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.

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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
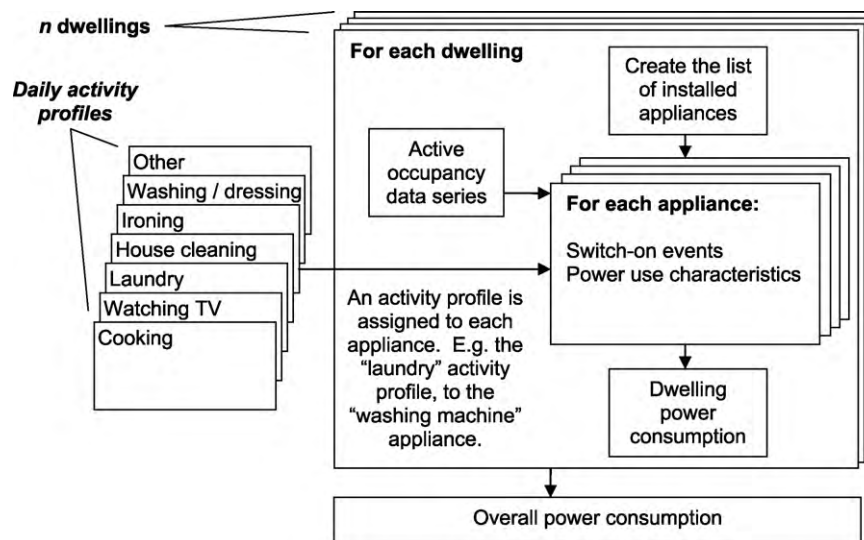
Fig. 1. Electricity demand model architecture.

the daily activity profiles. When an appliance switch-on occurs, the appliance power use characteristics are used to determine its electricity demand (including the reactive power demand). Adding the power demands of all appliances within a dwelling gives the whole-dwelling demand. The overall power demand for all dwellings is given by adding the whole-dwelling demands.

2.1. Daily activity profiles

Each daily activity profile, on the left of Fig. 1, quantifies the probability of the specified activity being undertaken as a function of time-of-day. The set of profiles includes variants to take account of the current number of active occupants (one to five) and whether it is a weekday or a weekend day.

Two example profiles are shown together in Fig. 2. Both are "cooking" activity profiles for a weekday. The two curves represent activity probabilities for different numbers of active occupants, in this case, one or two. For example, if a dwelling has one active occupant at 17:30, then the probability of that occupant doing cooking is 0.26. If however there are two active occupants, the probability of at least one of the occupants cooking rises to 0.37.

The expected peaks occur around meal times, but cooking can occur at any time of the day. Note that the series representing two active occupants becomes very volatile overnight. This is a result of the small number of applicable samples in the TUS source data set reflecting the fact that there were relatively few cases with two active occupants at night during the TUS study period.

The daily activity profiles are constructed from the TUS data by first finding the related codes that are used within the survey diaries to describe how people spend their time. The cooking activity profile uses the TUS codes in the range 3100–3190. These represent activities for "unspecified food management" (3100), "food preparation" (3110), "baking" (3120), "dish washing" (3130) "preserving" (3140) and "other unspecified food management" (3190). A full definition of all the codes is provided with the TUS documentation [8].

The TUS diaries are then grouped by the number of active occupants in a dwelling at each 10-min time period of the day. The data is further subdivided into weekday and weekend groups. The number of dwellings where the activity of interest is taking place can then be counted to determine a proportion of dwellings used in the daily activity profile.

For a weekday example, the number of dwellings that have one active occupant between 08:00 and 08:10 is 2082. The number of dwellings where the occupant is performing a cooking related activity is 288. The proportion is 288/2082 = 0.138, as may be seen in Fig. 2.

The full set of daily activity profile data is available from the activity statistics sheet of the downloadable example [13].

2.2. Installed appliances

At the beginning of a run, the model populates each dwelling with appliances. This is done on a random basis using statistical ownership data from the UK Department of Energy and Climate Change (DECC) [14], the UK Market Transformation Programme [15], the Lower Carbon Futures and 40% House reports from the ECI, Oxford University, UK [16,17] and the UK's Ofcom [18].

On this basis, the model is configured to include up to 33 appliances within each dwelling. To take account of multiple ownership, appliances are explicitly listed: for example, three of the 33 appliances are televisions. In the model, a single dwelling may therefore have zero to three televisions. A list of some of the appliances that are represented is shown later in the simulation example in Fig. 4. A full list is included in the appliance configuration sheet in the downloadable example [13].

2.3. Appliance annual energy use

Each appliance is assigned an annual demand in kWh/year. This data is based on the sources used in constructing the list of appliances above, together with further data from the UK Energy
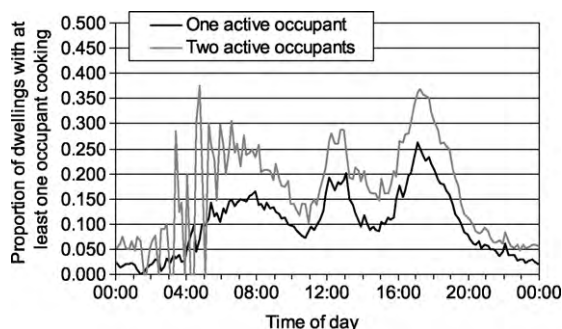

Fig. 2. Activity profiles for 'cooking', for one or two active occupants on a week day.

Saving Trust [19], and is adjusted to represent dwellings in the East Midlands region of the UK, where the annual mean demand is 4358 kWh [20]. A full list of the adopted, derived and adjusted values and their sources is provided on the appliance configuration sheet of the downloadable example [13].

2.4. Appliance power characteristics

Each appliance in the model has two states: it may be either on or off. The off state includes the representation of standby, in that an appliance may be configured to use power even when off.

Many appliances types, such as a television, are assumed to have a constant power demand when switched-on. However, in pursuit of a 1-min time resolution for the final model output, some appliances are represented by time-varying demands. For example, a washing machine that runs through various stages of water heating, washing and spinning, significantly varies its demand throughout a cycle. In this case, the modelled demand profile is based upon some suitable available measured data [21]. However, it is noted that such detailed appliance demand cycle data is not generally available.

Finally, each appliance is assigned an appropriate power factor, representing a mean value over a 1-min interval. A unity value is used for resistive heating appliances, such as a kettle, oven or iron. Electronic entertainment appliances are configured with a value of 0.9. Cooling and washing type appliances are configured with a value of 0.8. These figures are based on measurements made with a plug-in power meter on a small number of appliances.

2.5. Appliance-activity mapping

Appliances whose use is dependent upon a particular activity taking place are assigned to their relevant activity profile. There may be multiple appliances assigned to a single activity. For example, the electric hob, oven, microwave, small cooking appliance and dish-washer are all assigned to the cooking activity. This does not imply that all these appliances are necessarily used whenever cooking takes place; it simply models the possibility of their being used and possibly simultaneously.
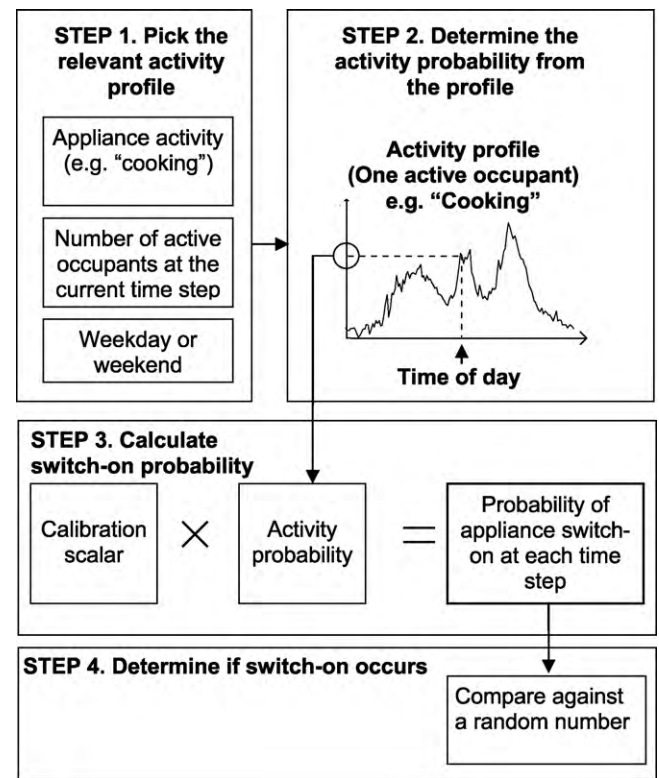
Appliances not associated with any particular activity are assigned to the 'other' activity profile, which covers three specific cases:

- For some appliance types, there are no activity profile categories that describe when the appliance is likely to be used. A telephone is an example. In this case, the appliance use is taken to be dependent only upon active occupancy within a dwelling.
- Some appliances do not depend on active occupancy at all. In this model, the cycling of cooling appliances such as a fridge or freezer, does not depend on people being active within a dwelling.
- Electric space heating appliances do not fit into the activity profile model as their use varies over the seasons. The daily activity profiles used in this work do not include seasonal effects. Furthermore, appliances such as storage heaters tend to have a timed overnight use profile. In this case, a simple approach to seasonal variation is implemented by using a value representing monthly temperature variation to replace the activity profile value.

The full mapping of appliances to activity profiles is shown on the appliance configuration sheet of the downloadable example [13].

2.6. Switch-on events

The procedure to determine whether an appliance switch-on event occurs at each time step of a simulation is presented in Fig. 3.

Fig. 3. Switch-on events.

The following steps occur:

- Firstly, the activity profile is selected according to the appliance activity, the current number of active occupants and whether it is a weekend or not.
- Secondly, the probability that any of the active occupants are engaged in the activity at this time is read from the activity profile.
- Thirdly, the activity probability is multiplied by the calibration scalar. A discussion of how the calibration scalar is derived is presented later.
- Finally, the result of the previous step is compared to a random number between zero and one. If the probability is more than the random number, then a switch-on event occurs.

2.7. Appliance calibration scalars

Each appliance has a "calibration scalar" which is factored into the probability of switch-on as shown in Fig. 3, and thus determines the average number of times that the appliance is used in a year. In the case of automatic appliances such as fridges, this corresponds to the number of times that the thermostat starts the compressor. A calibration scalar is adjusted so that, over a very large number of stochastic simulation runs, the mean annual consumption of the appliance will be correct. That is that it will match the input data discussed earlier in Section 2.3.

For example, the chest freezer in the model uses 271 kWh/year. It draws 190 W for 14 min on each operating cycle and uses no power on standby. It must therefore cycle 6116 times per year. Additionally, each 14 min run is followed by a delay of 56 min during which the appliance may not start again; this represents the effect of the thermostat dead band. This leaves approximately 95 000 min of the year when a start event can occur. Thus the mean time between start events, excluding the time when the appliance is in a cycle, is 95 000/6116 = 16 min. Since the freezer appliance is not dependent on active occupancy, its activity probability is taken

as unity, and thus, referring to Fig. 3, the calibration scalar is simply $1/16\,\text{min}^{-1}$.

A similar calculation can be performed for appliances that do depend on daily activity profiles, but it is more complex. This is because it is necessary to take into account the statistical distributions of both the occupancy and the activity profiles.

The overall mean value of an activity taking place at a time step must first be calculated. This may be achieved by using Bayes' conditional probability theorem. The first input to this is the probability of each level of active occupancy (none, one, two, three, four or five) at each time step of the day. This may be determined from the occupancy model. The second input is the conditional probability of an activity taking place, given each level of active occupancy. This information is available from the activity profile.

This mean probability of an activity taking place, when multiplied by the calibration scalar, should equal the mean probability of an appliance switch-on event. The former value is determined by the same method as described above, such that the required number of cycles per year occur as required to give the correct overall energy use. Of course, appliances that do depend on daily activity profiles may only start if there is active occupancy within the dwelling.

3. Example simulation

An example simulation output for a single dwelling, for a winter day, is shown in Fig. 4.

The simulated active occupancy for the dwelling throughout the day is shown in Fig. 4(a). In this example simulation the dwelling has four residents, but, on this particular run, a maximum of three are active at any one time. As is typical of such profiles, there is no activity at night, with varying levels of activity during the day.

The model initialisation routine has populated the dwelling with 20 appliances as listed in Fig. 4(b) alongside the modelled usage of these appliances throughout the day. The television, DVD, PC and CD player are used for relatively long periods throughout the day, whilst the microwave, kettle and small cooking appliances are used for much shorter periods. The washing machine is used just once during the middle of the day. Notice that the modelled usage of these appliances is closely related to the active occupancy in Fig. 4(a).

Towards the bottom of Fig. 4(b) the fridge–freezer can be seen to be cycling at intervals throughout the whole day and irrespective of active occupancy.

The lighting use presented at the bottom of Fig. 4(b) is consistent with this being a winter day. It is a simplified representation, indicating whenever any light is in use. The underlying lighting model actually represents each individual lighting unit present in the dwelling [1].

The aggregate demand is shown in Fig. 4(c). During the night-time period, when there is no active occupancy, only the fridge–freezer can be seen using electricity. A ramp in demand occurs as soon as the occupants become active in the morning. The spikes in demand are caused by the use of the short-time high-demand appliances such as the kettle and microwave.

A significant increase in the base demand is seen during the lunchtime period with the use of the washing machine.

4. Validation of the model

In order to validate the model, a substantial set of measured data was collected from 22 volunteer dwellings in and around the town of Loughborough in the East Midlands, UK. With the support of Central Networks, high-resolution whole-house demand meters were installed at each of the 22 dwellings and equipped with GSM

(a) Dwelling active occupancy profile

(b) Simulation output; disaggregated by appliance

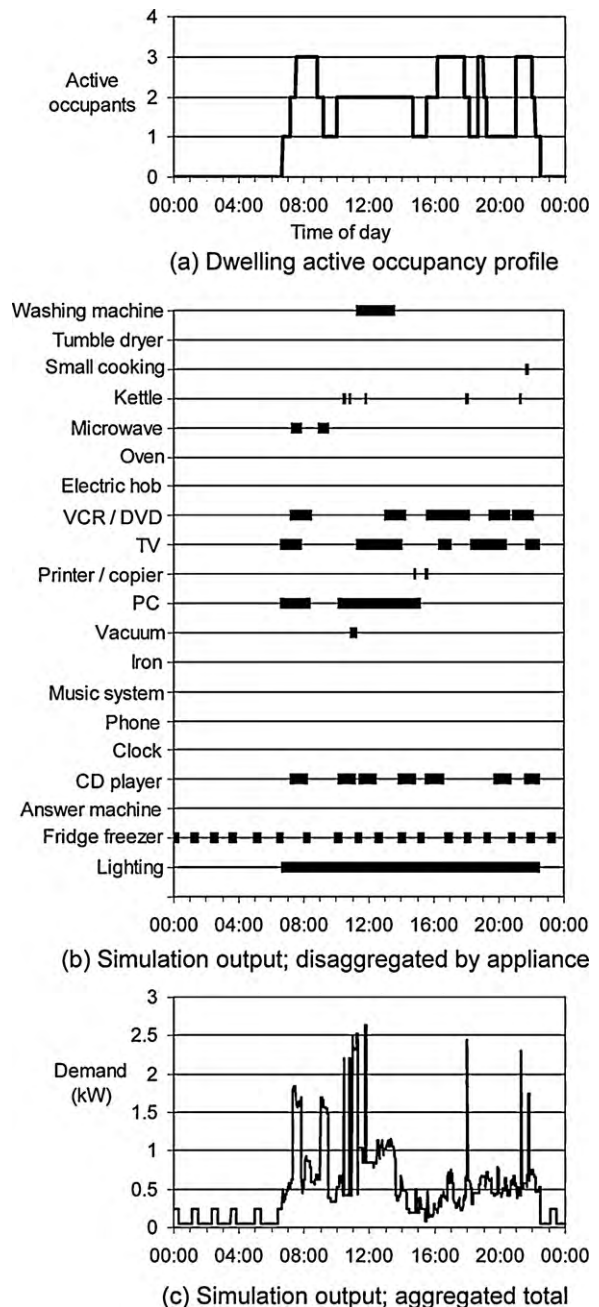(c) Simulation output; aggregated total

Fig. 4. Example simulation output (one dwelling, winter day).

modems to facilitate downloading. The meters were configured to record demand at 1-min intervals and approximately 90% of this potential data (~10 million data points) was successfully downloaded throughout 2008.

An example 24 h demand profile for a single dwelling taken from the measured data set is shown in Fig. 5 and may be compared with the synthetic profile shown previously in Fig. 4(c). They are of course random profiles and are not expected to be the same shape. What we are looking for is that they have similar characteristics. By inspection we can see that they do both exhibit low use of electricity at night, increased use throughout the day and similar overall spikiness.

The purpose of the following validation is to make more formal statistical comparisons between the measured and synthetic data. To this end, the model was used to create synthetic data for 22 dwellings covering a full year at 1-min resolution.
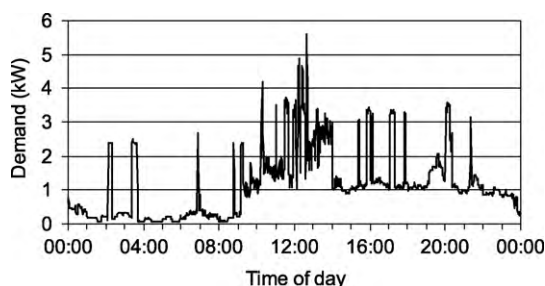
Fig. 5. A measured daily demand profile (1-min resolution).

Fig. 7. Mean daily demand per dwelling, by month of the year.

It is important to emphasise that the model was constructed entirely without reference to the measured electricity demand data from the 22 dwellings. It was, however, considered appropriate to disallow electric storage or space heating from being installed in the simulated dwellings. Storage heater installations can have a disproportionately large electricity demand over other appliance types. Only 2.8% of UK dwellings have electric storage heaters installed [22], but those that do, have significantly higher annual consumption figures [19]. It is known that none of the 22 measured dwelling have storage heating units installed. Validation of the electric heating aspect of the model is thus deferred in the absence of relevant measured data.

4.1. Mean annual electricity demand

The mean annual electricity demands per dwelling for the whole synthetic and measured data sets are 4124 and 4172 kWh, respectively: the difference is less than 1.2%. This is good, but must be understood in context: all it really shows is that the model has been suitably calibrated and that the measured dwellings are not atypical of those in the local geographic region.

4.2. Variation of annual demand between dwellings

Naturally some dwellings use more electricity than others, and this is apparent in the annual demand data of the 22 measured dwellings, which has a standard deviation of 1943 kWh. The model seeks to emulate this variability (primarily through its use of active occupancy). The synthetic data for the 22 simulated dwellings has a standard deviation of 1372 kWh. Thus it appears that the model is slightly under-predicting the variation between dwellings. A more thorough analysis, using a Mann–Whitney U-test with a 5% level of significance, shows that there is actually no significant statistical difference between the two data sets. Nevertheless, it is interesting to see the data plotted side by side.
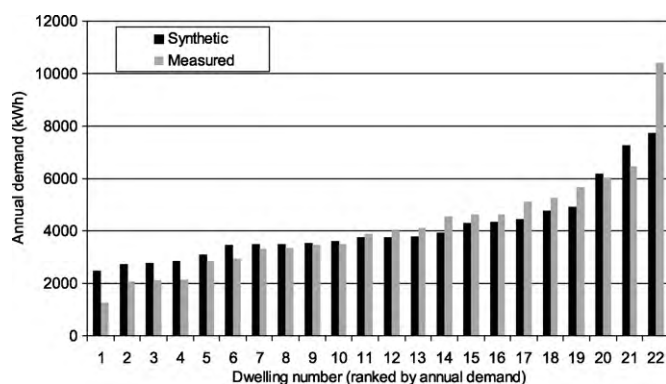

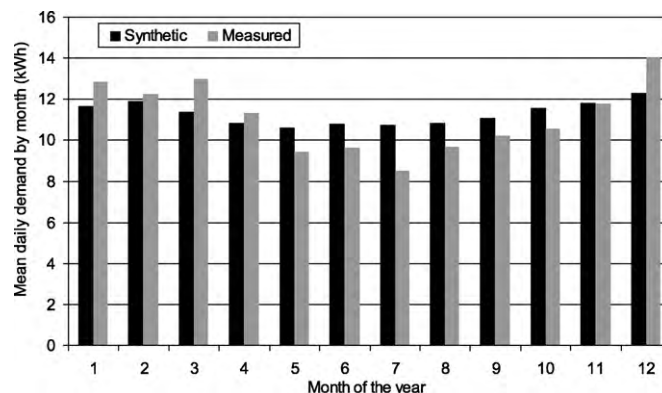**Fig. 6.** Annual electricity use by dwelling, ranked by the magnitude of demand.

With this in mind, Fig. 6 shows each set of 22 dwellings sorted according to annual demand. We do not expect a direct match in each pair; the purpose of the figure is to illustrate the overall trend. With the exception of cases 20 and 21, which illustrate the hazard of reading too much from small sample sizes, a possible under-prediction in the standard deviation is apparent and could be explained by several possible contributing factors:

- The occupancy model may be over-representing the time of active occupancy in the dwellings with lower energy use. For example, it was noted that the measured demand data for dwelling number 1 shows many consecutive days where only the cycling that is typical of cooling appliances is seen. This is a one-occupant dwelling and suggests that this occupant is away for a considerable amount of time, resulting in a low level of demand. The occupancy model creates profiles based upon the single day diaries surveyed from the TUS and would therefore not necessarily capture such behavioural patterns over a period of time.
- The variation of appliances between dwellings may not be fully representative because correlations in appliance ownership are not being taken into account by the model. For example, three of the four lowest demand dwellings use both gas ovens and gas hobs. The model considers these appliances independently. Therefore, a more even spread of dwellings with a combination of gas and electric ovens and hobs would result in less overall variation.
- The model takes no account of the attitudes of the occupants towards energy use. Some of the residents in the sample are known to be very "energy aware" and are therefore likely to purchase energy efficient appliances and to diligently switch them off when not in use. The other residents may be less conscious of their energy use, which could lead them to have higher annual consumptions, thus increasing the spread between dwellings in the measured data.

Despite these limitations, overall the variation in the levels of demand is considered statistically very similar between the measured and the synthetic data.

4.3. Mean daily demand by month

A comparison of the mean daily demand by month is shown in Fig. 7. The model has the right general shape, but appears to be underestimating the seasonal variation. The following factors are relevant:

- The occupancy model is not seasonal and thus does not represent the tendency for people to stay in on winter evenings and use more appliances.
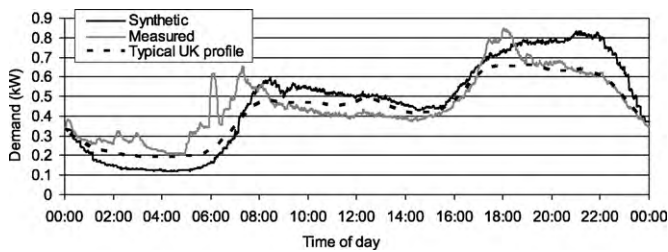
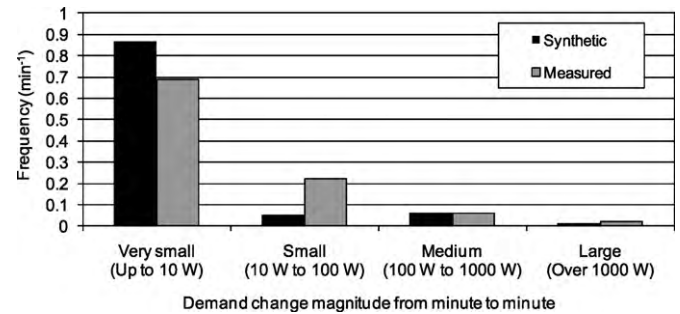Fig. 8. Annual mean daily demand profile.

- The model does not currently include central heating pumps or boiler fans. Most of the measured dwellings have oil or gas fired central heating.
- The only seasonal effect represented in the synthetic data is in the use of lighting, which is linked to natural daylight conditions.

4.4. Daily demand profile

The synthetic and measured mean daily profile throughout the year is shown in Fig. 8. Also shown on the diagram is a typical UK profile, which is discussed later.

In general, the profiles all follow a similar pattern. There is a reduced level of use during the night, followed by an initial peak at breakfast time. The demand is reasonably level during the day, until mid-afternoon, when demand rises towards an evening peak. The demand then falls in the later evening period.

Closer inspection reveals various discrepancies between the measured and synthetic data:

- The measured data shows considerably more demand during the night-time period (midnight to 6 AM). This is partly because the modelling of lighting does not take into consideration that occupants sometimes leave lights whilst sleeping.
- The model does not take into account the use of timers to run appliances, such as washing machines. This is particularly evident in two small blips that appear in the measured data at 2 AM and 3 AM, which are known to be caused by a washing machine and a dish-washer that were being used on timers in just one of the measured dwellings. As another example, the large blip that appears in the measured data at 6 AM is due to a 2 kW demand from a single dwelling occurring for the majority of the year. This also indicates the influence that an individual dwelling can have on the aggregated data when only 22 dwellings are considered, and reminds us not to read too much into the data.
- The rapid increase in demand that occurs when people get up and have breakfast is known as the "morning pickup" and its gradient and magnitude are well represented by the model, but it appears to be nearly an hour late. This could be due to the use of timers in the real dwellings (immersion heaters, central heating pumps and fans) but is more likely due to a discrepancy between the specific daily practices of the people in the 22 measured dwellings compared to the UK national practices reflected in the occupancy model. All the measured dwellings are thought to have at least one resident in employment, and thus dwellings with retired or unemployed residents are likely to be under-represented.
- The measured data also shows less demand during the day, an early evening peak and reduced demand later in the evening, all of which could again be associated with people in employment.

For a comparison with national data, the dotted line in Fig. 8 shows an annual demand profile for UK domestic unrestricted customers, from the standard profiles developed by the Electricity Association [23]. The synthetic data matches this UK domestic profile even more closely than it does the locally measured data.

Fig. 9. Minute to minute demand volatility.

However, it does appear that the model is over-predicting energy consumption in the evening (18:00 onwards). This could be due to people becoming more sedentary (less active) towards the end of the day and less likely to be multi-tasking. Whilst the model allows multiple appliances to run simultaneously, the activity profiles are determined solely from the primary activity shown in the TUS data and thus do not represent occupants' multi-tasking. The small remaining discrepancies can be explained as above.

4.5. Minute to minute demand volatility

The model creates synthetic data with a temporal resolution of 1-min. The purpose of choosing this high resolution was mentioned in the introductory Section 1.6; alternatively, it may be simply described as an intention to emulate the spikiness that characterises real domestic electricity demand as illustrated earlier in Fig. 5. The synthetic data shown in Fig. 4(c) did appear to have this spikiness, and the purpose of this section is to verify that this volatility is statistically similar to the measured data. In order to assess this we look at the transitions, and quantify how often and by how much the individual demands change from 1-min to the next.

A histogram showing a comparison of the volatility is shown in Fig. 9. Transitions, both positive and negative, are binned according to their magnitude (x axis); and their frequency (y axis) is counted across the whole synthetic and measured data sets.

It is immediately apparent that the model is under-representing transitions in the 10–100 W range. The following factors lead to this effect:

- The model represents the switching on and off of major appliances (typically well over 100 W) according to the detailed procedures outlined earlier. Smaller appliances and gadgets, such as mobile phone chargers, are not explicitly modelled; their aggregated demand is effectively subsumed into the major appliances through the calibration process. Thus the switching on and off of small appliances does not appear in the synthetic data.
- The model treats most major appliances as a constant demand, whereas in the real world the power drawn will vary slightly. For example, the freezer is modelled as having a 190 W demand for 14 min. In practice, the temperature and pressure of the refrigerant will vary during that time and therefore the exact power drawn may vary by several tens of watts, which will show as transitions in the measured data.

The number of medium size transitions appears to be very well captured. The large transitions, however, are under-represented by the model. An example explanation for this could be the "re-boiling" of a kettle, which would lead to four transitions in total, whereas the model would only show two.

Table 1
Non-coincident demand, diversified demand and diversity factor comparison.

Metric	Synthetic data	Measured data
Maximum non-coincident demand	260.0 kW	240.8 kW
Maximum diversified demand	49.6 kW	46.5 kW
Diversity factor	5.24	5.18

4.6. Time-coincident demand

A further objective of the model, set out in Section 1, was that it should appropriately represent the time-coincident demand between different dwellings. Statistical measures that represent the nature of the combined demand of groups of dwellings are discussed by Kersting [24] and are summarised here.

Taking the individual maximum demands from each dwelling over a period of time and summing them, gives the "maximum non-coincident demand". This provides a measure of the level of demand that would occur if the maximum demand for each dwelling occurred at the same time.

In reality, such coincidence is not likely to happen and the maximum time-coincident demand of all dwellings together is much lower. It is known as the "maximum diversified demand". The "diversity factor" is the ratio of these two metrics.

A comparison of the synthetic and measured data using these metrics is given in Table 1 and shows that the model is creating data with very realistic diversity characteristics. This result confirms that the underlying occupancy model is providing an effective way of representing the time-coincidence between dwellings.
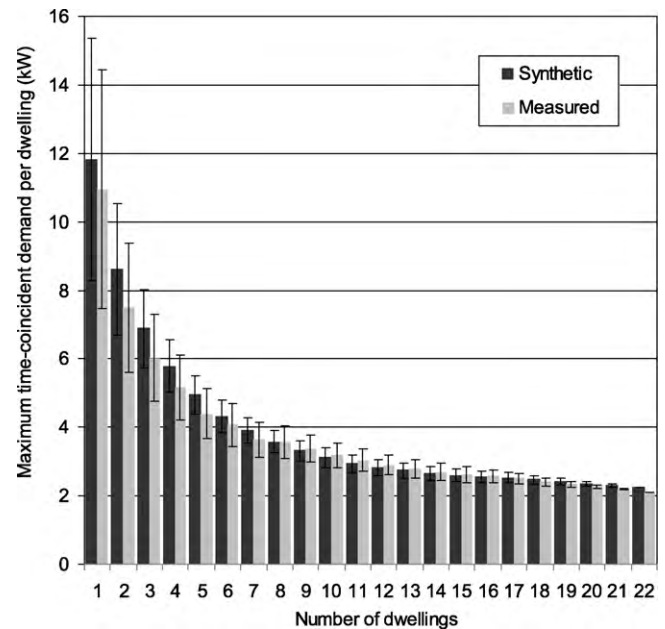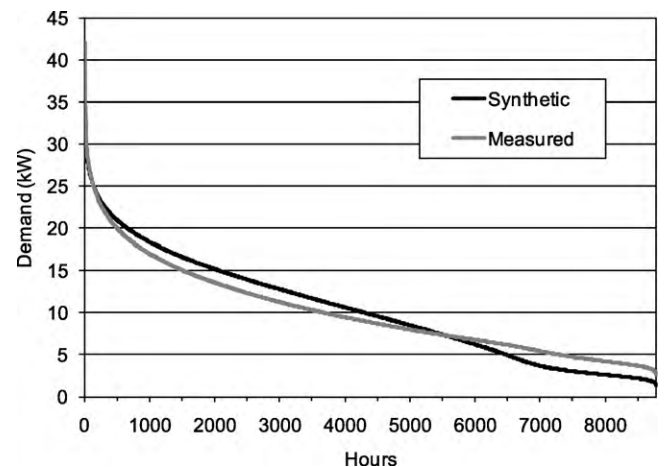
4.7. After diversity maximum demand (ADMD)

The "after diversity maximum demand" (ADMD) is often used in the design of electricity distribution networks serving large numbers of customers, where their demand is aggregated. A formal definition is "the maximum demand, per customer, as the number of customers connected to the network approaches infinity" [25]. Typical UK standards allow for a demand of 2 kW per dwelling, where there is no electric heating [26].

As a further verification that the model is creating data with the appropriate time-coincident demand characteristics, a comparison is now made using different numbers of dwellings. Using subsets of the synthetic and measured data for the 22 dwellings, Fig. 10 shows how the maximum time-coincident demand, on a per-dwelling basis, varies as the number of dwellings is increased. The figure indicates a strong correlation between the synthetic and measured data, and shows a trend towards an asymptote of approximately 2 kW, corresponding closely to the UK standard ADMD mentioned above.

The markers on each column represent one standard deviation each side of the mean, which is useful as an indication of the certainty with which the demand levels occur. With only a single dwelling, there is considerable uncertainty as to the maximum demand. As the number of dwellings increases, the maximum time-coincident demand per dwelling falls and the uncertainty decreases. The size of the markers reminds us not to be too concerned with the minor differences between the main bars for small numbers of dwellings.

4.8. Load duration curves

The load duration curves for the aggregated demands of the 22 simulated and 22 measured dwellings, over a 1-year period, are shown in Fig. 11. The area under the curves and general shape match very closely. The slight distortion in the shape is due to the model under-representing demand during the night when

Fig. 10. Maximum time-coincident demand, per dwelling.

Fig. 11. Load duration curve.

occupants are asleep, as shown earlier in Fig. 8 and previously discussed.

4.9. Power factor

A final comparison is the power factor seen from aggregate loads throughout the day. With the support of Central Networks, a logger was used to measure the power demand on a distribution circuit serving 56 dwellings (separate from the 22 dwellings previously discussed). This data was measured at a 1-min resolution on a day in November. The model was used to create synthetic demand profiles for 56 dwellings, also for a November day. The comparison is shown in Fig. 12.

The model is creating power factor data of a very similar nature to the measured data. The lower and upper limits of both data sets are approximately 0.99 and 0.86, respectively. In qualitative terms, both curves follow a similar pattern and the volatility characteristics are visually the same. During the night, the power factor is reduced and more volatile because cooling appliances (which have a low power factor) are a greater proportion of the demand. Similar reduction and volatility is apparent during the middle of the day.
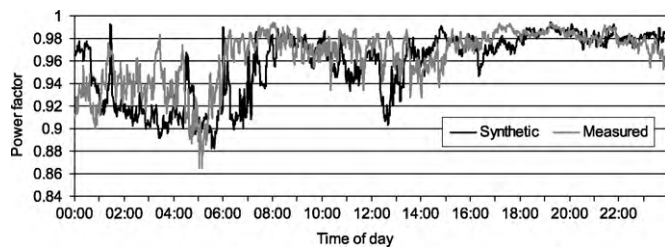
Fig. 12. Power factor comparison.

This is due to the use of washing machines at this time of the day, corresponding to the time of laundry activities in the TUS data.

5. Conclusions

A domestic electricity demand model based on occupant time-use data [7] has been presented. It maps occupant activity to appliance use and stochastically creates synthetic demand data with a 1-min time resolution. The model uses concepts previously developed by the same authors in the construction of a domestic lighting model [1]. It was constructed using individual appliance power consumption data and nationwide ownership statistics. High-resolution measured data from 22 local dwellings was used only for validation.

The synthetic data compares very well with the measured data and thus the model meets the general aims set for it. It appears particularly good at representing the time-coincidence/diversity of demand between multiple dwellings (Table 1 and Figs. 10 and 11). The representation of power factor also appears sound (Fig. 12). Both these aspects are important in the design of local electricity distribution networks. Volatility of the individual dwelling demand from minute to minute is well represented in the mid-range of transitions (Fig. 9). However, small and large transitions are under-represented.

The annual mean daily demand profile shows good agreement with the typical UK profile (Fig. 8), but under-represents the demand during the night, primarily because the model does not represent people leaving lights on whilst asleep or the use of timers to run appliances. Such behaviour could readily be included into the model, if it could be supported by quantifying data.

Further discrepancies in the daily demand profile (Fig. 8) and the possible under-representation of the variation of annual demand between dwellings (Fig. 6) are believed to be due to socio-economic factors, employment profiles, multi-tasking and individual attitudes to energy conservation. Enhancement of the model with regard to these aspects is certainly possible, but would require significantly more data than is available in the TUS data set. A guiding principal in the construction of the model has been that it be based upon available statistical data and not pure speculation. Indeed the greatest constraint in building the model has been in the availability of relevant data.

The model under-represents the seasonal variation of electricity demand (Fig. 7). This is partly because the extent to which people stay in more during winter cannot be quantified from the TUS data set, and so the resulting increase in general appliance use is not represented in the model. Again, enhancement in this respect is constrained by data availability. However, a more significant aspect of seasonal variation may be the greater use of electrical heating appliances (including central heating pumps) during winter, which is not fully represented in the model at this stage.

The model was developed particularly for the study of local electricity distribution networks, in which case the representation of demand correlation/diversity is critical. Initial use of the 1-min synthetic demand data from the model within network load-flow studies has already provided detailed voltage profiles, which compare very well with measured voltage data. This work will be reported in a forthcoming paper.

The demand model also has many other possible applications and the authors have provided an open-source freely downloadable example of the model [13] in the hope that other researchers will adopt and adapt it for their own purposes. The linking of electricity demand to occupant activities is central to the model and should facilitate its application to studies relating, for example, to human factors in domestic energy use.

6. Further work

Whilst the model is already complete and useful for many applications, there are of course plans to develop it further. In particular, the aim is to represent the building thermal behaviour alongside and linked to the occupant behaviour and thus provide stochastic, but duly correlated, thermal demand data for large numbers of dwellings. Initially, this may be used in relation to central heating pumps and direct electrical heating. More importantly, it will underpin the integrated simulation of heat pumps and micro-CHP. Similarly integrated simulation of electric vehicle charging is also planned.

In parallel, the model is being enhanced with regard to demand side management, and in particular flexible demand involving the time-shifting of appliance use. The switch-on probability calculation will be extended to include an external variable such as a real-time price, which will cause the bringing forward or delaying of appliance use within the model.

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