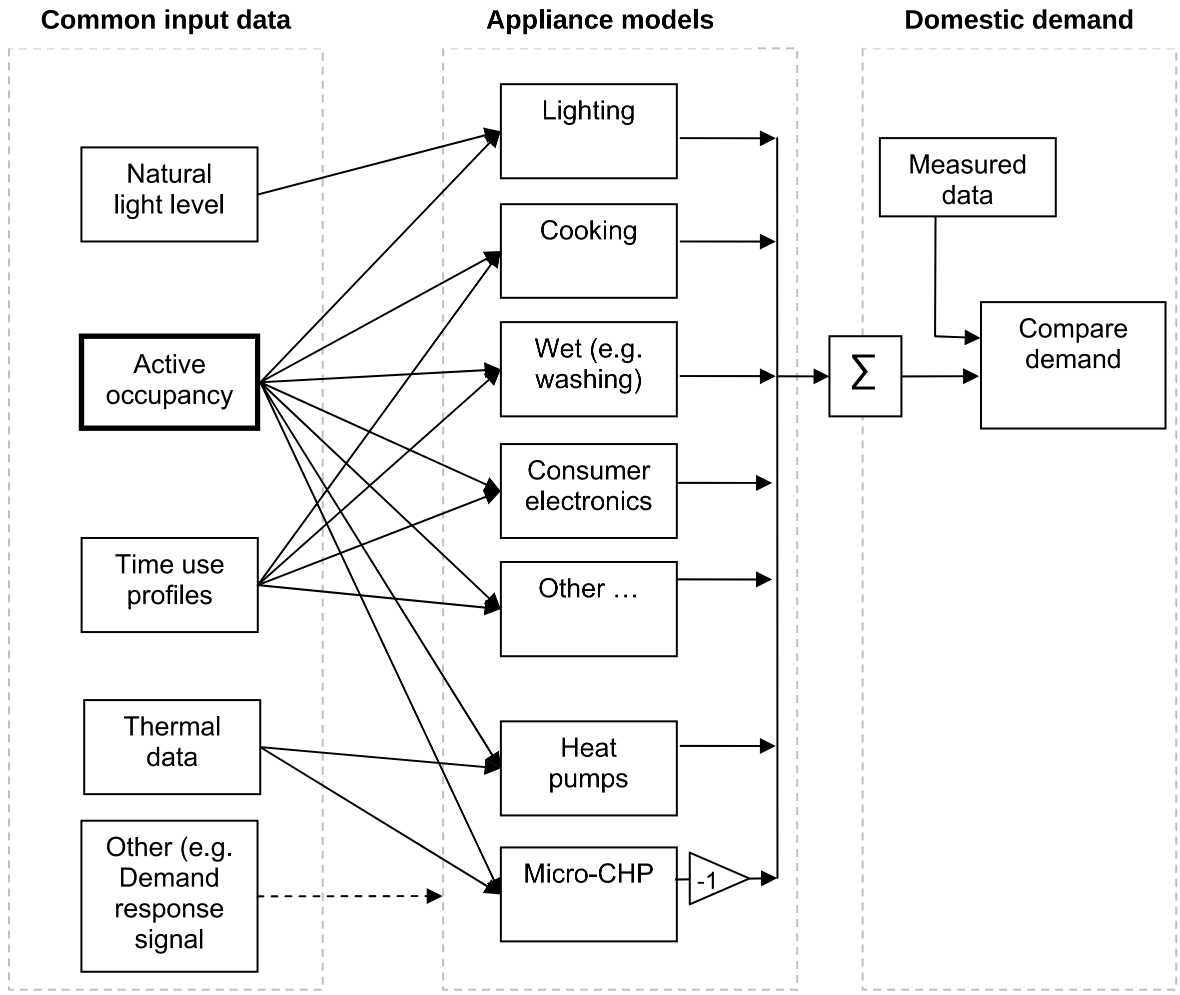


Fig. 1. Architecture of the integrated appliance model

In a high-resolution simulation, the power demand of all appliances in use at a given time is summed to give an overall domestic demand profile for each dwelling in the simulation. The model is validated by comparing the demand profiles against measured data that is being recorded as part of the study.

In the context of demand response, the model is capable of taking into account other data, such as pricing or electricity generation supply margin, in the form of a demand response signal as can be seen in Fig. 1. Furthermore, the fast demand response capability of heat pump or micro-CHP units will depend upon thermal constraints. For example, the internal temperature of the dwelling and the heating thermostat set-point will constrain the delay or advance of heating cycles. A simple building heat demand model will therefore be integrated to provide thermal data to the appliance model.

The core aspects of domestic occupancy pattern simulation and the approach to the modelling of individual appliance categories are presented in the following sections.

The Modelling of Domestic Occupancy

Why use occupancy as a basis for energy modelling?

The nature of appliance usage within domestic dwellings varies significantly throughout the day as a result of the behaviour of the occupants. The number of residents who live in a dwelling, together with the pattern of their active occupancy are key determinants of the energy demand profile of a dwelling [4],[8]. Active occupancy refers to occupants that are within a dwelling and are not asleep.

The modelling of domestic occupancy as a basis for energy demand simulations has three benefits:

Firstly, it is possible to take account of the sharing of appliance use. For example, a second occupant arriving home on a winter evening is likely to only incrementally increase, rather than say double, the lighting demand upon their arrival. An occupancy model can address this by providing a numerical sequence of the number of active occupancy over a number of time periods.

Secondly, active occupancy enables multiple different appliance models to use the same input data. For example, an actively occupied house on a winter evening is likely to have both lighting and television appliance loads. This correlation of appliance use is a particular issue for stochastic appliance models, as independently representing appliances will not provide the required realistic diversity in usage.

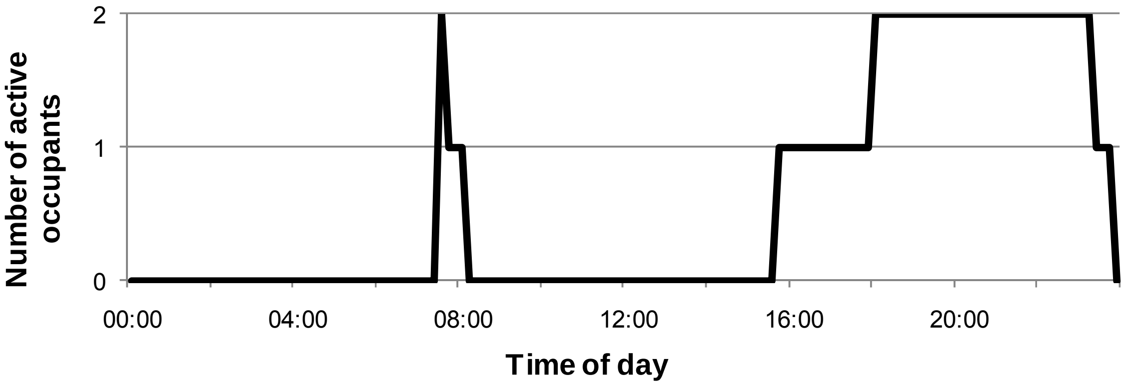
Thirdly, being able to apply stochastically generated occupancy patterns to a large number of dwellings allows for appropriate diversity in energy demand between dwellings over time.

Model Implementation

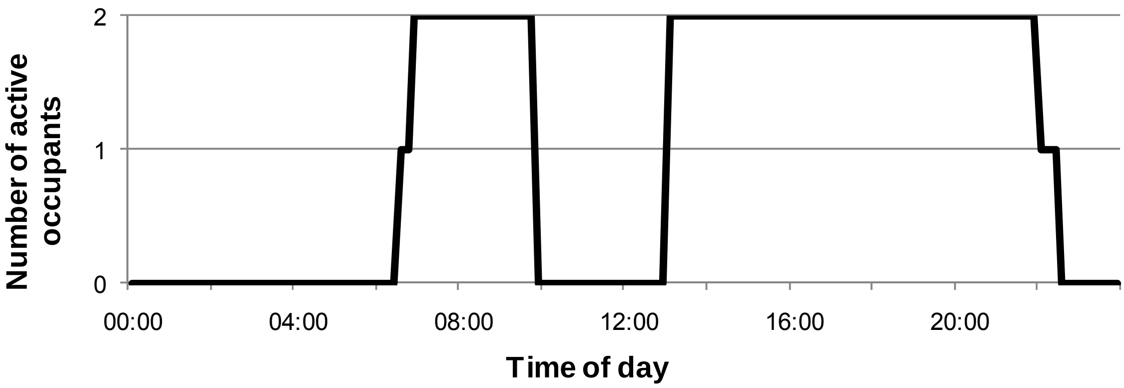
The occupancy model uses the data captured in diaries from the United Kingdom 2000 Time Use Survey (TUS) [9] as a basis for a stochastic simulation of occupancy. This data in the survey contains information on the location and activities the occupants were undertaking during the survey at a ten-minute resolution. This data is used to determine when occupants were active and not asleep. The model uses a Markov Chain method to generate statistically comparable data sets using a set of transition probability matrices to represent the likelihood of changes in the number of active occupants within a dwelling over time.

Using the Model

The model is run to generate stochastic active occupancy profiles. Two example occupancy profiles are shown in Fig. 2, both for dwellings with two occupants. The first example is representative of a dwelling lived in by a couple that both work. There is no active occupancy during the night, a short period of activity at breakfast, followed by absence through the day with further activity in the evening. The second example is perhaps more representative of a retired couple. In this case, both occupants are active within a dwelling for the majority of the day with a three hour gap in the morning. Note that the transition from two to zero active occupants occurs simultaneously at 09:00 AM. The state transition approach allows for correlated changes in dwelling occupancy.



(a) Example 1



(b) Example 2

Fig. 2. Example active occupancy profiles for two dwellings, each with two residents

The results of a simulation of 1000 dwellings for weekdays are shown in Fig. 3. Each dwelling in the simulation has been allocated a total number of occupants using UK household statistical data [10]. The plot shows the proportion of dwellings that have active occupancy, showing one, two or three or more active occupants throughout the day. As is to be expected, there is very low activity at night, with a sharp spike at breakfast time, a small activity increase at lunch time and a significant further rise in activity in the evening period. The graph shows that we can expect approximately 80% of houses to have active occupants in a given sample during the evening period.

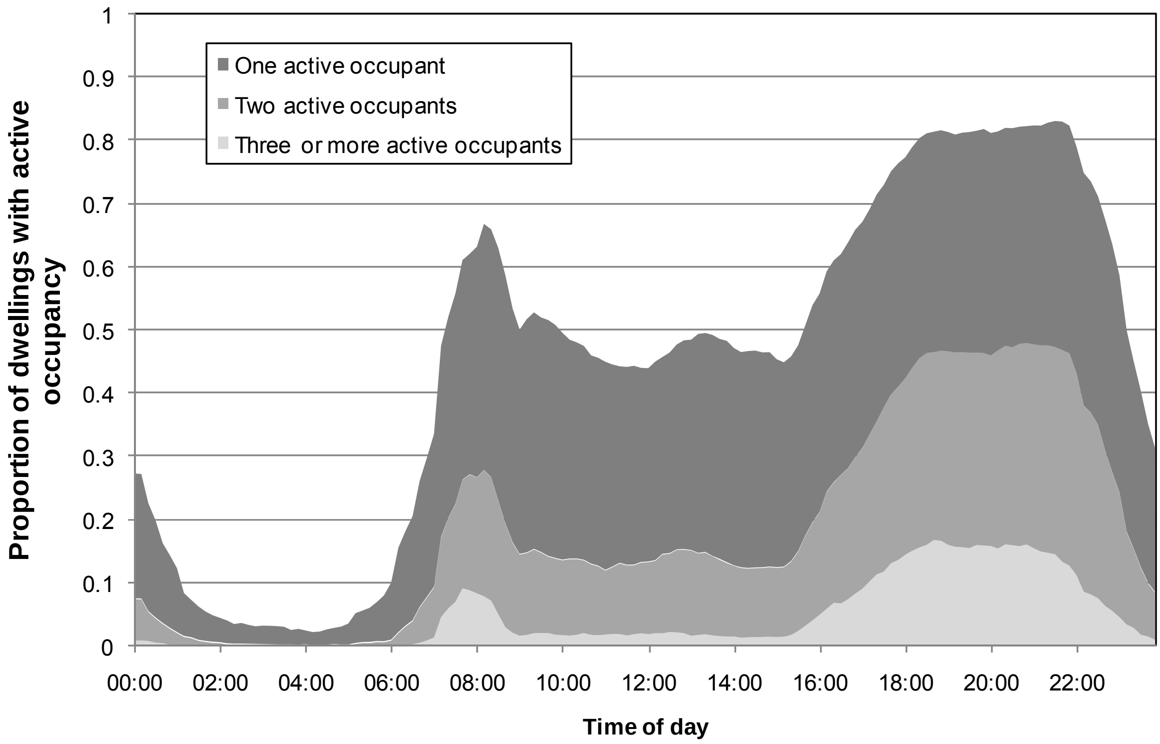


Fig. 3. Simulation results of the proportion of houses with different level of weekday active occupancy, over one day (from a pool of 1000 houses, averaged over one year)

The model is capable of the generation of large quantities of synthetic occupancy data. Each time a dwelling is simulated, a different profile will be generated. When aggregated together with other dwellings, the profile will tend towards that seen in Fig. 3.

It is notable that the active occupancy profiles shown in Fig. 3, which are based purely on people's time use diaries, already bear a strong resemblance to typical electricity demand profiles that may be measured in houses in the UK [4]. This strongly supports our earlier assertion that domestic electricity use varies as a result of the behaviour of the occupants.

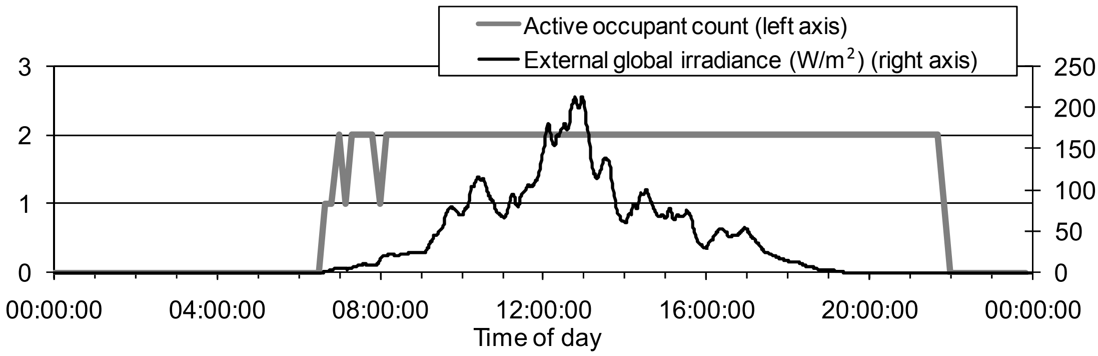
An Integrated Appliance Model

The active occupancy data is used as a common input to a set of appliance models that represent the typical range of consumer electronic devices found within domestic dwellings. The first component of the integrated appliance model is for domestic lighting use [5].

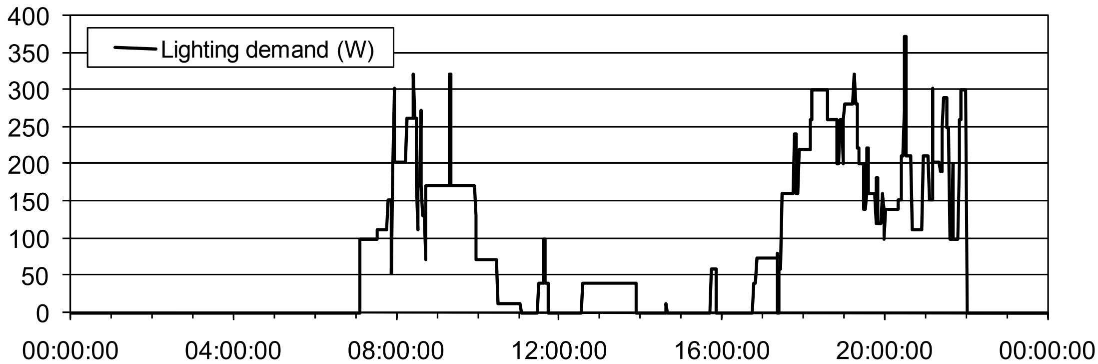
A Model of Domestic Lighting Use

In addition to utilising the state of active occupancy within a dwelling at a given time, the lighting model uses the physical concept of the level of natural light at a given time in determining domestic lighting demand. Using these two dynamic variables in a high-resolution time based model, allows a consistent light level to be applied to a number of dwellings, whilst demand diversity is accounted for by the variations in active occupancy between dwellings. The direct use of natural light level also introduces seasonality into the model, since winter evenings are dark, resulting in a greater lighting demand.

From a demand response perspective, it is important to be able to represent individual appliances within a dwelling such that it is possible to explore time shifting aspects on individual appliances. The model therefore has the capability to represent individual lighting units (typically a single bulb or multiple bulb light fittings). The model operates by stochastically determining the likelihood of a lighting unit switch-on event occurring for each bulb in each simulated dwelling at every time step. An example simulation output is presented in Fig. 4.



(b) Input data



(a) Simulated lighting demand (single dwelling)

Fig. 4. Single dwelling lighting simulation example (weekend day in September, two occupants living in the dwelling)

The physical input factors are shown in Fig. 4a. As a weekend day, both occupants are active for most of the day. Lighting is used mainly in the earlier morning and evening hours.

The aggregated demand for lighting in 100 dwellings is shown in Fig. 5. Examples are shown for both a winter and a summer day. The winter scenario shows a significant demand in the morning hours and the evening demand starts in the late afternoon as would be expected. In summer, lighting demand ramps up much later in the evening due to the longer daylight hours.

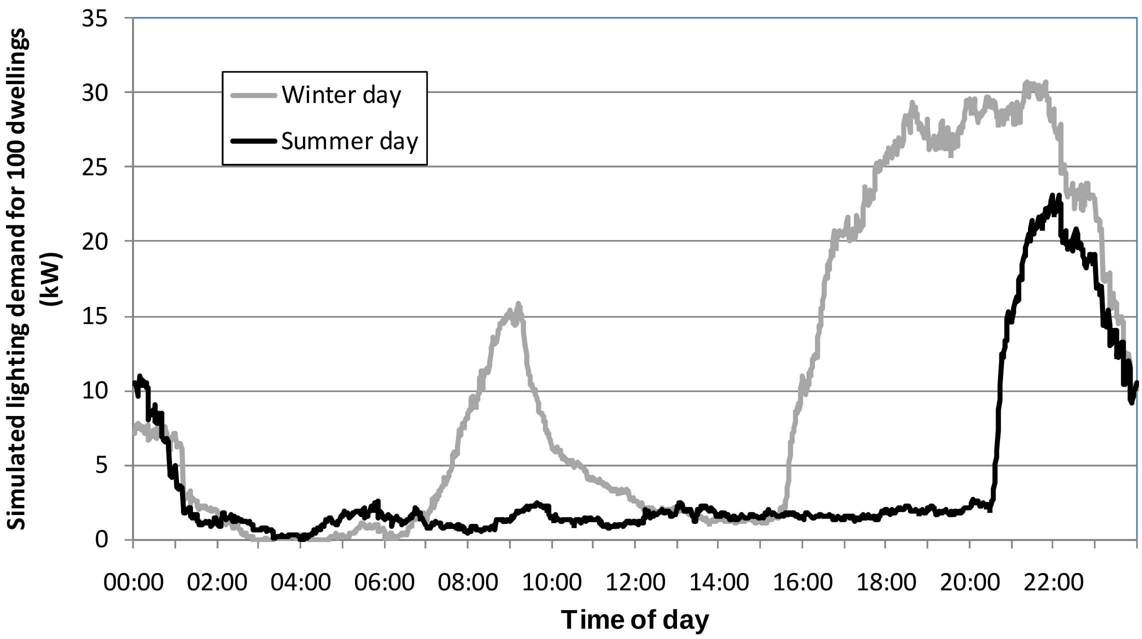


Fig. 5. Simulated aggregated lighting demand (100 dwellings) for winter and summer days

Extending the Model into an Integrated Dwelling Appliance Model

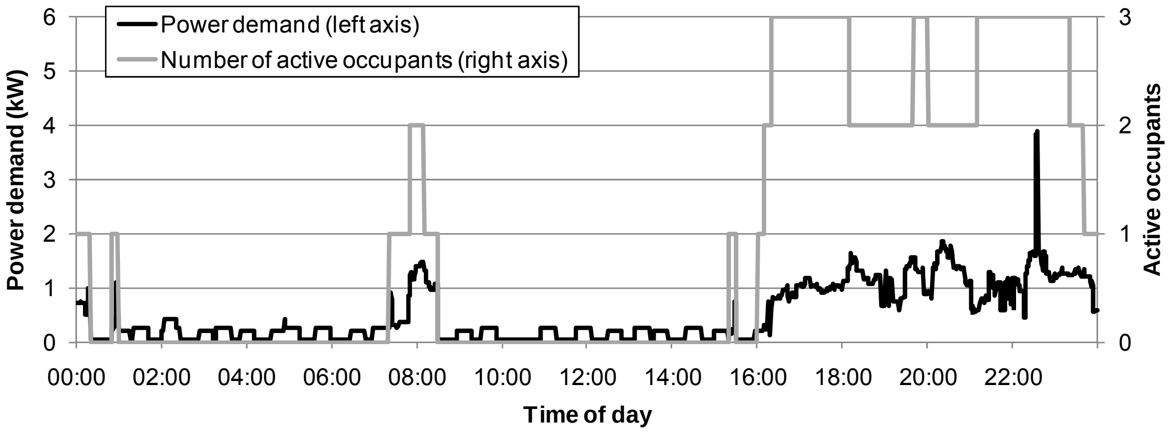
The authors are currently in the process of extending the model to provide a fully integrated domestic appliance energy demand model. Utilising the same common active occupancy data for a dwelling, an integrated appliance model can be constructed. Whereas lighting use was determined as depending upon occupancy as well as natural light, different appliance types will be used at varying times of the day. For example, cooking appliances will typically be used at meal times, and television usage may predominantly take place in the evening.

The TUS data [9] contains details on the survey participants' activities throughout each day of the survey. This data is used to determine daily probability profiles of particular activity categories. For example, activities such as cooking, washing, laundry, television and entertainment activities are reported in the diary data and the times when these activities take place each have a statistical daily profile. The stochastic model uses these distributions to assign relative weights of the likelihood of a particular appliance being used. For example, the TUS data shows that television usage does increase through the day, peaking in the evening. In the appliance model, an appliance structure similar to that described by Paatero and Lund [11] is used, together with a 'starting probability' function that is used to stochastically determine when appliances are switched-on.

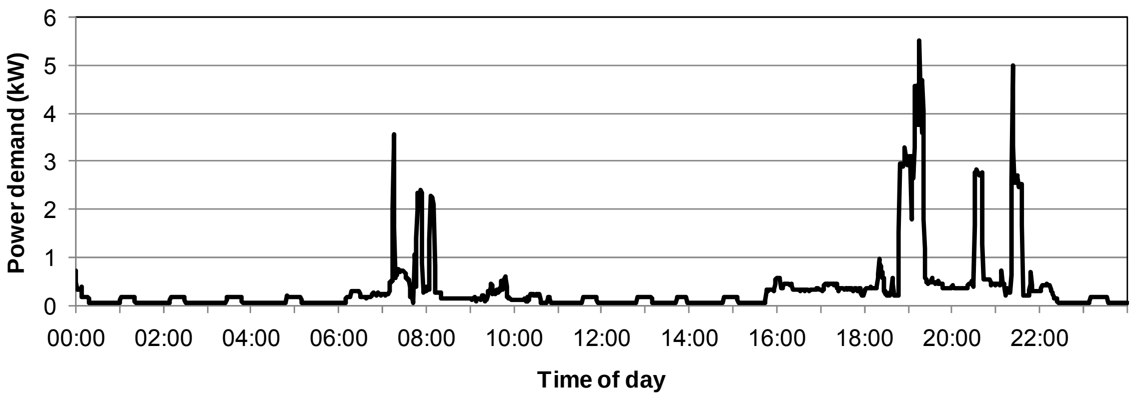
Prior to a simulation, each house is configured with a set of appliances, similar to that of the configuration of the number and types of bulbs within the lighting model. At each time step in the simulation, appliance start events are stochastically determined. When an appliance is used, its power demand is added to the aggregated total for the dwelling.

In parallel with the modelling work, electricity demand is being measured in 22 real households in Loughborough UK. The logging equipment has been in service for over a year and provides validation data with a one-minute time resolution.

Examples of both synthetic and measured domestic appliance profiles are shown in Fig. 6a and 6b respectively. Daily demand profiles vary significantly, both between different dwellings on the same day, as well as between different days for the same dwelling. The plots shown are random samples and it would not be expected for them to match. However, there are common characteristics and the example is shown to present how active occupancy is a significant driver of appliance usage. The cycling of cold appliances can be seen in both data sets. The active occupancy is shown against the synthetic data and it can be seen that the majority of demand takes places only when there is active occupancy in the dwelling. Similarly in the measured data, it can be seen that the use of appliances takes place mainly in the early morning and evening periods. In the measured data, the house can be seen to be inactively occupied throughout the night, and between the mid-morning and mid-afternoon periods. The occupants can be seen to retire for the day shortly after 10PM.



(a) Synthetic domestic profile for one day shown with active occupancy



(b) Example measured domestic demand profile

Fig .6. Synthetic and measured domestic demand profile examples

Application of demand modelling to demand side management

The construction of the high-resolution model at an appliance level, as has been described, was designed from the outset to allow the study of DSM, particularly with respect to appliance time shifting and to assess the impact of smart appliances.

For example, if the simulation determines that a washing machine start event is required at a point in time, then we can delay the actual start time by any required factor. Since the model can simulate large quantities of dwellings simultaneously, we will be able to make an assessment of the potential for different types of appliance to profile a demand response service.

Since each component of the model is constructed to take account of physical input conditions (such as lighting, which uses both active occupancy and the natural light level), it is also possible to take into account other conditions or signals, such as real-time pricing data or generation supply margin data.

In the context of domestic electricity micro-generation, signals, such as an indication of insufficient supply margin over a short time period, could be used to bring forward the firing cycles of micro combined heat and power units. Similarly, delaying the use of ground or air source heat pumps can provide demand response.

The model described is also capable of supporting the study of energy efficiency measures through the changing of the demand parameters of particular appliance categories. For example, the increased use of compact fluorescent light can be explored by changing the statistical distribution of lighting technologies within a particular group of dwellings.

Conclusions

This paper has outlined work to develop a high-resolution domestic electricity demand model. The model is based upon dwelling occupancy patterns, which are a key contributor to the patterns of energy use in the home. This approach provides significant advantages in terms of providing the appropriate levels of diversity in energy use between simulated dwellings and also allows appliance usage to be shared within the home, with appropriate usage correlation in time.

It is important that the model represents individual appliances, in order that the demand response potential of different appliance groups can be properly simulated. It would not be possible to perform such analysis solely with an aggregated demand profile.

The active occupancy and lighting elements of the model have already been published and example implementations of the models are freely available for use and integration in other energy demand studies. The detail of the full integrated appliance model is intended as the subject of a forthcoming publication.

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