Programme Area: Distributed Energy

Project: Micro DE

Title: Review of Previous Work on Energy User Behaviour

Abstract:

Please note this report was produced in 2010/2011 and its contents may be out of date. This deliverable is number 3 of 9 in Work Package 1. It assess the suitability of existing work in the area of home energy for use in the Micro DE projects modelling of the potential impact of micro DE systems within the home. It recommends that occupant behaviour models need to be built on available empirical data, such as Warm Front and HEED, as opposed to relying on existing market segmentation models

Context:

The project was a scoping and feasibility study to identify opportunities for micro-generation storage and control technology development at an individual dwelling level in the UK. The study investigated the potential for reducing energy consumption and CO2 emissions through Distributed Energy (DE) technologies. This was achieved through the development of a segmented model of the UK housing stock supplemented with detailed, real-time supply and demand energy-usage gathered from field trials of micro distributed generation and storage technology in conjunction with building control systems. The outputs of this project now feed into the Smart Systems and Heat programme.

UCL Energy Institute

ETI project report

Micro Distributed Energy and Energy Services Management Application to existing UK residential buildings

WP1.3 Review of previous work on energy user behaviour

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Executive Summary

This report addresses a range of existing UK market segmentation models and occupant behaviour modelling techniques in order to determine whether there is sufficient data to populate the Micro DE bottom up stock model with occupant characteristics.

In terms of geodemographic segmentation, the most widely known systems in the UK are CAMEO (by Eurodirect), A Classification of Residential Neighbourhoods (ACORN) by CACI and MOSAIC (by Experian). None of them targets directly to energy use, however, two separate classification systems relevant to energy consumption have been developed and they are both based on Experian's MOSAIC. The GreenAware and the Energy Saving Trust (EST) segments are made up of 10 distinct groups each and look at various aspects of environmental relevant behaviours.

Occupant behaviour modelling can be based either on a 'building physics' approach or on a 'statistical modelling' approach. The building physics approach is based on certain 'stiff' assumptions and is mostly useful when modelling a specific instance with known and fixed model structure and no variable uncertainty. On the contrary, statistical models incorporate a probabilistic approach to describe the variation of each variable and thus explicitly incorporate uncertainty. As such, the Bayesian Belief Network (BBN) models domestic energy use based on statistics relating occupant socio-demographics to home energy use. It can be especially useful when variables such as energy demand and income levels vary significantly across the population and factors affecting energy use are interdependent, making energy demand challenging to describe through simple equations.

Other multi-method approaches include crude take back and price elasticity. The 'temperature take back' factor can be quantified and refers to the phenomenon where improvements in energy efficiency usually result in increased energy use due to higher standardised internal temperatures. The price elasticity effect has been confirmed by many studies and refers to the complex relationship between households expenditure on energy use and fuel price.

Modelling occupant behaviour in the domestic sector is a complex task, governed by various environmental, psychological and social factors. In the absence of a well tested theory as well as due to the lack of clear identification of how segmentation models impact energy use (especially regarding Micro DE technologies), occupant behaviour models need to be built

on available empirical data, such as Warm Front and HEED. A simple comfort take back factor and price elasticity will be also considered.

1 Introduction

This report considers the range of existing UK market segmentation approaches and reviews the available occupant behaviour modelling techniques in order to investigate whether there is sufficient data to populate a bottom up stock model with occupant characteristics as part of the Micro DE project.

2 Review of existing market segmentation approaches

Geo-demographic segmentation is a marketing process that uses multivariable statistical classification techniques to discover whether the individuals of a population fall into different groups. The groups are defined by undertaking a quantitative comparison of multiple characteristics. The resulting segments and their characteristics can be used to identify the different markets and understand customers' lifestyle, behaviour and attitudes in order to identify profitable prospects, evaluate local markets and develop location planning strategies. This is particularly useful for people undertaking marketing activities as they can determine the most appropriate messages, communication channels and products to reach and influence each segment (Wright n.d.).

Widely known geo-demographic segmentation systems in the UK include CAMEO, A Classification of Residential Neighbourhoods (ACORN) and MOSAIC. We are not aware that any of these classification systems have been linked directly to energy use. However, we are aware of two separate classification systems relevant to energy consumption, which are both based on Experien's MOSAIC:

- the GreenAware segmentation of environmentally-relevant behaviours, attitudes and carbon footprint and
- the Energy Saving Trust (EST) segmentation developed to identify households with best potential for generating carbon savings.

2.1 ACORN system

The ACORN system claims to be the first geo-demographic tool used to identify and understand the UK population and the demand for products and services. The system was developed by Consolidated Analysis Centres Incorporated (CACI) and segments small neighbourhoods, postcodes, or consumer households into 5 categories, 17 groups and 56 types (Table 2.1a). It categorises all 1.9 million UK postcodes using over 125 demographic statistics within England, Scotland, Wales and Northern Ireland and employing over 287 lifestyle variables (CACI n.d.).

Table 2. 1a: ACORN Classification (CACI n.d.)

Category	Group	Type
Wealthy Achievers	Wealthy Executives	01 – Affluent mature professionals 02 – Affluent working families with mortgages 03 – Villages with wealthy commuters 04 – Well-off managers, larger houses
	Affluent Greys	05 – Older affluent professionals 06 – Farming communities 07 – Old people, detached houses 08 – Mature couples, smaller detached houses
	Flourishing Families	09 – Larger families, prosperous suburbs 10 – Well-off working families with mortgages 11 – Well-off managers, detached houses 12 – Large families & houses in rural areas
Urban Prosperity	Prosperous Professionals	13 – Well-off professionals, larger houses and converted flats 14 – older Professionals in detached houses and apartments
	Educated Urbanities	15 -Affluent urban professionals, flats 16 – Prosperous young professionals, flats 17 – Young educated workers, flats 18 – Multi – ethnic young, converted flats 19 – Suburban privately renting professionals
	Aspiring Singles	20 – Student flats and cosmopolitan sharers 21 – Singles & sharers, multi-ethnic areas 22 – Low income singles, small rented flats 23 – Student Terraces
Comfortably Off	Starting Out	24 – young couples, flats and terraces 25 – White collar singles/sharers, terraces
	Secure Families	26 – Younger white-collar couples with mortgages 27 – Middle income, home owning areas 28 - Working families with mortgages 29 – Mature families in suburban semis 30 – Established home owning workers

		31 – Home owning Asian family areas
	Settled Suburbia	32 – Retired home owners
		33 – Middle income, older couples
		34 – lower income people, semis
	Prudent Pensioners	35 – Elderly singles, purpose built flats
		36 – older people, flats
Moderate Means	Asia Communities	37 – Crowded Asian terraces
		38 – Low income Asian families
	Post Industrial Families	39 – Skilled older family terraces
		40 – Young family workers
	Blue Collar Roots	41 – Skilled workers, semis and terraces
		42 – Home owning, terraces
		43 – Older rented terraces
Hard Pressed	Struggling Families	44 – Low income larger families, semis
		45 – Older people, low income small semis
		46 – Low income, routine jobs, unemployment
		47 – Low rise terraced estates of poorly-off workers
		48 – Low incomes, high unemployment, single parent
		49 – Large families, many children, poorly educated
	Burdened Singles	50 – Council flats, single elderly people
		51 – Council terraces, unemployment, many singles
		52 – Council flats, single parents, unemployment
	High Rise Hardship	53 – Old people in high rise flats
		54 – Singles & single parents, high rise estates
	Inner City Adversity	55 – Multi-ethnic, purpose built estates
		56 – Multi-ethnic, crowded flats

2.2 CAMEO system

On an international scale, the CAMEO classifications (developed and maintained by Eurodirect) are used by organisations for the segmentation, profiling, analysis and targeting of consumers. CAMEO UK, in particular, has been built at postcode level and classifies over 60 million British consumers. It has been built using a wide range of actual data resources (Appendices, Table 7.1). In addition, a whole range of different geo-demographic, socio-economic and lifestyle variables have been used within the clustering and descriptive process, including four groups of data and 26 different variable types (Appendices, Table 7.2):

CAMEO segments the British market into 57 distinct neighbourhood types and 10 key marketing segments (Table 2.2a). Each of the 57 defined clusters has been comprehensively tested for their homogeneity in make-up, present in enough numbers to be of practical use and non-biased towards specific geographic regions in the UK. The CAMEO UK Classification has been tested against a range of different client datasets (Eurodirect n.d.).

Table 2. 2a: Key marketing groups (CallCredit Information Group n.d.)

Code	Key marketing group	CAMEO UK type
1	Affluent singles & couples in exclusive urban neighbourhoods	1A – Opulent couples & singles in executive city & suburban areas 1B – Wealthy singles in small city flats & suburban terraces 1C – Urban living professional singles & couples 1D – Wealthy & educated singles in student areas
2	Wealthy neighbourhoods nearing & enjoying retirement	2A – Opulent older & retired households in spacious rural properties 2B – Affluent mature families & couples in large exclusive detached homes 2C – Affluent mature couples & singles some with school age children 2D – Wealthy suburban professionals in mixed tenure
3	Affluent home owning couples & families in large houses	3A – Wealthy older families in spacious suburban & rural detached & semis 3B – Young & mature couples & families in large rural dwelling 3C – Well-off older couples & families in large detached & semis 3D – Wealthy mixed households living in rural communities
4	Suburban home owners in smaller private family homes	4A – Executive households in suburban & semis 4B – Professional home owners in detached & semi suburbia

		4C – White collar home owners in outer suburbs & coastal areas 4D – mature owner occupiers in rural & coastal neighbourhoods 4E – Couples & families in modern rural & suburban developments 4F – Mature couples & families in mortgaged detached & semis
5	Comfortable mixed tenure neighbourhoods	5A – Singles, couples & school age families in mixed housing 5B – Young & older single mortgages & renters in terraces & flats 5C – Mature & retired singles in areas of small mixed housing 5D – Young & older households in coastal, rural & suburban areas 5E – Mature households in Scottish industrial suburbs & rural communities 5F – Young & older households in areas of mixed tenure 5G – Older couples & singles in suburban family semis
6	Less affluent family neighbourhoods	6A – Less affluent communities in areas of mixed tenure 6B – Older & mature households in suburban semis & terraces 6C – Mixed households in mostly welsh suburban communities & rural areas 6D – Couples & families with school age & older children in spacious semis 6E – Mature households in less affluent suburban & rural areas 6F – Less affluent couples in suburban family neighbourhoods 6G – Young single & family communities in small terraces & rented flats
7	Less affluent singles & students in urban areas	7A – Single mortgages & renters in pre-school family neighbourhoods 7B – Singles & families in ethnically mixed inner city & suburban areas 7C – Young flat dwelling singles & couples in inner city student areas 7D – Young singles, couples & students in urban areas 7E – Young singles in privately rented & housing association properties
8	Poorer white blue collar workers	8A – Poorer retired households in owned & rented accommodation 8B – Older & mature households in suburban areas of mixed tenure 8C – Older households with school age children in towns & suburbs 8D – Poorer young singles in suburban areas

		8E – Mixed mortgages & council tenants in outer suburbs 8F – Singles & couples in small terraced properties
9	Poorer family & single parent households	9A – Poorer singles in outer suburban family neighbourhoods 9B – Poorer singles & families in mixed tenure 9C – Suburban Scottish households in small terraces & flats 9D – Ethnically mixed young families & singles in terraced housing 9E – Poorer couples & school age families in terraced & semis 9F – Flat dwellers in council & housing association accommodation 9G – Young & older households in housing association & mortgaged homes
10	Poorer council tenants including many single parents	10A – Hi-rise flat dwellers in cosmopolitan areas of mixed tenure 10B – Council tenants & morgages in Scottish suburbia 10C – Poorer mortgages & council renters in family neighbourhoods 10D – Singles & single parents in suburban hi-rise flats 10E – Mature households in small terraces 7 semis 10F – Poorer singles in local authority family neighbourhoods 10G – Single renters in mixed age hi-rise communities XXX – Communal establishments in mixed neighbourhoods

2.3 MOSAIC system

Mosaic (developed by Experian) is one of the biggest consumer segmentation models that is linked to postcodes with the aim of targeting all UK households (Wright n.d.). Mosaic UK is part of a family of Mosaic classifications that covers 29 countries that include most of Western Europe, the United States, Australia and the Far East. Mosaic Global is Experian's global consumer classification tool. It is based on the simple proposition that the world's cities share common patterns of residential segregation. Mosaic Global is a segmentation system that covers over 400 million of the world's households using local data from 29 countries. It has identified 10 types of residential neighbourhood that can be found in each of the countries (Experian n.d.).

The latest version of Mosaic UK was released in 2009 and is based on the analysis of the trends in UK society, a wealth of high quality, comprehensive data sources and a sophisticated proprietary approach to cluster analysis, supported by analysis of market research to validate the classification. 155 Mosaic person types aggregate into 67 household types and 15 groups (Table 2.3a), to create a 3 tier classification that can be used at the individual, household or postcode level (all UK postcodes are included). This classification is identical regardless of whether it is assigned to a person, a household address or a postcode to create one integrated and consistent classification that is easy to implement (Experian n.d.).

Table 2. 3a: MOSAIK UK groups and types (Experian n.d.)

Group	Description	Type
A	Alpha Territory	A01 – Global Power Brokers A02 – Voices of Authority A03 – Business Class A04 – Serious Money
B	Professional Rewards	B05 – Mid-Career Climbers B06 – Yesterday's Captains B07 – Distinctive Success B08 – Dormitory Villagers B09 – Escape to the Country B10 – Parish Guardians
C	Rural Solitude	C11 – Squires Among Locals C12 – Country Loving Elders C13 – Modern Agribusiness C14 – Farming Today C15 – Upland Struggle
D	Small Town Diversity.	D16 – Side Street Singles

		D17 - Jacks of All Traders D18 – Hardworking Families D19 – Innate Conservatives
E	Active Retirement	E20 – Golden Retirement E21 – Bungalow Quietude E22 – Beachcombers E23 – Balcony Downsizers
F	Suburban Mindsets	F24 – Garden Suburbia F25 – Production Managers F26 – Mid-Market Families F27 – Shop Floor Affluence F28 – Asian Attainment
G	Careers and Kids	G29 – Footloose Managers G30 - Soccer Dads and Mums G31 – Domestic Comfort G32 – Childcare Years G33 – Military Dependants
H	New Homemakers	H34 – Buy-to-Let Territory H35 – Brownfield Pioneers H36 – Foot on the Ladder H37 – First to Move In
I	Ex-Council Community	I38 - Settled Ex-Tenants I39 – Choice Right to Buy I40 – Legacy of Labour I41 – Stressed Borrowers
J	Claimant Cultures	J42 – Worn-Out Workers J43 – Streetwise Kids J44 – New Parents in Need
K	Upper Floor Living	K45 – Small Block Singles K46 – Tenement Living K47 – Deprived View K48 – Multicultural Towers K49 – Re-Housed Migrants
L	Elderly Needs	L50 – Pensioners in Blocks L51 – Sheltered Seniors L52 – Meals on Wheels L53 – Low Spending Elders
M	Industrial Heritage	M54 – Clocking Off M55 – Backyard Regeneration M56 – Small Wage Owners
N	Terraced Melting Pot	N57 – Back-to-Back Basics N58 – Asian identities N59 – Low-Key Starters N60 – Global Fusion
O	Liberal opinions	O61 – Convivial Homeowners O62 – Crash Pad Professionals

The key to understanding the behaviour of each Mosaic UK type is the richness of the descriptive data. Experian owns and sources a number of authoritative sources of media and market research that allows to build a rich picture of the nation's socio-cultural diversity. Mosaic UK relies on census current year estimates, which accounts for 38% of the data and on other sources of data that includes Experian's UK Consumer Dynamics Database, which provides consumer demographic information for the UK's adult population and households and accounts for the remaining 62%. This database is built from a variety of privacy – compliant public and Experian proprietary data and statistical models. These include the edited Electoral Roll, Council Tax property valuations, house sale prices, self-reported lifestyle surveys and other compiled consumer data. These estimates provide an accurate and up-to-data measure of the key demographic characteristics of local areas and address changes that have taken place since the 2001 Census. The information used to build Mosaic is continuously updated twice a year (Experian n.d.).

2.4 GreenAware

Experian's GreenAware segments are based on two Experian's segmentation systems:

- MOSAIC and
- Person level Bespoke Pixel, which combines Gender, Age, Household Composition and Council Tax to assign each one of the 48 million adults in the UK into different segments (TNT Post 2009).

GreenAware was developed in collaboration with the Stockholm Environment Institute and breaks down individual consumption and environmental impact by UK household and postcode and provides household level estimates of Greenhouse Gas and Carbon emissions. GreenAware is combined with Green Segments (Table 2.4a, Figure 2.4a) to define the UK population by eco-attitudes. Green Segments is made up of 10 distinct groups and includes the following data variables (Experian 2008):

- Emissions (Direct & indirect greenhouse gas, Total greenhouse gas, Direct & indirect CO_2, Total CO_2;
- Geographic Characteristics (Risk of flood, windstorm, freezing and subsidence);
- Property Characteristics (Age, Type of dwelling, Size, Sale price & Council tax band, Energy & water consumption);
- Household Characteristics (Number of occupants, Economic status, Income, levels of benefit & debt, Tenure, Lifestage, Small or home office);
- Behaviours (Electricity, Gas & water consumption, Number & type of vehicles owned, Type & number of holidays, Vehicle usage, White & brown goods ownership, Lifestyle)
- Attitude to the environment (Green segments, Green properties).

Table 2. 4a: Green Segments (TNT Post 2009)

	Segments	Description
1	Eco-evangelists	Generally have a conviction of green beliefs and eco-friendly behaviours but are let down by a reluctance to give up their customary lifestyles.
2	Convinced consumers	They have a strong willingness to change behaviours and a high awareness of green concepts, although convenience is often an issue
3	Green but doubtful	Despite being well-informed these people remain unconvinced about green issues, although they are surprisingly responsible with their behaviours
4	Confused but well-behaved	The people have an extreme concern for climate change and are willing to demonstrate green behaviours, but are held back by a lack of information on green issues
5	Doing their best	They are concerned about environmental issues despite a lack of information, they would act more 'green' if it were not for the high costs involved
6	Sceptical libertarians	They believe that they are contributing to environmental issues but display scepticism of ecological arguments meaning that their primary motivation is to save money
7	Too busy to change	They have an intermediate level of knowledge but it is financial incentives that encourage their moderate efforts to be green
8	Why should I bother?	Their lack of strong opinions and limited knowledge has led to them being eco-villains, who would respond only through compulsion and incentives
9	Constrained by price	They have an inclination to do more but demonstrate a lack of green behaviours, dependent on an extreme lack of finances and information
10	Wasteful and unconvinced	Fuelled by a lack of education and limited finances, this Type are very reluctant to give up their current lifestyle

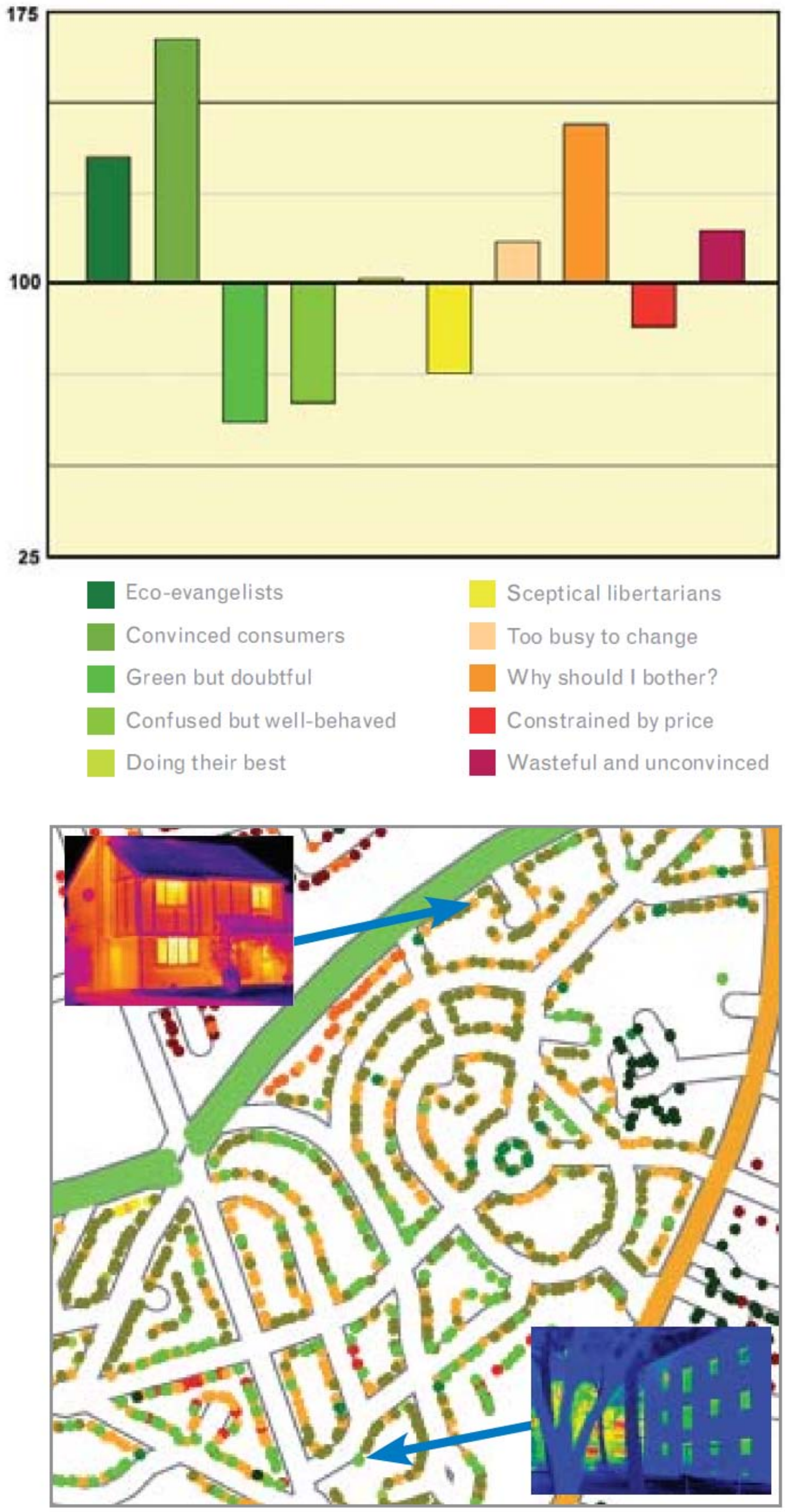

Figure 2. 4a: Green Segments Profile (Experian 2008)

2.5 EST segmentation

The Energy Saving Trust (EST) developed its own consumer segments (Table 2.5a) using 61 Mosaic types in order to identify households with best potential for generating carbon savings. This was done by overlaying energy consumption (relevant to household and transport) and attitudinal data across Experian's Mosaic model and thus classifying all consumers in the UK by allocating them to one of 61 Mosaic types. In turn these 61 types were grouped into 10 EST Segments based on their current attitudes. In particular, the EST model was constructed by measuring each Mosaic type for a) the amount of Homes' CO_2 emissions, using home energy bills data and comparing this with the average for that type of home; b) the amount of Cars' CO_2 emissions, using car ownership and mileage data and comparing this with average use and c) the attitude towards the environment (including concern for environment, recycling and pollution) and comparing these against average attitudes (Wright n.d.)(McGowan 2008).

Table 2. 5a: EST MOSAIC UK Segments (Wright n.d.)

	Segments	Description	Behaviour and Energy Consumption
1	Environmentally mature	Affluent Couples, Large homes. Well educated	High consumers of household (HH) and vehicle energy
2	Educated Advocates	Young couples & professionals. Well educated	Critical Gp in next few yrs as lifestyle will develop to larger homes and more cars
3	Discerning Elders	On cusp of retirement, mortgages paid off	Energy bills still quite high. Moderate vehicle ownership
4	Comfortable Conservatives	Professional couples. Don't like to be pressured into change	HH and vehicle emissions above average – scope for reducing emissions
5	Little Britain	Across section of modern Britain. Suburban couples	HH & vehicle emissions not high. Below average attitude towards environment
6	Restful Retirement	Elderly couples and widowers. Low car ownership	Those that are independent will want to save money & so potentially interest in saving energy
7	Driving Dependency	Young sharers or couples. Car is a lifeline	Relatively new houses with lowest CO_2 emissions score
8	Financially Burdened	Families with high expenditure on everyday living	New large housing. Demands of family make energy consumption relatively high
9	Ethnic Tradition	High importance on Family.	High proportion of extended

		Extended households	families resulting in high energy consumption
10	Fixed Horizons	Poorer families and elderly couples. Live in council or ex-council property	CO_2 emission just below average. Vehicle ownership low

The resulting segmentation is used to target those individuals most interested in protecting the environment and with the largest capacity for saving on CO_2 emissions through targeted market activities. Specifically, segments 1-4 (Environmentally Mature, Educated Advocates, Discerning Elders and Comfortable Conservatives) were found to have relatively high EST awareness and trust, higher likelihood of energy saving products in home, higher personal concern and motivation and higher interest in energy saving products and renewable technologies. On the contrary segments 7-10 (Driving Dependency, Financially Burdened, Ethnic Tradition and Fixed Horizons) were found to have lower EST awareness, fewer energy saving products in home and lower personal concern or motivation regarding environment issues. In addition, good correlation was found between the EST segments and various levels of behavioural change as can be seen in Figure 2.5a (Wright n.d.).

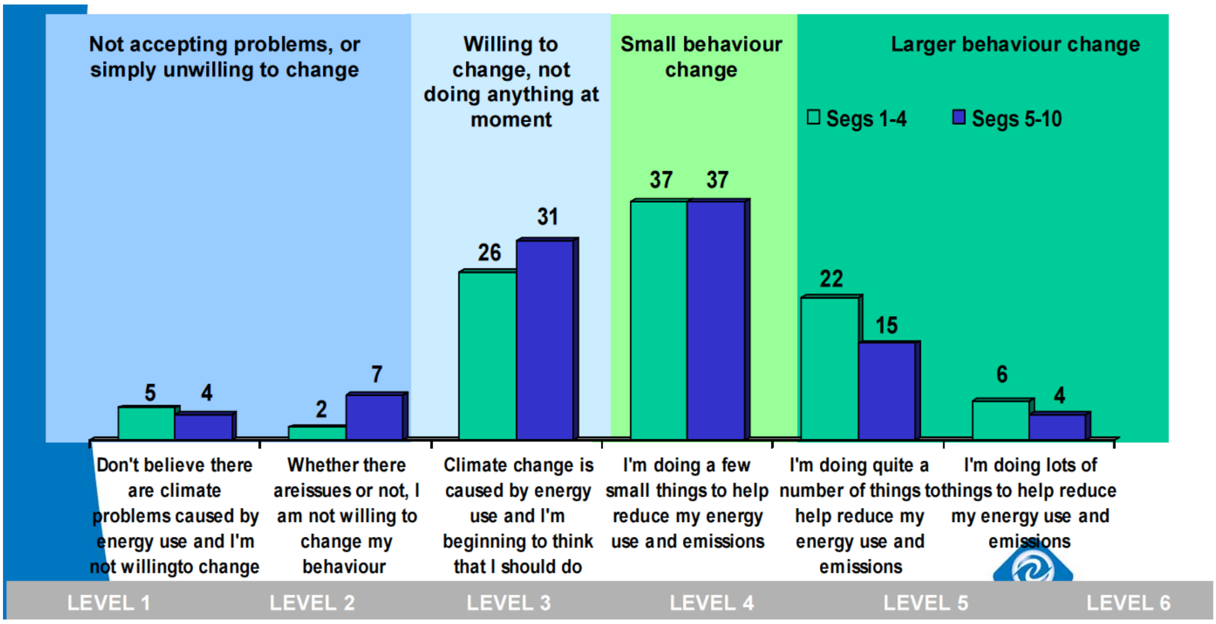

Fig. 2.5a Correlation between the EST Segments and the six levels of behavioural change (Feb 07).

3 Review of occupant behaviour modelling techniques

Home energy use is dependent on a complex socio-technical system driven by occupants. Habits and lack of awareness or feedback on energy consumption and cost, for example, can have a dramatic effect on energy use (Darby 2006). For this reason, even when houses are built to identical technical specifications, their energy consumption will vary significantly. Despite, and in part because of this, occupants are only crudely represented in building energy models. The current dominant approach is through the use of the so-called 'occupancy schedules', where assumptions are made about the behaviour of the occupants and the use of building controls, which are clearly influenced by physical conditions (D. Shipworth 2010). Another way to model occupant behaviour is through a statistical approach, where probability density functions describe the variation in each variable for each estate (Reeves 2009a).

3.1 Building Physics approach vs. Statistical Modelling approach

In general, model-based research on energy use in UK housing has most commonly taken a 'building physics' approach. This method specifies fixed relationships between model variables and 'archetypes' or average values to represent a whole population. (Reeves 2009b). A common-case is the use of a physical-based model based on BRE's Domestic Energy Model (BREDEM), which has achieved a dominant position in the UK market. Nicol (Nicol 2001) has also developed a physical influenced but more stochastic model that enables the probability that occupants in naturally ventilated building will use a variety of controls to be calculated as a function of outdoor temperature. However, occupant behaviour is still governed by many other environmental, psychological and social factors. Thus, such kind of models, based on certain 'stiff' assumptions (Table 3.1a) are mostly useful when modelling a specific instance, with a known and fixed model structure, with fixed variable relationship strength, no variable uncertainty and no instrumental error (D. Shipworth 2006).

The building physics approach enables relatively straightforward implementation using existing skills of the researcher and compatibility with previous research that the present research builds upon. It usually uses well established equations for estimating variables and their relationships (Reeves 2009b) and each additional variable modelled increases the explanatory power and completeness (D. Shipworth 2006). Even though increased disaggregation (namely the extent to which the considered housing stock is broken up into smaller units for the purposes of analysis) is likely to provide more accurate results, it can also be more demanding to model in terms of resources and required data (Reeves 2009b).

On the other hand, statistical models can loosen up most of these assumptions as they explicitly incorporate uncertainty (Table 3.1b). This is generally beneficial, however it means that it is difficult to distinguish reality as it is buried in a sea of uncertainty within the model. Measuring each additional observable carries an opportunity cost – so for given resources, there is no need to measure as many variables as possible (D. Shipworth 2006).

Table 3. 1a: Building physics approach – assumptions (D. Shipworth 2006)

Assumption	Example
1. Modelling specific instances	i.e. individuals or 'archetypes' – not populations
2. No variable instrument uncertainty	i.e. instruments measure perfectly
3. No variable aleatory uncertainty	i.e. modelling of specific instances
4. No variable relationship uncertainty	i.e the relationship between any two variables is fixed and hardwired into the model (e.g. spreadsheet models)
5. No epistemic model uncertainty	i.e. it is assumed that the right variables are wired together (usually dictated by theory)

Table 3. 1b: Statistical Modelling approach – assumptions (D. Shipworth 2006)

Assumption	Example
1. Modelling populations	-
2. Models include variable instrument uncertainty	-
3. Models include variable aleatory uncertainty (because populations are modelled)	-
4. Variable instrument & aleatory uncertainty are indistinguishable in empirical data	-
5. Model variable relationship uncertainty	i.e. the strength of the relationship between variables depends on the strength of your data and can change.
6. Epistemic model uncertainty	i.e there are many ways to wire the variables together – and we don't necessarily know which is best. This leads to the concept of a 'model space' – i.e. a set of models to chose between.

3.2 Bayesian Belief Networks approach

The Bayesian Belief Network (BBN) models of occupant influences on domestic energy use are data driven statistical models relating occupant socio-demographics and behaviours to home energy use (D. Shipworth 2010). They are essentially one type of statistical graphical model, thus combining probability theory and graph theory.

A Bayesian Network consists of a set of variables called ‘nodes’ and a set of links joining related variables called ‘edges’. In Figure 3.2a, for example, each circle represents a variable and each arrow represents a relationship between variables. Each variable contains within it a conditional probability table determining the nature of the probabilistic relationship between each variable and its parents. The network cannot have any cycles – otherwise the algorithms calculating the probabilistic interrelationships between variables will not work. The links are therefore directed (‘parent’ to ‘child’) and the networks are termed Directed Graphs (DAGs). In general, the Bayesian Network can be considered as a statistical graphical model that defines a joint probability distribution specified over a set of variables and their relationships as defined by the structure of the graph, which explicitly encodes conditional interdependencies between the variables (D. Shipworth 2010).

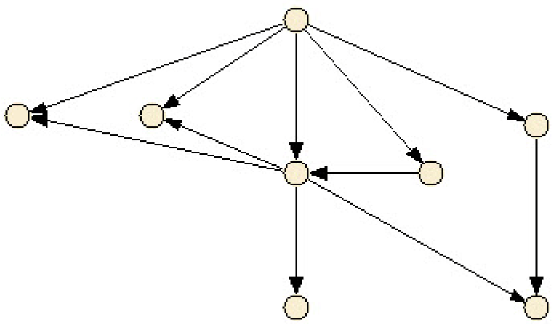

Figure 3. 2a: Generic example of a Bayesian Network approach

When constructing Bayesian networks, there are two epistemically distinct approaches. The first one is ‘elicitation’, meaning the process of eliciting the structure and probabilities for networks from domain experts and the second one, called ‘learning’, refers to the application of algorithms to extract the structure and probabilities from datasets. These two approaches can also be combined and in this case elicitation is usually used to determine the structure of the networks while learning to extract the probabilities within the models from datasets. However, in multidisciplinary environments, as is the case of energy use in homes, elicitation of either network structure or probabilities can be problematic, as there is no single domain of experts from which to elicit. Pilot work conducted on elicitation of network structure showed very little agreement between researchers and between fields that this approach was rejected in favour of the use of learning algorithms for both determining the network structure and probabilities (D. Shipworth 2010).

There are five main steps in the construction of Bayesian networks (Table 3.2a). The first three, variable selection, instrument development and variable measurement is as integral a component of Bayesian network construction as choices of modelling algorithms. It should be kept in mind that statistical models are only as good as the data they are built on. The next two steps, determining the structure of a Bayesian Network and determining the conditional probabilities linking the variables are equally important (D. Shipworth 2010).

Table 3. 2a: Bayesian network construction – basic steps

Step	Description
1. Variable selection	Encodes existing findings from a range of disparate cognate disciplines into the model through the process of variable choice.
2. Instrument development	Encodes a range of different epistemologies and methods into the model through instrument development.
3. Variable measurement	Similarly encodes domain specific methods and research designs into the data.
4. Model selection (network structure learning)	Computationally intensive – involves heuristic search over the space of possible networks.
5. Conditional probability learning	Parameter learning strongly related both to how the variables are discredited and the structure of the network.

Bayesian network models can be built to replace exogenously defined assumptions about occupant behaviour with endogenous statistical models of occupant behaviour as a function of existing or new model inputs. They can be compiled into a range of lower-level software programmes including C, C++, .NET, Java and DLLs for embedding within building physics model written in different languages (D. Shipworth 2006). Nevertheless, they can greatly increase the model's complexity, making it impossible to implement using software packages which require fixed values for variables and fixed relationships between them (Reeves 2009b).

Replacing occupancy schedules with Bayesian Network classifier models could be highly beneficial for a study of domestic energy use. (D. Shipworth 2006) reports some of their methodological advantages as follows:

- Integration of qualitative and quantitative data from experts, case studies, data-sets and models
- Integrate new data as it becomes available
- Highlight conflicts or synergies between variables
- Intuitive display of relationships between variables
- Straightforward sensitivity testing
- Create consensus based decision support systems
- 'Subjective probability' provides common epistemological 'common ground' between social and engineering approaches.

They can be especially useful in cases where variables such as energy demand and income levels vary significantly across the population and factors affecting energy demand (i.e income or dwelling size) are inter-dependent, making energy demand challenging to describe through simple equations (Reeves 2009b). In general, BBN's capacity to classify correctly is critically dependent on data quality and quantity (D. Shipworth 2006). However, such probabilistic models endogenise uncertainty, rendering difficult the correct interpretation of modelled results and create model structures that are theory - agnostic of the fields from which we draw the model's variables. On the other hand, they do have advantages in multidisciplinary modelling environments where theory agnosticism can provide a neutral territory for debate and their graphical representation makes them useful vehicles for negotiating understandings between disciplines (D. Shipworth 2006).

3.3 Crude take back

In most cases of domestic retrofits, improvements in the energy efficiency will result in higher levels of thermal comfort as opposed to lower energy consumption (Milne & Boardman 2000). This phenomenon, which is only partially responsible for the inconsistency between prediction and observation with regard to domestic energy use, is often referred to as 'take back', 'rebound effect', 'comfort factor', or 'take off' (Tadj Oreszczyn & Robert Lowe n.d.). It can be monitored before and after refurbishment or by comparing the effects of interventions according to model predictions (Lomas 2010). The results have shown that energy saving measures can stimulate energy use and thus reduce the energy saving potential of these measures.

The results of a relevant study (I G Hamilton et al. n.d.), based on hypothetical household energy interventions, are presented in Figure 3.2a. Based on heat loss and dwelling permeability distributions which derive from the Warm Front data set, it can be clearly seen that the standardised internal temperature increases when fabric quality improves, until it reaches a certain level of efficiency.

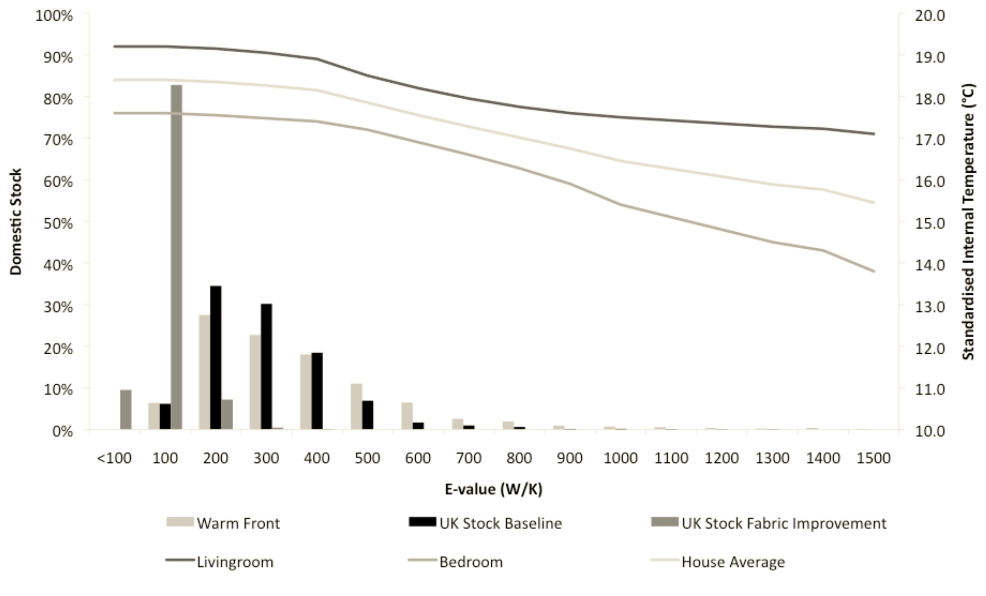

Figure 3. 2a: Scenario 1: UK Stock fabric heat loss distribution (W/K) and improvements against standardised internal temperatures (˚C) (I G Hamilton et al. n.d.)

In general, occupants appear to have an almost innate ability to increase energy use even though they have implemented energy saving measures (Tadj Oreszczyn & Robert Lowe n.d.). It has been noted that after improving the insulation standards in houses, users tend to heat the dwelling more, and to higher set points, partly because of the increased heating system capability and partly because this can now be done at a much lower cost than before the refurbishment (Lomas 2010). This can be considered as a ‘temperature take-back’ voluntary component as it involves conscious decisions to improve comfort conditions. However, there are also involuntary components which arise from interactions between intermittent heating and the changing dynamic behaviour of an insulated dwelling and from the changing balance between heated and unheated parts of partially-heated dwellings (I G Hamilton et al. n.d.). In general, the average winter temperatures maintained in dwellings have increased by approximately 6˚C since 1970 (D. Shipworth & M. Shipworth n.d.) In addition, there is already a small market in domestic air conditioning (Tadj Oreszczyn & Robert Lowe n.d.).

The Domestic Energy Model for Scotland, DEMScot (CAR et al. 2009), developed to answer policy questions about housing and climate change, was recently extended to include rebound effects. Even though research in this field is still at an early stage, DEMScot 2 (CAR & Cambridge econometrics 2010) uses an average rebound effect of 20%, which can be altered by users. It is interesting to note that the Scottish Government suggested higher rebound effects in the model for groups at risk of fuel poverty. DEMScot 2 users can now include this feature by selecting the appropriate worksheet option and different values can be set for Pensioner/CERT priority group/other and for fuel type. The values for the different end user groups are aggregated into a single rebound for each fuel type based on the housing stock selected. The rebound value is then applied to the saving in fuel consumption. There is no disaggregation of the effects to more detailed levels – only the total effect across the stock is calculated.

When the CERT scheme was being developed, EST/Defra commissioned a review of reports about the differences between measured and modelled energy savings. This review of 13 papers relating to cavity wall insulation and loft insulation gave a resulting best estimate of a 50% ‘reduction factor’ of which 15% was the ‘comfort factor’. The ‘reduction factor’ is the total amount by which measured savings are less than predicted, and the ‘comfort factor’ is the part of the reduction factor which can be identified as being caused by improved internal temperatures. These values are used in the current CERT scheme in GB (Sanders & Phillipson 2006).

Hamilton et al. (date n.d.) have developed a method for quantifying the ‘temperature take-back’ factor. They also account for the factor’s impact on health and carbon emissions resulting from interventions for improving domestic energy. They have provided details of the elements of the model that addresses the relationships between fabric and ventilation improvements and changes in indoor heating season temperature. On the whole, the inclusion of the temperature take back factor for the fabric and ventilation scenarios was found to reduce the relevant expected CO_2 reductions by 6%. (I G Hamilton et al. n.d.).

3.4 Price elasticity

There is a complex relationship between households expenditure on energy and fuel price. Price elasticity (or price elasticity of demand) is essentially the measure that rates the responsiveness of the quantity demanded for specific goods or service given a change in its price. Energy demand can be considered 'inelastic' when a big change in price results in a small change in energy demand (Poor 2007). However, according to the economic theory, energy price elasticity is typically in the negative range. This means that demand falls whenever prices increase and the converse (Bernsten & Griffin 2005). Energy price elasticity is usually analysed over short and long time periods, as consumers respond to price rises differently over time (Poor 2007).

Research has shown that fuel price should be considered as a key variable in home energy modelling and that it is highly correlated with specific state and regional consumer variables (i.e. disposable income of the household, place of residence etc). Bernstein and Griffin (2005), for example, found that there are regional and state differences in the price-demand relationship for electricity and natural gas. It is interesting to see though that both Berstein and Griffin (2005) and Utley and Shorrock (2008) concluded that fuel price variations have not affected the domestic energy demand much over the last decades - possibly implying few alternative options for the consumer towards changes in energy price (Bernsten & Griffin 2005). Nonetheless, both of them point out that in recent years there are signs of change in this area. In the past few years, demand growth seems to have slowed and at the same time some increases in energy prices have been noted (Bernsten & Griffin 2005). In any case, and despite any constancies of average expenditure, there is no doubt that many individual households are likely to be achieving a lower level of service than desired. Households up to a certain income level tend to invest a higher proportion of extra income on warmth compared to those earning above that level (Utley & Shorrock 2008).

In one of the latest studies, both the annual delivered energy, price and temperature (ADEPT) model and the seasonal temperature energy price (STEP) model showed that there is a high correlation between delivered energy and variations in external temperature and energy price, at least in short term. Even though UK household delivered energy is affected by many dynamic social and technological factors, none of them was found to be as significant as the variations mentioned above. It is interesting to note that the STEP model provides benchmarks for comparison using average power demand for price in response to external temperature that can be extremely useful for comparative analysis when the annual data available is incomplete. It is moreover capable of distinguishing to some extent between different categories of intervention and end-use categories. In general, both models require far fewer assumptions in comparison to bottom up models for parameters for which there is little empirical data and as they are empirically based themselves, they already account for factors such as 'take back' (Summerfield et al. 2010).

In addition, regression analysis of the HEED database (Steadman et al. 2010) has shown that energy use is highly correlated with key variables, such as household size and income quartile (Table 3.4a, Figure 3.4a). The impact of the price elasticity on energy demand shows that there is a difference in the way different socio-economic groups have reacted to the almost doubling of energy prices since 2005 and 2008. On the whole, there is a higher change in energy use for low income quartiles (Q1) and for smaller houses and a much lower one for high income quartiles (Q5) and bigger houses. In addition, people living in the outskirts of London seem to be affected much more by fuel prices compared to those living in the city centre.

As for the rebound effect (see chapter 3.3), DEMS Scot 2 users can now select the appropriate worksheet option to adjust CO2 savings, energy use and energy costs to reflect changes in prices. Again, there is no way of knowing exactly how the occupants' behaviour would change as a result of price rise or fall, but this model recommends a value of -6%, meaning that if cost of energy doubles, demand reduces by 6%. This value reflects only 'soft behavioural' changes in response to price changes and does not incorporate any physical upgrades as these have already been considered by the model. As with the rebound effect, values can be altered for different fuels. The user selects which future energy prices should be used for the calculation (e.g. DECC medium projections). The specified price changes are used to calculate the percentage change in demand for a fuel and then applied to the end result. There is no disaggregation of this calculation down to more detailed levels (e.g. between different socio-economic groups) (CAR & Cambridge econometrics 2010).

Table 3. 4a: Gas elasticity for different regions and income groups (Steadman et al. 2010)

Region	Income Quartile	2005	2007	Elasticity	Change in Gas use (2005-2007)	Average Dwelling Size (rms)
North East	Q1	19,983	16,589	-0.37	-17.0%	4.7
	Q2	21,308	17,963	-0.35	-15.7%	5.0
	Q3	22,339	19,084	-0.32	-14.6%	5.1
	Q4	24,121	21,037	-0.28	-12.8%	5.4
	Q5	27,985	25,011	-0.23	-10.3%	5.9
London	Q1	16,166	14,210	-0.27	-12.1%	4.2
	Q2	18,518	16,807	-0.20	-9.2%	4.5
	Q3	20,650	19,155	-0.16	-7.2%	4.7
	Q4	22,891	21,687	-0.12	-5.3%	5.0
	Q5	26,387	25,882	-0.04	-1.9%	5.2
South West	Q1	11,605	9,020	-0.49	-22.3%	5.0
	Q2	13,612	11,099	-0.41	-18.5%	5.4
	Q3	14,615	12,219	-0.36	-16.4%	5.5
	Q4	16,361	14,050	-0.31	-14.1%	5.8
	Q5	18,779	16,722	-0.24	-11.0%	6.1

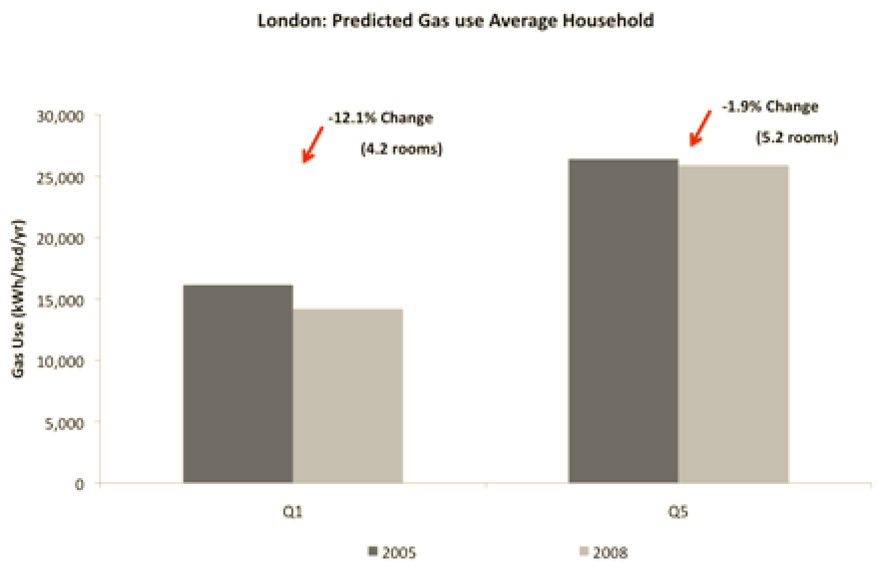

Table 3. 4a: Household change in energy use elasticity (Steadman et al. 2010)

4 Conclusions and way forward

Modelling energy use in the domestic stock accurately across a range of scales presents many challenges. Consumption patterns are the product of various physical and social parameters affecting both the building and its users. This report has focused on the impact of sociodemographics on energy use. It has highlighted the importance of taking into consideration the changing relationships of occupants with the building performance and operation. However, taking into consideration complex socio-technical systems when building a household energy model is not an easy task. There are currently no well substantiated bodies of theory that can be operationalised into models for reliably explaining occupant influences on building energy use. In the absence of a well tested theory, models need to be built on empirical data and it is the cost and difficulty in collecting accurate and representative, datasets that limits model development in this field. Thus, as a next step, we have to consider what data we have available to populate the occupant model by looking into detail at different available sources such as the following:

- House Condition Survey (HCS)
- Home Energy Efficiency Database (HEED)
- Survey of English Housing (SEH)
- Carbon Reduction in Buildings (CaRB)
- Warm Front

The segmentation models currently used by companies such as ACORN, CAMEO and MOSAIC are very opaque and their impact on actual energy is not clearly identified in the literature nor is it clear from published data that such approaches could be easily linked to the built stock as stock models are not normally segmented by post code. Also it is not clear that such approaches would be valid for distributed energy technologies which may be driven by feed in tariffs. We therefore propose for the DE project to account for occupant behaviour by integrating a simple comfort take back factor as shown in figure 3.2a and account for price elasticity using data from HEED as per section 3.4. The sensitivity of the model to incorporating these occupant algorithms will be tested and the stock model should be allowed to run both with and without these algorithms.

5 References

Bernsten, M. & Griffin, J., 2005. Regional Differences in the Price-Elasticity of Demand For Energy. Available at: http://www.rand.org/pubs/technical_reports/TR292/ [Accessed July 14, 2010].

CACI, *ACORN*, Available at: http://www.caci.co.uk/acorn-classification.aspx.

CallCredit Information Group, CAMEO UK. Available at: http://www.callcreditmarketing.com/pages/cameo-uk [Accessed July 1, 2010].

CAR et al., 2009. *Modelling Greenhouse Gas Emissions from Scottish Housing: Final Report*, Edinburgh: Scottish Government Social Research. Available at: http://www.carl.co.uk/downloads/DEMScot%20Final%20Report.pdf.

CAR & Cambridge econometrics, 2010. *DEMScot 2: Scotland's Housing Carbon Model The extentions*,

Darby, S., 2006. The effectiveness of Feedback on energy Consumption. *A Review for DEFRA of the Literature on Metering, Billing and direct Displays, April*.

Eurodirect, *Welcome to CAMEO, the World's Leading Consumer Segmentation System*, Available at: http://www.cartogen.co.uk/pdf/cameopreview.pdf.

Experian, Consumer classification for the UK - Mosaic UK - Experian. Available at: http://www.experian.co.uk/business-strategies/mosaic-uk-2009.html [Accessed June 28, 2010].

Experian, 2008. *GreenAware Factsheet - A Segmentation of environmentally-relevant behaviours, attitudes and carbon footprint*,

Hamilton, I.G. et al., The impact of housing energy efficiency improvements on reduced exposure to cold - the 'temperature take back factor'.

Lomas, K.J., 2010. Carbon reduction in existing buildings: a transdisciplinary approach. *Building Research & Information*, 38(1), p.1.

McGowan, J., 2008. The Energy Saving trust: Consumer Segmentation.

Milne, G. & Boardman, B., 2000. Making cold homes warmer: the effect of energy efficiency improvements in low-income homes. *Energy Policy*, 28, pp.411-424.

Nicol, J., 2001. Characterising Occupant Behaviour in Buildings: Towards a Stochastic Model of Occupant use of Windows, Lights, Blinds Heaters and Fans. In *Proceedings of the 7th International IBPSA Conference*. Oxford. Available at: http://www.ibpsa.org/proceedings/BS2001/BS01_1073_1078.pdf.

Oreszczyn, T. & Lowe, R., *Evidence to the House of Lords Select Committe on Science and technology: Energy Efficient Buildings*,

Oreszczyn, T. & Lowe, R., The evolution of a low carbon domestic energy system. Available at: http://www.ltnetwork.org/site/upload/document/IFS_-_4._Tadj_Oreszczyn.pdf.

Poor, A., 2007. *Fuel Price Elasticity: Synthesis*, Available at: http://www.wsdot.wa.gov/NR/rdonlyres/D9746FB3-664A-4924-B702-65459365C876/0/FuelPriceElasticityAPSynthesis12607.pdf [Accessed July 10, 2010].

Reeves, A., 2009a. *Achieving deep carbon emission reductions in existing social housing: The case of Peabody*. Energy and Sustainable Development. De Montfort University. Available at: https://www.dora.dmu.ac.uk/handle/2086/2629?show=full [Accessed May 21, 2010].

Reeves, A., 2009b. *Achieving deep carbon emission reductions in existing social housing: The case of Peabody*. Energy and Sustainable Development. De Montfort University. Available at: https://www.dora.dmu.ac.uk/handle/2086/2629?show=full [Accessed May 21, 2010].

Sanders, C. & Phillipson, M., 2006. *Review of Differences between Measured and Theoretical Energy Savings for Insulation Measures*, Glasgow Caledonian University & EST. Available at: http://www.decc.gov.uk/assets/decc/what%20we%20do/supporting%20consumers/saving_energy/analysis/insulationmeasures-review.pdf.

Shipworth, D., 2006. Bayesian Network modelling of home energy use. Available at: http://www.ukerc.ac.uk/Downloads/PDF/Meeting%20Place/Events/2008/01AEMC/0801AEMCShipworth.pdf.

Shipworth, D., 2010. *The vernacular architecture of household energy models*, Helsinki.

Shipworth, D. & Shipworth, M., ESRC/TSB Public policy seminar on 'How people use and misuse buildings'. Available at: http://www.esrc.ac.uk/ESRCInfoCentre/Images/Shipworth%20ESRC-TSB%20Seminar%20v4%20%282%29_tcm6-30558.pdf.

Steadman, P. et al., 2010. Regional and HEED databases.

Summerfield, A.J., Lowe, R.J. & Oreszczyn, T., 2010. Two models for benchmarking UK - domestic delivered energy. *Building Research & Information*, 38(1), p.12.

TNT Post, 2009. *Data Matters: A customer guide*, Buckinghamshire.

Utley, J. & Shorrock, L., 2008. *Domestic energy fact file 2008*, Available at: http://www.bre.co.uk/filelibrary/pdf/rpts/Fact_File_2008.pdf.

Wright, M., The Energy Saving Trust: Consumer Segmentation. Available at: http://www.bcse.org.uk/docs/events2007/matthew%20wright.pdf [Accessed June 25, 2010].

Appendices

Table 7.1: CAMEO datasets (CallCredit Information Group n.d.)

Output Area Geodemographics – from 2001 Cencus of England, Wales, Scotland & N.Ireland
Household Council Tax Band & Property Valuation Data – from all councils
Individual Shareholder Data – from all the Share Registers of the FT Top 500 companies
Individual Directorship Data – from Companies house
Consumer Credit Data – 6yrs of CCJ/Bankruptcies from sister company Callcredit
Individual Residency Data – from the Electoral Roll and our Core consumer universe

Table 7.2: CAMEO variables (Eurodirect n.d.)

Demographics	Economic Activity	Lifestyle	Housing
Adult Age & Child Age	Employment Status	Newspaper Readership	Housing Tenure
Marital Status	Occupation & Sector	Internet Usage	Housing Type & Size
Family Composition	Qualifications	Mail Order Responsiveness	Length of Residency
Ethnic Origin	Shareholdings	Car Ownership	Geographical Area
Social Group	Directorships	Transport to Work	Council Tax band
	Country Court Judgements		House Price
			Population Density

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