

Socioeconomic effects on the modelling of energy use of appliances, electronics, and lighting in dwellings

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Research question

The research question is – can a coefficient be developed from the socioeconomic profile of its neighbourhood for use in the modeling of the energy use of appliances, electronics, and lighting of a dwelling? Is a domestic energy model algorithm improved (enough to make the exercise valuable) by making an estimate of how energy profligate people are?

In the current energy models in place in the United Kingdom, the development of such a multiplier or divisor has stopped at a basic judgement of the person in charge of the assessment with four options available. With the wealth of energy, statistical and census data available for small areas, a method should be developed to use this data to more accurately simulate these energy end uses that depend so sensitively on choices in appliance ownership and behaviour of domestic building occupants.

Motivation

The area of examining the modelling of the energy end uses of appliances, lighting, electronics, and cooking is of interest to academic research because it continues to grow much faster than energy use overall, because most research has been done on space and water heating, and because it is getting easier to measure as the fuel in the home for heating and for lights and appliances is diverging to natural gas and electricity. Data from the current Domestic Energy Fact File for the United Kingdom reveals that from 1970 to 2006, the energy consumption of lighting and appliances grew by 148 per cent compared to 23 per cent overall (Shorrock and Utley 2008).

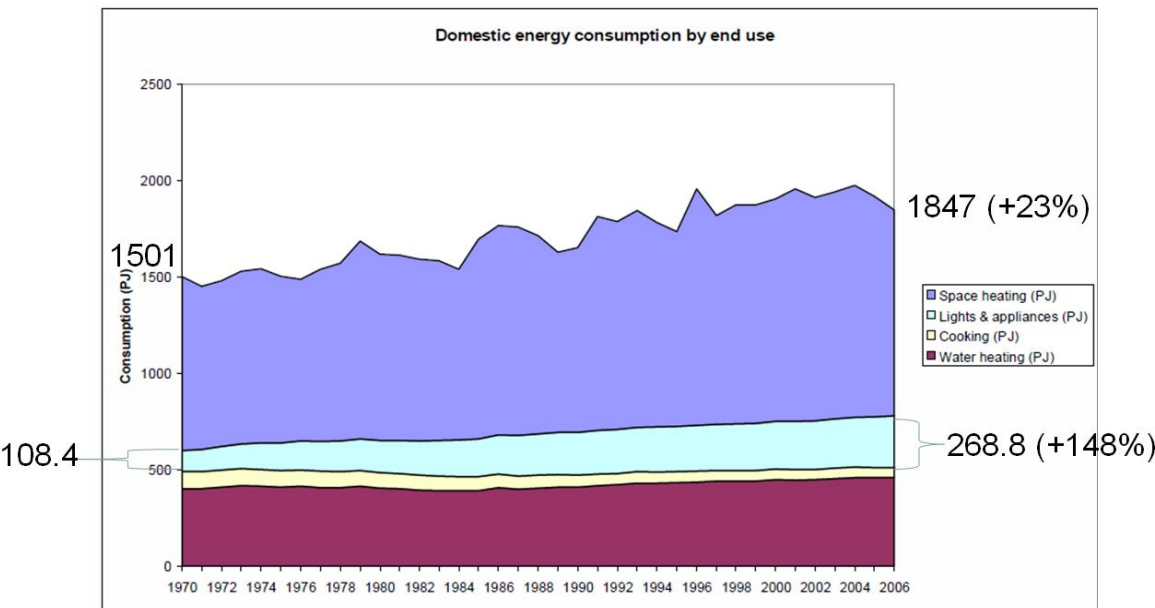
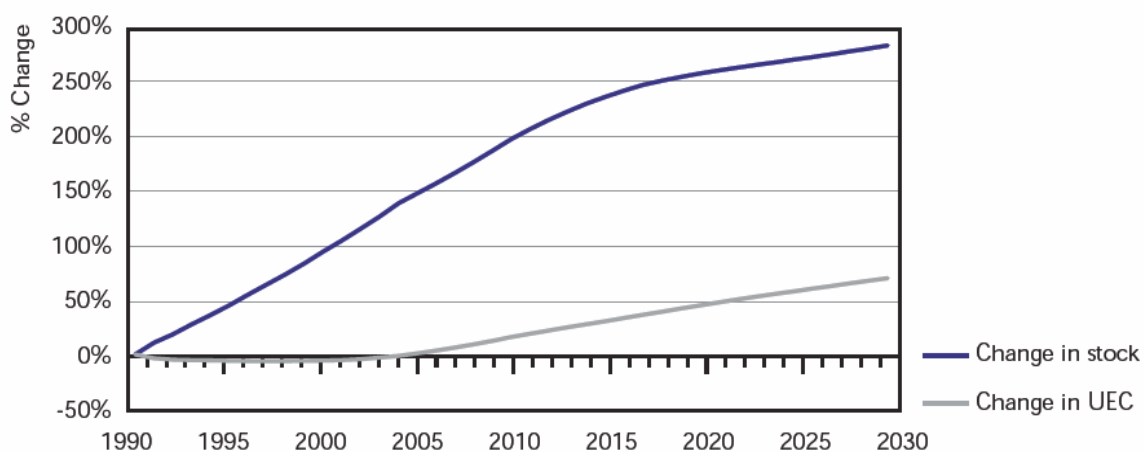


Figure 1: Domestic energy consumption by end use, 1990 to 2006 (Shorrock and Utley 2008)

Examining future forecasts, this trend is set to continue and even accelerate. The main driver of domestic energy consumption in this sector is information and communications technology (ICT) and consumer electronics (CE). In the period 1990 – 2030, the average unit consumption of electricity for these uses in Organisation for Economic Co-operation and Development (OECD) countries will have risen by 75 per cent. We will also have more of them – the average person will have three times as many of these ‘gadgets’ at the end of the 1990-2030 timeframe as the beginning. In other words, a person using 100 kilowatt hours (kWh) per year in 1990 using ICT and CEs is likely to be using $100 \times 3 \times 1.75 = 525$ kWh per year in 2030 (International Energy Agency 2009). Clearly, although not as much climate change impacts are currently caused by lights, appliances, and electronics currently and future planning is underway for changing the mix of electricity generation (Department of Energy and Climate Change 2009b), this growth is significant and needs further investigation as the potential for energy demand reduction in the medium term is greater than for gas-fuelled heating (Market Transformation Programme 2008b).

Figure 86 • Estimated change in stocks and average unit energy consumption (UEC) of residential ICT and CE appliances in OECD, 1990-2030



Source: IEA estimates.

The effect of structural changes, mainly the switch to flat screen technologies and laptop computers, is evident in the reduction of UEC values prior to 2005.

Figure 2: Estimated change in stocks and average unit energy consumption of residential ICT and CE appliances in the OECD, 1990 to 2030 (International Energy Agency 2009)

The amount of research in the domestic energy sector has been done on space and water heating since the advent of the discipline following the energy crises of the 1970s. The response to this crisis was a change in the way research in the built environment was conducted in from around 1980 by more active involvement by the government in directing research. The Building Research Establishment was formed in 1970 in a merger of previously independent government research centres (such as the Building Research Station) dealing with the built environment, its methods, materials, and threats – with heating and its large per cent of total energy use the primary target. The Establishment was part of the Department of the Environment and its research programme became more tailored to meeting the

Government's policy direction following the adoption of recommendations of the 'Rothschild' report *A Framework for Government Research and Development* (Command 4514, 1971). Work in support of the Building Regulations became a central feature in the BRE's work. Energy and environmental studies, stimulated by the energy crises in the 1970s, came into the BRE in the form of energy conservation measures in housing and other buildings. This work received new emphasis in the next decade, with a large programme promoting energy efficiency in the building sector that at its height employed 70 staff involving energy use in buildings by 1993. (Courtney 1997) The result of this work was the development of the Building Research Establishment Domestic Energy Model (BREDEM), last revised in 2001, with most of its algorithm addressing the modelling of space heating.

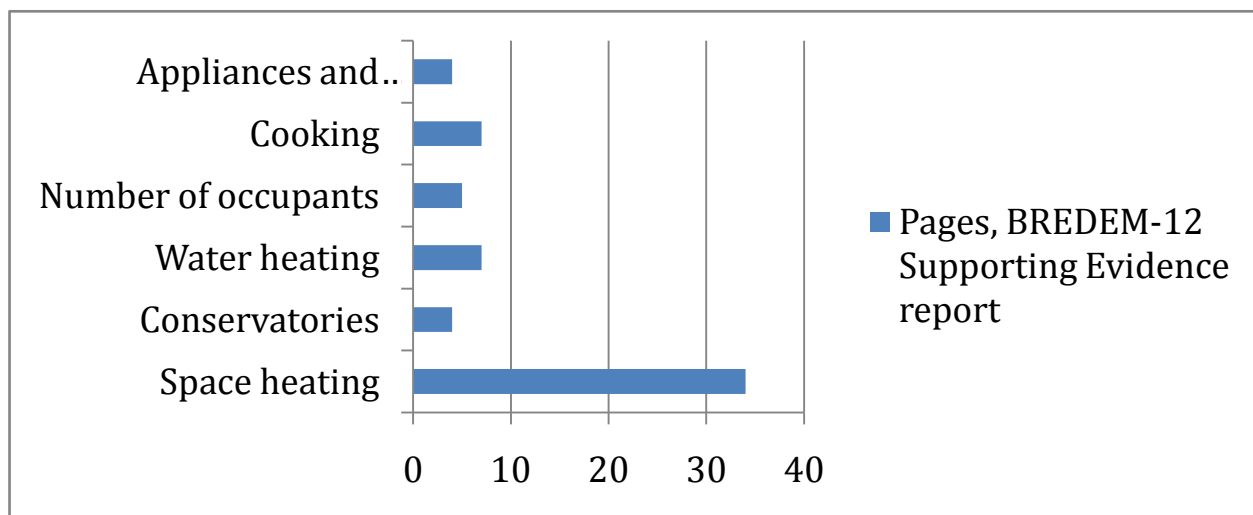


Figure 3: Pages, BREDEM-12 supporting evidence report (Energy Advisory Services 2001)

Finally, the source of energy in the home has continuously diverged towards natural gas for space and water heating, dual fuel for cooking, and electricity for lights and appliances since 1970. This means that energy data collected from gas and electricity meters has become more useful as they become closely correlated with end uses in the United Kingdom. One example is the preponderance of gas inside an increasing number of homes with central heating (Shorrocks and Utley 2008).

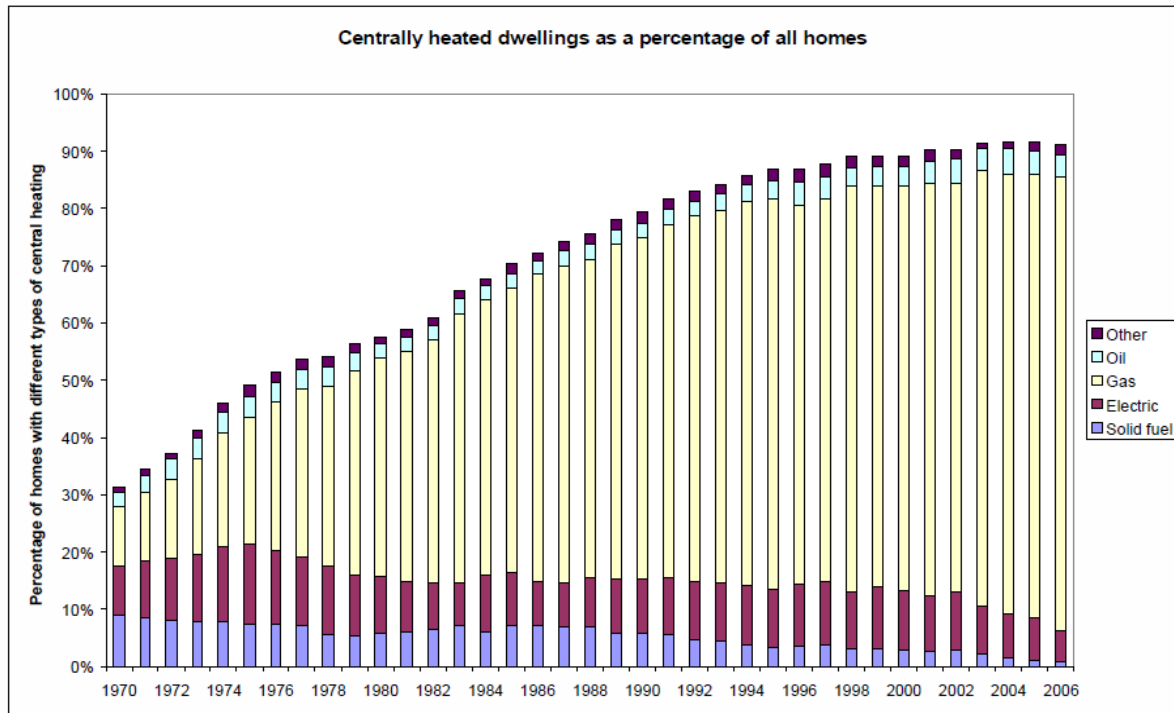


Figure 4: Centrally heating dwellings as a percentage of all homes – 1970 to 2006 (Shorrock and Utley 2008)

Current Literature

The current literature and statistics regarding energy modelling and energy use by occupants of their appliances and lights in domestic buildings show that it has been approached using both top-down (econometric) and bottom-up (engineering) approaches. The current approach in the United Kingdom (BREDEM) is based on a bottom-up building engineering method built on assumptions and parameterisations of algorithms for different end uses such as space heating or appliances. In other words, the model is built from a series of end uses totalling up to the expected energy demand of the dwelling unit. At a larger scale, BREDEM is used as a way of analysing the housing stock of an area or region using population distributions, typical appliance counts, and sampling target households (Kohler and Hassler 2002; Shorrock, Henderson et al. 2005; Natarajan and Levermore 2007). These parameterisations have been built in a top-down fashion (e.g. from a UK-wide source divided by total households). This means that the predictions made in the domestic energy model relates to typical households, but they are not tailored to specific households or even a typical household in a smaller

urban or regional subset.

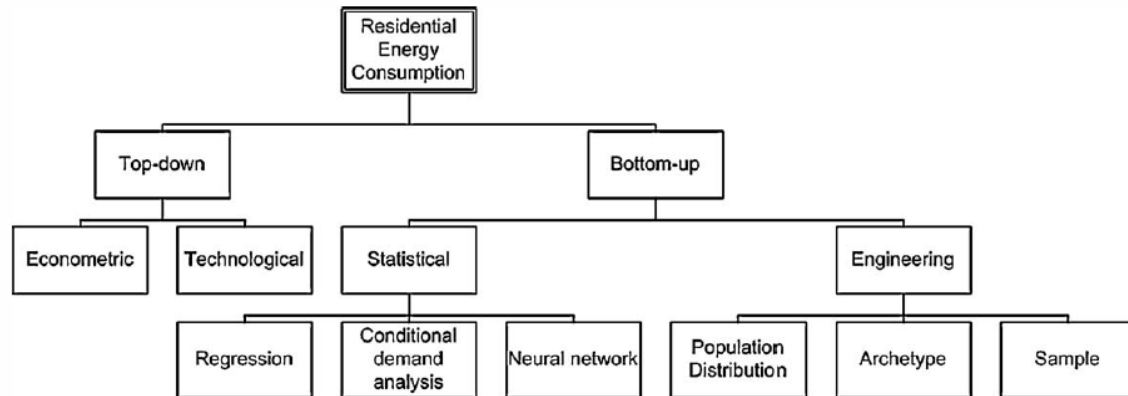


Figure 5: Top-down and bottom-up modelling techniques for residential energy consumption (Swan 2009)

The energy crisis of the late 1970s started the growth in modelling approaches at the national and regional scale. Governments with the energy shortage suddenly needed to understand consumer behaviour with dwindling supply and pricing, and broad models were developed for national energy planning. These models require little in the way of detail of consumption patterns as they treat the residential sector as a single consumer. The models then regress or add in factors that affect consumption to determine current and future trends. Most top-down models rely on large amounts of statistical data supported by economic theories of material consumption. (Swan 2009)

In the UK, the traditional approach to any time of analysis of the housing stock is through housing surveys, specifically the Survey of English Housing and the English House Condition Survey (which will be replaced by the English Housing Survey that will publish its first reports in 2010). The survey of English Housing generally has statistics at the local authority level and is therefore generally not local enough in order to be used in this thesis. The English House Condition Survey states in its documentation that the sample size is not adequate for assessment at the regional or local authority level (Department of the Environment 1986).

Building regulations that promote the conservation of energy use in domestic buildings in the United Kingdom are required under the building acts of its constituent nations as well as fulfilling the European Directive on the Energy Performance of Buildings. (HMSO 1984; Scottish Executive 2003; Department for Communities and Local Government 2007) For simplicity, this discussion will limit itself to the legislation and the current building regulations in place in England and Wales, which are supplemented by approved documents that provide supplementary guidance for fulfilling the requirements of the building regulations. For domestic buildings, this is Approved Document Part L1A which requires a target emissions rate (calculated as the number of kilograms of carbon dioxide per square metre) that is calculated from the Standard Assessment Procedure (SAP) or the Simplified Building Energy Model (SBEM) that are both derived from the Building Research Establishment Domestic Energy Model - 12

month (BREDEM-12) (Department for Communities and Local Government 2006). The basic BREDEM algorithm for appliances and lighting is follows:

if ($TFA \times N < 750$)
 $Elec = 0.022 TFA \times N + 2.16$
else if ($TFA \times N > 750$ and $TFA \times N < 2475$)
 $Elec = 9.84 + 0.014 TFA \times N - 2.63 \times 10^{-6} (TFA \times N)^2$
else
 $Elec = 28.8$

(Anderson 2002b), where *Elec* is electricity in gigajoules per year, *TFA* is the total floor area, or gross external area, in square metres, and *N* is the number of occupants.

The modelling of appliances and lighting in residential buildings is set to change dramatically as traditional appliances such as refrigerators and washing machines become more efficient and newer, more sophisticated electronic gadgets for communication and entertainment will mostly use more energy than the ones that they replaced. Although 54 per cent of people in the UK think that modern, high-tech kit is more energy efficient than older technology, the opposite is often true (Energy Savings Trust 2007b). From 2001 to 2020, entertainment, computers and gadgets is predicted to rise from 12 to 45 per cent of electricity used in our homes (Energy Savings Trust 2007a).

A supporting evidence paper (Energy Advisory Services 2001) was written during the last revision of BREDEM in 2001 that detailed the current rationale for socioeconomic impacts on energy use of appliances, lighting, and cooking. First there were two conclusions, that low income households have less appliances than average, and that they use the appliances they have less than average. The results shown in the Pennyland Project (an experiment on an estate of 177 houses in the Pennyland district of Milton Keynes to compare UK and Danish building energy efficiency standards) indicate that the ‘gap’ between measured and estimated fuel use is most severe at the low end of the scale, and that in this region the error has both a fixed offset and a slope error in the regression of energy use of households. The fixed offset was accounted for by tank losses; the slope error was accounted for by the lower ownership and use of appliances. (Chapman, Lowe et al. 1985)

In addition to the specific problems associated with low income households energy monitoring projects found a large spread of ‘average’ households. The seven houses at Linford with identical houses with identical numbers of occupants had electricity consumption in appliances ranging from 1805 kWh/yr to 4289 kWh/yr. The range from lowest to highest use of electricity used for cooking was from 446 kWh/yr to 1097 kWh/yr. The standard error implied by these results was about 25% of the mean. (Everett, Horton et al. 1985) A project in Pennyland, Milton Keynes yielded a standard error around 10% - but the Energy Advisory Services report states that this may not be a correct interpretation of the data presented. Everett et al. (1985) supports the assumption that the best explanation of this variation is household income.

When faced with the task of making a proposal to alter the model to take into account income, the supporting paper for BREDEM explained that “it is assumed that it is unacceptable to ask households for an estimate of their disposable income.” (Energy Advisory Services 2001) Nevertheless, surveyors were

expected to be able to determine if households were in higher or lower income bands. The assessment for input into the BREDEM model is based on looking at the overall level of appliance ownership and “indications of the level of household income.”

The surveyors were then instructed that around 70 per cent of all homes fit into the ‘average’ band with no alteration of the BREDEM algorithm, and that they should be placing about 15% households into cases higher or lower than average. Households could be ‘well below average’ in exceptional circumstances, and only for those in fairly extreme poverty, typically with no income other than benefit payments. (Energy Advisory Services 2001) The algorithm was then altered as follows for electricity use in lights, appliances and cooking:

Average case	as algorithm
Higher than average	+ 20%
Lower than average	- 20%
Very low use	- 40%

(Anderson 2002a)

The use of a more general socioeconomic model for energy use can be useful for obtaining accurate estimates of building performance without needing as much detail as currently required by SAP or SBEM. This could mean that the exact materials and U-values may not be needed and estimates can be made at the planning application stage with some confidence. Currently, planning policy of regional government and local authorities is only able to reflect the technical requirements of building regulations that take extensive time and research to comprehend (Greater London Authority 2004; Edwards 2009).

SAP entered the building regulations in 1990 as a way for the first time to calculate energy performance as a way of showing compliance with building regulations. Elements of the methodology were introduced, notably a target U-value method introduced in the BREDEM-3 methodology designed for computer calculations in 1985 (Anderson, Clark et al. 1985). In this version of BREDEM, all of the appliances still had a discrete gain in watts assigned to it as part of the model without taking into account the number or behaviour of occupants. SAP was based originally on technical energy monitoring work on hundreds of low energy homes in the Milton Keynes Energy Park as part of the Energy World exhibition of 1986 (Shorrock and Anderson 1995).

SAP is part of a continuing government intervention in conserving energy use in homes, but with a new focus on fuel poverty, defined as spending 10% of income on fuel, after major campaigning in the 1980s (Boardman 1984; Boardman 1991). Government support limiting energy use were aimed overwhelmingly at fuel poor homes which used a higher than average amount of energy on space and water heating through programmes such as the Warm Front programme. To this end, SAP as an energy model focused on reducing costs to the occupier for space and water heating. There is a new version of SAP currently being prepared for release in the near future (Lowe 2009).

In pre-2006 versions of the building regulations (1985, rev. 1991, rev. 2000) simplified versions of SAP calculations were allowed to be used (Office of the Deputy Prime Minister 2000). Appliances, lighting,

and metabolic use were placed together in a simple equation between square metres and energy gains (watts per square metre) as opposed to energy consumption (kilowatt-hours per square metre). After the EU Directive on energy performance in buildings 2002/91/EC needed implementation, the 2006 building regulations incorporated Target and Dwelling Emission Rates in its version of Approved Document L1A for domestic buildings, but the version SAP that it incorporated, SAP2005, remained unchanged (Office of the Deputy Prime Minister 2000; Department for Communities and Local Government 2006).

If socioeconomic factors are factored into BREDEM/SAP calculations, this would have a much larger reach because it is the basis for approving energy efficiency in all buildings under the current building regulations in England. This research would, if its hypothesis is correct and its recommendations are implemented, loosen the burden of transforming the housing stock away from housing associations and registered social landlord and onto the private sector providers. Current local policies implement tough new regulations on publically funded housing in order to meet carbon reduction targets through the Code for Sustainable Homes (Mayor of London 2006). This puts additional financial pressure on public housing providers as opposed to the private ownership and rented sector that may not necessarily be justified by energy use consumption data.

Building a socially, economically, and spatially accountable domestic energy model for appliances, lighting, and consumer goods

The goal for this piece of research is to develop a system of coefficients for the variables N (numbers of occupants) and TFA (total floor area) in the algorithms developed in domestic energy modelling in the United Kingdom. The methodology and workstream will be done in a way that the procedure could be applicable in international energy modelling systems with similar census data available. The first step is to identify data sources for energy use in small scale statistical areas (or more colloquially, urban neighbourhoods) alongside socioeconomic, building, and neighbourhood data alongside national trends in appliances and electronics ownership and low-energy lighting. The second is to perform exploratory data analysis on all of the data's relationships with energy use for appliances and lighting. The third step will be to develop a series of possible correlation coefficients and test them against real-life statistical areas in a variety of urban settings. Finally, the system of coefficients for variables N and TFA will emerge for any neighbourhood dependent on largely socioeconomic alongside some building and neighbourhood data.

Data available

The Department of Energy and Climate Change (and its predecessors the Department for Business and Regulatory Reform and the Department for Trade and Industry) developed a method of measuring energy in both the domestic and non-domestic sectors delivered in small scale statistical areas since 2004. These areas, called Middle Layer Super Output Areas (MLSOAs), were first introduced in the 2001 census as a new statistical standard. There are several advantages to using MLSOAs as a basis for energy use statistics; they are relatively consistent in terms of population (minimum population of 5,000 equating to around 2,000 households), the boundaries do not change greatly from census to census and

also geographical mapping software for SOAs is already available from the Office for National Statistics (ONS). Data is shown by consumption in kWh (split by ordinary electricity, economy7 electricity, industrial/commercial electricity, domestic gas and industrial/commercial gas), number of gas and electric meters and average consumption per meter (Department of Energy and Climate Change 2009a).

Thorough examination of the energy data is vital to isolate the end use of lights, appliances, and other consumer goods and electronics. The diversion of heating energy end uses to natural gas and lights and appliances to electricity as fuel in the home means that this energy data is useful for assessing the end uses of lights and appliances. In some cases, heating is supplied by electricity, significantly increases electricity usage, but also decreases the number of gas meters, and this data can be easily identified. Cooking can be and often is supplied by either fuel; national trends will be utilised to account for this energy use (Market Transformation Programme 2008a). Finally, DECC has reported that some gas meters in the domestic stock that actually are measuring small non-domestic users (Department of Energy and Climate Change 2009a). A study should be made in spatial areas with large amounts of small non-domestic premises, for example in areas that contain a high street, to see if these are also special cases where the data is unreliable.

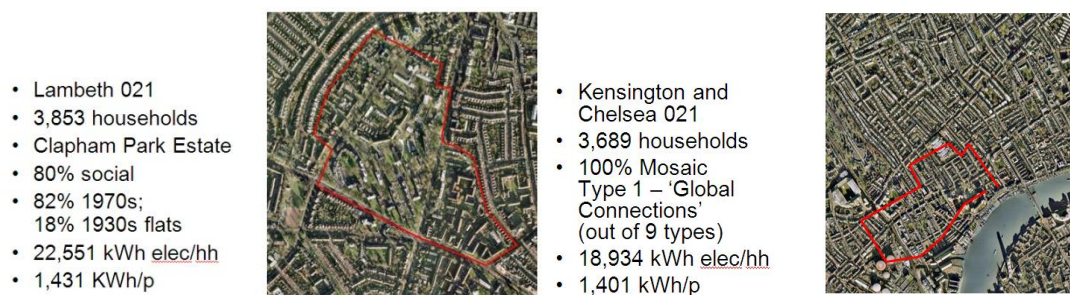


Figure 6: Examples of MLSOAs (Images, Google Maps UK 2009)

Each MLSOA is built out of adjoining Output Areas(OAs). After the 2001 Census, OAs were built from collections of unit postcodes. They were designed to have similar population sizes and be as socially homogenous as possible (based on tenure of household and dwelling type). They had approximately regular shapes and geographers working for the ONS constrained OAs by obvious boundaries such as major roads. The OAs are all required by the Office of National Statistics to have a specified minimum size to ensure the confidentiality of data. The target size of each OA was 125 households with a minimum OA size is 40 households and 100 people for data protection purposes. (Martin 2001)

The Data Protection Act 1998 (Great Britain. Office of the Data Protection 1998) does not allow any disclosure of information that might allow identification of an individual or individual's place of residence from small scale statistical data released by UK government sources. Anonymised or aggregated data is allowed by the Act, providing the anonymisation or aggregation has not been done in a way that is reversible. These disclosure issues prevent disaggregation at lower levels, for instance at the postcode level. For the built environment researcher, it can pose issues in verifying results, and that studies are limited in connecting exact social variables, such as age, sex, income, ownership of goods, or

lifestyle, to energy use of any one particular flat because of this requirement for protecting an individual's anonymity.

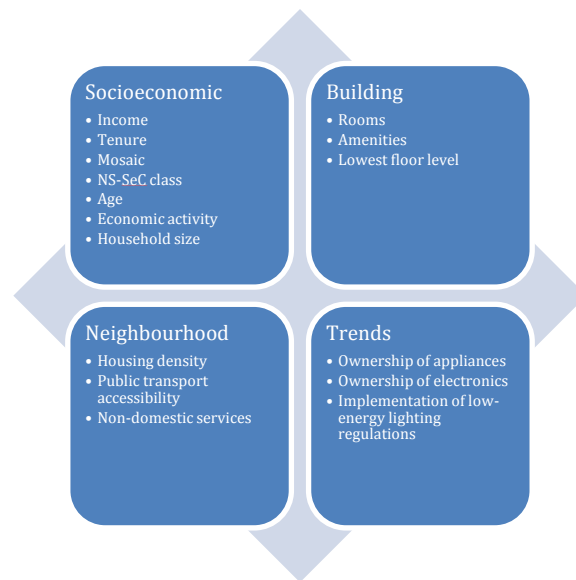


Figure 7: Types of data available at MLSOA scale

Socioeconomic variables for statistical areas of similar size are available through a variety of sources in both raw data and in processed classifications. The currently obtained and potential datasets available are detailed in appendix A. They include statistics on socioeconomic classification of individuals, accommodation types, household spaces, average numbers of people, household income, and tenure, as an example. The main source is the neighbourhood statistics data in the Office of National Statistics where this data can be found in a variety of sources and scales, and most pertinently at the MLSOA scale. The second major source is marketing and socioeconomic classifications developed at the MLSOA and Lower Layer Super Output Area (LLSOA) scale by the Experian group and made available to academic researchers. The Mosaic 2003-2008 classification mirrors the current years of energy data (2004-2008) with estimates of 11 person groups and 61 types along with personal income estimates for each of the years 2003-2008.

Trends of ownership of appliances, electronics at the UK level has been collected by various national agencies, universities, quangos, and charities concerned with energy use. The current main model for estimating total UK energy use of lights and appliances, the DECADE model, was built at the Oxford University Environmental Change Institute (Environmental Change Institute 1995; Shorrocks and Uteley 2008). It obtained data for the numbers of appliances of different types bought and disposed of per year, assigned a power consumption and use frequency measure, and totalled all of the electricity usage together. Simplified versions of the model, for example without use frequency, were also available. The Domestic Energy Fact File continues to use this model to estimate the UK-wide energy use of lights and appliances.

Exploratory data analysis

Exploratory data analysis is a vital step in understanding the amount of data that has been gathered other the course of this project. Examples of this analysis include linear regression, frequency distribution, cumulative frequency tables, cluster analysis, and correspondence analysis. As above, BREDEM is a bottom-up engineering model based on many assumptions and parameterisations that built up an algorithm for different end uses, e.g. space heating. Developing the parameterisations at a more aggregated level would ideally involved the assessment of the characteristics of individual homes and occupants but without invasive research that would break data protection guidelines, this can only be approached using an top-down approach at, in this instance, the neighbourhood (less than 5,000 households) scale. This project is intended to be a study of wide geographic areas that does not need to use individual observations. Instead, the study will be using small-scale census data to examine large socioeconomic groups. In order to do this, analysis will entail national, regional, neighbourhood, and personal trends in the use of energy inside of a residential building as detailed above.

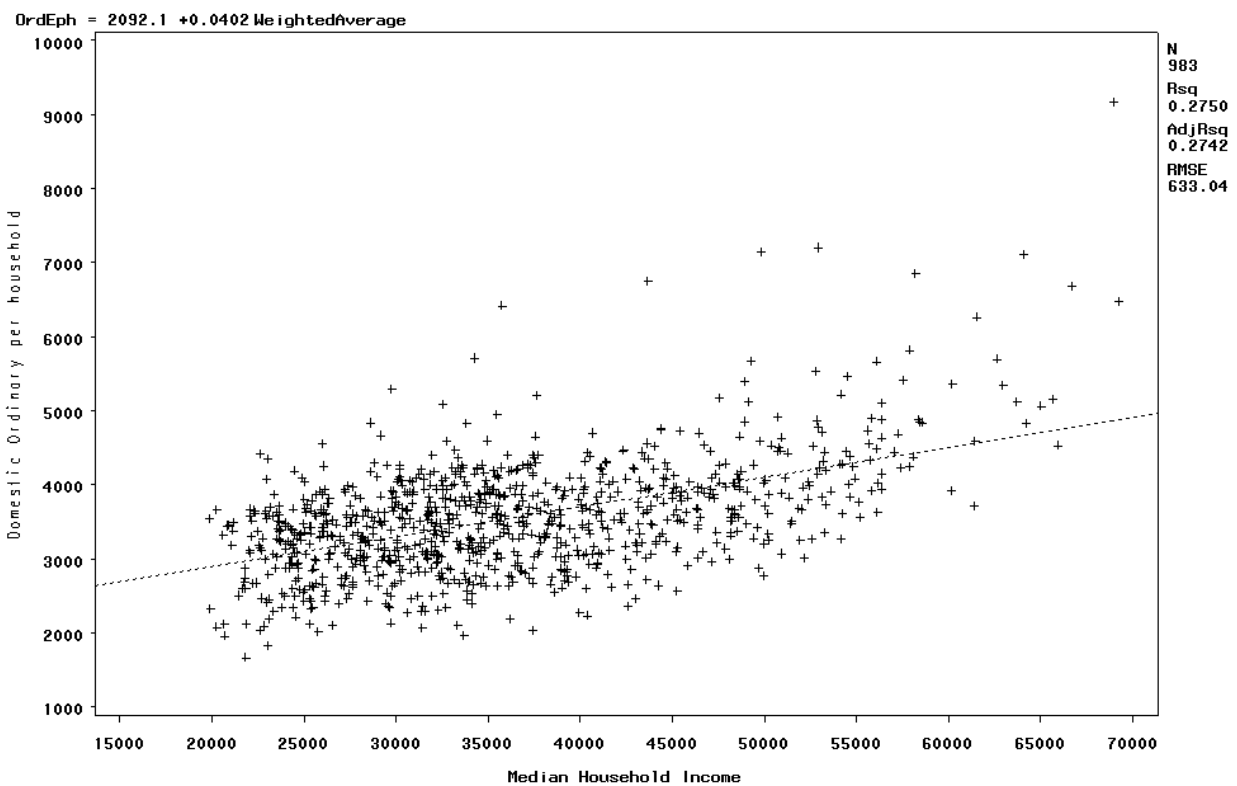


Figure 8: Example of single regression in exploratory data analysis (£/year v kWh/ph/year for Greater London MLSOAs, 2007)

Regression analysis is the creation of an equation that plots different socioeconomic, building, and neighbourhood variables (e.g. age, median household income) against energy use per household. A general linear regression model can be written as $Y_i = \alpha + \beta_1 X_{i1} + \beta_2 X_{i2} + \dots + \beta_p X_{ip} + \varepsilon_i$, where $i = 1, 2, \dots, n$; where p is an independent variable and n is the number of observations of the dependent

variable, in this case, energy use per household, and ϵ is the error in the linear equation – this is not observable and in regression analysis it is typical to assume a zero mean of all of the errors in all observations. This does not mean that the differences between observed and predicted values are ignored – a multiple regression coefficient can be obtained through further analysis that will be detailed later in this paper. An initial prediction equation, however, can be built after further analysis of the difference, or residual, between the observed and predicted values of the dependent variable (energy use per household). Examples of determining this are least squares, predicted or deleted, and recursive residuals (Du Toit, Steyn et al. 1986).

Frequency analysis attempts to explain why the count of the number of times an observation of the dependent variable occurs. This method will be useful if there are clusters of results with similar energy use per household or per person data for different small scale statistical areas. General characteristics that are shared between these areas can be plotted and analysed.

Cluster analysis takes this process a step further. In the case of socioeconomic and built environment characteristics, the cases might well be very homogeneous in respect of the characteristics that are measured and a systematic way of delimiting them into clusters can be useful for this process. Cluster analysis takes the distances in value between cases of energy use in small areas and assign a degree of similarity to them. The analysis starts with one large cluster then dividing into clusters until a number n is formed. This division could be horizontal or, more likely, hierarchical in nature. These types of clusters are useful to make generalised assertions about different types of energy user. One example of this type of analysis is marketing data and the assignment of different socioeconomic groups by the Office of National Statistics (Martin 2001; Experian UK 2009). Some of these groups could be later grouped into separate regression analysis prediction equations.

Exploration data analysis is an ongoing process in this project as data continues to be collected that could contain clues to the energy use of appliances and lighting in residential buildings. It is the start of a methodology of determining a system of coefficients for variables N and TFA in the algorithm for electricity use of lights and appliances. Currently, a system of frequency, then cluster, then regression analysis is the preferred path for exploratory data analysis, likely in an agglomerated, hierarchical manner.

Developing coefficients and testing

Developing the parameters for a new, spatially-defined algorithm for the energy modelling of appliances and lighting in residential buildings will require a mix of top-down and bottom-up approaches to arrive at two coefficients C_N and C_{TFA} , for example $C_N = \alpha + \beta_1 \left(\frac{I}{I_{avg}} \right) + \beta_2 \left(\frac{J}{J_{avg}} \right) + \dots + \beta_n \left(\frac{p}{p_{avg}} \right)$ where α is a constant, β is the number n weights of each independent variables I, J, \dots, p (socioeconomic, building, neighbourhood, and trend variables). Each of these coefficients will be derived from a set of socioeconomic, building, and neighbourhood variables as below:

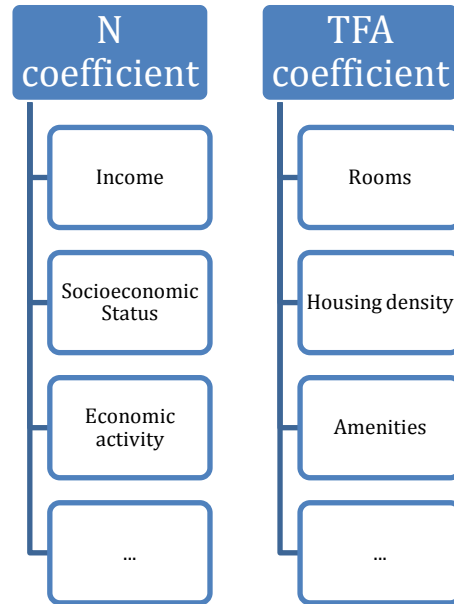


Figure 9: Coefficients for N and TFA

Arriving at these coefficients will first take some results from the exploratory data analysis processes, notably the prediction equations that emerge from regression analysis. A thorough correlation analysis of the different types of independent variables will occur. This as the simple question of if as x rises in value, does y or z also rise and at what rate? For example, the Pearson Product Moment Correlation coefficient is a common method of defining correlation (Smith et al. 2001; Hall 2005). It can be found by calculating $R = \frac{\sum(x-\bar{x})(y-\bar{y})}{\sqrt{\sum(x-\bar{x})^2 \sum(y-\bar{y})^2}}$ where x and y are two independent variables.

For example, in a list of MLSOA cases with a measured domestic electricity use (with cooking discounted) the correlation between household income, average number of rooms, amenities available in the home, and other variables can be brought to light. However, this will require extensive clustering of types of MLSOA to make sure that like for like correlations are being made. For example, in figure 6 above, the amount of energy use per household is about 25 per cent apart, but the energy use per person is very similar. These types of MLSOAs where the average number of people per household are very different do not offer as 'clean' a comparison as would be optimal in this research project.

It could also be possible to directly measure the weights by populating the data with a bottom-up schedule of appliance types and power consumption trends typical in the DECADE and PassiveHaus Design Package energy modelling techniques. This might be useful if it was correlated with socioeconomic and building data already in possession, especially if more detailed data on floorspace and the number of rooms becomes available from the Valuation Office Agency (see Appendix A). A comparison between this bottom-up approach and the top-down correlation and exploration data analysis will send valuable light on the limitations of the project.

An approach for testing the work would be to artificially de-agglomerate the datasets into individual homes and use the new algorithm for electricity use of lights and appliances onto each dwelling in an

MLSOA. If the difference between the observed and predicted energy use were less than an expected tolerance, the project will have been a success.

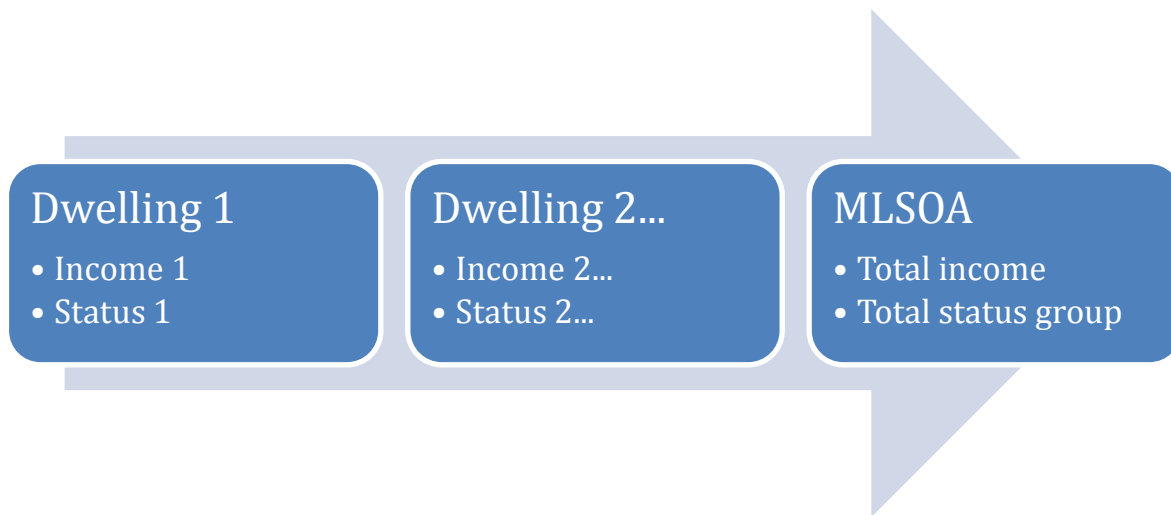


Figure 10: Testing mechanism example

Chapter outline

The thesis has already collected large amounts of small-scale data beginning with the Greater London region of energy and socioeconomic variables. The first step of the exercise is to define the parts of the energy use data pertinent to appliances, lighting, and electronics out of the MLSOA energy data. Once the applicable energy use has been identified, several socioeconomic, building, and neighbourhood factors will be analysed and correlated, notably marketing and income data against energy use in each geographic (MLSOA) area. Each of the socioeconomic categories will be randomised across the built characteristics of dwellings in each area. The results will then be tested against the current algorithm of BREDEM and SAP, the algorithms will then be adjusted through a re-calibrating of correlation coefficients that affect the weighting of each socioeconomic, building, neighbourhood, and trend variable, and the cycle repeated until the ‘gap’ between predicted and recorded data is reduced inside an acceptable error. Detailed steps follow in the chapter outline below.

Chapter 1: Introduction to the socio-economic modelling of domestic energy use / household energy consumption

This chapter will establish the rationale of thesis. It will discuss why this particular area of energy modelling is significant and the current work done on household energy consumption. It will outline trends in all aspects of domestic energy use and focus on the impact of human behaviour on energy use in the home and ask what is contributing to “high carbon” lifestyles and the current legislation and measures already in place to limit or reverse growth in energy use. It will summarise the current domestic energy models currently in use in the United Kingdom and other developed countries (e.g. USA, Canada, and Germany). It will outline current data sources both domestically and internationally.

Chapter 2: The context in the United Kingdom

The United Kingdom is an interesting place to look at socioeconomic factors on energy use in the home because of its diversity of socioeconomic groups and buildings, yet these groups and buildings are geographically concentrated in different parts of an urban area. The housing stock inside of small areas in the United Kingdom, especially in the inner suburbs of large conurbations, was built simultaneously and are often homogeneous collections of domestic buildings. The people who inhabit these buildings and their individual impact on domestic energy use is also important, as the numbers of occupants per household changes considerably and is likely to be correlated to several socioeconomic and building factors.

Chapter 3: Exploratory data analysis

Initial cluster and frequency analysis will expose areas of further research and interest following from the initial observations of the UK context in Chapter 2. Clusters of similar small areas (MLSOAs) will emerge in neighbourhood groups in socioeconomics, building types, and neighbourhood characteristics that will become useful when building regression analysis for building a revised algorithm for electricity use for appliances and lighting in residential buildings.

Chapter 4: Building coefficient C_N

A coefficient for the variable N (numbers of occupants) will be built out of regression and correlation analysis. Each of the MLSOAs in an urban area, and the first that will be evaluated will be in Greater London with other areas added later, will be ranked against individual socioeconomic characteristics and indices¹ both in ranked order and as a percent of the highest amount of energy use in each MLSOA. A discount for the socioeconomic effect on space and water heating will need to be devised. This process will be done whilst holding constant housing types (a homogeneous housing area defined as 75 per cent or more of the total housing stock) and the urban setting (density and proximity to transport and local services) of the area.

Chapter 5: Build coefficient C_{TFA}

A coefficient for the variable TFA (total floor area) will be built out of regression and correlation analysis. Comparisons will be made between places that have similar socioeconomic types, but are in different building and neighbourhood types. The location types can be defined using Transport for London's Public Transport Accessibility Level assessment mechanism, numbers of non-domestic hereditaments and with the density of dwellings per hectare across the MLSOA. General ages of each area can be obtained through sources such as Cities Revealed and using historical Ordnance Survey data outlining the growth and/or redevelopment of the urban conurbation. Another valuable resource is the Valuation Office Agency database used to assign domestic dwellings to council tax bands – aggregated data by house type, age, and floorspace are available.

Chapter 6: Testing and recalibration

¹ Experian Mosaic 2003 model; English Indices of Deprivation

Each of the coefficients will be tested against observed energy data. Outliers in the data will be identified, and additional research at this point will be necessary to identify reasons for observed energy use to vary significantly from predicted energy use. Reasons could be flat rate energy pricing in housing estates, low occupancy rates, or large numbers of non-domestic uses in the area. It is possible for additional financial or non-domestic variables to be added to the algorithm at this stage before re-testing.

Chapter 7: Results analysis and limitations

This chapter will analyse the results by examining the reliability of the predictions and their significant against the existing domestic energy model in place in the United Kingdom. The most important will be the significance of the results – further accuracy must be balanced against additional data input and the reliability of the census data continuing in 2011 and subsequent decades.

Chapter 8: Improvements in the future to the model

Anticipated future improvements will be outlined, especially the impact on this research of a more extensive data framework for energy research currently being developed by UCL and the EPSRC. This model could be linked in the future to a large GIS database that can incorporate postcode entries for advanced planning applications, but in the planning system sometimes only a vague address is given and that would also need to be accommodated. The situation would entirely change if individual homes' meter data could be placed alongside its total floor area and numbers of occupants, but this could be a long time coming in the future owing to data protection laws. International research and fieldwork in countries with similar patterns of electricity and gas diversion to lights and appliances versus heating could be used to further develop the model in the future.

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