Integrated High-resolution Modelling of Domestic Electricity Demand and Low Voltage Electricity Distribution Networks

by

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30th September, 2010.

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CERTIFICATE OF ORIGINALITY

This is to certify that I am responsible for the work submitted in this thesis, that the original work is my own except as specified in acknowledgements or in footnotes, and that neither the thesis nor the original work contained therein has been submitted to this or any other institution for a degree.

………Ian Richardson…………………………… (Signed)

………30th September, 2010…………………… (Date)

I. ABSTRACT

Assessing the impact of domestic low-carbon technologies on the electricity distribution network requires a detailed insight into the operation of networks and the power demands of consumers. When used on a wide-scale, low-carbon technologies, including domestic scale micro-generation, heat pumps, electric vehicles and flexible demand, will change the nature of domestic electricity use. In providing a basis for the quantification of the impact upon distribution networks, this thesis details the construction and use of a high-resolution integrated model that simulates both existing domestic electricity use and low voltage distribution networks. Electricity demand is modelled at the level of individual household appliances and is based upon surveyed occupant time-use data. This approach results in a simulation that exhibits realistic time-variant demand characteristics, in both individual dwellings, as well as, groups of dwellings together. Validation is performed against real domestic electricity use data, measured for this purpose, from dwellings in Loughborough in the East Midlands, UK. The low voltage distribution network is modelled using real network data, and the output of its simulation is validated against measured network voltages and power demands. The integrated model provides a highly detailed insight into the operation of networks at a one-minute resolution. This integrated model is the main output of this research, alongside published articles and a freely downloadable software implementation of the demand model.

Key words: Home appliances, domestic low-carbon technologies, low voltage electricity distribution networks, load flow, demand side management, demand modelling, demand response, flexible demand.

II. List of Publications and Research Outputs

The following works are outputs of the research presented in this thesis:

i. Published journal papers

[1] Ian Richardson, Murray Thomson, David Infield, **A high-resolution domestic building occupancy model for energy demand simulations**, Energy and Buildings 40 (8) (2008) 1560-1566. http://dx.doi.org/10.1016/j.enbuild.2008.02.006 (See Appendix A).

[2] Ian Richardson, Murray Thomson, David Infield, Alice Delahunty, **Domestic lighting: A high-resolution energy demand model,** Energy and Buildings 41 (7) (2009) 781-789. http://dx.doi.org/10.1016/j.enbuild.2009.02.010 (See Appendix B).

[3] Ian Richardson, Murray Thomson, David Infield, Conor Clifford, **Domestic electricity use: A high-resolution energy demand model,** Energy and Buildings 42 (10) (2010) 1878-1887 http://dx.doi.org/10.1016/j.enbuild.2010.05.023 (See Appendix C).

ii. Conference papers presented

[4] Ian Richardson, Murray Thomson, David Infield, Alice Delahunty, **A Modelling Framework for the Study of Highly Distributed Power Systems and Demand Side Management**, Proceedings of the 1st International Conference on Sustainable Power Generation and Supply (SUPERGEN), Nanjing, China, 6th-7th April, 2009. http://dx.doi.org/10.1109/SUPERGEN.2009.5348274 (See Appendix D).

[5] Ian Richardson, Graeme Hodgson, Murray Thomson, David Infield, Alice Delahunty, **Simulation of high-resolution domestic electricity demand based on a building occupancy model and its applicability to the study of demand side management**, The 5th International Conference on Energy Efficiency in Domestic Appliances and Lighting (EEDAL), Berlin, 16th-18th June, 2009. http://hdl.handle.net/2134/4972 (See Appendix E).

iii. Conference poster

[6] Ian Richardson, Murray Thomson, **Highly distributed power systems: Distribution network modelling and demand simulation**, The Universitas 21 International Conference in Energy Technologies and Policy, 7^{th} -10^{th} September, 2008, University of Birmingham, UK.

The poster was also displayed at the following event:
EPSRC Supergen 3 HDPS/HiDEF 2009 Dissemination Event
19^{th} June, 2009, UKERC.

iv. Software tools developed

[7] Ian Richardson, Murray Thomson, **Domestic active occupancy model - simulation example**, Loughborough University Institutional Repository (2008) http://hdl.handle.net/2134/3112

[8] Ian Richardson, Murray Thomson, **Domestic lighting demand model - simulation example**, Loughborough University Institutional Repository (2008) http://hdl.handle.net/2134/4065

[9] Ian Richardson, Murray Thomson, **Domestic electricity demand model - simulation example**, Loughborough University Institutional Repository (2010) http://hdl.handle.net/2134/5786

v. Archiving of measured domestic electricity demand data

The high-resolution domestic electricity demand data measured during the study that is described in Chapter 3 of this thesis, has been uploaded for archiving by the UK Data Archive [10] (as hosted by the University of Essex), a service provider for the UK Economic and Social Data Service (ESDS) [11].

III. Citations of this Research

The following journal articles, conference papers and report cite abovementioned research outputs of this work:

[12] M. Armstrong, M. Swinton, H. Ribberink, I. Beausoleil-Morrison, J. Millette, Synthetically derived profiles for representing occupant-driven electric loads in Canadian housing, Journal of Building Performance Simulation 2 (1) (2009)15-30.

[13] J. Widén, M. Lundh, I. Vassileva, E. Dahlquist, K. Ellegård, E. Wäckelgård, Constructing load profiles for household electricity and hot water from time-use data-Modelling approach and validation, Energy and Buildings 41 (7) (2009) 753-768.

[14] J. Widén, A. Nilsson, E. Wäckelgård, A combined Markov-chain and bottom-up approach to modelling of domestic lighting demand, Energy and Buildings 41 (10) (2009) 1001-1012.

[15] J. Widén, E. Wäckelgård, A high-resolution stochastic model of domestic activity patterns and electricity demand, Applied Energy 87 (6) (2010) 1880-1892.

[16] Y. Chiou, Deriving U.S. Household Energy Consumption Profiles from American Time Use Survey Data – A Bootstrap Approach, Building Simulation 2009, Eleventh International IBPSA Conference, Glasgow, Scotland, 27th-30th July, 2009.

[17] Y. Chiou, A Time Use Survey Derived Integrative Human-Physical Household System Energy Performance Model, 26th Conference on Passive and Low Energy Architecture, Quebec City, Canada, 22nd-24th June, 2009.

Citations of this research continued:

[18] S. Firth, R. Buswell, K. Lomas, A Simple Model of Domestic PV Systems and their Integration with Building Loads, Building Simulation 2009, Eleventh International IBPSA Conference, Glasgow, Scotland, 27th-30th July, 2009.

[19] S. Hay, A. Rice, The case for apportionment, Proceedings of the First ACM Workshop On Embedded Sensing Systems For Energy-Efficiency In Buildings, Berkeley, US, 3rd Nov, 2009.

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[22] R. Baetens, R. De Coninck, L. Helsen, D. Saelens, The impact of domestic load profiles on the grid-interaction of building integrated photovoltaic (BIPV) systems in extremely low-energy dwellings, Renewable Energy Research Conference 2010, Trondheim, Norway, 7th – 8th June 2010

[23] Young-Jin Kim, Cheol-Soo Park, Stochastic Model Based Prediction of Occupants' Presence in Residential Apartment Buildings, Architectural Institute of Korea 25 (3) 271-279.

[24] C. Liao, P. Barooah, An Integrated Approach to Occupancy Modeling and Estimation in Commercial Buildings, 2010 American Control Conference, 30th June - 2nd July, 2010, Baltimore.

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VIII. ABBREVIATIONS

ACE	Area Board Chief Engineers
ADMD	After Diversity Maximum Demand
AMR	Automatic Meter Reading
BSC	Balancing and Settlement Code
BSP	Bulk Supply Point
BST	British Summer Time
CCS	Carbon Capture and Storage
CCGT	Combined Cycle Gas Turbine
CFL	Compact Fluorescent Light
DNO	Distribution Network Operator
EV	Electric Vehicle
ER	Engineering Recommendation
FD	Flexible Demand
GIS	Geographical Information System
GLS	General Lighting Service
GMT	Greenwich Mean Time
GSP	Grid Supply Point
LED	Light Emitting Diode
LV	Low Voltage
MTP	Market Transformation Programme
μCHP	Micro-Combined Heat and Power
Solar PV	Solar Photovoltaic
TPM	Transition Probability Matrix
TSO	Transmission System Operator
TUS	Time Use Survey
VBA	Visual Basic for Applications

1. INTRODUCTION

1.1 Towards a low-carbon electricity system serving the domestic sector

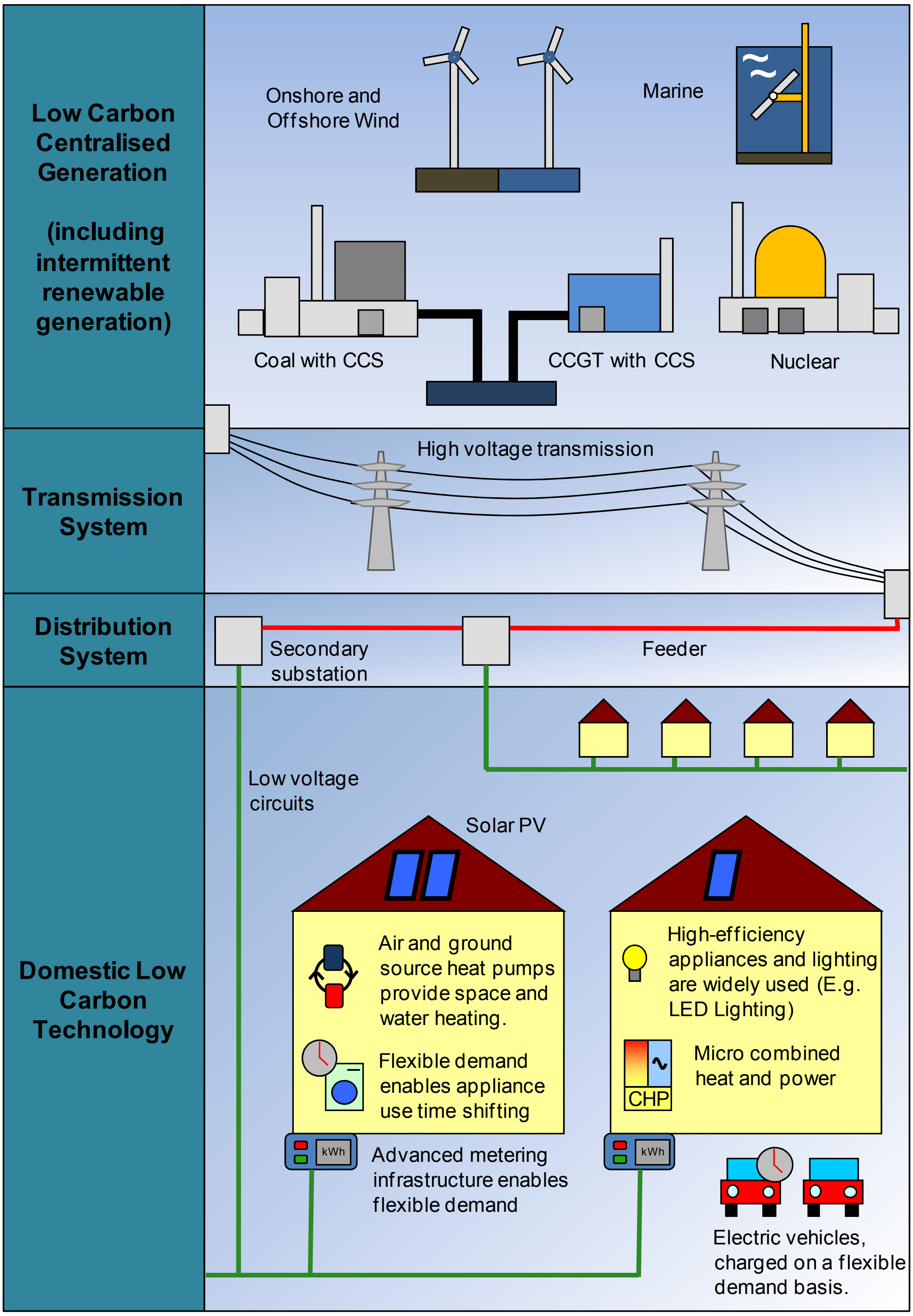


Fig. 1. A future perspective on the electricity system serving domestic consumers

With the aim of reducing emissions from the domestic sector, the widespread application of low-carbon technologies is of significant interest. An example that shows a future low-carbon vision of the power system is presented in Fig. 1. Whilst it is difficult to foresee the detail of the power system decades ahead of time with many possible scenarios arising [25,26], it is likely to include a combination of many of the different technologies shown in the figure.

From a centralised generation perspective, reduction of carbon emissions may include a considerable proportion of intermittent renewable generation, including wind and marine, combined with carbon capture technology used with fossil fuel plant, and new nuclear generation. The inflexibility of this centralised generation will present new challenges in balancing the supply and demand of electricity, as is discussed by National Grid [27].

From a domestic consumer perspective, shown in the lower part of Fig. 1, flexible demand could help with system balancing. This would require that the time of use of appliances could be shifted with the aim of better matching electricity demand with supply. The time of operation of some domestic loads may be shifted without inconvenience to the dwelling's occupants. An example is a fridge, where thermal storage provides scope to advance or delay a cooling cycle [28]. A further example is a washing machine, such as the one shown in Fig. 2, where a delay of a few hours may have a minimal impact on the household. When aggregated to include the whole population, there is significant potential for demand rescheduling to provide benefit to system operation [29,30], and as a result, enable more inflexible low-carbon generation to be connected to the grid.

Fig. 2. Washing machine “Delay wash” mode

Meanwhile, a low-carbon electricity system would likely involve the widespread use of other low-carbon domestic technologies, as is shown in the illustration in Fig. 1 and includes the following:

- Solar photovoltaics (PV), where electricity is generated from sun light, reducing the need for higher carbon centralised generation.
- Micro-combined heat and power (μCHP), a heat demand led technology that provides heating, as well as, micro-generation using otherwise wasted heat.
- Air and ground source heat pumps that efficiently provide low-carbon heat by sourcing heat from the air or ground, particularly if powered by low-carbon electricity.
- Electric vehicles that could support the decarbonisation of the transport sector by reducing the need to burn fossil fuels.
- Energy efficient technologies that reduce the overall level of demand, such as the replacement of incandescent light bulbs with LED lighting.
- Domestic energy use displays, made possible through advanced metering, that provide detailed energy use information resulting in household residents switching unused appliances off more often.

1.2 The consistent nature of domestic electricity demand

The nature of domestic electricity demand in the UK has changed little over time. Statistics from DUKES [31], taking into account the number of households [32], show that annual electricity demand per household in 1971 was 4475 kWh, compared with 4864 kWh in 2008.

Furthermore, when large numbers of dwellings are considered together, the shape of the daily aggregated power demand profile is very consistent. A national mean domestic demand profile is shown in Fig. 3. This represents the Domestic Unrestricted Profile Class 1 Group Average Demand (GAD) developed by the Electricity Association in 1997 [33] and used since in the UK Balancing and Settlement Code (BSC) [34]. The shape is also consistent with electricity demand measurements made as part of the work presented in this thesis, described later in Chapter 3. The power system is designed and operated on the assumption that this demand profile is consistent and therefore predictable.

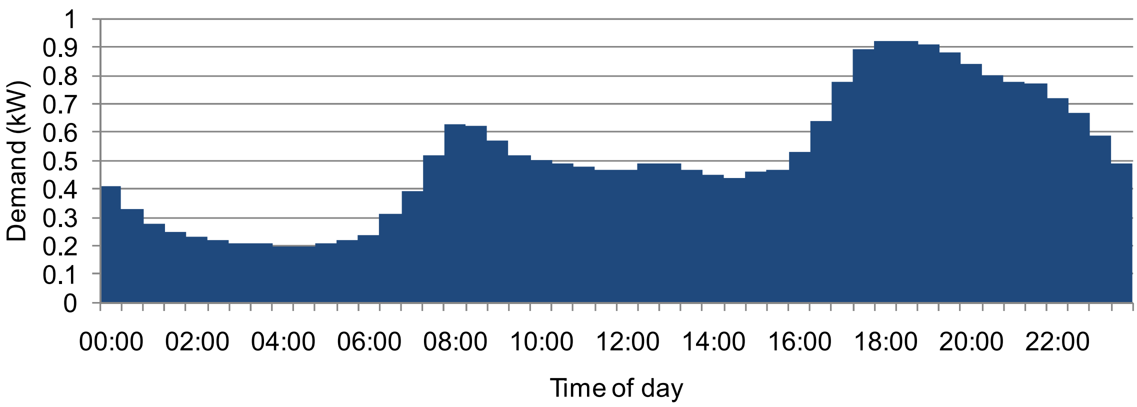


Fig. 3. Half-hourly winter domestic demand profile

Source: UKERC Energy Data Centre [33]

However, the widespread introduction of domestic low-carbon technologies will alter both the level of demand, as well as, the shape of the demand profile. Furthermore, different domestic technologies will affect demand in different ways, as is discussed in the following section.

1.3 Different low-carbon technologies affect demand in different ways

The ways in which different domestic low-carbon technologies introduced in Fig. 1 could impact the shape of the demand curve is illustrated in Fig. 4. The letters for each symbol, representing different domestic low-carbon technologies, refer to the discussion below:

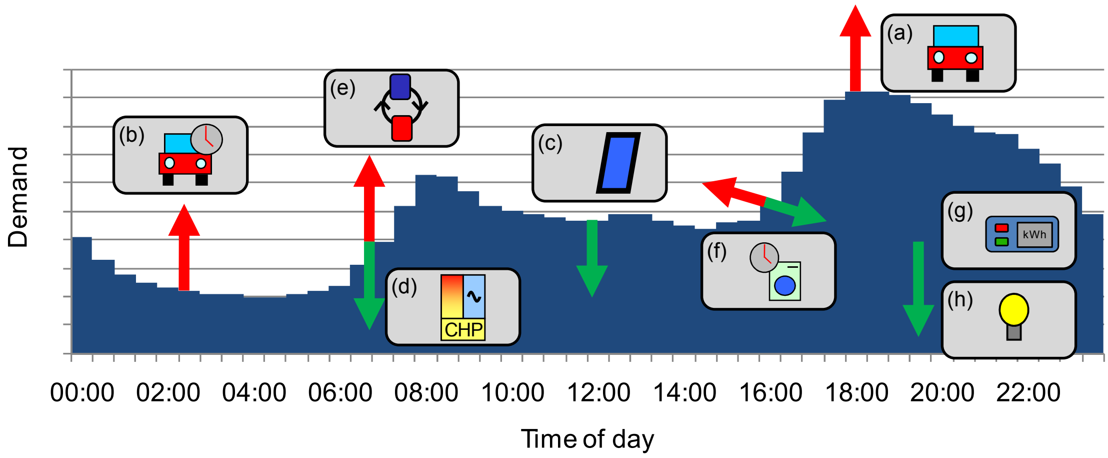


Fig. 4. Low-carbon technologies and the domestic demand profile

Electric vehicles (Fig. 4a, Fig. 4b)

Electric vehicles will place considerable new demands on the network. A small electric vehicle requiring an overnight charge of 25 kWh [35] demands over twice the energy of daily average domestic use of 12 kWh [36]. Furthermore, the timing of this demand will not be evenly spread through the day. Since the use of vehicles will follow the daily work-life pattern, domestic charging demand would be likely to peak when most people return from work (Fig. 4a), increasing the magnitude of peak demand in the demand profile in Fig. 3. In such a scenario, it would be necessary to consider the control of the charging cycle through appropriate overnight scheduling (Fig. 4b).

Domestic solar PV (Fig. 4c)

Domestic solar PV generation (Fig. 4c) will offset demand and at some times may export electricity to the grid. Subject to solar radiation intensity, the peak time of generation will be during the middle of the day. Since this does not coincide with the time of peak demand during the early evening, large penetrations of solar PV would therefore worsen the peak to mean demand level, resulting in a greater variance.

μCHP (Fig. 4d) and Heat Pumps (Fig. 4e)

μCHP is a heat led technology and its use is seasonal. Therefore, considerably more generation will occur in winter rather than summer months, and the time of generation will coincide with the time of peak heating demand in the morning. Conversely, heat pumps will operate at similar times, but have the opposite effect by placing additional demands on the network. Therefore, μCHP will reduce the morning peak demand (Fig. 4d), whilst heat pumps will increase it (Fig. 4e).

Flexible Demand (Fig. 4f)

If the time of use of appliances could be shifted with flexible demand, then the shape of the demand curve will change depending upon how the demand is scheduled. In the example in Fig. 4f, the washing machine demand at the beginning of the evening peak could be scheduled to occur earlier in the afternoon, or perhaps overnight, in which case there would be a levelling effect on the profile.

Energy Use Displays (Fig. 4g) and Efficient Technologies (Fig. 4h)

Finally, the use of energy use display meters (Fig. 4g) or more energy efficient technologies (Fig. 4h) could reduce the overall magnitude of the demand profile.

Therefore, the widespread use of one or more of the above technologies has the potential to considerably change the shape of the domestic demand profile. There may be increased variability, increased peaks and troughs and the mean level of demand could change, depending on the penetration and combination of the technologies used.

Whilst these low-carbon technologies are beneficial at a national level, as mentioned earlier, the change of the demand profile locally has significant implications for electricity distribution networks: these issues are discussed next.

1.4 Low-carbon technologies and electricity distribution networks

An example illustration of a section of distribution network is presented in Fig. 5, showing the use of low-carbon technologies in a number of dwellings.

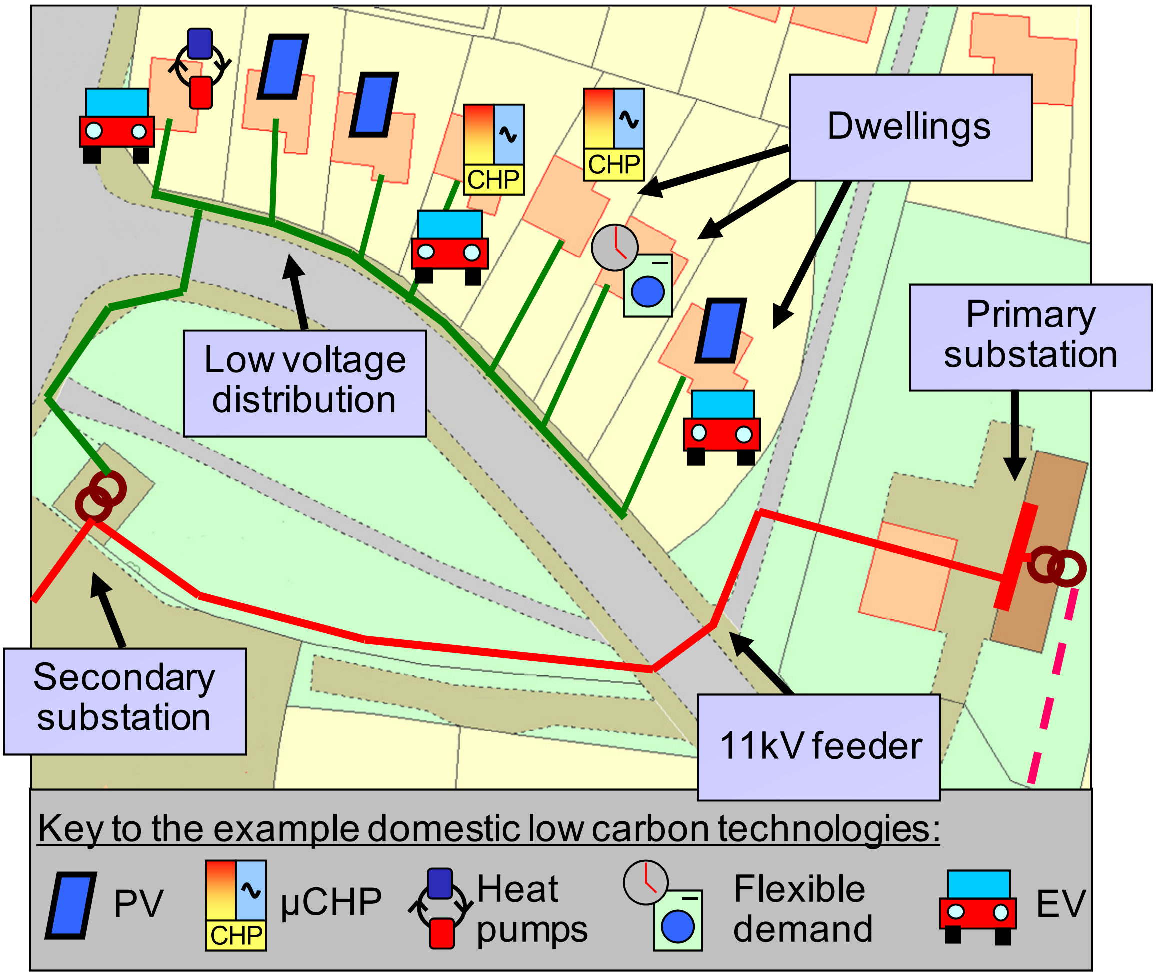


Fig. 5. Low carbon domestic technologies and the distribution network

(Area map: Ordnance Survey ©Crown Copyright. All rights reserved.)

The first major issue of concern to the Distribution Network Operator (DNO) is the network capacity limits. The cables and transformers must be rated such that they are not subject to undue thermal stress in supporting the level and duration of peak demand. As an example, the wide-scale use of electric vehicles and heat pumps, will provide a significant additional demand [37] that the network may be unable to meet.

The second major issue is that of voltage control. Power quality standards require voltages to stay within limits: in the UK this is currently a nominal voltage of 230 V +10% -6% [38,39]. The voltage varies depending upon the level of demand. Connecting low-carbon technologies to the low voltage distribution network will result in increased variability in demand, and therefore increased variability in voltage. Furthermore, voltage rise due to the connection of micro-generation is a particular concern [40].

This thesis will focus on these two major issues, with a view to providing tools in order to assess this. It is also noted that there are further concerns, including imbalance, flicker and harmonics [41, 42].

At present, the design procedure for distribution networks involves the use of simple calculations that are used to estimate the voltage variation along a circuit serving residential areas [43]. Whilst the physical characteristics of the cables are well understood, the parameter of particular importance is the "after diversity maximum demand" (ADMD). The term is commonly used to describe the supply capacity required for each consumer connected to the network. A formal definition is "the maximum demand, per customer, as the number of customers connected to the network approaches infinity" [44]. In the UK, an ADMD of 2 kW is a common design standard applied to dwellings that do not use electric space heating systems [43]. This takes into account that every appliance in every dwelling is never used all at the same time.

As discussed previously, ADMD relies on the consistent nature of demand: introducing low-carbon technologies change the nature of this demand and may therefore undermine the simple network design calculations.

The components of the distribution network have a long service life, such as the secondary substation transformer shown in Fig. 6 that was built in 1970 and is still in active use. When distribution network components such as this were installed, the design engineers would have had no access to the computational capabilities of modern computers. There have been huge advances in data storage and processing capacity and the advent of geographical information system (GIS) based design tools.

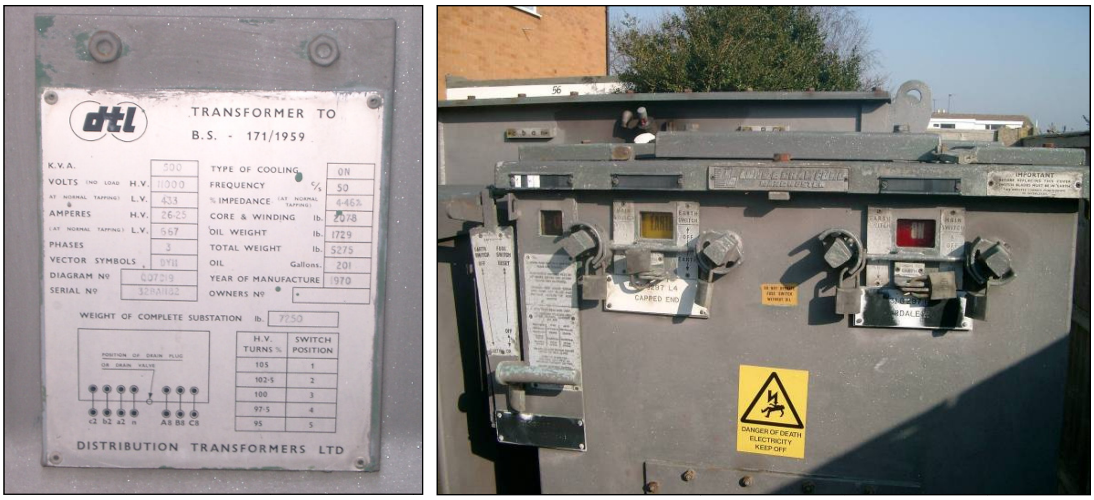


Fig. 6. A secondary substation and transformer name plate

Furthermore, in the context of the widespread integration of low-carbon technologies from an economic perspective, it is a business necessity for the DNO to maximise the use of existing network capacity, and minimise the need to upgrade or replace sections of network. The design decisions that are taken are of great importance, because the time horizons of infrastructural change are long term and the embodied investment is substantial.

The combination of the technical design issues, available computational technology and the economic considerations, point towards the development of more sophisticated models that more adequately represent future network configurations, with widespread domestic low-carbon technology use.

1.5 A new approach to the modelling of demand and low voltage networks

This thesis is concerned with the construction and validation of a comprehensive model of domestic demand and existing low-voltage network operation. The model therefore forms a basis upon which low-carbon technologies on distribution networks can be studied. An overview of this model is presented in Fig. 7.

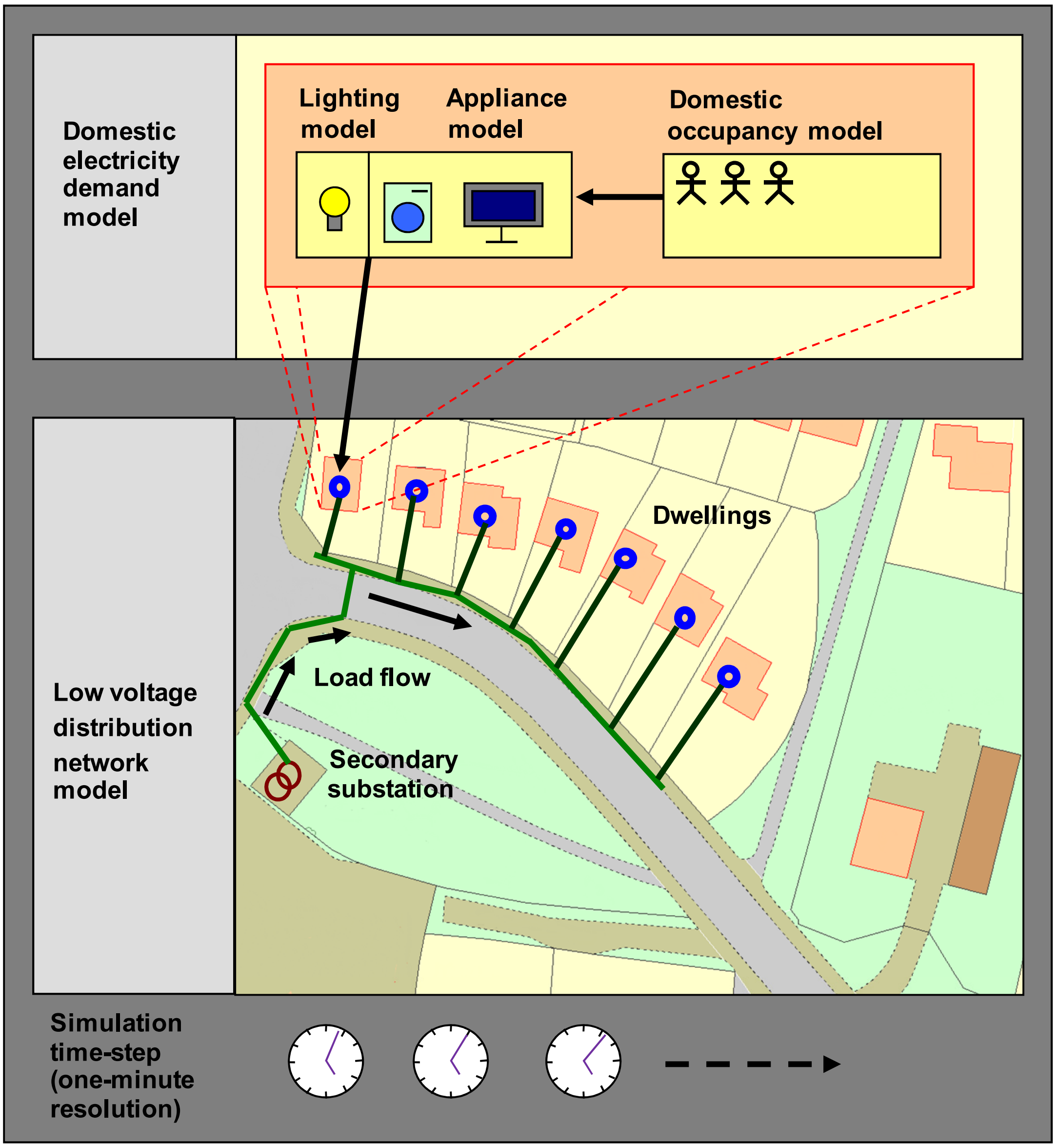
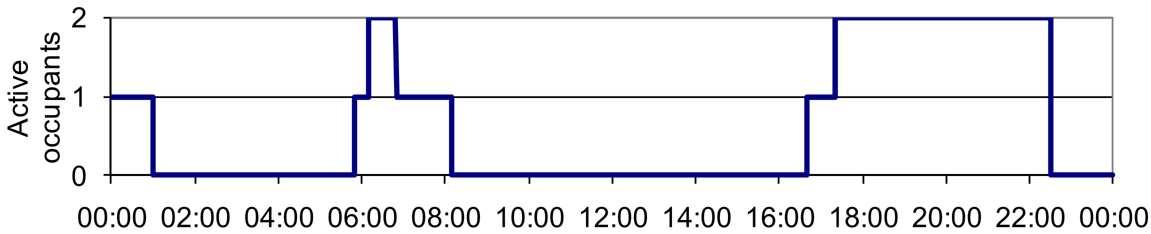


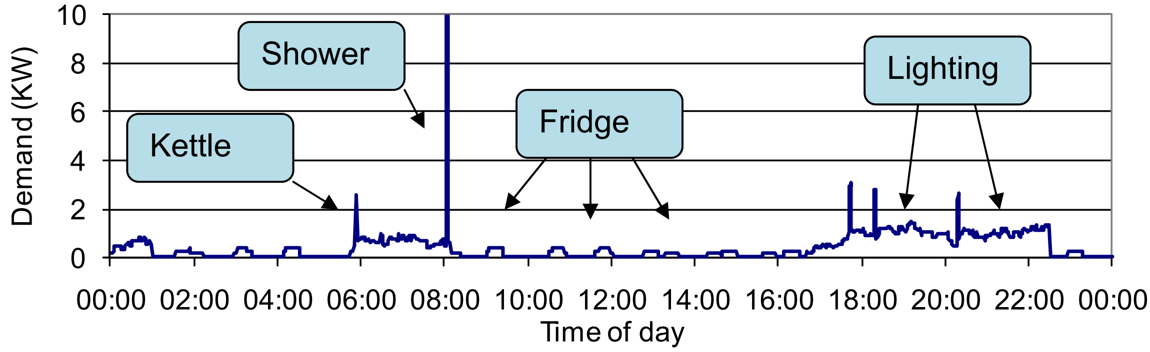
Fig. 7. Domestic demand and low voltage network model

(Map data: Ordnance Survey ©Crown Copyright. All rights reserved.)

With reference to Fig. 7, the domestic electricity demand model provides a simulation of whole-dwelling electricity use. At its core, is the representation of "active occupancy" (that is, when occupants are within a dwelling and not asleep). Using this occupancy data, in conjunction with other physical input factors, such as natural light level in the case of domestic lighting, the model simulates the use of all major categories of domestic appliances, including cold, wet, cooking, heating and entertainment categories. The model outputs realistic demand data on both shorter (e.g. minute to minute) and longer (e.g. annual) time frames, and is calibrated with annual electricity consumption data for individual appliance types.



(a) Active occupancy



(b) Electricity demand

Fig. 8. Example one-day output of the electricity demand model

An example of the output of the demand model for a single dwelling is shown in Fig. 8. The active occupancy profile is shown in Fig. 8(a) and the whole-dwelling electricity demand is shown in Fig. 8(b). When simulating many dwellings together, each will have a different output: this is important in order to achieve the appropriate diversity in demand over time.

Referring again to Fig. 7, the demand model is used to provide data for input to a simulation of a real electricity distribution network. In order to achieve this, the cables that form the low voltage network are represented together with the location of each domestic consumer. A screen print showing an example of the GIS interface of the model is shown in Fig. 9. In this case, the model is representing a residential area, with the low voltage cable topology clearly visible.

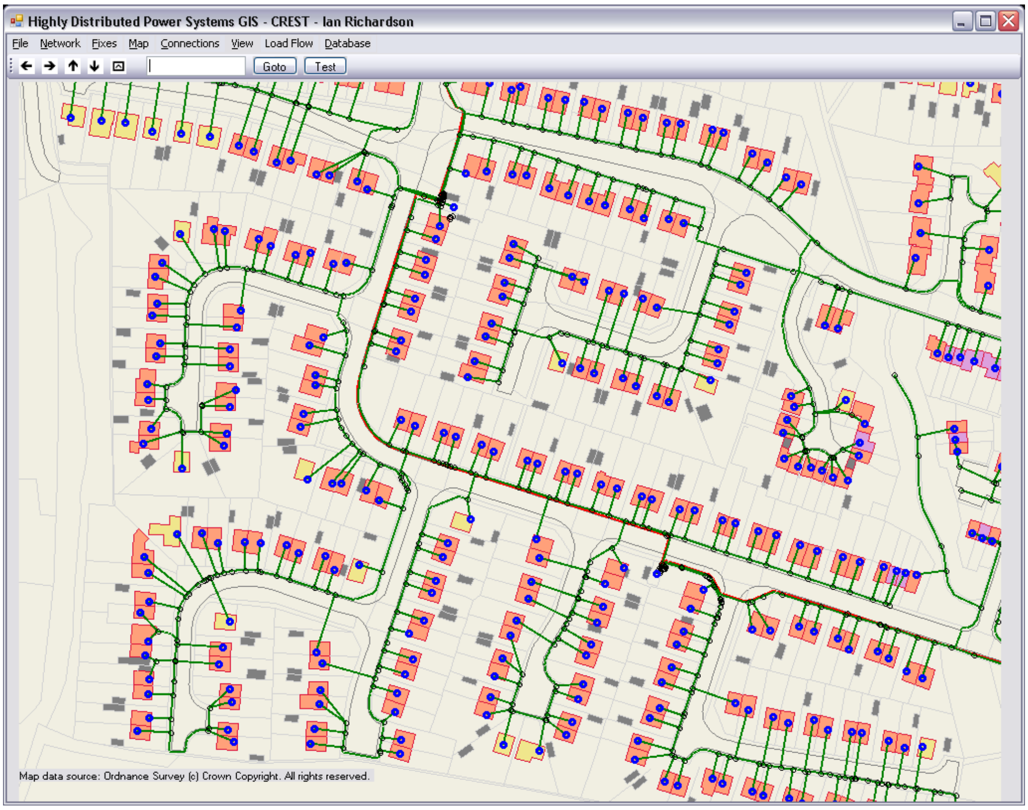


Fig. 9. The user interface of the integrated model GIS software tool

(Map data: Ordnance Survey ©Crown Copyright. All rights reserved.)

Using the combination of the demand data and the network structure, a three-phase unbalanced load flow is then used to determine the voltages and currents throughout the network.

The whole model runs on a time-stepped basis. At each step, the individual demand of each dwelling is determined and the load flow calculations are performed. The model thereby provides a very detailed insight into the operation of the network.

1.6 Thesis structure

The construction and validation of the model of domestic electricity demand forms a major part of this thesis. This begins with a discussion of the literature on domestic demand in Chapter 2 and is followed with a description of a study of the nature of domestic demand in Chapter 3, for which the measurement of real domestic electricity use took place.

The construction of the model of domestic occupancy is presented in Chapter 4. This occupancy data is used to construct a simulation of domestic lighting use in Chapter 5. The model is then extended to include all other major categories of domestic appliances in Chapter 6, where the model is subsequently validated against measured data.

The requirements for the modelling of low voltage networks are considered in Chapter 7, after which the construction of the integrated network and demand model is described in Chapter 8. The validation of this model is presented in Chapter 9 and the use of the model is presented in Chapter 10.

The conclusions of the work are presented in Chapter 11.

2. DEMAND MODELLING: A LITERATURE REVIEW

2.1 Introduction

The need for a detailed model of domestic electricity demand was discussed in Chapter 1. The aim of this chapter is to determine the requirements for building such a model by considering what is already available in the literature. The chapter concludes with a refined set of the features that the demand model must incorporate.

This literature review relates only to the demand modelling components of the work. The literature with respect to network modelling is considered separately in Chapter 7.

It is noted that the terms “demand” and “load” are frequently used interchangeably in the literature and are therefore interpreted here as having the same meaning.

2.2 Outline requirements

The proposed requirements for an ideal demand model with the purpose of providing data for a simulation of domestic electricity networks is present in Fig. 10. The requirements are categorised using a MoSCoW approach [45], in order to rank their relative importance: they are grouped into categories of “must-have”, “should-have”, “could-have” and “will-not-have” groups.

Must have …

- The capability to simulate **individual dwellings**, that when grouped together, have an **appropriate time-coincident demand.**
- **Seasonal variability** to reflect the changing level of demand between winter and summer.
- The capability to be **integrated** with other models and **easily re-used**.
- A **validated output** where the data is shown to have appropriate **statistical characteristics**.
- An appropriate **time base**, so that the model outputs a time-stepped data series that provides a useful level of detail.
- **Data requirements** that are **achievable** such that the model can be **self-contained**.

Could have …

- **Configurability** in order to change the magnitude of demand as required.

Should have …

- The capability to represent **reactive power demand**.
- The capability to be extended to **include future technologies** and also to be able to change the levels of ownership of different appliances**.**
- The capability to simulate **large numbers of dwellings** and therefore be computationally efficient.

Will not have …

- To include every single type of household appliance.
- To be based upon extensive and comprehensive household surveys.
- To be deterministic. The model does not need to exactly predict the use of domestic appliances. It needs only to be statistically representative of the patterns of use.

Fig. 10. Outline demand model requirements

With these general requirements in mind, the literature is now discussed in terms of the extent to which these have been satisfied before in other work.

2.3 Top-down and bottom-up models

The two general categories of energy demand model are known as “top-down” and “bottom-up” approaches. In the top-down case, the models are concerned with breaking-down an overall view of the whole system and are usually based upon aggregated consumption data. In contrast, a bottom-up approach involves the modelling of individual end-uses of energy, specifically the individual appliances used within a dwelling, and building this up in order to achieve a wider view. Swan and Ismet Ugursal (2009) [46] discuss these general categorisations in greater detail.

One common application of the top-down modelling approach is for national load forecasting. Gross and Galina (1987) [47] and Mogram and Rahman (1989) [48] discuss and review many of the available techniques. In general, these approaches typically have an hourly resolution and the data generated is suited to system wide demand simulation. Clearly, in order to meet the key requirement of modelling individual dwellings, a top-down approach is inappropriate, because the demand due to individual dwellings will not be suitably represented.

A bottom-up model that is concerned with the end-use consumption for an individual dwelling, as is discussed by Paatero and Lund (2006) [49], will be most appropriate to meet the modelling requirements of this work. The details of interest in such models include the types of the appliances within a dwelling, together with their patterns of use.

2.4 Stochastic methods

With reference back to Fig. 10, it is not necessary for the model to deterministically predict when the residents of a dwelling will use appliances. The model only needs to output demand data that has the appropriate statistical characteristics representing the patterns of use. Stochastic, rather than deterministic methods are better suited to this type of simulation.

In general terms, stochastic demand models use a set of probabilities that represent the likelihood of different appliances being used at different times of the day. At each time step of the simulation, random numbers are compared to determine if appliance use occurs. Such methods are useful because they allow the representation of random variation in individual dwellings. However, when groups of dwellings are considered together, the expected shape of the demand profile is seen, by means of an averaging effect. Three relevant demand models, that use stochastic methods, are introduced here and discussed throughout this chapter:

The first example is a model for generating household load profiles by **Paatero and Lund** (2006) [49]. This model uses hourly probability factors assigned to appliances or groups of appliances. These factors are used to determine the varying likelihood of the use of an appliance throughout the day. Summing the demand due to the individual appliances at each time step provides the whole dwelling demand. The model can be described as largely self contained: it may be implemented from the data and algorithms that are described within the article. The discussion of the suitability of this model will be returned to later.

The second example is the more complex residential load model by **Capasso et al.** (1994) [50]. As with the Paatero and Lund model, the characteristics of individual appliances, including their power demands and usage lengths are represented. However, it goes much further by taking into account factors such as psychological and behavioural traits. It does this by representing the human resources that are related to the use of particular appliances, including eyes, ears and hands. However, as Paatero and Lund [49] note, the issue with such approaches is the requirement for extensive data about the domestic appliances and how they are used by the occupants. The result is that whilst this is a comprehensive model, it is simply not practical to construct a working simulation without having first obtained a suitable data set, that details the nature of the appliances, and the interrelated behaviour of the household residents. This is a major constraint. Further, the model is too granular in the context of representing large numbers of dwellings: the modelling of the physical and socio-economic characteristics of individual occupants is considered unnecessary in the context of the requirements set out earlier.

The third stochastic model introduced here is that developed by **Stokes** (2005) [51]. This model can generate data at a one-minute resolution. For each appliance, for each half-hour time period of the day, a probability ratio is calculated. These ratios are used to determine the likelihood of an appliance being used within that time period. The ratio is formed using an expected mean half-hourly demand, taken from measured data, together with the power demand of the respective appliance. Within each half-hourly period, appliance switch-on events are randomly assigned. In a recent overview of demand modelling, Widén (2009) [52] describes this as “probably the most detailed domestic demand model up to date”.

2.5 Occupancy as a key driver of domestic energy use

An important difference, that sets the Capasso model apart from the other two models outlined previously, is that it takes into account the behaviour of the occupants of a dwelling in determining when appliances are used. It does this by representing the household resident's "availability at home profile", which is used to represent when occupants of a dwelling are at home and are available to use appliances. Within this thesis, this is the concept of active occupancy that was introduced earlier.

The concept of occupancy being a key driver of domestic energy demand is widely supported in the literature. Santin et al. (2009) [53] conclude that "occupant characteristics and behaviour significantly affect energy use". The Tyndall Centre report "Microgrids: distributed on-site generation" (2005) [54] comments that "electricity load profile depends mainly on the household size and occupancy pattern." Yohanis et al. (2008) [55] discuss how occupancy affects overall domestic electricity use, in terms of both the number of residents who live at a dwelling, as well as, the impact of daily occupancy patterns. Tso and Yau (2003) [56] examine energy usage patterns through a large survey of households in Hong Kong. Papakostas and Sotiropoulos (1997) [57] provide a survey of domestic occupancy patterns and energy use from a study in Greece. The time variation of use of appliances, lighting, heating and water, within a dwelling, are highly dependent upon the number of residents that live within, and their patterns of occupancy.

The literature therefore supports the idea that using occupancy is a good starting point in determining the times of electricity use within a dwelling. With reference back to the initial requirements set out previously in Fig. 10, this is a fundamental requirement of the model. The use of occupancy in meeting this requirement is explored further in the following sub-sections:

2.5.1 Occupancy within individual dwellings

Given the requirement for the model to output realistic demand profiles for individual dwellings, and the bottom-up approach found best suited to the modelling of appliance use, the use of occupancy provides a way to represent the use of many appliances at the same time. The use of appliances at the same time has a significant impact on the daily demand profile of a dwelling: Wood and Newborough (2003) [58] discuss how demand peaks occur.

As an example, an actively occupied dwelling on a winter evening is likely to have both lighting and television switched on and in use. A dwelling that is unoccupied may have neither. This implies a dependency, which is termed as concurrent appliance use. If a model uses active occupancy as the basis for appliance use, then a more realistic concurrency can be taken into account, since concurrent use will only occur at times of the day with active occupancy.

This correlation of appliance use is a particular issue for stochastic appliance models, as independently representing appliances will not provide the required diversity in concurrent appliance use. This is of great importance as models that do not take active occupancy into account may unrealistically spread the appliance usage over the full day, resulting in less concurrency and therefore a less realistic demand profile. This is an issue for both the Pattero and Lund, and the Stokes model, that represent individual appliances without regard to occupancy.

2.5.2 Multiple occupants within individual dwellings

A further benefit is gained by using occupancy data, in that it is possible to represent the concept of sharing appliance use. Sharing enables more realistic simulation of demand, since, for example, a second occupant arriving home on a winter evening is likely to only incrementally increase, rather than double, the lighting demand.

Crosbie (2008) [59] explores energy usage behaviours with a focus on television appliances. A trend towards "individualised electronic entertainment" and the energy efficiency implications of appliance sharing are discussed. Appliances, such as televisions, can of course be watched by more than one occupant at the same time.

Models of energy demand that take the number of active occupants into account can thereby take into account the effect of sharing.

2.5.3 Occupancy and multiple dwellings

Returning again to the fundamental requirement to represent the appropriate time-coincident demand between dwellings, Stokes et al. (2004) [60] note that ''Taking account of these [occupancy] patterns would improve the modelling of diversity.''

If each individual dwelling in a simulation is assigned a stochastically generated (and therefore unique) occupancy pattern, then this provides a good basis for providing diversity in the times of energy demand throughout a day. Therefore, it follows that when large groups of dwellings are aggregated together, the appropriate diversity in time-coincident demand will be seen.

2.5.4 Data availability

The requirement for the model to be self-contained in data terms was outlined previously. If occupancy is to be used as a basis for energy demand simulation, then the appropriate data is needed.

Many demand models have used the concept of occupancy as an input, but the lack of availability of input data is a common issue. Yao and Steemers (2005) [61] use a fixed set of five occupancy patterns. Jardine (2008) [62] points towards the scarcity of household occupancy data. In this case, occupancy data is derived, by visual assessment of a set of measured domestic demand profiles. This was done to determine when appliances were being used and therefore when the occupants were active. This data was then used to synthesise large quantities of activity profiles. In more recent work, Armstrong et al. (2009) [12] present another occupancy based demand model localised for Canada, where it is acknowledged that the availability of occupancy data was a constraint.

One detailed survey of time use is the UK 2000 Time-Use Survey (TUS) [63]. This study collected diaries from many thousands of people that captured how they spent their time. The diaries were recorded at a ten-minute resolution over 24-hour periods. The data is anonymous, but it is possible to identify what people do with their time within each dwelling within the survey. This data set clearly provides a good basis upon which to study patterns of domestic occupancy.

2.6 Seasonal demand and lighting

A key requirement noted earlier is that the model needs to represent seasonal variation in demand. Lighting is an example of one electricity end-use that varies throughout the year. Its use is dependent not just upon occupancy, but on a secondary factor, namely the level of natural light. This twin dependency is addressed by Reinhart (2004) [64] in a model for the automated control of office lighting. Hunt (1979) [65] discusses occupancy and daylight level effects in a non-domestic context. In domestic use, detailed studies that look at the complexity of the occupant behaviour and lighting are scarce. One exception is the detailed study by Bladh and Krantz (2008) [66] that investigates the factors that influence lighting use.

Stokes et al. (2004) [60] describe a model of domestic lighting with a one-minute data resolution. However, this is based upon measured lighting demand end-use data. Occupancy patterns or light levels as inputs are not considered.

The key point here is that the use of common physical input factors to a model, means that the same input data can be used for other model components. For example, if occupancy data is used to model lighting, then it will be appropriate to use exactly the same data as an input to a model of other household appliances, such as a television.

Only recently have domestic demand models been constructed that take into account multiple physical input factors, such as occupancy and natural light level. One such model is described in Chapter 4 as part of the published output of the work described in this thesis. Another more recent model is a domestic lighting demand model constructed by Widén et al. (2009) [14] that simulates lighting use in Sweden.

In summary, it is considered necessary to take seasonality into account by using the appropriate physical input factors, such as natural light level.

2.7 Modelling occupant activities

The most recent demand models reflect a trend towards the use of data that represents how people spend their time. This is known as time-use data. Such models are concerned not only with when occupants are active in a dwelling, but with what the occupants are doing.

The concept of "proclivity for home-activities" originally described by Capasso et al., is used to build a relationship between occupant activities and the usage of particular types of appliance. A similar approach is seen in the more recent model by Prudenzi and Silvestri (2009) [67] where different classes of time use, such as cooking, housework or leisure time are represented.

In their recent paper, Widén et al. [13] discuss how time-use data can be used to represent the behaviour of occupants in dwellings in terms of the appliances that they use. This particular model uses Swedish time-use data to construct hourly resolution demand data. The approach is extended in recent work in a one-minute resolution model [15] where time-use data from Swedish dwellings is used to construct a stochastic model, in which the activity patterns of individual occupants is represented.

Time-use data to construct bottom-up models is therefore of considerable interest because it allows the linking of occupant behaviour to the likelihood of particular appliances being used. This important concept is explored further in the following chapters.

2.8 Time resolution

In contrast to the load forecasting models previously discussed, an hourly or half-hourly simulation is less suitable for the study of demand at a local level, where it has already been identified that individual dwellings need to be modelled. For example, Wright and Firth (2007) [68] discuss how "…averaging data over periods longer than a minute is shown to under-estimate the proportions of both [electricity] export and import". To examine this further, Fig. 11 shows an example where the same demand data is plotted at five different time resolutions: three-second, one-minute, five-minute, fifteen-minute and half-hourly.

When viewing a whole day of demand, there is little difference seen between the three-second and one-minute resolution series, except for a number of short spikes. The cycling of cooling appliance can be seen throughout the day, with morning and evening increases in demand where other appliances are being used.

At a five-minute resolution, some loss of detail is evident. However, at a fifteen-minute resolution, there is a considerable loss of detail and the smoothing effect is very evident. At a half-hourly resolution, even more detail is lost: the peak demands and cycling of individual appliances can no longer be seen

Whilst maintaining a good level of detail, there is a trade-off between the quantities of data that has to be managed. One-day requires 28 800 data points at a three-second resolution compared to 1440 at one-minute. To store a whole year of data would require 10 512 000 and 525 600 data points respectively. When considering groups of dwellings together, this extra quantity of data at higher resolutions appears to offer little further benefit. A one-minute resolution is therefore considered a good compromise.

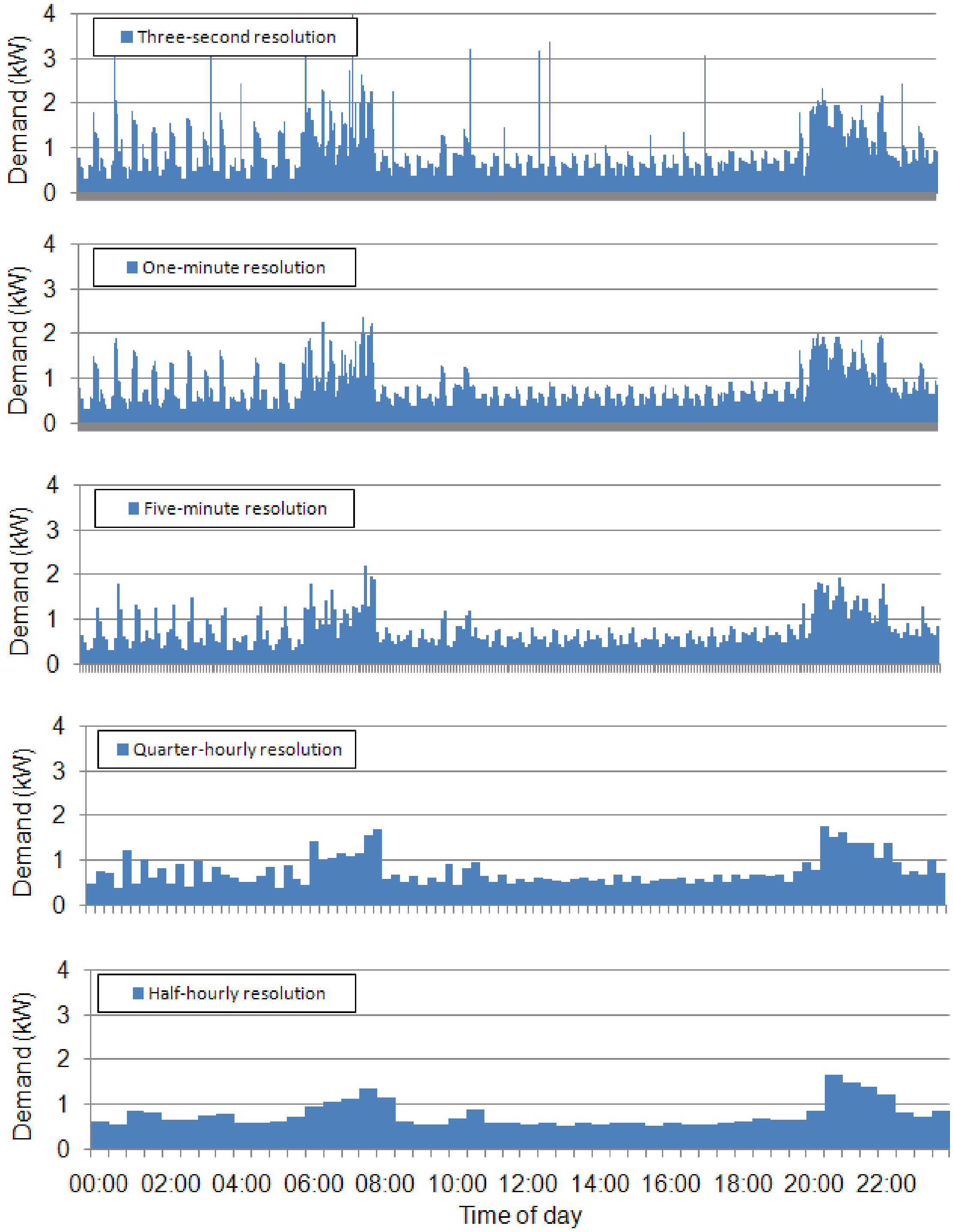


Fig. 11. Time resolution and electricity demand data

Data source: IEA/ECBCS Annex 42 COGEN-SIM [69]

2.9 Data sets for model validation

Wright and Firth (2007) [68] also comment that "The data-sets and the literature on UK domestic-loads are quite limited". Now in 2010, the availability of demand data in the public domain in the UK is still scarce.

At the most general end of the scale, national and regional electricity consumption data is widely available on an annual basis, such the MLSOA data set [36] that provides annual total demand figures based upon metered data. Monthly demand data is available from DUKES [31]. Clearly however, these are not of a suitable resolution to study usage in an individual domestic dwelling.

Daily mean profile data is available in the form of the GAD profiles [33] that were introduced in Chapter 1. As aggregated demand profiles, again, these are of little use in examining the detail of individual dwellings.

Hourly UK data is available from the UKERC Energy Data Centre [70] from 94 low energy dwellings recorded at the beginning of the 1990s, and half-hourly data is also known to exist for the UK as measured by the Load Research Group back in the mid-nineties [71]. However, hourly or half-hourly data has already been discounted as having too low a resolution. A five-minute resolution data set known to be publicly available is the electric load profile data set [69], available as an output of the IEA/ECBCS Annex 42 research project [72]. However, individual dwelling data is only available for two flats and one house and this is considered insufficient in terms of being representative of the wider population.

Whilst there have also been international studies, such as the domestic electricity data gathered by the Swedish Energy Agency [73], these are considered to be of limited use in the context of a UK based demand model.

With the absence of available and accessible data, the need to perform measurements becomes clear and this work is described later in Chapter 3.

2.10 Additional requirements

In the context of the outline requirements set out at the start of this chapter in Fig. 10, a summary of the additional key points gained from the literature is now presented in Table 1.

.

Additional notes and requirements
• The most appropriate structure for the model is a bottom-up type that allows for the representation of individual appliances. • Occupancy is a major factor that drives energy use that should be taken into account. This is necessary to appropriately simulate demand within individual dwellings (by modelling sharing and the concurrent use of appliances) and between dwellings (through the representation of occupancy within each dwelling). • Other physical factors, such as the natural light level, need to be taken into account where appropriate, to represent seasonality. • Activity modelling can improve the representation of the behaviour of dwelling occupants. This is a natural extension of the modelling of active occupancy. Representing what people are doing provides a basis for determining when different types of appliances are used. The UK 2000 TUS provides a data set upon which such modelling could be based. • With respect to time-resolution, a one-minute resolution is considered a good compromise between loss of detail through smoothing, and quantity of data. • The scarcity of high-resolution domestic electricity demand data is a constraint. It is necessary to perform measurements in real domestic dwellings, in order to make data available to validate a model.

Table 1 - Summary of the key points derived from the literature

2.11 Summary

The literature clearly points towards the use of occupancy as a good basis upon which to simulate the energy demand within dwellings.

Three existing electricity demand models in the literature were introduced: it is concluded that whilst each of these models partially meet some of the requirements set out, no existing model satisfactorily meets all of them. The Paatero and Lund [49] and Stoke's [51] model do not use occupancy as an input. The Capasso et al. [50] model is considered too granular and its comprehensive data requirements are a considerable limiting factor.

Chapters 4, 5 and 6 of this thesis address the construction of a new domestic electricity demand model. The work involved in measuring detailed domestic consumption data is discussed next in Chapter 3.

3. A STUDY OF DOMESTIC ELECTRICITY DEMAND

3.1 Overview

This chapter describes a study of domestic electricity use in the Loughborough area, East Midlands, UK. The scope of the project was to measure high-resolution domestic electricity demand, in order, to provide a data set for the validation of the model of domestic demand that is described later in this thesis. The work involved the measuring of demand in 22 domestic dwellings using high-resolution electricity meters that were installed by E.ON.

The purpose of this chapter is to describe how the data was gathered and to check that it is typical of domestic use and suitable for use in validating a demand model. Additionally, the latter part of the chapter inspects the data to find correlations between the electricity use within a dwelling and the characteristics of the household, in order to provide pointers in the construction of a new model.

3.2 Domestic electricity demand data capture

The project to capture domestic electricity demand data began in March 2007. The initial task was to recruit volunteer householders, who would agree to take part in the study, by having a high-resolution electricity meter installed at their dwelling. The meter installations were performed in the autumn of 2007 by E.ON, and the data capture took place by the author throughout 2008.

After a full year of data capture in January 2009, volunteers were each given a report on the detailed nature of their electricity use for the year. The purpose of the study was to observe existing electricity use and not attempt to modify behaviour. In the majority, volunteers were not given an insight into the detailed nature of their electricity use until after the year of data capture was complete. At this time, each volunteer was asked to complete a short survey form in order to gather data about each dwelling's characteristics.

The study resulted in the capture of a total of 7170 full days of electricity demand data covering 22 dwellings, at a one minute resolution, throughout 2008.

3.2.1 Objectives

A summary of the main objectives of the study is provided in Table 2.

Objective	**Justification**
To capture domestic electricity demand data at a one-minute resolution.	The time-averaging effect of lower resolutions discussed in the literature needs to be balanced with the quantity of data and capability of the metering technology. The one-minute resolution was considered reasonable in this respect.
To collect demand data for the period of at least one year.	Seasonal variations in demand need to be identified and therefore at least one year of data capture was necessary.
To collect data for as many dwellings as feasible.	A large sample set is desirable for statistical analysis. This was ultimately constrained by the ability to recruit volunteers.
To attempt to identify the energy use characteristics of each dwelling.	Understanding more about the dwelling characteristics supports the analysis of the demand data.
To validate the data in terms of checking that it forms a representative sample.	It is necessary to verify, as far as possible, that the data gathered is representative of the wider population. This is necessary if the data is to be used for validating a model.

Table 2 - Summary of the objectives of the study

3.2.2 Recruitment of energy study volunteers

Volunteer recruitment began with a Loughborough University press release [74] in conjunction with the publishing of a web page to promote the study. This led to the recruitment of 22 volunteers, who in the majority are University employees. It was necessary for volunteers to be owner-occupiers in order that they were able to give permission for the extra meter to be installed. It is acknowledged that this could slightly skew the profiles of the volunteers.

The dwellings included in the study consist of 11 detached properties, 7 semi-detached properties and 4 terraced dwellings. This housing stock profile differs from local statistics available from the 2001 census [75] as is shown in Table 3. There were no flats in the study.

Housing Stock Type	**Percentage of housing type in the Energy Study**	**Percentage of housing type from Charnwood local statistics [75]**
Detached	50 %	31 %
Semi-detached	32 %	40%
Terraced	18 %	19%
Flats	-	10%

Table 3 - Housing stock types: energy study compared to local statistics

It is further acknowledged that householders, who volunteer for an energy study, may also be energy use aware. Therefore, they may not be representative of the general population. The representativeness of the data as a result of these constraints is considered later in this chapter.

3.2.3 *Domestic statistical electricity meters*

The domestic meters utilised were manufactured by Elster Metering and are of type A1140 [76]. An example installation is shown in Fig. 12.

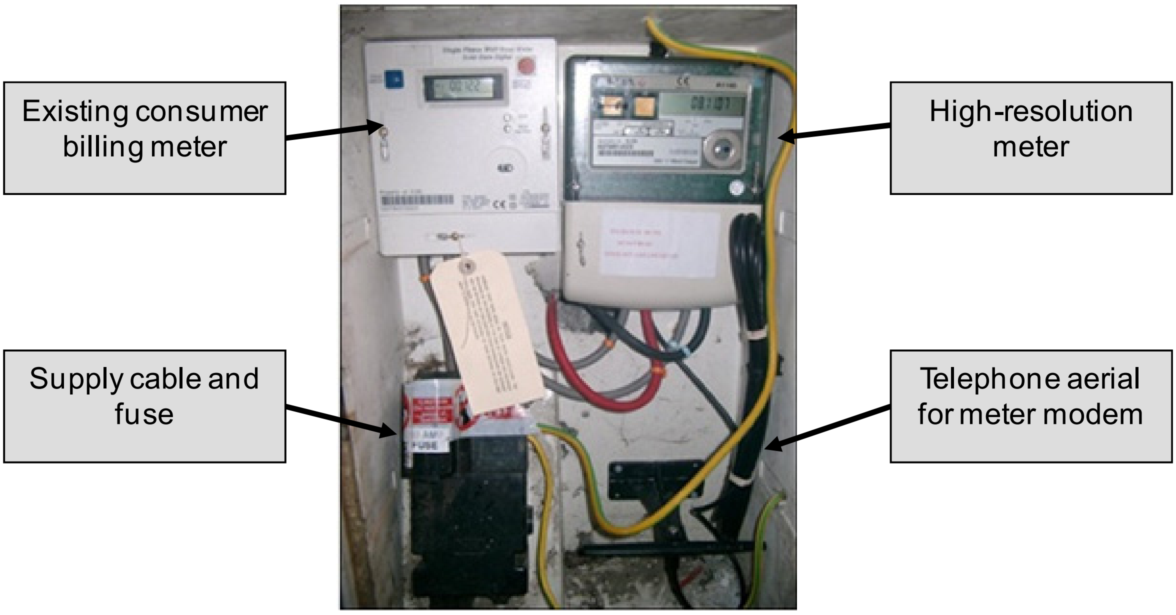


Fig. 12. Domestic high-resolution meter installation

This type of meter has two characteristics that differ from the traditional UK consumer billing meter that make it appropriate for this study. The first is that the meter has the capability to store demand data as a time series, rather than just a cumulative value of electricity used. The highest time resolution available was one-minute and this was selected. The second characteristic is that each meter has a mobile telephone modem installed. This enables the meter data to be read without having to visit the site. This capability is commonly known as automatic meter reading (AMR) support.

The geographic location of the first 17 meter installations is shown in Fig. 13, where the blue circles indicate approximate meter locations in the town. The remaining 5 meters were installed in dwellings in the surrounding area.

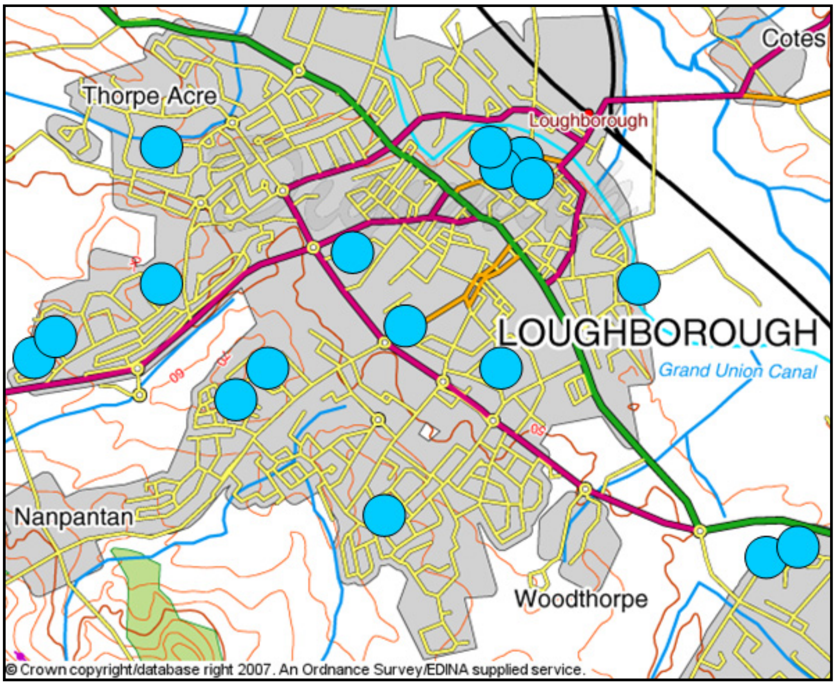
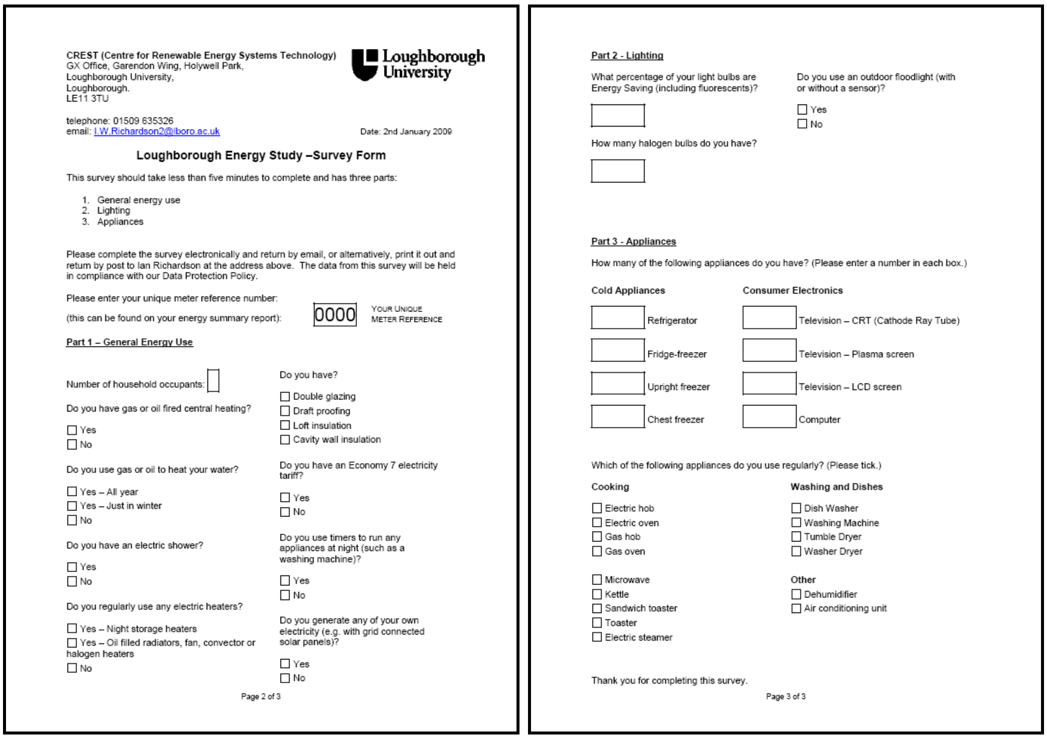


Fig. 13. Geographic location of domestic meters

The meters were read using Elster's Power Master Unit software using a dial up modem. The memory in the meters is sufficient to store three weeks of data, which meant that the meters had to be read frequently over the course of the year.

3.2.4 Domestic household survey form

The two page survey form is shown in Fig. 14 and a full size version is presented in Appendix G. The survey was divided into three sections. The first section asked about general energy use characteristics of the dwelling, the second aimed to gather information about the lighting installation, and the third aspect was to find out the numbers of main types of appliances. The survey was designed to capture important aspects of energy use, without being a major endeavour for the volunteers to complete. All 22 volunteers returned a survey form.



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Loughborough University

Date: 2nd January 2009

Loughborough Energy Study –Survey Form

This survey should take less than five minutes to complete and has three parts:

1. General energy use
2. Lighting
3. Appliances

Please complete the survey electronically and return by email, or alternatively, print it out and return by post to Ian Richardson at the address above. The data from this survey will be held in compliance with our Data Protection Policy.

Please enter your unique meter reference number:
(this can be found on your energy summary report): 0000 YOUR UNIQUE METER REFERENCE

Part 1 – General Energy Use

Number of household occupants:

Do you have gas or oil fired central heating?
☐ Yes
☐ No

Do you use gas or oil to heat your water?
☐ Yes – All year
☐ Yes – Just in winter
☐ No

Do you have an electric shower?
☐ Yes
☐ No

Do you regularly use any electric heaters?
☐ Yes – Night storage heaters
☐ Yes – Oil filled radiators, fan, convector or halogen heaters
☐ No

Do you have?
☐ Double glazing
☐ Draft proofing
☐ Loft insulation
☐ Cavity wall insulation

Do you have an Economy 7 electricity tariff?
☐ Yes
☐ No

Do you use timers to run any appliances at night (such as a washing machine)?
☐ Yes
☐ No

Do you generate any of your own electricity (e.g. with grid connected solar panels)?
☐ Yes
☐ No

Page 2 of 3

Part 2 - Lighting

What percentage of your light bulbs are Energy Saving (including fluorescents)?

How many halogen bulbs do you have?

Do you use an outdoor floodlight (with or without a sensor)?
☐ Yes
☐ No

Part 3 - Appliances

How many of the following appliances do you have? (Please enter a number in each box.)

Cold Appliances
Refrigerator
Fridge-freezer
Upright freezer
Chest freezer

Consumer Electronics
Television – CRT (Cathode Ray Tube)
Television – Plasma screen
Television – LCD screen
Computer

Which of the following appliances do you use regularly? (Please tick.)

Cooking
☐ Electric hob
☐ Electric oven
☐ Gas hob
☐ Gas oven

☐ Microwave
☐ Kettle
☐ Sandwich toaster
☐ Toaster
☐ Electric steamer

Washing and Dishes
☐ Dish Washer
☐ Washing Machine
☐ Tumble Dryer
☐ Washer Dryer

Other
☐ Dehumidifier
☐ Air conditioning unit

Thank you for completing this survey.

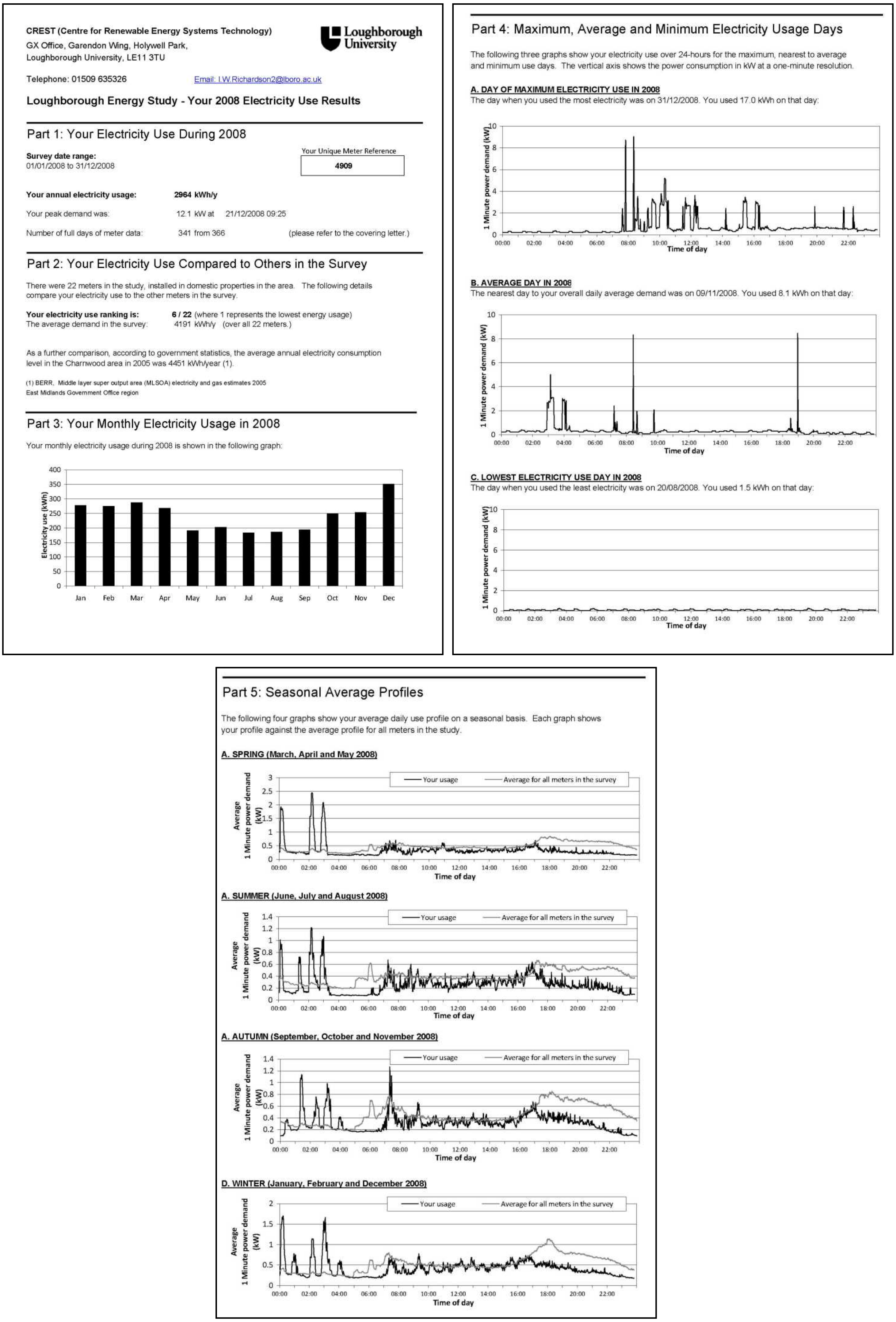
Page 3 of 3

Fig. 14. Dwelling characteristics survey form

3.2.5 Volunteer energy use report

An example of the end of year electricity use report is shown in Fig. 15 and is provided in full in Appendix H.

This report provided information to the householder in a number of areas, in far greater detail than would be available from a typical utility energy bill. In addition to providing annual and monthly electricity use, it was possible to indicate where they ranked relative to other anonymous participants in the survey. One-minute demand profiles were provided for the minimum, average and maximum electricity use days. Seasonal demand profiles were also provided and shown together with the average profiles for the whole study.



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Loughborough Energy Study - Your 2008 Electricity Use Results

Part 1: Your Electricity Use During 2008

Survey date range:
01/01/2008 to 31/12/2008

Your Unique Meter Reference: **4909**

Your annual electricity usage:	**2964 kWh/y**
Your peak demand was:	12.1 kW at 21/12/2008 09:25
Number of full days of meter data:	341 from 366 (please refer to the covering letter.)

Part 2: Your Electricity Use Compared to Others in the Survey

There were 22 meters in the study, installed in domestic properties in the area. The following details compare your electricity use to the other meters in the survey.

Your electricity use ranking is: **6 / 22** (where 1 represents the lowest energy usage)
The average demand in the survey: 4191 kWh/y (over all 22 meters.)

As a further comparison, according to government statistics, the average annual electricity consumption level in the Charnwood area in 2005 was 4451 kWh/year (1).

(1) BERR, Middle layer super output area (MLSOA) electricity and gas estimates 2005
East Midlands Government Office region

Part 3: Your Monthly Electricity Usage in 2008

Your monthly electricity usage during 2008 is shown in the following graph:

Part 4: Maximum, Average and Minimum Electricity Usage Days

The following three graphs show your electricity use over 24-hours for the maximum, nearest to average and minimum use days. The vertical axis shows the power consumption in kW at a one-minute resolution.

A. DAY OF MAXIMUM ELECTRICITY USE IN 2008
The day when you used the most electricity was on 31/12/2008. You used 17.0 kWh on that day:

B. AVERAGE DAY IN 2008
The nearest day to your overall daily average demand was on 09/11/2008. You used 8.1 kWh on that day:

C. LOWEST ELECTRICITY USE DAY IN 2008
The day when you used the least electricity was on 20/08/2008. You used 1.5 kWh on that day:

Part 5: Seasonal Average Profiles

The following four graphs show your average daily use profile on a seasonal basis. Each graph shows your profile against the average profile for all meters in the study.

A. SPRING (March, April and May 2008)

A. SUMMER (June, July and August 2008)

A. AUTUMN (September, October and November 2008)

D. WINTER (January, February and December 2008)

Fig. 15. Example dwelling electricity use report

3.2.6 Approach to the storage and analysis of the data

The number of domestic readings taken during 2008 exceeded ten million data points. A Microsoft SQL Server database was considered the most appropriate tool with which to store and query the data. This is because of its capability to manage database tables with large quantities of rows and the suitability of the SQL query language to manipulate the data. A single database table was used to store each time stamped demand level against a unique meter code.

The meters recorded data throughout the year with Greenwich Mean Time (GMT) time stamps. In the database, it was therefore necessary to time shift the measurements taken by one hour between 30th March, 2008 and 26th October, 2008, in order to take account of the period of British Summer Time (BST).

3.3 Checking that the results are typical of domestic electricity demand

It is necessary to check that the measured demand data is representative of the wider population. In summary, this section includes a set of comparisons between the measured data and published data from elsewhere. The annual electricity demand and seasonal demand profiles are considered. The time-coincident demand characteristics are compared in terms of ADMD, the concept of maximum time-coincident demand per dwelling, introduced earlier. Finally, the distribution of annual electricity consumption levels is considered.

3.3.1 Annual electricity demand

A comparison of the annual demand between the measured data from Loughborough and UK government statistics [31] is shown in Fig. 16. The measured annual demand is slightly lower than the local average. Nevertheless, the data set is fairly typical in terms of the average demand.

The most likely explanation for the difference is that none of the measured dwellings use electric storage heaters for space heating, which would be expected in a larger sample and which would contribute to a higher average annual demand.

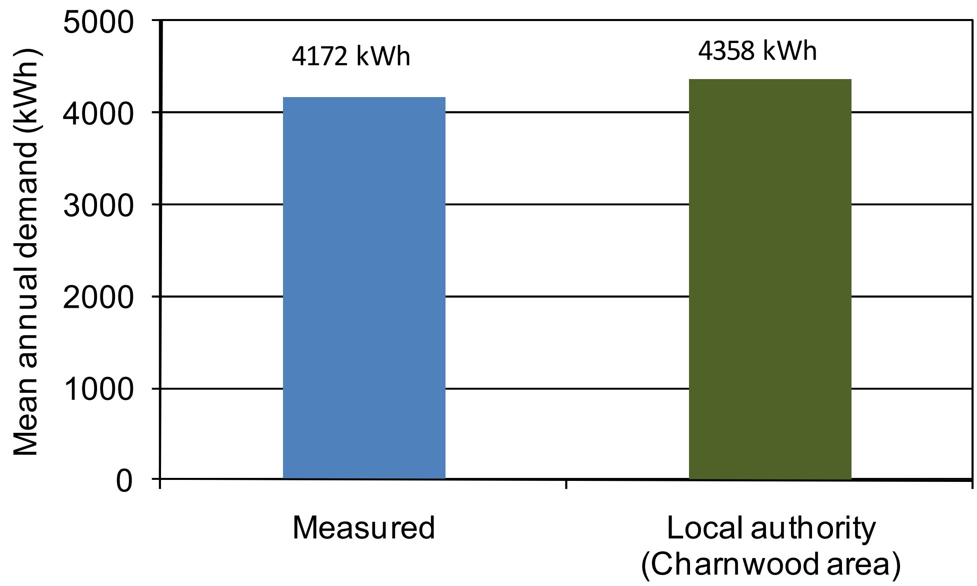


Fig. 16. Annual domestic electricity use comparison

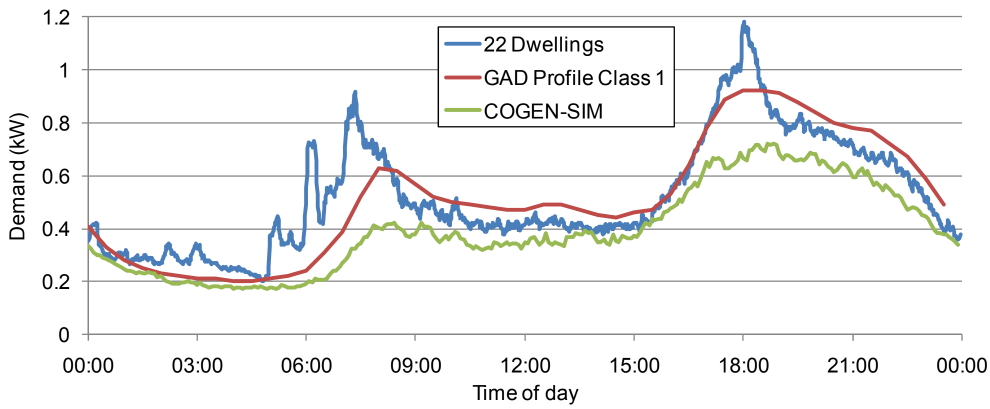
(Local authority data from [36]).

3.3.2 Daily demand profiles

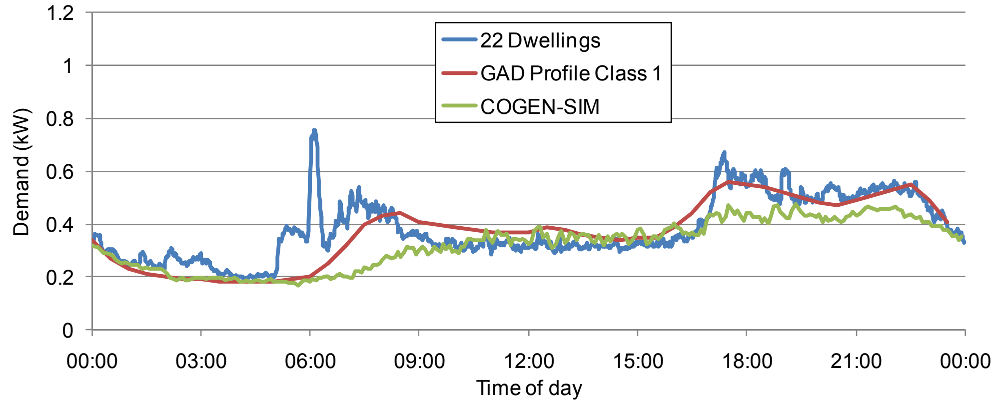
The average daily demand profiles measured in the 22 dwellings are now compared against other published data sets to check that the variation in demand through the course of a day is not atypical. The profiles shown in Fig. 17 include two comparisons. The first is against the national group average demand (GAD) Profile Class 1, introduced earlier. The second is the 5-minute resolution European demand profiles from the COGEN-SIM project [77] which is an average of 69 dwellings. The winter weekday profile is shown in Fig. 17(a) and the summer profile in Fig. 17 (b).

There is a particularly good match with the GAD profile in both winter and summer cases. The demand in the 22 dwellings shows an earlier rise in the morning with a particular spike around 06:00 that could be explained by timed electric water heating. The measured data shows earlier activity and there is a clear spike at 18:00. As was indicated earlier, most of the volunteers were university employees and as such would likely have a similar work life pattern, which could be a reason for the differences with the GAD profile.

The COGEN-SIM data shows a general lower level of demand, although the shape of the curve follows a similar pattern. It is noted that the measurements were made from social housing, which could explain the lower level of overall electricity consumption, as well as perhaps, the later morning ramp.



(a) Winter weekday profile



(b) Summer weekday profile

Fig. 17. Annual Comparison of summer and winter weekday demand profiles

(Data sources: [33], [77])

3.3.3 After Diversity Maximum Demand (ADMD) and Load Duration

The ADMD value, as was discussed in the introductory chapter of this thesis, is calculated for the 22 dwellings by taking the maximum time-coincident demand and dividing by 22.

The maximum time-coincident demand measured was 46.46 kW at 06:58 hours on 31st October 2008, at which time four of the dwellings have demands in excess of 8 kW, likely as the result of electric shower use. Given that this demand was for 22 dwellings, the ADMD is calculated as 2.11 kW.

It is acknowledged that this calculation is based only on one data point. To demonstrate that it is not an uncharacteristic value, the top five maximum time-coincident demands are shown in Table 4. The rank second maximum time-coincident demand differs by only 0.26 kW. Interestingly, this demand occurred at lunchtime on Christmas Day, when it would be expected that many households would be using cooking appliances.

Rank	Date	Time	Demand (kW)
1	31st October, 2008	06:58	46.46
2	25th December, 2008	12:53	46.18
3	19th December, 2008	07:09	45.38
4	28th March, 2008	18:03	45.27
5	19th December, 2008	07:06	44.71

Table 4 - Top five measured time-coincident demands

As was indicated in the introduction, typical UK network design standards allow for an ADMD of 2kW per dwelling, where there is no electric space heating [43]. The value derived from the measured data is very close to this design standard and the measured data can therefore be said to be exhibiting typical time-coincident demand characteristics.

In terms of looking at the full range of loads over time, the load duration curve per dwelling, taking all 22 dwellings into account is shown in Fig. 18. Rarely does the demand exceed 1 kW when averaged on a per dwelling basis. The ADMD value of 2.11 kW previously calculated can be seen as the peak, although this rarely occurs: for much of the time, the demand is well below 1 kW.

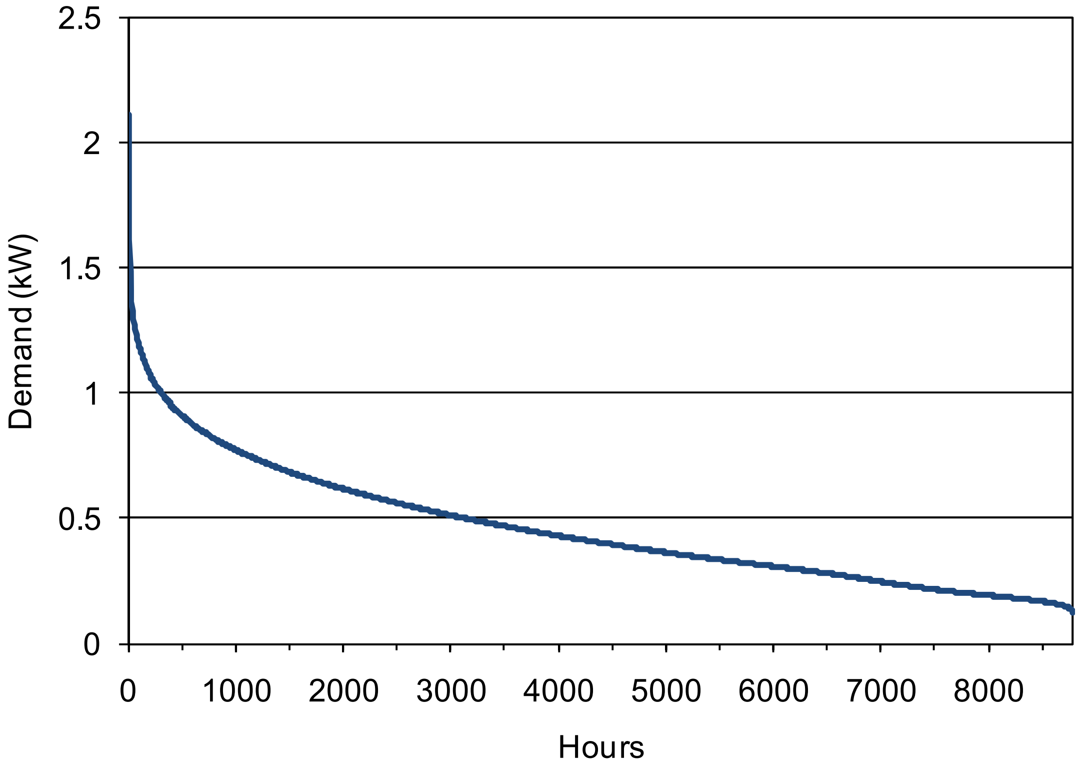


Fig. 18. Load duration curve (per dwelling basis)

3.3.4 Histogram of annual demand

A histogram of the distribution of annual consumption levels is shown in Fig. 19 in comparison with a frequency density plot by Skinner (1984) [78], with a sample size of 12 000 consumers, randomly chosen from Electricity Board billing records. The measured data consists of only 22 dwellings, which results in too few data points to form a smooth density plot. Nevertheless, the general shape of the distribution could be seen as being comparable to the shape of the Skinner distribution, albeit shifted to the right due to a greater mean demand.

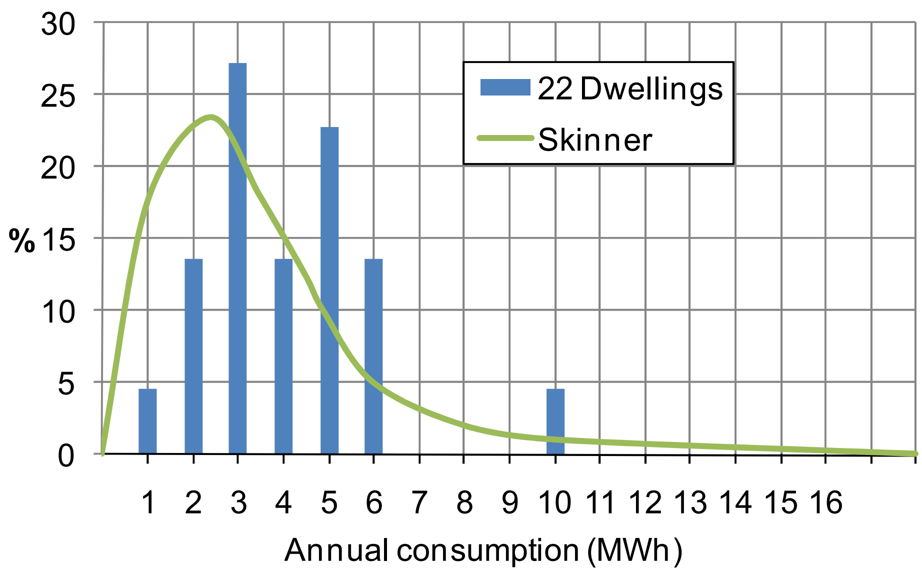


Fig. 19. Annual consumption distribution comparison

(Comparison with Skinner [78]).

3.3.5 Seasonal variation

The mean daily electricity use in each month of the year is shown in Fig. 20 for the 22 dwellings plotted with national statistics from DUKES [31]. As would be expected, an increased demand is seen in the winter months: the summer months see the lowest relative demand in both series.

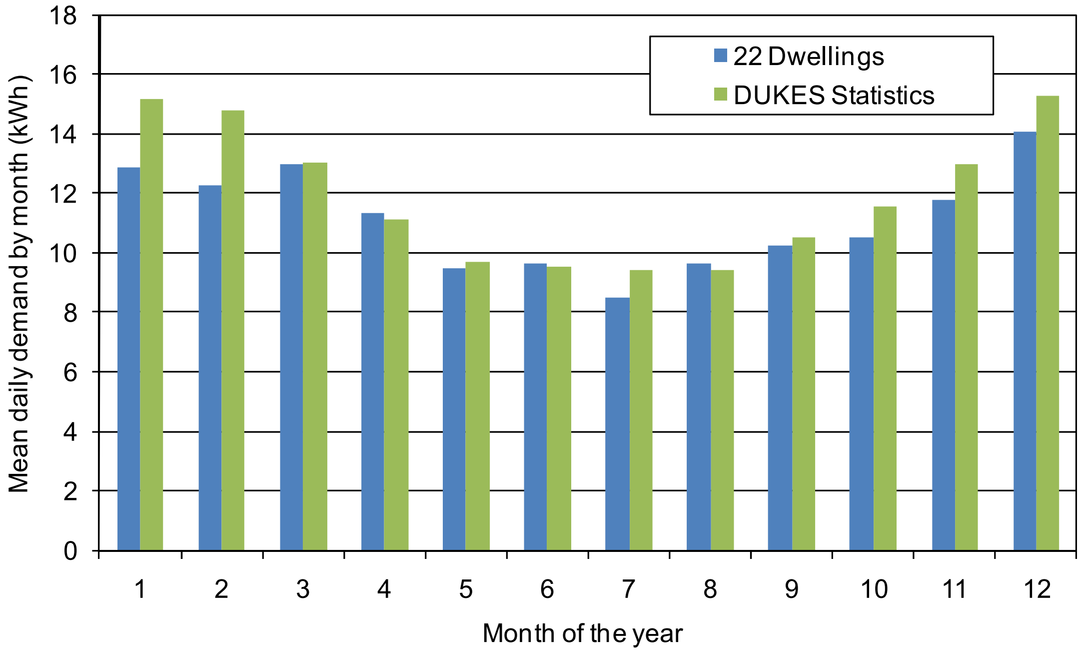


Fig. 20. Mean daily demand for each month of the year

(Sources [79,31]).

Both the magnitude of the demand and the shape are the same. The DUKES statistics show a higher demand over the winter months. One explanation for this is that none of the 22 dwellings have electric storage space heating, whereas the national data will take this into account.

* The DUKES data is converted to daily averages using the domestic consumption figures presented in Table 5.5 “Availability and consumption of electricity” for 2009 in [79] in combination with the figure of 26,334,000 households in 2008 given in Table 3.3 “Overall drivers of energy consumption”

3.3.6 Conclusions

This section set out to confirm that the data gathered from the 22 dwellings is representative of the wider population and is therefore usable in the context of the demand model output verification.

The main conclusion is that, despite having only 22 dwellings in the sample set, the measured data is representative when compared to generally available statistics. The magnitude of annual demand, the distribution of values and the daily profiles were found to be comparable with data published elsewhere. Using the measured data to validate a model of electricity demand can therefore be done with some confidence.

3.4 Dwelling characteristics and electricity use

This section examines the measured data to identify relationships between the dwelling characteristics and level of electricity use. Identifying such relationships is valuable in the subsequent construction of the new demand model described later in this thesis. As a summary, floor area, dwelling construction type, numbers of residents, their attitudes and occupancy patterns are considered.

3.4.1 Floor area

The floor area of a dwelling is a main factor that is used within the BREDEM-8 model [80] to estimate electricity demand of a dwelling from lighting and appliances. The model has two methods of calculating the annual electricity demand: a simple version that uses only the floor area, considered here, and a second calculation that takes into account the number of residents, considered later in this section. (Note also that the BREDEM calculations result in units of GJ per year and are converted to kWh for the purposes of comparison) .

For the 22 dwellings, the floor area is obtained using the footprint area of the house from Ordnance Survey MasterMap Data. (The use of this data is discussed in full later in Chapter 8). This data is plotted against the measured annual electricity consumption in Fig. 21, shown together with the results of the BREDEM simple estimate calculation, and the findings of Yohanis et al. in 27 dwellings [55].

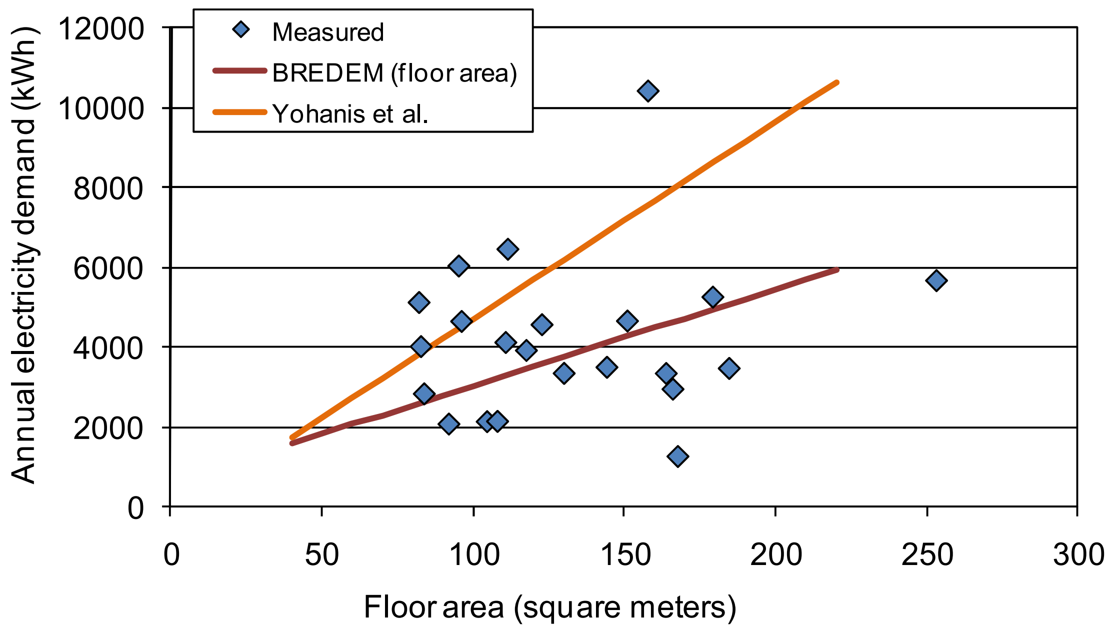


Fig. 21. Floor area and electricity use

(Sources [55, 80]).

Looking first at the measured data, there is little correlation between the two factors. Both BREDEM and Yohanis et al. show a linear approximation that demand rises with floor area, but neither fits the measured data. It is acknowledged that the BREDEM calculation used in this case does not take into account heating related demand, such as central heating pumps and fans. Nevertheless, the evidence from the 22 dwellings suggests that floor area alone is not particularly useful as a key determinant of electricity use.

The BREDEM calculations are returned to later in the context of additionally taking the number of residents into account.

3.4.2 Dwelling construction type

It is often assumed that there is a close relationship between dwelling construction type (e.g. detached, semi-detached, terraced or flats) and electricity use [55]. This section considers this relationship for the 22 measured dwellings. The electricity use for the each dwelling is shown in Fig. 22, as grouped by construction type.

Although it is necessary to be cautious because of the small sample size, the measured data provides counter-intuitive results in that detached dwellings used considerably less electricity (a mean of 4155 kWh) than semi-detached dwellings (a mean of 4434 kWh). However, there is considerable variation between dwellings in the data as is seen in the figure: the standard deviations are large. The measured data therefore provides little support for the idea that the type of dwelling is a major driver of electricity use.

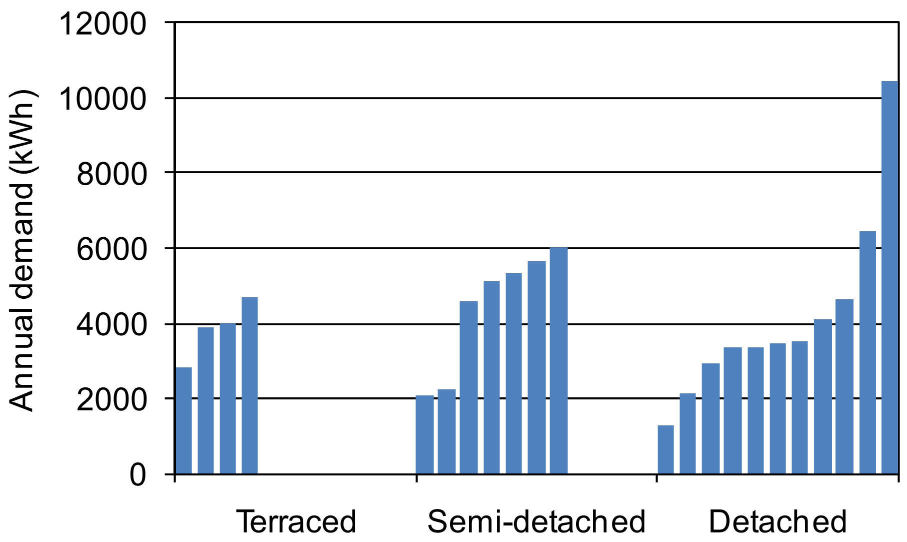


Fig. 22. Ranked demand by dwelling, grouped by construction type

3.4.3 Number of household residents

In terms of the number of household residents, a comparison between the measured data and US statistical household data from the EIA [81] is shown in Fig. 23.

It is noted that adding an extra resident to a single resident dwelling does not double the electricity use, but provides an increment. The magnitude of the increment is reduced for each additional resident added.

The pattern is the same as the US household data, although the US households use considerably more electricity. Therefore, the number of household residents is considered as a significant driver of the electricity demand.

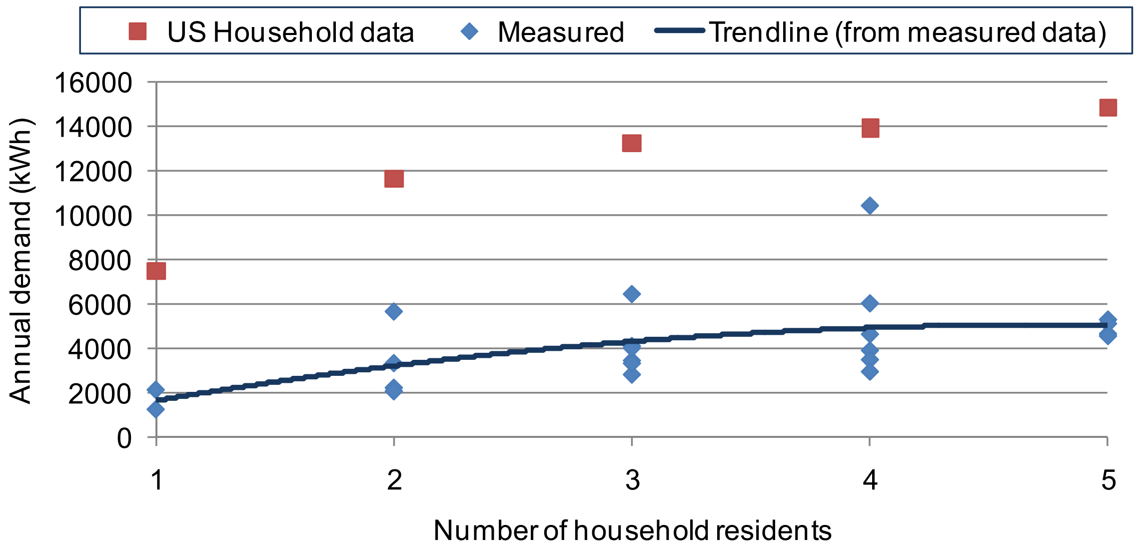


Fig. 23. Numbers of household residents and electricity demand

3.4.4 Floor area and the number of household residents

Returning now to the discussion of the BREDEM [80] electricity demand estimation calculations, a more complex calculation is provided for a "more accurate" estimate of demand. In this case, the number of residents is taken into account in conjunction with the floor area of the dwelling. The results from the 22 dwellings are shown against the BREDEM estimate for the electricity demand of lighting and appliances in Fig. 24.

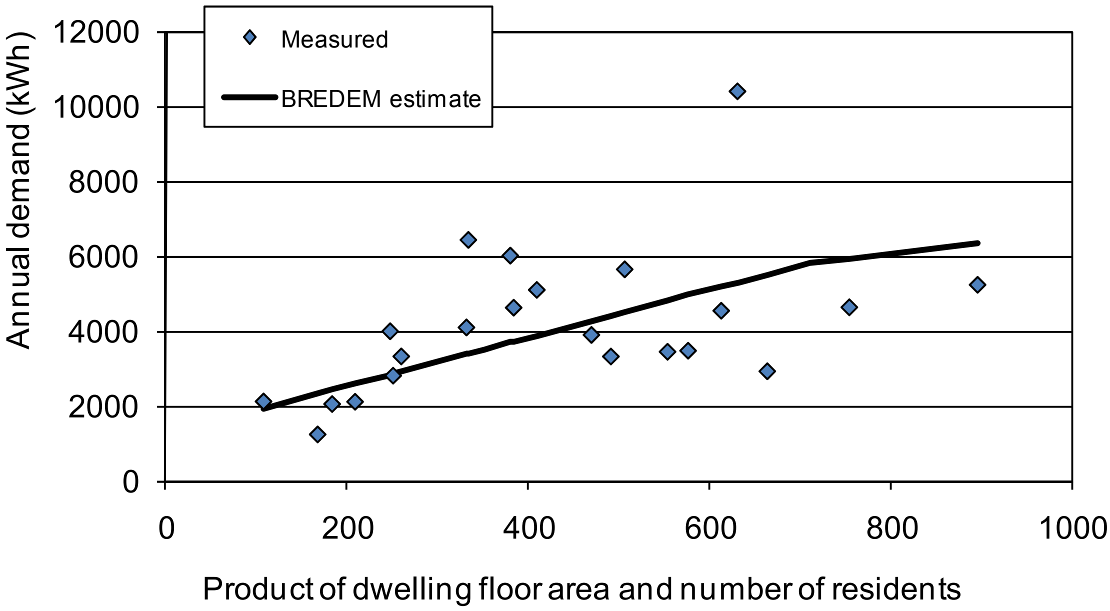


Fig. 24. Floor area, number of residents and electricity use

As was previously seen, the total number of residents does have an influence on the dwelling energy demand. Therefore it would be expected that by taking this into account in the BREDEM calculation, that a better correlation would be found over one that only used the floor area.

3.4.5 Energy consciousness

The dwelling characteristics survey form aimed to capture data that would infer the extent to which volunteers were energy use aware. Whilst the previous sections looked at physical relationships between a dwelling characteristics and electricity, energy consciousness is more concerned with the behaviour and attitudes of the occupants. In this case, data was captured on the use of switched-timers and the level of low energy lighting that had been installed.

Ten of the 22 respondents in the survey indicated that they used timers in order to run appliances at night time. Timers are usually used in this way to benefit from lower rate Economy 7 electricity. It might be expected that those household residents who used timers in this way were more energy conscious, and therefore would perhaps use less electricity. The data presented in Fig. 25 shows that this was not the case in this survey. Those dwellings in which timers are used showed a mean electricity demand greater than 500 kWh per year more than those that did not. The use of timers may therefore be considered as evidence of price consciousness, rather than awareness of overall electricity use.

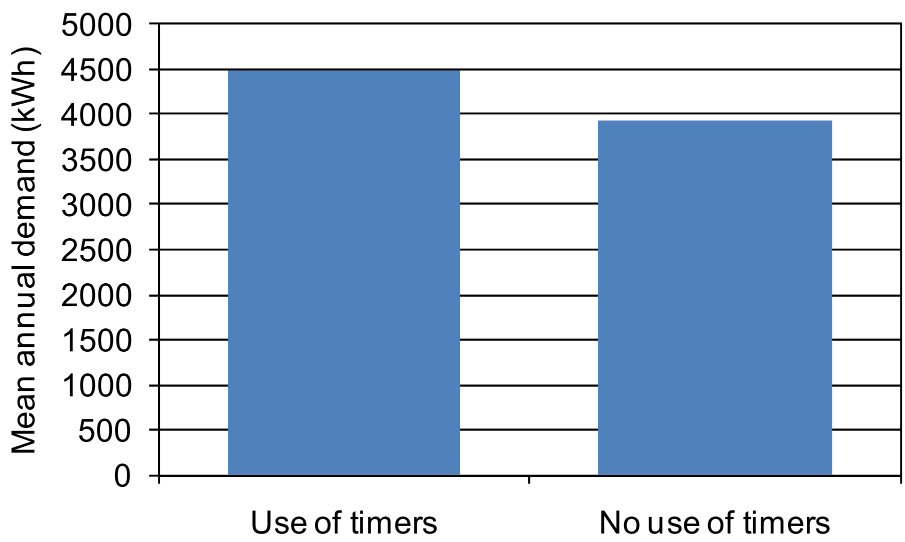
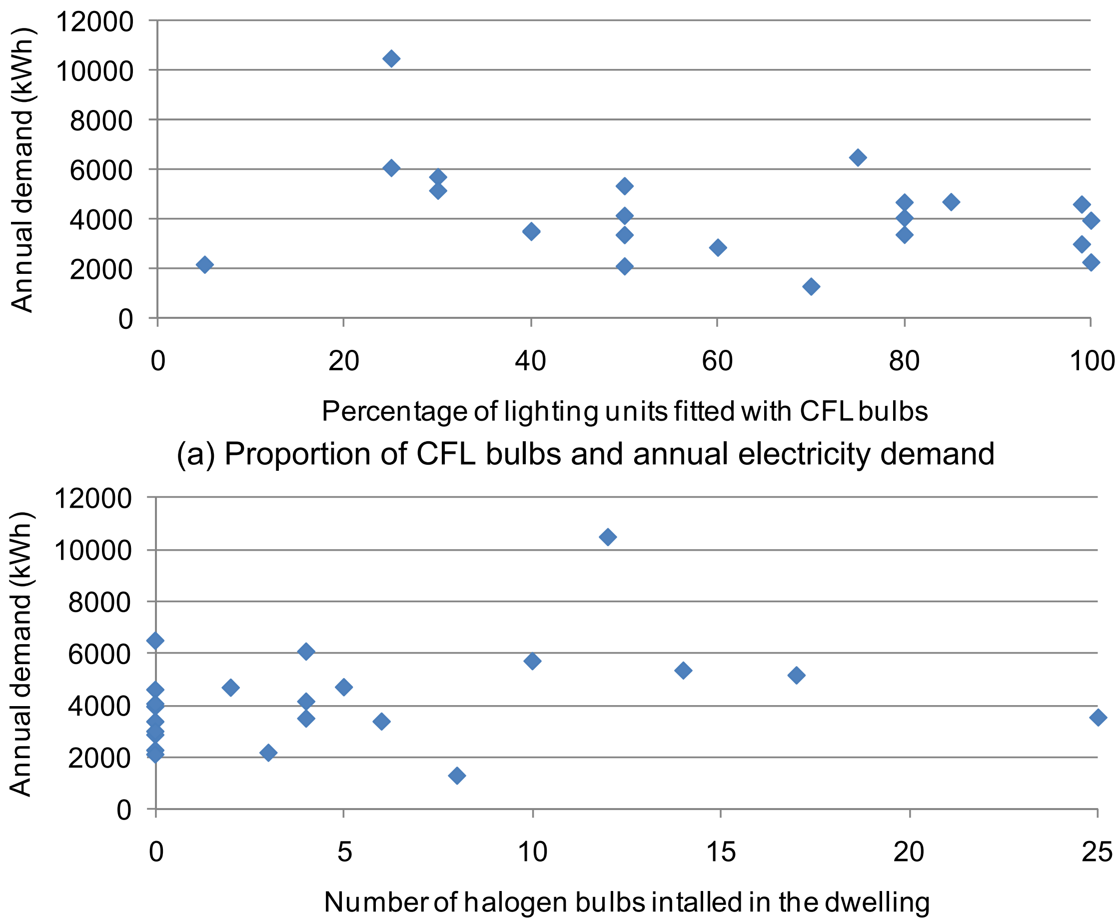


Fig. 25. Use of timers and electricity use

The electricity use plotted against the percentage of lighting units fitted with efficient CFLs is shown in Fig. 26(a). Perhaps surprisingly from the measured data, dwellings with a greater proportion of efficient lighting did not in general use less energy.

Looking specifically at higher demand halogen bulbs, Fig. 26(b) plots the bulb count against electricity use. Again, no particular correlation can be observed.



(a) Proportion of CFL bulbs and annual electricity demand

(b) Number of halogen bulbs and annual electricity demand

Fig. 26. Lighting configuration and annual electricity demand

3.4.6 Occupancy patterns and electricity use

The literature, as discussed in the previous chapter, suggested that occupancy patterns are a major factor in the timing of electricity use. To test this assertion, a diary of the number of active occupants within a dwelling was kept for a day, whilst the electricity demand in the dwelling was recorded. A plot of the results is shown in Fig. 27.

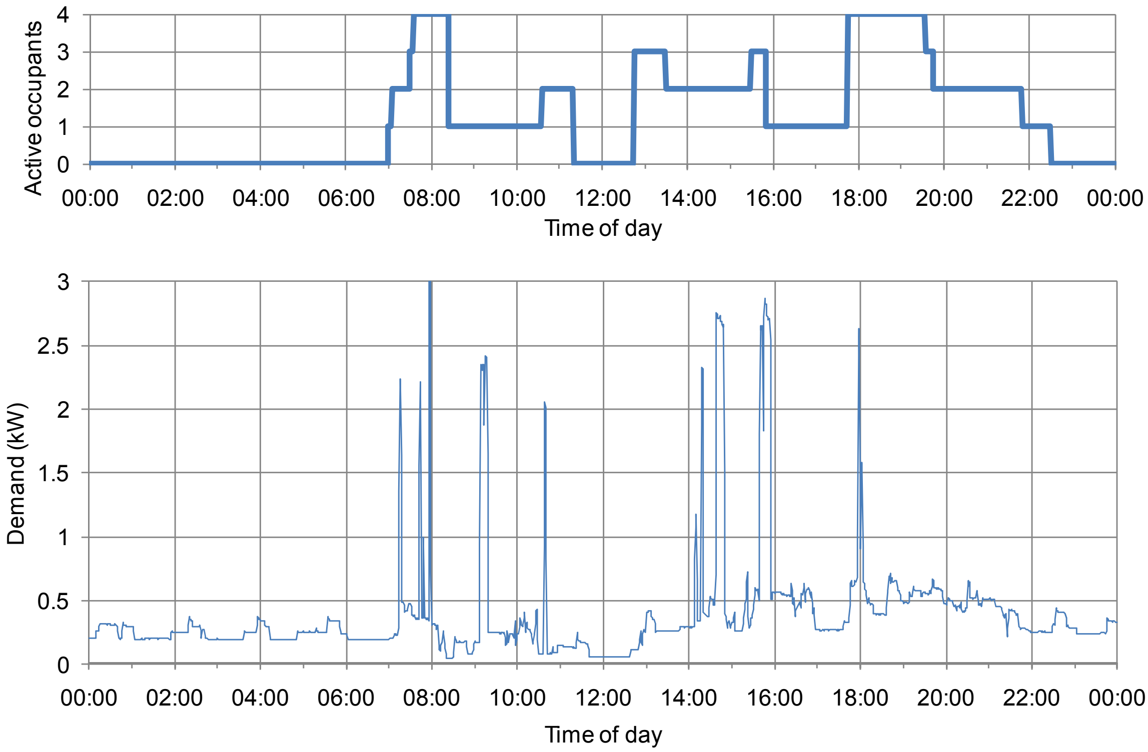


Fig. 27. Patterns of active occupancy and electricity demand

This dwelling has four residents. The occupants rise at 07:00 and there is at least one active occupant present for most of the day, with the exception of the lunchtime period and the late evening. During the times when there is no active occupancy, the cycling patterns of cooling appliances can be seen. However, during periods when there is active occupancy, there is clearly more electricity consumption. This illustrative example confirms that there is a relationship between the patterns of active occupancy and the times of demand for electricity.

As a general observation, it also shows how intrusive the data is. It is clearly possible to identify when the dwelling is actively occupied, and even possible to make a reasonable guess as to which appliances were used at what times.

3.4.7 Conclusions

The patterns of active occupancy within a dwelling are considered to be a key driving factor in the times of energy use. This was suggested by the literature in the previous chapter and was confirmed by the measurements taken in the work presented in this chapter. The data showed that there is a correlation between the number of household residents and the annual electricity demand.

Floor area was not found to be a key variable in electricity demand. Neither was it apparent that energy awareness, evident through the use of times or energy efficient lighting, correlated with lower overall electricity demand.

The next chapter of this thesis is concerned with the development of a model of active occupancy for use in energy demand modelling.

4. A HIGH-RESOLUTION DOMESTIC BUILDING OCCUPANCY MODEL FOR ENERGY DEMAND SIMULATIONS

4.1 Introduction

This chapter details the implementation and validation of a model of domestic active occupancy for the purpose of energy demand simulations. To re-cap, active occupancy refers to occupants that are within a dwelling and are not asleep. The context of this model was introduced in Fig. 7 in section 1.5 in describing its use as one input to the electricity demand model presented later in this thesis.

The motivation for developing such a model is that active occupancy was identified as being a primary driver of electricity use: this was suggested by the literature discussed in Chapter 2, and confirmed by the diary and measurements taken in Chapter 3. Being able to generate large volumes of data representing active occupancy, provides a way to show realistic activity within a group of dwellings, such as those within a housing estate, village or town. The model is based upon the UK 2000 Time Use Survey (TUS) [63] data set introduced previously, and is capable of generating data with the same statistical characteristics.

The work, as published in Energy and Buildings in 2008, is contained in full in Appendix A: this chapter provides a self-contained summary of the model and its validation.

4.2 Representation of active occupancy

4.2.1 Individual occupancy profiles

An example of the nature of active occupancy profiles is shown in Fig. 28, where fifty people are individually represented. The black horizontal bar shown for each person represents the times of the day when they are active within their dwelling. The active occupancy during the night time period (from 00:00 to 07:00) can be seen to be sparse, as would be expected. It can be seen that activity increases during the day, and reaches a maximum during the evening.

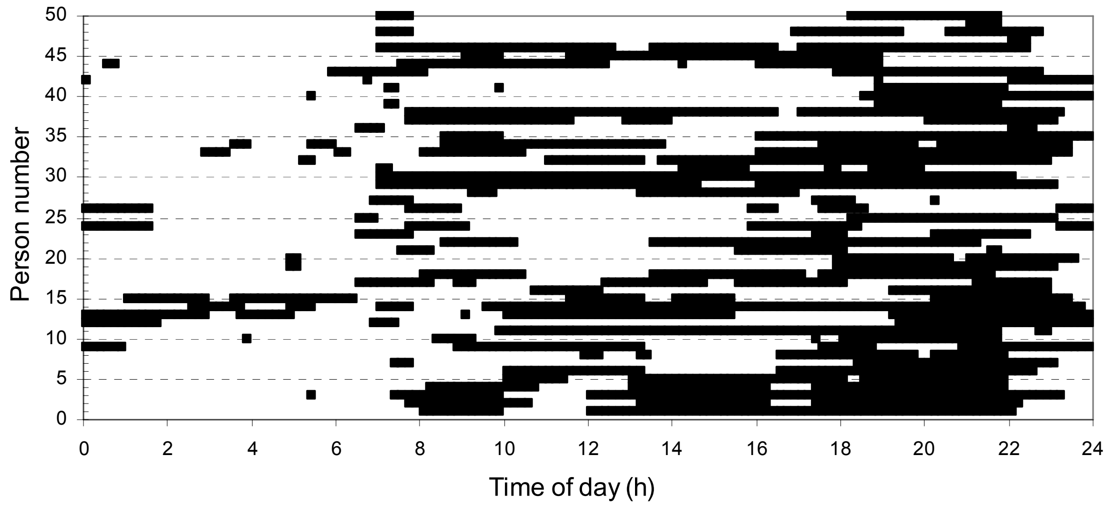


Fig. 28. Fifty example active occupancy profiles taken from the TUS data

4.2.2 Single dwelling occupancy profile

The TUS data provides sufficient detail to determine which occupants live together. People's activity within the same dwelling is often correlated and this is evident in the TUS data. For example, the occupancy profile for the dwelling in Fig. 29 shows how both occupants become active at 08:00 (when they get up) and then both become inactive at 14:00 (when they most likely leave the dwelling together).

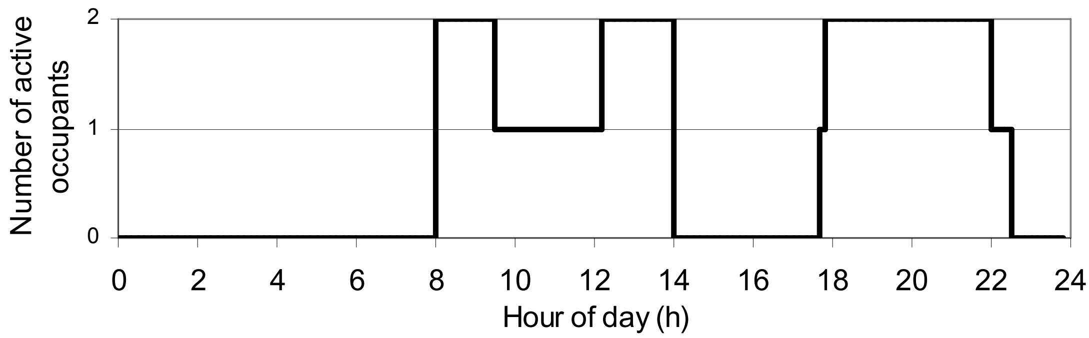
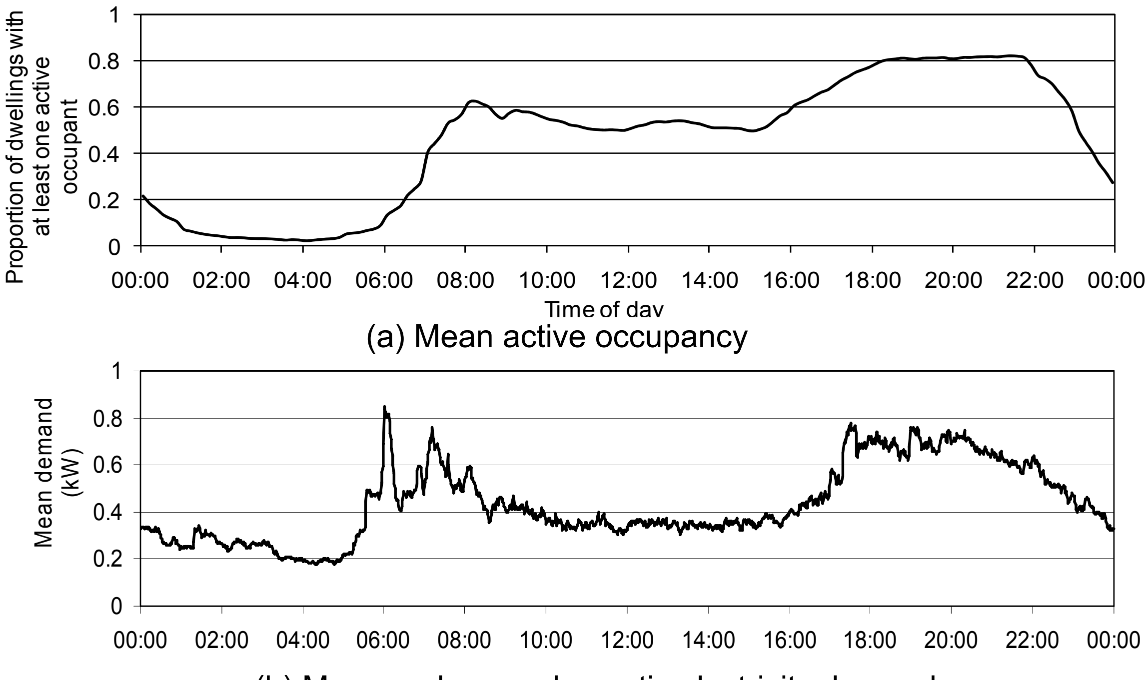


Fig. 29. An example active occupancy pattern

4.2.3 Relationship with electricity demand

Using the whole TUS data set, the proportion of dwellings with at least one active occupant throughout the day was calculated, in order to provide an average profile of active occupancy. The resulting plot is shown in Fig. 30(a). There is little active occupancy at night, but the ramp up towards breakfast time can be seen to start at 05:00. A second ramp up occurs during the evening period from 16:00.

For comparison, a plot of the measured mean electricity demand from the study described in Chapter 3 is shown in Fig. 30(b). A similarity between the shapes of the curve in the two plots can clearly be seen: this supports the notion that the two series are related and that active occupancy is a good basis for modelling electricity demand.



(a) Mean active occupancy

(b) Measured mean domestic electricity demand

Fig. 30. Active occupancy profile against measured electricity demand

4.3 Modelling

4.3.1 Approach

In order to construct a model capable of generating extensive synthetic occupancy data with the same statistical characteristics as the source TUS data, a first order Markov-Chain [82] technique was chosen as a well-established method. The technique requires the derivation of a set of Transition Probability Matrices (TPM) from the source data, that details the probability of a transition from one level of active occupancy to another, at each time step throughout a day. The number of active occupants within a dwelling for a particular ten-minute period is known as the state.

An example of such a TPM is presented in Table 5 for the transition period 00:00 to 00:10. A ten-minute time-step resolution is used since this is the resolution of the source data set.

		Next State (at 00:10)	
	Active Occupants	**0**	**1**
Current State (at 00:00)	**0**	0.994	0.006
	1	0.207	0.793

Table 5 - An example Transition Probability Matrix

This example represents a dwelling with a single resident, where there are two states: they are either active (state 1), or not active (state 0). The start state at 00:00 must already be known. The probabilities show the likelihood of the state remaining the same, or transitioning to the alternate state. As would be expected, if there is no active occupancy at 00:00, then it is most likely that that state will remain the same at 00:10, as is indicated by the probability of 0.994. Note that the sum of horizontal probabilities will always equal one as all possible state transitions are represented.

4.3.2 Constructing a transition probability matrix

Each TPM matrix is constructed by calculating the likelihood of each possible state to state transition from the source data, as is illustrated in Table 6. The table shows the transition probabilities for the 00:00 to 00:10 period, in this case for a single resident dwelling on a weekday.

Number of active occupants		Number of occurrences in the TUS data		Transition Probability
At 00:00	At 00:10			
0	0	1428	1428 + 8 = 1436	1428 / 1436= 0.994
0	1	8		8 / 1436 = 0.006
1	0	55	55 + 211 = 266	55 / 266 = 0.207
1	1	211		211 / 266 = 0.793

Table 6 - Constructing a TPM

Given two possible start and end states, there are four overall transition possibilities, as is seen in the first two columns. The number of occurrences of each transition is counted from the TUS data, as is seen in the next two columns. For each start state, the probability of each transition is then calculated, as is seen in the final column.

4.3.3 Numbers of required matrices

In order to represent a full day, 144 separate matrices are required to represent each ten-minute period. This is necessary because the probabilities change at each step throughout the day.

Furthermore, it is intuitive that occupancy patterns differ between weekday and weekend days due to the patterns of working life. Modelling these separately doubles the number of matrices required.

Finally, it is necessary to represent the total numbers of residents in different dwellings. This adds a further dimension by requiring the calculation of matrices for each number of total residents, in this case from one to six.

The numbers of matrices required in order to model all the necessary transitions, taking account of time of day, weekday and total residents, is shown in Table 7.

	Household size (residents)	Transition Probability Matrix for each time step	Overall Transition Probability Matrices
Weekday	1	2 x 2	2 x 2 x 144
	2	3 x 3	3 x 3 x 144
	3	4 x 4	4 x 4 x 144
	4	5 x 5	5 x 5 x 144
	5	6 x 6	6 x 6 x 144
	6	7 x 7	7 x 7 x 144
Weekend	1	2 x 2	2 x 2 x 144
	2	3 x 3	3 x 3 x 144
	3	4 x 4	4 x 4 x 144
	4	5 x 5	5 x 5 x 144
	5	6 x 6	6 x 6 x 144
	6	7 x 7	7 x 7 x 144
		Total elements	40 032

Table 7 - Numbers of transition probability matrices

4.3.4 Start states

In determining the start state, in this example at 00:00, the TUS is grouped by total number of residents (from one to six) and the proportion of dwellings with each level of active occupancy is calculated, as is shown in Fig. 31. These represent probability distributions from which a start state for each dwelling may be stochastically determined.

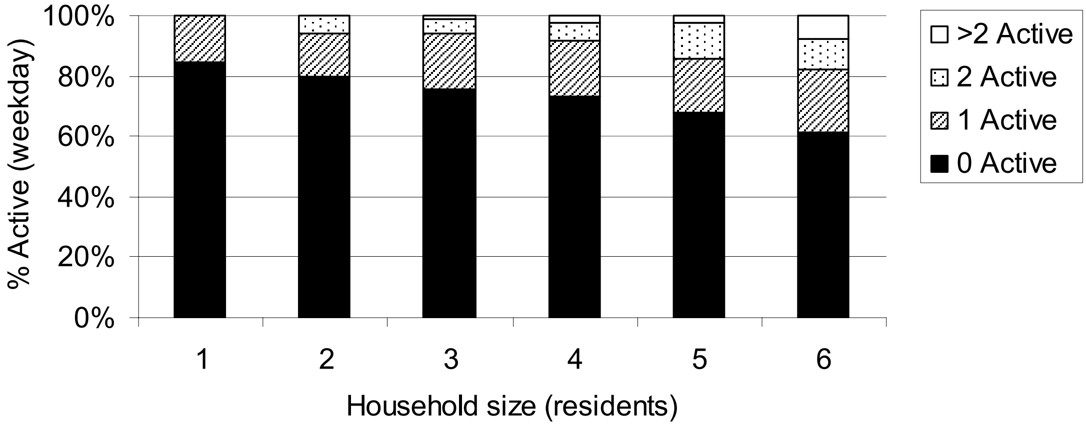


Fig. 31. Percentage distribution of active occupancy states at 00:00

4.3.5 Generating the data

Once a start state is known, the Markov-Chain is determined by first picking a random number for each time step, then using this in conjunction with the relevant TPM (taking into account the time of day, the total number of resident and the day of the week) in order to determine the next state.

4.4 Verification of the model

4.4.1 Simulation of individual dwellings

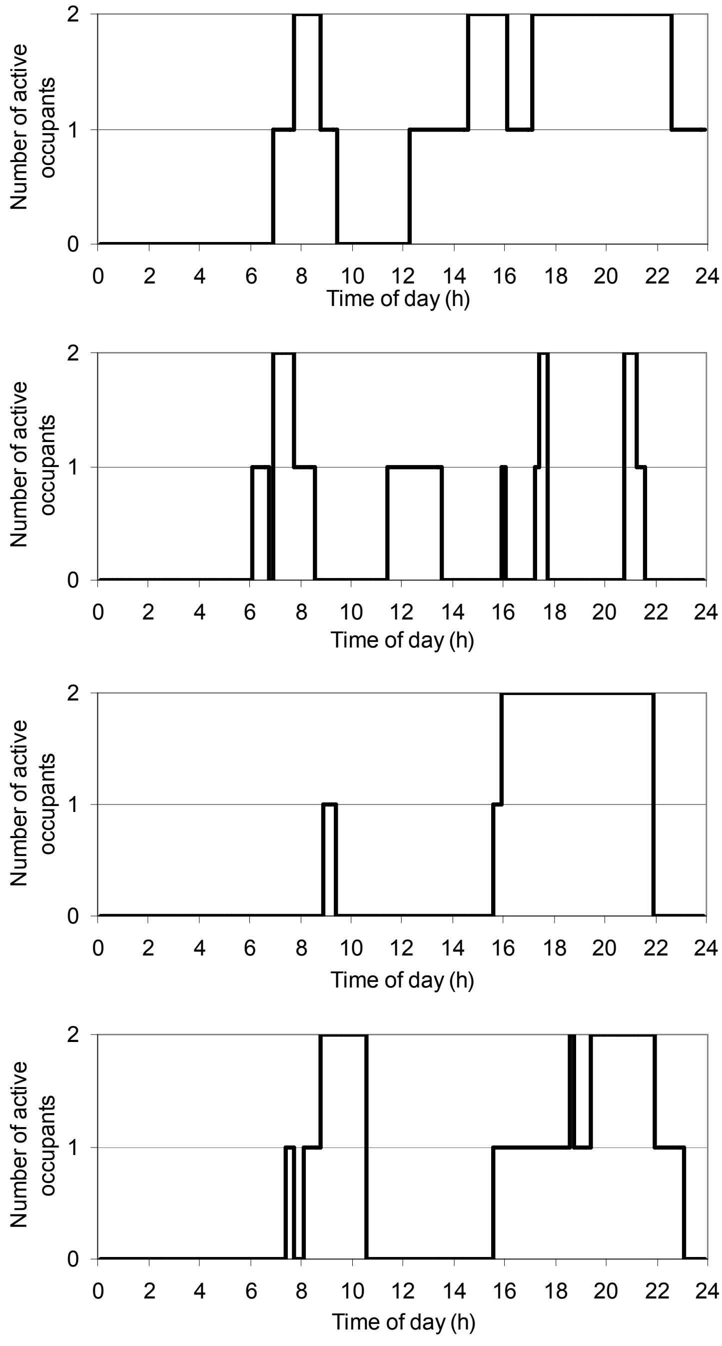


Fig. 32. Four occupancy model example run results

(two resident household, weekdays)

The results from four example simulation runs for a single dwelling, are shown in Fig. 32. Each simulation is different as a result of the different sequence of random numbers used to determine the transitions from state to state. However, they all display the common characteristic of little activity at night, activity starting in the morning, leaving the dwelling during the day and finally returning before retiring in the evening.

4.4.2 *Verification of aggregated patterns of active occupancy*

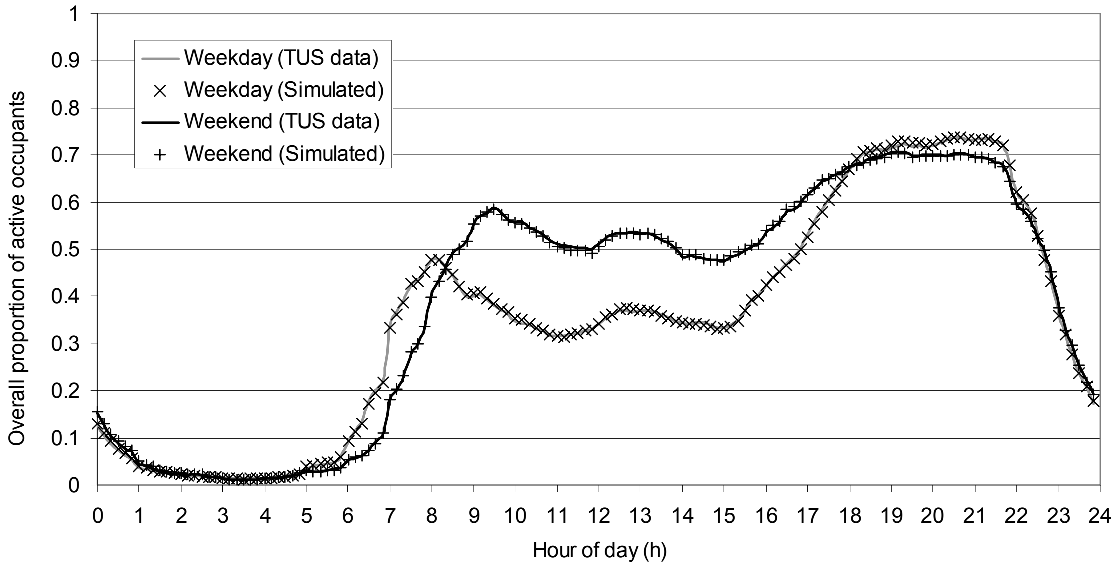


Fig. 33. Comparison of synthetic and surveyed data

The aggregated model output for 10 000 dwellings is compared to the aggregated active occupancy in 2000 dwellings in the TUS data in Fig. 33, for both weekend and weekday cases. This demonstrates the effectiveness of the Markov-chain technique in replicating the statistical nature of the original TUS data.

4.4.3 Verification of transitions

The number of people becoming active and inactive at each time-step through the day is compared with the synthetic model output and the TUS data, for 1000 two-resident dwellings. In both cases, as is seen in Fig. 34, the transition characteristics are very similar.

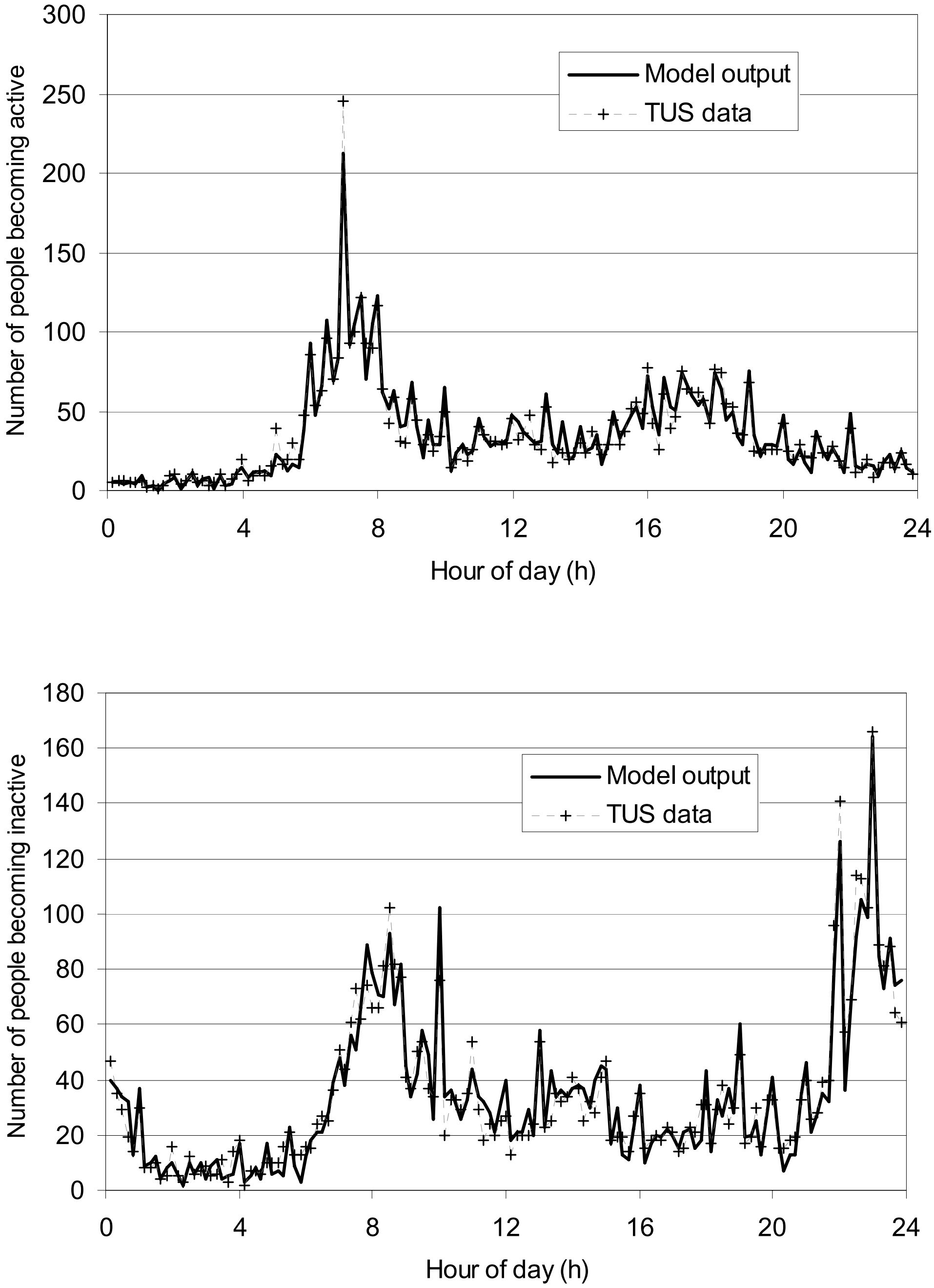


Fig. 34. Number of people becoming active and inactive

(2 resident household, weekday)

4.4.4 Verification of correlated occupancy changes

The correlation of changes in occupancy, when people become active or inactive, is compared in Fig. 35 for 1000 two-resident dwellings. The correlation between the model output and the TUS data is clearly evident.

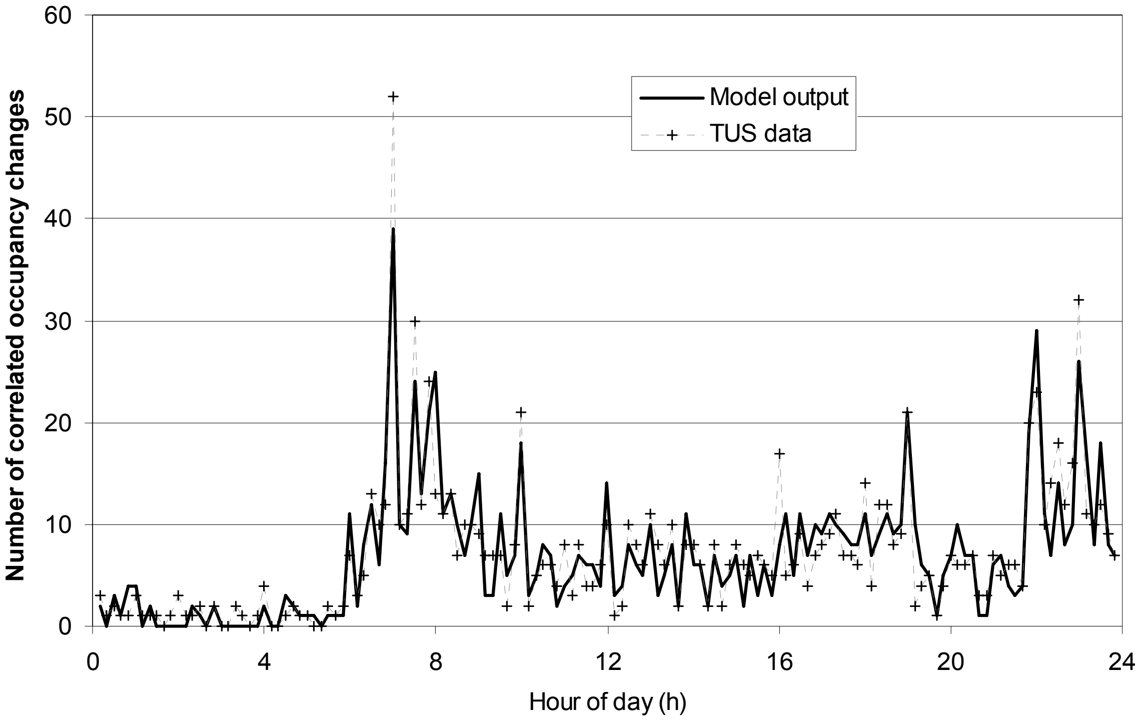


Fig. 35. Number of correlated occupancy changes

(two resident household, weekday)

4.5 Downloadable example

The model is implemented as an example as a Microsoft Excel spreadsheet with all the necessary data and VBA code to perform occupancy simulations. An example screen print of the model is shown in Fig. 36. The number of residents in the dwelling is specified, together with whether it is a weekday, as simulation input values. The graph shows the simulation of a single dwelling over one day. The execution of the simulation is computationally efficient, and it is possible to simulate large numbers of dwelling with this example.

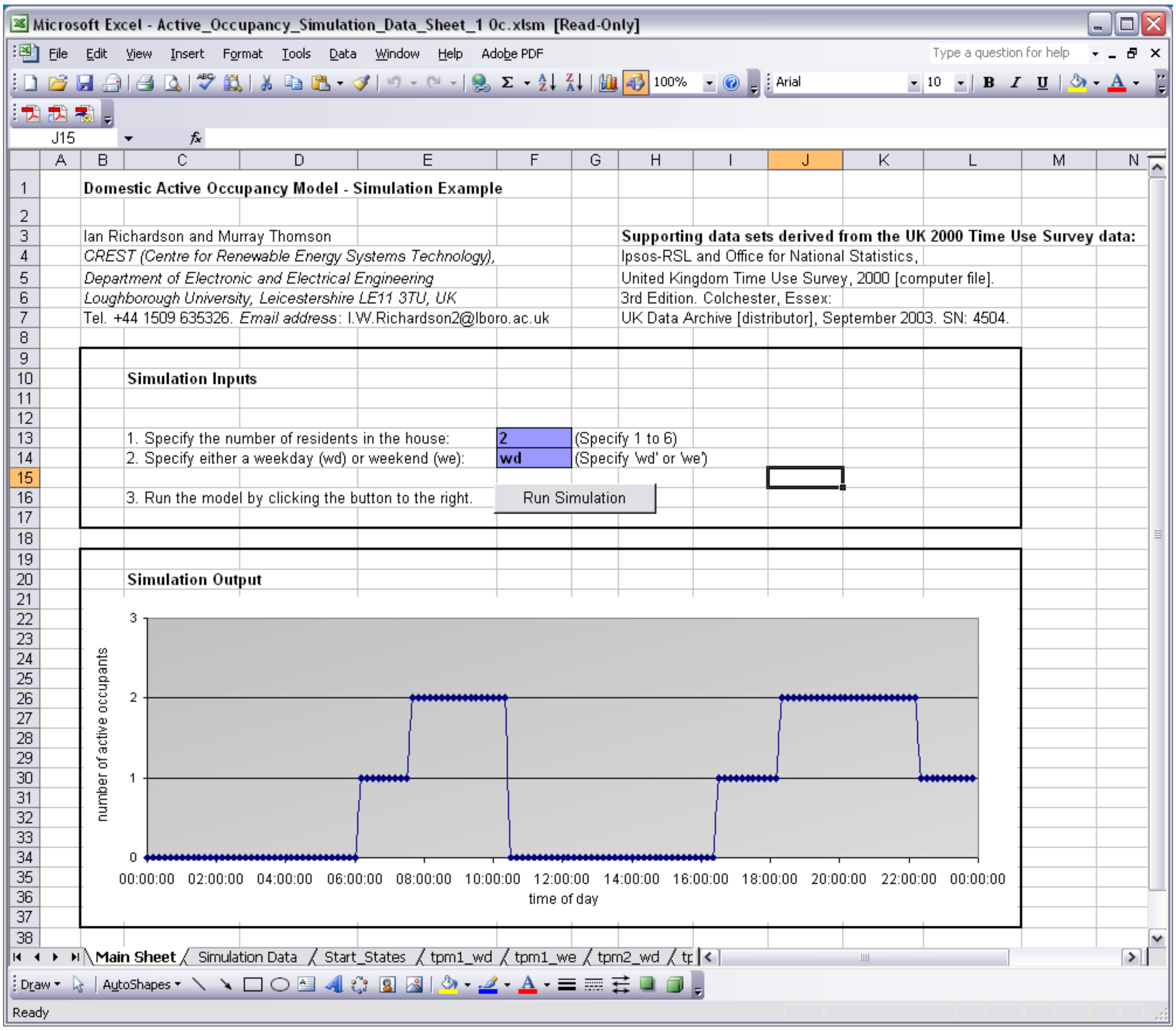


Fig. 36. Downloadable occupancy model

4.6 Conclusions

This chapter detailed the construction of a model of domestic occupancy. The Markov-Chain technique was found to be computationally efficient in generating synthetic data. It was shown that this data has the same statistical characteristics as the source data.

The next step, detailed in the following chapter, is the use of this active occupancy data in the construction of a model of the electricity use of domestic lighting.

5. DOMESTIC LIGHTING: A HIGH-RESOLUTION ENERGY DEMAND MODEL

5.1 Introduction

This chapter presents a high-resolution model of domestic lighting. The model simulates the use of individual lighting units within a dwelling, by using a combination of active occupancy (discussed previously) and the natural light level. This model represents the first component of the whole-dwelling domestic electricity model that is presented in the next chapter.

The work described in this chapter was published in Energy and Buildings in 2009, and is contained in full in Appendix B. This chapter provides a self-contained description of the construction of the model. For full details of the validation of the model, refer to the paper in the appendix.

5.2 Features of the model

5.2.1 Natural lighting

A key motivation for the use of domestic lighting is the occupant's perception of the natural light level. Clearly, people will use lighting after dusk or before dawn, or when weather conditions, such as overcast skies, reduce the available light.

5.2.2 Active occupancy

The majority of domestic lighting use is the result of people switching on lights as they move around the dwelling. The concept of active occupancy is therefore useful in determining when people are within a dwelling and be available to use lighting as is required. The model of active occupancy, described in the previous chapter, is used to provide simulations in this context.

5.2.3 Sharing

It is common for multiple occupants to share the use of lighting, for example, when two or more people are within the same room. Using the number of active occupants as an input enables this sharing to be represented.

5.2.4 Linking to other domestic demand models

As the first component of the electricity demand model described later in this thesis, it is important that it is possible for the model to be integrated with simulations of other appliances. Since the number of active occupants is closely related to the level of energy use within a dwelling, it is of benefit to use the same active occupancy data as input to all appliance use models.

5.2.5 Lighting units

The term "lighting unit" is used to describe one or more bulbs that are operated by a single switch. As an example, this could be a single bulb in a hallway, or it could represent a set of halogen down lights within a kitchen.

5.2.6 Installed lighting technologies and ratings

It is important to appropriately represent the numbers and types of bulbs within each dwelling that is to be simulated. In reality, the lighting configuration within each dwelling will vary as a result of choices made by the occupants. Statistics from the Lighting Association [83] are used to randomly populate each dwelling with an appropriately representative set of lighting units.

5.2.7 Relative usage of lighting units

The relative usage of different lighting units varies around the dwelling. For example, lighting units in living areas, such as kitchens, will be used more than loft or cellar areas. The model represents this variation of use with a weighting factor, picked at random from a probability distribution.

5.2.8 Temporal resolution

In common with the measured electricity demand data captured in the work described in Chapter 3, the model generates data at a one-minute resolution. The model is designed in such a way that this resolution could be varied.

5.2.9 Open-source downloadable model

An open source downloadable implementation of the model in Microsoft Excel VBA is available from [8].

5.3 Construction of the model

5.3.1 Outline structure of the model

The outline structure of the model is presented in Fig. 37.

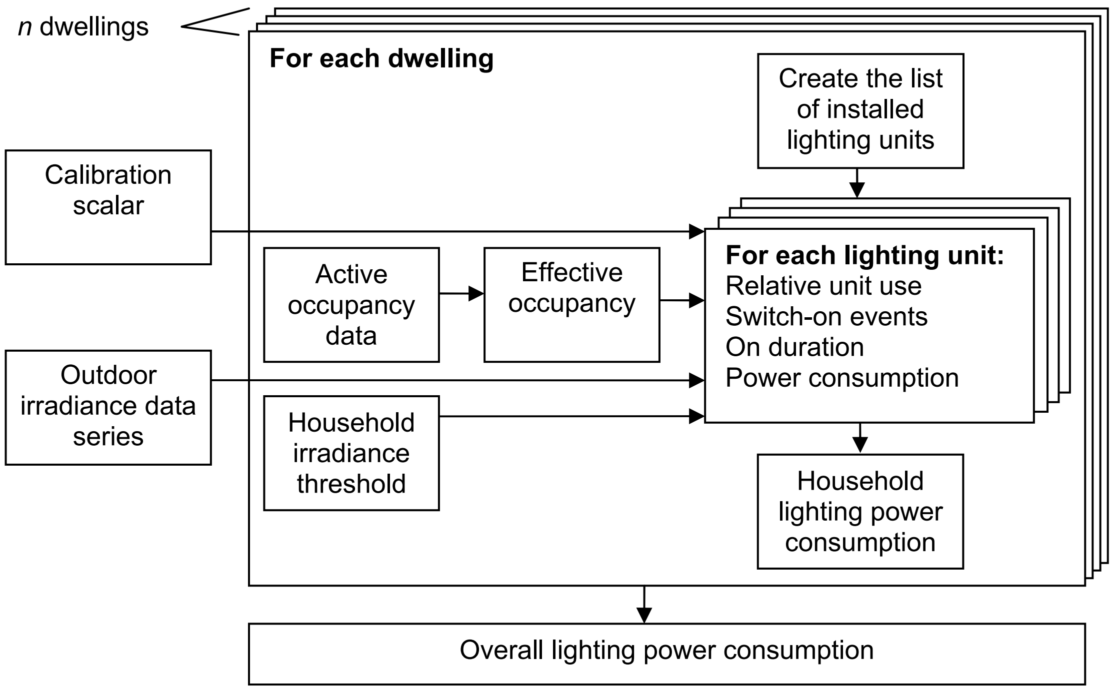


Fig. 37. Outline structure of the model

The outdoor irradiance data series has global scope, such that all dwellings in the simulation are subject to the same level of natural light.

A second global variable is the calibration scalar: this is used to calibrate the model, such that the overall mean electricity demand of the lighting over a large number of simulations, will meet a required level, such as that from national statistical data.

The main block of the diagram represents the inputs, outputs and processing performed for each dwelling in a simulation.

Each dwelling is assigned an active occupancy profile from the output of the model described in Chapter 4. The level of active occupancy is transformed into an ‘effective occupancy’ value, in order to take sharing into account.

Each dwelling is also assigned a set of lighting units: the number and power ratings of all lights are thereby determined.

Furthermore, each dwelling is assigned an irradiance threshold that defines the natural light level below which occupants will consider that lighting is required.

The inner block, shown in the figure, represents the processing that occurs for each lighting unit at each time step of a simulation. The combination of the effective occupancy, the irradiance level, the relative usage and the calibration scalar, is used to stochastically determine if a switch-on event occurs at each time step. When this does occur, the length of time that the unit remains on is determined stochastically, by picking a value at random from an appropriate distribution.

Finally, at each time step, the power demand of each lighting unit that is switched on, is summed at each time step to provide the overall demand.

5.3.2 Outdoor irradiance data series

The model assumes that the behaviour of an occupant in switching-on a light will be closely related to a threshold below which they consider that the current light level is insufficient. This light level is related to the outdoor global irradiance. The threshold level is represented by a normal distribution with a mean of 60 W/m^2 and a standard deviation of 10 W/m^2. This distribution is used to represent the variability in human response to different light levels between dwellings.

The model uses irradiance data from the CREST irradiance database [84]. To take into account delayed human response to a drop in irradiance (by nature of a cloud passing over), an exponential moving average filter is applied.

5.3.3 Creating the list of installed lighting units

The lighting technologies used within each dwelling are stochastically assigned from probability distributions derived from data from the Lighting Association [83]. The different types of technology that are represented, include incandescent general lighting service (GLS), compact fluorescent (CFL), fluorescent tubes and halogen. The stochastic assignment means that each simulated dwelling will have a different set of lights. An example of the assignment of numbers and types of bulbs to ten example dwellings is shown in Fig. 38.

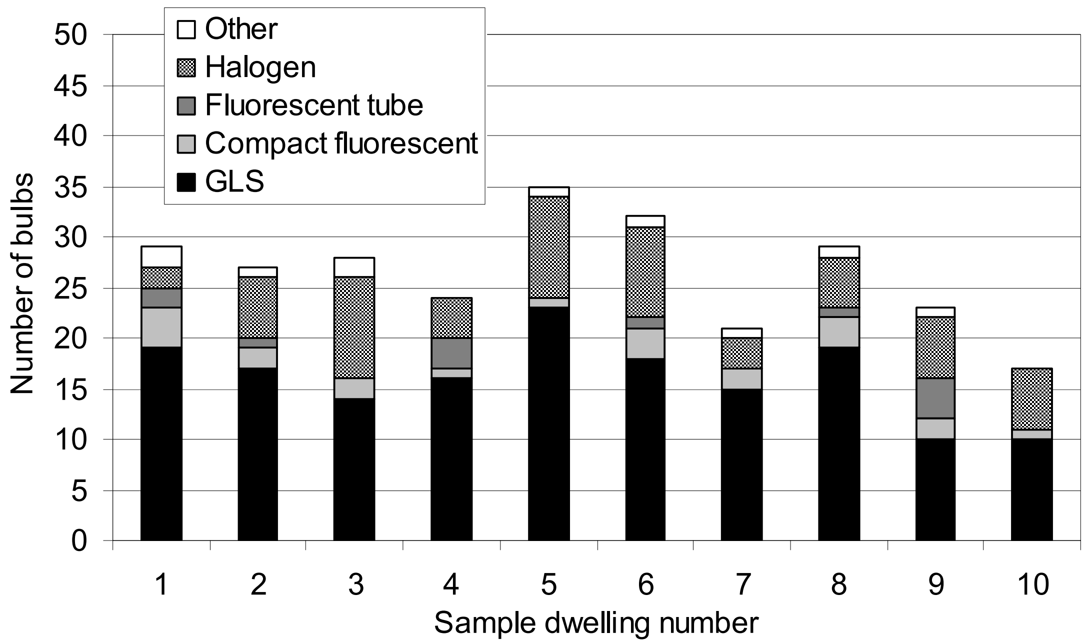


Fig. 38. Example allocation of lighting unit types in ten simulated dwellings

Within each technology category, there are bulbs with different power ratings. Each lighting unit is assigned a power rating based upon available statistics. For example, the UK Market Transformation Programme (MTP) [85] provides data on the usage of GLS bulbs of different power ratings (at levels of 100 W, 60 W and 40 W).

5.3.4 Switch-on events

In determining the likelihood of a switch-on event, and with reference to Fig. 39, there are four considerations that need to be taken into account:

- The current irradiance level is compared to the irradiance threshold for the dwelling. This is done to determine if the level of natural light is low enough such that the occupants may consider using lighting.
- The relative usage of lighting needs to be taken into account to differentiate between frequent or infrequent use.
- The effective occupancy is taken into account to determine the demand for lighting. If there is no active occupancy, then the effective occupancy is zero: in this case lighting will not be used.
- The calibration scalar is used so that the mean lighting demand over a large number of simulations will be at the required level.

$$\boxed{\text{Probability of switch-on at each time step}} = \boxed{\text{Light level condition test (0 or 1)}} \times \boxed{\text{Relative use weighting}} \times \boxed{\text{Effective occupancy}} \times \boxed{\text{Calibration scalar}}$$

Fig. 39. Calculation of the lighting unit switch-on probability

The details of each of these factors are outlined next.

5.3.4.1 Natural light condition test

The dwelling irradiance threshold is compared against the irradiance level at each time step. If the current irradiance is below the threshold, then the output of the test is one, otherwise 0. To take into account the use of lighting without regard to the natural light level (for example, in a home office used during the day), the model includes a five per cent chance that the irradiance level is ignored.

5.3.4.2 Relative usage of different lighting units

Some lighting units within a dwelling will be used more than others. Whilst this concept is discussed in the literature [86,87], no detailed statistics could be found, upon which to build a probability distribution to represent this concept. Instead, a negative natural logarithmic curve is used to represent the frequent use of a small number of bulbs, as is shown in Fig. 40. Commonly used bulbs would be those with a higher relative use weighting to the left of the curve, whilst infrequently used bulbs are represented to the right.

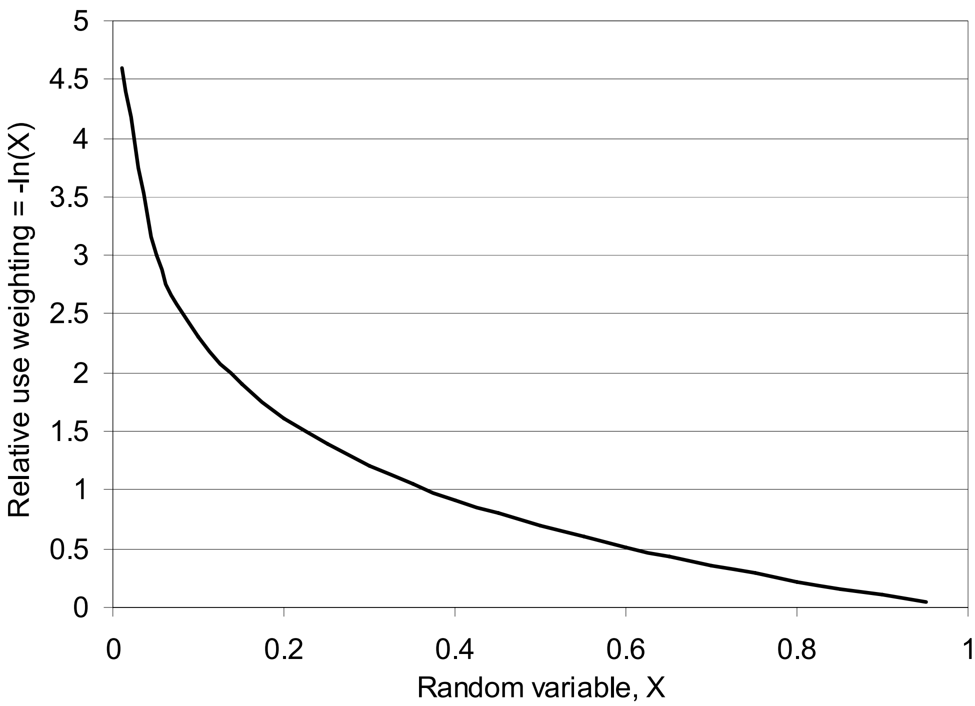
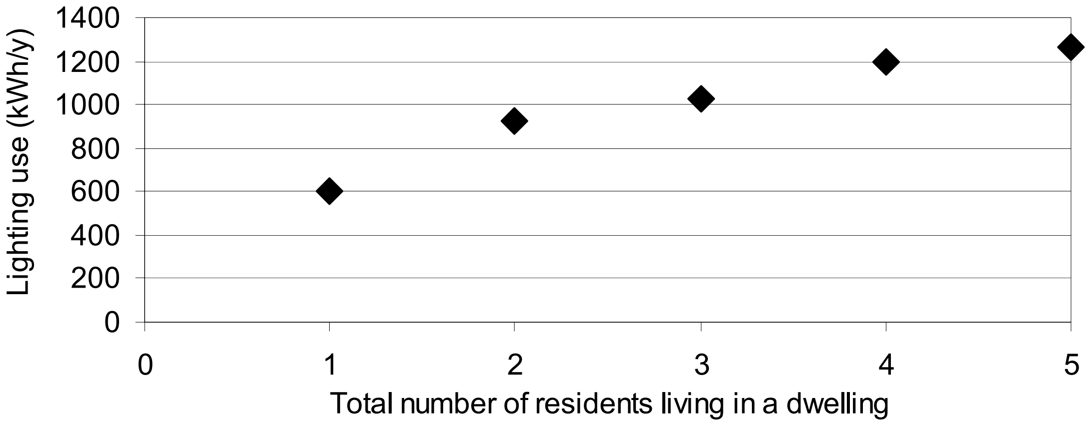


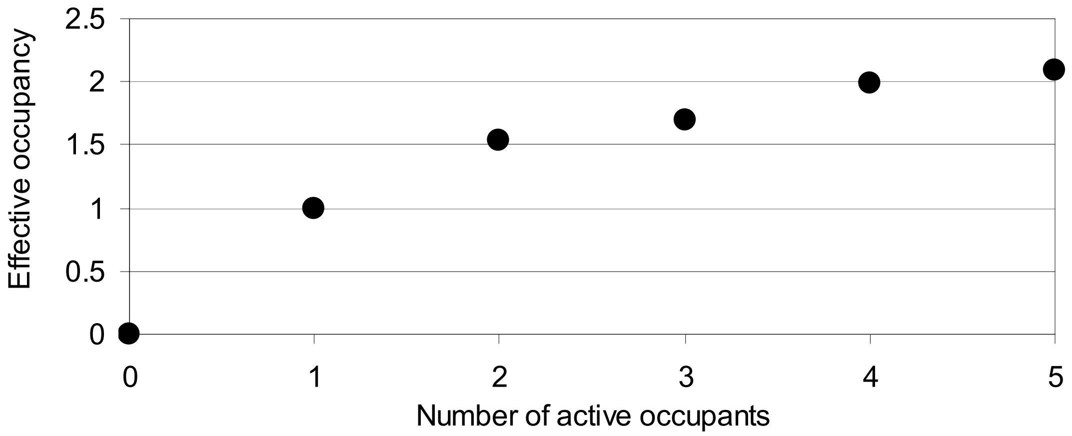
Fig. 40. Relative use weightings

5.3.4.3 Effective occupancy

Doubling the number of active occupants within a dwelling will not double the use of lighting: sharing or "co-use" [66] will occur. The value of effective occupancy takes this into account and is determined from the active occupancy, using the values shown in Fig. 41(b). This is derived from lighting use data from the US Energy Information Administration's Residential Energy Consumption Survey [88] shown in Fig. 41(a). As the number of residents living in a dwelling increases, so does the lighting demand, albeit, by a smaller amount each time. The assumption is made that this pattern also reflects the variation in use, as the number of active occupants varies. Fig. 41(b) is derived from Fig. 41(a) by scaling the data such that the effective occupancy of a dwelling with one active occupant is one.



(a) U.S. mean domestic lighting energy use



(b) Effective occupancy

Fig. 41. Mean annual U.S. lighting energy usage and effective occupancy

Source of (a) US EIA [88].

5.3.4.4 On duration model

The probability of lights being used for a particular length of time once switched-on is provided by Stokes et al. [60] based upon measured data. This distribution is shown in Fig. 42. At each switch-on event, a random lighting event duration is picked from this distribution, and assigned to the lighting unit. Note that if the active occupancy falls to zero, such as in the case when the occupants retire for the evening, then any switched-on bulbs will have their on-duration truncated. In doing this, the model assumes that the occupants turn off the lights before going out or going to sleep.

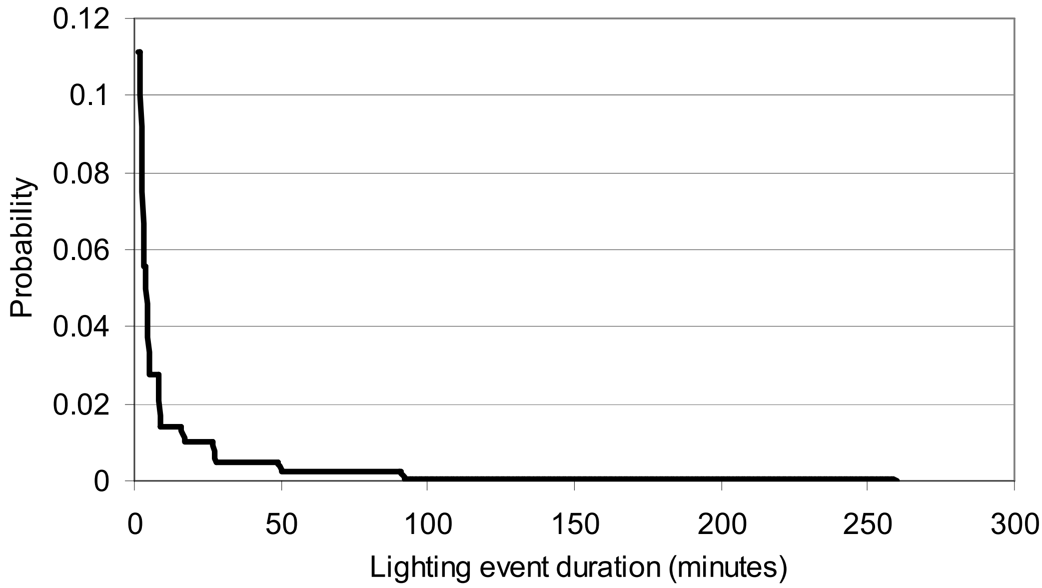


Fig. 42. On duration probability distribution from Stokes et al.

(Source: [60])

5.3.4.5 Calibration

Referring again back to Fig. 37, the calibration scalar is used in the switch-on calculation such that the model outputs a lighting demand of 715 kWh/y per dwelling. The calibration scalar value of 0.08154 is used to achieve this. This value was determined by running the simulation ten times, in each case representing 100 dwellings over one year, using a full year of irradiance data.

5.3.5 A review of the concepts

A review of the concepts is provided in Table 8.

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 [61] Reinhart [64] Hunt [65] CREST, Loughborough University [89]
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 [1] Yao and Steemers [61] Reinhart [64] Bladh and Krantz [66] Wright and Firth [68]
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 [83] Stokes et al. [60] Market Transformation Programme [85]
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 [88]
Relative unit usage. Some light units in a dwelling will be used more frequently than others.	Boardman et al. [86] Mills, Siminovitch [87]
Stochastic switch-on event model. The model requires a mechanism to determine if a switch-on event occurs.	Paatero and Lund [49]
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. [60]

Table 8 - A review of the concepts within the model of domestic lighting

5.4 Example simulation output

This section presents an example simulation output of the model.

5.4.1 Dwelling lighting unit allocation

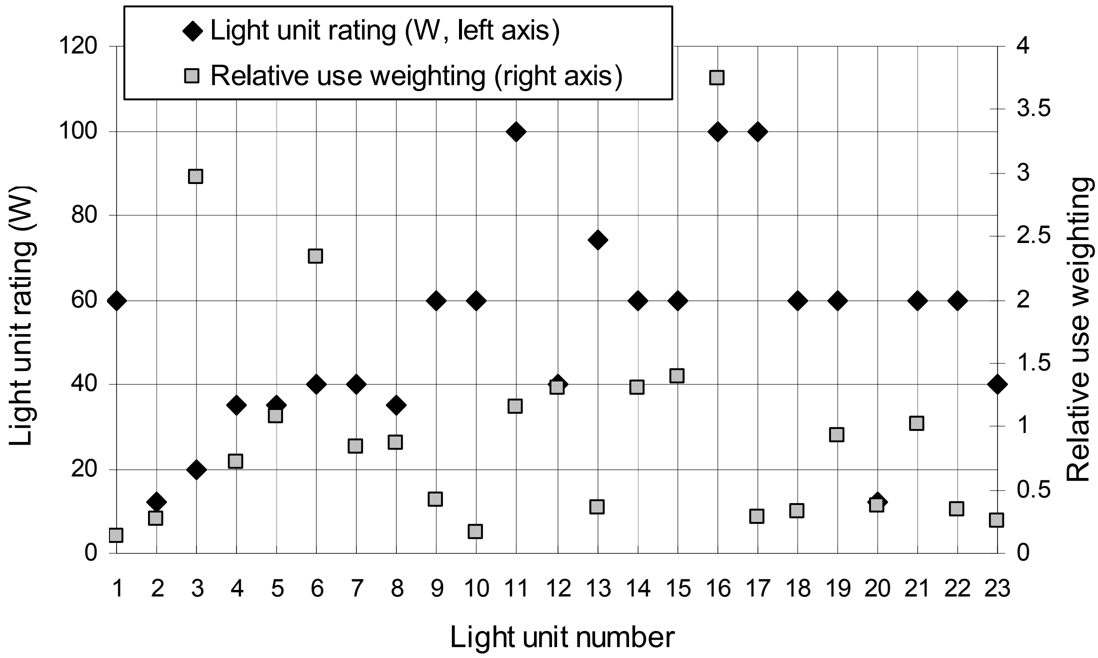
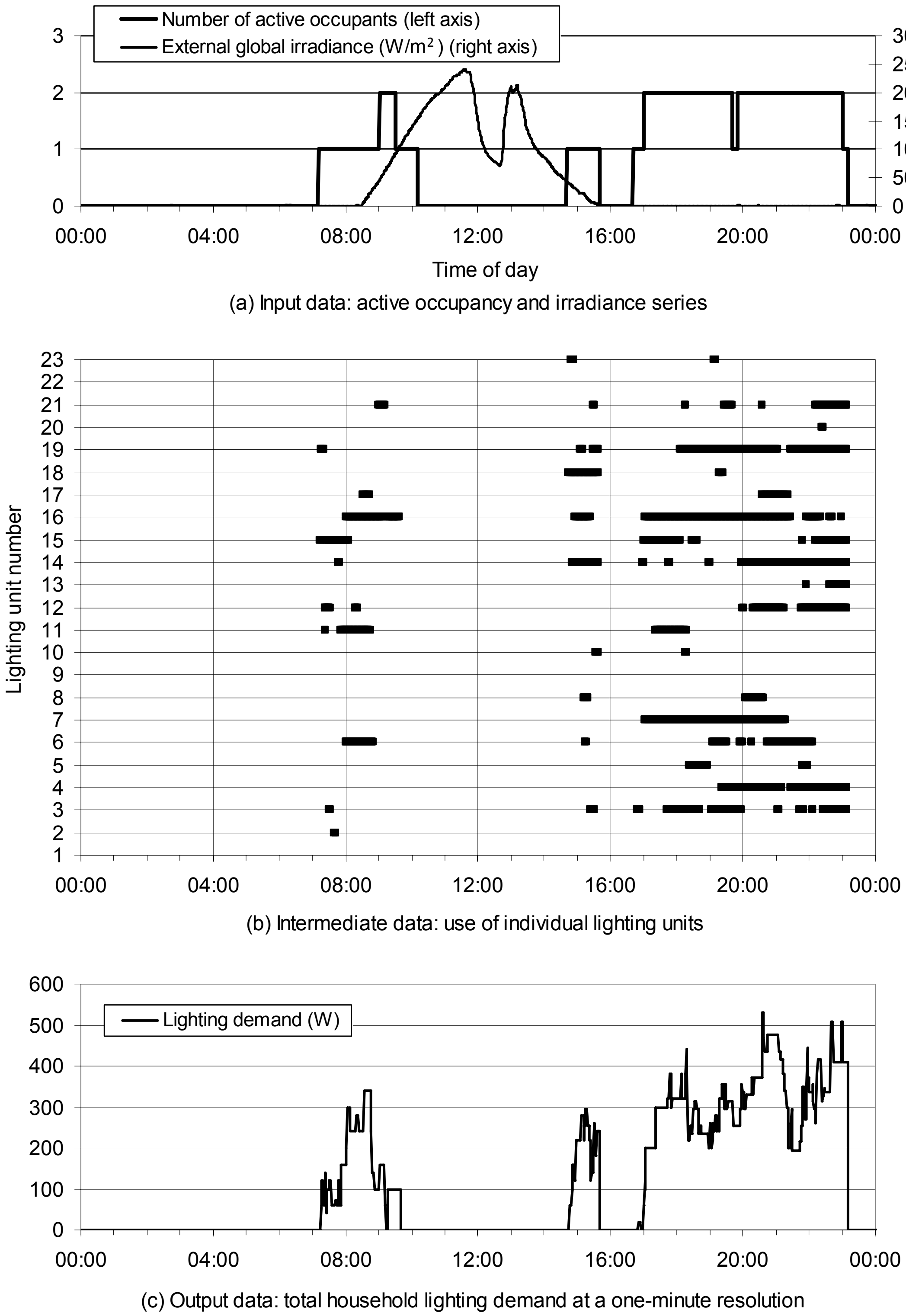


Fig. 43. Installed lighting unit configuration for an example dwelling

The stochastic lighting unit allocation for a single dwelling is shown in Fig. 43. This dwelling is seen to have 23 lighting units. The left axis shows the lighting unit rating and the right axis shows the assigned relative use weighing.

It can be seen that unit 16 has a power rating of 100 W and a high relative use weighting. Clearly, this bulb is used a lot and would likely be positioned in a living space area, such as a kitchen. In contrast, unit 17 has the same power rating, but has a low relative use weighting: it may be positioned in the loft, for example.

5.4.2 One-day simulation



(a) Input data: active occupancy and irradiance series

(b) Intermediate data: use of individual lighting units

(c) Output data: total household lighting demand at a one-minute resolution

Fig. 44. One-day lighting demand for a single dwelling

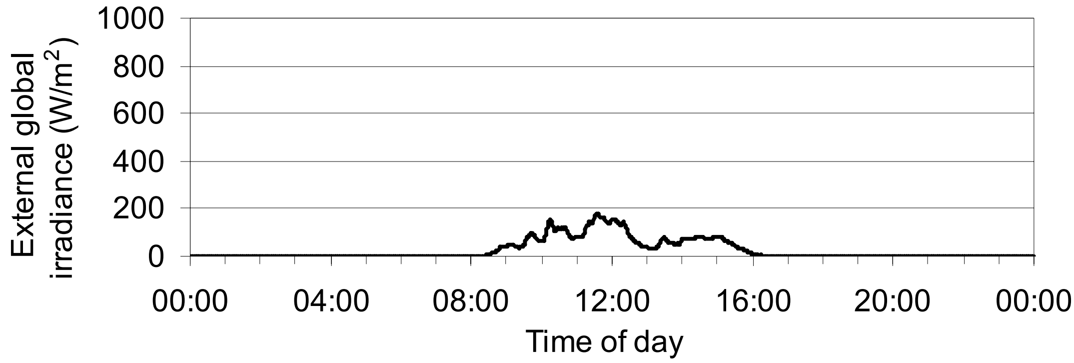
The simulation of a single day is shown in Fig. 44. The level of irradiance and the number of active occupants throughout the day are shown in Fig. 44(a), providing the input values to the simulation. The use of individual lighting units is shown in Fig. 44(b) and the aggregated lighting demand is shown in Fig. 44(c).

5.4.3 Multiple dwellings

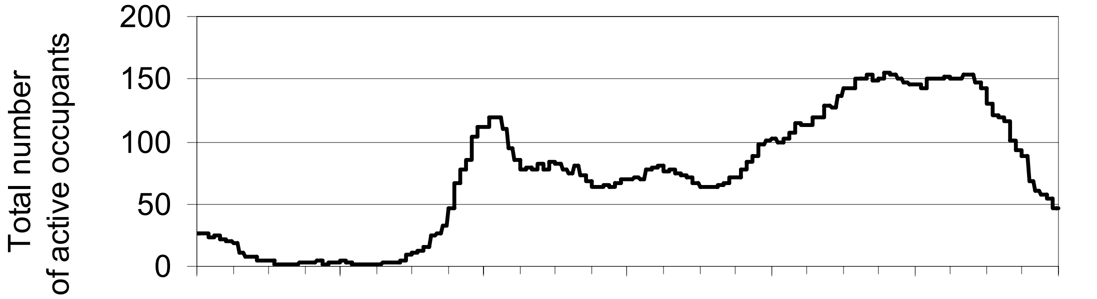
The model was used to generate the aggregate demand from 100 dwellings for both a winter day and a summer day and the simulation is presented in Fig. 45 and Fig. 46, respectively. In each case, the inputs in terms of the irradiance and active occupancy are shown together with the aggregate demand.

In the winter case, irradiance data for 2nd January, 2007 was used together with a weekday active occupancy profile. As the irradiance level increases in the morning, the lighting demand falls. The opposite occurs in the mid to late afternoon period and demand increases as the level of active occupancy increases in the evening. Around 13:00, the irradiance can be seen to drop significantly, likely as the result of heavy cloud cover. In response, the lighting demand can be seen to rise as the resulting switch-on of lighting is simulated in response.

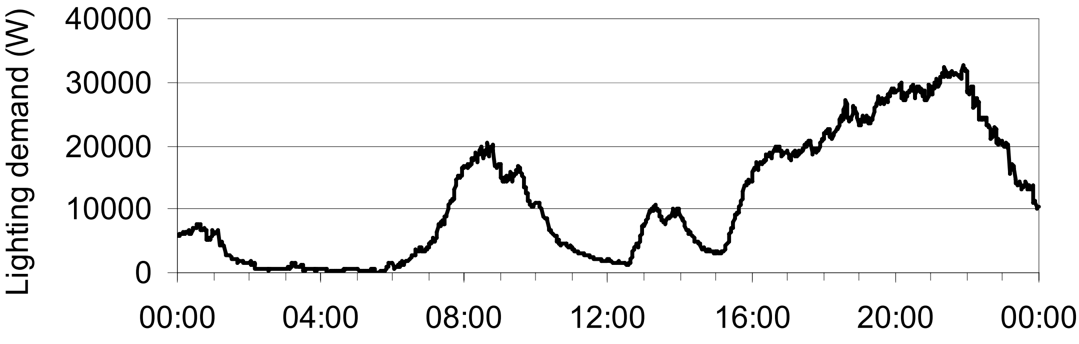
In the summer case, the level of irradiance during the day can be seen to be significantly higher. Apart from a small peak between 06:00 and 07:00, there is little demand for lighting in the morning, despite the increasing level of active occupancy. In the evening, little demand for lighting occurs until after 20:00 when the light level falls. The lighting demand ramps up quickly before reducing again, as occupants go to sleep.



(a) Irradiance level (one minute exponential moving average)

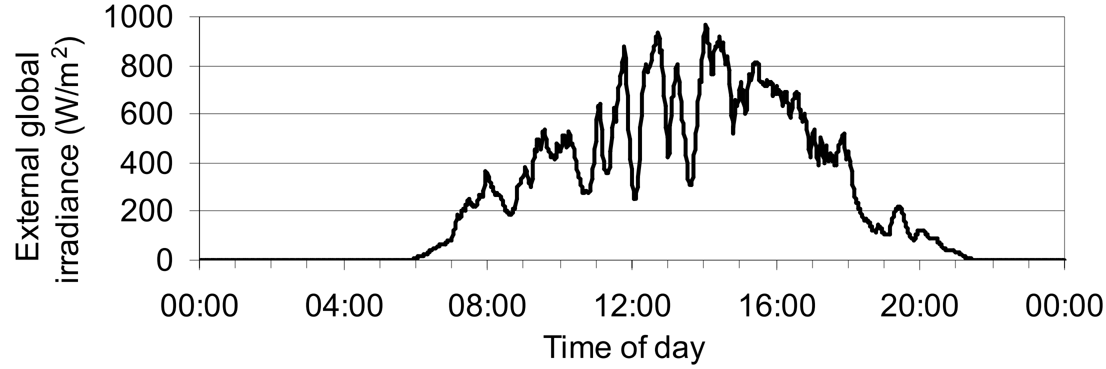


(b) Active occupancy in 100 dwellings

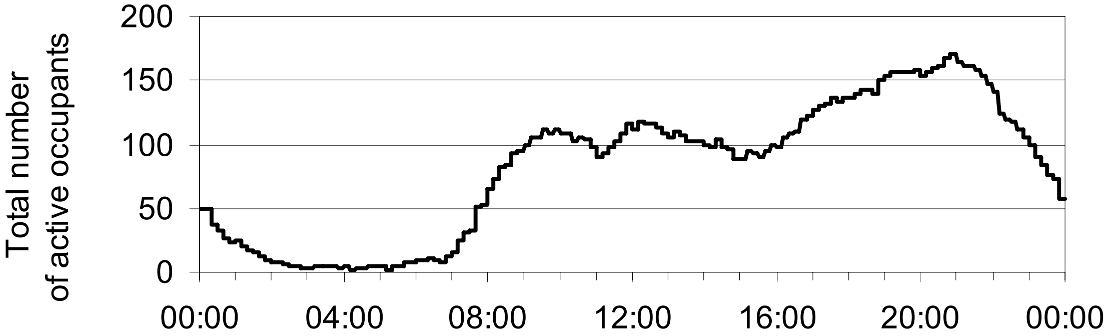


(c) Lighting demand for 100 dwellings

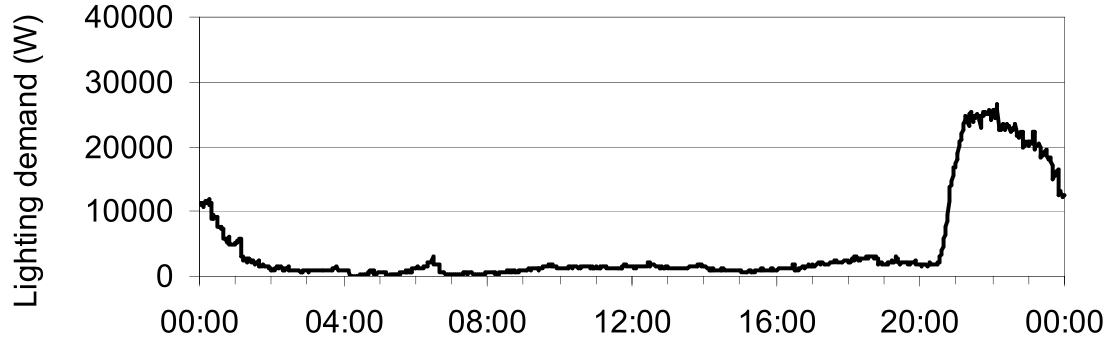
Fig. 45. Lighting load simulation output for 100 dwellings (winter day)



(a) Irradiance level (one minute exponential moving average)



(b) Active occupancy in 100 dwellings



(c) Lighting demand for 100 dwellings

Fig. 46. Lighting load simulation output for 100 dwellings (summer day)

5.4.4 Annual demand

The annual lighting demand for dwellings with different numbers of residents is shown in Fig. 47. The white columns show the required demand level, as scaled from the US EIA data [81] previously discussed, such that the overall demand across many dwellings will be 715 kWh/y. The grey columns show the output of the model in simulation of 100 dwellings. Since the model is stochastic, each time it is run it will output different results. However, the results are always close to the desired values. This can be seen in the error bars that show two standard deviations.

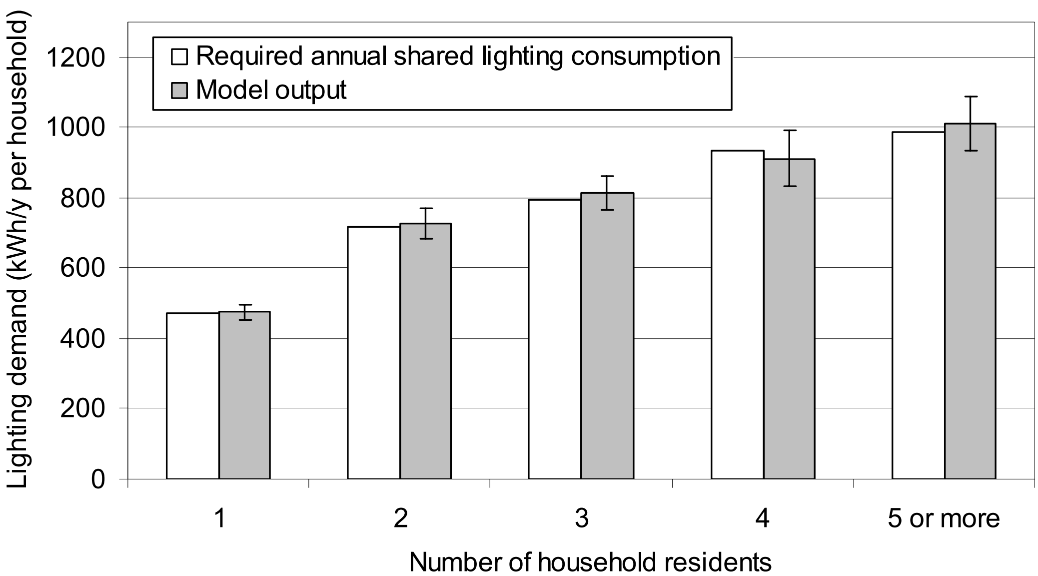


Fig. 47. Mean annual lighting demand per household by number of residents

5.5 Validation

In the full paper presented in Appendix B, the model is validated by comparing it indirectly against measured data using Stokes et al. [60], which is based upon half-hourly demand data from 100 dwellings. The seasonal variation is found to be very similar (as is seen in Fig. 48) in a comparison of monthly demand, as is the variation in demand throughout the day. For further detail, refer to the full published paper that is presented in the appendix.

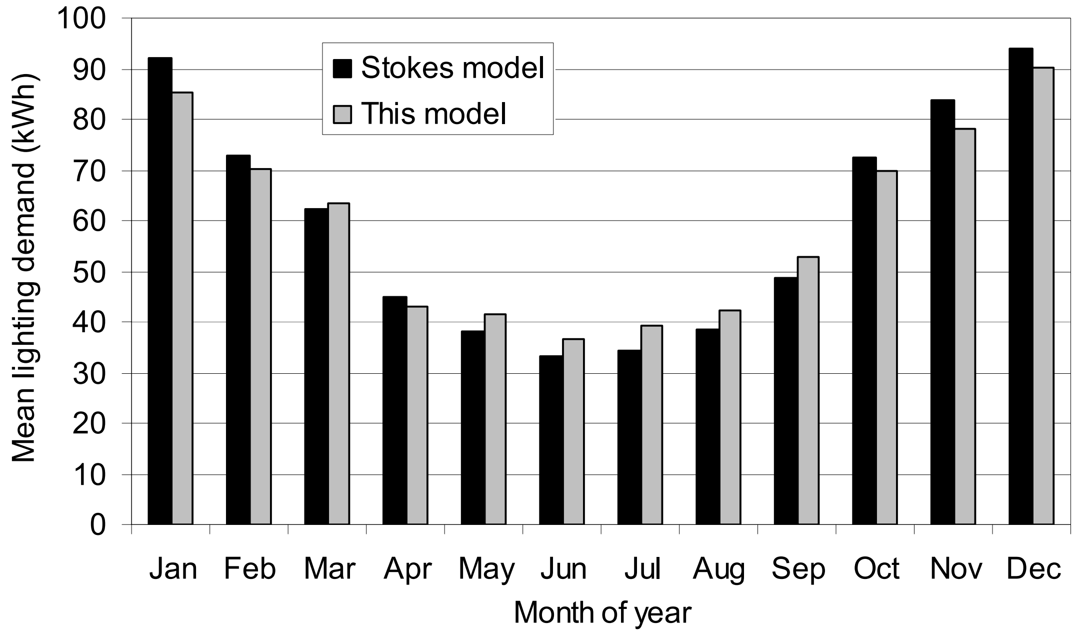


Fig. 48. Seasonal variation of lighting demand

5.6 Next steps

Having constructed and validated a model of domestic lighting, the next step is to extend this to include the representation of all major categories of domestic appliances, such that the electricity demand of the whole-dwelling can be represented. This is discussed in the next chapter.

6. DOMESTIC ELECTRICITY USE: A HIGH-RESOLUTION ENERGY DEMAND MODEL

6.1 Introduction

This chapter presents a high-resolution model of whole-dwelling electricity demand. Using the occupancy model presented in Chapter 4, and building upon the model of domestic lighting demand presented in the previous chapter, the model simulates the use of all major categories of household appliances.

A paper describing the model is published in the October, 2010, issue of Energy and Buildings. A copy of this paper is available in Appendix C. This chapter provides a summary of the construction of the model, together with a discussion of the model output and its validation.

6.2 Model concepts

6.2.1 Appliances

The basic building block in the model is an appliance: this refers to any individual load that is used within a dwelling. Examples are a kettle, iron, television or a washing machine. Each appliance is represented in the model as having particular power demand characteristics when in use. These may be either a steady-state electricity consumption (such as for a kettle) or typical use cycles (such as in the case of a washing machine).

6.2.2 Use of active occupancy

As with the lighting model developed previously, active occupancy is again used as a main input. In this whole-dwelling model, active occupancy enables the generation of realistic aggregate daily demand profiles, as well as, providing a mechanism to model time-correlated use both within and between dwellings.

6.2.3 Occupant activity and appliance use

In addition to the level of active occupancy within dwellings, a second concept is required in order to represent the use of different types of appliance at different times of the day, depending upon what activities the occupants are likely to be engaged in. For example, people will commonly use cooking appliances, such as ovens and hobs, around the meal times of the day, whilst television usage mainly occurs in the evening. This concept is represented using “activity profiles” which, like the active occupancy data, are also derived from the TUS data set.

The activity profiles are linked to the use of individual appliances. As an example, the activity of watching television will require a television appliance to be in use. Similarly, a laundry activity may well require a washing machine to be used. By assigning an activity profile to each appliance, the likelihood of that appliance being used at different times of the day may be represented.

6.2.4 Sharing of appliances

As with the sharing of lighting described in the previous chapter, it is important to represent the sharing of appliance use, when there is more than one active occupant within a dwelling. For example, the electricity demand of a cooking appliance will not double just because a second occupant arrives home. The simulated likelihood of appliances being used increases non-linearly as the number of active occupants increases above one.

6.2.5 Correlated use of appliances

The correlated use of appliances is an important concept in realistically representing the time coincident demands within a dwelling. For example, on a winter evening, it is likely that both lighting and the television will be in use in a dwelling that is actively occupied. Using active occupancy as an input to the model enables the appropriate representation of these correlations.

6.2.6 Temporal resolution

In common with the model of domestic lighting demand, the model generates time stepped data at a one-minute resolution.

6.2.7 Reactive power consumption

In looking forward to the use of the model in network load-flow studies (discussed in the next chapter), it is appropriate that the model represents reactive power demand. By assigning a power factor to each individual appliance, the model is able to represent reactive power demand.

6.2.8 Validation of the model with measured data

It is important to re-cap that the measured data presented in Chapter 3 of this thesis is used solely to validate the whole-dwelling demand model presented here. The model is constructed completely independently from this data.

6.3 Structure of the model

The structure of the whole-dwelling electricity demand model is presented in Fig. 49 and introduced below:

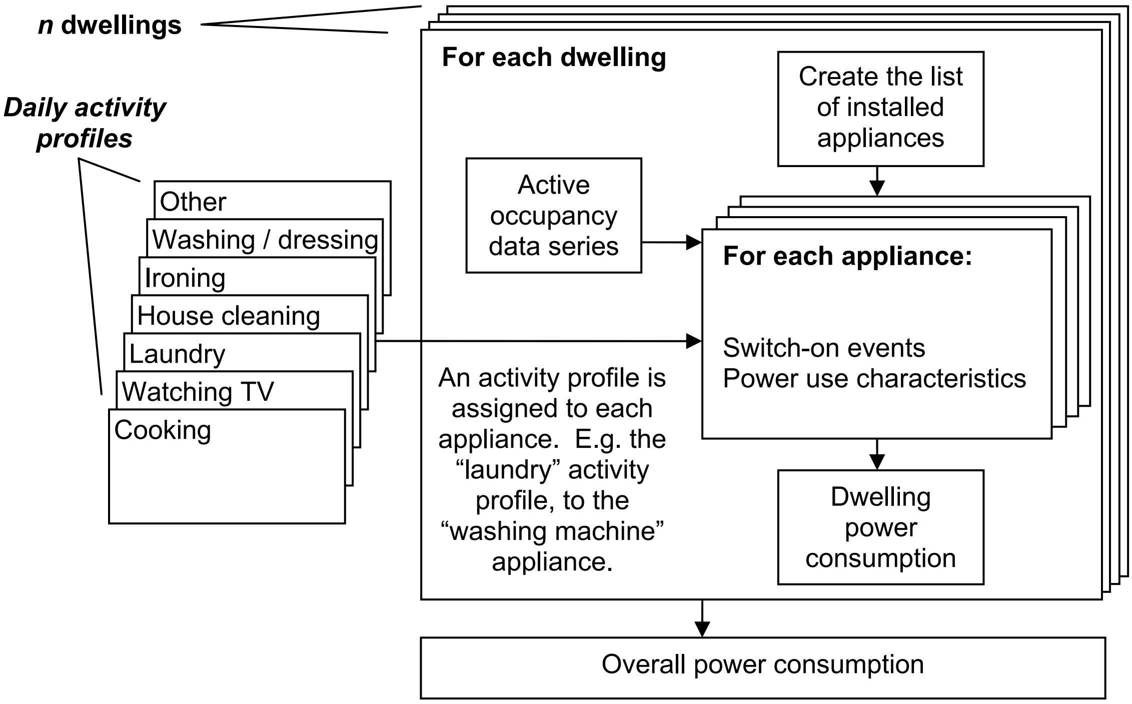


Fig. 49. Whole-dwelling electricity demand model architecture

To the left of the figure, a set of daily activity profiles can be seen. These represent the probability of people performing particular activities, such as cooking or watching television, at different times of the day. The profiles are static and apply to all dwellings.

The main outer square block of the diagram represents one or more dwellings. Each dwelling is assigned its own active occupancy series, as well as, a set of the main domestic appliances that are available for use within it, represented by the inner square block.

Each appliance is also assigned a mapping to one of the daily activity profiles.

At each time-step of the simulation, a stochastic approach is taken to determining whether an appliance is switched-on. If so, the power use characteristics are used to determine the appliance's electricity demand. Adding the demands of every appliance together at each time step gives the whole-dwelling demand.

6.3.1 Daily activity profiles

The activity profiles shown to the left of Fig. 49 include variants that take into account the current number of active occupants within the dwelling (one to five), as well as, whether the current day is a week day (Monday to Friday) or a weekend day (Saturday or Sunday).

In Fig. 50, two weekday activity profiles are shown that represent a cooking activity. The two profiles represent a different number of active occupants: one or two. They represent the proportion of dwellings in which at least one active occupant is engaged in a cooking activity at different times of the day. The probability of one active occupant performing a cooking activity at 17:30 is 0.26. However, if there is a second active occupant in the dwelling, the probability that either one of them is cooking is 0.37.

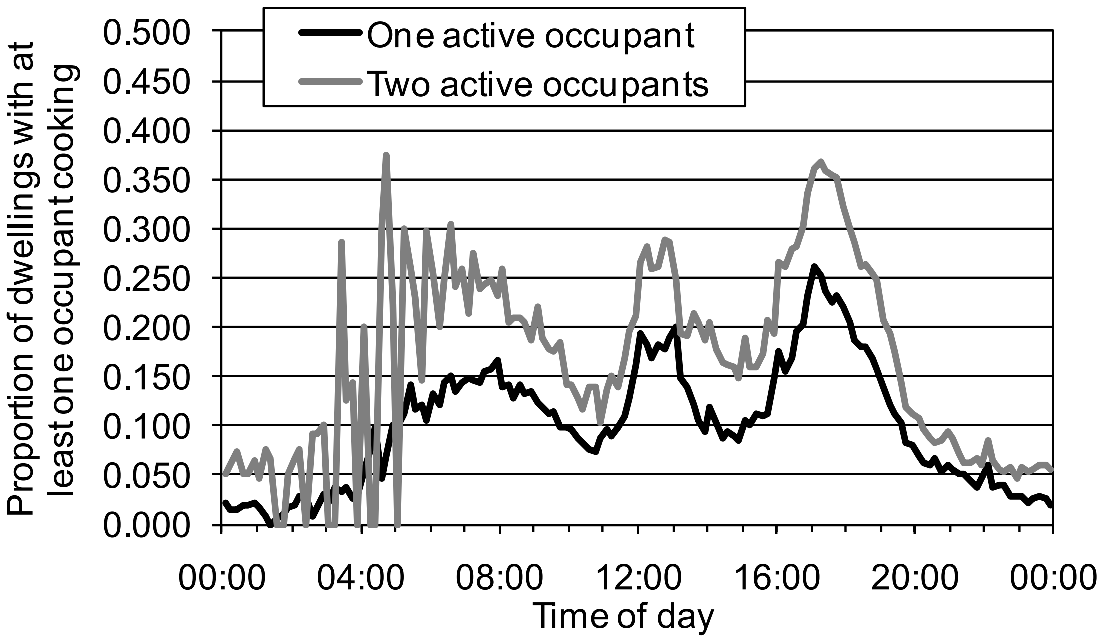


Fig. 50. Activity profiles for 'cooking', for one or two active occupants on a week day

As might be expected, the peaks in the profiles in the figure occur around meal times: lunch time and dinner time are clearly visible. However, it is important to note that cooking may occur at any time of the day. During the night time period from 00:00 to 08:00, the profile for two active occupants can be seen to be volatile. This occurs because of the scarcity of cases of two occupants being active at night in the TUS data set.

The first step in constructing the daily activity profiles from the TUS data, is to identify the numeric codes that are used within the survey diaries, to detail what activities are being performed. For example, cooking activities are represented by the codes in the range 3100 to 3190. The activity for “unspecified food management” is represented by the code 3100 and “food preparation” is represented by code 3110. The definition of all the codes is provided in the TUS documentation [63].

The TUS diaries are grouped by the number of active occupants within a dwelling at each ten-minute period of the day, and then further sub-divided into weekday and weekend groups. At each time period of the day, the number of dwellings in which a particular activity is taking place is counted so that a proportion can be determined. For example, on a weekday between 08:00 and 08:10, the number of dwellings represented in the TUS data set where there is one active occupant is 2082. The number of dwellings where cooking is taking place is 288. The proportion is therefore 288 divided by 2082, equal to 0.138, as can be seen in Fig. 50.

The full set of profile data is available in the downloadable example, available from [9].

6.3.2 Installed appliances

Before each simulation, the model allocates a set of installed appliances to each dwelling. A stochastic approach is taken using statistics on appliance ownership from UK Department of Energy and Climate Change (DECC) [90], the UK Market Transformation Programme [91], the Lower Carbon Futures and 40% House reports from the ECI, Oxford University, UK [92,93] and the UK's Ofcom [94].

The model is configured to include up to 33 of the major appliances typically used within dwellings. To take account of the multiple ownership of appliances, such as televisions, the model explicitly lists each appliance. For example, a dwelling may have zero, one, two or three televisions. A list of many of the appliances is shown later in Fig. 52. A full list of all the appliances, together with the statistical values used to represent the level of ownership is presented in the downloadable example [9].

6.3.3 Appliance annual energy use

Each appliance is allocated an average demand value in kWh/year, based upon the statistical sources used in section 6.3.2, in addition to data from the Energy Saving Trust [95]. The values are adjusted to represent an overall mean annual electricity demand of 4358 kWh, typical of dwellings in the East Midlands region [96]. The full list of values is provided in the downloadable example [9].

6.3.4 Appliance power characteristics

During a time-stepped simulation, appliances may be either on or off. The off state includes the representation of standby demand, where an appliance may consume electricity even when switched-off.

Appliances may be configured to have a constant power demand when in use, or a time-varying demand. The latter case is necessary to represent the demands of appliances such as washing machines, where demand varies over a wash cycle during water heating, washing, rinsing and spinning. Whilst this would be less important for an hourly resolution model, at a one-minute resolution, the demand of such appliances varies considerably over time. In this case, the modelled demand profile of this appliance is based upon measured data [97].

A power factor is assigned to each appliance representing the mean value over a one-minute period. Resistive heating appliances, such as a kettle or iron are assigned a unity factor. Electronic entertainment appliances are configured with a power factor of 0.9 lagging. Cooling and washing appliances are configured to use a power factor of 0.8. A plug-in power meter was used to measure a number of power factors from actual appliances.

6.3.5 Appliance-activity mapping

Appliances that are used when occupants are engaged in particular activities are mapped to the appropriate activity profile. More than one appliance may be mapped to an activity profile. In the case of cooking, for example, the electric hob, oven, microwave and dish-washer are all assigned to the cooking activity profile. This mapping relationship only models a likelihood of use of each appliance: just because cooking is taking place, it does not mean that all these appliances are used. In a stochastic simulation run, none may be used, or one or more of the appliances may be used together.

Some appliances are not associated with a particular activity. The “other” category that is seen in Fig. 49 is applied in the following three cases:

- For some appliances, the TUS data does not include sufficient data to determine when a relevant activity is being performed. The use of a telephone is one example. In this scenario, the use of the appliance is based only on the presence of active occupants within a dwelling.
- The power demand of some appliances does not primarily depend on active occupancy at all. The cycling of fridges and freezers is an example.
- Electric space heating does not fit well into the activity profile model because these profiles do not include seasonal effects. Storage heater appliances, in particular, usually have an overnight use profile controlled by the times of Economy-7 electricity. Storage heaters are represented in the model by using a monthly temperature variation instead of an activity profile.

6.3.6 Switch-on events

The process to determine if an appliance is switched-on is shown in Fig. 51.

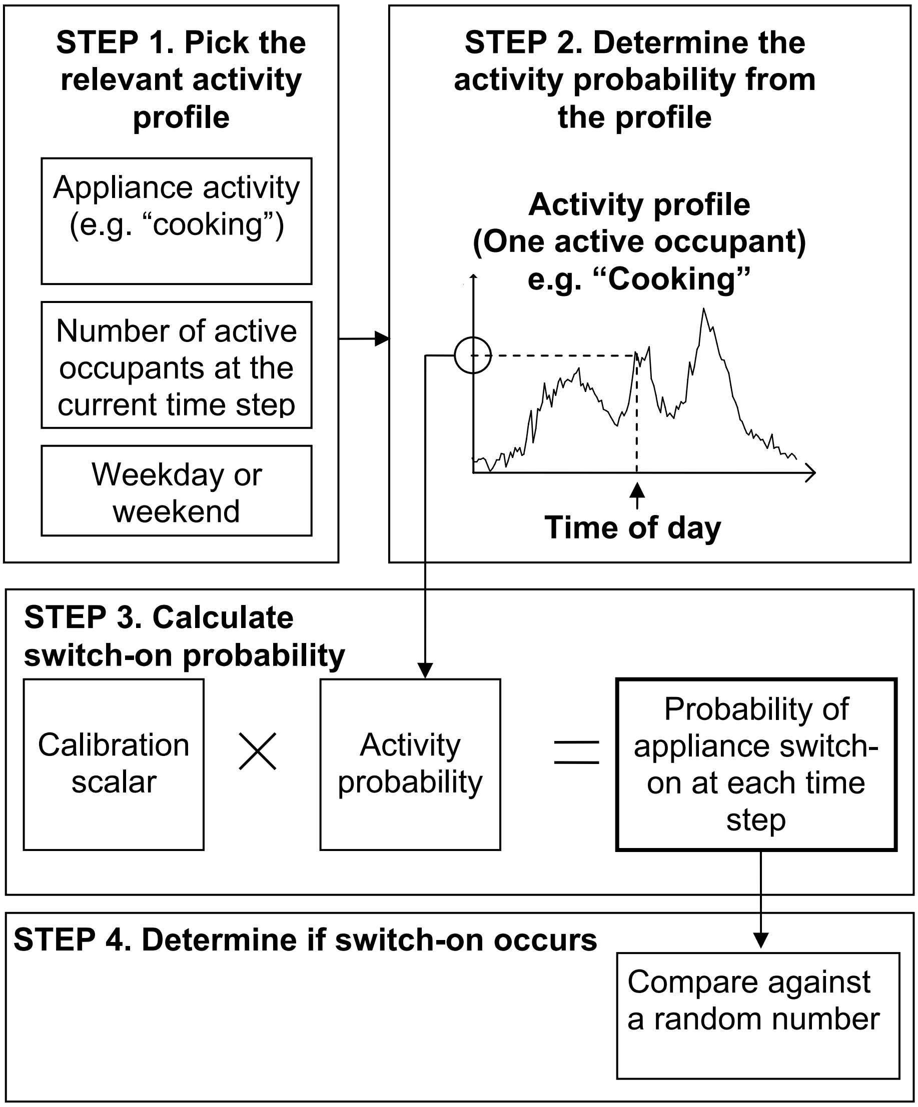


Fig. 51. Switch-on events

With reference to the Fig. 51, there are four steps:

- In step 1, the daily activity profile that has been mapped to the appliance is selected using the current number of active occupants and the current day of the week.
- In step 2, the probability that any of the active occupants are engaged in the activity is read from the activity profile.
- In step 3, the activity probability is multiplied by the calibration scalar for this appliance. The purpose of the calibration scalar is outlined in the following section.
- Finally in step 4, the result of the previous step is compared to a random number between 0 and 1. If the probability is more than the random number, then a switch-on event is said to occur.

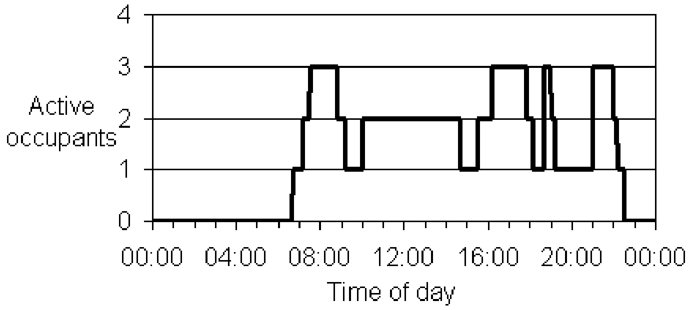
6.3.7 Appliance calibration scalars

The model is calibrated such that on a large number of runs, the mean annual demand will match the required level.

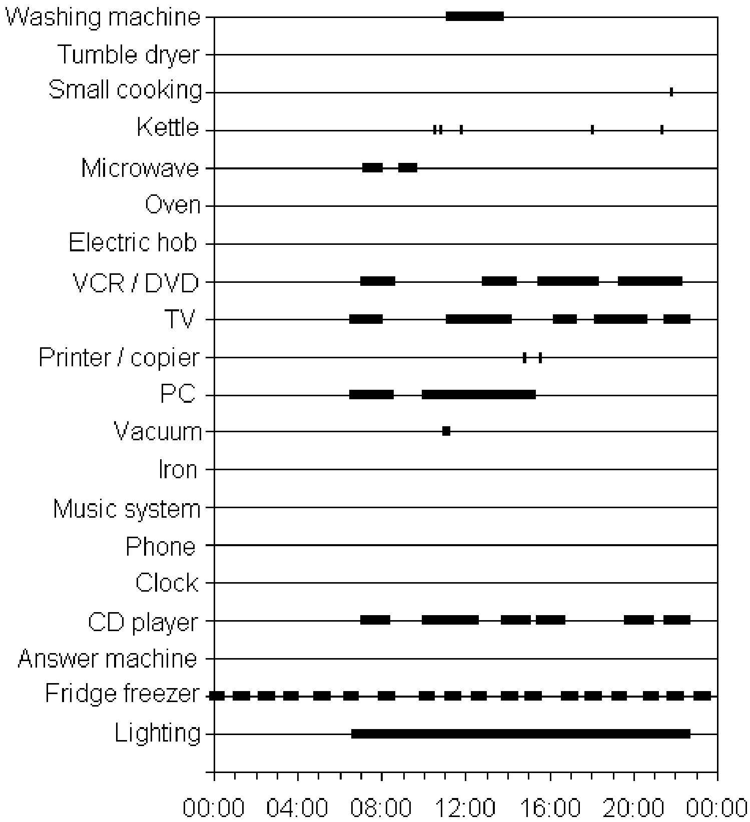
This is achieved by sub-dividing the overall level of domestic annual mean demand, into end-use demand by appliance, and ensuring that each appliance is used a particular number of times per year to meet its contribution level to the overall annual total. For example, in the model, a washing machine is allocated a mean annual electricity demand of 183 kWh, where installed, excluding standby demand. If the washing machine consumes 0.933 kWh each time it is used, then in order for it to consume 183 kWh over the course of a year, it must be used on 196 occasions.

Each appliance is allocated a “calibration scalar” which is used to calibrate the switch-on probability, such that the during a simulation run, the mean number of times that the appliance is used can be statistically predicted, and therefore the appropriate demand level for each appliance can be reached.

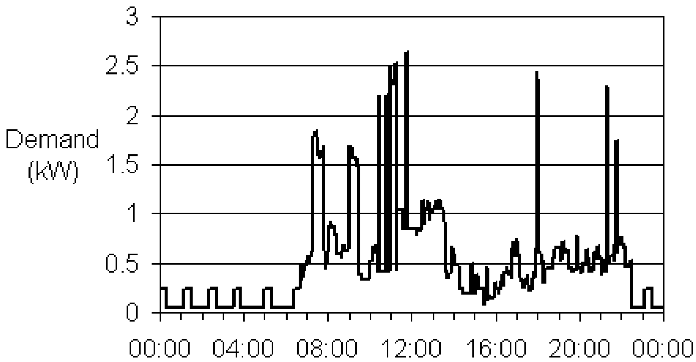
6.4 Example simulation



(a) Dwelling active occupancy profile



(b) Simulate output; disaggregated by appliance



(c) Simulation output; aggregated total

Fig. 52. Example simulation output (one dwelling, winter day)

An example of the simulation of a single dwelling on a winter day is shown in Fig. 52. The active occupancy profile for the dwelling is shown in Fig. 52(a). In this simulation, the dwelling has been allocated as having four total residents, but in this run, only three occupants are active at any one time. The profile is typical in that there is no active occupancy at night and the level varies throughout the day.

The list of appliances that has been allocated to the dwelling, before the simulation starts, can be seen in Fig. 52(b). The simulated use of these appliances throughout the day is represented by the horizontal black markers. Appliances such as the TV and PC are used for relatively longer periods during the day, whereas the microwave and kettle can be seen to be used for much shorter periods. The washing machine, shown at the top of Fig. 52(b), is used on one occasion in the middle of the day. Note that the time of use of most of the appliances coincides with the times of active occupancy in Fig. 52(a). The fridge freezer appliance, however, is seen to cycle at intervals throughout the whole day regardless of active occupancy.

The use of lighting is shown as a simplified single bar in Fig. 52(b), although the underlying lighting model (described in Chapter 5) does model the use of each individual lighting unit in the dwelling. As a winter day, lighting can be seen to be used throughout the period of active occupancy.

The aggregate demand for the whole-dwelling is shown in Fig. 52(c). The spikes can be seen to coincide with the use of higher power demand appliances, such as the microwave, the washing machine and the kettle.

6.5 Validation of the model

In the published paper that described the model of domestic electricity use (as presented in Appendix C), the validation of the model is fully presented. The validation is formed of a comprehensive quantitative comparison between the output of the model and the measured data that was discussed earlier in Chapter 3.

This section provides only a brief summary of the model validation that took place together with a short summary of the key findings: these are presented in Table 9.

Comparison Measure	Key Findings
Mean annual electricity demand	The model is appropriately calibrated. It outputs data with a mean annual demand of 4124 kWh, against 4172 kWh for the measured data.
Variation of annual demand between dwellings	The model outputs data with an appropriate demand variation between dwellings, although a slight under-representation of the standard deviation is seen in the synthetic data. It is considered likely that the occupancy model is slightly over-estimating the amount of time that dwellings are actively occupied.
Mean daily demand by month	The synthetic data shows an appropriate shape where demand is greater in the winter than the summer. The level of variation is underestimated. The occupancy model is not seasonal and the only seasonal effect represented in the output is the increased use of lighting in the winter.

Comparison Measure	Key Findings
Daily demand profile	The mean daily demand profile follows the expected pattern; however, there are a number of discrepancies. Demand during the night is lower in the synthetic data, although the overnight use of appliances and lighting is not taken into account. The measured data was from dwellings where at least one resident was in employment, which may account for discrepancies in the times of morning and evening peaks.
Minute to minute demand volatility	The synthetic and measured demand volatility is shown to be similar, but the model appears to under-represent the switching on and off of small appliances. This would be expected as the model does not represent every small appliance type used in domestic dwellings.
Time-coincident demand between different dwellings	The model realistically represents the time-coincident demand between dwellings, which is confirmation that the occupancy model is an effective basis for doing this.
After diversity maximum demand	The model outputs data with an ADMD of approximately 2 kW, which is close to typical UK standards discussed in the introduction.
Load duration curves	The load duration curves derived from the measured and synthetic data are very similar. The model is seen to be underestimating night time demand as can be seen in a slight distortion of the load duration curve for the synthetic data.
Power factor	The power factor of aggregate loads is realistically represented by the model.

Table 9 - Summary of model validation measures and findings

6.6 Summary

This chapter presented the construction of a domestic electricity demand model and summarised its validation. The model uses occupant time-use data as an input using the occupancy model presented earlier in Chapter 4. Occupant activity is mapped to appliance use, in a stochastic simulation, and the model outputs synthetic demand data at a one-minute time resolution.

Many of the concepts described in the model of domestic lighting, presented in Chapter 5, were built upon in the construction of this model. The model used individual appliance power consumption and ownership data from nationally based statistics. The measured data, discussed in Chapter 3, was used only for the validation of the model.

A comprehensive quantitative comparison took place, as is fully described in the published paper in Energy and Buildings as presented in Appendix C. The model is shown to output very realistic data: a particular strength of the model, is that is does realistically represent the time-coincidence of demand between dwellings, which was the objective of using the domestic occupancy model as its basis. This is of great importance in the modelling of domestic low voltage electricity networks, introduced in the next chapter.

7. MODELLING OF LOW VOLTAGE NETWORKS

7.1 Introduction

Referring again to Fig. 7 in the introduction of this thesis, the next step is to use the model of domestic electricity demand within a simulation of a low voltage distribution network, serving a residential area.

This chapter is concerned with determining the requirements for such a simulation, and begins with a brief overview of how electricity distribution networks are typically organised in the UK. The conventional industrial approach to low voltage network design is discussed, and the tools that are available to help network designers are introduced. The existing academic literature on low voltage network modelling is considered, and the chapter concludes with a resulting list of requirements for the construction of a new model.

Whilst distribution networks may comprise of both underground cabling and overhead lines (particularly in rural areas), the term “cable” is used throughout to cover both cases.

7.2 Terminology

The electricity distribution system consists of a number of layers that operate at difference voltages: this is illustrated in Fig. 53 and is discussed in the following sections.

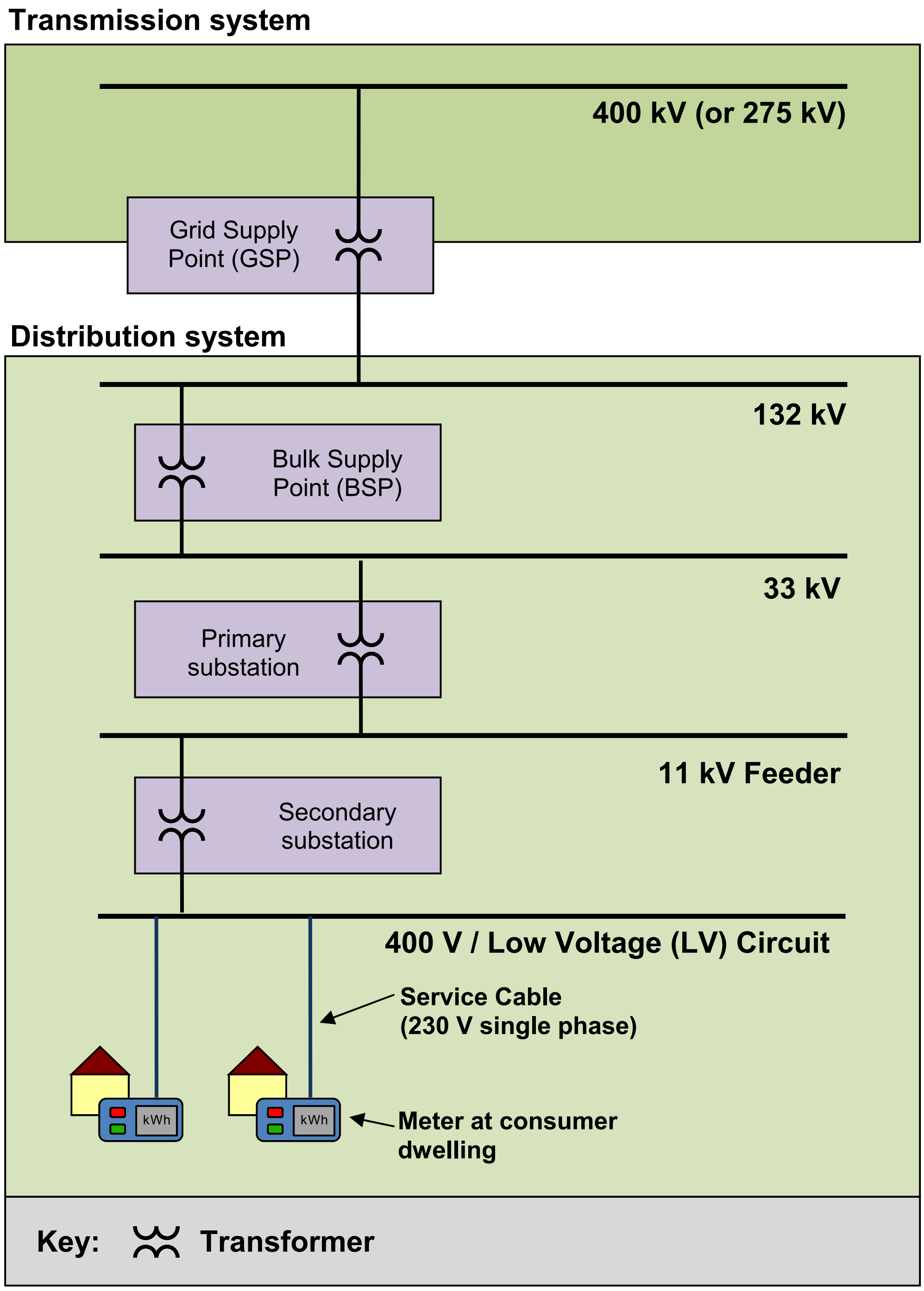


Fig. 53. UK Power system voltage layers (domestic context)

With reference to Fig. 53, the highest voltage level, at 400 or 275 kV, is seen on the transmission system. This network is managed by the Transmission System Operator (TSO) and feeds Grid Supply Points (GSP). At each GSP, transformers step the voltage down to 132 kV, feeding into the top level of the distribution system at a regional level.

The 132 kV network feeds Bulk Supply Points (BSP) where the voltage is again stepped down, typically to 33 kV (although other configurations do occur).

The 33 kV circuits serve a set of **Primary Substations**. As an example, four primary substations serve Loughborough and the surrounding towns: this includes approximately 35 000 domestic dwellings. One of these primary substations is shown in Fig. 54. At the primary substation, the voltage is usually stepped down to 11 kV, where it is distributed to a number of radial circuits called **Feeders** (also known as 11 kV secondary circuits).

Fig. 54. 33 /11 kV Primary Substation, East Midlands, UK

The 11 kV feeders distribute electricity to **Secondary Substations** by means of underground cable, or overhead lines mounted on poles. The number of secondary substations served by a feeder varies considerably: 17 is an average in the Loughborough area. As an example, the overhead lines of an 11 kV feeder can be seen to feed a secondary substation in Fig. 55.

Fig. 55. 11 kV /400 V Secondary substation, East Midlands, UK

In this figure, the secondary substation can be seen to consist of a **Transformer** (lower left in the figure), a set of **Switch Gear** (behind the transformer) and a **Distribution Board** (lower right). Whilst the switch gear controls the connection to the 11 kV feeder, the transformer steps the voltage down to a nominal level of 400 V. This is known as the **Low Voltage** (or **LV**) part of the distribution system. This particular example substation, serves a residential area of approximately 160 dwellings, although such substations may also serve non-domestic consumers.

Many urban secondary substations, particularly more modern ones, are internally mounted inside an enclosure. An example of this configuration is shown in Fig. 56. (Note that the doors are open for inspection in the photo, but are normally locked.)

Fig. 56. 11 kV / 400 V Enclosure mounted secondary substation

The distribution board connects a set of low voltage **Circuits** (sometimes called “mains”). The distribution board in Fig. 57 can be seen to serve four such circuits, which is fairly typical. The circuit cables are three phase, connecting to each of the horizontal phase bus-bars, and leave the distribution board at the lower part of the cabinet. Current meters can be seen to the right (one for each phase) together with fuses on each phase for circuit protection.

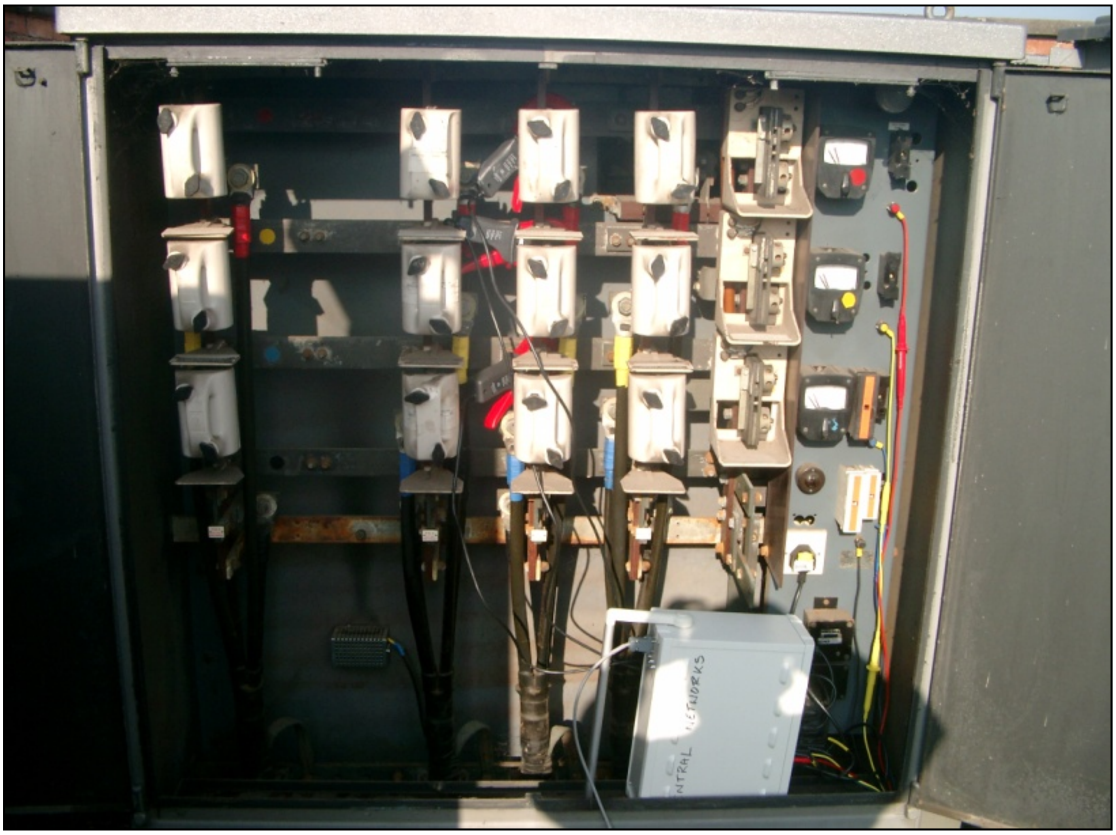


Fig. 57. Low voltage circuit distribution board

Each low voltage circuit is radial and runs along the street, usually buried, or mounted in underground ducts. The number of dwellings served by each circuit varies considerably, but is usually under 100. For each dwelling, a **Service Connection** cable connects the consumer to the low voltage cable in the street. The service connections are single phase.

The service connection cable terminates in the **Meter Cupboard** at the dwelling, such as the one at the lower left of Fig. 58, where the fused connection to the consumer's Electricity Meter can be seen. This particular example, shows a Radio Teleswitch to the right, which is used to switch between the normal and low metering rates for Economy-7 tariffs.

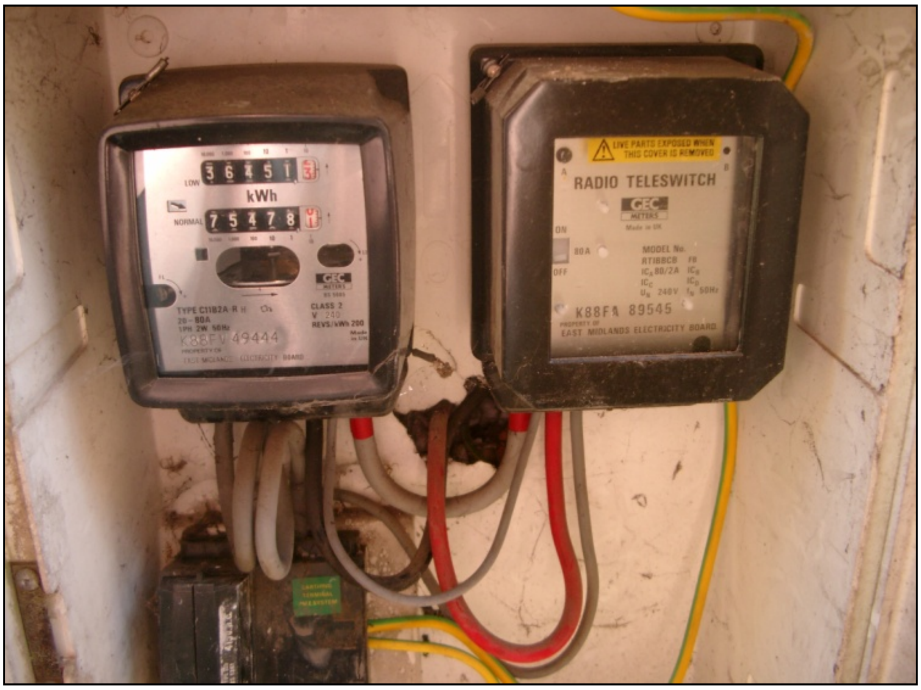


Fig. 58. Domestic Meter Cupboard

To place the domestic demand model (described in Chapter 6) in context here, its output is representative of the electricity demand seen at this meter in each dwelling.

Having looked at the structure of the distribution network, the conventional design approach is considered next.

7.3 Conventional low voltage network design

The distribution system in the UK is divided into fourteen regional areas [98]. Each area is managed by one of eight companies that perform the role of Distribution Network Operators (DNO). The DNO is responsible for the operation of existing networks, as well as, the design and build of new extensions to the network.

The framework in which the DNOs operate involves a range of regulations, standards and technical design guidelines. The number and structure of the regulations and standards is complex: a brief introduction to some of the primary relevant literature is provided here below. Further information is available in greater detail in a useful report by P B Power [99].

The Electricity Regulations [38] comprise key legislation defining statutory standards for the safety, quality and continuity of the network covering protection, substations, underground cables and overhead lines. In addition to this legislative basis, each DNO holds a license, which requires them to define and operate within a Distribution Code [100]: this is essentially a set of procedures and technical standards for the operation of the network. The Distribution Code in turn, refers to a set of industry design standards called Engineering Recommendations (ER), that are maintained by the Energy Networks Association [101]. Many of these standards have a history dating back to the Area Board Chief Engineers' (ACE) reports, developed many decades ago [102]. The standards relevant to the design of networks that serve residential areas, date back to ACE report 13 (1966) [103,43] and ACE report 105 (1986) [104] and exist now in Engineering Recommendation P5/5 (1987), with other key recent standards including ER G81. The design approach to low voltage networks in residential areas has changed little over this time [99].

Referring back to the introduction of this thesis, the main concern for the Distribution Network Operator (DNO) is the network capacity limits. To re-cap, the cables and transformers must be appropriately rated, so that thermal operating limits are not exceeded.

A further concern in that the voltage seen by each consumer is within the mandatory standards. In conventional low voltage design, the voltage drops that occur along a circuit are calculated by using a simple formula, that takes into account a combination of knowledge of the proposed cable size, as well as, the level of demand. As was defined at the beginning of this thesis, the demand is represented by the after diversity maximum demand (ADMD). To re-cap, the ADMD represents the supply capacity required for each consumer connected to the network.

The ADMD is used to calculate the voltage drop along a low voltage circuit, also taking into account unbalance and diversity, as is required by Engineering Recommendation G81. This approach involves a relatively straightforward calculation that works because of the consistent nature of ADMD. As was discussed in the introduction, adding low carbon technology changes the nature of ADMD, and therefore the calculations will no longer adequately represent the demands that the network must support.

As a commercial entity, the DNO seeks to meet the obligatory standards at the minimum cost. This is an important economic consideration that motivates the DNO to maximise the use of existing assets to their full extent. Clearly, uncertainty as a result of a changing ADMD, through low carbon technology, makes this task more difficult.

7.4 Industry software tools for network analysis and design

Whilst ADMD is the common method used to represent demand in conventional low voltage network design, the advances in computer technology over the past three decades have enabled enhanced approaches. An early example is that of a computer program called DEBUT (Demand Estimation Based on Units of Time) [99], that took a statistical approach developed in ACE report 49 (1981) [105], where demand is represented using normal distributions. A whole range of software tools now exist to support the network designer, some of which are listed in Table 10.

CYMDIST, Cooper Power Systems [106]
DINIS, ITC Software [107]
PowerFactory, DIgSILENT, [108]
OpenDNA, Open Systems International Inc. [109]
Gaia LV Network, Phase to Phase, [115]
PSS Sincal, Siemens, [110]
Smallworld Design Manager and Power System Analysis Software, GE Energy [111]
WinDEBUT, EA Technology [112]
ETAP, Operation Technology Inc. [113]

Table 10 - Examples of software usable for distribution network analysis and design

Many software tools, for distribution network analysis and design, are better suited to the high voltage layers (i.e. 11 kV and above). This is because the load representation is typically lumped together: the demands of individual dwellings are not simulated and in many cases, are simply lumped as static demands at the secondary substations. There are many widely used tools which fall into this category, such as IPSA.

Elkwue, Roscoe and Lynch [114] report the results of a recent and interesting international survey looking at the software tools being used by DNOs. For the UK, they found that the majority of DNOs use PSS/E, IPSA and DINIS and further that DNOs usually use the same tools for both 11 kV and 33 kV networks.

However, this discussion is concerned with low voltage networks. Elkwue, Roscoe and Lynch report that many DNOs did not use software tools networks at all: where a tool was used, it was one of ITC Software’s DINIS, Cooper Power System’s CYMDIST or EA Technology’s WinDebut, the latter being an updated version of the DEBUT tool described above.

A geographical information system (GIS) user interface is a useful feature of those tools that are better suited for low voltage network analysis. This provides the capability to show not just the network schematic, but the network in geospatial map form, with the routes of cables and locations of the distribution system components. All the software tools listed in Table 10, have some form of network graphical presentation capabilities. To pick one example, Phase to Phase’s Gaia LV Network design [115] is a tool where a network topology can be specified, in terms of the cables, transformers and loads. The package incorporates an unbalanced load flow and provides a range of analysis capabilities.

7.5 Existing low voltage network models and studies

Many studies of distribution systems focus on the 11 kV voltage level and above, and simply lump the low voltage layer demand, representing it simply as a single load at the secondary substation. An example study at the 11 kV level is the EA Technology report [116], discussing changes to network design due to the introduction of significant embedded generation. Whilst these studies are useful at the 11 kV feeder sections of the distribution network, they do not address what is happening within the low voltage networks.

The Task V Report IEA-PVPS [117] examined the impact of photovoltaic penetration in distribution networks, taking low voltage aspects into account. Whilst multiple circuits being serviced from each secondary substation are represented, the detail of the demand spacing, and low voltage circuit topology is not considered. This is an example where low voltage networks are taken into account, but are simplified into network of only a few nodes.

Another study also addressing the integration of distributed generation from a control perspective was conducted by Econnect [118]. This included the construction of a low voltage network model, but under a limited number of maximum or minimum demand levels.

Another study by P B Power [99] examined the impact of micro-generation connected to the low voltage network, but represented load using the Load Research Group profiles, again using minimum and maximum demand levels: notably, demand is indicated as resistive, and reactive power demand is not taken into account.

P B Power also worked on a detailed distribution network study [119], including the representation of 384 dwellings with a simplified network, with partially lumped loads, together with assumed minimum and maximum demand levels.

Mott MacDonald followed up this work with their SIAM study [120], where different types of network were considered (urban, suburban and rural), but again used only minimum and maximum demand values derived from domestic profiles.

The impact of PV generation on low voltage networks was considered in another EA Technology study [121], that looked at the issue on voltage levels, imbalance and the affect of network design given commercial, domestic retro-fit and domestic new build scenarios. The study uses WinDEBUT for its analysis, again with the Load Research Group profiles [34], and only a generalised network topology is utilised.

Trichakis, Taylor, Lyons and Hair [122] consider the impacts of generation connected to low voltage networks. In this case, a generic simplified network model is utilised, again using only maximum and minimum demand values.

More recently, P.Richardson and Keane [123] present an interesting study of the impact of micro-generation on Irish low voltage distribution networks, with a focus on voltage rise. This study used network data representing a suburban area in Dublin. Power Factory was used to look at the network performance under minimum load conditions, through the assignment of a fixed minimum demand level to each dwelling.

Whereas the above studies use either generic or simplified network topologies, or a simplified representation of demand, Thomson and Infield [124] attempt to model low voltage networks using real topology with a time-stepped demand model. The study examines the high penetration of distributed generation using, a sizable area of real network based in a UK city. It is detailed in its representation of the physical location of loads, by representing individual dwellings. Furthermore, it uses one-minute resolution demand data, generated by the Stoke's model [51] that was introduced earlier in Chapter 2. One important shortcoming with this demand model, is that it is does not use domestic occupancy as an input: although the discussion of the model notes this as a suggestion for future development. Not taking into account occupancy, constrains the ability with which a model can represent the realistic diversity of the electricity use between different dwellings, as people perform their daily activities.

Nevertheless, the combination of the Thomson and Infield study with the Stoke's demand model, is the most detailed attempt to link high-resolution demand with a real network model, and study the network operation in conjunction with an unbalanced load flow.

Most recently, Widén et al. (2010) [125] present a study of PV integration in three low voltage networks in Sweden. The study uses their stochastic time-use based demand model constructed from Swedish data, and cited earlier [15]. In this case, an hourly resolution is chosen for simulation on an annual basis. A balanced load flow is utilised, in conjunction with, a constant secondary substation source voltage.

7.6 Outline model requirements

Having considered the conventional industrial approach to low voltage network design, looked at some of the available software tools, and considered the existing academic literature on low voltage network modelling, the requirements for the construction of a model are presented as follows:

- The model must properly represent the realistic time varying demands of individual dwellings, through a time-stepped simulation: therefore the network model and demand models need to be closely integrated.
- The model must realistically represent the physical topology of a UK low voltage distribution network. The variety of cables and their related electrical parameters must be represented.
- The location of dwellings, and therefore the consumers, must be realistically modelled with regard to their geographical spacing.
- The network model must implement a three phase unbalanced load flow.

7.7 Network topology data

In representing a UK low voltage network, there is a need to represent the physical network topology of the lines and cables, together with, the location of the secondary substations.

An obvious suggestion would be to use a generic test network. There exist generic models of distribution networks, that provide typical topologies and characteristics. One example is the United Kingdom Generic Distribution System (UKGDS) [126], which provides a set of network structures typical of those found in the UK. A further example, is the set of IEEE radial feeder test models [127], of which the 123-node model is the most detailed. Whilst useful for analysis of typical feeder topologies, these generic representations do not include the low voltage parts of the network, and are therefore not suitable for this study. Recently in 2010, a new 8500 node example has been made available by the IEEE [127]. This does include low voltage distribution, although it is based upon a US feeder.

For the purposes of the model described in this thesis, the network data representing the town of Loughborough, a medium sized town in the East Midlands, UK, was extracted from the utility data base of Central Networks. The use of this data meets the requirement to represent a realistic UK distribution network. Furthermore, it links well with the logged domestic demand data discussed earlier in Chapter 3.

7.8 Approach to the implementation of the model

A significant consideration is whether to utilise an existing software tool, or to construct an entirely new model as a bespoke application. With regard to the outline model requirements detailed in section 7.6, the latter approach was chosen for the reasons that are discussed below:

None of the software tools, introduced previously, has the domestic demand simulation capability with the characteristics of the one set out in Chapter 6 of this thesis. Approaches using constant and/or lumped representations of demand, as was seen in many of the existing studies, are not considered adequate to meet the requirements of this work. Those approaches using only minimum or maximum anticipated demand levels ignore the statistical variation in the load durations. The importance of this is discussed by Widén [52], in the context of micro-generation causing over voltage events, in terms of how frequently these events occur.

In addressing the requirement to realistically represent the topology of the low voltage network, simplified network approaches with a small number of nodes are not considered sufficiently representative or diverse for this purpose. Many of the existing studies, discussed in this chapter, take a simplified approach at the low voltage level. Given the representation of individual dwellings required in this work, the low voltage circuits must be fully represented in detail. The constraints of existing tools, particularly with respect to demand representation in low voltage networks, point towards the need for a bespoke development.

Furthermore, as is seen in the next chapter, data that represents the detail of low voltage circuits tends to be both large in volume and complex. Indeed, a major challenge exists in the handling of the data: building a bespoke application enables the use and management of the data in the most efficient way.

The development of a bespoke application means that it can be tailored to exact requirements and extended as needed. One example is the need to represent a DY11 configuration transformer, based upon the DY1 model described by Kersting [128]. With a bespoke development, such an enhancement may be integrated, whereas an existing software tool may not offer such flexibility.

A benefit of using an existing software tool is that the load flow calculation capability would already be available: however, this is not considered a major drawback to a bespoke development. Load flow calculation techniques are well documented and their implementation is not considered a significant constraint.

It is acknowledged that some of the commercial packages provide macro languages, or integration methods, that could be used to implement integrated demand and network modelling functionality. The integration of existing tools with the demand model presented in this thesis, would likely involve more work than writing a bespoke software application.

The integrated approach to the construction of the new model is presented in the next chapter.

8. Construction of an Integrated Demand and Network Model

8.1 Overview of the integrated model

An overview of the structure of the integrated network model is shown in Fig. 59. The demand model, as described earlier in this thesis, is shown as an embedded component in the blue box. The approach to the implementation of the model and discussions of each of the inputs and outputs, is presented in the subsequent sections.

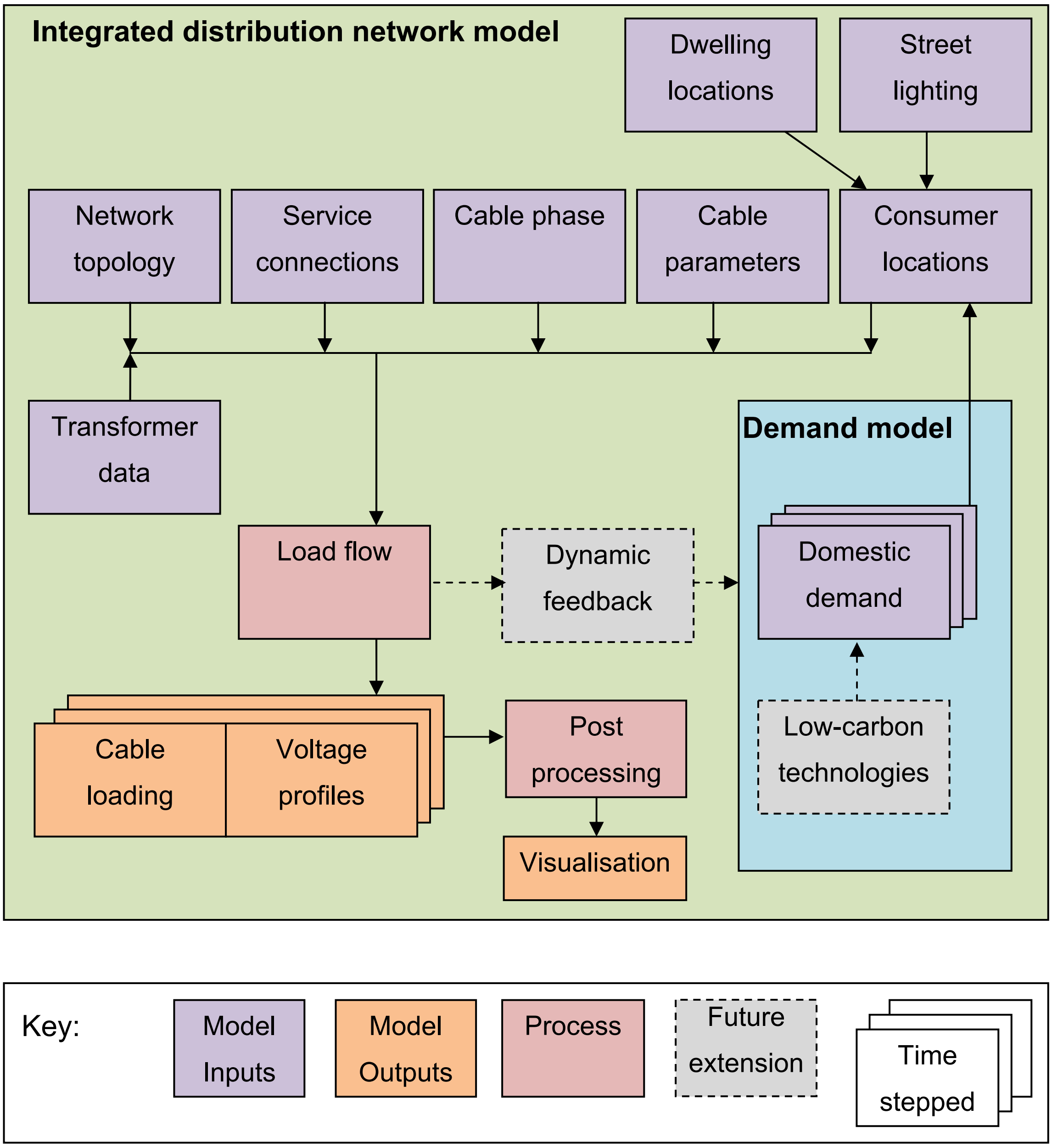


Fig. 59. Structure of the integrated network and demand model

8.2 Model implementation

8.2.1 Software development approach

The Microsoft.NET C# language was chosen for the implementation of this model. This is because of its suitability for the development of an application requiring the fast handling of large quantities of structured data, fast file input and output, and capable of providing a flexible graphical user interface.

With reference to Fig. 59, it can be seen that the load flow aspect is only one small part of the whole model. As was concluded in the previous chapter, the use of an existing software tool to perform this function would not be a significant gain in bringing together all the other aspects of the model.

8.2.2 *Use of the network topology data*

The data files containing the physical topology of the network, from the utility GIS database discussed previously in section 7.7, are parsed and loaded into the model. The data is vector based and consists of physical geospatial point locations, called network nodes, connected by vector paths that represent the cables. A node may be sited at a cable end point, or as a connection between two or more cables. It has a physical location, specified in geographic coordinates, as well as, a unique logical identifier.

An example area of low voltage distribution network served by a single secondary substation is shown in Fig. 60. The green lines represent the routes of the cables. The purple circle shows the location of the substation. This particular secondary substation serves five separate radial circuits. One of these circuits, shown as a thick green line, is examined in detail to validate the model in the next chapter.

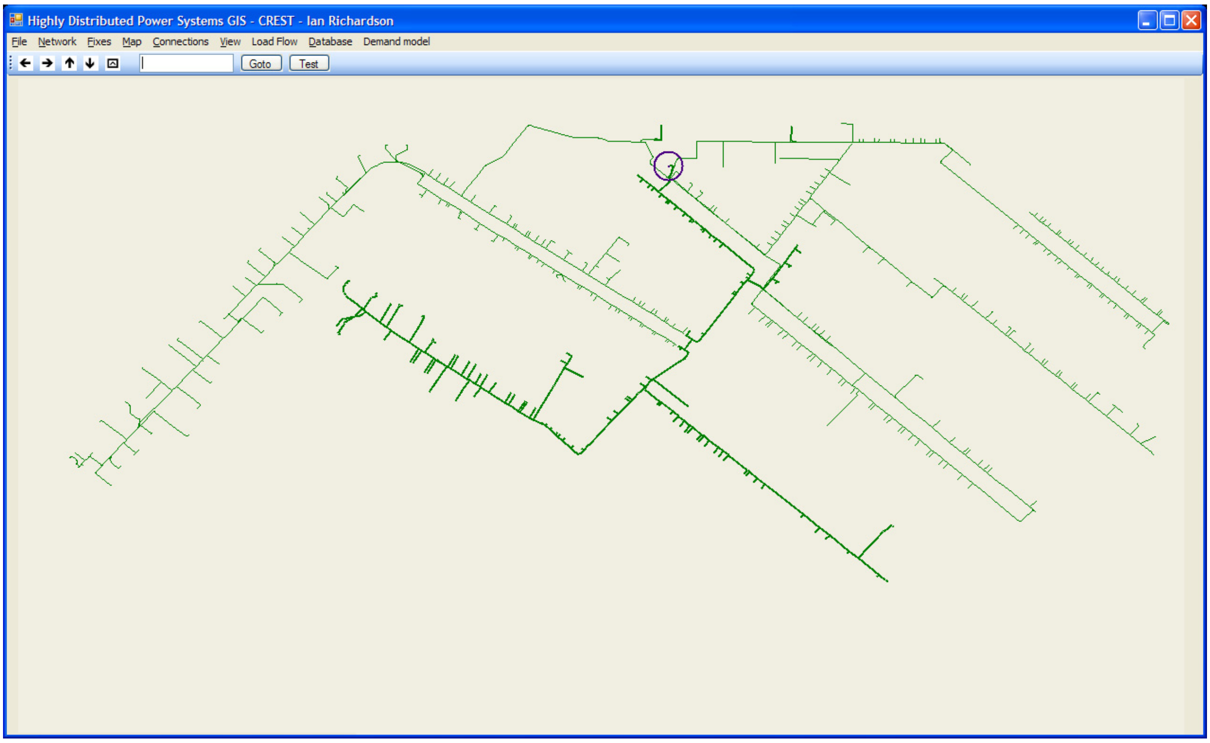


Fig. 60. Low voltage cable topology from a single secondary substation

(network data source: Central Networks)

Network topology data in visual GIS display applications is typically used for DNO asset management. In day to day use, the cable routes and transformer locations simply need to be plotted in map form, such that contractors can be informed where components are physically located. This is a very different application to network data use for load flow calculations as is required here.

There exists a major issue with using GIS data in load flow applications: the vectors which describe the network must be logically connected. It is not sufficient for them to appear to end in the same place on a map. For the Loughborough area, significant effort was spent in checking the data and resolving any issues. This required the development of suitable algorithms to analyse and validate the data. In some cases, it was necessary to physically visit a location in order to check the network configuration.

It is emphasised that the effort involved in the management and validation of GIS data, for use in network load flow applications, should not be underestimated.

8.2.3 Dwelling locations

The next step is to approximate the location of consumers: the starting point to achieve this, is to represent the location of domestic dwellings. In the UK, the Ordnance Survey (OS) MasterMap [129] data sets provides detailed mapping data, that represents the locations of all buildings. This data is provided in an XML format that details polygons representing the physical building footprints.

It is necessary to parse the XML to extract the coordinates of these polygons. The Microsoft C#.NET XmlTextReader class was used to perform this parsing and the data was loaded into a structured in-memory format, such that, it could be displayed in a bespoke Windows forms application. An example of the data shown by the user interface is shown in Fig. 61, where a number of dwellings are shown in map form surrounding the street.

Fig. 61. Representing the location of dwellings

(Map data: Ordnance Survey ©Crown Copyright. All rights reserved).

The data contains information on the type of building, so that it is possible to identify domestic dwellings. Furthermore, by comparing the proximity of the polygons, it is possible to determine whether the dwelling is detached or semi-detached. In Fig. 61, the yellow dwellings in can be seen to be detached and the orange buildings are semi-detached.

8.2.4 Domestic consumer locations

Whilst the building location data provides a very good way of representing individual dwellings, it does not represent the common case where buildings are divided into flats. In this scenario, each flat will have its own electricity meter. Therefore there may be multiple consumers within a single building.

The UK Ordnance Survey's (OS) Address Layer 2 [130] data provides the geographic locations of all GB addresses. These address points can therefore be used to represent the approximate locations of the consumers. An example is shown in Fig. 62 where the blue dots represent these address points.

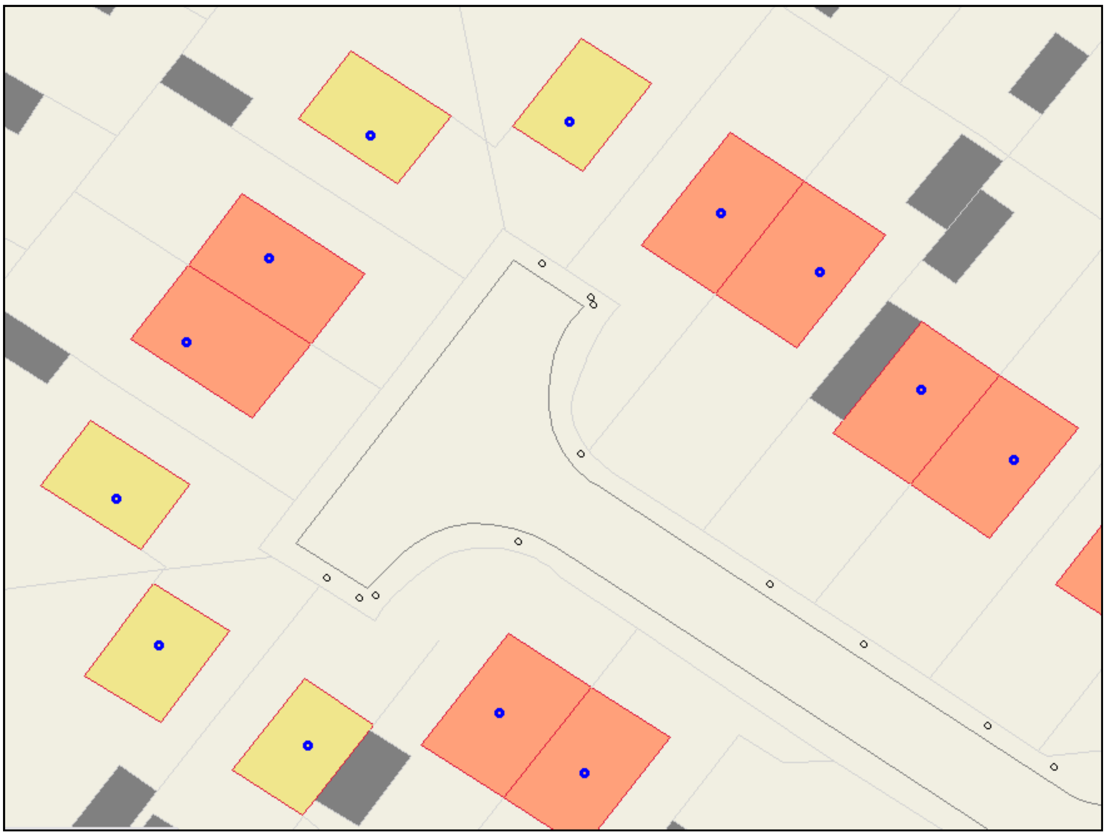


Fig. 62. Representing the location of consumers

(Map data: Ordnance Survey ©Crown Copyright. All rights reserved).

Since in the case of flats, multiple addresses will exist at the same dwelling, the use of this address point data resolves the problem of representing multiple consumers in a single building.

8.2.5 Service connections

In general, the DNO network data does not include the location of the service cables, from the main in the street, to the electricity meter at a dwelling. Since the location of consumer loads is being represented by the address points previously discussed, it is necessary to connect these points to the network by adding in the service cables to the topology. This is achieved by making the assumption that each address point connects the consumer to the nearest available low voltage cable in the distribution network.

An example is shown in Fig. 63, where the black circles represent the nodes from the topology data, and the blue circles represent the address point locations. The low voltage cable is shown in green, and the service cables that have been added to the topology, are shown as purple lines.

An algorithm was developed to find the nearest low voltage cable for each address point. To re-cap, the cable data is represented by chains of vectors connected by nodes. This gives rise to two scenarios: the first simple case is when a node is already available at the nearest point, in which case, a new line representing the service cable may be added to the topology, connecting to an existing node, represented as a black circle. The second more complex scenario arises if there is no available existing node to connect to. In this case, it is necessary to insert a new node at the desired location, by splitting an existing cable vector. This requires a considerable amount of vector manipulation computation. Again with reference to Fig. 63, cases where nodes have been inserted are shown as purple circles on the green low voltage cable.

It is acknowledged that the nearest node approach to the connection may not represent the precise reality of the actual connections, but it is a good approximation.

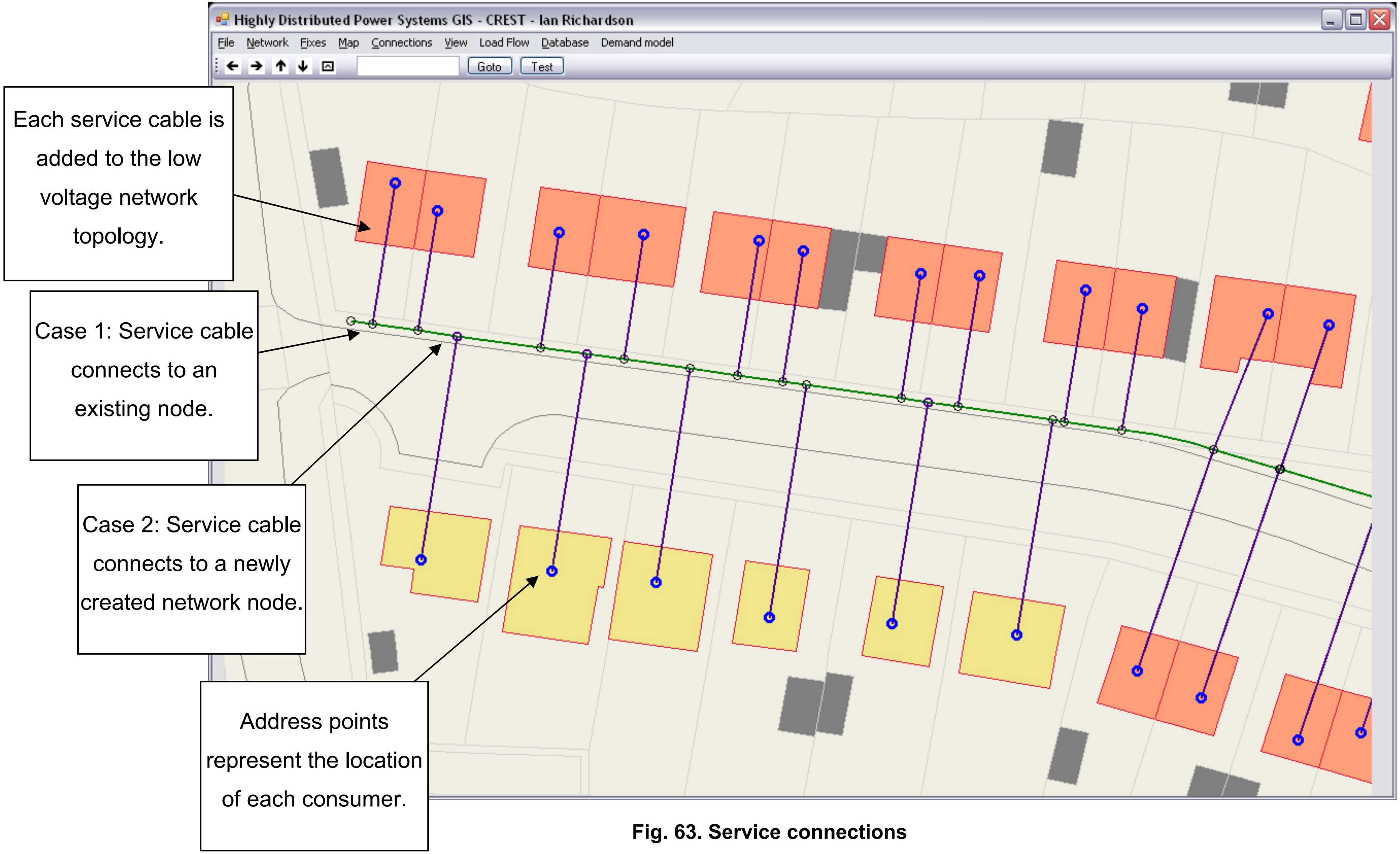
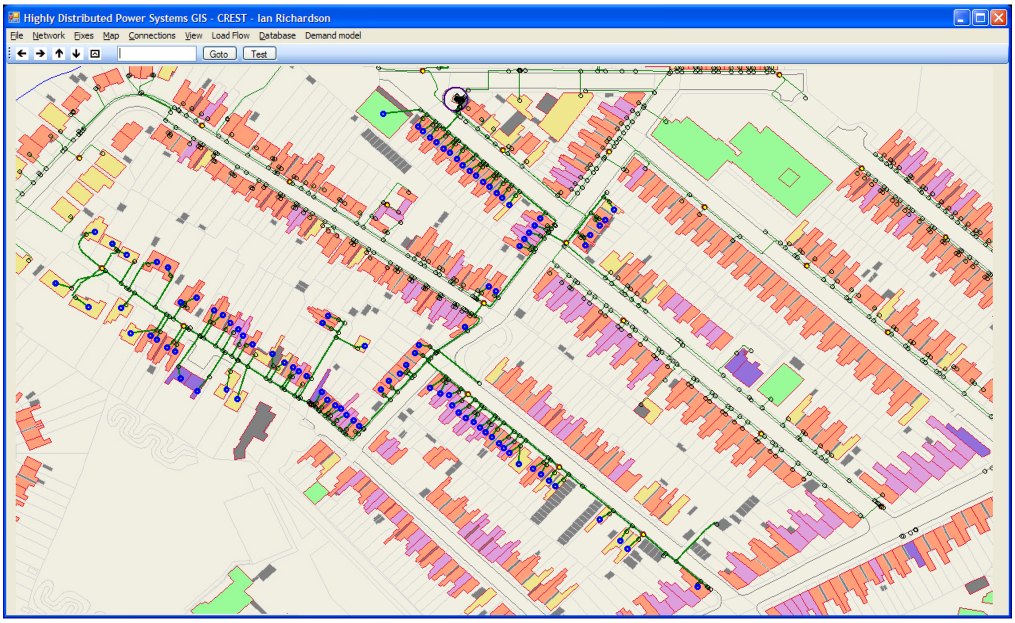


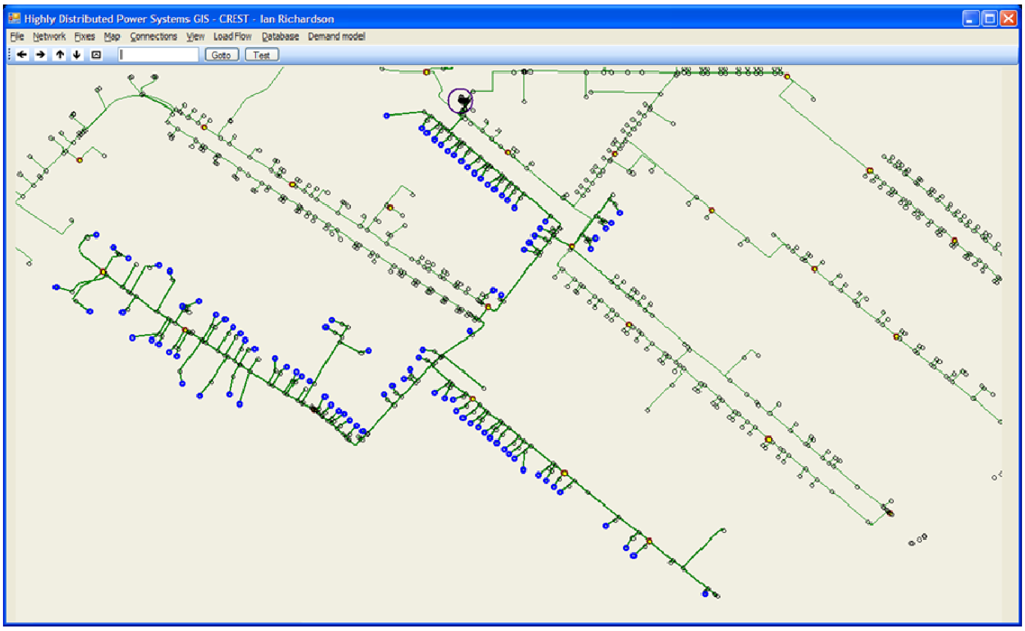
Fig. 63. Service connections

(Map data: Ordnance Survey ©Crown Copyright. All rights reserved).

A larger scale example is shown in Fig. 64(a), showing the location of the loads for the single circuit referred to previously in Fig. 60. For clarity, the same figure is shown without the buildings in Fig. 64(b).



(a) The network area shown together with the location of buildings



(b) The network area showing the cable topology and consumer load locations

Fig. 64. Representing the location of consumer loads

8.2.6 Service cable connection phase

Since domestic connections are usually single phase in the UK, it is necessary to determine to which phase each consumer is connected. Archived historical records of the phase configuration are not generally available. Where data was found, it was archived by the DNO on micro-fiche, in a format that was not practical to import into a database containing a large number of dwelling locations.

In the case where a three phase cable is routed along a street, the model approximates the connections by a sequential assignment to one of the three phases (A, B or C) as each dwelling is encountered. An example of the phase connections to a number of dwellings is shown in Fig. 65.

Fig. 65. Assignment of connection phases

Where the network data indicates a single phase cable, that cable is assigned a phase at the point where it connects to the three phase network. All dwellings connected to a single phase cable will thereby be connected to the same phase.

8.2.7 Cable parameters

In addition to the topology, the DNO data details the types of cable that are used throughout the network. From the same utility database as the GIS topology data, a table of cable impedance parameters was extracted. In conjunction with the topology data, the impedance values of each cable throughout the network can be estimated by taking their length into account.

8.2.8 Integration of the demand model

In order to represent the time-varying demands on the network, it is a key requirement for the network and demand models to be integrated.

This is achieved by assigning each consumer load (represented by each address point) an electricity demand, using the demand model. In data handling terms, this means that the occupancy is simulated within each dwelling. The use of each individual lighting unit, and each individual appliance, in every dwelling, is simulated at a one-minute resolution. The scalability of the demand model, in terms of its computation efficiency, is most important when representing larger numbers of dwellings.

The computation involved is therefore considerably more complex than representing static aggregate demands for each dwelling.

8.2.9 *Street lighting*

In addition to the demand from the dwellings, there is also demand for street lighting. Unfortunately, there was no detail describing the location of street lighting in the network GIS data. In order to represent street lighting, design guidelines from the British road lighting standards [131] were used to approximate the layout and electricity use. There are many considerations involved, but for the purposes of this model, an approximation is made. Street lights are placed approximately 47m apart, at locations on the low voltage distribution network. Each street light is represented in the model as a 70 W SON/T (high pressure sodium) lamp. The street lights are represented as yellow spots in Fig. 66.

Fig. 66. Representation of street lighting

(Map data: Ordnance Survey ©Crown Copyright. All rights reserved).

The model uses the lighting up time (in this case, defined as a half-hour after sunset, to a half-hour before sunrise) as a means of determining when the lights are switched-on. The daily sunrise and sunset times for Loughborough were generated using the data services of the US Astronomical Applications Department of the US Naval Observatory [132].

Although it is noted that street lighting is considered a relatively small proportion of the demand in residential areas, its inclusion involves little extra computational demand and enhances the realism of the model.

8.2.10 Secondary distribution transformer data

Since the model is concerned with the simulation of the low voltage circuits, it is necessary to represent the source voltage on each low voltage phase at the secondary substation transformer. With the support of Central Networks, voltage data was recorded, at a one-minute resolution at four secondary substations in Loughborough, to provide data for this purpose.

8.2.11 Future expansion possibilities

The model is constructed in such a way as to make it extensible for future enhancement outside the scope of this thesis: three of the main ways are noted below:

Whilst the focus of this thesis is low voltage circuits, the model is constructed so that it may also represent 11 kV feeders.

Furthermore, as a platform for the study of low-carbon technologies, the demand model is capable of being expanded, to include new modules representing the various forms of technology already discussed.

Finally, for studies of network response to flexible demand, the way that the demand and network model are integrated, mean that future studies could take place, where demand may be controlled in response to network conditions.

8.3 Load flow implementation

Having built the model, a three-phase unbalanced load flow is required to calculate the voltages and currents throughout the network, as a result of the demand of the domestic consumers. At each time step of network simulation, a steady state is assumed with a sinusoidal waveform. An efficient load-flow was required because of the number of nodes and the time step loops. Specifically, Newton-Raphson or Gauss-Seidel methods were not appropriate because of the need to manipulate very large sparse matrices. Instead, Kersting's ladder iterative unbalanced three-phase load flow [128] is implemented. This method is known to be computationally efficient and works well for radial circuits [133]. The method is sometimes known as a "forward backward sweep" approach. On the outward sweep, from the voltage source, the voltages are calculated at each node. On the backward sweep, the current carried by each cable is calculated. The process is continued until the voltages converge to a suitable precision, in this case chosen to be 0.1 mV.

This load-flow is implemented computationally by representing the network topology as a tree structure, in memory, using an appropriate C# object structure design. Starting from the voltage source at the secondary substation, a depth-first traversal of the tree takes place, using a recursive algorithm. The tree search is performed in a "post order" way, which means that the sub-trees, at a particular node, are all traversed before the parent node is visited. This means that the currents flowing deeper into the network, from a parent node, are all available on the backward sweep, where they are summed to determine the current flow on the parent cable.

8.4 Raw output and post-processing

The model outputs raw data, comprising the voltages at each node in the network, and the current flowing along each cable: the raw data is written to comma separated files. These values are available for every time step performed in a simulation. In addition to the raw data files, the GIS interface of the model is capable of showing the voltage and current data in a map form.

An example, showing the phase voltage and current on each service connection, for a number of dwellings, is shown in Fig. 67. On each phase, the voltages can be seen to drop towards the lower-right of the figure.

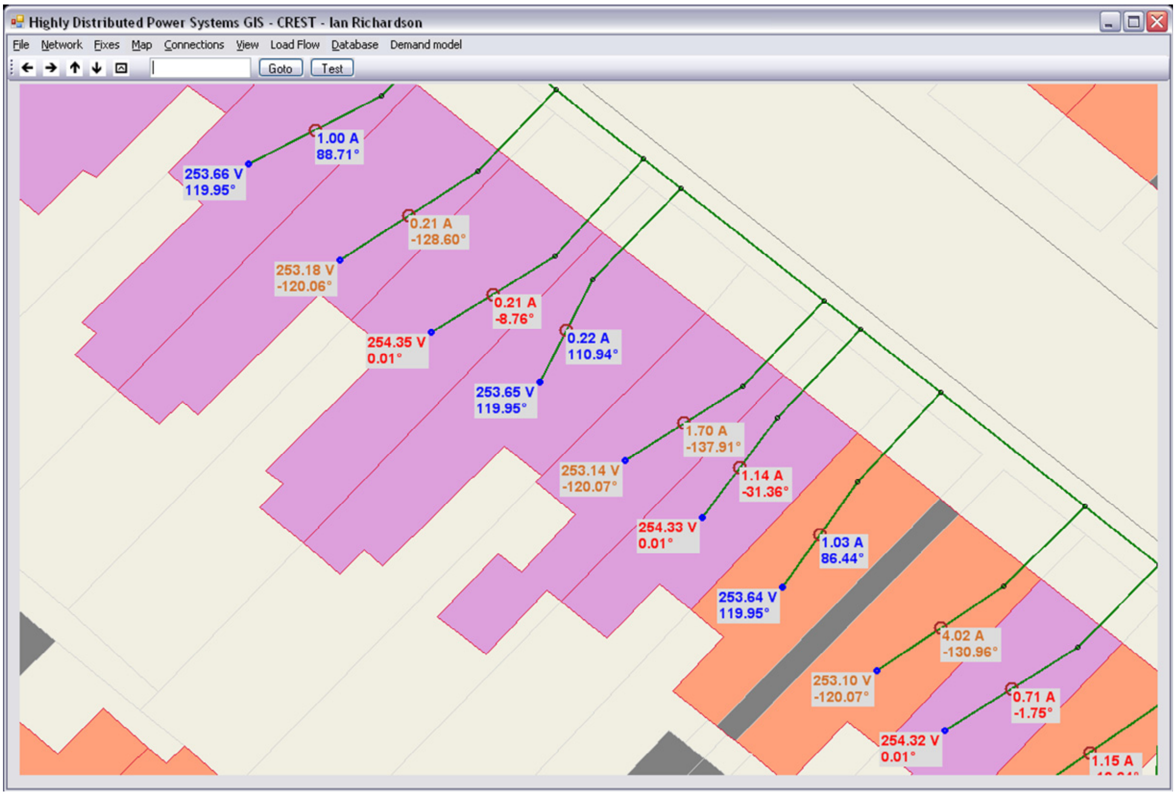


Fig. 67. Raw load flow results displayed by the GIS interface

(Map data: Ordnance Survey ©Crown Copyright. All rights reserved).

With reference back to Fig. 59, post processing of the raw data may be performed to structure the data for visualisation. This is performed for the purposes of validating the model, the subject of the next chapter, and later in the use of the model described in Chapter 10.

9. VALIDATION OF THE INTEGRATED DEMAND AND NETWORK MODEL

9.1 Scope

Having constructed an integrated model of the distribution network and domestic demand, as detailed in the previous chapter, the next step is to validate it against data measured from the actual physical distribution network. In line with the original scope of the model, described in the introduction, the validation of the model is performed, in terms of the demand, taking into account network losses, as well as, the voltage variation that occurs along low voltage circuits.

9.2 Measuring data for comparison against the model output

With the support of E.ON, voltage, current and energy demand was measured on the low voltage side of four secondary substations serving residential areas, in the town of Loughborough. An example showing how the data was logged is presented in Fig. 68. A distribution board is seen to serve five separate circuits. The five low voltage distribution cables can be seen on the lower part of the distribution board, where the left-most circuit cable is being logged in this case.

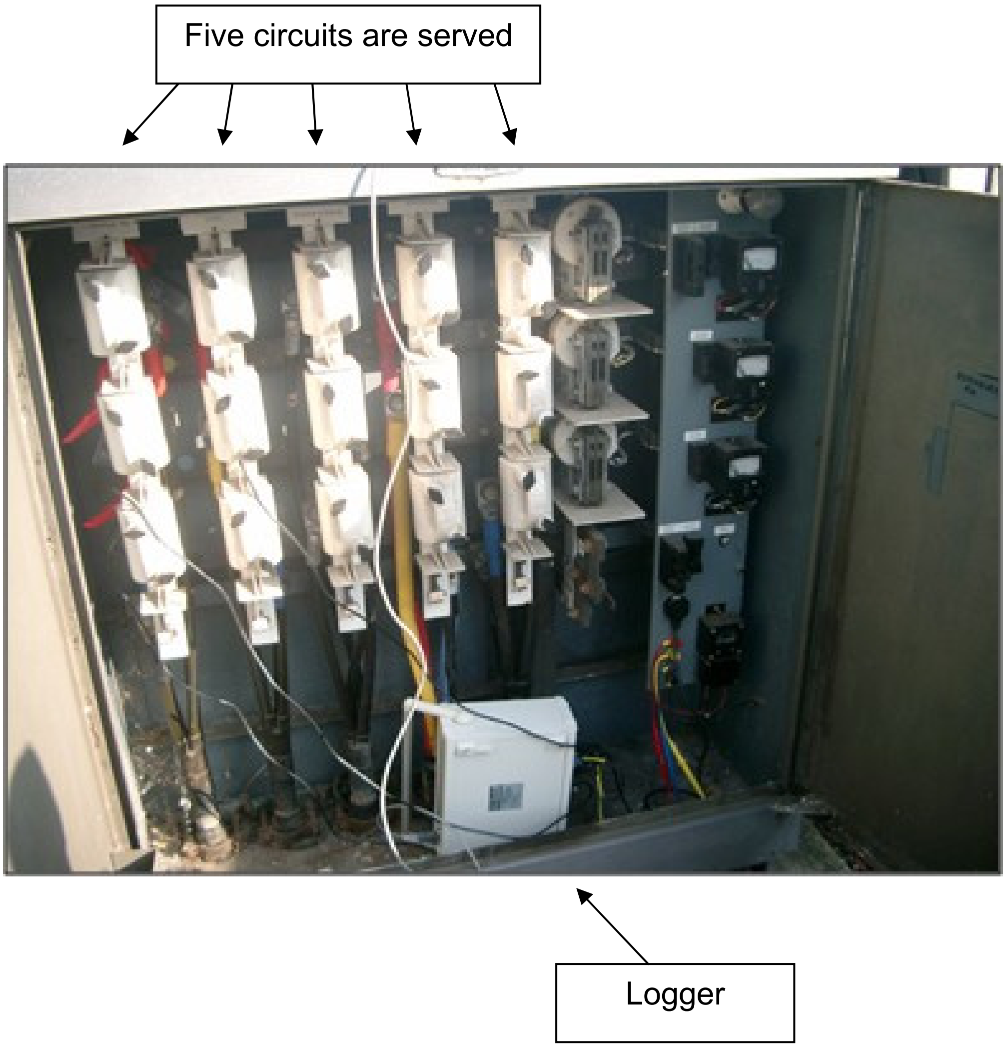


Fig. 68. Substation monitoring equipment

To the lower centre of the figure a Rochester Instrument Systems power and quality recorder can be seen. The voltages are measured by connecting the logger to pins on the test panel, to the lower right hand side. The current is measured using current transformers, that are placed around each phase cable, and the clamps can just be seen behind the left most circuit connectors.

In particular, the voltage and current data for the circuit presented in Fig. 64(b) was recorded at a one-minute resolution. This circuit was determined as serving 99 domestic dwellings, and one small community centre, and therefore chosen because is serves mainly residential loads.

Furthermore, it was possible to install a number of voltage loggers within dwellings served by this substation. The voltage loggers used were Electrocorder plug-in types and these were also configured to capture data at a one-minute resolution.

9.3 Aggregated demand

9.3.1 Comparison of measured and modelled demand profiles

The first comparison to make, is that between the measured and modelled real power demand, served by the test substation circuit. The model was used to generate a week of data to compare against measured data taken during September, 2009. Note that the integrated network and demand model will take network losses into account. A graph showing both data series is presented in Fig. 69.

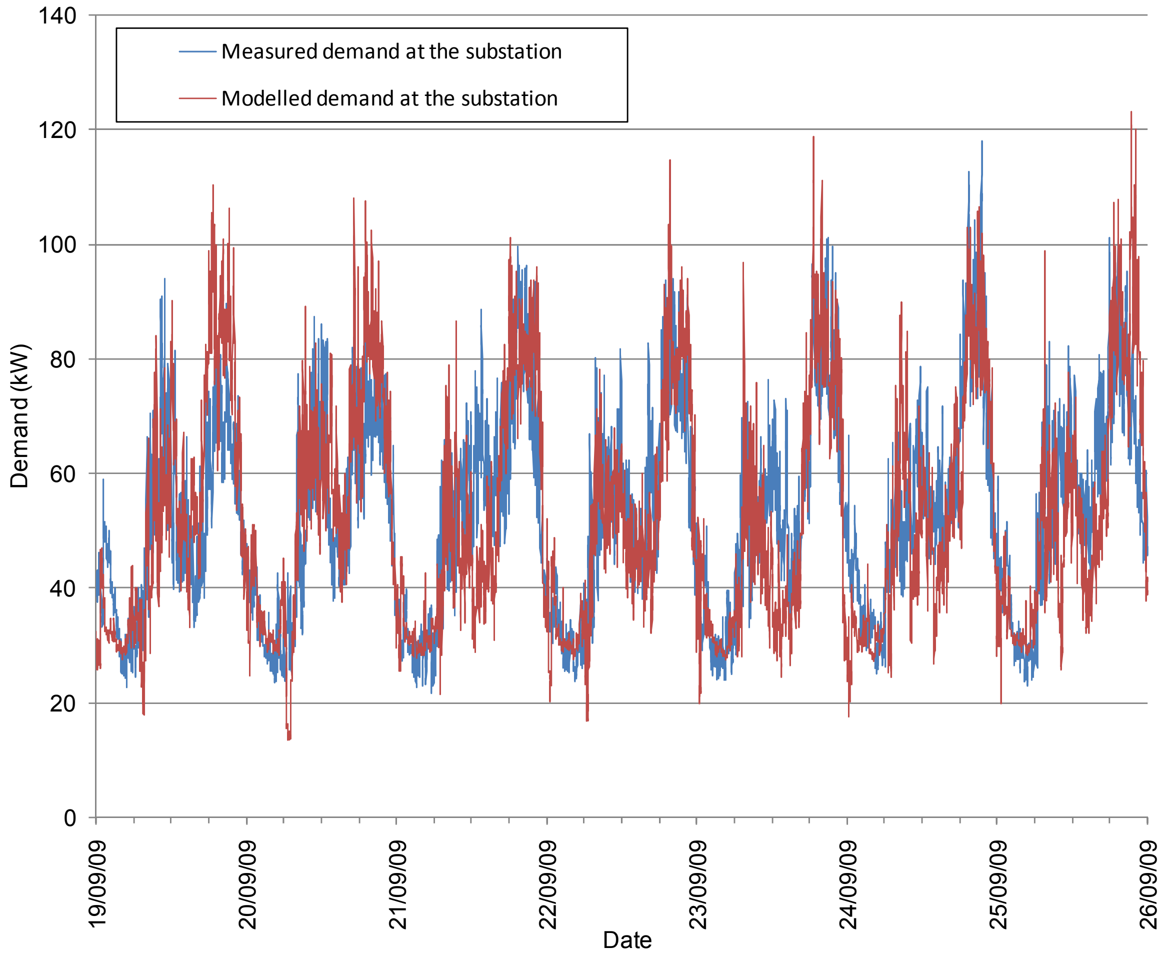
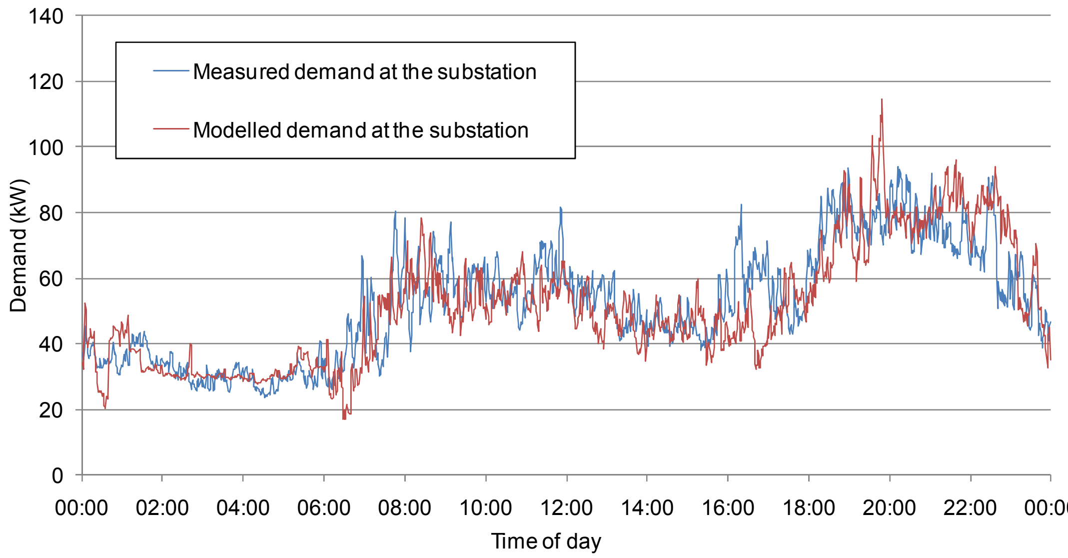


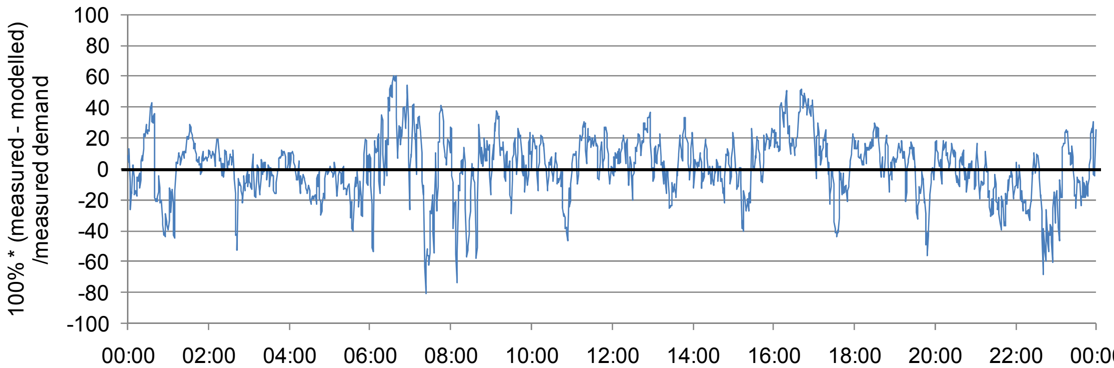
Fig. 69. One-week demand comparison

The modelled and measured data have very similar characteristics, in terms of both magnitude of demand, and the daily cycling that can be seen. The mean values are 52.8 kW for the measured data and 52.2 kW for the modelled data. The peak demand is 118.0 kW as measured and 123.2 kW as modelled. The seven daily cycles can be clearly seen in both series. Each day is characterised by low demand at night, followed by two peaks: one in the morning and a second in the evening.

For a more detailed perspective on a daily basis, an individual daily profile is presented in Fig. 70(a).



(a) Absolute comparison of modelled and measured demand



(b) Relative comparison of modelled and measured demand

Fig. 70. One-day demand comparison (Tuesday 22nd September, 2009)

With reference to Fig. 70(a), the model is generating very realistic demand profiles: the measured and simulated demand has very similar characteristics. Demand is lower at night and less volatile. In the morning, the magnitude and volatility of demand increases. The peak demand occurs during the evening in both data sets. The daily cycling pattern is consistent between the two data sets. Over the full week, the mean values differ by only 0.6 kW, which is particularly close. Over the same time period, the peak value of the modelled data is only 5.2 kW above the measured data.

As a stochastic simulation, on a minute to minute basis, the level of demand would not, of course, be expected to match exactly. The important consideration is that very little is physically known about the consumers served by this circuit. Despite this, Fig. 70 (b) shows a percentage based comparison between the modelled and the measured demand. In this case, the mean difference is 0.9%, which shows that the overall mean level of demand over time is very similar.

The following is not known and therefore cannot be used as input to the model:

- The total actual number of residents in each physical house.
- The real occupancy patterns of the residents.
- The actual numbers and types of appliances and lighting in each dwelling.
- The actual resident's attitudes to energy use and how their behaviour affects the use of lighting and appliances.

The following is known and the model is configured accordingly:

- That there are approximately 100 domestic dwellings served by the circuit.
- The physical geographical distribution of these dwellings.
- The topology and impedance parameters of the low voltage network.
- The typical demand characteristics of UK dwellings, calibrated to a demand level typical of the East Midlands region.

Despite the lack of detailed input data, the integrated model is generating data that is highly representative of this circuit.

9.3.2 Discrepancy in midday demand

It was noted that in some cases, the measured demand during the mid-day period exceeded that of the modelled demand. This is more clearly visible in the plot of average weekday demand shown in Fig. 71, over a one-week period. The measured data shows greater demand during the period 10:00 to 16:00

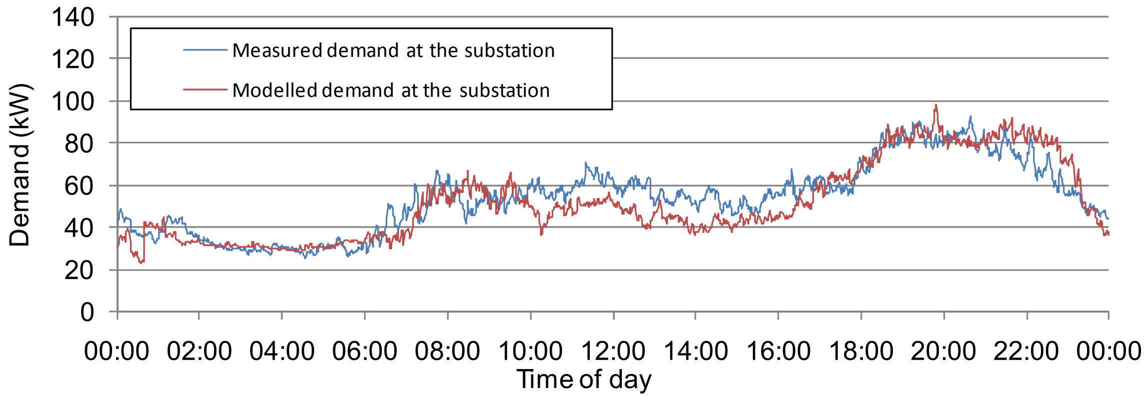


Fig. 71. Comparison of average daily demand profiles

One explanation for this, could be that the model is not fully representing the occupancy pattern characteristics of the dwellings in this area. For example, if there was greater active occupancy during the day than the average level simulated by the occupancy model, then a higher level of demand during the day would be expected in the measured data.

The occupancy model uses a data set that is assumed to be representative of a national average occupancy profile. From census data [134], it was found that this area has a relatively higher proportion of residents of Asian origin. Again using the TUS data, a comparison of the average occupancy profile is shown, against a profile correctly weighted to represent the structure of ethnic groups resident in the area, and is presented in Fig. 72.

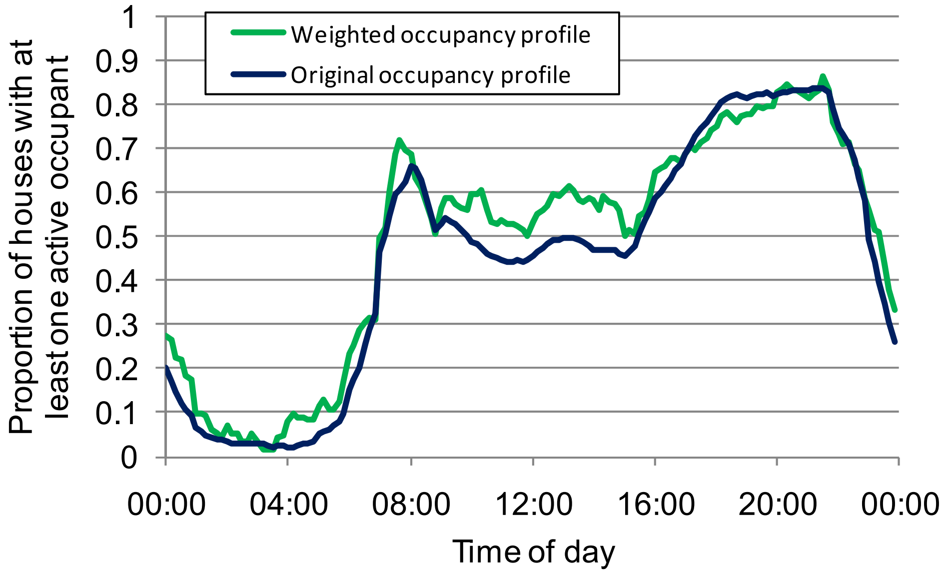


Fig. 72. Comparison of occupancy profiles (weekday)

(Derived from the TUS data set [63]).

Greater daytime occupancy can clearly be seen in the weighted profile. This greater occupancy would account for higher demand for electricity during this period.

9.4 Voltages

9.4.1 Daily voltage profile

A comparison of one-day voltage profiles is shown in Fig. 73. The dark blue line shows the measured voltage on the phase C circuit at the secondary substation. The red line shows the modelled voltage at the test house. The lighter blue line shows the measured voltage at the test house.

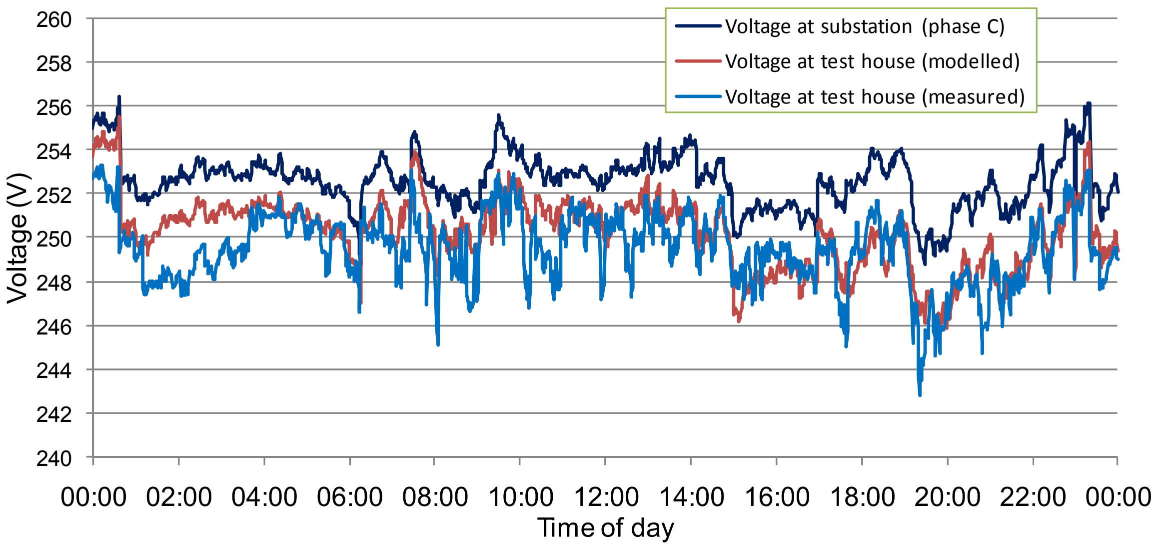


Fig. 73. One day voltage profile at two network locations (19th September, 2009)

The voltage at the substation varies considerably throughout the day. These variations are a function not only of the demand served by this substation, but the variation of the voltages on the 11 kV feeder serving the substation. A significant voltage drop is seen to occur at 00:30 that could be related to the Economy-7 start time, but could also be a tap change at the primary substation, or even a large industrial load switching-on. The measured and modelled demand will not match exactly, due to the stochastic nature of the modelling, and therefore, it is not expected that there should be an exact match between the voltages at the test house. However, the magnitude and volatility of the voltages are approximately the same.

9.4.2 Voltage histogram

For a whole week, the voltage at the test dwelling is plotted in histogram form in Fig. 74.

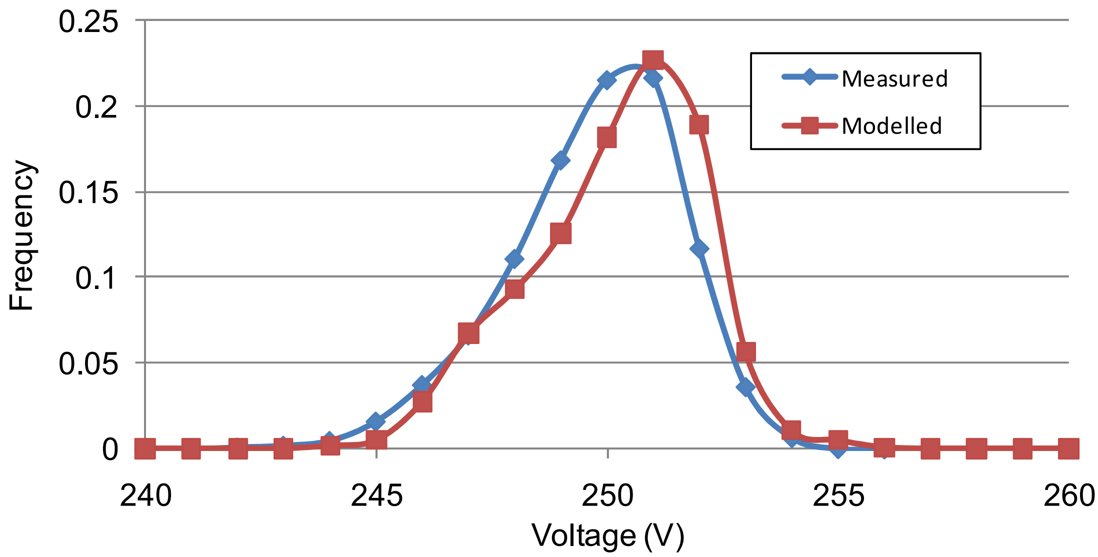


Fig. 74. Voltage histogram comparison (19th - 25th September, 2009)

Since it was concluded previously, that the voltage variation at the voltage source within the secondary substation is dominant, all this really shows is that the model is slighting underestimating the voltage drop that occurs in the circuit, between the secondary substation and the test dwelling.

9.4.3 Voltage drop histogram

Looking now at the relative proportions of voltage drop over the week, the model slightly underestimates the voltage drop: this can clearly be seen in the histogram presented in Fig. 75. The model is generating results where smaller voltage drops (up to 2 V), occur more frequently than in the measured data. However, to put this in context, the voltage drop levels are only a small proportion of the phase voltage.

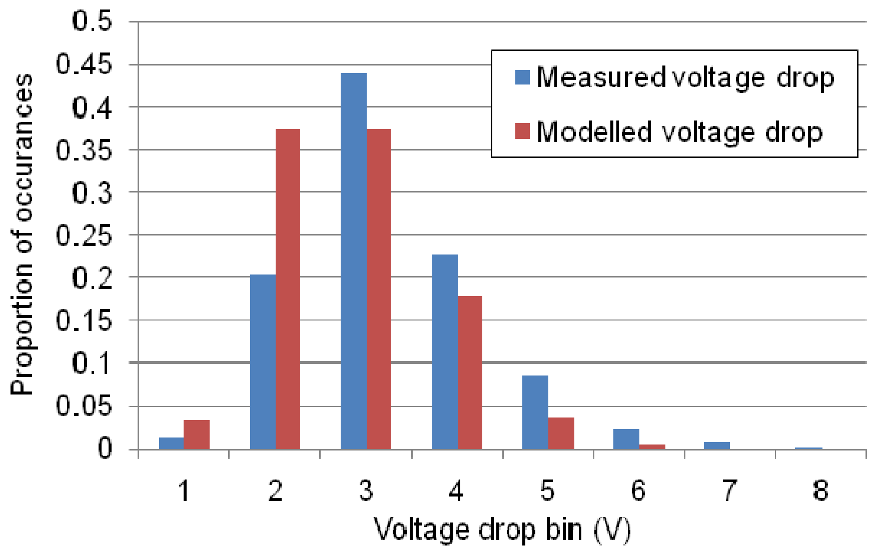
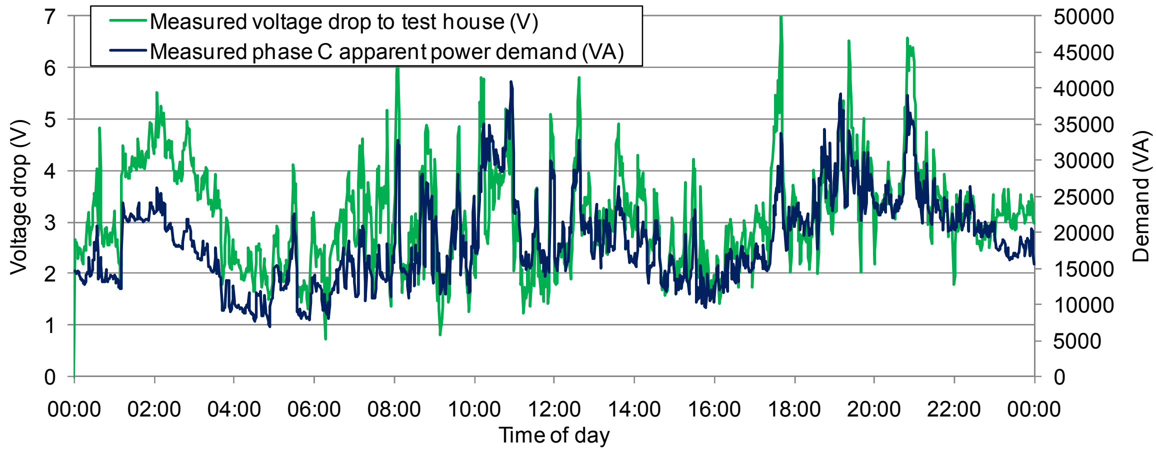


Fig. 75. Voltage drop histogram

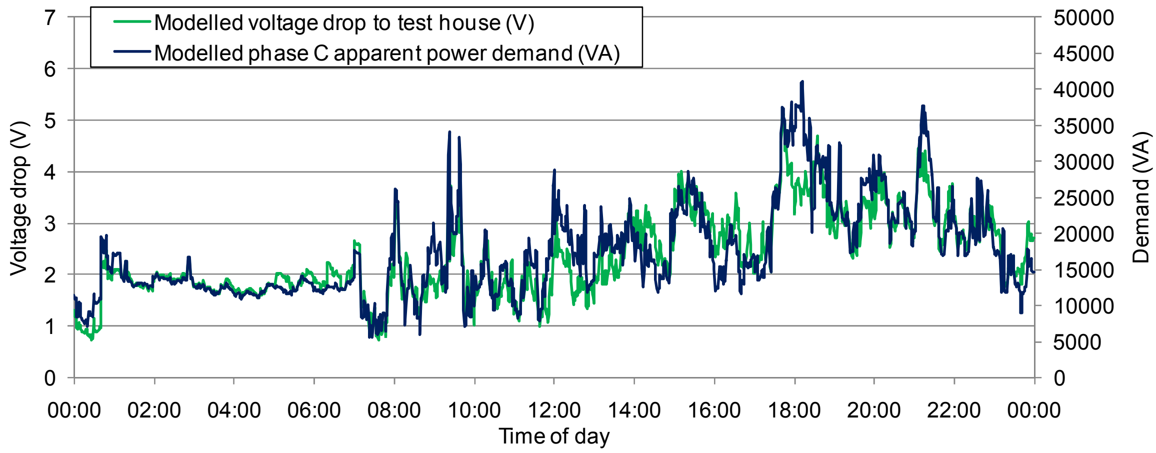
As was previously discussed, the model has limited input data for the actual dwellings served by this circuit. One factor, which will affect the voltage drops, is the relative distribution of demand along the circuit. Some dwellings may have large demands and others may have small demands. Where these different dwellings connect to the circuit will affect the mean voltage drop. It is quite possible that in reality, there are dwellings at the distant ends of the circuit that result in the greater measured voltage drop, although it is not possible to verify this with the available data.

9.4.4 Voltage drop and relationship to demand

A correlation between the demand on a particular phase and the voltage drop is anticipated. The voltage drop is plotted against the apparent power demand for both measured and modelled cases, and the results are shown in Fig. 76.



(a) Measured on 19th September, 2009.



(b) Modelled

Fig. 76. Comparison of single phase demand and voltage drop

Note that it is not appropriate to compare the measured and modelled voltage drops directly together over time: the stochastically generated synthetic demand data will not match the measured demand on a minute to minute basis, as in Fig. 76(a) and Fig. 76(b) respectively. There is, however, a correlation between the voltage drop and the demand in both cases.

The correlation is not perfect in either case, as the voltage drop will depend upon the distribution of demand along the circuit. For example, a large demand located next to the substation will result in a lower voltage drop, than a distant demand of the same magnitude. The measured data shows significant voltage drops between 01:00 and 04:00, perhaps as the results of a large load, such as an electric storage heating system, distant from the substation.

9.5 Summary

In summary, the model output compares very well with the measured data. The comparison is good in both aggregate demand, taking into account the network losses, and the voltage drops that occur along the circuit. The output of the model is considered particularly good, given that nothing is known about the actual individual demands and behaviours of the residents in the dwellings in the measured area.

10. USE OF THE INTEGRATED MODEL

10.1 Data post-processing and visualisation

Referring back to the structure of the integrated model presented in Fig. 59 in Chapter 7, post-processing the raw simulation output of the model, allows for many possibilities in terms of visualising the operation of the network. This output of the model enables the user to observe voltages and currents, with both geospatial distribution, as well as, over high-resolution time series. Such visualisation would not be possible with simple models.

This chapter shows how the integrated model is used to explore cable loading, voltages and losses in the low voltage network.

10.2 Geospatial current representation

A diagram showing the simulated geospatial cable loading on 19th September, 2009 at 00:00, for the test circuit is shown in Fig. 77. The width of the green line representing the cable is proportional to the current and the blue dots again represent the location of the consumers. As would be expected, the cables nearer the secondary substation are more heavily loaded, where a thick line is evident. The further away from the substation, the less current is carried.

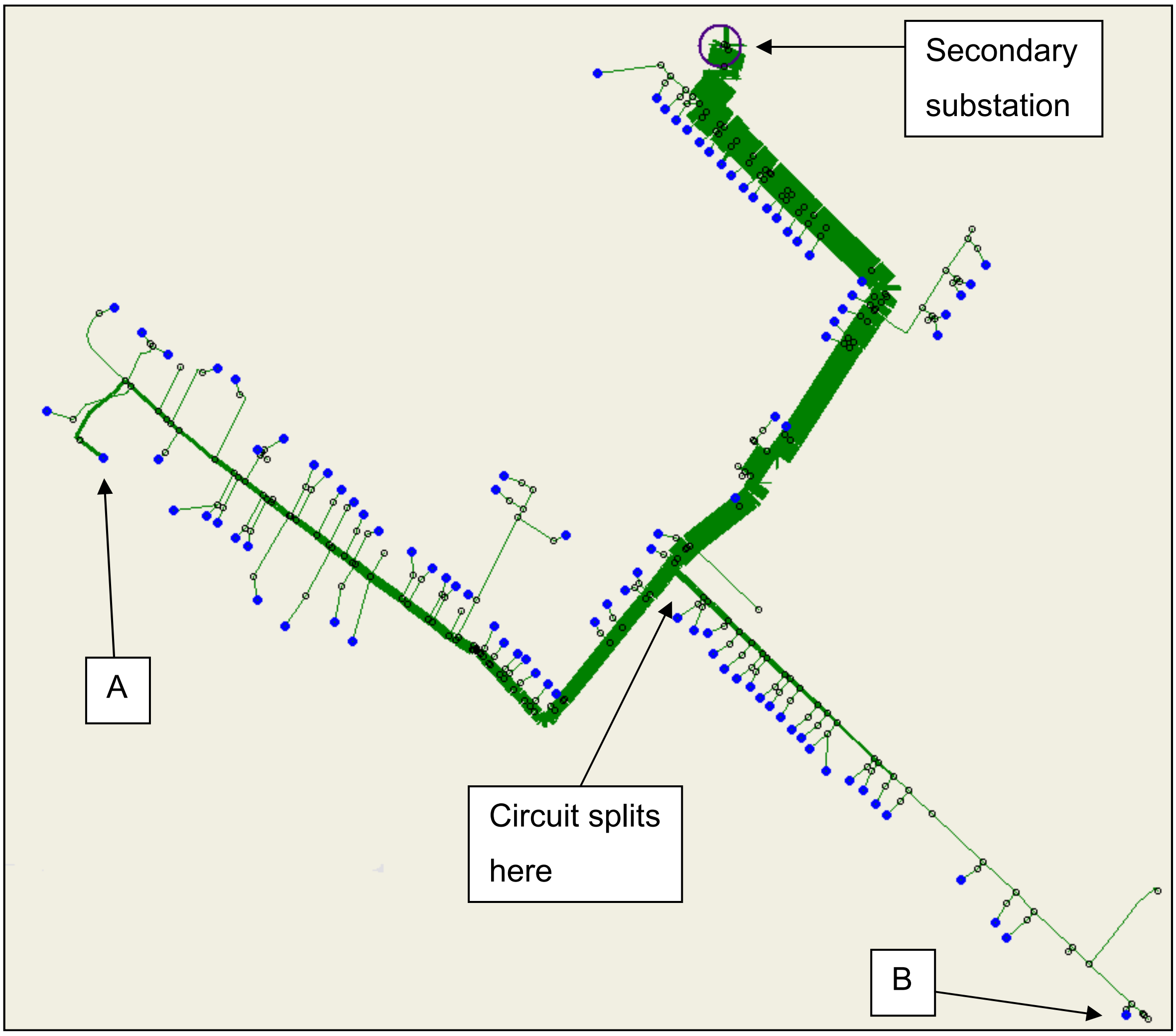


Fig. 77. Modelled low voltage network current at 00:00

Again referring to Fig. 77, it is interesting to note that the individual service cables are generally lightly loaded at this point in time. The dwelling to the left of the figure marked with the letter 'A' is seen to have a greater demand than the other dwellings at this time. As a stochastic simulation, this particular dwelling has been allocated a 3 kW immersion heater by the demand model: at this point in time, it is in use. This illustrates that the model does capture the random nature of the real world.

10.3 Current flow of a circuit route over a time-stepped series

The previous visualisation, shown in Fig. 77, presented the current loading conditions at a single point in time.

The next visualisation, shown in Fig. 78, adds a time dimension and replaces the geospatial layout by a cable distance from the secondary substation. In this case, this represents the distance along the circuit route formed by the cables from the secondary substation to the dwelling marked ‘B’ in Fig. 77. For clarity, only the current flowing in phase conductor A is shown.

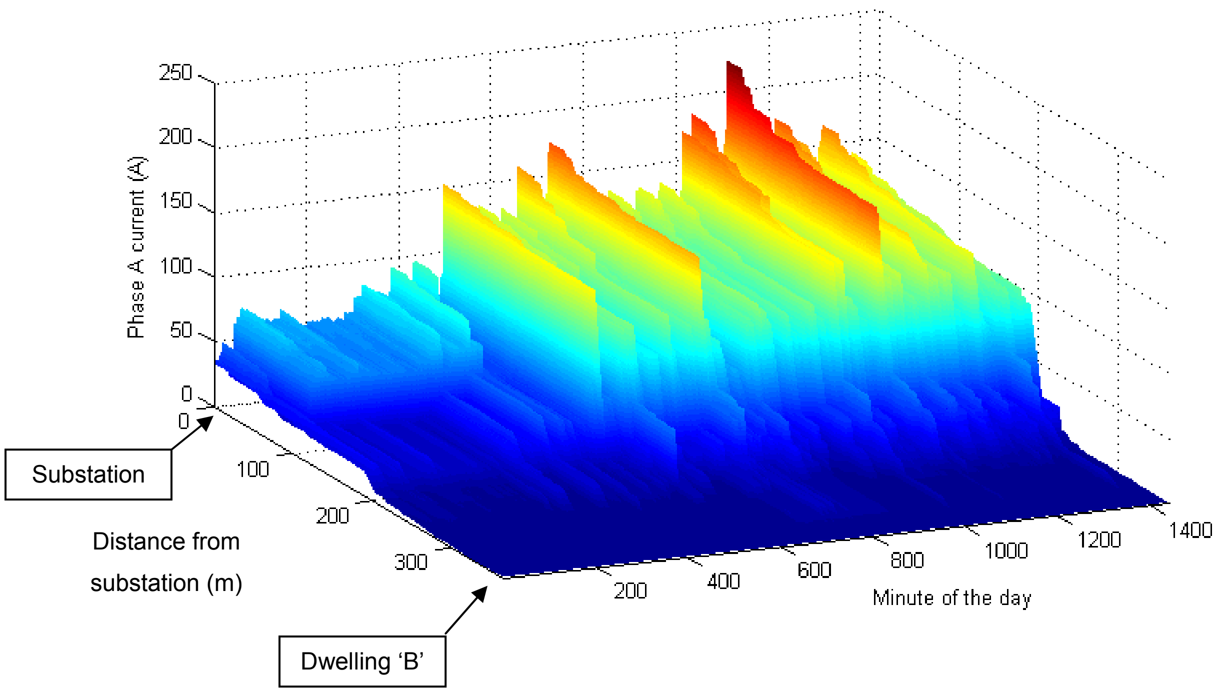


Fig. 78. Modelled phase A current over one day at one-minute resolution

With reference to Fig. 78, the current at night can be seen to be relatively low. A sudden drop can be seen at approximately 200 m along the cable length through the day. This ridge represents the point at which the circuit splits to feed two separate streets (referring back to Fig. 77). The current infrequently exceeds 150 A, which is well within the rating of 290 A. Peaks can be seen to occur: the highest is seen to be in the early evening, coincident with the time of peak domestic demand.

A significant benefit of using stochastic models over a time stepped series, is that it is possible to estimate the probability of different cable loading conditions, occurring at each time step: this is considered next. It is important to note that a conventional calculation, based on a peak demand, would yield only a single figure.

10.4 Cable loading probability density visualisation

A histogram is a useful way of visualising the cable loading. For example, Fig. 79 shows the modelled cable loading of the cable at a point adjacent to the substation.

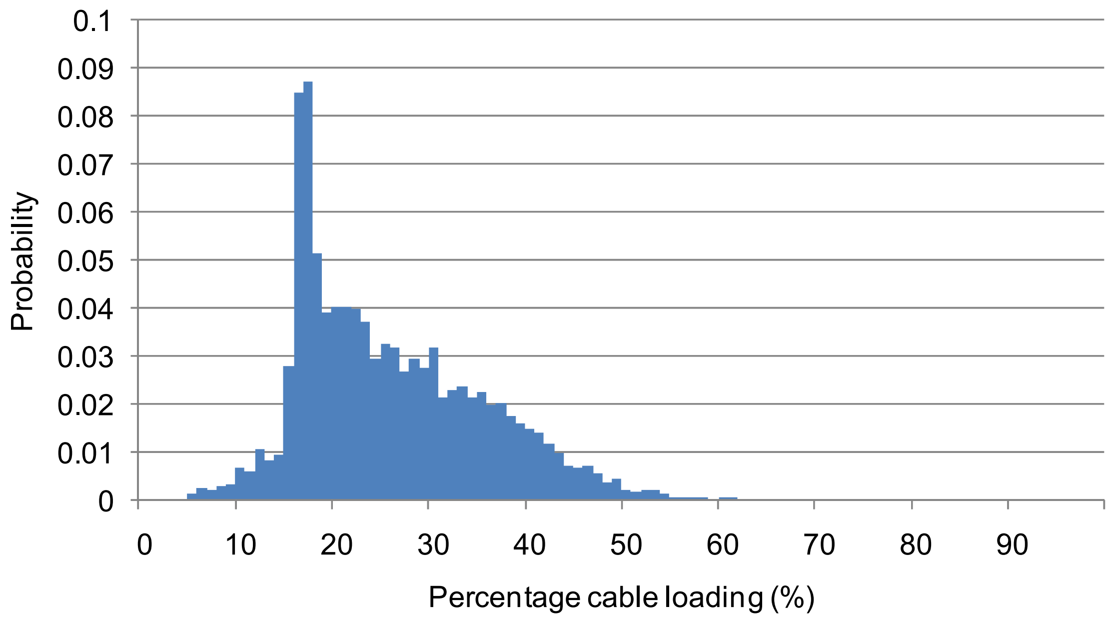


Fig. 79. Modelled cable loading histogram (adjacent to substation)

At this location in the circuit, the loading is rarely less than 10% or great that 50% of its rating.

The integrated model outputs data for the whole circuit, and therefore it is possible to see the cable loading all the way along from its beginning, to the end of the cable, which is considered next.

The dimension of distance is added in Fig. 80, which shows a probability density plot representing the simulated phase A cable loading conditions over one-week. The figure represents the same route through the circuit, from the secondary substation to dwelling ‘B’. In this figure, each vertical cross-section represents a histogram like the one seen before in Fig. 79. The more common loading conditions are indicated by a darker colour.

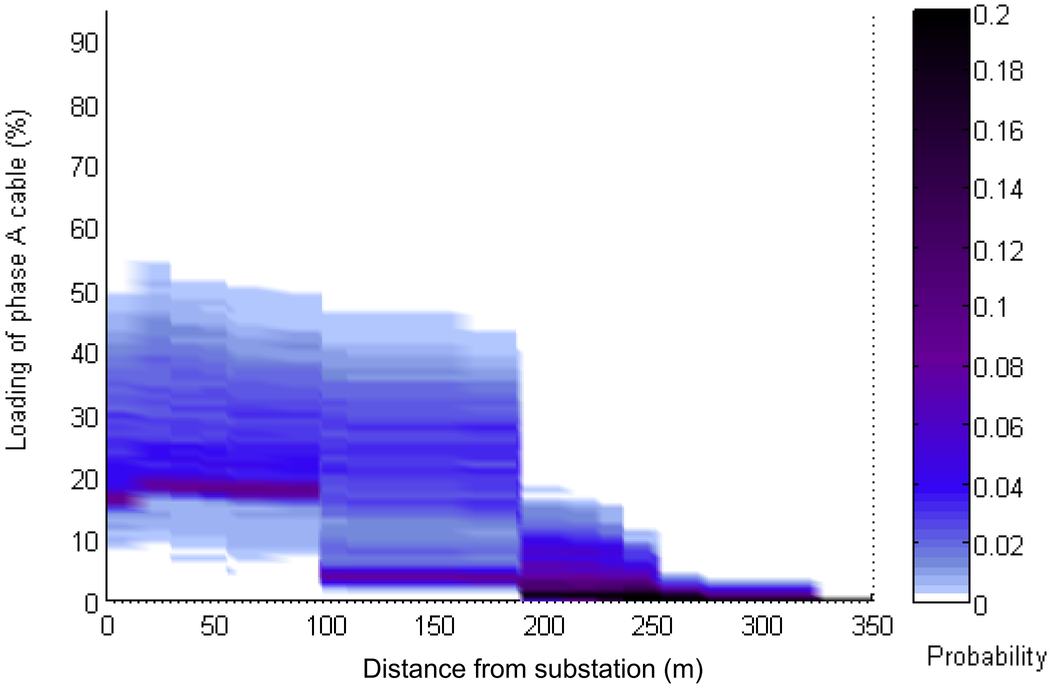


Fig. 80. Modelled cable loading probability density

It is immediately apparent from the graph that the cable rarely experiences greater than 50% of its rating in the first 200 metres. Beyond that distance, rarely is the loading above 20%. The most distant section of cable does not exceed 5% of its rating.

The loading on the cable beyond 190 metres is considerably less and a big drop can be seen in the figure at this point. This is the result of the split in the circuit (that can be seen in the middle of Fig. 77).

The first 20 metres of cable from the substation in this circuit has a 335 A rating, whereas the rating is 290 A elsewhere. The loading is seen to be slightly lower in this region.

The other steps that can be seen are due to large loads within dwellings at these points along the cable. Electric storage heaters and electric stored water heaters, in particular, are the cause of these changes in the loading. It is possible to look into the detailed output of the demand model, to identify which individual appliances were switched on.

The voltage variations that occur along the cable are considered next in the following section.

10.5 Voltage drop profiles

As was discussed in the introduction, standards require that the voltage remains in the range from 216 V to 253 V (230 V +10% -6%). It is useful to see the voltage drops that occur, with respect to the source voltage at the secondary substation. Looking only at the voltage drops excludes the voltage variations on the 11 kV feeder.

The model is used to calculate the voltage drop along the same circuit, as has been discussed previously, from the secondary substation to dwelling 'B' in Fig. 77. A visual representation of the phase A voltage drop at a one-minute resolution over the period of a day, is shown in Fig. 81.

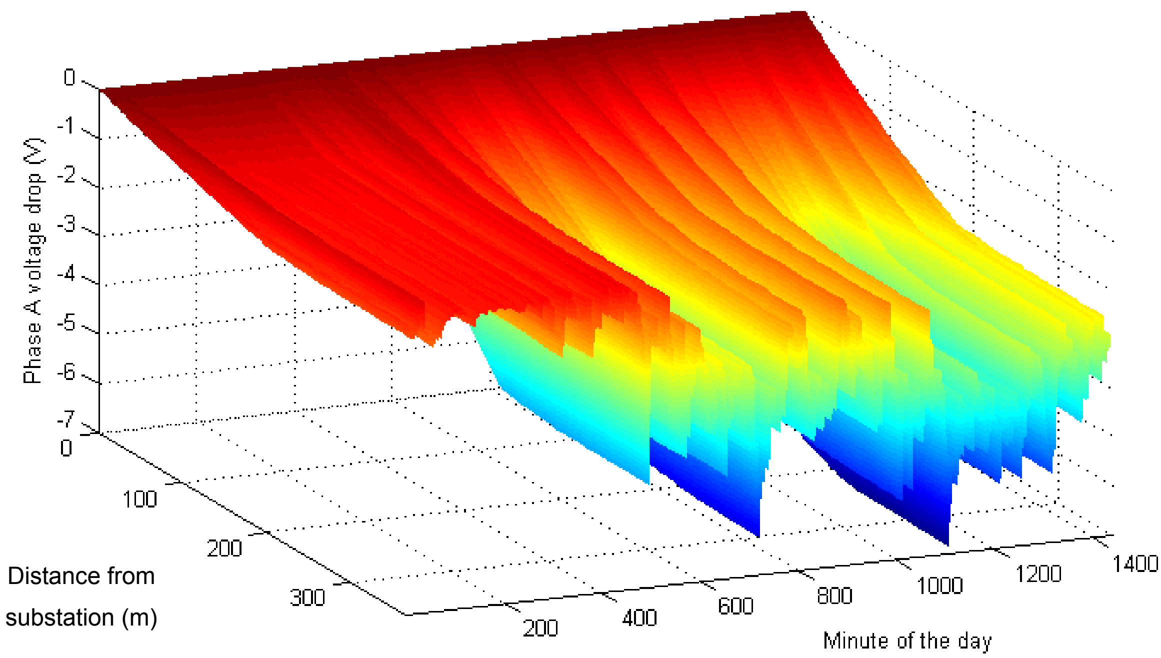


Fig. 81. Modelled voltage drop by distance and time

The voltage drop at the secondary substation is zero by definition. The greatest voltage drop occurs at the most distant point from the substation. The maximum drop seen is approximately -7 V, during the evening peak demand. To put this in context, the range of acceptable voltages is 253 – 216 = 37 V. It is interesting to observe that the 7 V drop seen in this simulation, is a significant slice of this acceptable range: particularly, as this is a relatively short circuit within a densely populated urban area. With a longer cable, say in a rural area, the slice of this range would be even greater.

The stochastic high-resolution simulation enables visualisation of the likelihood of different voltages, at different distances along the cable. A density plot of the phase A voltage is shown in Fig. 82. The darker the colour, the greater the likelihood of a particular voltage, at each point along the cable.

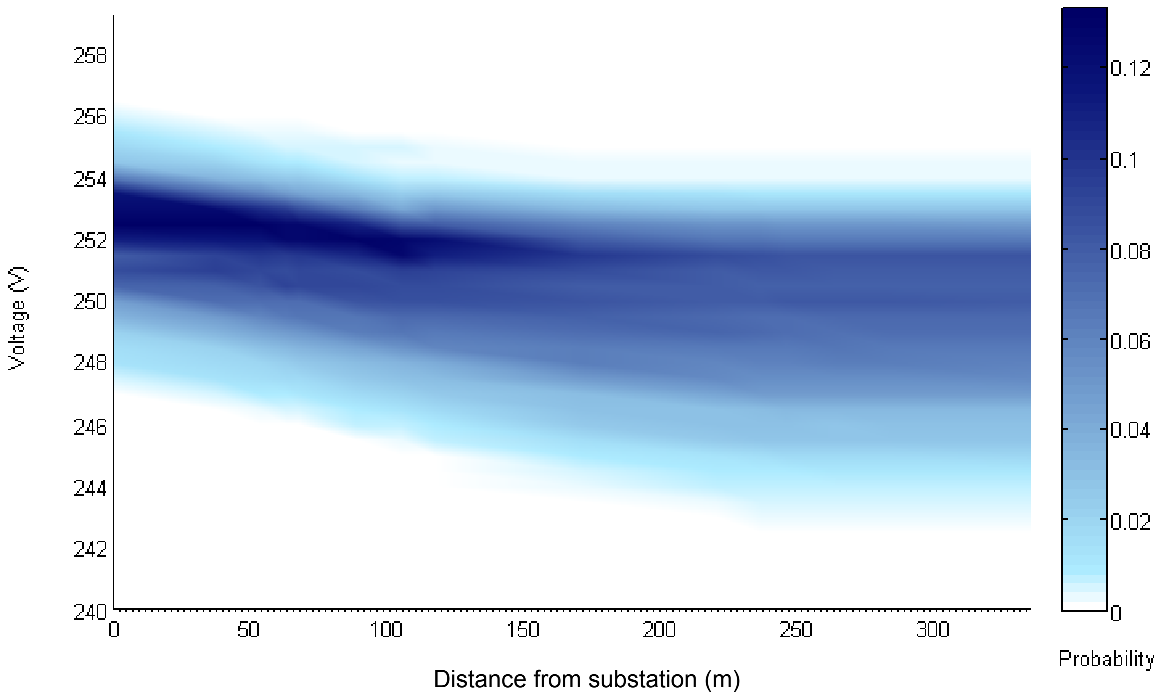


Fig. 82. Voltage drop probability density plot

To the left of Fig. 82, at the secondary substation, the voltage is commonly within the 252 V to 254 V range, although it does vary between 247 V and 256 V: the spread here is wide to begin with. As the distance from the substation increases, the voltage level falls and has an even greater spread. The voltage does not fall below 243 V, showing that this circuit is well above the nominal level of 230 V.

In terms of the voltage standards, the voltage is on the high side: the implications of this are that the connection of micro-generation would increase the likelihood of over voltage conditions. Similarly, connection of electric vehicles could significantly widen the spread of voltages.

10.6 Comparison with half-hourly data

A histogram is shown in Fig. 83 representing the spread of voltages seen at dwelling ‘B’ at the end of the circuit, for both one-minute and half-hourly data.

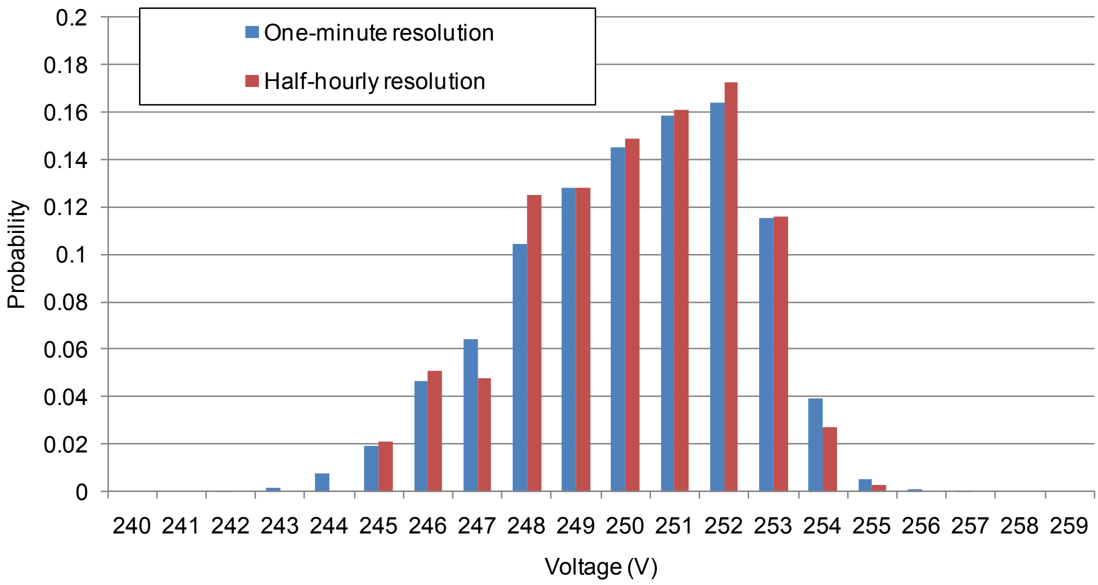


Fig. 83. Comparison of one-minute and half-hourly voltages

It is interesting to note that at a half-hourly resolution, there is not generally a significant difference, when compared to the one-minute data. However, it is noted that the standard deviation of the voltages at a one-minute resolution is slightly greater, as can be seen by the occassional lower values of 243 V and 244 V, and higher numbers of peak voltages over 253 V (i.e. more over voltage conditions are seen to occur with a one-minute resolution). The difference between the two resolutions was not as great as was anticipated.

10.7 Cable losses

The cable losses over the whole low voltage circuit, serving 100 consumers, are calculated, and the results are shown over the course of a week in Fig. 84.

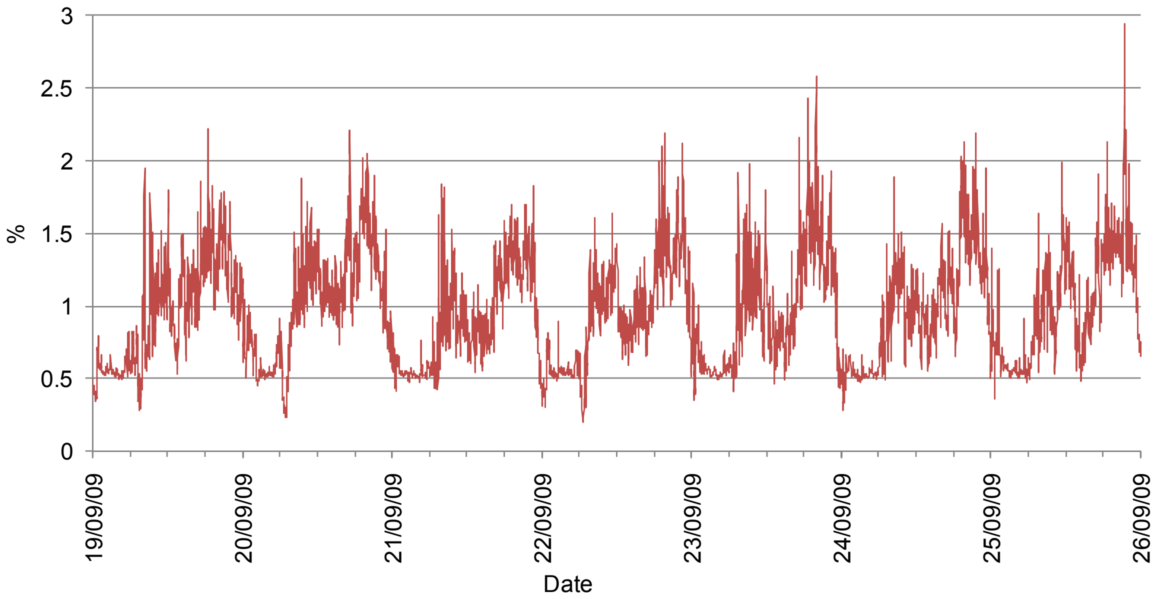


Fig. 84. Modelled losses

The average loss over the course of the week is 0.96 %. The peak loss seen over this period is 3%. In terms of energy, the losses in the circuit amount to 95 kWh over one week, which in a simplistic extrapolation, based on this simulation in a September shoulder month, would amount to 4930 kWh/year.

This value compares well with data published elsewhere. Ofgem provides figures for annual losses within distribution networks [135]. For the East Midlands area, a loss of 4.9% across the whole distribution network is given. However, it is necessary to take into account only technical losses from the low voltage part of the network. An estimate of the proportion of these losses, within a low voltage distribution network, is given by Shaw et al. [136] at 28%. Therefore, 28% of 4.9% results in a total anticipated loss of 1.4%. This is close to the value found in the simulation above. The next section considers the case for cable reinforcement in this circuit, in order to reduce these losses.

10.8 Network reinforcement

Given that losses are proportional to the square of the current, it follows that that the majority of losses occur nearer the substation. This is to be expected, since it is these parts of the circuit that carry the most current, as was seen earlier in Fig. 78.

With the aim of finding out if network reinforcement would be worthwhile in the test circuit; the replacement of the first 100 m of cable with higher specification 300 mm^2 copper cable was simulated using the integrated model.

In annual terms, it was found that this reduced losses to 3276 kWh/year (instead of 4930 kWh). However, a saving of 1654 kWh/year is little justification for digging up a considerable section of street, and it is clear that there would be little economic case for doing so: particularly given that the cables are already underutilised, as was discussed earlier.

10.9 Summary

This chapter presented how the close integration of the demand and network models, enables detailed visualisation of the operation of networks: the model provides the capability to shed considerable light on network utilisation, as well as, performance with respect to voltage constraints.

The electricity distribution industry is concerned with the capability of existing networks to cope with the integration of low-carbon technologies, such as electric vehicles and heat pumps. The visualisation that has been shown in this chapter is a way of providing far greater insight into network operation, than has been available with conventional methods.

11. CONCLUSIONS

11.1 Drivers of domestic electricity use

The number of residents at a dwelling, specifically their active occupancy, was observed to be a major factor in electricity use: this was expressed in the literature discussed in Chapter 2 and validated with measured data in Chapter 3.

For large numbers of dwellings, and by using the UK 2000 TUS data set, it was shown that there is a strong similarity between the shape of the mean annual demand profile, and the mean active occupancy profile.

Within an individual dwelling, by taking measurements of electricity demand and active occupancy, a clear correlation was observed between the times of active occupancy and the times of electricity use.

It was also concluded from the data gathered, as presented in Chapter 3, that floor area is not a good basis upon which to estimate electricity use. This is relevant to the BREDEM-8 model which uses floor area as a main input variable.

11.2 Using stochastic methods to model domestic occupancy

Realistic active occupancy patterns may be generated in a stochastic simulation. This was performed by using a Markov-Chain technique, through the calculation of transition probability matrices, from the UK 2000 TUS data set: a novel application of this method. It is a computationally efficient method, and the model of domestic occupancy described in Chapter 4, was confirmed to output data with the same statistical characteristics as that of the original survey data.

11.3 High-resolution domestic lighting demand modelling

The use of individual lighting units, within a domestic dwelling, can be effectively simulated using a bottom-up stochastic modelling approach.

A high-resolution model of domestic lighting demand was constructed and validated, as described in Chapter 5. The model works well: in particular, when simulating many dwellings together, the lighting demand aggregates appropriately.

Two time-varying input factors, representing active occupancy and natural light level, were found to be a good basis for modelling lighting demand. Using natural light level as an input, takes seasonality into account.

An important strength of the model is that changes in lighting technologies can be taken in account: the model may be configured as required. This would not be possible using less granular models, or those based upon aggregate lighting data alone.

11.4 Aggregated whole-dwelling demand

The whole-dwelling high-resolution aggregated demand from domestic appliances, may be simulated by modelling using a bottom-up approach, in conjunction with stochastic methods. In reaching this conclusion, a whole-dwelling electricity demand model was constructed, and shown to output data with the appropriate statistical characteristics.

The model was built using UK statistics on appliance ownership and electricity demand. It was successfully validated by comparing the output against the measured electricity demand data described in Chapter 3. The quantitative comparisons included time-coincidence of demand, minute-to-minute volatility, mean daily demand profiles, seasonal variation, ADMD and power factors.

The use of activity profiles was found to be an effective way of modelling the use of different types of appliances, at different times of the day. This was achieved by linking the activities that an occupant may be performing, and the appliances that they use in performing that activity.

11.5 Integrated demand and network modelling

An integrated demand and network model was constructed: the model works and is validated against measured network data. The modelling is both high-resolution, in its time stepped simulation capability, as well as, detailed, in its representation of the low voltage distribution network and domestic electricity consumers.

11.6 Insight into the operation of low voltage networks

The integrated modelling approach enables a new level of detailed visualisation of the operation of the low voltage networks, over conventional methods. Given the need to maximise the utilisation of existing networks, as low-carbon domestic technologies become more common, this visualisation has great potential for supporting the network design process. When considering, both cable capacity and voltage limits, it is important that network designers have the appropriate tools. The integrated approach presented in this thesis can thereby facilitate the uptake of such technologies: this visualisation facilitates the making of network design decisions with greater confidence, such that the deployment of low-carbon technologies is not unnecessarily constrained.

11.7 Contribution of this Research

11.7.1 Provision of freely downloadable models

The occupancy, lighting and whole house electricity demand models, described in this thesis, were developed in the C# software language. Despite their sophistication, the model implementations were migrated to VBA, within Microsoft Excel, to make them convenient for others to use.

In the existing literature, regarding electricity demand modelling, some papers provide all the information needed to build the model, whilst others are lacking in this respect and the reader is left to gather their own data. In either case, it is usually a time consuming activity to re-construct any model in software, from the text of an article, and verify the output.

In contrast, this research has provided self-contained working examples that may be downloaded and used immediately, or configured, or integrated with other models. At the time of writing, these example models have been downloaded in excess of 350 times [7,8,9]. The models have been used elsewhere [22].

11.7.2 Availability of measured electricity use data

As was mentioned in Section III at the start of the thesis, the one-minute domestic meter data (collected as described in Chapter 3) has been accepted by and uploaded to the UK Data Archive (hosted by the University of Essex).

11.7.3 Citations of this research in parallel work

The papers describing the occupancy and lighting models, published in Energy and Buildings, have been cited in other research as was detailed in section III at the beginning of this thesis (13 citations at the time of writing).

11.8 Potential for further work

Possible areas for further work are summarised in Table 11.

Potential	Comments / benefits
Study active network management.	Since the model presented in this thesis includes the simulation of both high-resolution demand and network operation, it would be possible to model active network management.
Modelling of flexible demand.	The demand model could be utilised to simulate demand flexibility. This could be achieved by adding control parameters to the appliance switch-on probability calculations. This would require the "dynamic feedback" loop, shown in Fig. 59, to be implemented.
Refinement and improvement of the electricity demand model.	Although the demand model has been shown to simulate whole house electricity use in a realistic fashion, there are refinements that could be made, in particular, in support of the modelling of flexible demand. It is noted that many of these are constrained by the availability of statistical data, but nevertheless include: • Improved linking of occupant activities and the appliances that are used during these activities, and the correlations of ownership and use of different appliances. Bringing such behavioural aspects into the model would be considered highly beneficial. • Refine the model to account for different socio-economic profiles in different localised areas.
Inclusion of a thermal model of dwellings in the demand model.	Thermal modelling would enable improved modelling of electric heating, including night storage and other forms of direct electric heating, as well as, heat pumps and μCHP.
Model non-domestic demand, thereby extending the capability of the model to include 11 kV feeders.	It would be useful for distribution network studies to expand the modelling of domestic electricity demand into industrial, public-sector buildings, commercial buildings and others. This would enable the high-resolution modelling of demand on 11 kV feeders.
Real-time network visualisation.	The integration of real-time data from smart meters would enable the capability to visualise distribution network operation in real-time.

Table 11 - Potential areas for further work

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Appendix A

Ian Richardson, Murray Thomson, David Infield,

A high-resolution domestic building occupancy model

for energy demand simulations

Energy and Buildings 40 (8) (2008) 1560-1566

http://dx.doi.org/10.1016/j.enbuild.2008.02.006

Appendix B

Ian Richardson, Murray Thomson, David Infield, Alice Delahunty,

Domestic lighting: A high-resolution energy demand model

Energy and Buildings 41 (7) (2009) 781-789

http://dx.doi.org/10.1016/j.enbuild.2009.02.010

Appendix C

Ian Richardson, Murray Thomson, David Infield, Conor Clifford,

Domestic electricity use: A high-resolution energy demand model

Energy and Buildings 42 (10) (2010) 1878-1887

http://dx.doi.org/10.1016/j.enbuild.2010.05.023

Appendix D

Ian Richardson, Murray Thomson, David Infield, Alice Delahunty,

A Modelling Framework for the Study of Highly Distributed Power Systems and Demand Side Management

Proceedings of the 1st International Conference on Sustainable Power Generation and Supply (SUPERGEN), Nanjing, China, 6-7th April, 2009.
http://dx.doi.org/10.1109/SUPERGEN.2009.5348274

Appendix E

Ian Richardson, Graeme Hodgson, Murray Thomson, David Infield, Alice Delahunty,

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

The 5th International Conference on Energy Efficiency in Domestic Appliances and Lighting (EEDAL), Berlin, June 16th-18th, 2009.

http://hdl.handle.net/2134/4972

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.

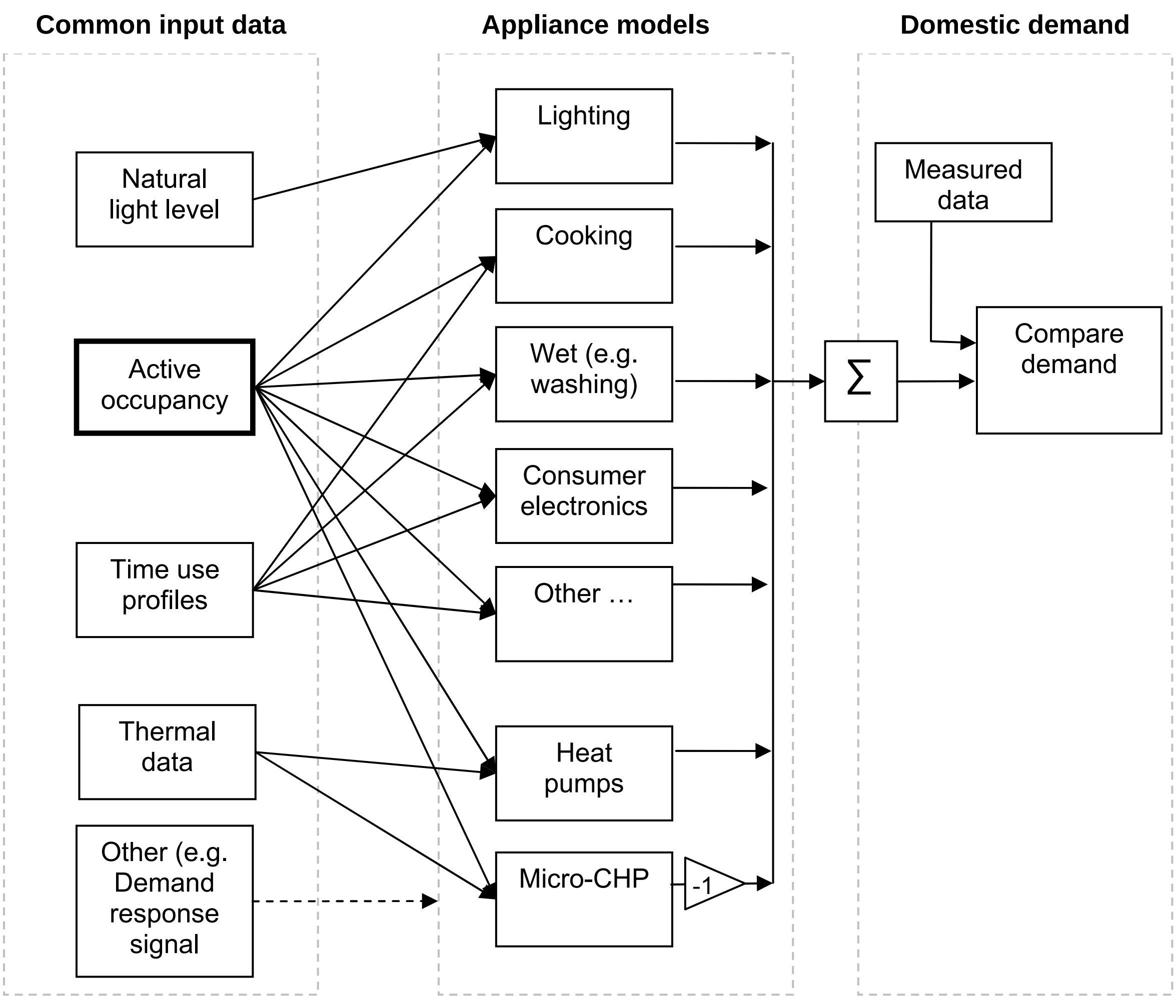


Fig. 1. Architecture of the integrated appliance model

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.

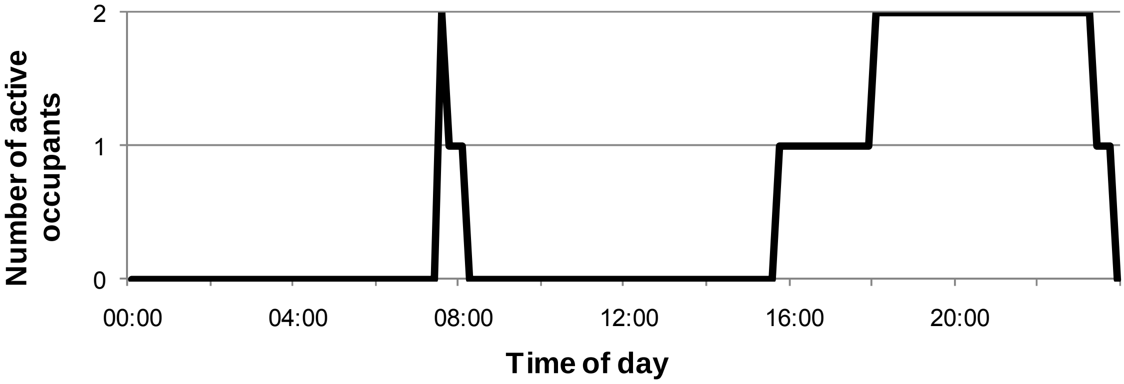
Thirdly, being able to apply stochastically generated occupancy patterns to a large number of dwellings allows for appropriate diversity in energy demand between dwellings over time.

Model Implementation

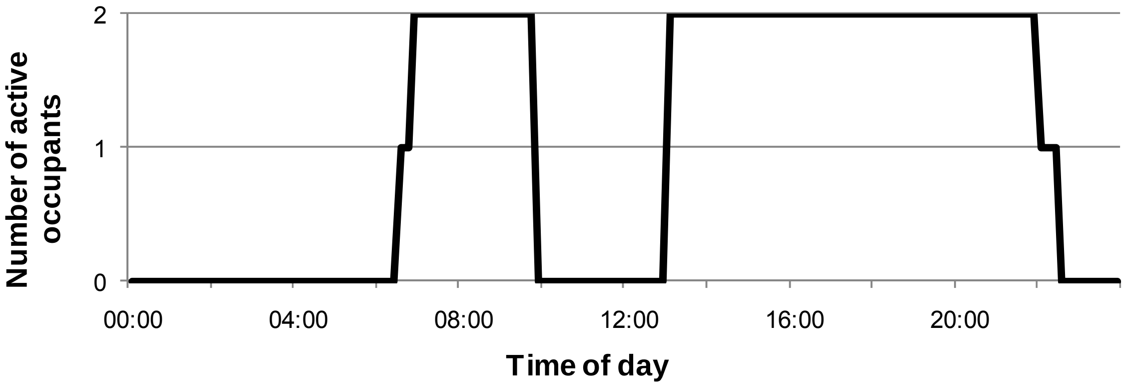
The occupancy model uses the data captured in diaries from the United Kingdom 2000 Time Use Survey (TUS) [9] as a basis for a stochastic simulation of occupancy. This data in the survey contains information on the location and activities the occupants were undertaking during the survey at a ten-minute 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.

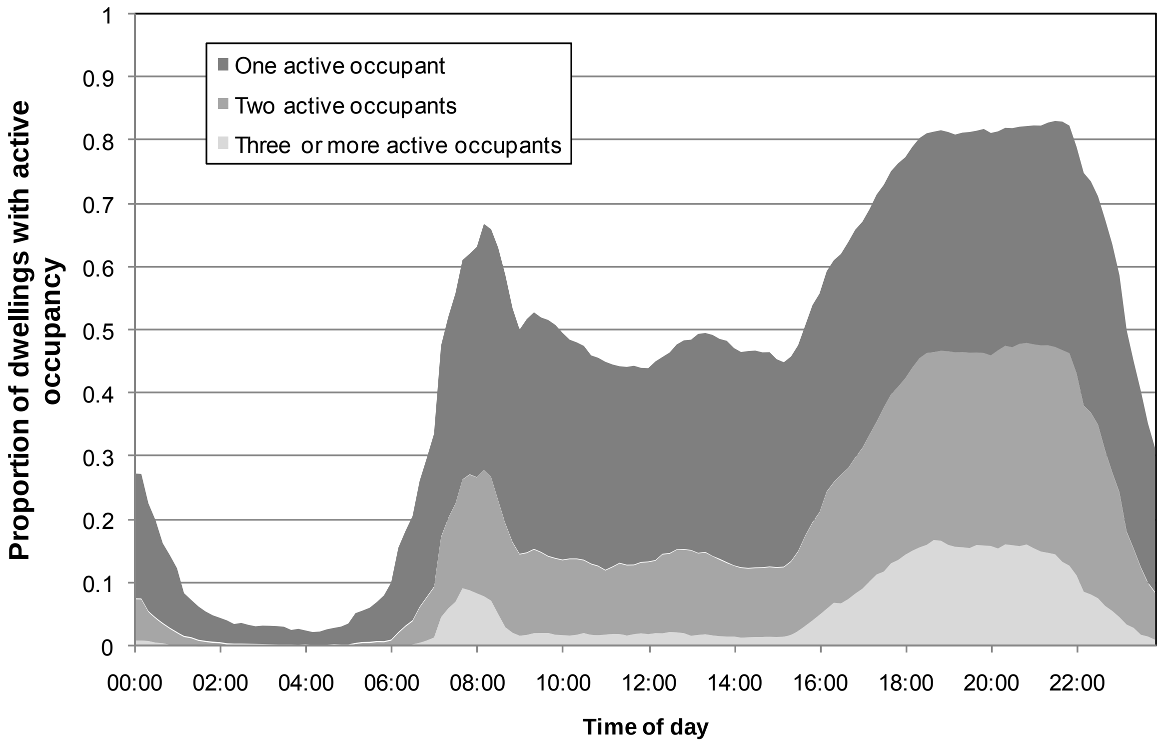


Fig. 3. Simulation results of the proportion of houses with different level of weekday active occupancy, over one day (from a pool of 1000 houses, averaged over one year)

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.

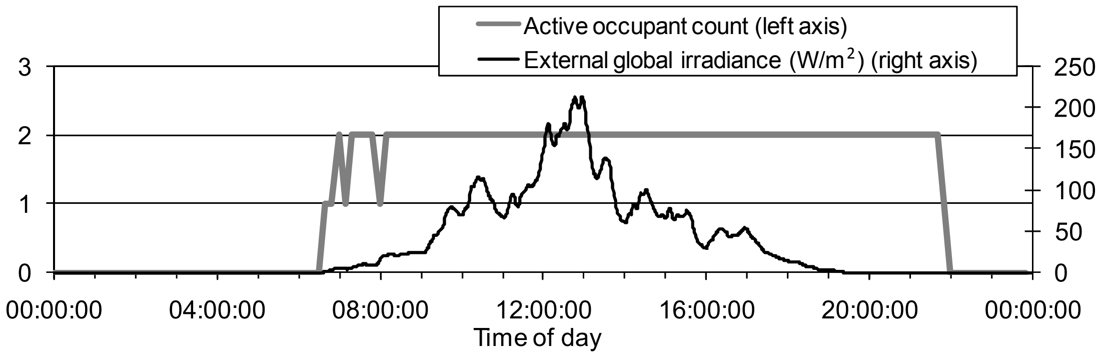
An Integrated Appliance Model

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].

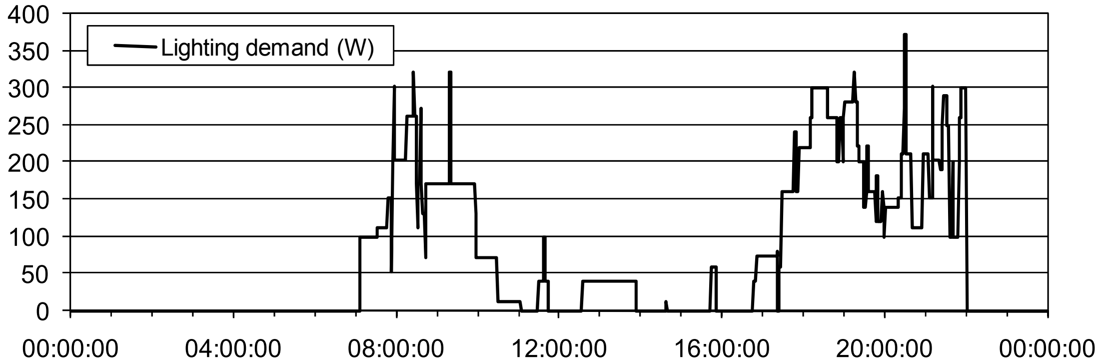
A Model of Domestic Lighting Use

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.

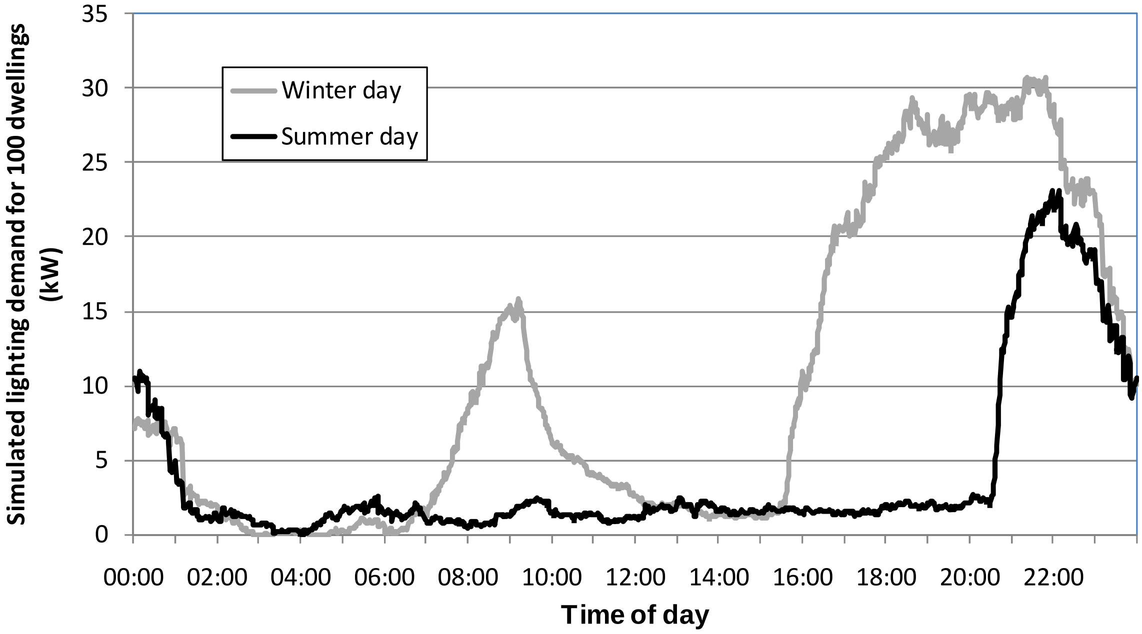


Fig. 5. Simulated aggregated lighting demand (100 dwellings) for winter and summer days

Extending the Model into an Integrated Dwelling Appliance Model

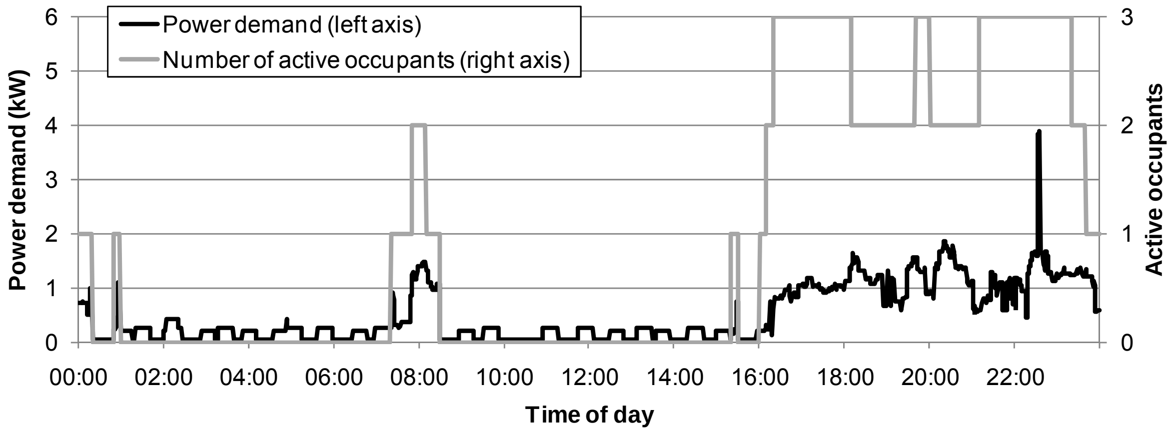
The authors are currently in the process of extending the model to provide a fully integrated domestic appliance energy demand model. Utilising the same common active occupancy data for a dwelling, an integrated appliance model can be constructed. Whereas lighting use was determined as depending upon 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.

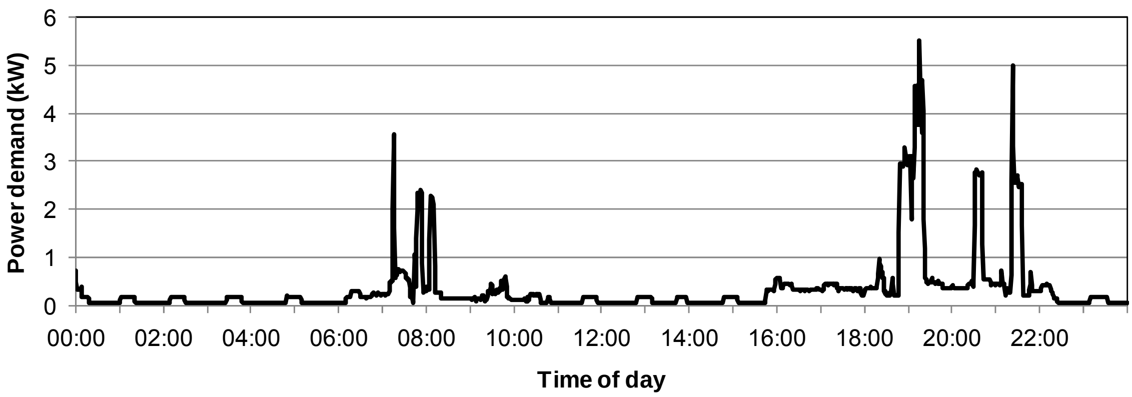
Prior to a simulation, each house is configured with a set of appliances, similar to that of the configuration of the number and types of bulbs within the lighting model. At each time step in the simulation, appliance start events are stochastically determined. When an appliance is used, its power demand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

Ian Richardson, Murray Thomson,

Highly distributed power systems:

Distribution network modelling and demand simulation

(Conference Poster)

Presented at the poster session at:

The Universitas 21 International Conference in Energy Technologies and Policy

7th-10th September, 2008, University of Birmingham, United Kingdom.

http://hdl.handle.net/2134/5103

Highly distributed power systems: Distribution network modelling and demand simulation

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motivation

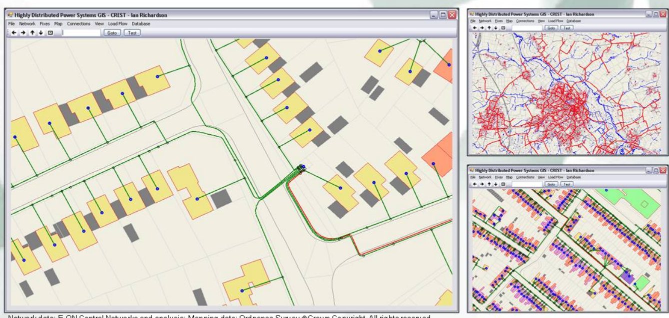
Assessing the impact of domestic micro-generation on the electricity distribution network, requires detailed simulation of the existing networks and the power demands.

This project aims to construct a high-resolution model of an actual distribution network, to include the simulation of the minute-by-minute demands, particularly in residential areas, where high penetrations of micro-generation could be deployed.

The resulting model will provide a platform to assess the implications of highly distributed power systems (HDPS) and to examine the network response to demand side management (DSM) measures.

image source: I Richardson

distribution network modelling



Network data: E.ON Central Networks and analysis; Mapping data: Ordnance Survey ©Crown Copyright. All rights reserved.

The model represents a real 11kV and low voltage distribution network topology, that supplies an area with approximately 35,000 domestic properties, in both urban and rural environments.

A load flow analysis is integrated into the model to calculate the power flows throughout the network.

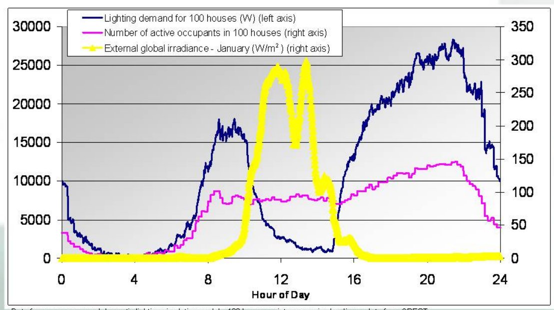
Each individual electrical load on the network (such as a residential dwelling) is represented using Ordnance Survey address point data. A geographical information tool has been built to integrate the network topology and the demand model.

domestic electricity use demand model

A high-resolution domestic electricity demand model has been constructed that simulates individual appliance categories, including lighting, cooking, cooling and wet appliances.

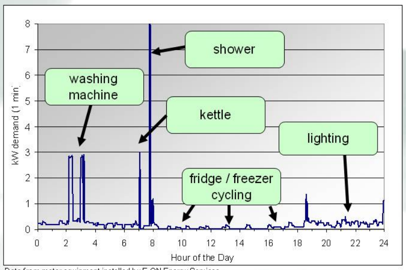
The demand model is based upon the activity of occupants within a dwelling at a given time of the day. In the case of lighting, the model also takes into account the solar irradiance level. The graph shows an example of a single day lighting simulation for 100 houses.

The aggregated demand output for each dwelling will be integrated into the network load flow model to provide a high resolution simulation of the low voltage network.



Data from occupancy and domestic lighting simulation model – 100 houses, winter scenario. Irradiance data from CREST.

validation of the model with measured data



Data from meter equipment installed by E.ON Energy Services.

An energy study is being run in Loughborough to examine domestic electricity usage and to obtain real data.

Statistical electricity meters have been installed into a number of domestic properties through the recruitment of energy study volunteers.

Aggregated demand data is also being captured in a number of distribution substations. The data is being used to validate the demand modelling simulation outputs.

image source: I Richardson

CREST | SUPERGEN Highly Distributed Power Systems Consortium | Loughborough University

This project is supported by E.ON Engineering Ltd and by the Engineering and Physical Sciences Research Council, UK, within the Supergen 3 Highly Distributed Power Systems Consortium.

Appendix G

Loughborough Energy Study Dwelling Characteristics Survey Form

CREST (Centre for Renewable Energy Systems Technology)
GX Office, Garendon Wing, Holywell Park,
Loughborough University,
Loughborough.
LE11 3TU

telephone: 01509 635326
email: I.W.Richardson2@lboro.ac.uk

Date: 2nd January 2009

Loughborough Energy Study –Survey Form

This survey should take less than five minutes to complete and has three parts:

1. General energy use
2. Lighting
3. Appliances

Please complete the survey electronically and return by email, or alternatively, print it out and return by post to Ian Richardson at the address above. The data from this survey will be held in compliance with our Data Protection Policy.

Please enter your unique meter reference number:

(this can be found on your energy summary report): 0000 YOUR UNIQUE METER REFERENCE

Part 1 – General Energy Use

Number of household occupants: ☐

Do you have gas or oil fired central heating?

☐ Yes
☐ No

Do you use gas or oil to heat your water?

☐ Yes – All year
☐ Yes – Just in winter
☐ No

Do you have an electric shower?

☐ Yes
☐ No

Do you regularly use any electric heaters?

☐ Yes – Night storage heaters
☐ Yes – Oil filled radiators, fan, convector or halogen heaters
☐ No

Do you have?

☐ Double glazing
☐ Draft proofing
☐ Loft insulation
☐ Cavity wall insulation

Do you have an Economy 7 electricity tariff?

☐ Yes
☐ No

Do you use timers to run any appliances at night (such as a washing machine)?

☐ Yes
☐ No

Do you generate any of your own electricity (e.g. with grid connected solar panels)?

☐ Yes
☐ No

Part 2 - Lighting

What percentage of your light bulbs are Energy Saving (including fluorescents)?

[ ]

How many halogen bulbs do you have?

[ ]

Do you use an outdoor floodlight (with or without a sensor)?

☐ Yes
☐ No

Part 3 - Appliances

How many of the following appliances do you have? (Please enter a number in each box.)

Cold Appliances

[ ] Refrigerator

[ ] Fridge-freezer

[ ] Upright freezer

[ ] Chest freezer

Consumer Electronics

[ ] Television – CRT (Cathode Ray Tube)

[ ] Television – Plasma screen

[ ] Television – LCD screen

[ ] Computer

Which of the following appliances do you use regularly? (Please tick.)

Cooking

☐ Electric hob
☐ Electric oven
☐ Gas hob
☐ Gas oven

☐ Microwave
☐ Kettle
☐ Sandwich toaster
☐ Toaster
☐ Electric steamer

Washing and Dishes

☐ Dish Washer
☐ Washing Machine
☐ Tumble Dryer
☐ Washer Dryer

Other

☐ Dehumidifier
☐ Air conditioning unit

Thank you for completing this survey.

Appendix H

Loughborough Energy Study Example Electricity Use Report

CREST (Centre for Renewable Energy Systems Technology)
GX Office, Garendon Wing, Holywell Park,
Loughborough University, LE11 3TU

Telephone: 01509 635326 Email: I.W.Richardson2@lboro.ac.uk

Loughborough Energy Study - Your 2008 Electricity Use Results

Part 1: Your Electricity Use During 2008

Survey date range:
01/01/2008 to 31/12/2008

Your Unique Meter Reference

4909

Your annual electricity usage: **2964 kWh/y**

Your peak demand was: 12.1 kW at 21/12/2008 09:25

Number of full days of meter data: 341 from 366 (please refer to the covering letter.)

Part 2: Your Electricity Use Compared to Others in the Survey

There were 22 meters in the study, installed in domestic properties in the area. The following details compare your electricity use to the other meters in the survey.

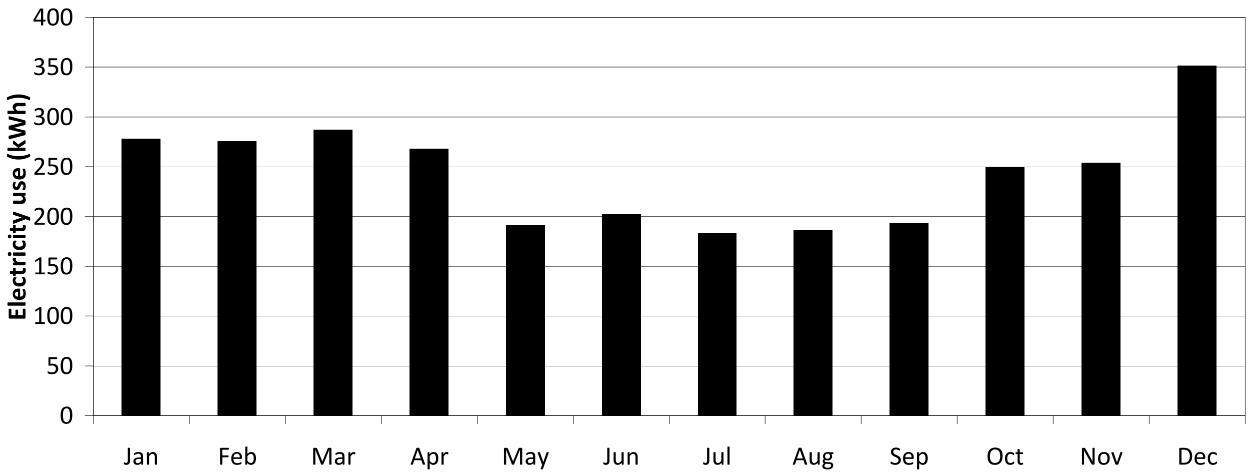
Your electricity use ranking is: **6 / 22** (where 1 represents the lowest energy usage)
The average demand in the survey: 4191 kWh/y (over all 22 meters.)

As a further comparison, according to government statistics, the average annual electricity consumption level in the Charnwood area in 2005 was 4451 kWh/year (1).

(1) BERR, Middle layer super output area (MLSOA) electricity and gas estimates 2005
East Midlands Government Office region

Part 3: Your Monthly Electricity Usage in 2008

Your monthly electricity usage during 2008 is shown in the following graph:

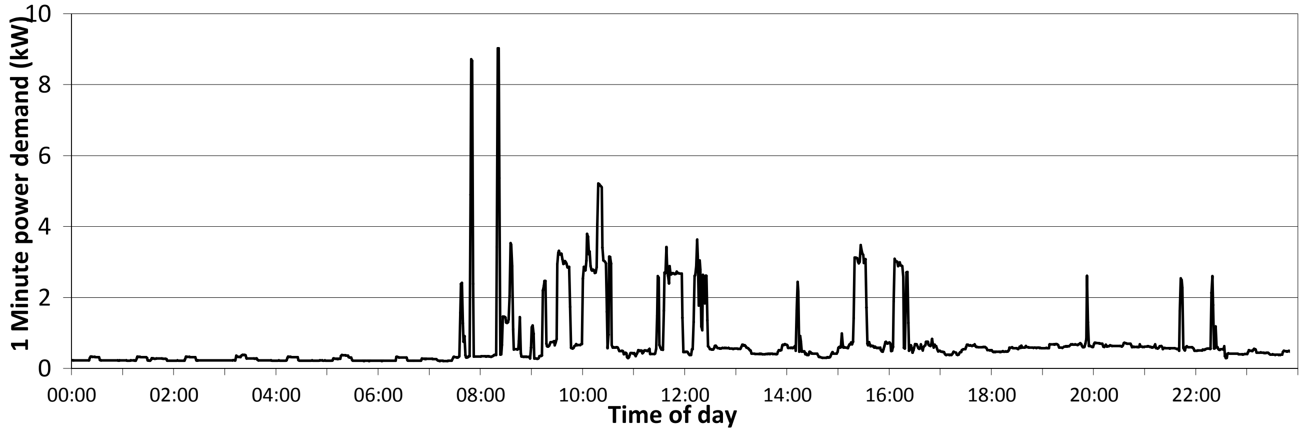


Part 4: Maximum, Average and Minimum Electricity Usage Days

The following three graphs show your electricity use over 24-hours for the maximum, nearest to average and minimum use days. The vertical axis shows the power consumption in kW at a one-minute resolution.

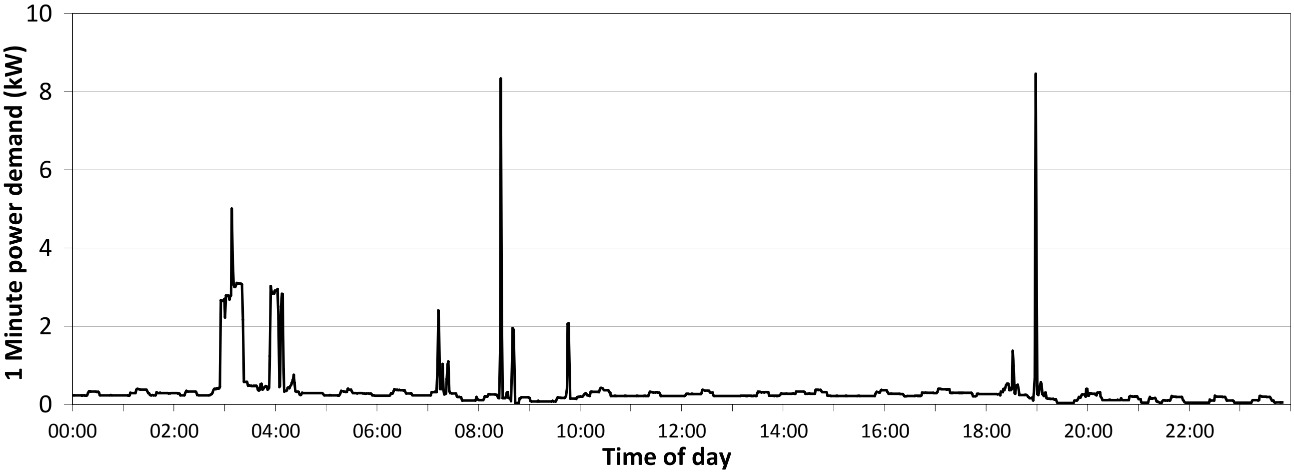
A. DAY OF MAXIMUM ELECTRICITY USE IN 2008

The day when you used the most electricity was on 31/12/2008. You used 17.0 kWh on that day:



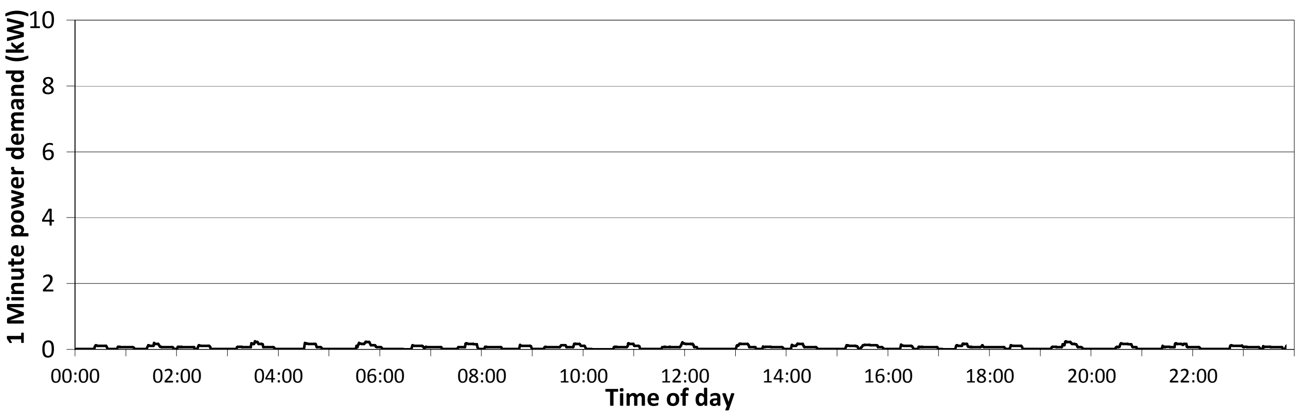
B. AVERAGE DAY IN 2008

The nearest day to your overall daily average demand was on 09/11/2008. You used 8.1 kWh on that day:



C. LOWEST ELECTRICITY USE DAY IN 2008

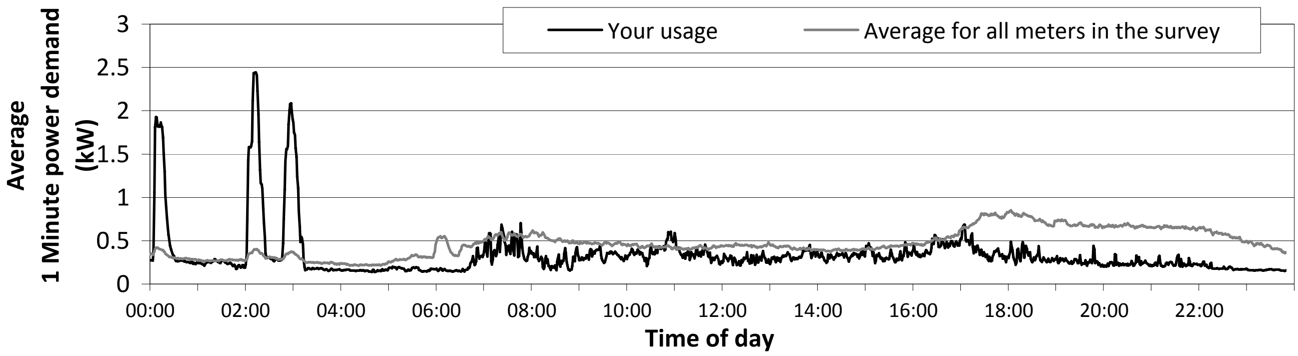
The day when you used the least electricity was on 20/08/2008. You used 1.5 kWh on that day:



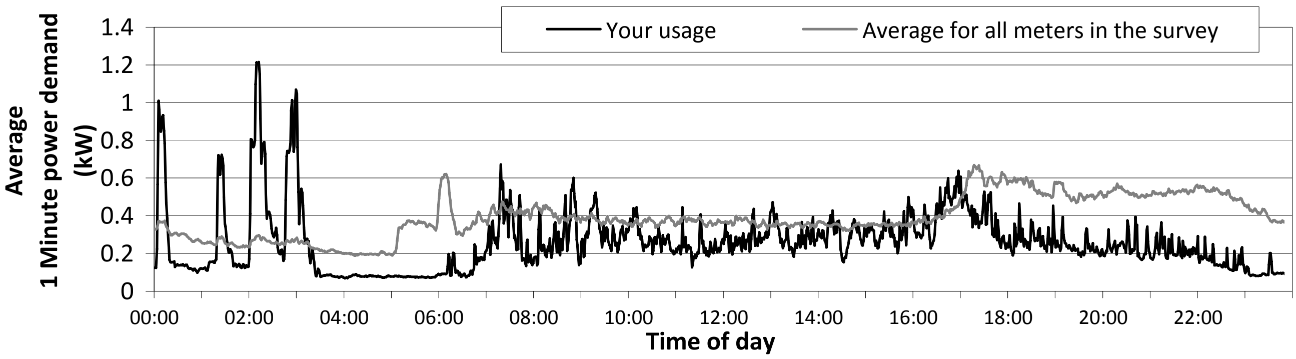
Part 5: Seasonal Average Profiles

The following four graphs show your average daily use profile on a seasonal basis. Each graph shows your profile against the average profile for all meters in the study.

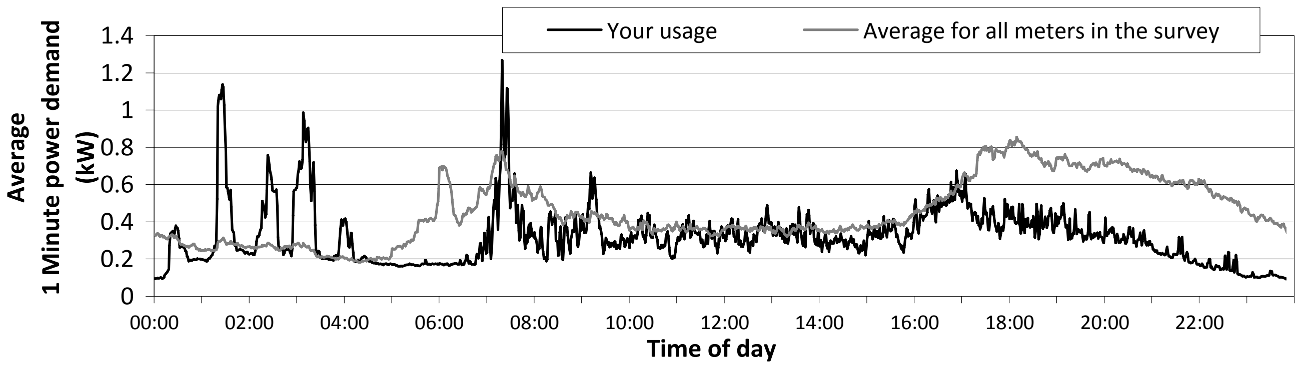
A. SPRING (March, April and May 2008)



A. SUMMER (June, July and August 2008)



A. AUTUMN (September, October and November 2008)



D. WINTER (January, February and December 2008)