Department of Mechanical Engineering

A Specification for Measuring Domestic Energy Demand Profiles

Author: Katalin M Svehla

Supervisor: Professor Joe Clarke

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Copyright Declaration

This thesis is the result of the author's original research. It has been composed by the author and has not been previously submitted for examination which has led to the award of a degree.

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Abstract

Demand profiles, which show how energy use varies over time, are being increasingly used to look at the impacts of changes in energy supply and use. Applications range from investigating how well intermittent, renewable energy sources can fulfil demand, to evaluating the impacts on distribution networks and to underpinning strategic decisions about future energy scenarios. Domestic energy demand fluctuates by the minute and exhibits daily, weekly and seasonal patterns; however, the only data that are available widely are aggregated and averaged national statistics, so researchers tend to make their own measurements when they need demand profiles. These measurements are necessarily limited in the number and types of households, the range of energy use they cover, and in duration. On the other hand, those measurement programmes that have covered a wider scope have found that apparently similar households can have very different consumption patterns due to differing habits and attitudes. It is difficult to compare results between studies because they typically measure different things, and most cases the source data are not published for commercial or data privacy reasons.

If future studies were to follow a common standard for measuring domestic load profiles and pool the source data in a suitably non-personalised way, this could eventually yield better insights into what drives energy use and how it varies by geography and over time; in the worst case, higher quality statistical data would be available. A set of requirements for a standard, comprehensive methodology for collecting demand profile is derived from a systematic review of the literature as well as further analysis on one good-quality data set that has been made publicly available. A specification is proposed for the measurements, in which demand is collected by end use as well as by fuel type, prioritising the biggest energy users and those which have the potential for demand shifting or fuel substitution – heating, hot water, cooking, washing. Measurement is at the highest level of resolution needed to give a clear picture of events and peak loads – 1 minute for electricity and 5 minutes for gas. Around 40 sets of data are collected per house, together with a survey of the house and household context. Compared to recent large-scale monitoring programmes in New Zealand and parts of the European Union, this approach would yield less information on individual appliances, but would give high-resolution, yearly profiles on all fuels used domestically, and on all major end-uses apart from transport. Observations were made on the energy use in one household to look how the measurement plan would be implemented in practice: these indicate that the significant end-use categories would be covered between 80-100%.

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1. Introduction

The world of energy is changing, driven by the need to ensure future security of supply and fears about the possible impacts of climate change. Intermittent renewable generation from wind, and eventually waves and tides, is accounting for an increasing proportion of supply, often in locations far from the centres of demand. Increasing deployment of distributed and micro-generation is making it more complicated to manage electricity distribution networks. At the same time, new consumer appliances are offering ever greater possibilities for using more energy. While new technologies such as heat pumps or electric vehicles may help to reduce carbon emissions, their spread will cause a large-scale switch from gas or petrol to electricity as an energy source.

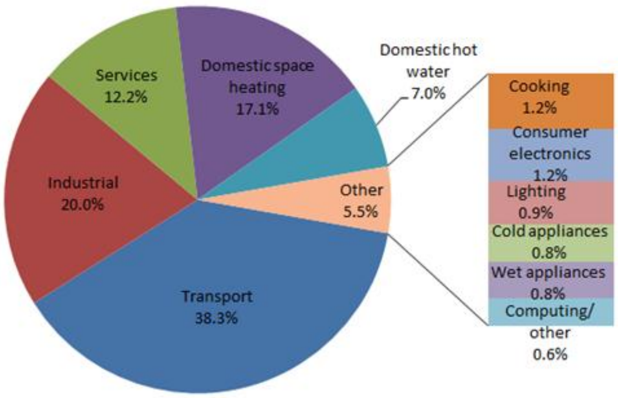


Figure 1-1 UK energy end use 2008
Source: Energy Consumption in the UK - Overall & Domestic Data Tables (DECC, 2010)

Domestic energy use accounts for 30% of the UK total; more than half of this is for space heating (Figure 1-1). However, there is considerable geographic variation in fuel type and usage, especially in Scotland where large tracts of rural areas have no access to piped gas and seasonal variations in daylight are more pronounced.

Appendix 1 illustrates the extent of regional diversity. In Scotland, gas makes up a lower proportion of all energy use than in the UK as a whole, but the average individual customer uses more. Glasgow, a city in the central belt, shows similar patterns of fuel usage to central England, but individual customers consume less gas and electricity – perhaps because of the high proportion of flats. Argyll & Bute has a limited gas network so much of its heating comes from other fuels; the high individual gas usage may be related to the fact that it has a low proportion of people of working age. In Shetland, piped gas is not available at all. By contrast, there is much less variation between urban and rural areas in central England.

Changes in usage over time have also been quite dramatic. Table 1-1 shows that, over the last 10 years where data is available, the number of electrical appliances has grown faster than either population or the number of households. This is especially pronounced for consumer electronics and computers, but also applies to more energy intensive items such as dishwashers and tumble dryers.

Population	5%
No. of households	10%
Appliance numbers	
Fridges and freezers	12%
Electric ovens	20%
Tumble dryers	40%
Dishwashers	69%
Lights	20%
TVs	29%
Games consoles	129%
Computers	137%

Table 1-1 Growth in UK 1998-2008
Source: Energy Consumption in the UK Domestic Data Tables (DECC, 2010)

In many cases, it is not just the number of appliances that has increased but also their average energy consumption – American style fridge freezers; more elaborate light fittings; combined washer/dryers replacing more efficient, single use models (Owen, 2006). Plasma screen televisions consume four times as much power as those with cathode ray tubes; they are also on for more of the time because they are being marketed as a replacement for computer screens, radios and even pictures (Crosbie, 2008).

The problems arising from these changes are often localised: how many wind turbines can be connected safely in a particular distribution circuit; how much heating fuel can be saved if a local council promotes insulation for houses in its area; how will electricity flows in a particular low-voltage circuit be affected if many householders install photovoltaic roof panels. Understanding how energy is used in detail – over time, across geography and by fuel type - is fundamental to answering this kind of problem. Such insights should also enable more meaningful answers to larger scale, strategic questions. However, most of the accessible information is highly aggregated, held at the level of national and regional energy statistics (DECC, 2010).

Demand profiles measure how energy use varies over time – by day, by week and by season. Profiles can be made at different levels of aggregation, ranging from individual appliances, to groups of appliances by end use, to whole buildings and groups of users of a particular type. They have historically been particularly important to utility companies for short-term planning and marketing demand-side management opportunities such as off-peak tariffs (Schrock, 1997). However, they are also critical inputs to longer term infrastructure planning models used by utilities, regulators and others to examine different technology and incentive options and test scenarios for their uptake (Willis, 2004).

1.1 Objectives

This project aims to specify a standard, comprehensive data set to be collected by programmes involving measuring domestic energy demand profiles, which would eventually build up a consistent picture of how energy use patterns vary over time and across the country. The methodology began with a literature review to understand the range of uses for energy profiles, and the experiences of past measurement programmes (Chapter 2). A systematic review was made of the lessons from published data collection exercises (Chapter 3) and analyses were made on the one, high-quality data set that was found in the public domain (Chapter 4). A set of requirements was derived from these, and a standard comprehensive data set to meet the requirements proposed (Chapter 5). Finally, insights into the practical aspects of such a data collection exercise were made through observing energy use in one house (Chapter 6).

The scope covers domestic heating, hot water and appliance demand only. Demand profiles for domestic transport - which could for example be used to model the impacts of charging electric vehicles at home - have not been considered.

2 Literature review

This section reviews how energy demand profiles are used: for operational support, for developing and validating energy demand models, and as an input for models that support decision making on issues ranging from supply-demand balancing and behaviour of networks to strategic choices about renewable energy technology options. A number of published measurement programmes are then studied; in particular those made in the UK over the last 10 years, as well as selected examples from elsewhere which illustrate more general lessons on diversity of behaviours, and experiences with making measurements. The data sets discussed here are summarised in Appendix 2. Finally, a selection of studies is presented which investigated how attitudes and behaviours drive energy use.

2.1 Operational support

2.1.1 Scheduling and despatch

Demand forecasting and distribution planning has to be carried out for all fuels, but their varying characteristics mean that the same activities must be done in different ways and over different timescales. At the most basic level, a householder who uses solid fuel or oil for heating will order once or twice a year: since heating oil, coal and wood can be stored safely in the home, it is not particularly critical that he gets quantities exactly right, or even the timing of the order - unless of course he has left it until the last minute at the start of a cold snap. Accuracy in volume and timing becomes more important for transport fuels. Petrol stations typically have storage for between one day and one week's sales, so how demand patterns vary daily, weekly and by season at each site must be well understood and scheduling is generally centralised (BP, 2009).

In the case of piped gas and electricity, the customer has no storage, and utility companies must meet demand as it arises. Gas travels through the high-pressure National Transmission System at around 25 mph (National Grid, 2007) so it is difficult to make effective short-term interventions if the forecast is wrong. Small fluctuations from forecast volume can be compensated by varying the line pressure; however, this is costly as it calls for increased use of compressors (Smith et al, 1996). Demand forecasting is done daily, using measured load shapes from a small sample of customers for three types of day - weekday, Saturday and Sunday/holiday; these are combined with long-term statistical correlations between total daily consumption and weather. This forecasting process is carried out for each of 8 customer segments across 13 geographical zones. Domestic customers, defined as those who use less than 73 MWh/year, drive most of the weather related variability: on the coldest winter days they account for 75% of total demand, but less than 25% in the summer (National Grid, 2007). The average domestic consumption across all gas customers in Great Britain is only 16.9 MWh/year (DECC, 2010), so it is possible that this one segments contains sub-segments with very different patterns of use. In countries where gas is less ubiquitously linked to heating, domestic customers are segmented depending on gas appliances present, and different load shapes are developed for each segment (Brabec et al, 2009).

Electricity is particularly sensitive because a momentary mismatch between supply and demand affects the voltage in the network. Even very short outages can switch off equipment such as clocks and computers, and some industrial applications are affected if the voltage halves for as little one fifth of a second (Willis, 2004). Supply planning however is done at much longer intervals. In the UK, electricity is traded by the half-hour, so the system operator needs a high-quality forecast of total demand for each half hour in the year in order to contract firm and balancing supply economically (Clark, 2011). Figure 2-1 shows forecast and actual demand profiles over 3 summer days.

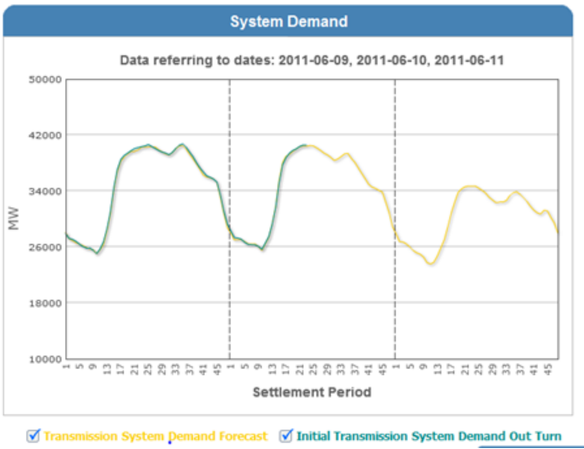


Figure 2-1 UK electricity system forecast and actual daily profiles
Source: New Electricity Trading Arrangements Balancing Mechanism Reporting *http://www.bmreports.com/bsp/bsp_home.htm, 10 Jun 2011*

A multitude of mathematical and numerical forecasting methods has been developed for this purpose, using fuzzy logic, expert systems and neural networks to analyse recent actual overall daily demand profiles. These are pattern recognition techniques that require minimal inputs – just day type and temperature - to generate forecasts (Alfares & Nazerruddin, 2002).

Measured half-hourly load profiles are also used for short term distribution planning (Willis, 2004). As part of the national programme to roll out smart meters in small commercial and domestic customers' premises, the Electrical Networks Association recently formulated a functional specification for smart meters to measure electricity and gas, based on analysing their envisaged end uses for such data. The highest resolution they specify for electricity is half-hourly data collection: this would allow monitoring of current flows and voltage levels, forecasting network loads, and determining demand hidden by microgeneration. For gas however, they ask for meters to be capable of measuring demand every 6 minutes, for planning purposes over the winter only (ENA, 2010). It is not altogether clear from the document why gas would need higher frequency data than electricity.

2.1.2 Settlements

Electricity markets in the UK and elsewhere have been opened up for competition over the last 20 years. Multiple suppliers operate from the same physical infrastructure in any given area, so it is important to be able to tell who has bought and sold what quantities each half hour. Most sales are to end customers whose actual usage is metered only at monthly intervals or less, and load profiling is used to allocate volume, and therefore costs, correctly to suppliers (Bailey, 2000).

Systematic annual collection of half-hourly load profiles from customers in each distribution region was started in the UK by the Load Research Association in the late 1990s, although Scotland was included only after 2005. The 29 million non-metered customers are split into 8 different classes: the two domestic classes account for 89% of the number and 69% of the energy consumed by non-metered customers. Samples are chosen from each class, in each electricity distribution region, and stratified by high, medium and low users (Elexon, 2011). Half-hourly consumption is logged over a full year in 2500 premises, with around 10% of these replaced each year for various reasons (K Spencer, Elexon, personal communication, 6 April 2011).

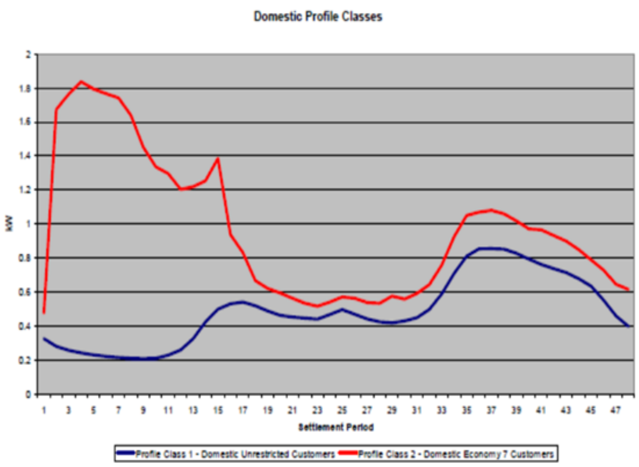


Figure 2-2 Domestic electricity profiles for a winter weekday
Source: Load profiles and their use in electricity settlement (Elexon, 2011)

For analysis purposes the year is divided into 5 unequal seasons: summer is split in two, with a 6-week 'high summer' holiday period. Winter lasts for the entire period between the October and March clock changes.

Regression coefficients relating consumption to temperature and day length are calculated for each half hour in each season, for each day of the week, and for each customer class. A good estimate of total unmetered volume delivered to the customers of each electricity supplier can then be built up using the coefficients and their number of customers within each class (Elexon, 2011). Figure 2-2 shows the typical constructed profiles for the two classes of domestic customers, non-restricted and restricted tariff users.

2.1.3 Managing energy use

Monitoring daily, weekly and annual patterns of energy use can identify opportunities for reducing consumption. This has mainly been done by facilities managers of commercial and industrial buildings where energy costs are large. In Leicester, many commercial and public buildings have half-hourly electricity, gas and water meters connected to a central data gathering system run by the city council. An analysis of 125 of these over a five year period indicated that this has led to a significant reduction in heating and in electrical appliances being left on when the building is unoccupied (Brown et al, 2010). At a smaller scale, one charity halved their gas consumption after installing an optical character reader which measured their half-hourly usage: the information allowed them to change the boiler settings to match heating better with occupancy patterns (Leicester Energy Agency, 2010).

A method of automating benchmarking between commercial buildings was proposed by Ferreira (2009), who applied a set of coefficients calculated from daily profiles for gas, electricity and water in 81 different buildings to identify opportunities for saving on utilities in a selection of the Leicester buildings. The benchmarks included load factors, and other comparisons of mean, peak and minimum loads in working hours, over the full working day and at weekends

The forthcoming roll-out of smart meters that display half-hourly electricity and gas use presents the possibility of taking a similar approach at a domestic level. The recently completed Energy Demand Research Project (EDRP) aimed to understand how effective different forms of feedback are in reducing or shifting the energy demand of consumers. During the four years that the programme ran, half-hourly electricity and gas demand was measured in 17000 domestic and small commercial premises across the UK. It is due to report in the summer of 2011 (Ofgem, 2010).

2.2 Developing and validating energy demand models

Energy demand models range from those which pro-rate based on simple parameters such as house type, temperature and number of occupants, to ones which aim to simulate the complexity of real energy flows and human behaviour.

2.2.1 Household energy consumption models

Models for electricity consumption use two approaches. The first is based on measuring actual load profiles for households, and deriving statistical relationships with possible drivers:

temperature and day length are the main inputs, but floor area and number of occupants are also commonly used. The second approach builds household level profiles from data on end use, with some probabilistic overlay to account for different timings in different households.

In Finland, Paatero & Lund (2006) took hourly measured electricity consumption from a set of 702 dwellings – all were apartments in large blocks, which had no electric heating. They identified and removed daily and weekly cyclical components from the measured profiles, and compensated for weather. The variation in residual electricity load was considered to represent a 'social probability factor' that any individual household is using any individual appliance at any one time. The model was then used to estimate the total hourly consumption profile for 10,000 households, assuming that each used an average amount of electricity, and owned an average number of appliances with average power rating. Although a large number of households were measured, they were all very similar in type; and a further limitation on the model's realism is the assumption that the 'social probability factor' is normally distributed and does not vary over the year.

A similar approach at the end-use level was taken at de Montfort University in Leicester, where a 5-minute resolution stochastic model for lighting was developed from analysing measured half-hourly lighting consumption in 100 houses over a full year. The shape of the average variation was analysed for each half-hour in the day and for each season. This shape was very different over the day – for example, at night the usage in each half-hour was constant, with no variation from one season to the next, while a typical early evening shape was flat and low in the summer, flat and high in the winter, and increasing and decreasing in between (Figure 2-3). A second layer of modelling then added a variability factor for each half hour to represent random householder activity. Although the underlying shape was based on 100 houses, the random probability factors were derived from analysing the individual on-off switching patterns in one house only (Stokes et al, 2004).

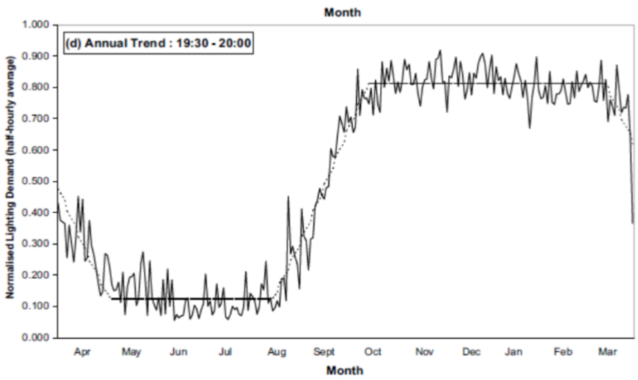


Figure 2-3 Annual variation in lighting demand for one half-hour in the day

Source: A simple model of domestic lighting demand (Stokes, Rylatt, & Lomas, 2004)

Heating demand is more difficult to measure and model – the link between fuel use, heating demand, temperature, and occupant perception of comfort is not straightforward as for electricity where the act of turning an appliance on generates an instant and predictable demand on the grid.

Wind direction, solar gains, and the presence of occupants and appliances which emit heat as a by-product all affect the internal temperature. The thermal mass of the building and furnishings can store and release heat, which then alters the time profile of demand on heating fuels. The BREHOMES energy model has calculated that on average only around half of the useful heat in housing is supplied directly by heating systems – the rest comes from gains from electric appliances, water heating losses, and solar and metabolic gains (Shorrock & Utley, 2008).

Yao & Steemers (2005) developed a simplified analytical model to try to predict demand profiles for all energy used in a typical UK house, based on occupancy patterns and using national statistics for household size and appliance ownership. Electrical appliance loads, hot water and heating profiles were modelled for each of five different occupancy patterns. Hot water consumption was calibrated against measurements of actual quantities of and temperatures of water used by a three-person family for baths, dish washing and clothes washing; however, no details were given of the number of data sets or the circumstances these were collected. Modelled heating demand profiles for three different typical dwellings were used to validate the heating component of the model rather than measurements; the thermal model used to generate these had previously been calibrated using a more detailed simulation. Standard, typical seasonal electricity consumption profiles from the Load Research Association were used to validate the electricity component.

Hot water demand in South African households was modelled by Lane & Beute (1996), hourly at community level. Each house was assigned an average-sized hot water cylinder and total daily demand. The time profile was split into five elements: a high morning load; a high evening load; a moderate midday load; plus small unpredictable and standby loads which varied only slightly through the working day. Within each element a normal distribution was assumed for the on-off timing of an individual household's hot water tank. These distributions were based on surveys on the timing of hot-water using activities in an unstated number of houses, together with 15-minute measurements of the electricity supply to the hot water cylinder; however, these measurements lasted only 14 days. The authors calibrated the model against total hot water load profile measurements from utility companies supplying three different communities in S Africa. Each community had a similar population, and each exhibited a similar overall demand profile which agreed well with the model prediction. The size of the peaks was around +/-10% different to the model, and the timing varied by +/- 1hr.

Heating demand models have also been built using expert systems and neural networks to search for patterns and correlations within measured data. In Sweden, a neural network model to estimate daily heating demand was trained using measurements in 8 houses over 2 years; these were reported to included indoor and outdoor temperatures and energy demand for space and water heating (Olofsson et al, 1998). Yu et al (2010) developed a decision tree model for predicting overall energy demand for buildings in Japan; this claimed to have used data from 55 residential buildings to train the model, and a further 12 to calibrate it. Inputs included measurements of indoor environment at 15 minute intervals and of energy use for each type of fuel, as well as socio-economic data collected on the households involved, their appliances and energy related behaviours. In Korea, a Community Energy System design toolkit is being developed which includes a model to generate the hourly demand profile for electricity, heating, cooling and hot water in a group of buildings. The input for this was reported to be statistical correlations metered daily electricity and gas consumption for a large number of buildings, together with 3-5 minute resolution measurements for a sample of buildings in different cities (Chung & Park, 2010). None of these papers however gives any detail about the actual measurements made or what the profiles looked like.

2.2.2 Energy demand simulation

Simulation, as opposed to modelling, attempts to mimic the complexity of the real world, and generate more realistic results than the simple models described above. However, validating simulations against measurements is challenging because not only the outputs need to be compared but also the inputs, and at this level of detail measurement error may be just as significant as modelling error.

Simulation of electricity profiles through modelling human behaviour is being developed by various groups. Loughborough University has built a 1-minute resolution household occupancy model, using a Markov-chain technique where the activity state in each household at each time step depends on the previous one, together with the probability of that state changing. This starts with inputs for house size, occupancy and number of appliances owned; a simulation is carried out for the number of persons in the house and active at any time, using national time-use survey data. Then, the same time-use survey is used to predict the probability that the occupants in the house will change their activity, depending on what they happen to be doing at any one time. This in turn drives which electrical appliances are on (Richardson et al, 2008). The load profiles for individual appliances are taken from measured data where possible. Figure 2-4 illustrates the steps for simulating the demand profile for one house on one winter day.

The electricity consumption profile generated by the model was calibrated against 1-minute overall electricity use measurements from 22 houses. At the averaged level, the model output showed the same mean and other statistical properties as the measured data. However, it was less good at simulating individual houses, and in particular did not fully represent the variation between highest and lowest demand households. Hot water and heating were not included in the model. No input level data was collected on activities to allow comparison of simulated and actual usage at appliance level (Richardson et al, 2010).

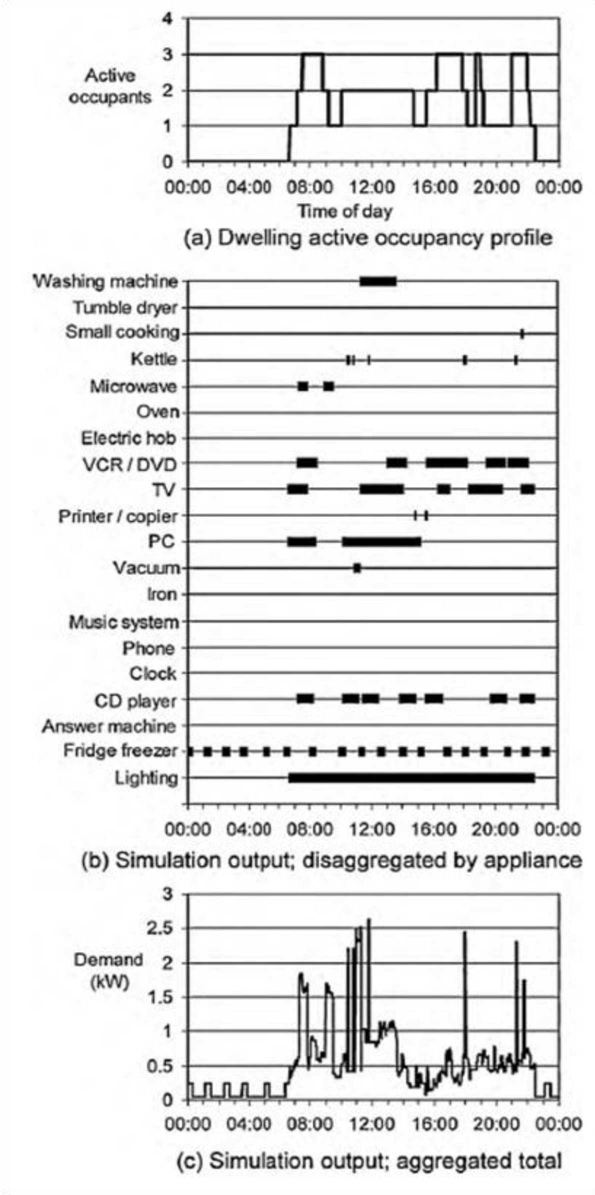


Figure 2-4 Example simulation of electrical demand profile on one day
Source: Domestic electricity use: a high-resolution energy demand model (Richardson et al, 2010)

A similar approach was used for a simulation developed at the Angstrom laboratory in Sweden. The model starts with an even more detailed representation of activity of individual members of the household. The source data came from analysing time-use diaries which had been completed for a previous project: entries were made at 10-minute intervals, against a structured, detailed standard taxonomy for describing activities (Ellegard, 1999). The model can generate end-use profiles at various level of resolution from 10 minutes to 1 hour. It gave good results for variation in total energy use by appliance group for different types of dwellings, when calibrated against measurements made in 14 individual houses and flats during a national energy use survey (Widen & Wackelgard, 2010).

When used to model an individual house, the shape of a four-day long hourly profile for each end-use showed good agreement with measurements, and the overall electricity use variation across houses and by day was realistic. Average load profiles at 1-hr intervals for many households were also generated for individual appliance groups such as lighting, cooking and computer use and compared well to equivalent measurements in 217 households, although the modelled peaks were generally higher than the measured. Load profiles for hot water were compared against 10-min resolution measurements in 10 households over a 9-month period, but these showed less agreement. The authors speculated that some of the differences could be due to the fact that the time-use data was collected more than a decade before the energy consumption profiles and that household appliances and habits may have changed since then (Widen et al, 2009). This model has used a broader range of data for validation than any other reviewed, but at a resolution one-tenth as fine as in the Loughborough study.

In the case of heating, where demand profiles are difficult to measure directly, simulations are often used rather than measurements to validate simpler models. Building simulation programs model the complex interactions of heat flow, air flow and light, with changes in weather, occupancy patterns, heating and cooling system settings, in a building of a given location, geometry and construction detail. ESP-r is a simulation program at the University of Strathclyde that has been used by others to produce or validate heating demand profiles for their own models such as Yao & Steemers (2005).

The ESP-r program starts with a detailed model of the building under study: its size, layout and orientation. The materials that make up the fabric are modelled in detail, with the thermodynamic properties of each layer in each wall described separately, in addition to the optical properties of each transparent surface. Casual gains from occupants, lights and other electrical equipment are modelled as a function of time. Variations in weather induced heating, cooling, and lighting are modelled using a climate profile consisting of time series data for wind speed and direction, direct and diffuse solar radiation, and relative humidity. The building is split into a series of connected discrete volumes. Partial differential equations are set up to describe conductive, convective and radiative heat flow and mass flow between each pair of volumes at one point in time; a measured climate profile supplies the changing external boundary conditions. The simultaneous differential equations are solved numerically for each time step by a finite difference technique. An air flow network for fluid flow, an electrical network and a separate HVAC network can also be included, each tied into the building by a series of nodes at critical locations. This method allows realistic modelling of interactions, such as changes in convection coefficient with temperature, or the impact of changing external light levels on the air temperature and hence on energy demand for heating or cooling (Clarke, 2001). However, electrical demand from appliances is not simulated at the same level of detail.

A history of the validation tests carried out on ESP-r was reported by Strachan et al (2006). In addition to validating the program itself by code checking and analysis, comparisons were made with other programs and with measured data from test houses. Early comparisons included two houses in Livingston, Scotland where air and surface temperatures were measured with 24 sensors per house, and air infiltration was measured with tracer gas; and two houses in Australia. In each case one out of the two houses agreed better with prediction than the other. Experiments were carried out in a test environment to calibrate individual parts of the model, such as: a double glazed window in an insulated wall; a conservatory; a Trombe wall. Under these controlled circumstances, measured and predicted temperatures agreed to within 0.56C. Another set of comparisons were carried out against measurements in a house in Lisses, France. Measured and simulated energy consumption over two winter months agreed to -4% to +26% for the whole house, but less well in detail for individual floors. This was thought to be because actual air movements in the hallway moved a greater amount of heat from the ground floor to the first than in the simulation.

Calibrating such models against real consumption is difficult because the process is detailed and intrusive in terms of instrumentation required, and may need to be done without people actually present. However, heating demand is influenced by human behaviour as well as by climate and thermal properties, which adds even more complexity to a simulation. An example is a module that has been developed for ESP-r to simulate window opening behaviour. Thermal comfort data were collected from occupants in 15 office buildings in Oxford and Aberdeen. 890 people were surveyed one day a month over 6 months about their comfort level, clothing, and use of building controls including windows. 219 of those surveyed completed a detailed record of these factors, 4 times each day for 3 months; and temperature was logged near their work area and outside. This data was used to build a model of window-opening behaviour based on the difference between indoor and outdoor temperature (Rijal et al, 2007).

2.3 Inputs for other modelling

Demand profiles are used as inputs for other types of model; directly measured profiles are used in some cases but modelled ones are also used. This section describes a number of examples illustrating different approaches, but is not intended as a literature review on modelling in general.

2.3.1 Supply-demand balance with renewable and distributed generation

The need to understand heating demand profiles in detail has been accelerated by the development of CHP systems, as these must be matched to a combined heating and electricity demand. Veitch & Mahkamov (2009) modelled daily energy demand for a typical semi-detached house at 1-minute resolution in order to test the performance of a pre-production model of a micro-CHP system in a laboratory; measurements included the gas consumption, heat output, and the emissions in the exhaust gases. The simplified modelling approach was very similar to that of Yao & Steemers (2005); however, additional refinements were made to model the differences between weekdays and weekends, and seasonality. The model generated a consistent set of heating, hot water and electricity demand profiles for the test, although the conditions were limited to one location (SE England), one house with one occupancy pattern, using one set of appliances. The modelled profile was calibrated only against national statistics on annual gas and electricity use.

An operational application for using load profiles in a CHP system was tested by Bakker et al (2008). The controller for the micro CHP system of a single house was set up to record time series data on production, thermostat settings and weather. It used these measurements to generate an hourly profile of heat demand for the day ahead, using a neural network to analyse the previous few days' records, by day type. This was tested with data from 4 houses in Netherlands, where a year's worth of 1-minute measurements on hot water tank and µCHP appliance status had been measured by the Dutch utility company. The controller was able to predict the shape of the profile quite well in each case, although the magnitude of the predicted heat demand could be +/-25% different to the measured. The measurement data were not described in detail.

Hawkes & Leach (2005) investigated the impact of using load profiles at different time steps on models to determine the optimised operation of a CHP system. For electricity, they reported using 5-minute demand profiles measured by BRE on 3 houses. However, they could not find any equivalent data on heating demand, so they made one set of measurements themselves at 5-min intervals on a winter day and used that for all simulations – see Figure 2-5. Using this limited data set, the authors concluded that if the time step used is greater than 10 minutes, it leads to undersized systems and overestimation of CO2 reduction.

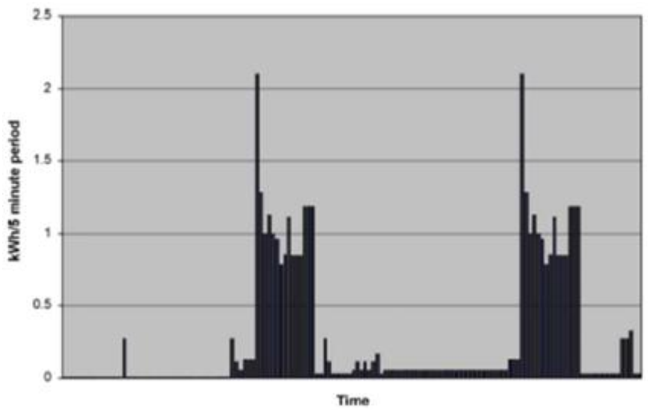


Figure 2-5 Daily heat demand profile used to model CHP system
Source: Impacts of temporal precision in optimisation modelling of micro-Combined Heat and Power (Hawkes & Leach, 2005)

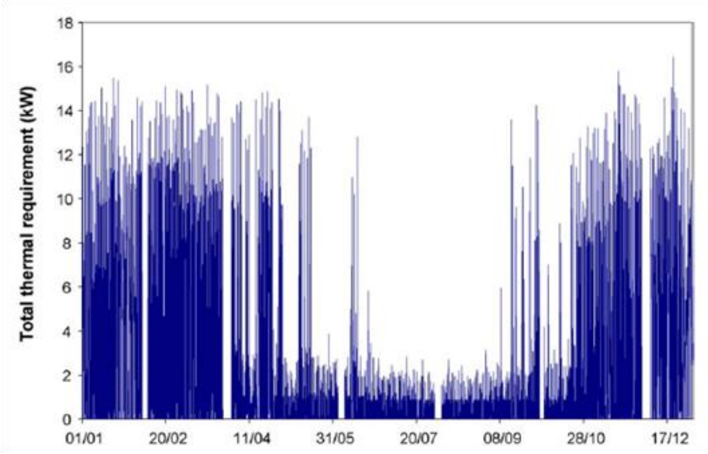


Figure 2-6 Hourly measured thermal demand for a UK house
Source: Modelling the carbon-saving performance of domestic ground-source heat pumps (Jenkins et al , 2009)

Jenkins et al (2009) used the measured hourly thermal demand profiles from one house to estimate the cost and carbon savings from using a ground source heat pump to replace a gas boiler. The data were reported to have been sourced from Newborough & Augood (1999), although the cited reference does not actually include the data which is reproduced in Figure 2-6. One issue they found with the data was that hot water and heating demand could not be distinguished. They therefore had to assume that both were supplied at the same water output temperature – although in reality hot water must be stored at a minimum of 60^{0}C in order to guard against Legionella disease, whereas a heat pump's output is between 35-55^{0}C; this led to an over-estimate the CO_2 savings.

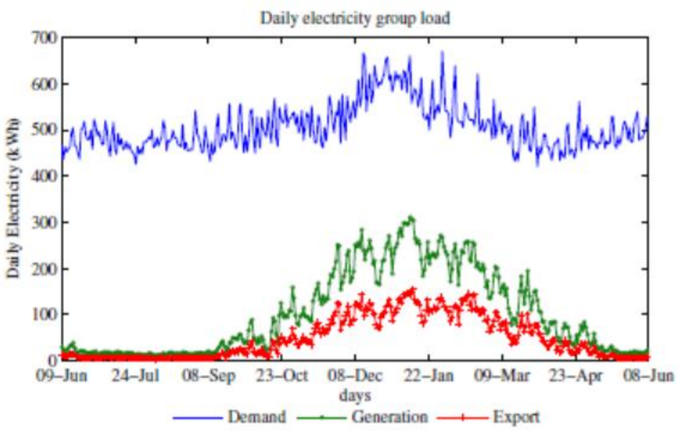


Figure 2-7 Annual electricity profiles for 40 houses with CHP system
Source: Vuillecard et al (2011): small scale impact of gas technologies on electric load management

Vuillecard et al (2011) looked at the impact of domestic micro-CHP systems on reducing peak electrical load. They used measurements from 40 houses with CHP systems in Southeast France, collecting a year's worth of 1-minute resolution data on: electricity generation, import and export; gas and hot water consumption; indoor and outdoor temperature, as well as hot water tank temperature. Information was also collected on house size and year of construction, as well as occupancy patterns, in order to see how typical of the local population their sample group was. They observed an increase in electricity demand over the winter, but this was more than counterbalanced by the increased electricity production from CHP plants in the cold season. Overall, the effect of CHP system was to redcue peak load for the group by 17%. They also used this data to model the impact of other technologies on peak load, such as heat pumps and Joule heaters.

Hawkes (2011) showed that timing effects are also important when assessing carbon savings of demand-side management and microgeneration technologies. He calculated the half-hourly CO_2 intensity of the UK generation mix as it varied with demand through the day, and showed that the actual carbon savings from heat pumps fall dramatically at times when the grid carbon intensity is high, whereas those from fuel cell CHP systems rises.

Chen & Lee (2010) looked at the fuel savings available from using rejected condenser heat from air conditioners to preheat domestic hot water in Hong Kong. They constructed daily hot water demand from measurements of incoming water temperature, shower temperature and flow rate in 36 flats over a 3-month period in the winter, together with information about daily occupancy and air conditioning use patterns. Using this limited information they calculated potential heat recovery in different seasons, and estimated that the air-conditioners are able to supply hot water needs for around two-thirds of the year.

Hong et al (2011) used ESP-r to examine the extent to which thermal storage available in the fabric of a typical UK detached house could allow an air-source heat pump to be operated outside peak electrical demand periods without impacting occupant comfort – defined simply as air temperatures over 18^0C and water over 40^0C. They modelled heat flows in a house during one winter week under four different conditions: with standard and elevated temperature settings for the heat pump switch, plus the introduction of two different hot water tanks for thermal buffering. A 1-minute time step was used to model the heat flows, temperatures, and demand on the heat pump at an appropriate level of resolution.

The integration of solar photvoltaic systems with household energy use was investigated by Firth et al (2009). They used 5-minute resolution measurements of electricity generated by the PV system, and electricity imported and exported to the grid, to derive household demand profiles and analyse what types of household would benefit most from installing such technology. Here again the time resolution used made a difference to the estimated ability to provide the household's needs from on-site generation: although average demand and average supply from the PV system could look balanced over half an hour, this could mask large fluctuations with a high-short term demand on the grid followed by a short period of export (Wright & Firth, 2007).

A tool for modelling renewable energy generation matching with demand over time was developed at the University of Strathclyde. MERIT can model the generation profiles of various technologies such as wind, solar and CHP, from a time series climate profile. Auxiliary technologies such as batteries for storage, or standby generators, can also be added. These can then be matched to demand profiles for electricity, heating and hot water. Diversified demand for larger groups of houses and businesses can be built up from individual profiles (Born et al, 2001a). This tool was used to evaluate whether a small island community could become 100% self-sufficient in energy through a combination of wind and biodiesel from energy crops. The electricity demand profiles used the Load Research Group's standard, average half hourly load shapes for electricity, scaled to meet typical annual consumption for buildings of that type, and estimates for heating demand based on occupancy (Born et al, 2001b).

A combination of ESP-r and MERIT was used to develop hybrid renewable energy system options for a large apartment block in Korea: heating and cooling demand for one vertical block of apartments was modelled in detail in ESP-r; electricity and hot water demand were reported to be based on measurements in similar apartments; and a half-hourly demand profile for the whole block was modelled from combinations of these using an information management tool, EnTrak. The overall profile was then imported to MERIT, where various combinations of renewable energy technologies could be assessed to see which gave the closest match (Clarke et al, 2005). In all these cases the usefulness of the outputs depends on the quality of the input demand profiles.

2.3.2 Behaviour of electricity distribution networks

Detailed electricity demand profiles are becoming more commonly used for network planning as this gives possibilities for getting more out of existing distribution systems than current design practice allows. The basic design parameter for sizing distribution networks is the expected contribution of each individual consumer to the maximum overall load in the network, called 'After Diversity Maximum Demand' (ADMD). As the number of consumers on the network increases, the contribution of each to the overall peak goes down because each individual customer's peak will occur at a slightly different time. If there are more than around 100 similar customers, the average load per customer at the peak approaches a constant figure which is approximates to ADMD (Willis, 2004). The actual value varies by customer area and has to be established empirically, so utilities use appropriate historical ADMD values for network planning. 2kW is commonly used in the UK for domestic premises without electric heating (Central Networks Design Manual, cited by Richardson (2010)).

McQueen et al (2004) argued that the ADMD formulae in use in New Zealand are conservative. They used measured 1-minute resolution demand data from 21 houses to construct a probabilistic model that would allow better estimates. The model's predicted load distribution compared well against 10-minute load measurements at one transformer for one month, and the predicted maximum loading over the whole year was only 2% higher than the measured. However, the data used to build the simulation was measured over only 2 weeks. Also, the comparison transformer was from the same geographical area – possibly, although not clear from the paper, on the same network. A further comparison was made of the predicted and actual 10-year maximum on each phase of each of 557 transformers in different city, and here there was a considerable scatter in the outcomes, with predicted phase load if anything slightly lower than actual on average.

A study on demand side management (Infield et al, 2007) looked at the impact on UK load profiles if a utility could control individual domestic appliances on or off in real time, according to a priority list based on customer selection and peak load contribution. Vacuum cleaners, water heating and laptops were the first contributors to load shifting, followed by freezers and refrigerators and then irons.

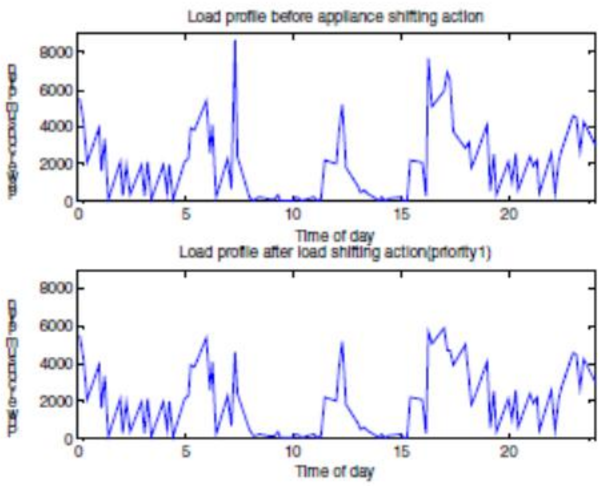


Figure 2-8 Impact of load shifting on a domestic electricity profile
Source: Potential for domestic dynamic demand-side management in the UK (Infield et al, 2007)

The load profile used in this study was not based on measured data but constructed from an assumed usage profile for the various end uses; the resolution was not stated but looks to be at 15 minute intervals (Figure 2-8). They also examined whether this switching control could be semi- automated by using frequency changes in the grid to trigger switching, and concluded that not only would this help to spread peak loading but also would provide a positive feedback loop to help maintain grid frequency.

Modelling networks with a high penetration of distributed CHP generation has been done at Leicester, using the electrical demand model of Stokes et al (2004) – described in section 2.2.1 - to generate 1262 different household electrical demand profiles. Heat demand was modelled more simply: measured demand from a community heating system serving 350 homes was scaled to represent the average gas consumption in Leicester, and then allocated randomly to each of the modelled households. No details are given about these measurements. The CHP systems were set to run for heating and exported any surplus electricity. The voltage rise at each house and over the network as a whole was modelled for various levels of penetration of CHP systems (Thomson & Infield, 2008). A network-level study on the effect of large-scale deployment of household level PV systems was carried out by Richardson et al (2009). Using the 1-minute resolution Loughborough model described in section 2.2.2, they simulated electricity demand profiles for 35,000 households and aggregated them to represent the total for a network.

A large-scale model of a suburban distribution network with several thousand houses and many PV, micro-wind and –CHP installations was studied by Burt et al (2008). ESP-r was used to simulate the net electrical demand profile of 24 individual houses with different occupancy patterns and types of microgeneration, at 5-minute time steps. These net demand profiles were then combined, with slight variations in timing and scaling, to represent a diversified aggregated demand for an entire 11kV circuit with 5 secondary substations. This gives a good model of overall energy demand including heating, although the electrical appliance model was less detailed than those used by Thomson & Infield (2008) or Richardson et al (2009).

Sulka & Jenkins (2008) built a simple, integrated model of an estate of houses each equipped with a Stirling engine CHP system, and linked to the same electric feeder. They investigated the effect on the overall power flows of various house types and temperature settings. The model generated hourly demand profiles for each house, using a simplified thermodynamic model of that house type with a hot water tank in it, together with a separate electrical model based on random assignments of one of five types of occupancy pattern. Hot water demand was modelled based on one set of measurements, apparently the same as that used by Yao & Steemers, 2005).

Active network management is being trialled in Orkney, with the aim of allowing a higher proportion of wind turbines to be connected to the grid provided that some of them can be switched off if the supply exceeds demand (Currie et al, 2006). However, the economics of running a plant under such 'regulated non-firm generation' rules depends critically on how much down time they may expect. This in turn requires good understanding of the variability of local demand profiles; the methodology described in the paper requires historical, half-hourly, local load demand data.

2.3.3 Decision support for policy changes

A University of Edinburgh study on the potential for renewable electricity generation in Scotland looked at supply and demand projections geographically by Grid Supply Point (GSP). They approximated geographic variation in using the maximum recorded demand at each GSP transformer to scale the overall daily profile supplied by each of the two Scottish Transmission

Network Operators. However, the authors warn that this introduces inaccuracies into the analysis because the shape of the load profile would generally be different at each (Boehme et al, 2006).

A study was carried out on the potential benefits of using smart meters to control demand in a future world where electric vehicles, heat pumps and smart appliances are being used widely (Strbac, et al., 2010). For each scenario, hourly demand profiles were modelled for each of the technologies. In the case of electric vehicles, the National Transport Survey database was used to create a time profile of the number of vehicle miles driven, and this in turn generated an average energy expenditure profile for travel. This was turned into an electricity demand profile by first assuming that an increasing proportion of the travel profile was coming from electric cars, and secondly assuming that these could draw up to 6kW each when stationary and recharging. Heat pumps were modelled to mimic a typical boiler load profile in a house with average heat demand at the highest possible grade insulation. Smart appliances were assumed to be the wet appliances - washing machines, tumble dryers and dishwashers - because customer surveys reported that it would be acceptable to shift the timing of when these are run by 1-6 hours. Diversified demand profiles for each of the technologies was superimposed on the current national daily profile, and the impacts of all three technologies on model networks representing urban, suburban and rural areas were examined.

At a very high level, a Lorenz curve of total energy use among individual households was used by Jacobson et al (2005) to compare inequalities between different developed and developing countries (Figure 2-9). This is a method traditionally used in social science to study income inequality; it requires data on total energy use by household. The Gini coefficient describes how close to equality the Lorenz curve is, with zero denoting perfect equality. No figures were shown for the UK, whether because of lack of data or lack of interest was not clear.

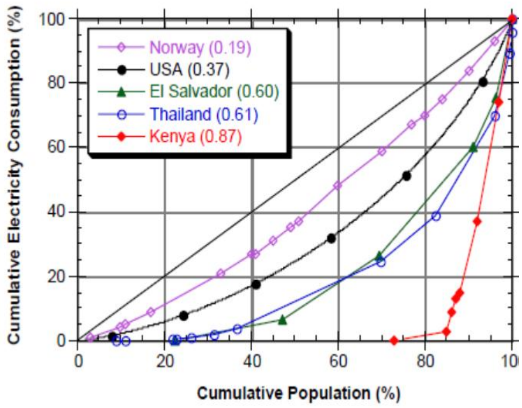


Figure 2-9 Lorenz curve and Gini coefficient for domestic electricity by country
Source: Letting the (energy) Gini out of the bottle (Jacobson et al, 2005)

2.4 Demand profile measurements

Investigations on the amount of energy used by households, how it varies over time, and what drives this, have been carried out in the UK and elsewhere. Structural differences exist between countries, as different climates drive very different heating and cooling needs, and normal working hours vary from country to country. Fuel use is linked to different end-uses in each country: in the UK, where piped gas is available, it is used for heating as well as cooking (DECC, 2010); in parts of East Europe where the standard form of heating is district heating in apartment blocks (Brabec et al, 2009) or in France where nuclear electricty is cheap (REMODECE, 2008) this is not always the case. Cultural factors also come into play, such as the fact that southern Chinese cooking uses very high amounts of gas for stir-frying (Chen & Lee, 2010). This section therefore looks in detail at a number of UK energy demand measurement programmes, and at selected examples from outside the UK which illustrate general lessons on diversity of behaviours, and experiences with making measurements. The studies are compared in tabular form in Appendix 2.

2.4.1 UK studies

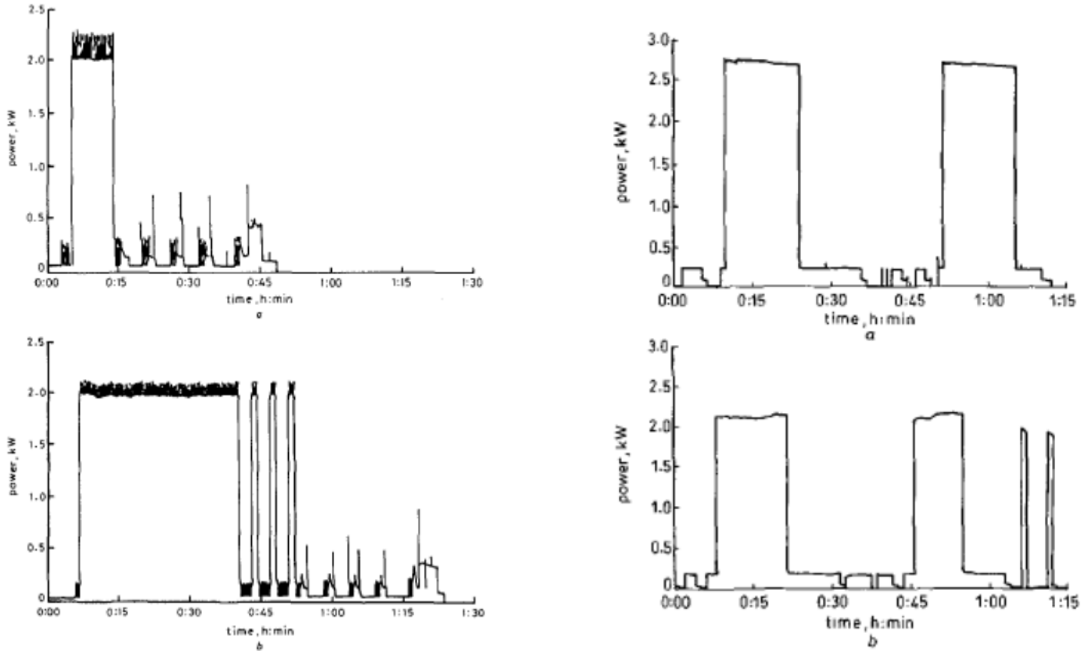
An important study on how overall energy use has changed over time was carried out on a group of 36 low-energy houses in Milton, Keynes. It compared energy use in 1989-91 when the houses were newly built, with that 15 years later (Summerfield et al, 2010). In the original programme, temperature and relative humidity (RH) were measured hourly in the living room and main bedroom, as well as gas and electricity consumption and weather data. In the follow-up, only temperature and RH were monitored at that resolution, although gas and electricity meters were read at weekly or fortnightly intervals. Social surveys of the households were carried out on both occasions; however, the data from the earlier study had been lost. The authors reported that the original groupings of low, medium and high users remained the same 15 years later. The high users had increased their consumption to a much greater extent than the medium and low energy groups. Heating still used the same amount of energy per unit floor area as in the original study, but the high users had built extensions which increased their total consumption. Average indoor temperatures had not changed over the period, although the authors point out that these were well-built, low-energy houses to begin with (Summerfield et al, 2007). Electricity use had however gone up, by 72% among the high users, although less significantly in the middle and low use groups.

Shipworth et al (2010) published the results of a survey on reported and estimated central heating use in 427 homes across England and Wales. Estimated thermostat setting and heating hours were derived from temperature sensors installed in the living rooms and bedrooms between July and February. The readings from these were compared with people's reported thermostat settings and heating hours. The estimated average setting was 21°C, but there was some variation: 44% of households were over 22ºC while 30% were at 20ºC or less. They found that householders consistently under-estimated their thermostat settings, with the mean reported values around 2ºC lower than measured, although there was enormous individual variability. People's estimates of the length of time that the central heating systems were run were closer to that deduced from the sensor measurements. Although the trends were clear, there was some uncertainty about how significant the size of the difference was, as the sensors were put in place by the occupants themselves and there was no way of checking whether it was the right location.

Energy and water use in low carbon, affordable housing heated with a biomass district heating system was monitored over 15 months by Gill et al (2011). The buildings belonged to a housing association and comprised one-bedroom flats and two-and three-bedroom houses. Electricity and hot water meters were read 'periodically' for all the houses; only 4 had detailed, 10-minute logging of electrical load, water volumes and heat input, as well as temperature and relative humidity in the kitchen/living area. These houses consumed 43% less energy and 52% less carbon per unit area than the national average. However, compared to other low-energy houses they did use 11% more electricity because they had forced rather than natural ventilation.

There was considerable variation in the total energy used per house: the highest consumer had double the usage per square meter of the lowest. Considering space heating alone, the highest consumer used more than three times as much energy per square meter as the lowest; this was because of individual differences in thermostat settings. When two of the houses with detailed monitoring were compared, a reduction of 1.5ºC in average internal winter temperature resulted in around 38% less energy for space heating for the same floor area. Electricity consumption per person decreased with increasing numbers of occupants, because appliances such as lights can be shared. As in the Milton Keynes study, the high users of space heating were high users of hot water and electricity as well. Among the four houses with detailed monitoring, the one with the highest space heating per unit area also used the highest amount of hot water per person; and the two higher heating users were also the two which used the most electricity, and showed the highest peak loads. Hot water usage varied more than two-fold, between 19.0 and 47.1 litres per person per day. This compares with the average use of 26.4 l per person per day quoted in Yao & Steemers (2005) – excluding clothes and dish washing - assuming that these new houses had washing machines and dishwashers with cold water intakes.

Newborough & Augood (1999) measured electricity profiles in 30 houses in an investigation of the potential to shift the timing of appliances that make a large contribution to peak load. Average power and power factor were logged at 1-minute intervals for a period between 1-4 weeks, as were internal and external temperatures. A survey was varied out of each household's characteristics and ownership of appliances, and some were asked to complete a diary on appliance use for one weekday and one weekend day. In parallel, they recorded the electrical signatures of various common brands of washing machine and dishwasher operating at different temperatures, as well as those of electric hobs and ovens. These signatures were used to disaggregate the total load profiles by major end-use. Each type of appliance had a characteristic basic pattern, although the actual signature varied considerably by make and by temperature setting used. These differences are illustrated in Figure 2-10, where the same washing machine run at 40^0C draws a 10% higher load, for around one-third of the time, as the



a) One washing machine, two different temperature settings

b) Two different dishwashers, same nominal setting

Figure 2-10 Load signatures of washing machines and dishwashers
Source: Demand-side management opportunities for the UK domestic sector (Newborough & Augood, 1999)

same machine at 83^0C. On the other hand, two different dishwashers run on a similar nominal cycle have different peak loads and profiles. Over the limited timescale of the measurements, average daily power was generally below 1 kW, with a base load around 0.25 kW. Peak loads were between 4-7 kW without electric heating, and load factors were 8-15%. Where electric heating was used, peak loads of up to 15 kW were measured, and load factors up to 43%. Occupancy and household income were reported to be the dominant factors in influencing total demand. The big contributors to peak load were cooking and wet appliances.

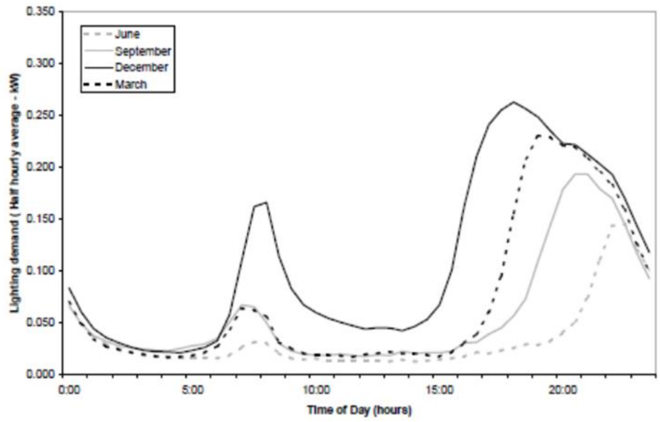


Figure 2-11 Average daily lighting profile by season
Source: half-hourly measurements made by Load Research Group, March 1996-April 1997, cited in Stokes et al (2004)

The lighting model described by Stokes et al (2004) uses the half-hourly lighting demand profiles measured in 100 houses by the Load Research Association. This showed that, on an average winter evening, lighting accounts for about a quarter of the total household demand. There is a pronounced seasonal variation due to varying day length (Figure 2-11).

Wright & Firth (2007) measured 1-minute resolution electricity profiles in 8 houses over a 9 month period, and compared weekly frequency distributions and statistics across the houses. The shape of the distribution varied by house, although each one exhibited a long tail of low-frequency, high power events. Weekly load factors were between 0.06-0.15, similar to the findings of Newborough & Augood (1999) over a shorter timescale. The greater the average load in a house, the higher the variation they found in the profile. They also investigated the effects of different levels of time averaging: the same data averaged over 5 minute intervals showed up many, but not all of the individual appliance peak. There were periods when there were large, rapid oscillations of around 1 minute frequency – typical of the cycling in an electric cooker. All the appliance peaks disappeared with half-hour averaging.

Electricity consumption patterns in 72 housing units were investigated by Firth et al (2008). Most were social housing, and all were equipped with photovoltaic systems. 5-minute readings were made of the PV system generation, as well as imports from, and exports to the grid; this information was used to construct demand profiles. Without collecting any survey data about the households, the authors used the recorded profiles to infer the various categories of appliances being used, distinguishing between base and standby load which was continuously on; cyclic loads due to refrigerators and other cold appliances, which could be read from the night-time record; and all the rest which were categorised as 'active use' appliances. Total consumption ranged between 902 kWh per year for the lowest, to 7743 kWh per year for the highest consumer; the average was 3100 kWh, almost 24% lower than that year's national average consumption. There was a large variation in the total energy used in continuous and standby appliances, from around 200 kWh for the lowest to 3300 kWh for the highest; although in general the high consumers used more standby energy than low or medium (Figure 2-12). Over the two years of measurements, standby energy grew by 10.2%. Actively used appliances

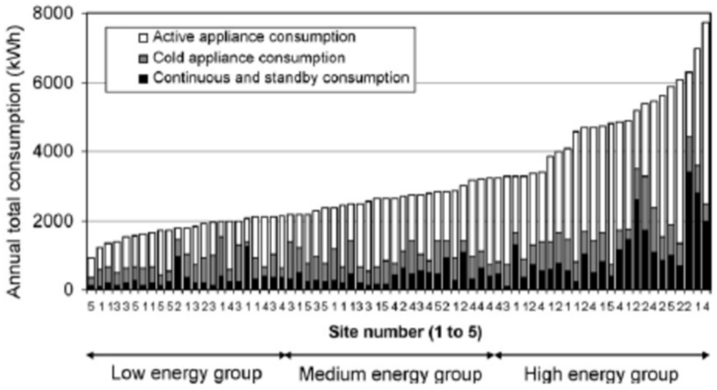


Figure 2-12 Annual consumption by appliance group for 72 houses
Source: Identifying trends in the use of domestic appliances from household electricity consumption measurements (Firth et al, 2008)

consumed on average 61% of total electricity and consumption grew by 4.7% over the two years. Less variation was to be seen in the cycling appliances, either between high, medium and low users or from the first year to the second. The high users showed the biggest increase in total consumption from one year to the next.

Yohanis et al (2008) measured electricity load profiles at half-hourly intervals over 18 months in 27 houses in Northern Ireland. In contrast with other studies they found a strong correlation of demand with floor area, and a pronounced seasonal variation in average usage per m^2 for all house types; however, half of these houses used supplementary electric heating and three-quarters had electric showers. Within one house type there was a two-fold difference between high and low users; the highest user of all was a house where different lodgers used the kitchen separately and had booster electric heaters in their rooms.

The average daily load profiles for each type of house were very similar in terms of kWh per unit area, both for timing and magnitude of peaks (Figure 2-13). Here again the average contained variations between individuals particularly during evening hours. They did not look at seasonal variations.

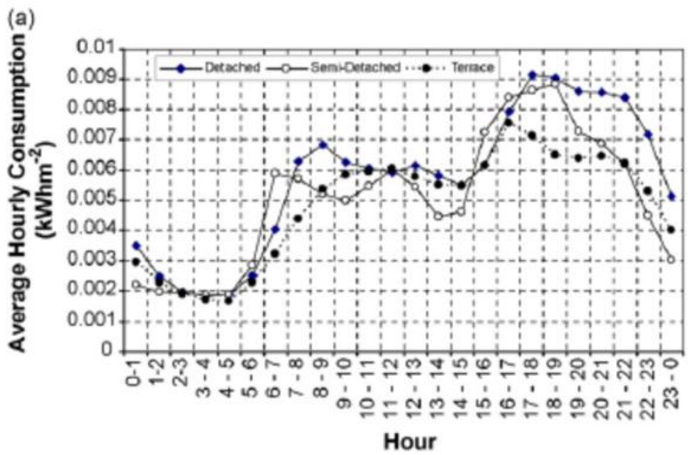


Figure 2-13 Average daily electricity profile per square meter, by house type
Source: Real-life energy use in the UK (Yohanis et al, 2008)

A high correlation was found between electricity use and income: retired and unemployed people used the least amount of electricity overall, even though they were in the house more of the time. In the evening, high-earning households used two-and-a-half times as much electricity per unit floor area than those with low incomes; the authors speculated that these would not only have more appliances but would also be less careful in how they used them. Middle-aged people used more electricity late into the evenings than older or younger ones; and owner-occupiers more than those renting. The electricity usage per unit floor area was similar for most of the day irrespective of the number of occupants; however, the usage in the evening hours went up with the number of occupants.

The Loughborough electricity demand simulation described in section 2.2.2 was validated by 1-minute measurements made in 22 houses in the area over two years (Richardson, 2010). This study confirmed the relationship found elsewhere that total energy use rises with the number of occupants, but that this effect flattens as the numbers rise beyond 4. However, there was little correlation between electricity use and floor area, or between electricity use and house type – the detached houses in the sample using on average less than the semi-detached. The best correlation found was between the product of floor area and the number of occupants, illustrated in Figure 2-14, which also shows the estimates made using the UK BRE Energy Model. There was no apparent relationship between total electricity use and the energy awareness of the residents, using the proportion of low-energy bulbs in a house as a proxy for the latter. High demand occurred when occupants were in the house and active.

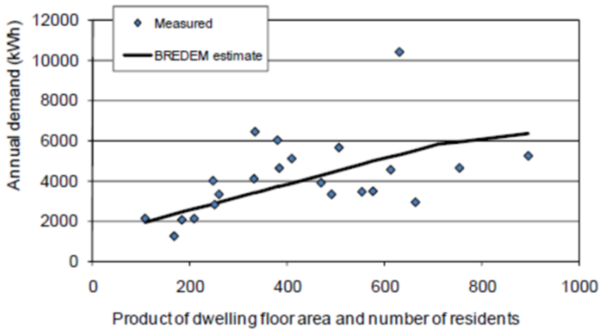


Figure 2-14 Correlation of electricity demand with floor area x occupants: Loughborough

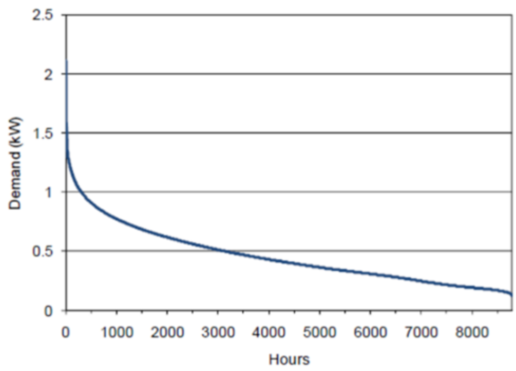


Figure 2-15 Load duration curve, averaged over 22 houses in Loughborough

Source: Integrated high-resolution modelling of domestic electricity demand and low voltage distribution networks (Richardson, 2010)

The average load per house at the point of peak loading, which occurred just before 7 am on an October morning, was 2.11 kW, which is only slightly above the 2 kW ADMD commonly used UK network design standards for houses without electric heating, from which the authors concluded that 22 is a large enough sample to start showing the characteristics of networks. However, for most of the time the average loading was less than 1kW – see Figure 2-15. The original data is available in the public domain (Richardson & Thomson, 2010) and was used in the analyses in Chapter 4.

2.4.2 Outside the UK

An early lesson in how significant behavioural differences can be in determining energy use came out of a study on low-income housing in Florida (Parker et al, 1996). Here, ten single storey houses with identical construction techniques and two slightly different floor areas were equipped with identical large appliances: air-conditioning system, water heater, refrigerator, stove, washing machine and clothes dryer. The houses had been occupied for around a year at the time of the study, occupant numbers ranged from 3 to 8. All ten were monitored for one year at 15 minute intervals: major appliances individually, as well as the whole house consumption. The opening status of the most commonly used window was tracked via a magnetic contact switch. Internal temperature and humidity and hot water temperature and flow rate were also measured.

The amount of energy used for space cooling varied between 4.7 and 24.4 kWh per day, the variation being driven mainly by different thermostat settings. In the highest consumption house, the thermostat was continuously turned down to the minimum (10^{o} C); the lowest consumer left it at 26^{o} C. Average internal temperatures were between 22.7 and 26.7^{o} C. Windows were most often opened during the day, when the outside temperature and humidity were highest, and there was little seasonal pattern to opening. There were big differences in both total energy used by the appliances and the daily pattern of use, only partially driven by the number of occupants. Figure 2-16 illustrates the range in the use of clothes dryers. One family used their machine quite a lot, and at different times of the day; a second family used theirs much less, and mainly in the evening. Of the two 8-person households, one used almost twice as much energy for drying as the other. Similar orders of magnitude differences were observed for cooking, lighting, and hot water.

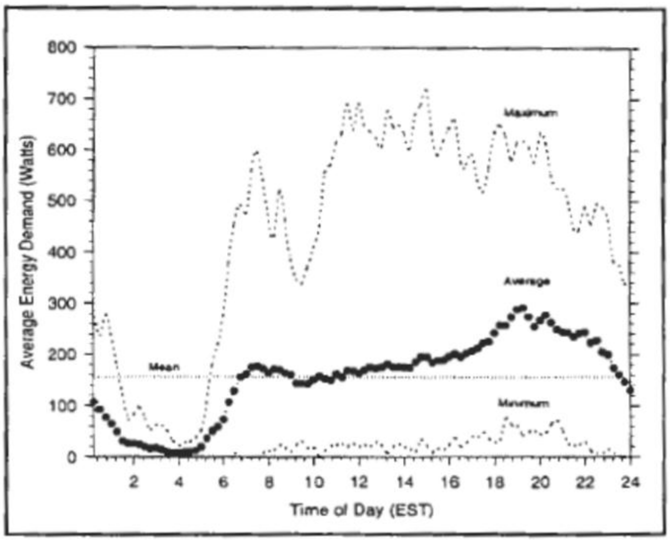


Figure 2-16 Range of daily load profiles for clothes drying in 10 identical houses
Source: Monitored energy use patterns in low-income housing in a hot and humid climate (Parker et al, 1996)

An interdisciplinary study of heating and thermal environment was carried out in 20 identical 3-bedroom, low-energy houses in the south of Sweden. The houses were designed to be heated mainly by casual and solar gains, with just a backup 900 W air heater. Two temperature time-series were measured in the 19 inhabited houses, as well as the annual electricity consumption.

In order to understand the heat transfer and air movement going on in the buildings, a detailed set of readings was made in the one house which was empty – thermal mannequins were introduced to simulate the presence of people. Temperatures were measured at 24 different locations and heights. Air flow measurements were made in 4 locations, and an undisclosed number of humidity measurements were also made. In addition, a series of semi-structured, qualitative interviews lasting 1-2 hours was carried out with members of each household. There was some divergence between measured indoor temperatures and the subjective view of inhabitants who all found the houses to be colder than comfortable; on further investigation it was concluded that this was because the air heaters were not in fact functioning as designed, and were blowing a little air even when switched off (Isaakson & Karlsson, 2006). The published report focuses on the interviews and contains little detail on the energy use measurements.

Measurements of climate, comfort and energy use in five low-energy, individually designed houses in Australia were reported by Williamson (2010). Hourly readings of temperature and relative humidity were made in the living areas and bedrooms. Outdoor temperature, wind speed and solar radiation were measured, and energy and water consumption were taken from bills. Interviews were carried out with the architects and with their clients who were in each case the current occupants. These houses all used significantly less energy than equivalent houses in that district, although according to the Australian method of assessment, all the buildings fell below the current standard for energy efficient buildings. In fact, internal conditions fell outside of the theoretically acceptable comfort limits much of the time. The occupants however said that they were happy to live with a range of internal conditions that varied with the weather as this made them feel ‘more connected to the environment’.

A wider range of households was covered in a study of 4000 premises in central Finland where hourly profiles were collected over a year (Räsänen et al, 2010). Here, only limited data was available about each customer, chiefly the type of house or business, heating, and hot water and cooking fuel. A two-stage, top-down analysis with neural networks was used to find the most appropriate groupings whose members exhibited similar daily and seasonal profiles. Odd combinations of user types emerged in some of the groupings: in one, 70% were households but another 18% were customers describing themselves as commercial services, and a smaller number of public sector, industrial and agricultural users. The worst-correlated cluster contained a large proportion of holiday cottages and rental properties.

A 10-year study of household energy use (HEEP) was completed recently in New Zealand (Isaacs et al, 2010). In this programme, 397 houses were monitored for a year each, with data collected at 10 minute intervals. Each type of energy use was measured, including output from LPG heaters, open fires, and solid fuel burners – a method of estimating the output of the latter was developed during the course of the survey. Temperatures were measured in living- and bedrooms. Hot water consumption was measured separately, and over 13,800 individual electrical appliances were monitored over the course of the study. Each house was surveyed at the start of the collection programme, and socio-economic data were collected. The final report gives information on practical experiences with various types of instrumentation and issues faced in collecting data: for example, one third of the thermostats on hot water cylinders were found to be inaccurate to more than +/-10^{0}C, and one in every 6 refrigerators turned out to be faulty – this could be seen in the extended on-cycles they measured.

New Zealanders apparently also have only a vague understanding of how they actually use heating: when asked about how long they heated their houses, responses indicated over a month less than the measured heating season. The warmest houses were those with solid fuel burners because it was difficult to control their heat output. The average evening temperature in the living rooms was 17.9° C in the winter and 23.1° C in summer, implying that New Zealanders are more willing to live with seasonal variation than their UK or US counterparts. Newly built houses were warmer than older ones both in summer and winter: various possible reasons were suggested such as increased insulation, better draught-proofing or higher levels of glazing relative to floor area, but these did not account for the difference. In the end the authors suggested that occupant behaviour must be responsible.

The authors were not able to identify correlations with survey data that would explain differences in energy use. Income level was found to explain less than 2% of the variation in domestic hot water or appliance use, and not to be correlated at all with heating energy. Household size drove a quarter of the variation in hot water use, and 9% of other use, but was not correlated to heating either. A combination of income level, household size and life stage of the family were found to explain only about a quarter of the variation in overall energy use. The top 20% of households used 38% of the total hot water.

Baseload power (standby plus cycling appliances) was the equivalent of 112 W continuously for all houses. Although it formed only 10% of the energy used, baseload had a large impact on the total network as it contains a significant reactive power component from refrigerator motors and small transformers – measured power factors were in the range 0.5-0.7. The report provides a table of average measured standby power and energy use of a long list of common appliances.

A similar, detailed national survey was carried out on 400 houses in Sweden, although covering electricity consumption only (Zimmermann, 2009). The focus was on understanding end-use, so in addition to measuring total consumption at 10-minute intervals, up to 15 power meters were used per house on high-power circuits and individual appliances. Another 16-20 lower power appliances per house were measured with serial watt meters, and 25 'lamp-meters' were used to record the profiles of lights switching on and off. Internal and external temperatures were also measured. Results for houses and flats were presented separately and sorted by age group of inhabitants and the family type (single person, couple, or family with children).

Households of the same age and family type showed a wide variation in energy use, whether expressed as a total, by unit floor area or by person, although those which had electric heating showed a smaller range in annual use per unit area. Older people used slightly less electricity than younger ones. The largest energy users, and those responsible for the highest peak loads, were couples of working age without children – probably an indicator that disposable income is more important than age as such. Baseload power averaged 87 W across all the houses and flats, but around 5% used 0.5 kW or more.

The daily load curves for refrigerators showed about 25% difference between the peak consumption in the early evenings – when food preparation might be expected to be happening, with the fridge being opened frequently – and the lowest level in the early morning. A small seasonal effect was also apparent. Freezers showed much less variability. Washing machine consumption was reasonably constant at 60-70 kWh/person per year, reducing only for families of 5 or more. Energy use in clothes drying and in dishwashing did not show such a trend, although more is used per person in apartments than in houses where there might be more space for drying indoors or drying clothes outside. There was a strong seasonal effect in cooking, with 40% more energy used in an average midwinter week than in summer. Most of the energy used in cooking went to the hob and oven. The annual consumption per person reduced slightly with household size up to 3, but after that it was constant at around 110 kWh per person per year. There was greater variation in the actual use of energy for lighting than in the installed wattage of light fittings in houses. 50% more energy was consumed for lighting in the middle of the winter than in the summer. A smaller seasonal variation was observed for televisions and other consumer electronics. There was a very large variability in hot water use per person. Air dryers, water beds and aquaria were found to consume significant energy in some houses.

Data on energy used for lighting in 69 of these Swedish households was analysed further by Bladh & Krantz (2008). They tested two hypotheses: first that lighting use per person goes down if there are more people in the house sharing the same lights. This turned out to be true, but the effect was significant mainly when moving from 1 to 2 persons in the household, but beyond that the reduction is smaller than the variation in individual households of the same size. The second hypothesis was that older people are less profligate in their use of lighting than younger ones. Although the older households did use less energy than the younger age groups, the sample was not large enough to draw conclusions about whether it was age as such or different generational expectations that accounted for the difference.

The authors also conducted detailed interviews with 7 of the households, including a 'lamp-tour' of each house, during which the occupants explained how and when each light source was used. They found very different levels and patterns of usage even between households of the same size, depending on how much they were home and to some extent on income. However, each house showed a consistent pattern, especially on weekdays. Most explained their use of lighting in terms of cosiness and atmosphere rather than utility – lights were left on in dark spaces most of the day, or were operated with timers to provide a welcoming feeling when coming home. All the houses had many light fittings that were not used regularly, and in some cases not used at all - no household used more than a quarter of the total installed wattage of lamps. The authors also incidentally discovered that even though an average of 25 lamps had been monitored in each house, the study had failed to pick up some of the most frequently used ones.

A monitoring campaign on electricity use by appliance and end-use was carried out in 12 European countries in 2006-08 (REMODECE, 2008). Measurements were made at 10-minute intervals in around 100 houses per country, with overall consumption and that of various appliances monitored, and an extensive survey of households and household behaviours carried out. Around 2 weeks' worth of data was collected at each house, and this was extrapolated to give annual demand and hourly average daily demand profiles by end use; given the seasonal variation observed in longer-term studies, this is a limitation in quality. The most interesting outcome from this programme for the present study lies in the differences seen between countries in how electricity and appliances are used.

2.5 Influence of social attitudes and habits

Occupants' attitudes and habits appear to be very important, causing large variation in energy use between two apparently similar families living in similar circumstances. This section reviews lessons from some relevant studies.

In the UK, BRE's regular fact file on domestic energy shows how general expectations on comfort levels have increased over time. Average winter temperature in houses has risen from around 12ºC in 1970 to 18ºC by 2008, because the spread of central heating has allowed the whole house to be heated evenly. The authors expect that this trend may plateau at 19-20ºC, although they warn that German experience with passive houses is that people are now looking for a mean internal temperature of 22ºC (Shorrock & Utley, 2008).

Prescriptive temperature and humidity standards in offices have accustomed people working in closely conditioned buildings to expect little seasonal variation. However, a range of studies reviewed by Roaf et al (2010) shows that a much wider range of temperatures can feel perfectly comfortable, provided that changes are gradual and that people are dressed appropriately. An extreme example quoted is the government sponsored 'Cool Biz' programme in Japan, where gradual social conditioning permitted workers to wear loose, informal clothes to work and therefore allowed public buildings to operate without air-conditioning at temperatures up to 28ºC without the people in them feeling uncomfortable.

A government sponsored report describes how changing social patterns have a big impact on energy use – if teenage children using computers and TVs in their bedrooms, not only are there more appliances but more rooms have to be heated and lit. If families eat home-cooked meals together, more energy is used, and in a narrower time period, than if individuals microwave ready-made meals for themselves at different times. New mobile consumer electronic products are constantly introduced, and now become widespread within a matter months. Microwaves, TVs and mobile gadgets use standby power, so more of these appliances results in more baseload power consumed. Low energy light bulbs are becoming more acceptable to consumers, but fashions for more, and brighter light fittings can counter the savings (Owen, 2006).

Technology developments appear to offer increasing numbers of ways for people to consume more energy, but their actual effect depends how quickly appliances become a 'must-have' item. Until recently, consumer products were not considered to be a major user of energy; however when plasma televisions were introduced they were marketed as not only a more stylish product, but also one that could replace many others such as radios and computer screens. Households replacing a cathode ray set with plasma are thus using not only four times as much electricity when watching TV, but forty times as much when listening to the radio; and some even use them as replacements for pictures (Crosbie, 2008). In an attempt to understand how products could be designed so as to minimise consumption in use, Tang & Bhamra (2008) recorded interviews with customers and observations of refrigerators and freezers being used in homes. They discovered that although people did seek out energy efficient appliances when buying new, they did not relate how they used it to energy consumption or carbon footprint – so fridges were routinely placed beside cookers, and doors were left open for long periods while unpacking and repacking. Although younger people declared themselves to be more environmentally conscious, they were more likely to behave in a wasteful manner than older people.

IBM conducted a 12-country survey of 5000 domestic and small commercial energy consumers, who were questioned about their views on energy costs, on actively managing their usage, and on green issues. They found that 26% of respondents were not at all interested and that another 31% were concerned about costs only. The remaining 43% said that they did take an active interest for environmental and social reasons, although around half felt that they could not do much about it because they could not afford improvements. IBM proposed that utilities should use this segmentation in order to understand how to communicate with different types of customer in an appropriate manner (Figure 2- 17). However, they did not collect any information on the actual energy use of the respondents so it is not clear whether these attitudes are reflected in behaviours (IBM, 2009).

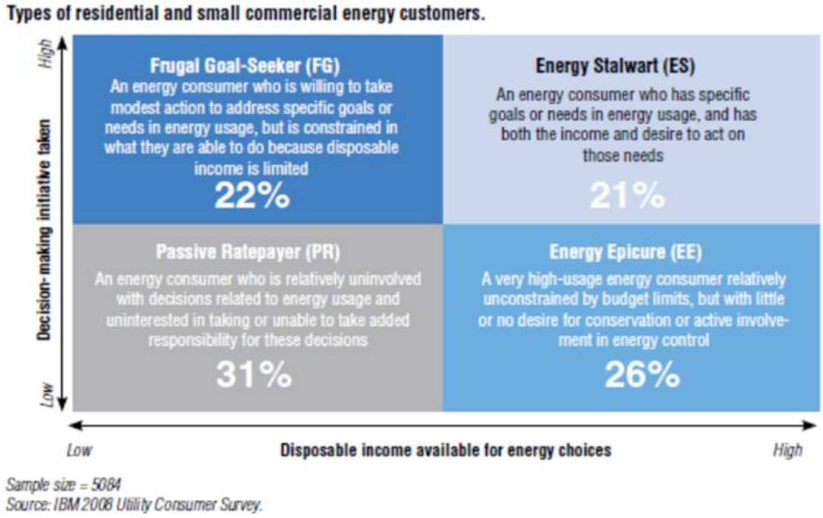


Figure 2-17 Segmentation of users by interest in energy and by income
Source: Lighting the Way (IBM, 2009)

Gram-Hanssen (2008) reviewed the history of how household appliances had become widespread in Denmark over the last 100 years, and analysed interviews with 40 people of different ages about their energy consumption, lifestyle, and experiences of new technology. In small matters such as switching lights off when leaving a room, or leaving appliances on standby, or how often clothes are washed, people seem to establish routines which are hard to change, and which are influenced but not totally dictated by experiences in early life. However, in the larger decisions that influence energy use – which particular appliance to buy, or the comfort temperature in the home - energy use is wrapped up in wider considerations. The home represents the biggest emotional and financial investment that most people make, and they want their consumption choices to express something about themselves. This whole issue is neatly summarised in a sentence in this paper:

"The answer to the question of whether campaigns to keep low indoor temperatures have influenced the temperature level is that those who prefer to have a lower temperature also use energy consumption as an argument"   (Gram-Hanssen, 2008)

3 Lessons from demand profiling

This chapter presents a systematic review of the key lessons from the literature surveyed in Chapter 2 as regards energy demand profiling. A tabular comparison of the measurement programmes outlines in Section 2.4 is included in Appendix 2.

3.1 Data availability

Measured data on energy demand profiles is hard to find. In the UK, utility companies keep their data confidential for commercial and data privacy reasons, and have not always been able to retrieve it when needed (Boehme et al, 2006). Electricity profiles produced by the Load Research Association in the late 1990s have been used by others (Yao & Steemers 2005; Born et al 2001b; Stokes et al 2004). However, only the original national average profiles by customer class proved easily retrievable by the present author – the source for the detailed lighting data cited by Stokes et al (2004) for example could no longer be found. Elexon does make its annual regression coefficients available for purchase, and from these it would be possible to reconstruct updated, regional average electricity profiles for each year, but the original data is not kept. No equivalent data is available from National Grid on gas profiles (J Ryder, XOServe, personal communication, 22 August 2011). The EDRP programme does promise that its half-hourly gas and electricity data will eventually be made available to researchers, but a request for access to this is still on the waiting list.

Outside the UK, data from the Swedish Energy Agency measurement programme were made available to Widen et al (2010) for model calibration, and are said to be accessible to other researchers, as in the data from the HEEP programme in New Zealand (Isaacs et al, 2010). The REMODECE (2008) data are accessible via the internet, but only at the level of hourly averaged profiles for the end uses measured.

In some cases, data collected by one research group has apparently been used by others, but little information is given: Jenkins et al (2009) cite Newborough & Augood (1999) as the source of demand profiles they used, although this data were not actually published in the original paper; Hawkes & Leach (2005) used electricity demand measured by BRE for a different project.

Most commonly, researchers have collected their own data when needed. Because their focus is on the application, they do not always fully report what was measured and how. Examples are: the number of hot water tanks monitored by Lane & Beute (1996), the specific CHP data items measured by Bakker et al (2008), the electricity and hot water measurements in Korean apartments by Clarke at al (2005), the heating demand profile in Hawkes & Leach (2005).

Richardson et al (2010) alone among those reviewed have made their source data available on a public database. The data is accompanied by the detailed survey results of the households concerned, but presented anonymously without information that could identify an individual family.

3.2 Fuel inputs versus energy end use

Most of the published work concerns electricity, because of its high sensitivity to timing. However, most domestic energy in the UK is in fact used for space heating and hot water and the predominant fuel is gas (Figure 3-1). Gas use and heating demand profiles are much sparser in the literature - the only UK data found were in Smith et al (1996) who give one set of 'typical' gas use profiles by day type, and Hawkes & Leach (2005) who show their own measured, one-day heating demand profile.

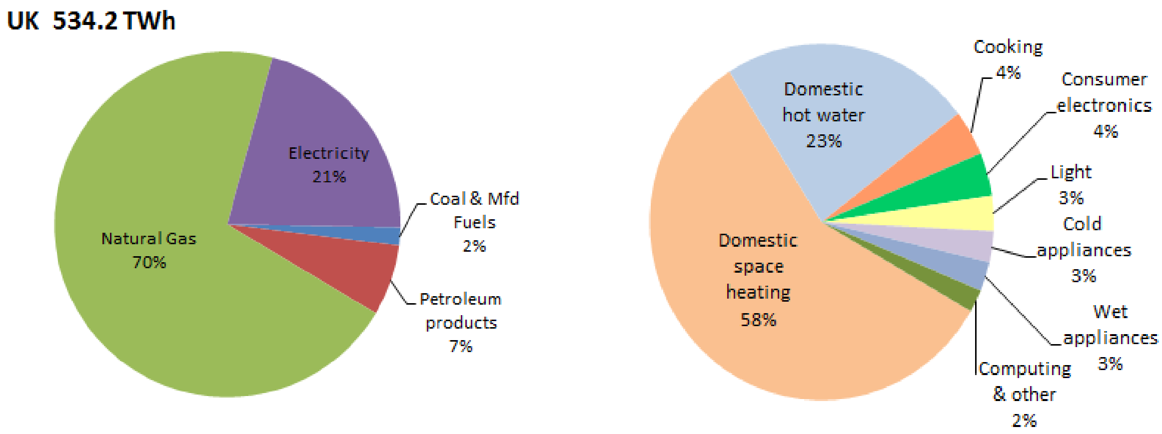


Figure 3-1 UK Domestic energy use by fuel type and by end use
Source: Energy Consumption in the UK Overall & Domestic Data Tables (DECC, 2010)

Most of the published data at the level of end use are from outside the UK – the exception is the lighting data used by Stokes et al (2005). The most systematic approach was the New Zealand HEEP programme (Isaacs, 2010) which measured all fuel inputs and all end uses. Parker et al (1996) collected data by end use, in houses that used electricity for heating and hot water. The Swedish monitoring programme (Zimmerman, 2009) and REMODECE (2008) measured end use, but for electricity only, in a mix of households with and without electric heating. Vuillecard et al (2011) however measured both gas and electricity use, as well as hot water consumption, so they were able to distinguish between heating and hot water use; however, they do not mention whether the houses concerned used gas for cooking as well as heating.

Different fuels can be used for the same end use. In the UK, gas fired central heating is installed in 78% of UK houses but 8% have electric and 5% solid or oil fired central heating. Where gas is available it is often used for cooking as well as fuelling the heating and hot water system; but electricity accounts for 15% of domestic hot water and around 50% of cooking demand (DECC, 2010). If only fuel inputs are measured, these differences can confuse the interpretation of differences - an example is in Yohanis et al (2008) where houses with and without electric heating are analysed as a single sample.

Another set of end-uses that it is important to distinguish separately is those whose timing could potentially be shifted away from peak load period. Wet appliances are one category (Strbac, et al., 2010), but hot water storage has also been investigated (Lane & Beute, 1996) and well as heating (Hong et al, 2011) - electric storage heaters are a familiar technology that could be brought up to date as a smart appliance. Cold appliances are being introduced which are capable of using grid frequency changes to guide switching off for a short period to ease peak loading.

Lighting, consumer electronics and other miscellaneous appliances all use electricity only, and it is unlikely to be acceptable to consumers to attempt to shift the time when they are on. However, both lighting and consumer electronics are areas where technology changes are happening: in the case of lighting, technology is encouraging lower energy use - low energy bulbs and fittings now constitute nearly a quarter of all lighting appliances – while in the case of consumer electronics the drive is in the other direction (Owens, 2006).

3.3 What the sample represents

3.3.1 Size and composition

The ideal method of selecting properties to measure would be to choose a random sample which includes appropriate proportions of high, medium and low energy users as well as types of property and household in the area (Schrock, 1997). However, this is rarely possible as it requires access to meter readings from all the suppliers in the area; it has been used only in large national data gathering programmes (Elexon, 2011; Isaacs, et al, 2010; Zimmermann, 2009).

Much of the published work on demand measurement relates to one locality and a limited number of households. In some cases, this is because the project set out to investigate low-energy or affordable housing (Isaakson & Karlsson, 2006; Gill et al, 2011; Parker et al, 1996; Summerfield et al, 2010) or test new energy systems (Firth et al, 2009), and here the samples were predefined. Some researchers whose primary concern was to generate data for investigating technologies without too much concern about how representative this might be, limited themselves to eight, four (Olofsson et al, 1998; Bakker et al, 2008) or even one (Yao &

Steemers, 2005; Hawkes & Leach, 2005).

Other programmes found it hard to recruit volunteers except by convenience sampling – asking for volunteers by whatever means available (Wright & Firth, 2007; Richardson, 2010), or even snowball sampling where the volunteers then ask their friends to take part (Chen & Lee, 2010), (Crosbie, 2008). This can result in small samples (Wright & Firth, 2007), participants who come from similar backgrounds, and have similar income levels and attitudes (Firth et al 2008); they are likely to be interested in energy use in the first place, so the sample can be from a very narrow base (Chen & Lee, 2010). Even Paatero & Lund (2006), who measured over 700 households, ended up with a very homogeneous group, dwellers in large blocks of flats.

3.3.2 Energy consumption

The most important aspect of the sample is how well it covers the full range of energy consumption. The distribution of consumption of both gas and electricity is skewed (Ofgem, 2010) and relatively few very high consumers are responsible for a disproportionate contribution to the total (Elexon 2011). These however tend to be the people who are least likely to want to participate (Isaacs et al, 2010). Regional and local energy statistics are published but as annual means only so they do not help with assessing range (DECC, 2010).

Distribution range data is available from a recent review of typical high, medium and low consumption bands, but at national level only (Ofgem, 2010). The methodology used means that the Ofgem bands do not correspond to distribution quartiles as such, but to the percentage difference between consumption at the median and 1st and 3rd quartiles, respectively.

	Lowest kWh	Low kWh	High kWh	Highest kWh
Electricity – ordinary tariff	0-2,100	2,100-3,300	3,300-5,100	>5,100
Electricity – restricted tariff	0-2,900	2,900-5,000	5,000-8,300	>8,300
Gas	0-11,000	11,000-16,500	16500-23000	>23,000

Table 3-1 Energy use bands based on annual consumption
Source: (Ofgem, 2010), Model 2

Elexon uses a different segmentation for electricity, where ordinary tariff under 3000 kWh/year is defined as low and over 7500 as high use (Elexon, 2011). Also, National Grid defines domestic gas customers as those who use less than 73,000 kWh/year (National Grid, 2007), so the Ofgem 'high' banding potentially included 50,000 kWh/year variation. In spite of these drawbacks the Ofgem do however provide a useful external standard within the UK to assess the sample's coverage – see Table 3-1.

3.3.3 Other context

Many measurement programmes restrict themselves to looking at energy use, without caring too much about the context (Elexon, 2011; Wright & Firth, 2007; Räsänen et al, 2010) However, to understand what drives consumption, information is needed about the households concerned. Various kinds of data have been collected, often different for each programme – Appendix 2 lists the variants. Housing type and number of occupants is the most consistently reported. Appliance ownership is also often used, although this can be at a high level only (Yohanis et al, 2008; Richardson, 2010) or a full appliance audit (Isaacs et al, 2010). Household income data was collected by Summerfield et al (2007), Yohanis et al (2010), and Isaacs et al (2010); age and/or life stage of occupants was also recorded by these and by Zimmermann (2009).

Statistics on housing type at local level are available from Department of Commerce & Local Government (Dept. Comm & Local Govt, 2011) or the Scottish Government (2009). Household size, and disposable income bands, are published at national level in the annual Social Trends report (ONS, 2009). Annual statistics on ownership of appliances are also published (DECC, 2010).

A potentially illuminating context category would be attitude to energy use. One model for this is provided by the four-sector segmentation used by IBM (2009), which is based on structured interview questions on income level and interest in matters to do with energy. Richardson (2010) tried without apparent success to use the number of low-energy light bulbs in a household as a proxy for energy-consciousness. However, the findings of Tang & Bhamra (2008) and Bladh & Krantz (2008) suggest that awareness of energy and environmental issues does not necessarily translate into low-energy behaviours. The survey used by REMODECE (2008) includes questions on specific behavioural aspects of appliance use.

Interviews appear to give a better understanding of the context of the measurements than simple questionnaires (Isaakson & Karlsson, 2006; Williamson, 2010). The best results are obtained from structured but not closed questions. Training the interviewers beforehand, and using the same people for all the interviews, gives consistency in interpreting and recording answers (Crosbie, 2008).

3.4 Data collection

3.4.1 Frequency

There is a wide range in the frequency of data profile measurements, ranging from hourly to 1-

minute frequency, detailed in Appendix 2. For electricity measurements, a 1-minute resolution was found best to capture the peaks and short duration events (Newborough & Augood, 1999; Richardson et al, 2009). Firth et al (2009) argue that 5 minutes makes it easier to store longer data sets without losing too much detail; and indeed one of the problems experienced by Richardson (2010) with 1-minute data was the limited storage capacity of the data loggers. Longer than 5 minutes can give false estimates when looking at the behaviour of new technologies: average demand and average supply from a PV system may balance over half an hour but this can mask large fluctuations with a high-short term demand on the grid followed by a short period of export (Wright & Firth, 2007).

Less discussion is available around gas and heat flow measurement frequency. Hawkes & Leach (2005) showed that 10 minutes is the longest time step that gives good data for sizing CHP systems; the gas smart meter use cases ask for 6 minutes (ENA, 2010). Room temperature and humidity do not vary as fast; 15 minutes was the shortest frequency for these (Parker et al, 1996). Vuillecard et al (2011) report measuring both gas use and hot water flow at 1-minute intervals as well as electricity and even their temperature measurements may have been at that resolution.

3.4.2 Duration

Most data collection has been run for between one and two years (Appendix 2), to ensure that high heating consumption in winter or high cooling in summer is covered adequately, and seasonal fluctuations become apparent. However, Newborough & Augood (1999) restricted their electricity measurements to 1 month, and Wright & Firth's electricity profiles (2007) missed out an autumn. In the Swedish study only 10% of households were measured over a full year, the rest for one month only, and REMODECE (2008) generally managed only 2 weeks for each household – although they originally set out to cover twice that period. Hot water demand was also measured over shorter periods - three months (Chen & Lee, 2010; Gill et al, 2011), or even just 14 days (Lane & Beute, 1996) - on the assumption that this will not vary much.

Experience from various programmes (Gill et al, 2011; Isaacs, et al, 2010) suggests that adequate results can be obtained from a data collection plan which covers some of the sample properties in detail, and the rest at a reduced level, as long as a whole winter is included in each case.

3.4.3 Immediacy

Most programmes have logged data on site, and retrieved it periodically at a later date. Elexon (2011) is the most extreme, collecting the loggers and analysing the data only after the end of a full year. In both the Swedish and the New Zealand programmes, data was logged in each house for a month before being downloaded during visits by a dedicated collection team (Zimmermann, 2009; Isaacs et al, 2010). Firth et al (2008) were able to download remotely using the public telephone system and Richardson (2010) and Yohanis et al (2008) also used dial-up modems, but in both cases this was done only at intervals of several weeks, by which time it was difficult to investigate anomalous data. The DATA BIRD automatic meter reading system in Leicester has a one-day turnaround, using a network of radio repeating stations through the city to collect low-power transmission from local data loggers and forward them to a central receiver; from here they are downloaded daily to the analysis system (Ferreira, 2009).

3.4.4 Consistency and accuracy

The instrumentation used in measurements is not always reported, but where this is, overall electricity demand profiles were measured with a power meter close to and at the same level of accuracy as the utility meter (Richardson 2010; Isaacs et al, 2010). Accuracy standards for meters vary by country but in the UK this is +2.5%/-3.5% (Ofgem, 2005).

For heating, the common approach is to measure temperature profiles in living rooms and at least one bedroom, and fuel consumption only periodically (Isaakson & Karlsson, 2006; Summerfield et al, 2007; Williamson, 2005;). Where instrumentation was mentioned, the temperature sensors were rated at +/0.5 ^{o}C accuracy (Shipworth, et al. 2010). Heat flow was measured by Gill et al, (2011), in the context of a district heating system where hot water is metered by the utility company. Vuillecard et al (2011) alone reported measuring heat flow into the heating system, separately from hot water consumption.

Where end-use or individual appliances were measured, different approaches were used. REMODECE’s methodology gives two different lists of priority items, both individual appliances and groups; however, dishwashers or cooking are not in either priority list; and it is not clear from the database how well the methodology was followed in each individual country. HEEP looked at end-use in a quarter of their sample houses. They measured power at circuit level for electric heating, hot water and cooking to the same standard as overall electricity consumption. However, for individual appliances they deployed only 2-3 transponders per house, using a random selection procedure each month to decide which to monitor; this meant that some of the time they were monitoring equipment that was hardly used (Isaacs et al, 2010). The Swedish programme took the most systematic approach, monitoring 30 circuits and appliances plus 25 lamps in each house (Zimmermann, 2009). However, even they did not always manage to measure the right things: the follow up interviews by Bladh & Krantz (2008) in seven houses showed that some of the most frequently used lights had been missed.

3.5 Practical issues

3.5.1 Finding volunteers

This is the first major problem encountered by all measurement programmes. These can be perceived as intrusive, and as passing judgement on lifestyle and consumer choice (Ofverholm, 2009). Those who volunteer are almost always people who are interested in energy use in the first place, so the sample can be from a very narrow base (Chen & Lee, 2010; Firth et al, 2008). Some kind of incentive for participation helps (Elexon, 2011; Richardson, 2010),

3.5.2 Data privacy

Data privacy / security considerations must be planned for carefully. For example, at Strathclyde, such an exercise would fall into the University Ethics Committee's definition of

"a situation where highly personal, intimate or other private or confidential information of a personal nature is sought" (University of Strathclyde, 2009)

for which approval must be sought from either the University or Departmental Ethics Committee. Their guidelines specify how volunteers may be recruited, and require assuring participant anonymity and security of any personal information collected – in this case, addresses and meter numbers. There may be a need to register the database with the Information Commissioners' Office, under the Data Protection Act. If data is being transmitted from the volunteer house via modem or internet, security during transmission will be an issue, as load profiles alone contain a lot of information about when people are in or out of the house during the day (Richardson, 2010).

3.5.3 Access and equipment location

Access to premises to install equipment may be an issue especially if people are out during the day – this was a problem reported by all four utilities participating in EDRP (Ofgem, 2010). Other recurring problems reported are whether there is space to install a second meter on the existing meter box (Isaacs, et al., 2010), (Richardson, 2010).

3.5.4 Data transmission and storage

Collecting, cleansing and handling such large amounts of data are a big challenge in any collection programme. Wright & Firth (2007) found that their transmissions dropped out periodically, and when they resumed the transmission for next period started with spikes that accumulated all the data missed previously. Richardson (2010) lost data because the modems could break down and transmission was sensitive to interference, even a car parked in the wrong place could cause drop-out.

The rapid growth of computing power does mean that tasks that were too large to handle a few years ago can be carried out easily today. In 2008, Richardson (2010) needed to use a Microsoft Server SQL database to handle one year's worth of 1-minute data. Three years on, it has been possible to analyse those 500,000 lines of data per house, including graphing, on a normal laptop using Excel.

3.5.5 Cost and effort considerations

Instrumentation costs have been one of the barriers in reported measurement programmes. (Schrock, 1997) reported that orders of magnitude at that time were:

- Run-time meter with 1-4 channel logger: $100-200
- Multi-channel data loggers: $800-$4000
- 3-phase power analyser: $3,000-15,000

The HEEP project (Isaacs, et al., 2010) found it cheaper to build their own loggers than buy them - building 750 temperature a dozen 16-channel electricity loggers. However, a cursory Internet search showed that sensors and loggers are now available for the consumer market at relatively low prices. A ThermaData combined temperature and RH logger, with an accuracy of +/-0.5% T and +/-2% RH that will record 75 days' worth of 15 min readings can be bought for around £90. A home electricity monitor such as the Current Cost meter marketed by Envi which is capable of measuring up to 10 channels of current only, costs under £100 including sensors.

The effort involved in installing, testing, downloading data and checking for data quality is high. One and a half days out of every 3 weeks was required for data download and checking for the 22 meters in Loughborough (Richardson, 2010) HEEP reported 800 person days to install monitoring equipment in 400 houses (including travelling time) and employed 12 full-time download field staff (Isaacs, et al., 2010). The Swedish study had a similar level of costs for analysis and reporting as for equipment and installation (Ofverholm, 2009).

3.6 Consistency in outcomes

3.6.1 Energy use

Peak loads measured over 1 minute for one month by Newborough & Augood (1999) were 4-7 kW if no space heating used, and up to 15kW where it was (N&A); Wright & Firth (2007) found 8-9 kW peak loads, measuring average load over 1 minute for 9 months. Both also found similar weekly load factors, 0.06-0.15 in the first instance and 0.08-0.15 in the second. The Swedish study reported 3-16 kW with, and 3-16 kW peak loads without electric heating (Zimmermann, 2009), but this may in reality be higher because the load was averaged over 10 minutes. The average power over the year reported in UK measurements was consistently under1 kW per household (Newborough & Augood, 1999; Wright & Firth, 2007; Richardson et al, 2010; Gill et al, 2011, Yohanis et al, 2007). This was also largely true in New Zealand, except in the far South where more electric heating is used (Isaacs et al, 2010). In Florida, the average in the low-income houses surveyed was around 1kW, excluding air conditioning and air handling (Parker et al, 1996). Sweden alone has reported significantly higher overall power usage – for homes without electric heating, the lowest user band averaged 1.7 and the highest 4.7 kW, - the lower values applied to flats and to smaller families (Zimmermann, 2009).

3.6.2 Correlations

Some work has assumed that only heating and lighting is subject to seasonal variation and that most appliances or hot water demand can be treated as constant (Lane & Beute, 1996; Newborough & Augood, 1999; Yao & Steemers, 2005 REMODECE, 2008). However, the Swedish measurement programme which looked in detail at end-uses showed significant seasonal variation in several end-uses: refrigeration, cooking, consumer appliances (Zimmermann, 2009).

Yohanis et al (2008) whose sample included a large proportion of houses with electric heating found that electricity use is well correlated with floor area, however, others such as Gill et al (2011) or Summerfield et al (2010), whose sample houses used other forms of heating did not. Floor area is a driver of energy used for space heating (Summerfield et al, 2010). Occupancy pattern (Richardson 2010) and to a lesser extent occupant numbers are the main drivers of other end-uses, although the effect of increasing occupant numbers levels off as more are added (Zimmerman 2009); indeed, the biggest difference is seen between single and two-person dwellings (Bladh & Krantz, 2008).

Income and energy use were found to be well correlated by Yohanis et al (2008), and by inference also by Summerfield et al (2007) who found that the higher energy consumers in the first survey were the ones that had built extensions onto their houses, and Zimmerman (2009) who found that two-adult households consumed more electricity than families in similar properties, presumably because of higher disposable income.

Observed trends in energy use with time are ambiguous, partly because the data sets are very few. Firth et al (2007) found that although the average energy use in their 72-house sample had increased by 4.5% from one year to the next, this increase was mainly in the sub-group that were high users to begin with. Summerfield et al (2010) also found that 15-year increase in average consumption was almost all among the high-using group, whose electricity use has gone up 72%; the low users also registered a 34% increase but at the end of the period the absolute difference between them and the high users had widened: they were now using only one-third as much, down from the proportion of half at the beginning. Among mid-range users, consumption had actually dropped over 15 years. It is possible that these changes are driven by income.

3.6.3 Attitudes and behaviours

Every study reports wide variation in consumption between houses and households that apparently look similar. High consumers are high across all end-uses (Gill et al, 2011; Parker et al, 1996); they also appear to be increasing their level of consumption at a faster rate (Summerfield et al, 2007; Firth et al 2008).

Even for heating, human behaviour will influence whether the building performs as expected given its size, thermodynamic properties and the climate. A common finding in measurement programmes in inhabited houses is that thermostats are either not understood, or set very high (in cold climates: Shipworth et al, 2007 and Summerfield et al, 2007) or very low (in hot ones: Parker et al, 1996). The findings of Williamson (2010) also show that people can be quite happy to live in a wide range of different conditions provided that they see it as their choice. On the other hand, where a technological solution is felt to be imposed, people will easily circumvent it by installing additional portable heaters (Isaakson & Karlsson, 2006) or by turning thermostats to maximum (Parker et al, 1996, Shipworth et al, 2010).

Households are not always consistent in their behaviours: those who used low energy bulbs in some areas also used some of the most energy-intensive light fittings elsewhere (Bladh & Krantz, 2008) and people who go out of their way to ensure that they are buying energy efficient refrigerators will put them an unsuitable location such as built in beside the oven (Owen, 2006), or leave them open regularly when in use (Tang & Bhamra, 2008). They do not notice or take action when appliances start to malfunction – such as the high percentage of broken thermostats in hot water tanks or refrigerators which were stuck in compression cycle (Isaacs, et al., 2010).

4 Analysis of a high quality data set

Data from the measurements used to validate the simulation model developed at Loughborough University (Richardson et al, 2010) were found to be available on a public database, the Economic and Social Data Service operated by Essex University. Data analysis reported by Richardson (2010) was discussed in section 2.4.1. This chapter presents additional analyses of this data aimed at testing the lessons from Chapter 3.

4.1 Background

The measurements were carried out in 22 houses in Loughborough during 2008 and 2009. This data set consists of 44 data files in csv format, each giving the date, time and average power used per minute for one house in one year, as well as files containing survey data and the questionnaire used. It can be accessed via the internet (Richardson & Thomson, 2010).

The questionnaire was filled in by each household at the end of the first year of measurements, and asked about house type, number of occupants, heating and hot water systems, level of insulation, and major appliances owned. The sample households were volunteers who were recruited via a press release, although in fact most of them turned out to be associated with the university.

Of the 22 houses, 10 were on ordinary domestic tariff, and 12 on restricted - Economy 7. All of the houses had central heating except for two, and neither of these used electricity for space heating. All used electric water heating, although 3 reported that they used this in winter only. Less than half had electric showers. Every house had at least one cold appliance and a washing machine, but only 8 had tumble driers while 15 had dishwashers. Only 3 had electric hobs, but 15 had electric ovens. 15 reported that at least half the lights in the house used low-energy bulbs. Interestingly, 5 out of the 12 who were on Economy 7 tariff did not have timers in the house. The average household size was 3.45. Floor area and income level were not surveyed, but an estimate of floor area was gained from the Ordnance Survey footprint in the original study – however, this is not included in the public data. A house by house summary can be seen in Appendix 4.

4.2 Accuracy, immediacy and quality of the data

Measurements were made using Elster A1140 electricity meters installed beside the normal electricity meter in each house. These were able to read power and calculate energy consumption at the level of accuracy of the utility meter, +2.5/-3.5% (Ofgem 2005). The meters could store 3 weeks' worth of 1-minute resolution data before downloading via a modem.

Missing and anomalous data could be identified only after downloading.

Three kinds of problems were common:

- Large blocks of data missing. The missing periods could be anything from a few hours to several weeks. However, the data stream returned after even the longest break, re-starting at midnight GMT, except in two cases where no data was transmitted after summer 2008.
- Short bursts of missing data, ranging from a couple of seconds to 40 minutes. These were harder to identify than the longer blocks
- Strings of zeroes in the data, these were of similar length to the short missing bursts.

Missing data	2008	2009
>20%	3	12
10-20%	2	9
5-10%	6	1
<5%	11	0

Table 4-1 Number of houses by level of missing data

Data quality was better in 2008 than in 2009. Half the houses had 5% or fewer lines of data missing, whereas in 2009 all of the houses had more than 5% missing data and half had over 20% missing (Table 4-1).

The data loggers in Houses 2 and 16 broke down in summer 2008 and were not replaced, but the remaining loggers continued to work.

Richardson (2010) indicated that the problem was not with the data loggers but with the transmission modems which occasionally stopped working. As the data logger's capacity was only 3 weeks, any data that was not picked up on time was lost. The download signal was also sensitive to interference, sometimes even a car parked in the wrong place would cause a short dropout, and this was thought to be the cause of the short bursts and the zero strings. It took time to find and fix problems as the data were reviewed some time after they had been captured, and the householders had then to be contacted.

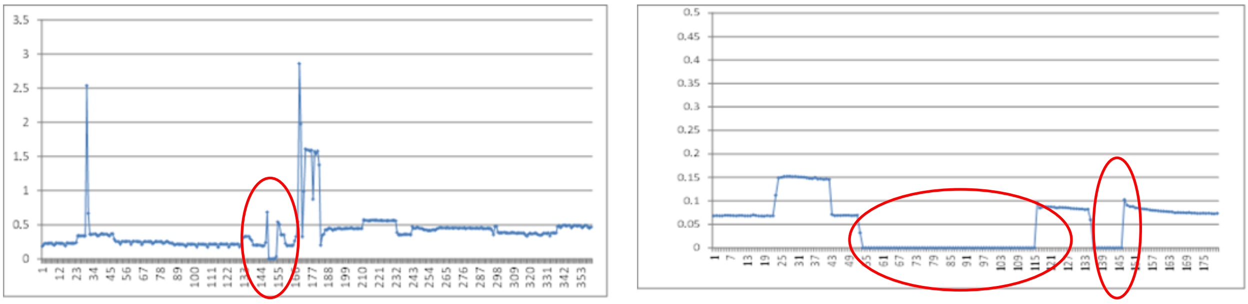


Figure 4-1 Typical traces with missing data

Missing data or zeroes did not affect the readings on restart, for example by showing accumulated rather than discrete readings. Figure 4-1 shows illustrates this: the very short outage in the first chart was in the middle of a spike, and the readings return to the previous level. In the second chart, with a longer outage there may be a tiny blip on restart; however, it is not big enough to affect the pattern. Missing data were therefore not corrected or interpolated, they were just left out of averages.

One significant piece of context data was missing in the original files was that although the date and time had been recorded, the day of the week was not – although this was not difficult to reconstruct, it was time-consuming.

4.3 Data processing approach

The time series data for each house was first sorted by season and by day of week. Definition of the seasons was according to (Elexon, 2011), but with winter split into two:

> **Winter 1**: from 1 January, up to and including the day before the clock change from GMT to BST in March
>
> **Spring**: the period from the day of clock change from GMT to BST in March, up to and including the Friday before the start of the summer period
>
> **Summer:** the ten-week period before High Summer, starting on the sixteenth Saturday before the August Bank Holiday
>
> **High Summer**: the period of six weeks and two days from the sixth Saturday before August Bank Holiday up to and including the Sunday following August Bank Holiday
>
> **Autumn:** from the Monday after the August Bank Holiday, up to and including the day before the clock change from BST to GMT in October
>
> **Winter 2**: from the day of clock change from British Summer Time (BST) to Greenwich Mean Time (GMT) in October, up to and including December 31st

This definition means that seasons are of unequal length, and the number of weeks can vary from year to year except for Summer and High Summer. It was chosen because it does reflect experience of how activity patterns actually vary over the year, with High Summer corresponding to the school holiday period, and the start of winter and spring with abrupt changes in daylight hours. The time-series analysis was done by season and by day of week; Bank Holidays were treated as Sundays, in line with Elexon practice.

Each year's data contained an extra hour on a Sunday at the start for winter when the clocks changed, and was missing an hour of data in the first Sunday in Spring when they were brought forwards. Local time was used in all the analyses as this is what is important for people day to day. In these analyses the extra hour's data was dropped (ie, the second set of data for 2-3am), and the missing hour was treated as missing (ie, no data between 2-3am on the relevant day) As the time change occurs when activity is lowest, this was not considered to introduce much error.

4.4 Comparison with population

In the original study, the sample was compared against the distribution of housing types in the local area. This was found to reasonably representative, although detached houses were over-represented at the expense of flats. The overall average annual electricity use was within 5% of that in the local area (Richardson 2010). However, on other criteria the fit is not so close. Table 4-2 compares household sizes in the sample with that in the UK population. It shows that the sample over-represents large households, with 50% of the houses having 4 or more occupants compared to the national average of 20%. This would require more investigation if the results were to be extrapolated more widely: it could be that the local area's demographics are different, or that the sample does not represent the area, or both.

Household size	Sample	National[2]
1	9%	29%
2	14%	35%
3	27%	16%
4	27%	13%
5	18%	5%
6+	5%	2%

Table 4-2 Distribution of household size compared to national average
Source 2: Social Trends 39 (ONS, 2009)

The annual consumption for each house was estimated by pro-rating for the missing time at the average measured rate of consumption. This means that the totals are inaccurate, especially where the missing data was mainly in one particular season. The 2008 numbers are more reliable, but even there totals for Houses 2, 10 and 16 are more approximate than the rest. Totals are not shown if more than 50% of the data in a year was missing.

Figure 4-2 shows the range of consumption by the two tariff classes. The mean Ordinary tariff consumption in 2008 was 3712 kWh, whereas the average for the local authority area of Charnwood was 3481 kWh. However, for this small sample the difference is 0.58 of the

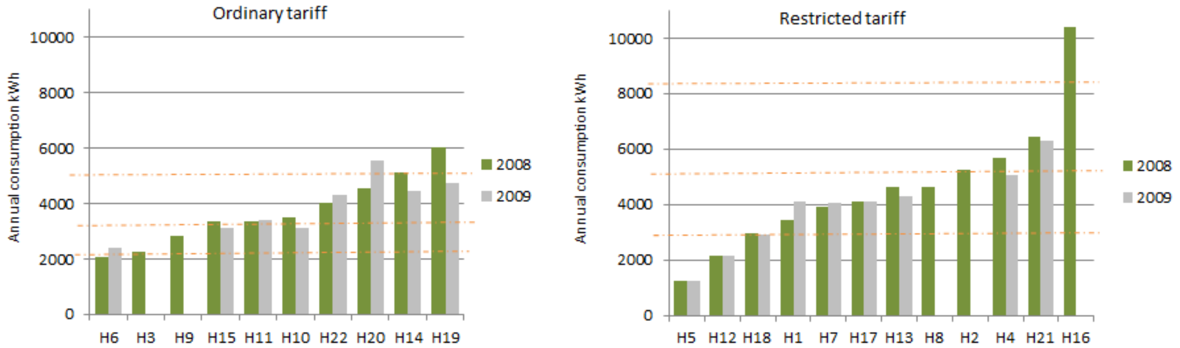


Figure 4-2 Annual consumption of the sample Loughborough households
Dashed lines show Ofgem low, medium and high consumption cut-offs for each tariff level
No data is shown if 50% or more data missing in a year

standard error. For the Restricted tariff households, the average is 4588 kWh/year, compared to a Charnwood mean of 4671, and the difference is just 0.12 of the standard error. Restricted tariff users make up 55% of the total sample, close to the Charnwood district council average of 50%. In average electricity consumption terms therefore the sample represents of the bulk of the population well.

	Ordinary	Restricted
Highest	10%	8%
High	50%	25%
Low	30%	50%
Lowest	10%	17%

Table 4-3 Distribution of sample houses by Ofgem consumption band

Figure 4-2 shows the range of consumption by tariff type, with the Ofgem band cut-offs shown as dotted lines. It would appear that the sample under-represents the very highest consumers – another potential limitation to how far the data can be generalised. None of the ordinary tariff houses would fall into Elexon's highest band, over 7,500 kWh per year.

Another perspective on the range of consumption is given on the Lorenz curve in Figure 4-3. This compares actual cumulative use by houses, ordered from least to highest, against the straight line that would represent equal consumption. The more the actual line bows away from the straight, the greater the range of use between highest and least. The Gini coefficient of this distribution is 0.24, which indicates the level of inequality closer to that of Norway (G=0.19) than the US (G=0.37).

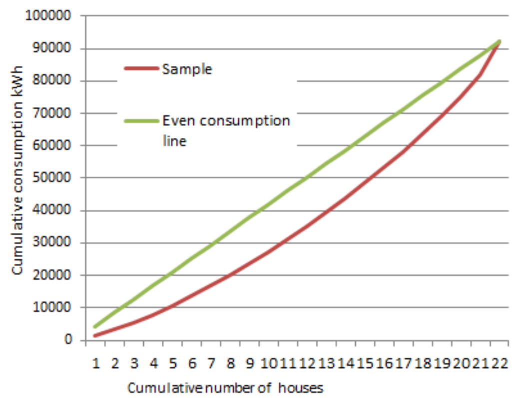


Figure 4-3 Cumulative consumption across sample houses (Lorenz curve)

Ownership	Sample	National
Non-electric central heating	91%	85%
Electric oven	68%	62%
Electric hob	14%	46%
Dishwasher	68%	38%
Tumble dryer	36%	59%
No. of cold app/house	1.8	1.5
No. TVs/house	1.7	2.2
Households with computers	100%	72%

Table 4-4 Appliance ownership in sample compared to national statistics for 2008
Source: (DECC, 2010)

The level of appliance ownership in the sample is compared to national ownership statistics in Table 1-1Table 4-4. If end-use had been measured, it would be a reasonable expectation that a lower proportion of electricity was used for space heating and cooking, but a higher proportion for cold appliances and computing.

4.5 Further analyses

4.5.1 Energy use

Peak power by house ranged from 5-20 kW, higher than those found by Newborough & Augood (1999) for similar houses at the same resolution. Weekly load factors were mainly in the region of 0.04-0.09, although occasionally could be as low as 0.01 or as high as 0.15; this is wider than the 0.08-0.15 recorded by Newborough & Augood (1999) over 4 weeks. Where a load factor of over 0.15 was seen, examination of the week's profile showed that the inhabitants were away and the peak was around 0.5kW. There was no obvious correlation with level of consumption: although the highest and lowest consumers in each class also happened to show the highest and lowest load factors, the second highest consumers had consistently lower LFs. LFs were slightly lower in the summer than in the winter. Average power was below 0.5 kW in over half the houses, and the highest consumption house averaged 1.19 kW. Only real power was measured so power factor could not be established.

4.5.2 Individual houses and appliance use

Individual traces were examined to see whether they do give much insight into the activity patterns of the various households, as proposed by Firth et al (2007). Figure 4-4, Figure 4-5 and Figure 4-6 show a typical week's trace for three ordinary tariff houses, the lowest, a medium and the highest user respectively. Each house shows daily peaks at the same time of day and the peaks are at a similar level. The higher consumers have more peaks during the day, rather than higher overall peaks.

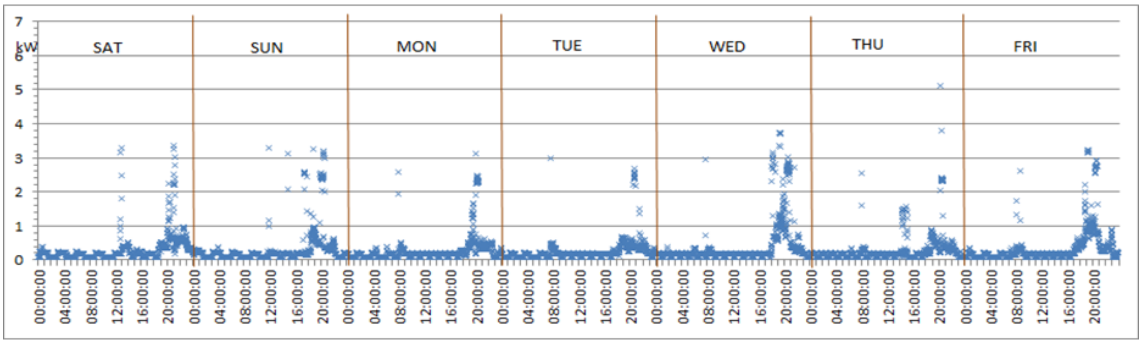


Figure 4-4 House 6, week 38, 45kWh (autumn 2009)

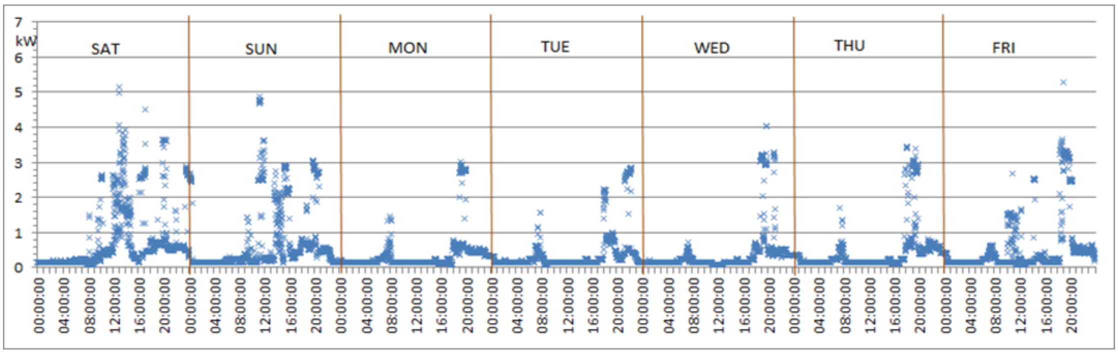


Figure 4-5 House 10, week 9, 79 kWh (winter 2009)

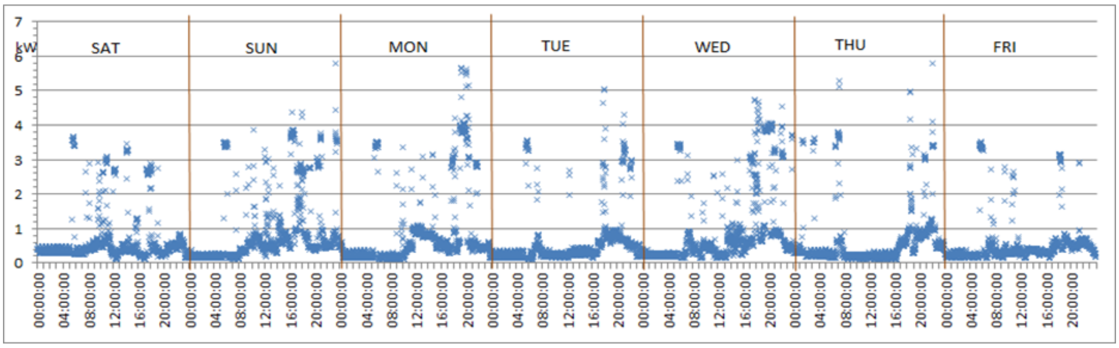


Figure 4-6 House 19, week 15, 114 kWh (spring 2008)

Figure 4-7 and Figure 4-8 show the weekly pattern in one of the medium-use Economy 7 houses, for a week in June and one in October. This house shows low evening and high early morning peaks – apparently effort is being made to maximise use of the cheaper tariff. There is little visible seasonality in the pattern of peaks and the overall consumption.

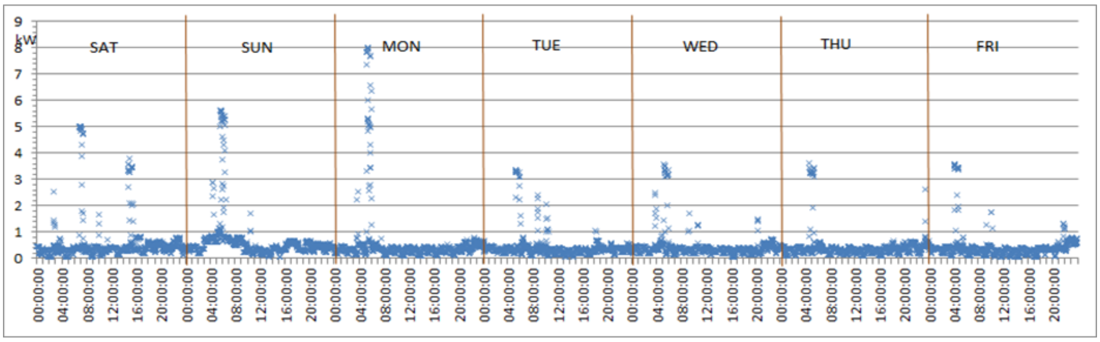


Figure 4-7 House 17, week 25, 74kWh (summer 2008)

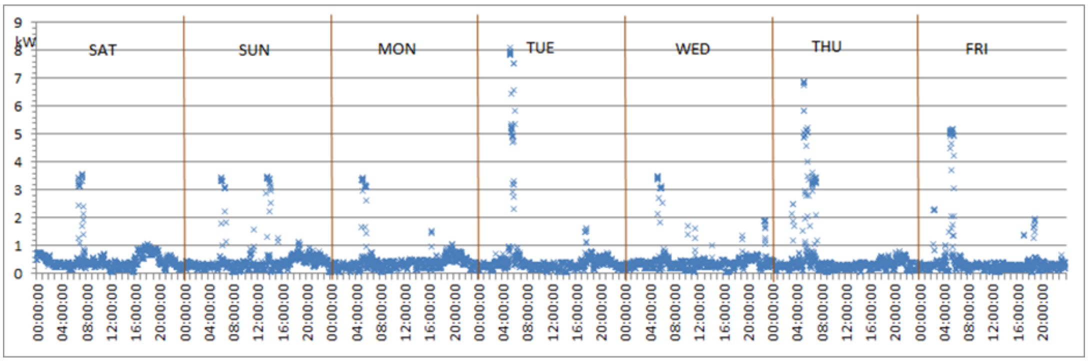


Figure 4-8 House 17, week 41, 74 kWh (autumn 2008)

Visual examination of a whole year's profile for several houses confirmed that there seems to be a characteristic shape for each house, but the timing is not absolutely periodic and the shape varies considerably from one house to another. Variations in consumption over a year show up in the duration of the small 'humps' under 1 kW that are visible in the weekly profiles above. The fact that the individual patterns are consistent across the year but different from each other supports the hypothesis that households establish their own strongly embedded routines (Gram-Hanssen, 2008).

It is not straightforward to deduce which appliances are running from just analysing the profiles, as suggested by Firth et al (2008), even with information about the level of appliance ownership. The figures below compare the night-time consumption in four houses on a summer Tuesday, for each individual day – the black lines show the seasonal average, and in each case one day is highlighted in red for clarity. In House 6 (Figure 4-9), a standard 45 minute refrigerator cycle can be seen, slightly time shifted from day to day, with a constant background consumption of around 70 W. This looks very similar to the classic refrigerator cycle profile measured by Newborough & Augood (1999), shown in Figure 4-10: the cycle is most apparent between midnight-8 am, although it can also be seen superimposed on the larger occasional loads during the day.

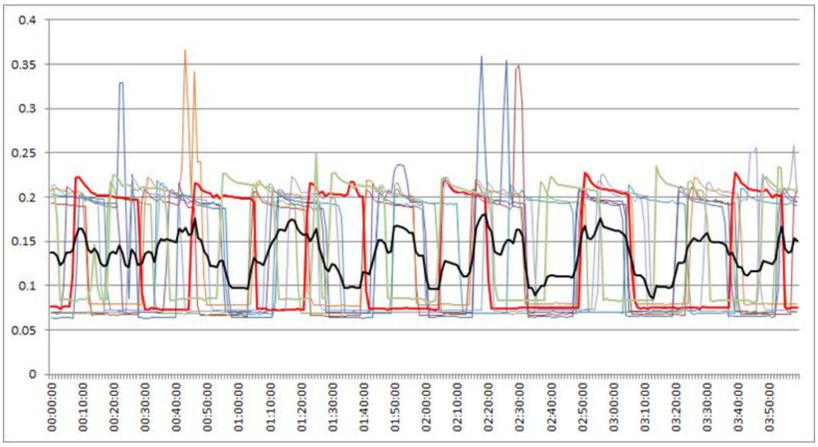


Figure 4-9 Summer Tuesday profiles midnight - 4am, House 6
Black line shows the average

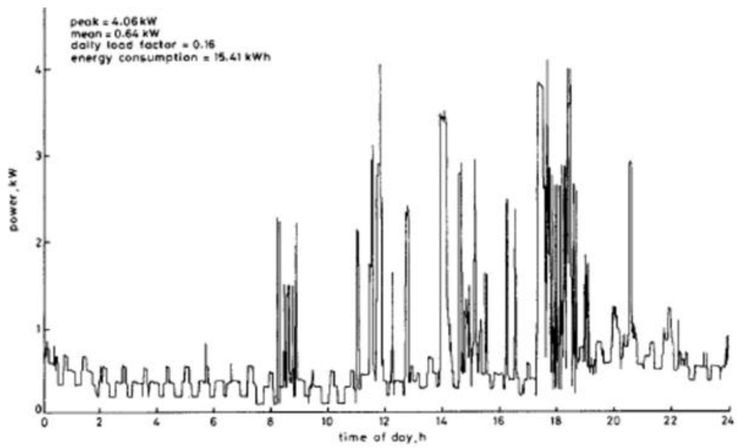


Figure 4-10 1-min electricity demand showing characteristic refrigerator cycle
Source: (Newborough & Augood, 1999), Demand side management opportunities in the UK domestic sector

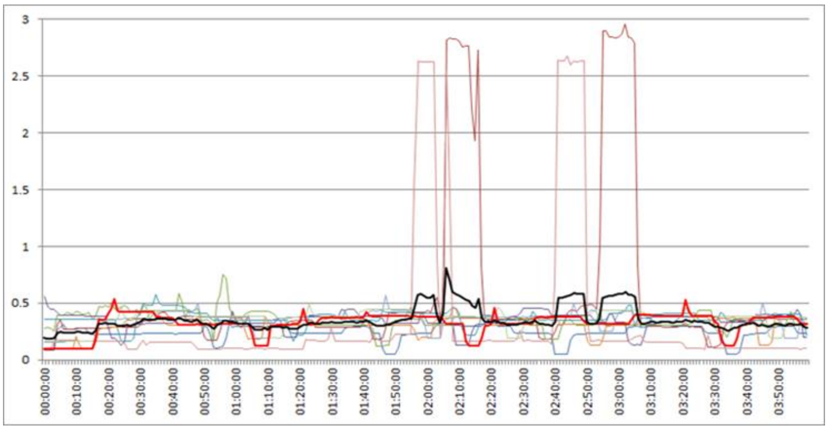


Figure 4-11 Summer Tuesday profiles midnight-4am, House 22
Black line shows the average

However this pattern is not visible everywhere. House 22 is an Ordinary tariff user with three cold appliances and the interaction of their cycles does show up as some kind of periodicity (Figure 4-11), but this would be hard to deduce without that information. The background power level varies by day; and on a couple of occasions something major happened around 2am.

House 20 (Figure 4-12) shows something different again, with cycling at 10 minute intervals every night, on top of what may be a longer cycle. Large 10-min spikes to 7kW occur on many mornings which may be the electric shower.

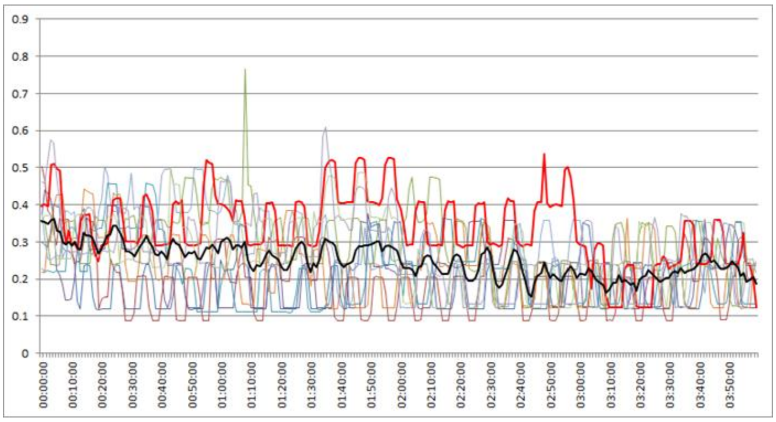
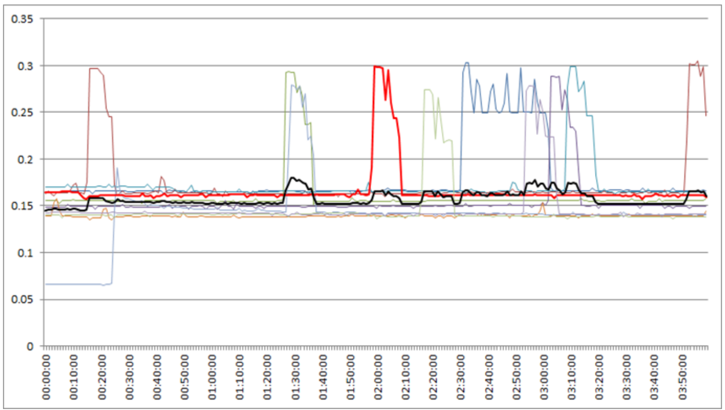


Figure 4-12 Summer Tuesday profiles midnight-4am, House 20
Black line shows the average



In House 9, (Figure 4-13) which has one cold appliance, there is only one event that looks like a refrigerator cycle to be seen on any one night over the same period. The constant baseload is 150W.

Figure 4-13 Summer Tuesday profiles midnight-4am, House 9
Black line shows the average

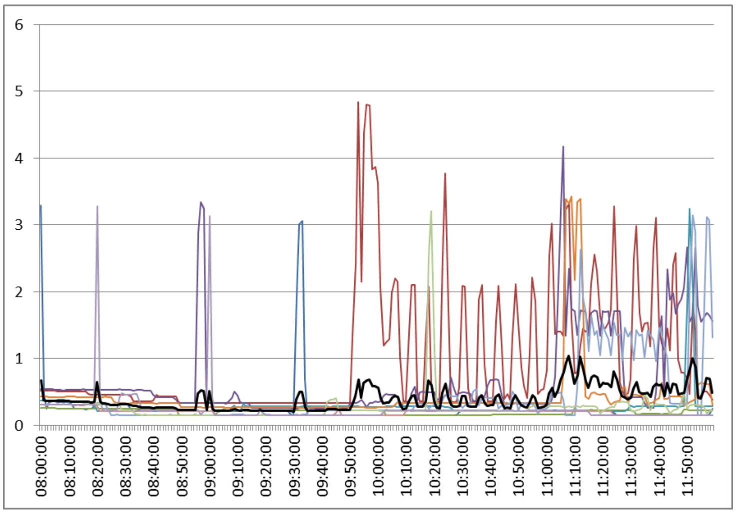


Figure 4-14 8am-midday House 4, Summer Tuesdays
Black line shows the average

Other appliances are even harder to pick out. Figure 4-14 shows a trace for one house with an electric hob, The cycling evident on some days before midday might be interpreted as cooking, with a heating up period followed by thermostatic cycling (Wright & Firth, 2007); however, this pattern is not seen on other days.

The main driver of electricity use was concluded by Richardson (2010) to be occupancy. In about half the cases it was possible to see when people are in the house during the day because a lot of electrical activity is evident on most working days. In the other half however it is not so obvious. Figure 4-15 is an example where it is not clear whether the house is occupied during the afternoons.

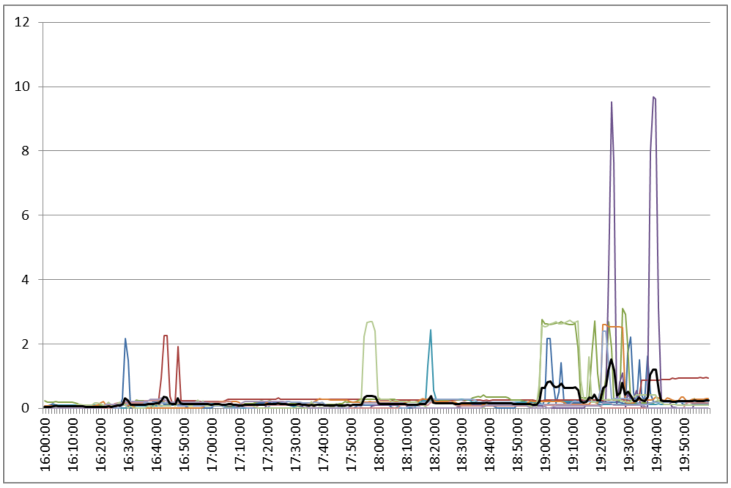


Figure 4-15 Evidence of active occupants in the afternoons?
House 3, Summer Wed, 16.00-20.00

The survey data were very useful in trying to interpret the patterns. Among the restricted tariff users, only five use the overnight tariff regularly, but the pattern of use varies. House 21 runs a 3kW appliance just about every night but at different times (Figure 4-16). House 18 also runs a couple of appliances overnight, but at set times (Figure 4-17). House 4 appears to set appliances to run when going to bed – they do not have a timer. In fact, five out of the restricted tariff houses do not possess a timer, so apart from House 4 their overnight profiles are very similar to those of the ordinary tariff users. And of the seven who do have a timer, three appear not to use it at all.

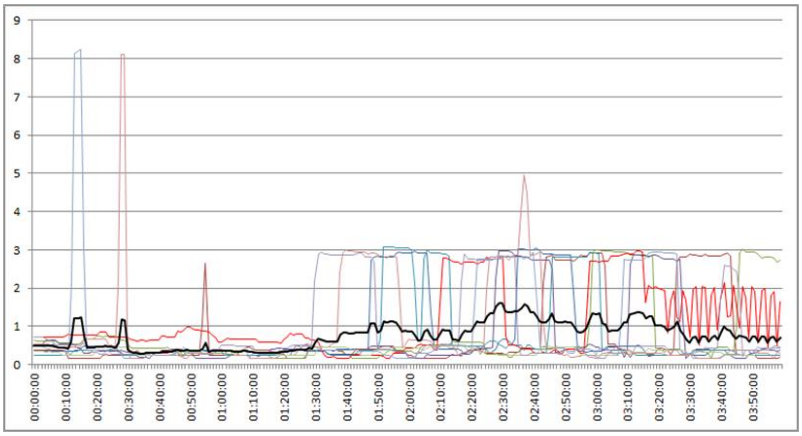


Figure 4-16 Summer Tuesday profiles midnight-4 am, House 21

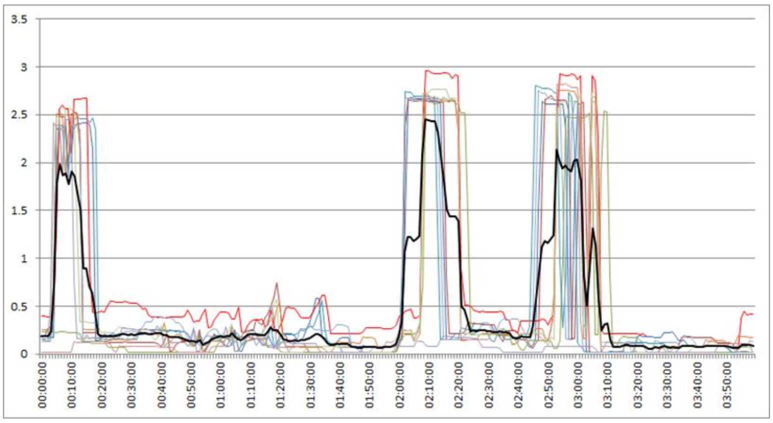


Figure 4-17 Summer Tuesday profiles midnight -4am, House 18

4.5.3 Groups of dwellings

The diversified 1-minute resolution profile by tariff class was calculated for each day in each season, together with the weekday, Saturday and Sunday average for the season. Figure 4-18 and Figure 4-19 show the summer weekday averages, with the minimum and maximum loads for the season. For ordinary tariff, the average weekday diversified peak is 0.89kW, and the load factor 0.42. However, on any given day the actual peak can be nearly three times as high. There are three periods of high load, with the peak between 10pm and midnight.

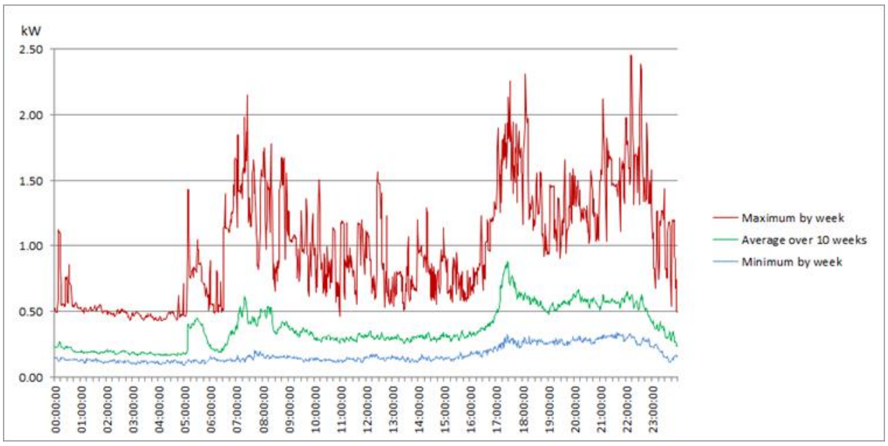


Figure 4-18 Ordinary tariff users: 1-min resolution average profile

Summer weekdays

For restricted tariff, the summer weekday average peaks at 0.98kW and has a load factor of 0.38. But at any time, the actual level can be four times as much as the average. The highest loads for this category occur in the morning just before 8 am.

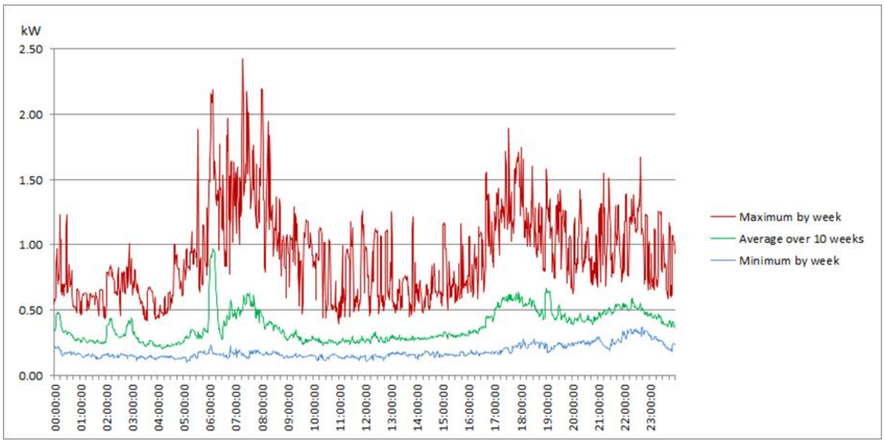


Figure 4-19 Restricted tariff users: 1-min resolution average profile
Summer weekdays

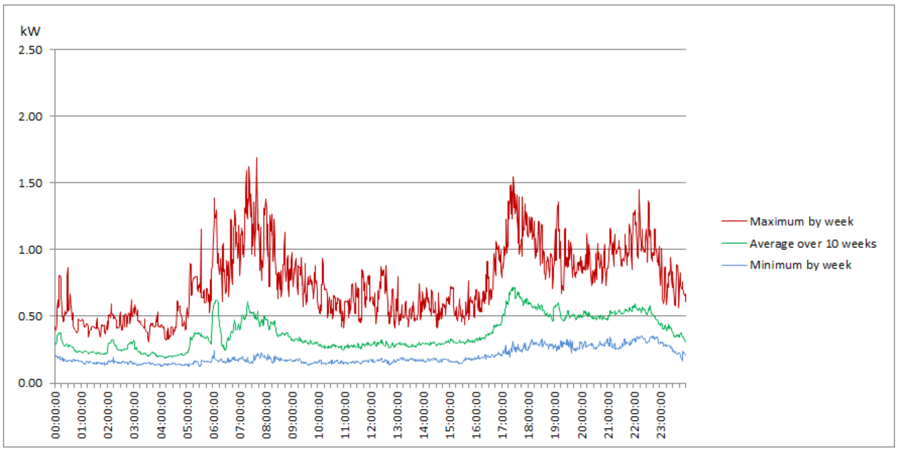


Figure 4-20 All users: 1-min resolution average profile
Summer weekday, 22 houses

When all 22 houses are included (Figure 4-20), the average peak load drops to 0.72 kW and the load factor rises 0.51. The highest average load in the season is now also lower because of the diversification introduced through the different tariff bands. In each case, the variability of the diversified load is highest at peak loading periods.

4.5.4 Effect of measurement resolution

The effect of collecting data at longer time steps is illustrated in Figure 4-21. This shows one house on one day, with the data averaged to mimic different time resolutions. The peak load at 5 minute resolution is 5% lower than what would be observed with 1 minute, and at 30 minute resolution the peak is 39% lower. The overnight refrigerator cycling pattern is still visible at 5 minutes but disappears at 30 minutes.

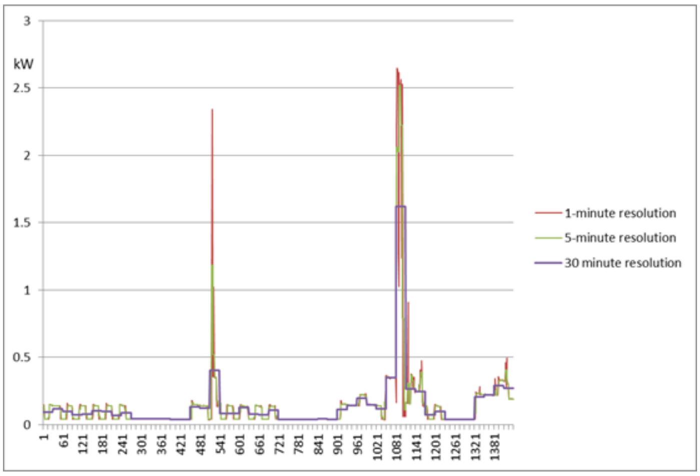


Figure 4-21 Load profile at different resolutions – one house
House 5, Saturday 14 April 2008

Resolution also matters for diversified data. The 12-house average profile at 30 minute sampling also misses the peaks seen at 1 minute by up to 50%, and even at 5 minute resolution up to 15% of peak load is missed (Figure 4-22).

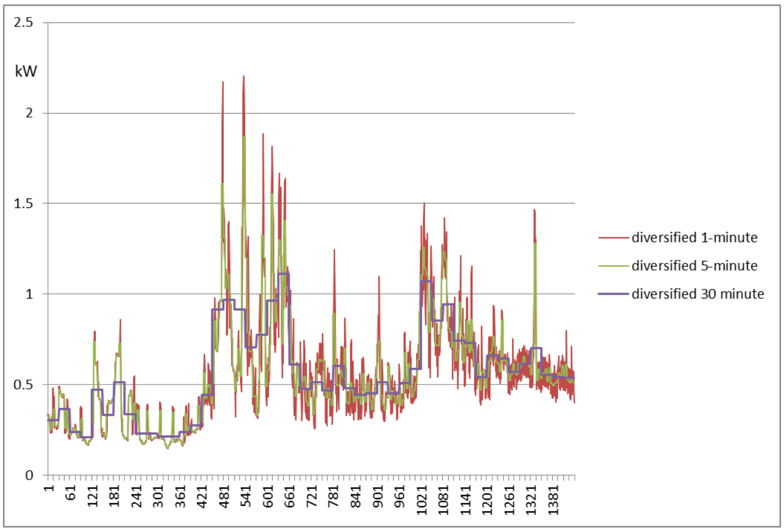


Figure 4-22 Load profile at different resolutions – diversified
All Economy 7, Saturday 14 April 2008

4.5.5 Evidence of trends

Firth et al (2007) saw a 4.5% average increase in electricity consumption in their sample over the two years of their study, and Summerfield et al (2007) found a 30% increase over 15 years. In this sample however average use went down slightly over years: 2.3% in the Ordinary tariff, and by 2.9% among the Restricted tariff users who had data for both years.

Week-by-week daily average consumption was calculated for a number of houses to see if seasonal variations could be observed. Two examples are shown in Figure 4-23: House 15 is a mid-level Ordinary tariff consumer, with four occupants and all the large appliances including five televisions. House 6 is the lowest consumer in the Ordinary tariff group, with

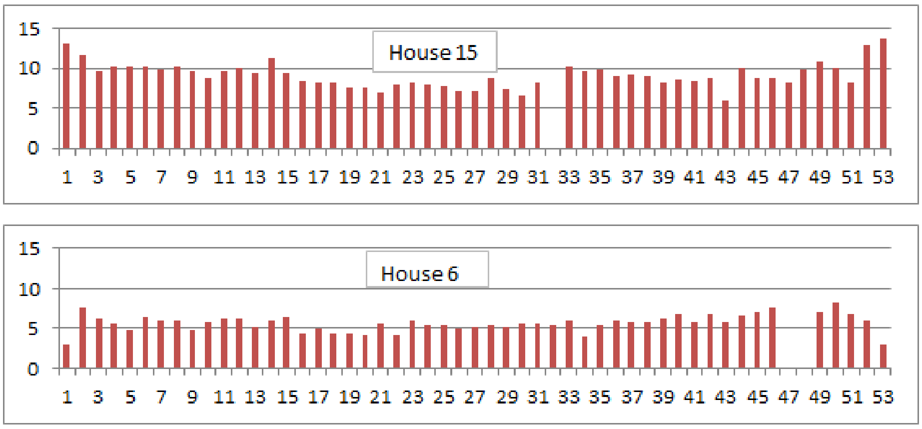


Figure 4-23 Individual daily average consumption by week, 2008
Missing bars denote no data exists for that week

only one occupant, no central heating, electric cooking appliances, tumble drier or dishwasher. In both cases only a very mild variation with season is apparent, although House 15 shows a definite increase over the Christmas holiday period while House 6 shows a decrease – probably due to different visiting patterns.

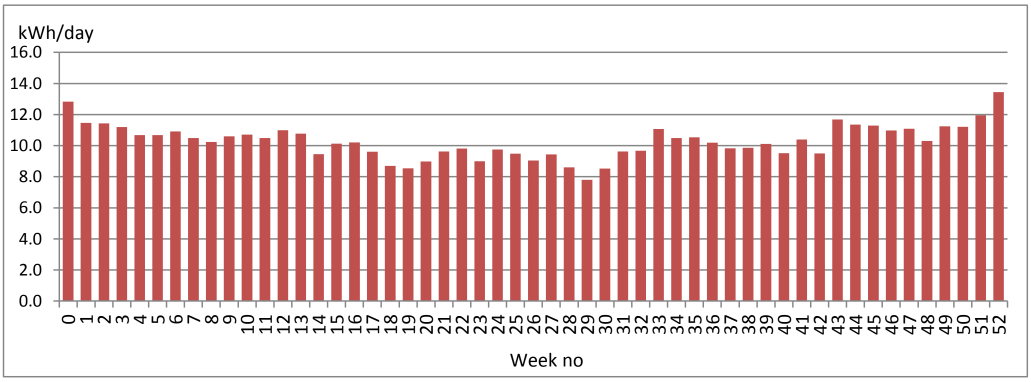


Figure 4-24 Averaged daily consumption by week, 2008
All ordinary tariff houses

Seasonality is easier to see in averaged data: Figure 4-24 shows the 2008 daily average by week for Ordinary tariff users, and Figure 4-25 shows the average across these houses by season for the two years of monitoring. In both years, the Summer period, which includes the longest nights in the year, has the lowest consumption, rising for the winter.

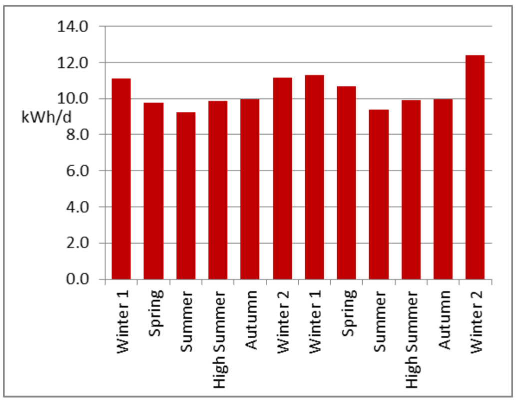


Figure 4-25 Averaged daily consumption
All ordinary tariff houses

The seasonal profiles over the two years were compared with the standard load profiles published by Elexon (2011). Here, the Loughborough data were averaged across all the relevant days at 1-minute resolution by tariff class, and then rolled up to 30-min averages for comparability. The ordinary tariff profile (Figure 4-26) has a very similar level and shape to the Elexon, although the lower daytime level during weekdays indicates that a higher proportion of this sample was out of the house regularly. The pronounced peak in the early morning is due mainly to one house which regularly showed an appliance switching on at 3kW for about an hour early in the mornings.

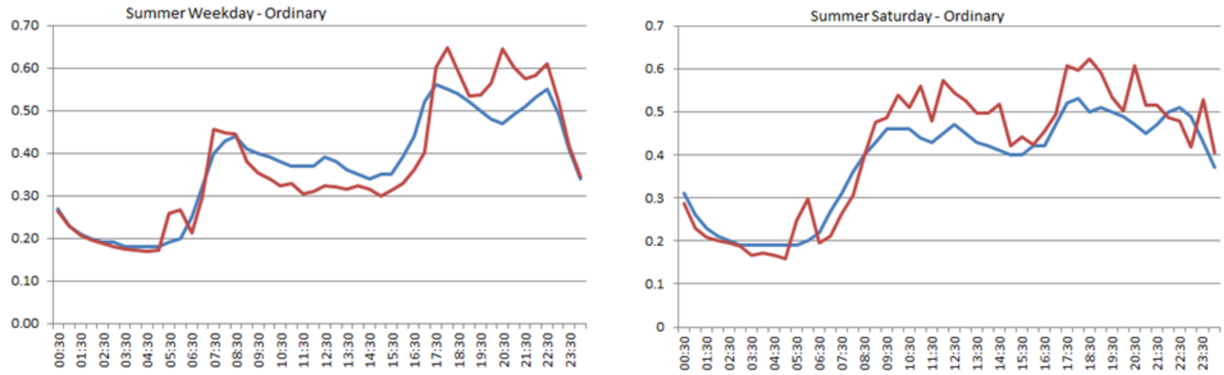


Figure 4-26 Ordinary tariff: Comparison with national typical profile

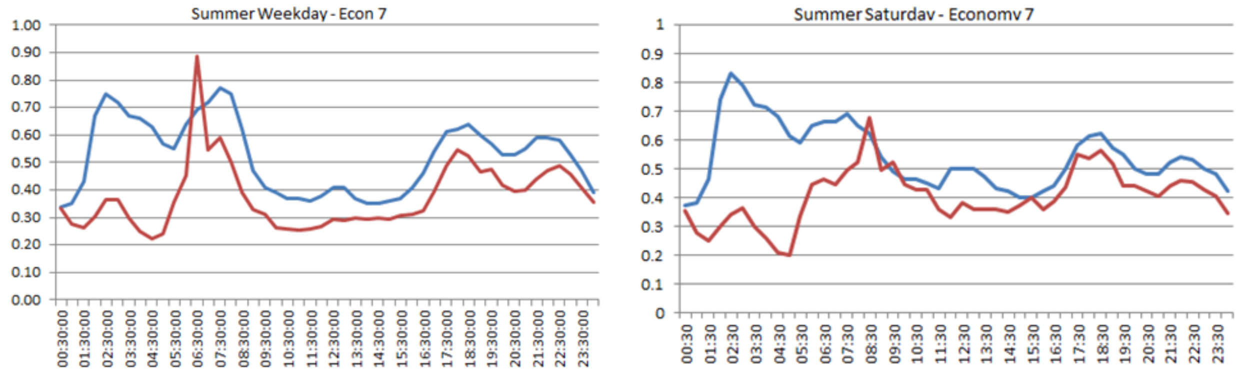


Figure 4-27 Restricted tariff: Comparison with national typical profile
Summer weekday and Saturday; Red line: Loughborough data, blue line: Elexon profile

However, restricted tariff houses were markedly different (Figure 4-27). First none of the houses had electric storage heaters, so they were not using as much energy in total as the national average. The average national daily summer consumption in this class is 12.6 kWh on weekdays and 13.0 kWh on Saturdays: this sample used 9.0 kWh on weekdays and 9.6 kWh on Saturdays. Secondly, since only 7 of these houses actually had timers, the amount of load shifted to night-time was lower.

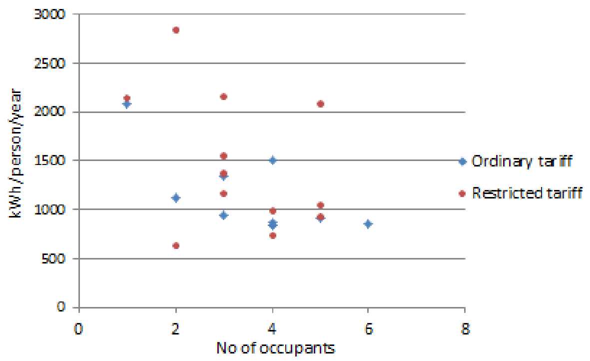


Figure 4-28 Electricity consumption per person by household size

The study of low-energy houses by Gill et al (2011) noted a decreasing tend in energy use per person, with increasing household size. This is not readily apparent from the Loughborough sample, where without the single outlier point near 3000 kWh/person, no trend at all would be visible (Figure 4-28). Both lowest and highest consumption per person are in restricted tariff households – the former is the more surprising finding.

The average daily consumption was plotted against appliance ownership, trying out a number of different ways of counting appliances. Figure 4-29 shows the best correlation, which is with large appliances owned. These comprised electric shower, refrigerators and freezers, hobs and ovens, washing machines, tumble driers and dishwashers, and TVs and computers.

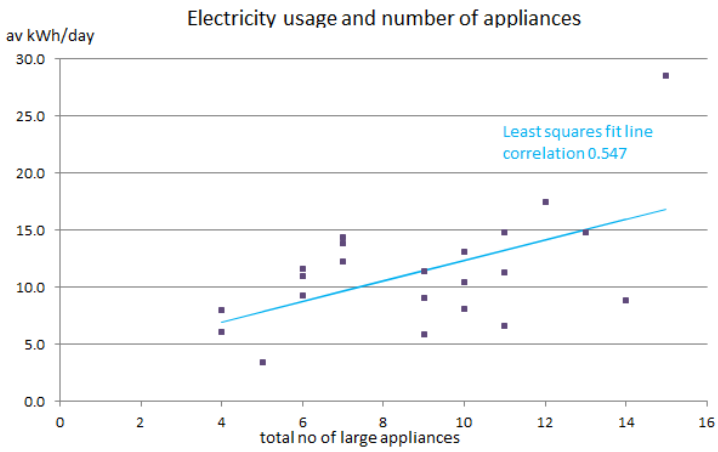


Figure 4-29 Electricity consumption and large appliance ownership

Some kind of trend is evident here, although it is not enormously strong, and the correlation is only 54%. Table 4-5 shows the ownership of various large appliances within the top and bottom quartiles in the whole sample. Although there is one case where electric heating is used, this g

	No. among highest 5 consumers	No. among lowest 5 consumers	No. in all houses
Electric heating	1	0	2
Electric showers	2	3	9
Electric hobs	1	0	3
Electric ovens	5	1	15
Tumble driers	0	3	8
Dishwashers	1	4	15
Av. Occupancy	1.8	3.8	3.45

Table 4-5 Ownership of large appliances in top and bottom quartile

house is in fact only the 5th highest user. Ownership of electric showers is fairly evenly spread in the rankings. The only appliance where ownership and energy use ranking seem to be correlated is electric ovens, where 9 of the top 11 consumers have them, and dishwashers, which are owned by 10 of the top 11. It is however significant that the bottom quartile has low numbers of occupants while the top quartile has higher.

4.6 Conclusions from data analysis

This was a relatively homogeneous sample group, reflecting the average users in the district but not the extremely low or extremely high consumers. The lack of the latter limits the extent to which the outcomes can be extrapolated to the wider area. One large, regular user in the sample did affect the overall shape, even over a 22-house group.

They give a reasonably typical picture of the pattern of ordinary tariff users but less so for restricted tariff users. In the sample, many of the people who have the Economy 7 tariff do not actually make use of it, especially not for heating.

It is harder to tell which appliances are being used appliances from time series readings than implied in the literature, even with survey data is available on which household owns how many of each. One-minute resolution data gives a different picture of the size of peak loads even when diversified over a group of houses. Even a five-minute average loses around 15% of the peak.

Total electricity use did increase as the household size went up. However, there was no observable trend in the amount used per person with increasing household size. There is some correlation between large appliances owned and total electricity use, but this is weak. Ownership of dishwashers and electric ovens in particular was significantly higher among the highest users than the lowest. There was no evidence of increasing usage from one year to the next.

The fact that only electricity was measured means that energy consumption is not truly comparable across the various houses. The proportion of electrical energy used for hot water and for cooking, in particular, will be very different in a house that has electric showers, and electric oven and hob than one where it is not. However, since only total electricity use was measured, and end-uses and other fuel consumption were not, it is not possible to use this data for modelling what-if scenarios on fuel switching or demand management.

The aim of the original programme was to validate a model of electricity demand for a group of houses, in order to carry out network analysis, and it met this aim well. The present analysis exercise has demonstrated is that it is possible to use that same data for other investigations and purposes. The survey information was very important in enabling this.

5 Specification for a standard, comprehensive data set

Data collection programmes always have a specific purpose, with limited budgets and people available, so they measure only that which is strictly required. However, any such exercise is time-consuming both to set up and carry out, so there ought to be some value in thinking beyond the specific demands of the question in hand. This section outlines the requirements for a standard, comprehensive data set, based on the findings in Chapters 3 and 4, and proposes a specification for data collection whose outcome could be used more widely.

5.1 Measurement plan requirements

The requirements for the measurement plan are:

- Measure inputs for all fuels – even where this can only be approximated.
- Measure consumption by end-use – by groups of appliances that are used together where possible, individual appliances where not.
- Prioritise based on the importance of each in terms of: potential for time-shifting; potential for change of fuel; overall consumption; contribution to peak load
- Measure inputs/activity drivers as well as outputs / consumption
- Be consistent in what is measured, frequency and accuracy level
- Understand the individual context of each household through a structured survey at the start, preferably face-to-face
- Tailor the plan to the context so that all the important end-uses are covered without collecting too much low-impact data
- Collect and analyse the data quickly, preferably in real time, so that anomalies and problems can be investigated
- Use consistent categories for context and analysis
- Make the cleansed data available publicly as well as the analyses, but without personal data that could identify the participants
- Aim for a quantity of data that could reasonably be expected to be collected by monitoring programmes without a large incremental cost

5.2 Data

The data items are shown in two categories: those which are most important to collect consistently in every case, and those which would be very useful but could be dropped if circumstances dictate. Also, survey information includes some which can be gathered effectively only through face to face interviews and not by a questionnaire. In the sections below, the second-tier measurements, and the interview-only questions, are shown in italics.

If resources are constrained, experience from other programmes suggests that adequate results can be obtained from a data collection plan which covers some of the sample properties in detail, and the rest at a reduced level. This would however restrict the usefulness of the data for statistics and some model calibration.

5.2.1 Fuel use and general context

This is data on the house and its occupants that gives the context for energy use, and its overall consumption of different fuels that ties together the end-use level measurements. The general survey includes a full set of context data. The survey on attitudes to energy use lists the areas to be covered in an interview; the actual questions will need to be couched more colloquially and follow-up and clarification questions designed.

MEASUREMENT – FUEL USE

- Gas: utility revenue meter readings
- Electricity: utility revenue meter readings
- Oil: tank level measured via hydrostatic gauge, together with delivery records of volume and specific gravity
- Bulk LPG: tank level gauge or electronic monitor – most domestic tanks are equipped for telemetry by the supplier
- Solid fuel: log of volumes used, with delivery records of volume
- On-site generation: output of generator for electricity, and/or temperature and flow rate for hot water

SURVEY – GENERAL DATA

- Location to level of 1st three digits of post code
- Number of people in the household, and their ages and stage of life
- Occupancy pattern: morning/ lunchtime/ afternoon/ early evening/ late evening; hours of employment and schooling
- Highest education level in household: no qualifications/GCSE or A level/ vocational qualification/ University degree
- Household disposable income level, by week: grouped by 10th, 50th and 90th percentile in Social Trends (currently: under £200/200-400/400-700/over 700)

- Property type - house, bungalow, flat; detached, terraced, semi; top, middle, ground floor
- Approximate floor area (this can also be estimated from Ordnance Survey Master map data)
- Number of living and bedrooms – including any bedrooms used as living rooms
- Main heating system, type and fuel
- Gas, electricity and any other fuel usage from bills for the last 12 months; time-of-use tariff if any

SURVEY – ATTITUDES TO ENERGY USE

- *How much time and attention is given to managing energy use and cost;*
- *What energy efficiency measures have been put in place; how much did they cost to implement; what else would be good to do; what are barriers to this*
- *Why was the particular electricity/gas provider and tariff chosen – what other providers and tariffs considered; how often looked at*
- *How important are energy costs in overall monthly or weekly budget*
- *What information would be useful / interesting concerning cost and impact of energy use;*
- *How much interest in environmental issues; what changes this has made to lifestyle; willingness to make other changes; where the line is drawn*

5.2.2 Space Heating

Space heating input will not equal to fuel input, partly because of combustion inefficiency and the fact that some heat may escape to the outside (for example through under-floor pipes); and partly because the heating fuel generally also supplies hot water and cooking needs.

For output measures, the minimum are temperature in living rooms and one bedroom However, if more than one room is regularly used as a living room – for example, teenagers entertaining and watching TV in their bedroom - then the temperature there should also be measured. If the thermostat is in the hall, the temperature near it should also be read as this is an area where householders do not necessarily know the facts.

MEASUREMENT

- central heating: heating circuit temperature and flow rate
- fixed or portable electric or storage heaters: appliance load(s)
- fixed gas heaters: gas flow rate(s)
- portable LPG heaters: status of each heating panel from panel temperature:
- solid fuel: log books of quantity used; moisture content measurements; stove temperature measurements
- *external conditions- temperature, RH, wind speed and direction, direct and diffuse solar radiation – however these can be measured in common or taken from nearby met office*

measurements

- living room temperature and relative humidity
- main bedroom temperature
- *temperature in additional 'living area'*
- *temperature beside thermostat*

The first set of survey questions are attributes of the house itself: its size and orientation, exposure level, and details about its construction that together determine its thermal mass, heat transfer behaviour and level of airtightness. The second set concerns how the heating – and where it exists, cooling - system is used. The third set is about family habits and perceptions of what is comfortable.

SURVEY

- general surroundings and orientation of house
- floor area, ceiling height, window size
- external wall, floor, and roof materials
- insulation level, including any improvements made since building
- on-site generation if any
- type of boiler, age and rating
- whether air conditioning is used, and under what circumstances
- control system and thermostat settings, thermostat location – awareness, how often changed, is it perceived to be working properly
- secondary heating fuel, if any, and pattern of use
- seasonal routines and changes – regular visitors or B&B in the summer or regularly away for part or winter etc.
- *pattern of room use – does the family sit in one place evenings and weekends, or are they dispersed*
- *comfort perceptions of different parts of the house: temperature, stuffiness, draughtiness, problem areas such as damp or mould*

5.2.3 Hot Water

Hot water can be supplied either from the heating system or by a dedicated boiler; it can be stored in a tank or used directly. Although there are not quite so many permutations as with space heating, the measurement plan needs to be flexible to accommodate individual differences. Drivers of hot water used are the number of residents, temperature of the incoming water, type of appliances used such as power showers, or washing machines or dishwashers with a hot water intake. Personal preferences are important in terms of timing

MEASUREMENT

- if there is a combination or instant hot water boiler, then supply and demand are matched in time: measure output water temperature and flow rate
- if there is a hot water tank, supply does not have to match demand in time, and there will be standing losses. Both the heat input and the hot water output should be measured
- *incoming water temperature - however experience shows that this is generally around 10°C*

SURVEY

- hot water system and types of appliances that use it including showers, spa baths etc.
- dishwasher and washing machine feeds – hot or cold (the age of the machine is a good proxy, new ones all have cold water intake)
- general household patterns – baths vs. showers, evenings vs. mornings, fast or long duration
- *are dishes are washed by hand at times or is dishwasher use ubiquitous*

5.2.4 Cooking

The main influences are the size of the household, and age, life stage and personal preference: for example, if young children are present then the opportunities for eating out are limited; families who eat home-cooked meals together will show a very different consumption pattern to those where people eat individually, often just microwaving ready-made meals.

Most of the energy used in cooking goes to the hob and oven. Electric ovens and hobs are wired on a separate circuit, and gas appliances have a dedicated gas line, so direct measurements should be possible. If resource constraints or accessibility makes it difficult to meter the gas flow to the cooker, a one-off reading can be made from the gas meter while a typical meal is being prepared – this will indicate the overall level of use. Other types of appliance, and numbers, are less significant: most houses will have a kettle and microwave oven which may be used regularly, plus a battery of electric kitchen equipment that is used occasionally - if at all. If the survey discovers that one of these is in fact used a great deal then it should be monitored.

MEASUREMENT

- electricity: total electricity consumption on cooker circuit
- gas: flow rate of gas on cooker pipe – if not accessible, gas consumption at meter measured during preparations for one or more typical meals
- *load for any plug-in appliances identified as large users in the survey*

SURVEY

- type of hob, type and number of ovens and their power rating
- ownership of various kitchen appliances, and any that are used very frequently
- general household patterns – family or individual meals
- *enjoyment of cooking, time spent on meal preparation or baking per week by various family members*
- *whether kettle is filled each time or just enough for immediate use*
- *whether defrosting is regularly done in microwave or oven*

5.2.5 Lighting

Lighting is complicated to measure because although the total energy used is high, this is the product of multiple small power light bulbs. Lighting use varies during the year depending on the number of daylight hours, as well as on occupancy patterns. However, attitudes also have a large influence on whether or not low energy fittings are used, on how many lights are switched on at any time, and whether or not lights are routinely switched off when occupants move from room to room.

The fixed lights are on separate circuits, but there will also be a multitude of plug-in lamps – some of which may not be used most of the time. The systematic review suggests that most of the lighting use can be captured by measuring the lighting circuit loads plus monitoring the on-off patterns in 3-5 selected plug-in lamps which are used a great deal - for example, a standard lamp which is on in the living room, a light that is on permanently in a dark corner, a desk lamp in a study, or lamps left on for security overnight and when the occupants are out.

MEASUREMENT

- energy consumption on lighting circuits
- on-off pattern of selected frequently used plug-in lamps – suggested maximum 5
- *single measurement of actual power used in these lamps*

SURVEY

- location map of number of lights in each room, grouping in individual areas within rooms, not forgetting outdoors
- rating of each, and type: incandescent, halogen, low–energy bulbs, fluorescent lights
- which plugged in lamps are used most often, morning and evening, and which tend to be left on for long periods
- *in a typical evening, which lights would be used and in what sequence*
- *which lights are on a timer*
- *perceptions on lighting levels in various parts of the house through the day – any dark*

areas where light is generally left on most of the day

- *replacement bulbs – are low energy versions routinely sought out, if not why*

5.2.6 Cold Appliances

Households will have one or more cold appliances which are on all the time: refrigerators, freezers, fridge freezers and drinks coolers. These consume electricity in a cyclical pattern over 40 minutes-1 hour, at a more or less constant rate unless they are unsuitable location or are being left open regularly when in use. If resources are constrained, a reasonable approximation can be made by monitoring the on-off periods together with a one-off measurement of the power drawn.

MEASUREMENT

- appliance load for each OR
- appliance on-off cycle especially if a refrigerator is in an unsuitable position, or if it is a large American style fridge with icemaker PLUS
- check actual power consumption cycle manually for 1 hour during survey

SURVEY

- number, age, energy consumption rating and efficiency rating of freezers, fridges, and chiller
- location – whether next to cooker or in cool utility room
- *habits of use – temperature setting, how frequently opened during day, leaving door open or closed when filling shelves, whether defrosted regularly*

5.2.7 Wet appliances

Dishwashers, washing machines and tumble driers are heavy electricity consumers – they draw high peak power, and have long cycle times. Their energy use per cycle varies depending on the cycle length and temperature setting, and also on whether they take in hot as well as cold water. However their total contribution to household energy depends on household size, attitudes and practices. For example, some households who have dishwashers may choose to use them all the time whether they are full or not, others will prefer to wash small loads by hand and only deploy the machine when there is a large party. If clothes drying takes place indoors regularly, the heating system provides the latent energy input to evaporate water, and the humidity in the drying area will also increase.

MEASUREMENT

- Consumption of each separate appliance: washing machine, dishwasher, tumble dryer
- *Temperature and relative humidity in drying area*

SURVEY

- number and energy consumption rating of appliances
- hot or cold water intake of appliances
- number of times a week each is used, and temperature setting and cycle used most often
- preferences for dishwashing – by hand at times, or machine all the time, full or part loads
- preferences for clothes drying – indoors, outdoors, by machine all the time; full or part loads
- *timing of when machines run – whether planned, for example to make use of overnight tariffs or to fit in with a schedule, or random, as and when enough dirty clothes are collected*
- *willingness to allow time-shifting of when loads are run, and by how much; how big would the tariff discount need to be*

5.2.8 Consumer electronics

Televisions and appliances associated with them such as speakers, set top boxes, games consoles and DVD payers is the highest growth area of household energy. Many households have multiple groups of these, in use simultaneously as different family members pursue their own activities in different rooms. Energy use depends partly on how many appliances there are and their power rating, but also very much on how they are used – whether they are the main form of entertainment, as a constant background to other activities, whether they are switched off or on standby when not in use. The survey should establish the number of measurements needed: the ideal situation is where the whole group is plugged in together via a distributor board.

MEASUREMENT

- *Consumption of main group of related appliances: TV/set top box/DVD – which are often plugged in at the same place and used together*
- *Consumption of secondary group(s) e.g. in kitchen or in teenagers' bedroom*

SURVEY

- number of TVs, size and type: CRT/plasma/LCD/LED
- location map of other related appliances e.g. speakers, set top box, DVD, games console
- night-time pattern of use - standby or switched off overnight
- daytime pattern of use of TV and associated appliances – one or several on at one time; left on, standby or switched off when not watched during the day,
- average hours each TV is watched

5.2.9 Computers and other miscellaneous appliances

The extent to which computers and other miscellaneous devices contribute to a household's energy use is not possible to predict in advance. If someone in the house is regularly working from home, then the computer and associated peripherals may be significant. If the house has a sauna or hot tub, these will probably be big consumers – unless they are never used. Other applications may not be so obvious - for example, the instance highlighted in Chapter 6 where the security system turned out to be the single largest energy using appliance in the house. Other things to notice are power-consuming hobbies – over the last 6 months the author has been in houses which contained respectively: a sauna; a greenhouse heater; a pottery kiln; a hot tub; and a professional bread oven, all of which were in regular use. The survey is essential in establishing which if any appliances should be monitored

MEASUREMENT

- *Consumption of appliance or appliance groups that appear to be significant*

SURVEY

- number of computers, and what associated peripherals each has
- what other significant energy using appliances are in the house, garage or garden, and their power rating
- *pattern of use of computer and associated appliances – one or several on at one time, working from home regularly*
- *average hours each computer is switched on, and average hours actively used*
- *security system, type and power rating*

5.3 Frequency and duration of measurements

If measurements are made at short time-intervals, they can always be averaged over longer time steps; however, if they are made at longer time steps the detail is lost. The quantity of data to be stored and handled is becoming less of an issue all the time as computers become faster and cheaper. A 1-minute resolution is required to capture the peaks and short duration events in electricity measurements. Most gas and heat flow processes are slower so a 5-minute interval should be adequate for these. However, hot water flow and gas for cooking will have peaks and switching events at a shorter time scale so if possible these should also be measured at 1-minute intervals. 15 minutes should be adequate for room temperature and humidity readings.

The ideal period of monitoring is 13-14 months, starting and ending in the spring or summer so that a full year of data is captured including an entire heating and winter lighting season. If only a shorter period is available, then this should be over the winter – end uses such as cooking, clothes drying and television watching are all also heavier in that season.

As well as recording date and time, the database should also include the day of the week, whether it is a public holiday, and the season – these can be added easily during the review and cleansing process, but it becomes more of a chore later.

5.4 How typical is the sample

It is important to establish how representative the volunteer group is by comparing their attributes against data on the wider community. This should be done early in the programme after an initial meeting and survey at the volunteer properties; if there are significant gaps then a more targeted search for further volunteers should be carried out. The most important attribute is energy consumption by household, in particular, getting sufficient volunteers from the high consuming category. Household disposable income is the second most important as there are indications that it is strongly correlated with consumption. The categories to be compared, and sources of statistical data for each, are presented in section 3.3 and summarised below.

- Energy consumption, against local energy averages and Ofgem consumption bands
- Household disposable income by band, against local or national data
- Household size, against local or national data
- House type, against local statistics
- Appliance ownership, against national energy statistics
- Attitudes to energy use, following the IBM segmentation

5.5 Data capture and storage

Energy consumption at whole house and circuit level should be measured with an integrating watt-meter that measures both voltage and current and records the average over each minute. These can be connected in series with the current measured via an inductive clamp fitted round the cable, and only the meter's voltage circuit connected directly. For plug-in appliances these can be connected in series, and the appliance is connected to the mains via the meters; however a cheaper but less accurate measurement can be made using current-only devices aimed at the home consumer: these assume a constant network voltage to calculate energy use.

For appliances which have constant or near-constant power, a run-time meter that records when the device is switched on and off is enough to record the profile; in the case of cold appliances, spot measurements of actual energy consumption should be carried out.

Non-intrusive methods of measuring fluid flow and heat flow use ultrasonic pulses to measure the flow. Doppler flow meters measure the change in frequency of the pulse when it is reflected by small particles or bubbles moving in the flow; these are usable on water pipes in the heating system, but will not work so well with clean water and not at all on gas. Transmissive flow meters do not require particles; they have two piezoelectric transducers that act as both transmitters and sensors; one is located downstream of and diagonally across the pipe from the other. The meter calculates the flow rate based on the time difference that it takes a sound wave to carry when going with the flow and when going against the flow. (Boyes, 2003). However, the normal gas revenue meter will measure more accurately, so in this case an Optical Character Recognition (OCR) system could be used to record meter readings against time.

Temperature sensors need to be able to read remotely to a data logger, and this generally means a suitable thermocouple or bimetallic thermometer. A type ‘T’, copper/constantan sensor has an accuracy of +/-1°C at normal temperatures, while a class ‘K’ which is suitable for high-temperature environments such as the radiator of a solid fuel stove has an accuracy of +/-0.75% at that level (Boyes, 2003).

Table 5-1 lists the instruments and data logging capacity to record the full set of metrics outlined in section 5.2. Nearly 40,000 data items are logged per day, as 1 minute frequency data generates 1440 items for one channel, and 5-minute frequency generates 288 lines.

Data should be downloaded at least once a day, and quality controlled and analysed immediately on receipt to allow problems and anomalies to be identified and investigated. Continuous on-line data retrieval, quality control and analysis would be the ideal.

5.6 Data collection process

5.6.1 Starting out

It is really important to talk to the volunteers and if possible take a look at the houses in order to target what needs to be measured, as early as possible.

Ideally, the survey should be in two stages. First a shorter, general level interview, before the

What measured	Where	How	Number	Interval
Gas into house	At revenue meter	OCR recorder	1 or	5 min
Oil or other fuel	At tank or other (alternative to gas)	OCR recorder or telemetry gauge	1	5 min
Electricity into house	At revenue meter	Integrating wattmeter (voltage and current)	1	1 min
On-site energy production	*At delivery point – depends on technology used*	*Heat meter (if hot water)* *Integrating wattmeter (if electricity)*	*1 or* *1*	*5 min* *1 min*
Gas volume	Cooker/oven feed	Ultrasonic flow meter	1	1 min
Heat flow	Central heating circuit Hot water supply circuit *Hot water tank heating circuit*	Heat meter (combined temperature and flow rate)	1-2 1 *1*	5 min 1 min *5 min*
Air temperature	1-2 x living rooms 1 x bedroom *1 x thermostat area* *1 x indoor drying area*	Temperature probe/ logger	2-5	15 min
Water temperature	*Incoming water*	*Temperature probe/ logger*	*1*	*15 min*
Relative humidity	1 x living room 1 x drying area	Humidity sensor combined with temperature loggers	1-2	15 min
Electric circuit load	1 x Cooker/oven 2 x Lighting *1 x hot water tank heater*	Integrating wattmeter with current clamp	2-4	1 min
Appliance load – specifics depend on survey results	1 x Washing machine 1 x Dishwasher 1x Tumble dryer 1-3 x cold appliances Plus some combination of *1-2 xTV/ DVD/box group* *1 x computer group* *1 x kitchen appliance* *1-3 x other*	Serial wattmeter	6-12	1 min
On-off status	3-5 lights *1-2 x cold appliances*	Lamp meter *Run-time meter*	3-5 *1-2*	1 min *1 min*
Other	*LPG panel monitors, or solid fuel stove temperature*	*Thermocouple loggers*	*1-3*	*5 min*
Data logging and transmission	No of channels Local storage capacity Download interval	40 60,000 items 1 day maximum	1	

Table 5-1 Instrumentation for full load profile measurement programme

specific household data collection plan is put together, and during which enough information is collected to establish which category of user is involved, what appliances should be monitored, and also to highlight any practical issues with locating sensors and data loggers. A second, more detailed interview should be carried out after a plan has been established.

Survey questions need to be prepared in detail and tested out beforehand to make sure they are clear while being worded tactfully – for example, household income appears to be a major driver for energy use, but in British culture this is seen as asking very personal questions. It goes without saying that there should be a clear explanation of the benefits of the exercise, and what to expect, which need to be carefully prepared and rehearsed before contacting the volunteers.

The sheer quantity of data presents a challenge in itself: the database structure and the data cleansing and quality control activities need to planned and tested in advance.

STARTUP PROCESS:

1a: Prepare speaker notes, Qs and As for interviewers, and survey questions; test with a friendly but not too closely involved group of 'guinea pigs'.

1b: In parallel: Ask for volunteers; make initial visit to collect basic data and complete short survey, and establish what problems might occur when locating equipment in the house

2: Collect information on local population, housing, household size, energy use statistics; work out ideal stratification and sampling outcome work out what coverage of ideal the volunteers comprise;

3: If important strata are missing e.g. high consumers, look for more volunteers in target group

4: Decide specific measurement plan for each volunteer household; document

5a: Install and test meters, collect data on house construction

5b: In parallel: complete long survey on attitudes and use patterns

5c: In parallel: set up database

6: Test run of data collection and data cleansing for 1-2 weeks

5.6.2 Running and completing the data collection

During period of data collection some of the volunteers' circumstances may change: some will move or lose interest, some will acquire new appliances, and others may interfere with appliance meters. Meters or transmitters may fail. So there is a need to maintain relationships with the volunteers in order to spot problems quickly and fix them if needed. The end of the exercise presents an opportunity to say thank you, but also to learn from the experience for the future.

COMPLETION PROCESS:

1: Debrief volunteers; check on what has changed since start, and when this happened; how they felt about living with instrumentation

2: Remove equipment,

3: Give some feedback on how it has gone and how this will benefit them/general knowledge

4: Use feedback to improve next round of data collection

5.7 Comparison with methodology used elsewhere

The proposed specification was compared against the methodology used in HEEP (Isaacs et al, 2010), REMODECE (2008) and the Swedish monitoring campaign (Zimmermann 2009).

The coverage of total energy inputs to the household – other than transport fuels for cars – was attempted only by HEEP, the others looked at electricity only. In terms of end-use, the present proposal uses the same level of breakdown as all three others. It does not cover individual appliances to the same level of granularity as either REMODECE or the Swedish study, which had a specific aim of gathering information to guide energy efficiency interventions with appliance manufacturers. The proposed data set's usefulness would be restricted in this respect; however, it was felt that if systematic appliance level data were to be added to the specification, it would no longer meet the criterion of 'reasonable incremental cost and effort'.

Data resolution in this specification is higher than the 10-minute standard used in all three comparators. This was deliberately done in order to ensure that the short period, high power events that are of interest for supply-demand balancing, new technologies, and network analysis, are picked up. The period for data collection is comparable to the detailed-level houses in HEEP and the Swedish study, but much longer than REMODECE, this is because seasonal patterns for end –uses other than heating and lighting are not well understood.

Compared to the other studies, more context data is collected than in any of the others, although fewer specific questions are asked about appliance-level behaviours than in REMODECE.

Cost and effort reasons also dictated meant that the scope of temperature and RH measurements in the specification is not wide enough to be able to use for validating complex thermodynamic simulations. Similarly, no attempt was made to include time-use logging in the data collection that could be used for occupant behaviour simulations.

6 Observations of energy use in one house

A series of observations was made of the energy use patterns in one house where full knowledge was available about the house, appliances and owner attitudes: that of the author. The aim was to test the practical aspects of implementing the data collection plan in Chapter 5, and the factors that might affect the interpretation of such data

6.1 Description

6.1.1 House and occupancy

The house is a ground floor conversion of an old Victorian mansion, with high ceilings and sash windows. The main living rooms face south while the bedrooms are at the north-facing back which is sheltered by an embankment and slope. Exterior and most interior walls are thick stone; finishes vary from the original Victorian to new plasterboard with insulation. The windows have been recently draught-proofed, with double glazing in two rooms. Under-floor insulation has been installed in the living areas and some of the bedrooms.

The heating and hot water system is new, with a condensing combination boiler supplying two separate heating circuits and all the hot water. The boiler has temperature compensated control system; each heating circuit has its own thermostat, set at 18^{o} C in the bedroom area and 20^{o} C in the living area; all the radiators have TRVs. Secondary heating includes a fan heater in the bathroom, and a wood-burning stove in the living room.

There are normally two occupants who are in the house most of the day. However, frequent resident visitors means that the average year-round occupancy is around 2.5. As many of these are elderly or very young, the thermostats have to be set at 22^{o} C in the living area and 21^{o}C in the bedrooms for around 8 weeks in the year.

6.1.2 Instrumentation

Daily and hourly consumption were read from the revenue meters, whose required accuracy is +2.5/-3.5% for electricity, +/-2% for gas (Ofgem, 2005). Other measurements were made with cheap instruments designed for home use. Appliance power signatures were read with a Current Cost Envi meter, which produces an instantaneous power reading every 6 seconds, based on a current measurement to a precision of +/-50mA, and assuming nominal voltage of 240V. Given the allowable range of voltages therefore the accuracy of the Envi power readings is estimated at around +/-17% at the lowest recorded level of 125 W, and +/-7% in the upper range of measurements (5-8 kW). Temperature readings were made with two domestic mercury thermometers, one a min-max thermometer which was re-set daily. No calibrations were carried out, however, both mercury thermometers were placed for a day at a time beside one of the thermostats; temperatures read by all three agreed to the nearest degree Centigrade.

6.1.3 Observation method

First a room-by-room survey was made of every item that uses electricity and its power rating. The hours that each appliance is used per year was estimated. Finally, an estimate was made of the fraction of each use cycle where the appliance is drawing rated power: this was based partly on published data (Newborough & Augood (1999) for dishwashers and washing machines, Wright & Firth (2007) for electric ovens); partly on consulting manufacturers' websites and technical helplines; and partly on reading the signatures of some of the higher rated items with the Current Cost meter. Annual consumption was estimated by multiplying power rating by annual hours by fraction of use cycle at rated power.

Over one week in February, the electricity meter was read several times a day, always including at 8am and just before going to bed. A log was kept of major electricity consuming activities through the day. Over 3 days in April the gas meter was read periodically during the day, including just before the heating started in the morning and after it had switched off at night. The outdoor temperature as seen by the boiler control system was recorded as well as the temperature at the front and back of the house. A log was kept of gas-consuming activities such as cooking and washing. It proved difficult to maintain an hourly schedule of readings while still living normally, so measurements ended up being at irregular intervals.

Some selected detailed observations were made in order to gain better understanding of major end-uses. A download of the raw data from the Current Cost meter was made on four occasions, with recordings made at 6-sec intervals for 2-3 hours each time, together with an activity log. The rate of gas usage while cooking a typical meal, and the rate when the boiler was operating were measured with a stopwatch.

6.2 Observations on energy use

6.2.1 Electrical appliances and overall electricity use

A total of 136 items that use electricity were found in the house and garage, with a combined rating of over 55 kW. However, many of them are used only occasionally and account for minimal consumption (Figure 6-1). 70% of the appliances account for only 6% of electricity used. On the other hand, the 16 items that use more than 200 kWh/year each make up 65% of the total. This overall picture is insensitive to quite large errors in the individual estimates of the hours of use: as long as the estimated hours were in the range of the possible, and the total annual consumption was roughly correct, individual appliances move just a few places up and down in the consumption ranking.

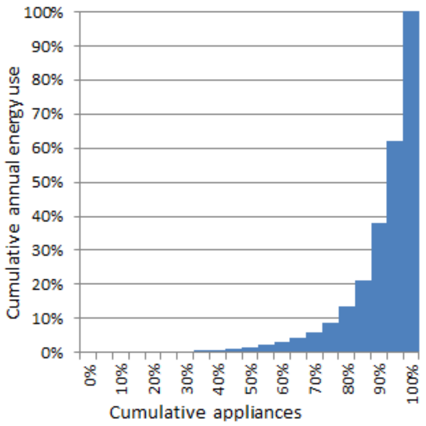


Figure 6-1 Electricity use in one house by appliance

The high consumption appliances consist of two groups. One group has high power ratings and long use cycles – oven, dishwasher and washing machine. The others have low or very low power rating but are on all or much of the time – in this category, refrigerator and freezer were expected, but more surprising were the low-energy lights in a poorly lit part of a corridor, and the intruder alarm system which came out as the highest user of all. In order to check this unexpected result, an hours' worth of readings was made with the Current Cost meter one morning when all appliances other than the meter, the telephones and the intruder alarm were switched off. This showed a steady consumption of 120-125 W, 20 W higher than the combined nominal power rating, but this is within the meter's range of error.

	National[1]	One house
Cooking	15%	15%
Lighting	19%	20%
Cold appliances	16%	13%
Wet appliances	15%	13%
Consumer electronics	23%	7%
Computing	7%	12%
Other	5%	20%

Table 6-1 Electricity end use compared to national statistics
Excluding heating and hot water
1: Source (DECC, 2010)

The end-use distribution in this house compares well with national statistics for most categories Table 6-1. The main difference is that less is used for entertainment, taking consumer electronics and computing together, and more in the 'other' category – this is largely due to the intruder alarm system.

The average consumption over the one measured week was 19.2 kWh/day, which is reasonably close to the 2-year average of 18.5 kWh/day (Figure 6-2). However, there was considerable variation, with the highest day seeing double the consumption of the lowest. No real pattern was visible across the days as high-consumption activities such as clothes washing were randomly distributed during waking hours (Figure 6-3).

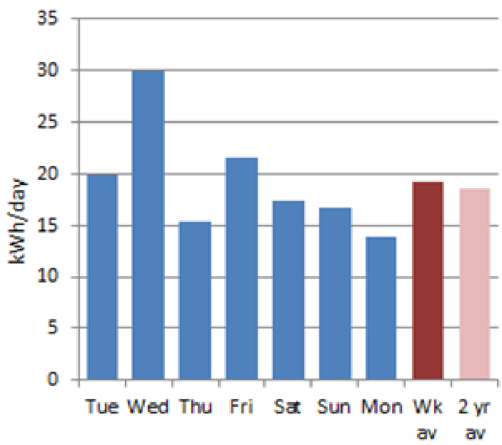


Figure 6-2 Daily electricity consumption over 1 week in February

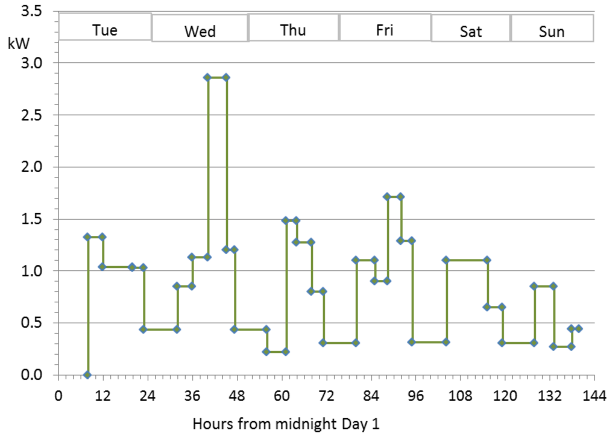


Figure 6-3 Electricity consumption over 6 days Irregular frequency logging

Looking at the 6-second traces showed that several commonly used high-power appliances are on for 2 minutes or less at a time: examples are kettle, iron, coffee grinder, microwave, vacuum cleaner. The effect of time averaging these can be seen in Figure 6-4, which shows a 40 minute period during which the vacuum cleaner was being used: the original 6-second readings are shown together with the same data averaged over 1 minute and 5 minute intervals. At 1 minute, the peaks still show up at the right levels, but with 5-minute averaging this disappears and the actual peak load is 30-60% higher than the measured.

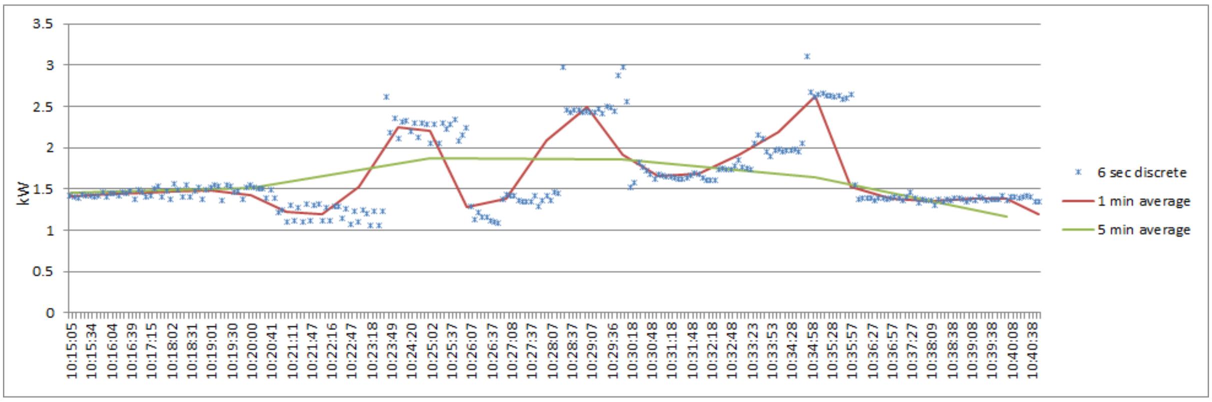


Figure 6-4 Effect of time averaging data – vacuum cleaner use

Lighting had the largest number of appliances - 39% of the total count - but they are individually small and different lights are used interchangeably in the same space. 12 lights out of a total of 53 accounted for 85% of lighting energy. Of these, only two were not wired into the lighting circuits. It was difficult to distinguish lights switching on and off in the time traces because they have individual ratings and patterns of use similar to many of the electronic and computer peripherals.

For cooking, the two ovens and the electric kettle were the only appliances that used more than

100 kWh per year; these represent 78% of the electrical energy for this end-use. There are three separate cold appliances in the house. When only one was on its typical cyclic pattern could be picked out in the time series data however with more than one, the pattern was hard to distinguish.

6.2.2 Gas consumption and secondary heating

Annual gas use is 135.7 kWh/day, two and a half times the regional average. This is thought to be because of high ceilings, stone walls whose U-value is in the region of 1.0-1.4 (Baker, 2008) , and an L-shaped layout with a high perimeter to floor area ratio.

Even over three days, the gas profile shows much more of a daily pattern than electricity (Figure 6-5). A long period in the morning when the boiler comes on to warm up the house, is followed by short booster bursts. Cooking and showering events are identifiable even when readings are taken at 1 hour intervals, and these activities happen more predictably than for electricity.

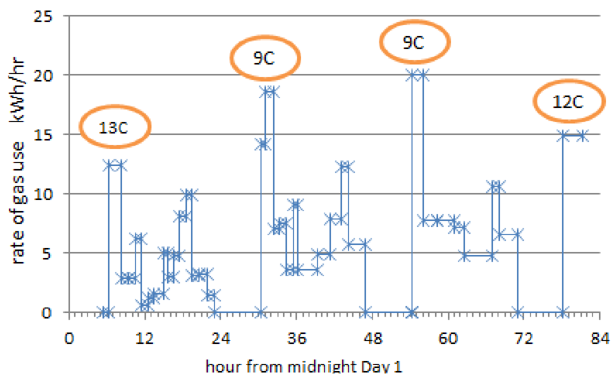


Figure 6-5 Gas usage over 3 days in April
circles show early morning temperature outdoors

The linkage between weather and gas use can easily be seen. On Day 1 the sun was shining and only 80 kWh of gas was used. The next night the temperature was lower, and the next day was cloudier – more heat had to be provided in the morning to bring the house back up to normal temperature, and it had to be boosted more often, using 125 kWh. Day 3 was wet and cloudy so the heating boost and consumption were even higher although less hot water was used.

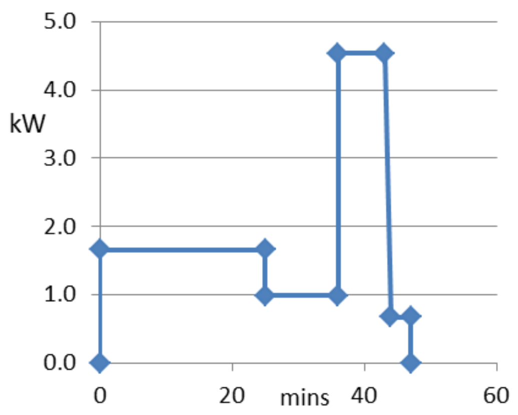


Figure 6-6 Gas demand profile while cooking a meal

Detailed observation while cooking one evening meal showed that 1.4 kWh gas was used over a 45 minute period. This would indicate that gas consumption for cooking is no more than 1-2% of the total. The demand profile is shown on Figure 6-6.

Some of the changes in level occurred at intervals of 5 minutes or less. From observations of the rate at which the boiler used gas when it was firing, it was calculated that, when it is boosting the heating during the day, it fires for short periods only, between 2-10 minutes each hour.

The wood-burning stove is used very erratically – it is lit to provide cheerfulness after a tiring or grey wet day rather than for basic heating needs. Estimated contribution to heating is in the region of 40 kWh on a night when it is on – one basket of logs weighing around 9 kg and with a moisture content of 18% was burned during one typical evening. On those occasions the room temperature rose to 23°C, rather than the normal 20-21° C, and the radiators switched off. Bathroom booster heater use is also related to how individuals happen to be feeling rather than a direct function of temperature – however the total contribution to electricity consumption was between only 0.2-0.7 kWh on the days when it is used.

The observation house did not possess and oil tank, however, photographs taken in neighbouring premises showed the kind of challenge that they can pose (Figure 6-7). In one, the tank gauge is clearly visible and possibly could be read with an OCR equipped with a light; but in the second case not only is it hidden behind climbing plants, it consists of nothing more sophisticated than a transparent tube to indicate the rough level remaining in the tank.

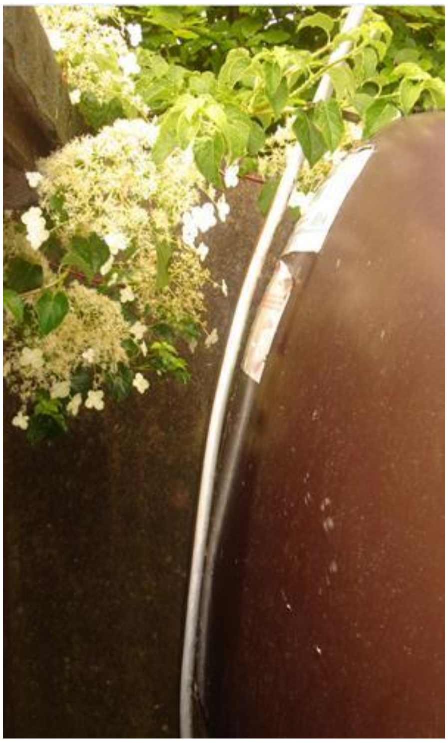


Figure 6-7 Oil tank gauges in situ, illustrating access challenges

6.3 The plan as applied to the observation house

If the data collection plan had been applied to this house, the instrumentation required and the fuel and end-use coverage are listed in Table 6-2:

End use	coverage	Sensors
Fuel in	89%	1 x Electricity meter - 1 x Gas meter - OCR
Heating	100%	2 x heat meter 1 x thermocouple on stove 2 x series watt meters
Hot water	100%	1 x heat meter
Cooking	86%	1 x current clamp wattmeter 1 x gas flow meter 1 x series wattmeter (kettle)
Wet appliances	99%	3 x series wattmeter
Lighting	92%	2 x current clamp wattmeter 3 x on-off lamp-meters
Cold appliances	100%	3 x series wattmeter or run-time meters
Consumer electronics	84%	1 x series wattmeter
Computing and other	73%	2 x current clamp wattmeter (security system, central heating pump) 2 x series watt meters (computer station; iron)
Internal climate		2 x temp/RH logger – living room 1 x temp/RH logger – indoor drying area 1 x temp - bedroom

Table 6-2 Instrumentation needed and fuel and end use coverage for observation house

6.4 Lessons for planning data collection

For electricity use, the annual consumption of a house can be estimated quite well from a survey of appliance ownership and a discussion about patterns of use. However, daily profiles can be unpredictable if there are people in the house all day and heavily consuming appliances are not used in a regular pattern. Annual gas consumption is difficult to estimate because the heating demand depends on so many construction and location related factors as well as the weather. The shape of the profile over a day appears to be more predictable because people tend to bathe and cook at the same time of day even when they are not out at work.

It is important to establish the major electricity users and monitor those. Some will probably be the same in all houses – oven, washing machine, tumble dryer - but others need to be judged based on the individual survey. In general, look for high rating appliances with long use cycles and anything that is on a lot of the time. Measuring lighting use at circuit level should give a good approximation to the total lighting load profile.

Data on house construction details is not easy to find. Changes made by successive owners are not visible or known. There can be a lot of variation in different parts of old houses.

A resolution of one minute for electricity readings would have showed up the short duration peaks recorded at 6-second intervals. Gas 'events' such as boiler firing or adjusting the heat when cooking can also occur on a time scale as short as 1-2 minutes.

Where secondary heating is used with central, it may be run more for comfort than for basic heating, depending on how people are feeling rather than the temperature, so it does not conform to a straightforward daily pattern. Energy used in secondary heating will not necessary translate into the same energy use pattern if the fuel source is switched. However its use can make a big difference to recorded temperatures.

Normal house occupancy can be altered if there are frequent visitors. This may be an important factor in rural areas where many homes may do bed and breakfast business.

It is difficult to maintain a reliable time/ activity log. People are living lives and even with highest possible motivation they will not always remember to update records.

7 Conclusions

A need has emerged for good quality energy demand data on local patterns of energy consumption for a whole host of purposes: to calibrate models; to allow scaling up of demand profiles to a community level for supply-demand and network planning; to give a baseline against which to track the effectiveness of specific energy saving initiatives; to investigate the impact of shifts in fuel use for heating; and to quantify the extent of local opportunities for demand management and smart appliance implementation.

Studies so far have demonstrated that predicting even current demand patterns is not straightforward, especially in the domestic environment. Historically, domestic electricity demand patterns were mainly looked at as statistical processes occurring in large groups, and it is only relatively recently that investigations have started to be made into understanding what drives consumption at a detailed level. Some of these measurement programmes have produced seemingly contradictory results. Where clear trends have been noted, they are at a very high level: when nights are longer, more electricity is used for lighting; if more people live in a house, on average that house will use more electricity; if they have higher disposable incomes they will be able to buy more and bigger appliances and therefore use more energy. However, every measurement programme has found a very wide range of consumption among houses and households that are apparently very similar. Household attitudes and habits appear to be the most important factor that determines energy use and its daily pattern.

A major blocker to developing a consistent understanding is the fact that different data collection programmes have measured different data sets, at different collection frequencies, and often just for small or homogeneous groups of households and for total electricity use only. Source data is generally not available, either because of commercial confidentiality, data privacy concerns or simply because it has been lost. Translating findings from these projects to other parts of the country requires making assumptions which may turn out to be inaccurate. The literature shows that big differences in energy use exist between even neighbouring countries, so the assumption that different parts of a single country as diverse in geography and population as the UK must be open to question.

If future measurement programmes across different regions were to follow a consistent and comprehensive measurement plan, and if the data were to be made available generally, this would eventually build up to give better insights into what drives energy use and how this varies by geography and over time. In the worst case, it would supply higher quality statistical data. Using the insights gained from published measurement programmes, in conjunction with observations on one house, a data collection plan is proposed for this purpose. This involves collecting around 40 sets of data per house, and measuring all fuel inputs as well as consumption by each end use, with the highest priority given to end uses which might be subject to fuel switching, demand-side management by time-shifting, or technology change. The data is collected at the highest level of resolution needed to give a clear picture of short high-energy events, 1 minute intervals for electricity and no more than 5 minutes for gas or heat flow. A survey of the house and households involved is crucial for interpreting the data, and is most effective when carried out face to face.

Most data collection programmes have a specific goal in mind, and this would go beyond the needs of any individual investigation. However, much of the effort involved in any programme is in setting it up, recruiting volunteers, and ensuring that clean data is being collected, so a slightly larger data set should not require a huge incremental effort. Many practical difficulties need to be overcome, particularly in finding an appropriate range of volunteers to represent both the highest and lowest energy consumers in the area. Other challenges lie in in locating equipment unobtrusively in the house, or in finding suitable monitoring equipment for difficult places such as oil tanks. Privacy of personal data is extremely important.

However, one high-quality set of electricity demand data, accompanied by a household survey, has now actually been put into the public domain, and shows that it is possible to include all the useful context information without giving away information that could identify the participants. It has been used for further analyses successfully, demonstrating the value that could be gained from such data beyond the original purpose of the investigation.

7.1 Recommendations for further work

- Revise the wording of the survey questions to make them straightforward and non-technical to users, while maintaining a ‘semi-structured’ approach
- Investigate further whether there would be a benefit from collecting gas and heat flow data at 1 minute rather than 5 minute intervals
- Extend the scope of the measurements to include domestic transport demand profiles, as these will be increasingly important as electric cars start to become available. Possibly, water use could also be included.
- Engage other researchers to support implementing a publicly available database – where could this be held, ownership and maintenance

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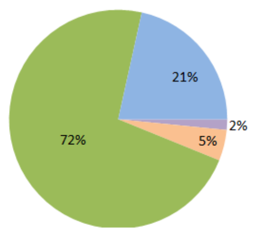
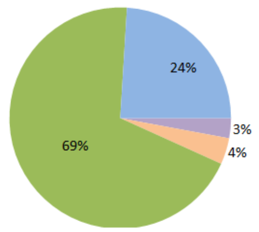
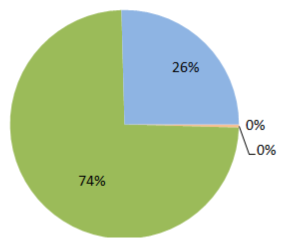
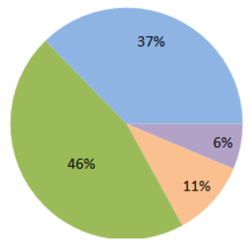
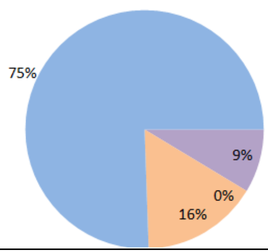
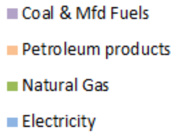
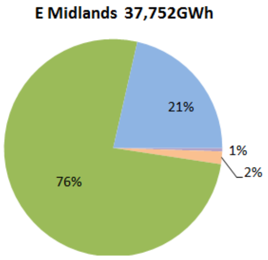
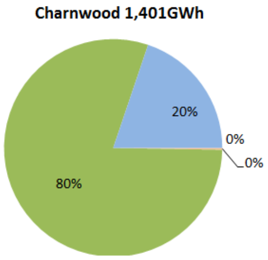
Appendix 1: Regional variations in domestic energy use - 2008

Fuel Mix[1] Coal & Mfd Fuels Petroleum products Natural Gas Electricity	Av electricity per meter Ordinary tariff Restricted tariff[2] kWh pa	% Restricted tariff meters[2]	Average gas used per meter[3] kWh pa	Population: Number % working age[4,5,6]
Great Britain 521.7 TWh 	O: 3,784 R: 5,880	20%	16,907	59,623,200 62.0%
Scotland 48,184GWh 	O: 3,752 R: 6,307	24%	18,043	5,194,000 62.6%
Glasgow 4.726GWh 	O: 3,281 R: 4,531	19%	15,004	588,470 67.4%
Argyll & Bute 828GWh 	O: 4,043 R: 8,200	30%	19,991	90,040 58.6%
Shetland 134GWh 	O: 4,382 R: 7,726	50%	0	22,210 61.0%

Fuel Mix[1] 	Av electricity per meter Ordinary tariff Restricted tariff[2] kWh pa	% Restricted tariff meters[2]	Average gas used per meter[3] kWh pa	Population: Number % working age[4,5,6]
	O: 3,537 R: 4,887	44%	17,025	4,429,400 61.8%
	O: 3,481 R: 4,671	50%	17,464	163,300 64.6%

Sources:

1. *Energy Consumption in the UK, Overall & Domestic Data Tables* (DECC, 2010)
2. *Middle Layer Super Output Area (MLSOA) domestic electricity estimates* (DECC, 2008)
3. *Middle Layer Super Output Area (MLSOA) domestic gas estimates* (DECC, 2008)
4. *UK and regional: Population estimates for UK, England and Wales, Scotland and NI 2008* (Office for National Statistics, 2010)
5. *Scotland Local Authority: Scottish Neighbourhood Statistics* (Scottish Government, 2009)
6. *England Local Authority: Department for Communities and Local Government: Housing - Table 406 Household Projections by district 2008* (Dept. Comm. & Local Govt, 2010)

Appendix 2: Summary of data sets reviewed

Source	Location, houses	Frequency, Duration	Data collected	Survey	Not given or not available
Summerfield et al, 2007	Milton Keynes 14 low energy houses	Monthly / 10 mins, then half hourly 15 months Baseline (1990): hourly 18 months	Gas, & electricity consumption / Internal temperature – living Internal temperature - bedroom Relative humidity (max 10 separate loggers) Baseline data as above, from 1990 study when houses newly built	Age and type of house, changes to fabric since 1990 Heated floor area No. of bedrooms No and age of occupants Household income Appliance ownership Primary heating and hot water supply Baseline: type and size of house	Occupancy pattern Baseline: most survey information missing
Summerfield et al, 2010	Milton Keynes 22 low energy dwellings incl flats	Monthly Baseline: hourly 18 months	Gas & electricity consumption Baseline: hourly energy consumption only	Survey as above Baseline: none available, but floor area deduced	Internal temperature Occupancy pattern
Shipworth et al, 2010	England and Wales 358 houses with central heating	45 min 6 months	Living room and bedroom temperature External temperature	Type of house and year built Insulation level and draughtproofing, if known Thermostat settings and active hours	Household size and age Electricity, gas or oil usage

Source	Location, houses	Frequency, Duration	Data collected	Survey	Not given or not available
Gill et al, 2011	Mid-Suffolk 25 low energy/ affordable houses and flats with district heating	'periodically' 6 monthly 15 months	Electricity consumption Water consumption at meter Heat consumption Plus: district heating total energy production	House size Occupants	Appliance ownership Age of occupants Occupancy pattern Household income
	4 terraced houses, subset of above	10 mins 15 months 30 mins Summer, winter	Electrical energy consumption Instantaneous current and load Heat consumption at heat exchanger Water consumption to 1l Temperature, RH in kitchen/living area	As above plus Thermostat settings	
Newborough & Augood 1998	Not clear, assume Home Counties (Cranfield U study) 30 homes	1 min 1-4 weeks	Average electric power, power factor Inside & outside temperature	'Primary characteristics of household' Appliances owned Some tick-box on appliance use, 1 each weekday & weekend	Size & type of dwelling Occupants Space heating & hot water where not electric
Stokes et al, 2004 (Quoted in)	UK wide (Load Research Group 1996-97) 100 homes	30 min 13 months	Total average consumption Lighting consumption – main circuit and significant portable lamps	Not known	Not known
Wright & Firth, 2007	NW England 8 homes	1 min Dec 2004-Sep2005	Electric load, VA, voltage frequency at one house	None	Size & type of dwelling Occupants Appliance ownership Space heating & hot water where not electric

Source	**Location, houses**	**Frequency, Duration**	**Data collected**	**Survey**	**Not given or not available**
Firth et al, 2008	UK, at 5 sites 72 households, incl flats, semi-detached and detached houses and bungalows; mainly social housing	5 min 2 years	Electricity import from grid PV system generation Electricity export to grid	None	Size & type of dwelling Occupants Appliance ownership Space heating & hot water where not electric
Yohanis et al, 2008	Northern Ireland, 27 houses; mix of city, suburban and rural; and of house type incl flats	30 min 18-21 months	Average electric load per half hour	Age and type of house Floor area No and age of occupants Employment status and income Occupancy pattern Appliances owned	Space heating & hot water where not electric Appliance use survey
Richardson et al, 2010	Loughborough, 22 houses	1 min 24 months	Whole-house electric demand	House type, insulation measures Occupants Electricity tariff Primary heating and hot water source Appliances owned	Size of dwelling Space heating & hot water where not electric
	Loughborough 56 dwellings	1 min 1 day	Power demand, power factor	n/available	

Source	Location, houses	Frequency, Duration	Data collected	Survey	Not given or not available
Parker et al, 1996	Florida 10 housing project homes	15 mins 12 months	Total electricity use 7 individual end-uses incl. aircon, hot water, dryer, cooker, washer External weather (temp, humidity) Internal temperature & humidity Hot water temperature & flow rate Window opening status	House size Occupants Appliances How the system is controlled Attitudes	
Isaakson & Karlsson 2006	Gothenburg, Sweden 20 low-energy houses	Not clear – possibly daily?	Living room temperature Bedroom temperature Humidity (6 houses only) Annual electricity use (?)	Building size layout Construction and insulation Occupants number Heating system Opinions on energy use and comfort	Electricity use Other fuel use
Isaacs et al, 2010	New Zealand 397 houses in 29 clusters	10 min 11+ months	Energy consumption by fuel type (electricity, gas, solid fuel, LPG, solar) Hot water temperature and flow rate Living room temperature x2 Bedroom temperature External temperature by cluster	House location, orientation House size and number of rooms Occupants: number, age, employment Household income Construction details Heating system and hot water system details including flow rates Appliance audit incl photographs Appliance use questions	
Isaacs et al, 2010 (as above)	New Zealand 104 houses out of the above	As above	As above plus individual end uses: Load on fixed lighting circuits Cooking Individual appliances	As above	

Source	Location, houses	Frequency, Duration	Data collected	Survey	Not given or not available
Swedish Energy Agency 2009	Sweden 40 households	10 min 1 year	Total electricity – av power & current Heating circuit x3 – av power & current Water heater – av power & current Electrical appliances energy use x 25 Individual lights on/off x25 Internal and external temperature	House size and layout Number and age of occupants Heating method Appliance audit	Energy use where not electric
	Sweden 360 households	10 min 1 month	As above	As above	As above
Bladh & Krantz (2008)	Sweden 7 households Part of above	10 min 1 month	As above Individual lights on/off x25	Survey on lamps in the house, usage patterns and reasons for having particular lights	
Räsänen et al 2010	Finland 3989 buildings in one community	1 hr 1 year	Electricity use Daily average external temperature – min and max	User type Heating method Hot water and cooking fuels	-
Williamson et al 2010	Australia 5 custom designed sustainable houses	1 hr 1 year	Internal temperature Internal RH multiple locations Weather – temperature, humidity, wind speed, solar radiation Energy and water consumption for year	House size, layout, construction Occupant numbers Heating / cooling system details Open ended questions concerning usage patterns, effectiveness of building and perceived comfort	

Appendix 3: Data collection plan

<table>
<tr><th>End use & Appliances</th><th colspan="2">% of total
domestic energy / electricity</th><th>Contrib. to energy use</th><th>Contrib. to peak load</th><th>Potential for time switching</th><th>Possible fuels</th><th>Influences on Consumption</th><th>Measures – Input
Necessary/Optional</th><th>Measures – Output
Necessary/Optional</th></tr>
<tr><td>Space heating

Central heating
Open fireplaces
Portable heaters
Stoves
Storage heaters
Heat pumps
Solar collector</td><td>58%</td><td>14%</td><td>V High</td><td>Yes</td><td>Yes</td><td>Gas – piped
Gas - LPG
Electricity
Oil
Coal
Wood
On-site generation – hot water
On-site generation - electricity</td><td>House size & orientation
Immediate surroundings
House age, materials & insulation level -> U-values, thermal mass
Ventilation
Efficiency of heating system and controls
Weather/ time of year: temperature, sunlight, wind, RH
Casual gains from other appliances
Occupancy pattern –> # rooms heated over time
Attitude to energy use -> tariffs
Personal discomfort level – what is ‘too cold/hot’ (may vary with age/life stage) -> thermostat settings , changes, overrides</td><td>Primary fuel input – all fuels

Heat input (appliance dependent)
• If liquid CH: gas or oil usage; heating circuit temperature and flow rate
• If fixed or portable electric or storage heaters: appliance load(s)
• If fixed or portable gas: gas flow rate(s)
• If solid: quantity used log, moisture content; stove temperature
• If on-site generation: electricity or heat input from device

Secondary heating fuel input, if appropriate</td><td>Air temperature – bedroom
Air temperature – living room(s)
Air temperature – by thermostat
RH – living room
RH – kitchen, bathroom
Air temperature - hall
Floor temperature –living room(s)
Window open status - living room</td></tr>
</table>

End use & Appliances	% of total domestic energy	% of total electricity	Contrib. to energy use	Contrib. to peak load	Potential for time switching	Possible fuels	Influences on Consumption	Measures – Input Necessary/*Optional*	Measures – Output Necessary/*Optional*
Space heating (cont)								**Survey:** General surroundings and orientation of house Layout, number of living and bedrooms Floor area, ceiling height, window size External wall, floor, and roof materials, insulation level Primary and secondary heating fuels Last year's heating & electricity usage from bills On-site generation, if any Number of occupants, age, occupancy pattern incl. visitors/vacation use	**Survey:** Comfort perceptions: temperature in different rooms, stuffiness, draughtiness, problem areas Pattern of use in rooms – e.g. teenage children use bedrooms as living rooms Control system and thermostat settings, thermostat location – awareness, how often changed, Pattern of secondary heating use Views on heating costs – degree of knowledge, degree of concern
Hot water Hot water tanks Back boilers Combi boilers Instant boilers	23%	14%	High	Possible	Yes	From heating system Direct • Gas - piped • Electricity • On-site generation – hot water	No. of occupants Type of appliance e.g. power shower Incoming water temperature Personal preference – frequency, timing, length of shower, depth of bath… Whether dishwasher and washing machine have hot or cold water feeds	Hot water fuel usage • If tank: Hot water tank output temperature and flow rate • If combi or instant: heater output temperature and flow rate (s) *Incoming water temperature* **Survey:** Hot water system and types of appliances Dishwasher and washing machine feeds	**Survey:** General household patterns – baths vs showers, evenings vs mornings *Time use diary*

End use & Appliances	% of total domestic energy	% of total electricity	Contrib. to energy use	Contrib. to peak load	Potential for time switching	Possible fuels	Influences on Consumption	Measures – Input Necessary/*Optional*	Measures – Output Necessary/*Optional*
Cooking Hobs, Ovens, Kettles, Microwaves, Slow cookers, Breadmakers,	4%	11%	High	Yes	No	Gas Electricity LPG Wood Coal	Household size, age/ life stage Personal preference – cooking vs heating ready-made meals, enjoys cooking or not, family meals or individual Type of appliance & rating	Cooking fuel usage • If electric cooker: load on hob/oven circuit • If gas: flow rate to cooker Other appliance consumption e.g. kettle, depending on use pattern **Survey:** Type of hob, type and number of ovens Ownership of various kitchen appliances	**Survey:** General household patterns – family or individual meals, enjoyment of cooking Number of hours a week spent cooking Kettle filled each time or just enough for number of cups Kitchen appliances/ gadgets used most frequently *Time use diary*

End use & Appliances	% of total domestic energy	% of total electricity	Contrib. to energy use	Contrib. to peak load	Potential for time switching	Possible fuels	Influences on Consumption	Measures – Input Necessary/*Optional*	Measures – Output Necessary/*Optional*
Consumer electronics TV, Set top box, Games console, set top box, Power supplies, speakers…	4%	16%	Med	Possible	No	Electricity	Number and type of appliances esp TVs Occupancy pattern Personal preference – use of free time, family vs individual use, other sources of entertainment by time of year Attitude to use – switching off, leaving on standby, leaving on when not in room	Consumption of appliance group(s) e.g. TV/set top box/DVD *On-off state of TV(s)* Total electricity - overnight steady load for standby use **Survey:** Number of TVs, type: CRT/plasma/LCD/LED and size Other related appliances e.g. speakers, set top box, DVD, games console,	**Survey:** Pattern of use of TV and associated appliances – one or several on at one time, Average hours each TV is watched *Time use diary*
Lighting Standard, Halogen, Fluorescent, ESB, LED Indoor, outdoor	3%	13%	Med	Yes	No	Electricity	Number, type and rating of lights/lumieres Time of year and climate -> ambient light levels Occupancy pattern Attitude to use – lights switched off when room unoccupied or not	Lighting circuit(s) consumption Individual light on/off state, for important fixtures **Survey:** Number of lights in house, grouping in areas such as living room or hall Where & how many low –energy lights, fluorescent lights In a typical evening, how many lights on through the house Plugged in lamps most often used, morning and evening - power Number of outdoor lights, and whether on timer or manual switch	*Light level in living room* *Light level in study* *Light level in kitchen* **Survey:** Comfort perceptions on light levels through the day – any areas where light is generally on

End use & Appliances	% of total domestic energy	% of total electricity	Contrib. to energy use	Contrib. to peak load	Potential for time switching	Possible fuels	Influences on Consumption	Measures – Input Necessary/*Optional*	Measures – Output Necessary/*Optional*
Cold appliances Freezer, Refrigerator, Fridge-freezer, Drinks chiller	3%	12%	Yes	No	Yes	Electricity	Number and energy consumption rating of appliances Location – e.g. next to cooker or in cool utility room Attitude to use – temperature setting, opening frequency, leaving door open when filling shelves	Individual appliance consumption *Total electricity - overnight cyclical load* **Survey:** Number of fridges, freezers, chillers; where located Are age and energy rating known	
Wet appliances Washing machine, Tumble dryer, Washer –dryer, Dishwasher	3%	11%	High	Possible	Yes	Electricity	Number and energy consumption rating of appliances Hot or cold water intake of appliances Incoming water temperature Occupancy pattern Electricity tariff Weather / time of year -> outdoor or indoor drying Household size and life stage Attitude to use – frequency and temperature setting of loads, flexibility to use off-peak tariff if exists	Individual or grouped appliance consumption *Incoming water temperature* **Survey:** Number of appliances Number of times a week each is used Temperature and cycle used	*Temperature and RH in normal indoor drying area* *Time use diary* **Survey:** Preferences for dishwashing – by hand or machine all the time Preferences for drying – indoor, outdoor, machine Timing of when machines run – random or planned

End use & Appliances	% of total domestic energy	% of total electricity	Contrib. to energy use	Contrib. to peak load	Potential for time switching	Possible fuels	Influences on Consumption	Measures – Input Necessary/*Optional*	Measures – Output Necessary/*Optional*
Computing Desktop, Laptop, Monitor, Printer, Speakers, Scanners	1.2%	5%	Low	No	No	Electricity	Number and energy consumption of appliances Working from home pattern Occupancy pattern Attitude to use – switching off vs standby	Consumption of appliance group e.g. computer/monitor/printer **Survey:** Number of computers Number of associated peripherals each has	**Survey:** Pattern of use of computer and associated appliances – one or several on at one time, Average hours each computer is switched on, and average hours actively sued *Time use diary*
Other Vacuum cleaners, Personal products, Power tools, Garden tools, Security systems, Hot tubs, Saunas, Water beds	0.9%	4%	Possible	No	Some	Electricity mainly But possible alternatives e.g. portable gas	Number and energy consumption rating of appliances Occupancy pattern Attitude to use – switching off vs standby	Individual appliance consumption, if large (e.g. hot tub) Security system - part of overnight base consumption **Survey:** Ownership of other large consuming appliances e.g. sauna, hot tub, security system; and their power rating and frequency of use	

Appendix 4: Loughborough 1-minute resolution electricity demand data

ORDINARY TARIFF	H6	H3	H9	H15	H11	H10	H22	H20	H14	H19
2008 CONSUMPTION										
Average kW	0.24	0.26	0.32	0.38	0.38	0.40	0.46	0.52	0.58	0.69
Max kW	7.86	14.25	6.43	8.26	6.75	10.15	8.30	11.15	19.68	9.88
% missing data	6%	6%	14%	4%	10%	23%	5%	6%	0%	2%
kWh per day	5.7	6.1	7.7	9.1	9.1	9.6	11.0	12.5	14.0	16.5
Annual kWh	2076	2248	2835	3346	3349	3501	4021	4570	5127	6044
2009 CONSUMPTION										
Average kW	0.27	0.29	0.35	0.35	0.39	0.36	0.49	0.63	0.51	0.54
Max kW	7.27	12.48	5.92	7.93	6.86	8.02	7.72	11.40	17.97	8.26
% missing data	25%	87%	77%	16%	38%	38%	29%	17%	11%	16%
kWh per day	6.5	6.9	8.3	8.5	9.3	8.5	11.8	15.2	12.2	13.0
Annual	2385	2534	3023	3098	3408	3114	4295	5540	4462	4730
Elexon Stratum	Low	Low	Low	Mid	Mid	Mid	Mid	Mid	Mid	Mid
Ofgem band	1	2	2	3	3	3	3	3	4	4
SURVEY RESULTS										
Type of dwelling	semi	semi	terr	det	det	det	terr	semi	semi	semi
Occupants 2008	1	2	n/a	4	4	4	3	5	6	n/a
Occupants 2009	2	2	3	3	2	4	3	5	5	4
Timers	n	n	n	y	y	n	y	n	n	n
Central Heating	y	y	y	y	y	y	y	y	y	y
Electric Heating	n	n	n	n	n	n	n	n	n	n
Electric water heating	all yr	winter	all yr	all yr	all yr	all yr	all yr	winter	all yr	winter
Insulation types (4 max)	3	3	2	3	4	4	3	3	1	3
% Low Energy bulbs	50%	100%	60%	50%	80%	40%	80%	99%	30%	25%

ORDINARY TARIFF	H6	H3	H9	H15	H11	H10	H22	H20	H14	H19
Electric Shower	0	1	0	0	0	0	0	1	1	0
Floodlights	1	0	0	1	0	1	1	0	1	1
Cold appliances	1	2	1	1	2	2	3	1	1	2
Electric hob	0	0	0	1	0	0	0	0	0	0
Electric oven	0	1	0	1	0	1	0	1	1	1
Washing machine/wd	1	1	1	1	1	1	1	1	1	1
Tumble drier	0	0	0	1	0	1	1	0	0	1
Dishwasher	0	1	0	1	0	1	1	1	1	1
TV	1	2	1	5	1	1	1	1	1	4
Computers	1	3	1	3	2	2	2	1	4	3
No of people	1	2	3	4	4	4	3	5	6	4
kWh/person, 2008	2076	1124	945	836	837	875	1340	914	854	1511

ECONOMY-7 TARIFF	H5	H12	H18	H1	H7	H17	H13	H8	H2	H4	H21	H16
2008 CONSUMPTION												
Average kW	0.14	0.24	0.34	0.40	0.45	0.47	0.53	0.53	0.60	0.65	0.74	1.19
Max kW	5.78	13.90	12.06	7.94	9.11	13.01	15.45	10.87	9.14	14.69	14.58	11.59
% missing data	15%	4%	5%	5%	1%	4%	0%	7%	50%	0%	9%	50%
kWh per day	3.5	5.9	8.1	9.5	10.8	11.3	12.7	12.7	14.4	15.5	17.7	28.5
Annual kWh	1263	2144	2955	3472	3944	4124	4652	4663	5264	5675	6463	10438
2009 CONSUMPTION												
Average kW	0.14	0.25	0.34	0.47	0.47	0.47	0.49	0.44		0.58	0.72	
Max kW	5.42	14.41	11.76	8.27	9.09	10.83	14.08	7.55		13.97	14.23	
% missing data	8%	12%	17%	25%	26%	17%	12%	87%	100%	31%	13%	100%
kWh per day	3.4	5.9	8.0	11.3	11.2	11.3	11.8	10.5		14.0	17.2	
Annual kWh	1259	2163	2935	4117	4080	4127	4317	3830		5093	6294	
Elexon Stratum	Low	Low	Low	Mid	Mid	Mid	Mid	Mid	Mid	Mid	Mid	High
Ofgem band	1	1	2	2	2	2	2	2	3	3	3	4
SURVEY RESULTS												
Type of dwelling	det	det	det	det	terr	det	det	terr	semi	semi	det	det
Occupants 2008	2	1	4	n/a	4	3	3	5	5	n/a	n/a	5
Occupants 2009	1	1	4	3	4	3	4	5	5	2	3	4
Timers	n	y	y	y	n	y	y	n	n	n	y	y
Central Heating	y	n	y	n	y	y	y	y	y	y	y	y
Electric Heating	n	n	n	n	n	y	n	n	y	n	n	y
Electric water heating	all yr	all yr	all yr	all yr	all yr	winter	all yr	all yr	all yr	all yr	all yr	all yr
Insulation types (4 max)	3	3	3	4	3	4	4	2	2	1	3	1
% Low Energy bulbs	70%	5%	99%	40%	100%	50%	80%	85%	50%	30%	75%	25%

ECONOMY-7 TARIFF	H5	H12	H18	H1	H7	H17	H13	H8	H2	H4	H21	H16
Electric Shower	0	1	1	0	0	0	1	0	0	1	1	1
Floodlights	1	1	0	1	0	0	1	0	1	0	1	0
Cold appliances	1	3	3	3	1	3	2	1	2	2	1	2
Electric hob	0	0	0	0	1	0	0	0	0	1	0	0
Electric oven	0	0	1	1	1	1	0	1	1	1	1	1
Washing machine/wd	1	1	1	1	1	1	1	1	1	1	2	1
Tumble drier	0	0	0	1	0	1	0	0	0	1	0	1
Dishwasher	0	0	1	1	0	1	1	1	0	1	1	1
TV	2	1	1	1	1	3	1	1	2	1	4	1
Computers	1	2	2	2	1	1	1	1	1	2	2	6
No of people	2	1	4	3	4	3	3	5	5	2	3	5
kWh/person, 2008	632	2144	739	1157	986	1375	1551	933	1053	2838	2154	2088