Domestic lighting: a high-resolution energy demand model

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Abstract

The use of electric lighting in the domestic sector depends mainly on the level of natural light coming in from outdoors, coupled with the activity of the household residents. This paper presents a detailed model of domestic lighting use that takes these two factors as its basic inputs. The operation of individual bulbs is represented within the model and is used to construct high-resolution lighting electricity demand profiles for individual dwellings. The model is computationally efficient and can easily provide data at one-minute resolution for large numbers of dwellings. As a primary input, the model uses a time-series representing the number of active occupants within a dwelling (people who are at home and awake). This allows it to represent the sharing of lighting between the occupants of a given dwelling and facilitates correlated linking to models of other energy use within the dwelling. Appropriate correlation between dwellings is achieved through the use of appropriate active occupancy data and outdoor ambient light data. An example implementation of the model in Microsoft Excel is available for free download.

Keywords: domestic lighting, energy demand modelling, occupancy

1. Introduction

The lighting energy use model described in this paper is one component within a comprehensive domestic electricity demand model that is being developed for the study of low-carbon strategies and technologies, such as demand-side management, demand response and micro-generation. One of the aims is to provide high-resolution electricity demand profiles that realistically represent the highly stochastic nature of real electricity demand at the individual dwelling level and provide the appropriate levels of correlation between dwellings in a given locality. This data is required, for example, to properly model the effects of low-carbon technologies on electricity distribution networks.

With this application in mind, the features of the model that are considered important and that have been implemented are as follows.

1.1 Natural lighting

Human perception of the natural light level within a building is a key factor determining use of electric lighting. This concept is supported by Reinhart [1] in the context of control of lighting in office buildings, by Yao and Steemers [2] for demand modelling and by Hunt [3].

1.2 Active occupancy

The number of people who are at home and awake (active occupancy) is the other key factor for domestic lighting use [2,4,5] and is used as a main input to the model developed here. Bladh and Krantz [6] conclude that “Presence in the home is important for consumption” and Wright and Firth [7] discuss how occupancy contributes to the patterns of domestic load.

A previously published occupancy model [8] is used to provide a scalar variable that indicates the number of active occupants within a dwelling throughout the day.

1.3 Sharing

It is natural that people within a particular dwelling will often share lighting by virtue of being in the same room, and it is important that this sharing is properly represented within the model. Having the level of active occupancy as an input parameter allows this to be achieved.

1.4 Linking to other domestic demand models

The time of use of energy for many other purposes within dwellings (household appliances, hot water use, etc) is also closely related to active occupancy, and using this parameter as a common input to various models will allow the correlation of such energy use to be correctly represented, and thus result in realistic aggregated demand profiles.

1.5 Lighting units

A lighting unit represents one or more bulbs connected to a single switch. In most instances, a lighting unit equates to a single light bulb. However in some cases, lighting units may comprise multiple bulbs operated from a single switch. Halogen downlighters are a common example, and such arrangements are stochastically represented within the model. The same approach could be used for other bulb types, but this has not been implemented due to a lack of available surveyed data on multiple bulb configurations.

1.6 Installed lighting technologies and ratings

The number of installed lighting units, the specific lighting technologies used and their power ratings, varies from one dwelling to the next through human choice. The model uses statistics from The Lighting Association [9] to randomly populate each dwelling with a different, but representative, set of lighting units.

1.7 Relative usage of lighting units

Some domestic lighting units will be used more frequently than others. Frequently occupied rooms, such as kitchens and general living space, will have a greater lighting demand than loft or cellar areas. A weighting to indicate this relative usage is applied to each lighting unit in the model.

1.8 Temporal resolution

Electricity demand is often measured and analysed on a half-hourly basis, particularly in the UK. Stokes et al. [10] describes a lighting demand model that is built upon half-hourly measured demand data and comments that “Very little data are available at the 1 min demand level”. The Energy Saving Trust report “Energy Monitoring Project for Lighting” [11] points out that “there have not been many studies where lighting use was monitored in detail”.

Whilst a half-hourly resolution is acceptable for trading and high-level network studies, it is of little use for studying the detailed operation of low-voltage distribution networks or fast-acting demand-side management. Consider for example the demand peak that occurs at the end of a popular television program, which would be largely smoothed over in half-hourly data. With this in mind, the model described in this paper has been initially configured to provide data at one-minute resolution, which is considered a reasonable compromise between the data volume yield for higher resolution modelling and the excessive demand curve smoothing produced by lower time resolutions. It is possible though to reconfigure the model to provide data at a different time resolution.

1.9 Open-source downloadable model

An open-source example implementation of the model has been constructed within Microsoft Excel and is freely available for download [12].

This software is ready to run and provides a 24-hour simulation of the lighting load for a single dwelling. The user may configure the number of residents, the month of the year and whether a weekday or weekend occupancy pattern is required. The lighting unit configuration is randomly chosen from a representative set of examples. Twelve sample irradiance profiles are provided to represent each month of the year. In each run, an active occupancy pattern is generated and this is used in conjunction with the selected irradiance profile to generate a lighting demand profile.

The source code for both the lighting model and the supporting occupancy model is provided as Visual Basic for Applications (VBA) macros within the file. As such, the model may be modified or integrated into other applications as required.

2 Construction of the model

2.1 Outline structure of the model

The structure of the model is outlined in Fig. 1. The outdoor irradiance data series on the left of the figure is a global programme variable: all dwellings experience the same irradiance and it feeds directly into the likelihood of any individual lighting unit being turned on. Another global variable, the calibration scalar, is used to calibrate the model to give a particular overall mean energy demand over a large number of simulation runs, so as to provide overall lighting loads in accordance with available statistics.

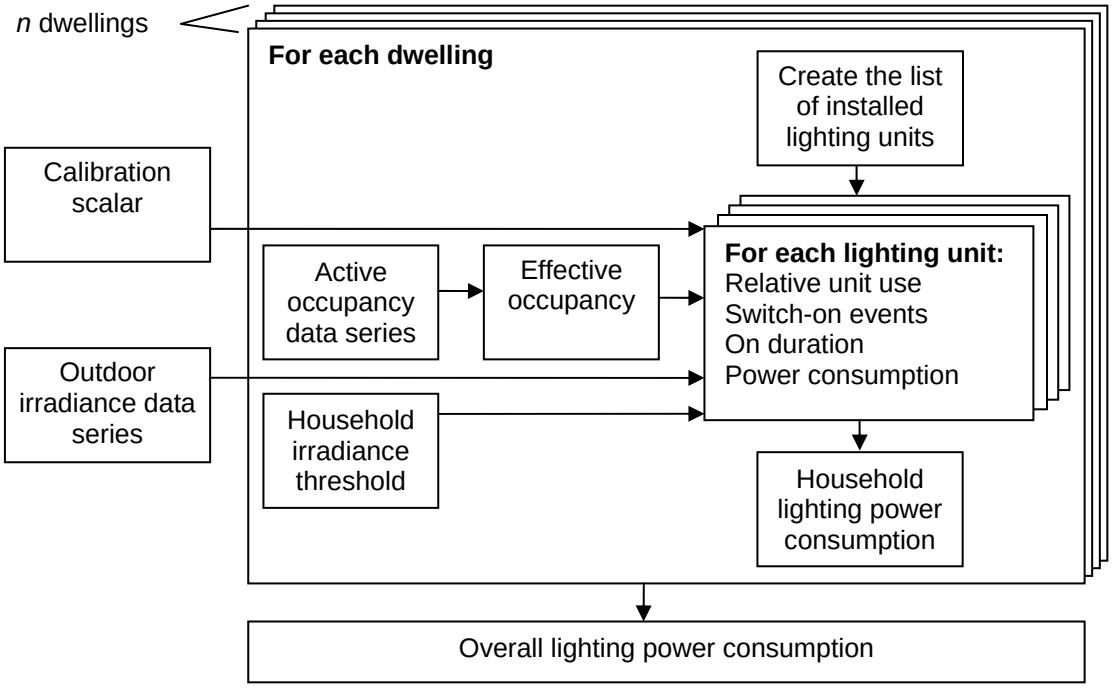


Fig. 1. Outline structure of the model

The main block in the figure represents the data held and processing undertaken for each dwelling being modelled. Each dwelling is assigned an active occupancy data series, which represents the number of active occupants within the dwelling over a period of time. This active occupancy level is adjusted to provide an effective occupancy value that takes account of the sharing of lights. Additionally, each dwelling has a household irradiance threshold, which defines the natural light level below which the occupants will consider using lighting.

The inner block is executed for each lighting unit that is installed in the dwelling. Each unit is assigned a relative use weighting that determines how frequently it is used compared to other units within the dwelling. The model uses the effective occupancy, the outdoor irradiance level, the weighting of relative lighting unit use and the calibration scalar to determine the likelihood of each unit being switched on. This likelihood is then compared against a random number to determine stochastically if the unit is to be switched on at any given time-step. The approach of using such a “starting probability function” is discussed by Paatero and Lund [13] in their work on household electricity load profile modelling.

Once on, the duration for which the unit stays on is then determined through a further stochastic calculation. Finally, the on/off status of the units are combined with their individual wattages, and then aggregated to provide energy consumption profiles.

2.2 Outdoor irradiance data series

The model assumes that a person's tendency to turn on a light is largely influenced by the level of outdoor global irradiance. An irradiance threshold is chosen for each dwelling by picking a value at random from a normal distribution with a mean of 60 W/m^2 and a standard deviation of 10 W/m^2. The probability distribution is included in order to represent the combined effect of two factors: first, the complex nature of daylight coming into the dwelling and the high variability of resulting indoor illuminance; and second, the high variability of human response to low light levels.

Furthermore, occupants may not respond immediately to a sudden reduction in illuminance, for example caused by passing clouds, and to allow for this an exponential moving average filter is used to smooth variations in the measured one-minute irradiance data that is fed into the model.

The model uses data from the CREST irradiance database [21]. This data set provides high-resolution irradiance data recorded on-site at Loughborough University. In constructing the model, a full year of data from 2007 was used, although any suitable irradiance data set could be substituted. Some examples of daily irradiance profiles for each month of the year are provided in the downloadable example introduced in section 1.9.

Lastly, the model allows for the fact that lights are sometimes used regardless of irradiance levels, such as in the case of a room without windows, a loft or cellar for example. The model takes this into account by allowing lighting units to be switched-on irrespective of the irradiance level in five percent of the time steps.

2.3 Active occupancy data series

Each dwelling is assigned an active occupancy profile, which is provided by a high-resolution domestic building occupancy model that was published previously [8,14]. In summary, this model provides the number of active occupants within a dwelling as a variable throughout the day. The model can generate data for any number of dwellings. It is based upon the United Kingdom 2000 Time Use Survey [15], which is a very detailed survey of how people spend their time.

With this basis, the occupancy model is able to represent the random nature of people's behaviour and to provide the appropriate correlations between residents of the same dwelling and between residents in other dwellings. These factors make it suitable both as a data input to the lighting model described in this paper and as an input to linked concurrent models of other domestic energy use (through cooking, entertainment, etc.), and thus possible to achieve appropriate correlations between all domestic energy uses.

2.4 Creating the list of installed lighting units

Each house in the simulation is allocated a characteristic set of installed lighting units based upon industry statistics. Data on the mean numbers of installed bulbs and the relative proportions of different bulb technologies are provided in The Lighting Association's In Home Lighting Audit Report [9].

To create the list of installed lighting units for each dwelling, the total number of units in each property is first picked at random from a normal distribution based upon the data provided in the above report. Secondly, the technology category of each unit is picked as one of either incandescent general lighting service (GLS), low energy compact fluorescent (CFL), fluorescent tube, halogen or other bulb type, again using the above statistics. The 'other' category is a miscellaneous grouping for less commonly used bulb types, such as light emitting diode (LED) or parabolic aluminised reflector (PAR) bulbs. An example allocation of lighting unit technologies to ten dwellings is shown in Fig. 2. Since a stochastic approach is used to allocate these to dwellings, the allocation will be different each time the model is run.

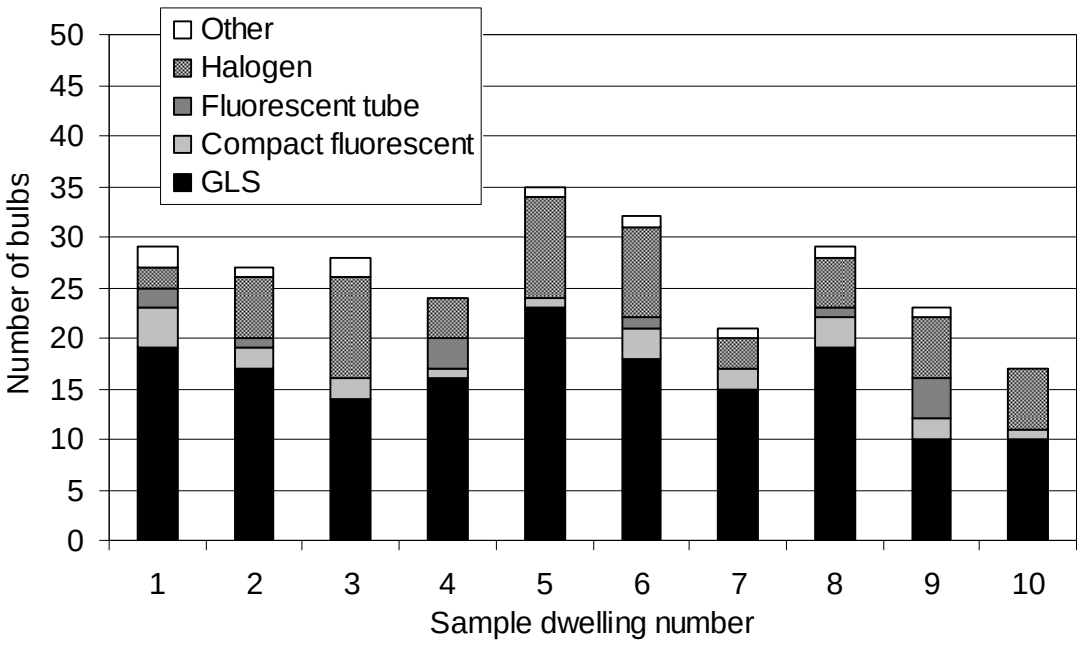


Fig. 2. Example allocation of lighting unit types in ten simulated dwellings

The power rating of each unit is then determined as follows. The UK Market Transformation Programme (MTP) document “Assumptions for energy scenarios in the domestic lighting sector” [16] contains data on the relative distribution of power ratings of incandescent technology bulbs. For incandescent bulbs types, a power rating is randomly assigned from this distribution. Assuming that a 100W GLS bulb is equivalent to a 20W CFL, the same split of power ratings of 9W, 12W and 20W CFL bulbs is used for 100W, 60W and 40W GLS bulbs respectively. The power ratings of fluorescent, halogen or other category bulb types are based upon a random value selection from the most commonly available types.

Some lighting configurations are installed such that a single switch will control more than one light bulb. It is difficult to generalise on typical grouping configurations for the purposes of modelling. However, the model will randomly group lower power halogen bulbs, which are typically configured in this way.

2.5 Switch-on events

In determining whether a particular lighting unit is switched on at a point in time, the following factors are assessed:

- The current irradiance level is compared to the allocated dwelling irradiance threshold to determine if natural light levels are low enough such that artificial lighting may be required, as discussed in section 2.2.
- The second consideration is the relative usage of different lighting units within a dwelling. Some units will be used more frequently than others. Each unit is allocated a fixed weight at the start of the simulation, to indicate how much it is used in comparison to other units.
- The third consideration is the effective occupancy, which is a function of the number of current active occupants in the dwelling. If there are no active occupants, then the value will be 0, and therefore a switch-on event cannot occur.
- In order for the model to provide an overall average lighting energy use, per dwelling per year, over a large number of runs, a calibration scalar value is used to configure the mean energy demand output to a required level.

At each time step, the calculation shown in Fig. 3 is performed for each unit in every dwelling and the result is compared to a random number to determine if the switch-on occurs. If a switch-on does occur, it is then necessary to determine the duration of the unit use. This is done by picking a random value from a probability distribution of lighting unit use durations. The details of the above calculations are presented in the following sections.

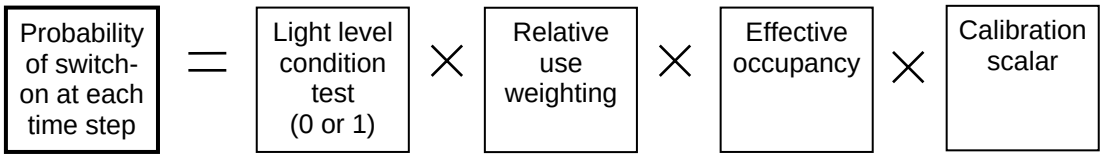


Fig. 3. Calculation of lighting unit switch-on probability

2.5.1 Natural light condition test

The dwelling irradiance threshold (pre-determined as described in section 2.2) is compared against the current level of outdoor irradiance at each time step. If the current irradiance is below the threshold then the resulting value of this test is 1, otherwise 0.

The model also allows for a five percent chance that a lighting unit may be used regardless of the current natural light conditions, in order to represent the daytime use of lighting, as previously discussed in section 2.2.

2.5.2 Relative usage of different lighting units

Some lighting units within a dwelling are used more than others. This concept is briefly discussed in the DECADE project report [17] and is supported by Mills [18], although detailed statistics could not be found that specify the relative usage of units within a dwelling.

A distribution of weightings formed from a natural logarithmic curve is therefore used to represent this concept and an example is shown in Fig. 4. Each unit in every dwelling is assigned a scalar value from this distribution by picking a random number between 0 and 1 and picking the relative usage weight from the curve. Each unit is assigned a value at the start of the simulation and this remains constant throughout the run.

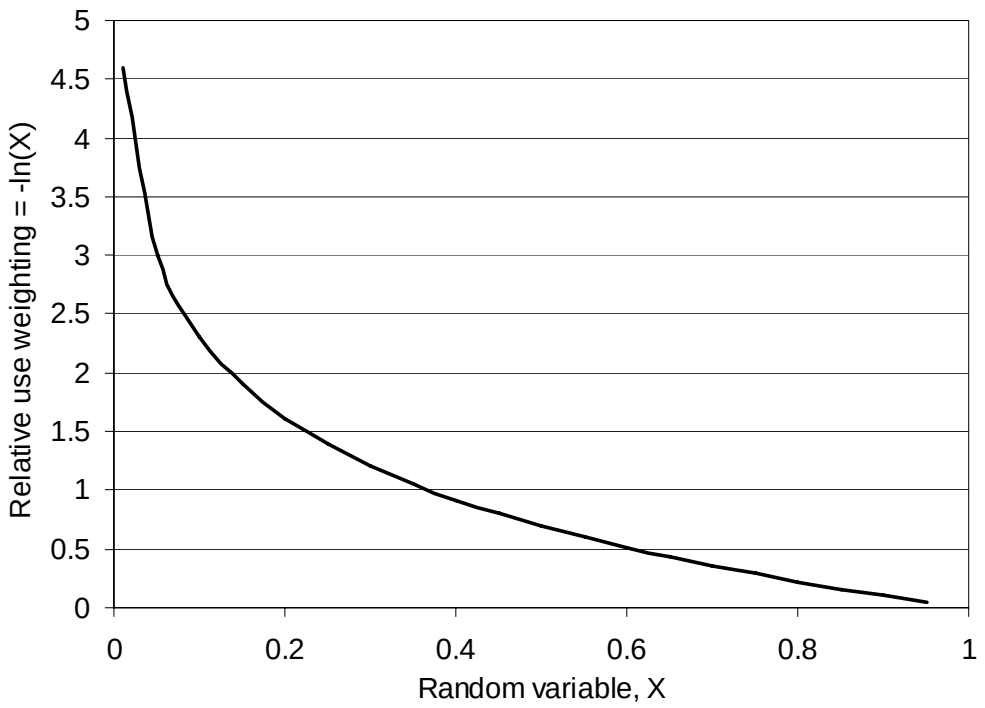


Fig. 4. Relative use weightings

In practical terms, a frequently used lighting unit, such as one installed in a kitchen, would have a higher use weighting (towards the left of the graph), compared to an infrequently used unit, such as a cellar light (towards the right). In the calculation of the switch-on probability, a higher relative use weight will result in a higher switch-on probability.

2.5.3 Effective occupancy

The model takes account of the sharing of lights, also known as “co-use” [6]. For example, if there are two active occupants in a property, they may well be in the same room and will naturally share the lighting in that room. Thus, on average, doubling the number of occupants does not lead to a doubling of lighting usage. To allow for this, the model defines an “effective occupancy” value, which is a function of active occupancy, as shown in Fig. 5(b) and derived as follows.

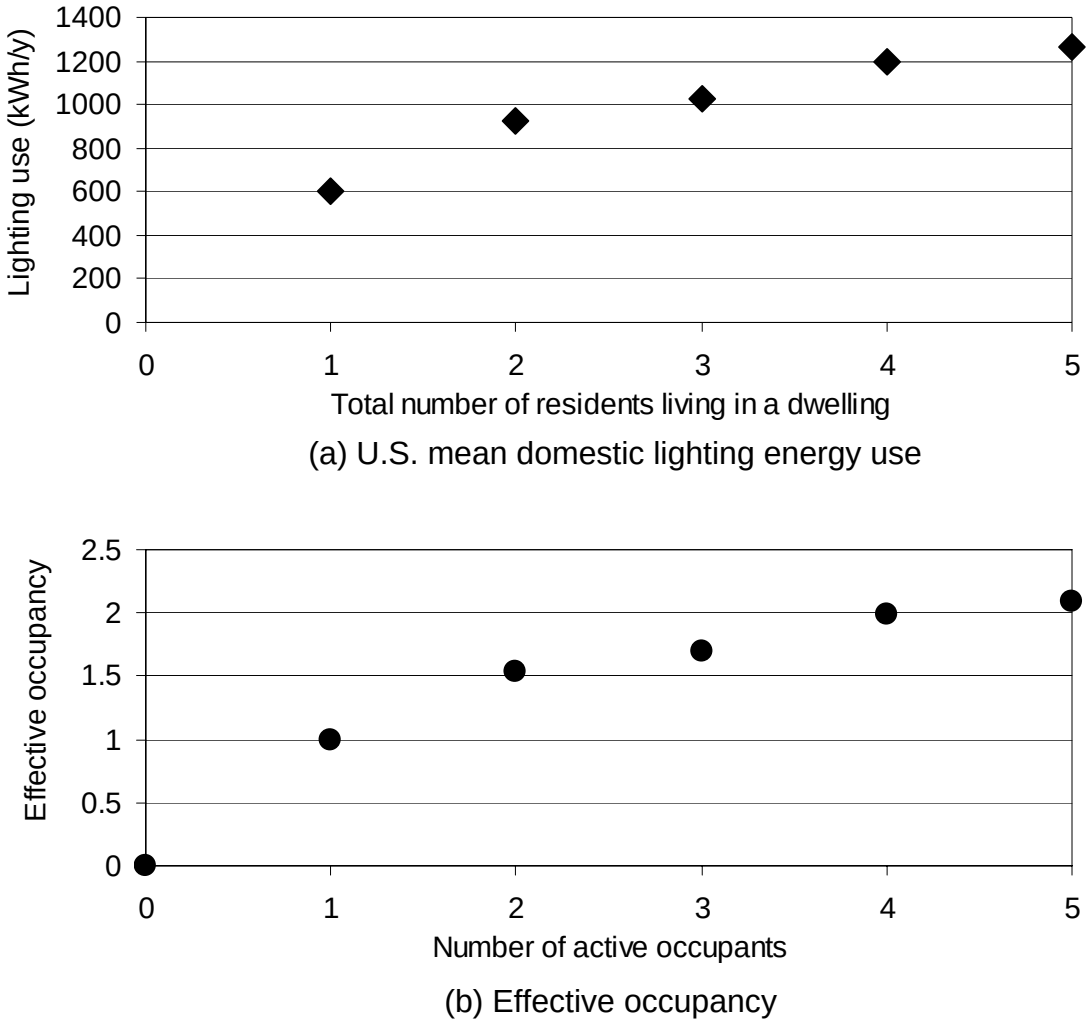


Fig. 5. (a) Mean annual U.S. lighting energy usage [19] and (b) effective occupancy

Data on the annual lighting usage in dwellings, by number of total occupants, is available for U.S. dwellings from the EIA 1993 Residential Energy Consumption Survey [19]. The decreasing gain in lighting use, as the occupancy numbers increase, can be seen in Fig. 5(a). The assumption is made that the shape of this usage will be also applicable to the UK and therefore that a set of effective occupancy values, as shown in Fig. 5(b) can be derived that represent the variation in light use as the number of active occupants varies. The values are derived by scaling the EIA demand data, such that the effective occupancy of a dwelling with one active occupant is one. The shape formed by the data points remains the same. It can be seen in Fig. 5(b) that demand will double only when there are four or more active occupants in a dwelling, compared to a dwelling with only one active occupant.

The effective occupancy at each time step therefore depends upon the number of active occupants within the dwelling at that time step. As can be seen in Fig. 5(b), if there are zero active occupants in the household, then the effective occupancy will be zero, meaning that switch-on events will not occur.

2.5.4 On Duration Model

Stokes et al. [10] comments that “lights remain on in occupied rooms for several hours, together with events that last a few minutes” and provides a probability distribution of light event durations based upon a survey. This concept and data (as shown in Fig. 6) are adopted here as follows. A duration is picked randomly from the distribution each time a switch-on event occurs. If the duration picked is longer than the prevailing period of active occupancy in a dwelling, then the duration is truncated at the time when the active occupancy becomes zero. The model therefore assumes that occupants will turn off lights upon leaving the property or before going to sleep.

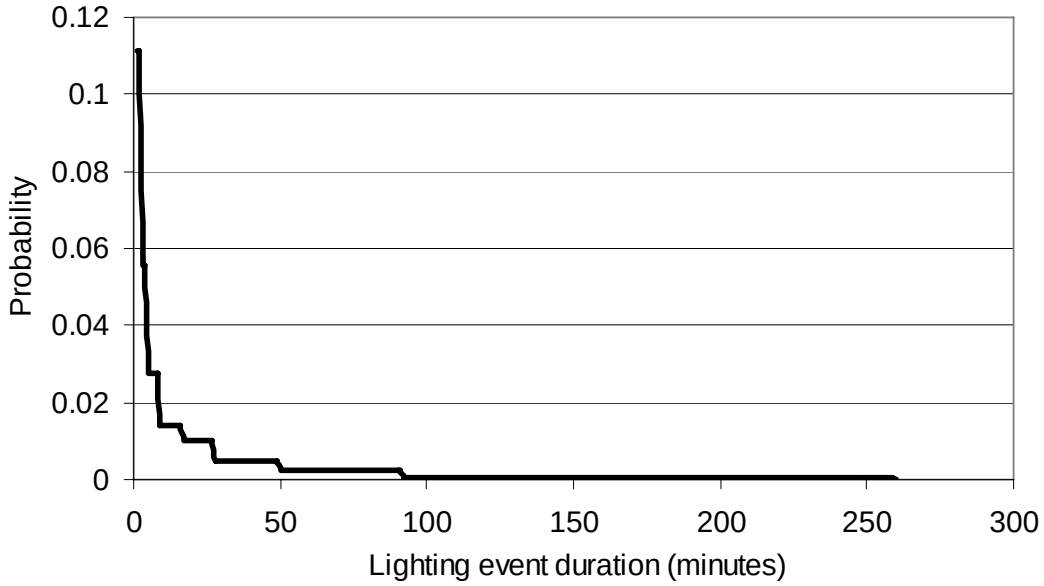


Fig. 6. On duration probability distribution from Stokes et al. [10]

2.6 Calibration

The calibration scalar, shown in Fig. 3, allows the model to be adjusted such that the overall mean annual lighting energy demand equals any required value. In this paper, and in the downloadable model, the calibration scalar is set to achieve an average of 715 kWh/y per household which is appropriate for the UK [20]. In particular, the calibration scalar value is set to 0.008154, which was determined by simulating 100 dwellings, over one year, ten times, using a full year of daily irradiance data [21].

2.7 A review of the concepts

A review of the concepts and sources upon which the model is based is presented in Table 1.

Concept	**Main concept references and data sources**
Irradiance model. Lighting usage is dependent upon daylight levels. The model needs to simulate the human behavioural response to low natural light levels.	Yao and Steemers [2] Reinhart [1] Hunt [3] CREST, Loughborough University [21]
Active occupancy model. Lighting usage is dependent upon active occupancy within a dwelling. The model therefore requires high-resolution active occupancy time series for domestic properties.	Richardson, Thomson and Infield [8] Yao and Steemers [2] Reinhart [1] Bladh and Krantz [6] Wright and Firth [7]
Installed lighting unit count, types and ratings. The lighting model needs to define the number, type and power ratings of the lighting units in each dwelling.	The Lighting Association [9] Stokes et al. [10] Market Transformation Programme [16]
Sharing. Where there is more than one active occupant in a dwelling, it is likely that lighting will be shared. An effective occupancy value is used to represent this concept.	U.S. Energy Information Administration lighting demand data [19]
Relative unit usage. Some light units in a dwelling will be used more frequently that others.	Boardman et al. [17] Mills, Siminovitch [18]
Stochastic switch-on event model. The model requires a mechanism to determine if a switch-on event occurs.	Paatero and Lund [13]
Lighting event duration model. If a unit is switched on, the model needs to determine for how long the unit remains on.	Stokes et al. [10]

Table 1 - Model concept review

3 Example Simulation Outputs

The model was implemented and example outputs are provided in this section. The downloadable model [12], described previously in section 1.9, may be used to generate additional sample lighting demand profiles.

3.1 Dwelling lighting unit allocation

In running the model, the number and configuration of lighting units within the simulated dwelling is determined. In the example presented in Fig. 7, the dwelling has been determined as having 23 units. The power rating of each of the units is shown on the left axis. The relative use weighting that has been allocated to each unit is shown on the right axis.

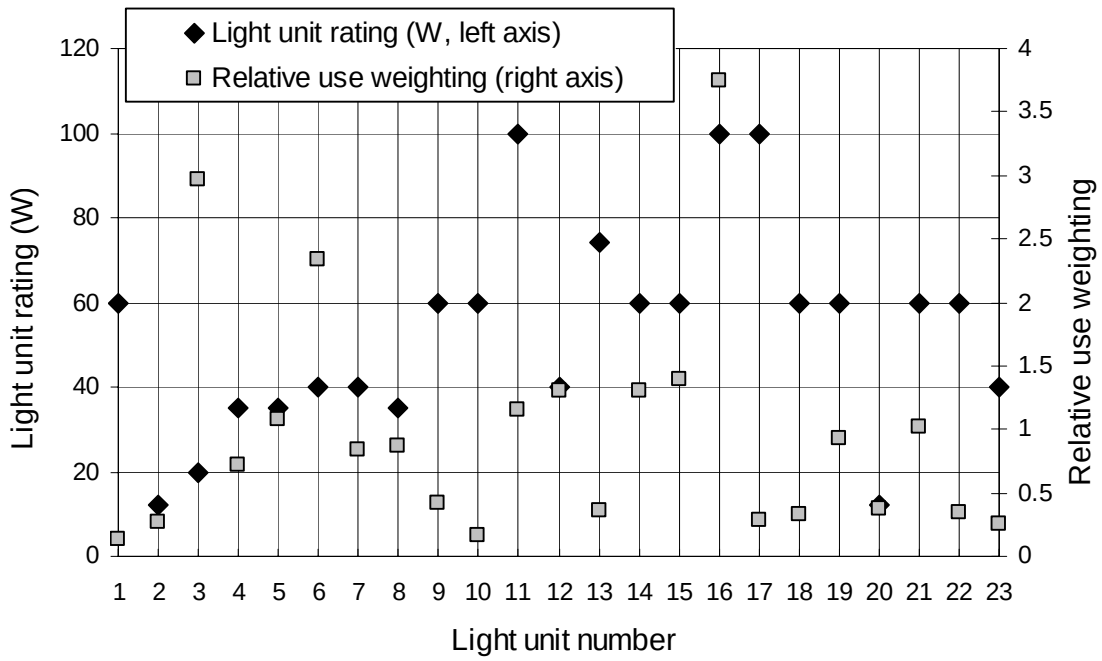


Fig. 7. Installed lighting unit configuration for an example dwelling

For example, unit 16 consumes 100 W and has a high relative use weighting, meaning that is it used a lot: perhaps it is in the kitchen. Unit 17 has the same wattage but is used much less frequently: it could be in the cellar.

It can also be seen that the many of lighting units in this dwelling are 60W rated incandescent bulbs, as is comparable with the example distributions shown earlier in Fig. 2.

3.2 One-day simulation

The results of a one-day simulation are shown in Fig. 8. The active occupancy and irradiance conditions over the one-day period are shown in Fig. 8(a). These data series provide the dynamic input values to the lighting demand model. The results of the simulation of the individual lighting units is shown in Fig. 8(b). The total household lighting demand is shown in Fig. 8(c).

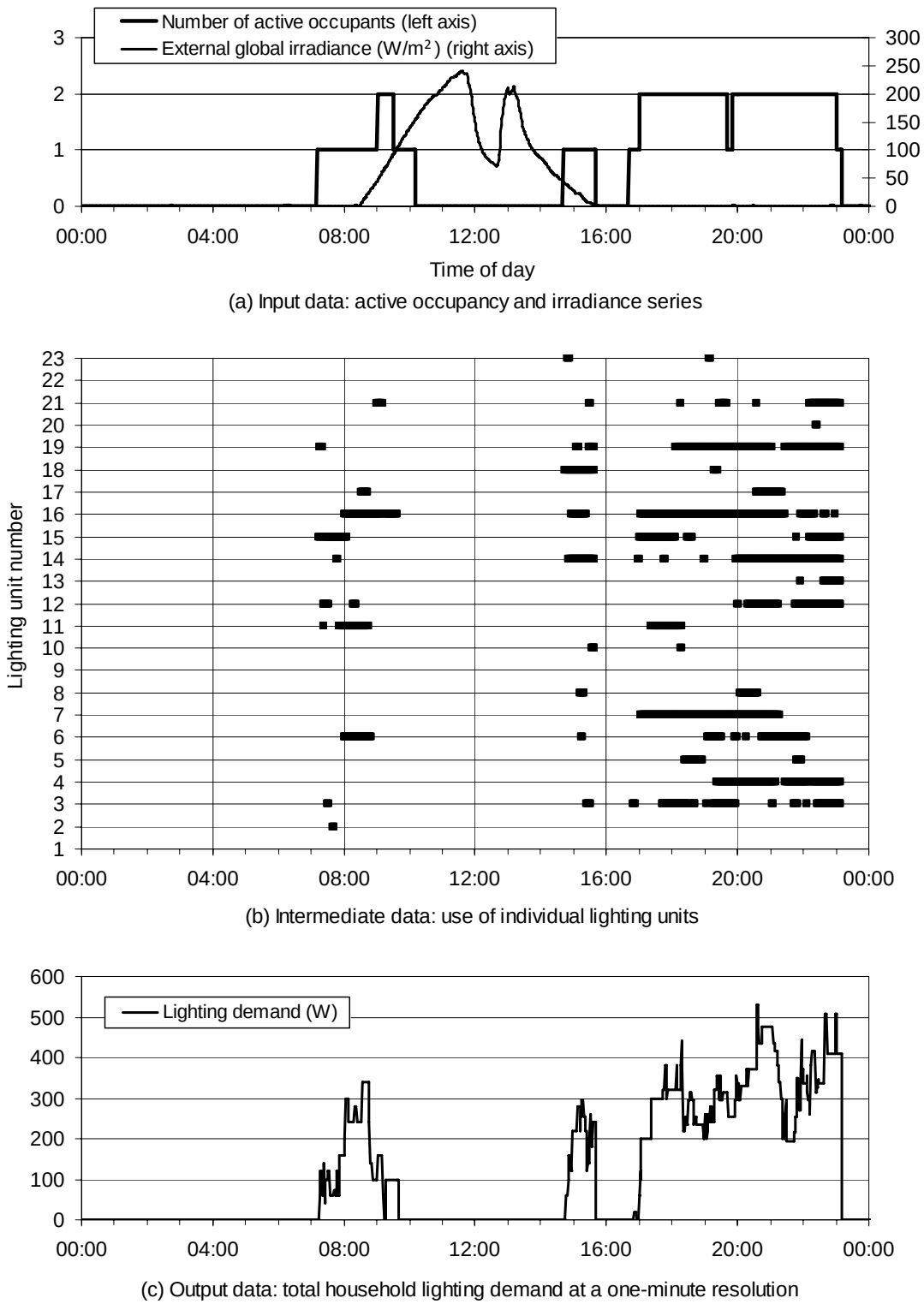


Fig. 8. One-day lighting demand for a single dwelling

3.3 Aggregated Lighting Demand Simulation Examples (100 dwellings)

The model was used to simulate 100 dwellings on a winter day as shown in Fig. 9, and on a summer day Fig. 10. In both cases, the input values of irradiance and active occupancy are shown, together with the total simulated lighting demand for the 100 dwellings.

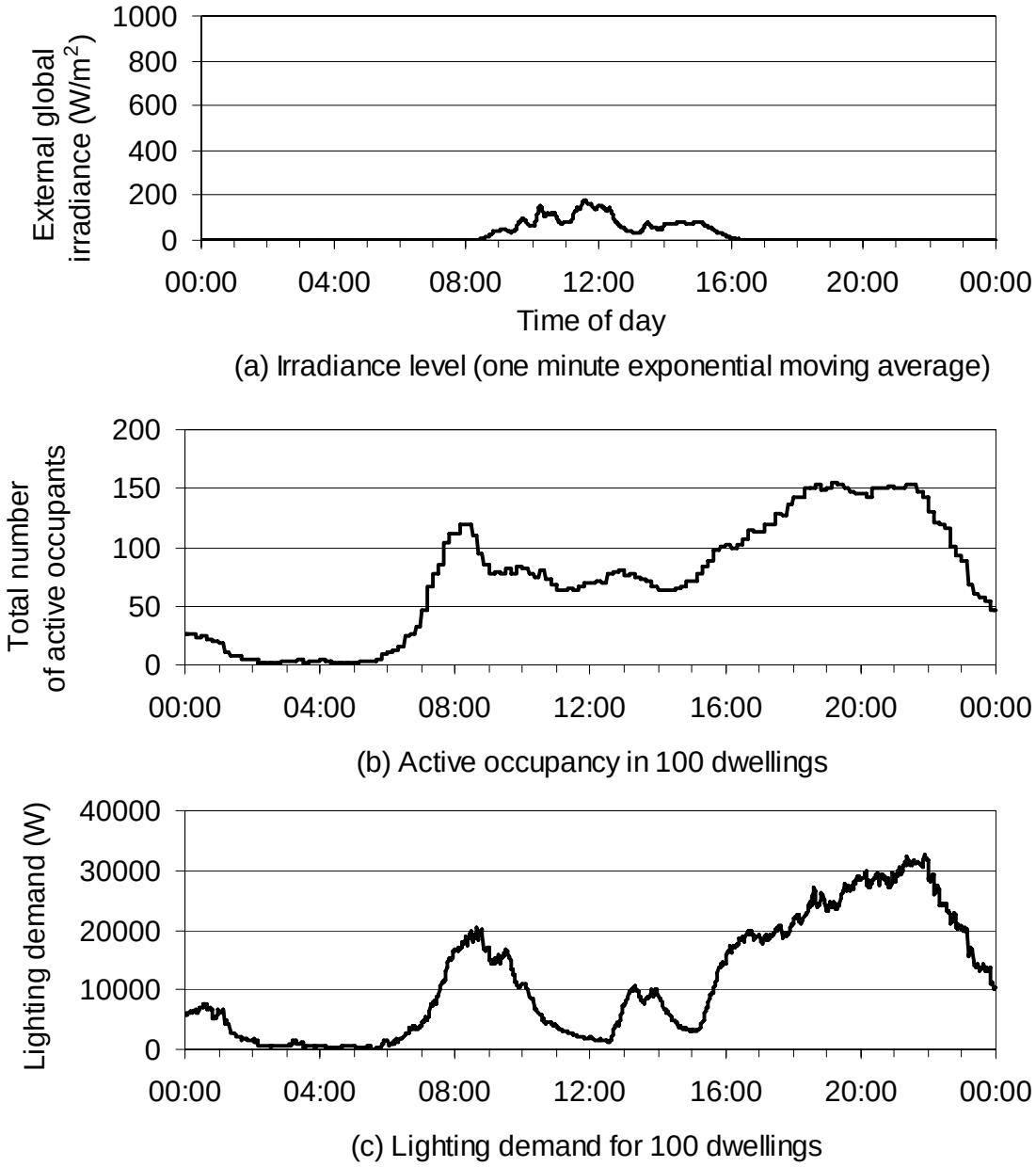


Fig. 9. Lighting load simulation output for 100 dwellings (Winter day)

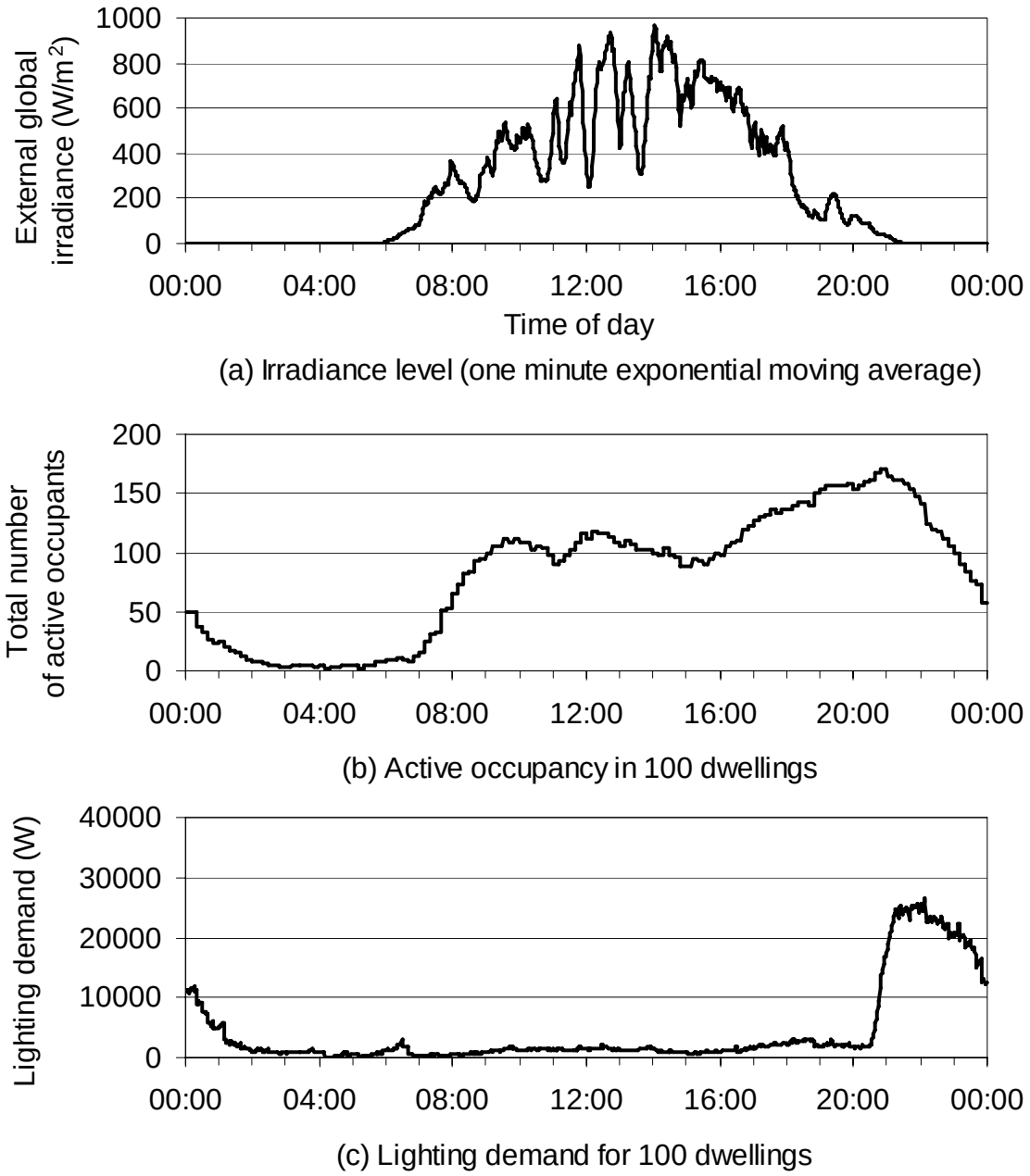


Fig. 10. Lighting load simulation output for 100 dwellings (Summer day)

In the winter scenario, irradiance data for 2nd January 2007 was used in conjunction with a weekday active occupancy profile [8]. It can be seen that as the irradiance level increases in the morning, the lighting demand falls, and that the reverse occurs in the evening when the active occupancy level rises. There is a significant fall in irradiance commencing after 12:00 hours, likely to be the result of heavy clouds passing overhead. In this case, the lighting demand graph shows a corresponding rise in lighting use during the period of low daytime

irradiance. Demand then reduces later in the afternoon as irradiance levels rise again. At sunset, which in this case happens to align with increasing active occupancy, there is a significant increase in lighting demand, peaking at about 22:00.

In the summer case, irradiance data for 1st July 2007 was used, in conjunction with a weekend occupancy profile. Fig. 10 shows the longer and increased levels of irradiance throughout the day, and an increased level of active occupancy, compared to the winter weekday example above. It can be seen that there is much less use of lighting in the morning compared to the winter case, and a smaller evening peak. Also, the evening peak occurs later in the day as a result of the later sunset time.

3.4 Annual Lighting Energy Demand and Sharing

The annual lighting energy use for households with differing numbers of residents is shown in Fig. 11. The white columns represent the required overall annual lighting energy demand as scaled from the U.S. EIA lighting data (see Fig. 5) to represent an overall UK usage of 715 kWh/y per dwelling, to which the model has been calibrated. The grey columns indicate the average annual demand as calculated by the lighting model over 100 dwellings.

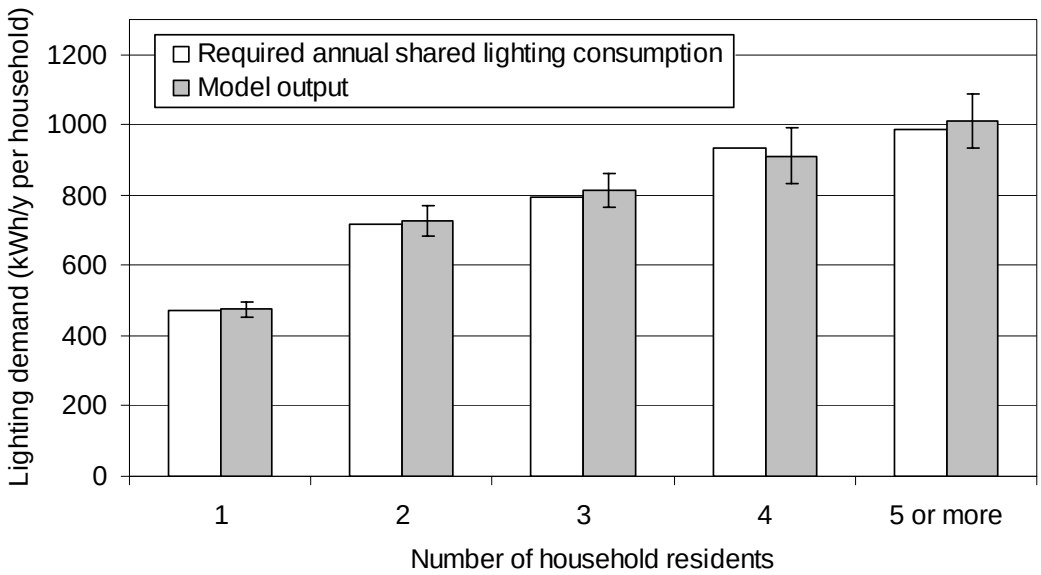


Fig. 11. Mean annual lighting demand per household by number of residents

Being a stochastic model, each run will yield different results. Error bars are shown to represent two standard deviations, given 10 simulation runs. As intended, it can be seen that the model is providing demand values that are very close to the required values to which it has been calibrated.

4 An Indirect Comparison Against Measured Data

4.1 Approach

In order to validate the model, an indirect comparison against measured data is made. In particular, the model is compared against the first layer model due to Stokes et al. [10], which is based on half-hourly measured electricity demand data from 100 dwellings.

The Stokes model was implemented and calibrated such that it yielded an annual lighting demand level of 715 kWh/y, which matches that used in the model as described in section 2.6. Comparisons were also made at both monthly and half-hourly resolutions as outlined below.

4.2 Monthly energy demand comparison

The monthly lighting energy demand given by the two models is compared in Fig. 12. With an r-squared value of 0.99, it is clear that there is a close correlation. This is particularly interesting since the Stokes model is based upon measured electricity demand data, whilst the new model is based upon physical factors including measured irradiance data and a model of active occupancy. The strong correlation provides good evidence that the core assumptions made in the new model are valid.

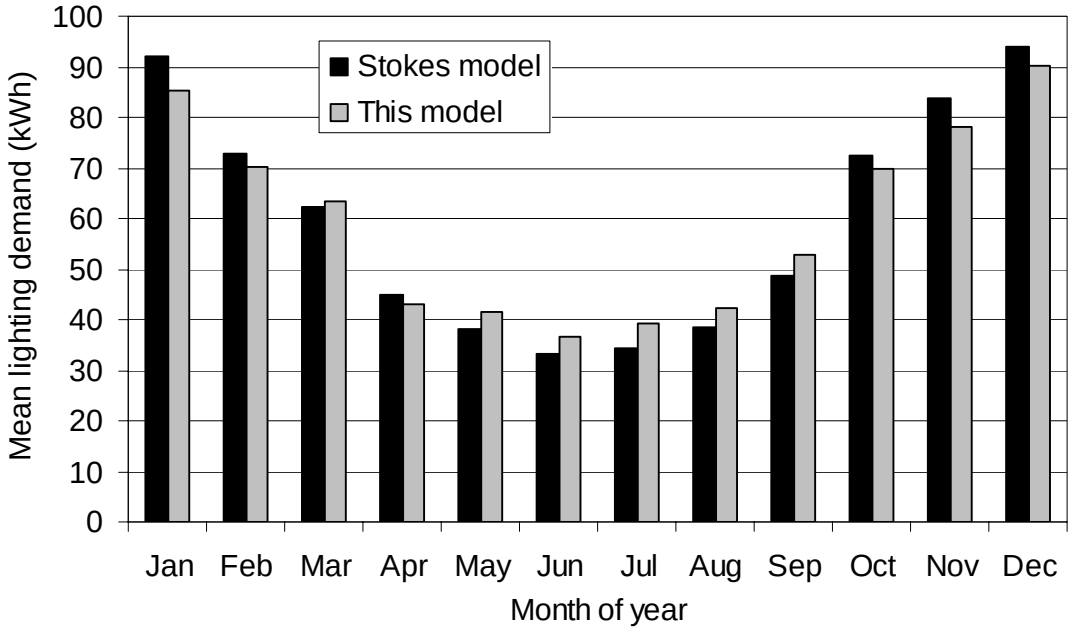
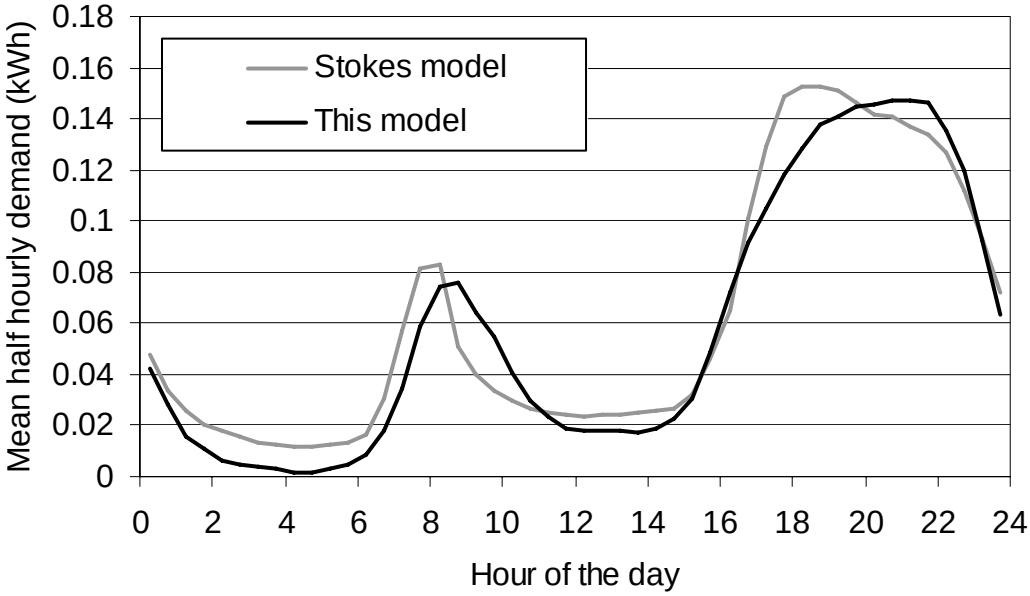


Fig. 12. Monthly comparison of the Stokes et al. model, against the model presented in this paper

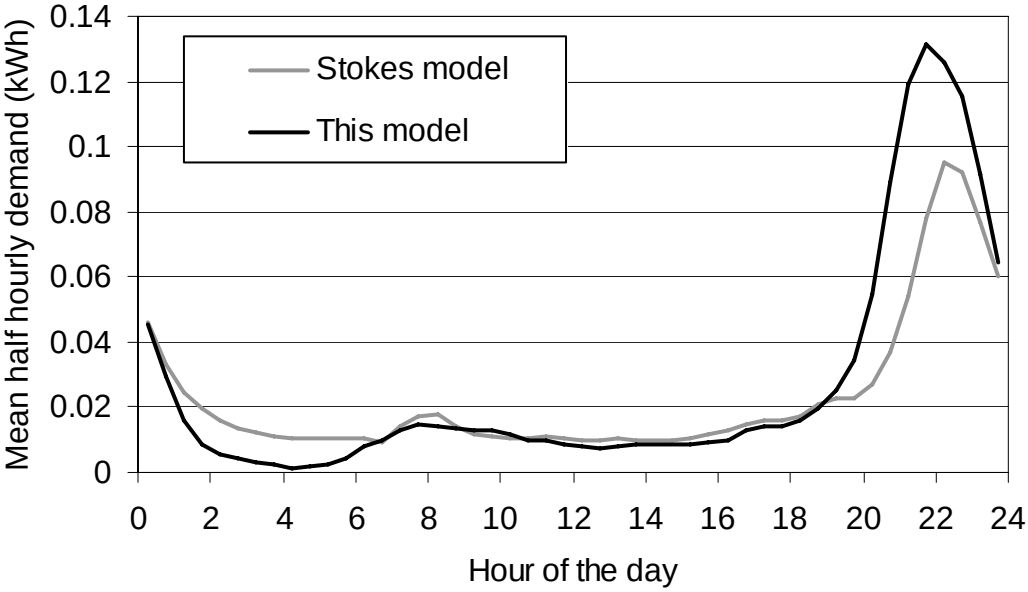
Closer inspection of Fig. 12 shows that the model has a slightly higher demand in summer and a lower demand in winter than those resulting from the Stokes model. This is perhaps explained by the “cosiness” factor described by Bladh and Krantz [6], where lighting is used because “People want to create a nice atmosphere at home”. The model presented here does not presently include this factor.

4.3 Half-hourly demand comparison

The half-hourly results from the two models are compared in Fig. 13, for both January and July.



(a) January



(b) July

Fig. 13. Mean half-hourly demand comparison – (a) January and (b) July

In January the correlation is close, with an r-squared value of 0.95. The new model shows less use of lighting in the evening, which may again relate to the cosiness factor. Also apparent in the model is less use of lighting throughout the night. This may be because the current model discounts the use of lighting when there are no active occupants, whereas in practice people may leave lights on whilst asleep.

In July the overall shape of the curves again shows good correlation, although the r-squared value is reduced to 0.88. There are slight differences in the timing of the morning and evening peaks and again the new model shows less use of lighting throughout the night.

Overall, the correlations are considered good and appear to support the core assumptions made in the new model. Further tuning of the model is possible, although this is constrained by the availability of measured lighting demand data of sufficient resolution.

4.4 Conclusions

A domestic lighting demand model that can generate high-resolution synthetic lighting demand data has been presented. Whilst the demand for lighting is, in reality, driven by complex human interactions with the domestic environment, the model is based on just two physical input factors: outdoor irradiance and active occupancy within the dwelling. The validity of this approach has been supported through the comparison of the resulting synthetic data against profiles based on measured electrical energy demand.

This approach allows the model to be used in investigations in which these factors may change: for example, an increase in the number of people working at home. Additionally, the model configuration can be changed, for example, to reflect the uptake of new lighting technologies. It also allows the model to be linked and synchronised to other energy demand models. This flexibility is in contrast to models that are based on statistical analysis of measured electricity consumption data.

The overall structure of the model is considered good, but improvements could be made particularly if better data sets were available, for example on the duration of lighting unit usage and the distribution of different lighting unit power ratings within dwellings. The availability of high-resolution electrical power consumption data for lighting use would also be beneficial to enable further validation.

The downloadable example simulation can be used as-is or may be re-configured or incorporated into other models as required.

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