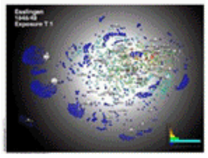

Title:

COMBINING DIVERSE DATA SOURCES FOR CEDSS, AN AGENT-BASED MODEL OF DOMESTIC ENERGY DEMAND

Journal Issue:

Structure and Dynamics, 7(1)

Author:

Gotts, Nicholas Mark, Independent researcher
Polhill, Gary, The James Hutton Institute Craigiebuckler Aberdeen AB15 8QH Scotland UK
Craig, Tony, The James Hutton Institute Craigiebuckler Aberdeen AB15 8QH Scotland UK
Galan-Diaz, Carlos, The School of Social Science University of Aberdeen, Dot.Rural Aberdeen AB24 3QY Scotland UK

Publication Date:

2014

Permalink:

http://escholarship.org/uc/item/62x9p0w4

Acknowledgements:

The work reported was funded by the European Commission Seventh Framework Programme, Socio-economic Sciences and Humanities Theme, under grant agreement 225383, the GILDED project (Governance, Infrastructure, Lifestyle Dynamics and Energy Demand: European Post-Carbon Communities

Author Bio:

Nick Gotts trained in psychology and artificial intelligence. Until 1996, his research was mainly concerned with qualitative spatial representation and reasoning in humans, other animals, and computers. Since then he has concentrated on complex systems dynamics, particularly on cellular automata, and on agent-based social simulation. Since July 2012 he has been an independent researcher, particularly interested in ways of comparing agent-based models, and in the relationships between analysis and simulation in the study of complex systems.

Information and Computational Sciences; Senior postdoctoral scientist.Gary Polhill did a degree in Artificial Intelligence and a PhD in Neural Networks before spending 18 months in industry as a professional programmer. In 1997 he joined the Macaulay Land Use Research Institute to work on agent-based modelling of land use and related systems. The Macaulay Institute merged with the Scottish Crop Research Institute to form The James Hutton Institute in April 2011. Gary now works on agent-based modelling of everyday pro-environmental behaviour and coupled human-natural systems; the latter focusing on agricultural land use change and biodiversity. He is also interested in methodological issues in agent-based modelling, and semantic approaches to addressing these challenges.

Tony Craig is an environmental psychologist working in the Social, Economic and Geographical Sciences group within the theme of values choices and behaviour. His work focuses on the relationship between psychological factors and environmental behaviour. Tony has a background in environmental psychology, and has worked on a variety of research projects looking at people's attitudes to various issues, including sustainable wastewater management, prefabricated housing, sustainable housing, and public participation in urban design. Between 2002 and 2006, he was on the board of the International Association of People Environment Studies (IAPS). Over the last two years Tony has led a large (ongoing) study of energy consumption involving 1200 households in partnership with Aberdeenshire Council and Aberdeen City Council.

Carlos Galan-Diaz is an environmental psychologist and my job is to deliver the impact assessment of dot.rural. He has recently joined the RCUK dot.rural Digital Economy Hub at Aberdeen University after 4 years in the Social, Economic and Geographic Sciences Group (SEGS) at The James Hutton Institute (2009-2013) where he was in charge of OrkCEmP, a project looking at perceptions and experiences of living in Scotland's rural communities and the particular challenges and opportunities this provides. Previous to this he was a graduate student and lecturer at Robert Gordon (2005-2009). His Ph.D focused on psychological perspective-taking and emotion in environmental evaluation and environmental preference. His current research interests span a wide range of the social sciences (evaluation, environmental preference, well-being, climate change, empowerment, resilience, adaptation, sustainability, psychological restoration, public participation, tacit knowing).

Keywords:

Agent-Based Modelling, Empirical Data, Calibration, Validation, Social simulation, energy studies

Local Identifier(s):

imbs_socdyn_sdeas_19009

Abstract:

CEDSS (Community Energy Demand Social Simulator) is an empirical agent-based model designed and built as part of a multi-method social science project investigating the determinants of domestic energy demand. Ideally, empirical modellers, within and beyond social simulation, would prefer to work from an integrated dataset, gatheredfor the purposes of developing the model. In practice, many have to work with less than ideal data, often including processed data from multiple sources external to the project. Moreover, what data will be required may not be clear at the start of the project. This paper describes the approach to dealing with these factors taken in developing CEDSS, and presents the completed model together with an outline of the calibration and validation procedure used. The discussion section draws together the most distinctive features of empirical data collection, processing and use for and in CEDSS, and argues that the approach taken is sufficiently robust to underpin the model's purpose – to generate scenarios of domestic energy demand to 2049.

Supporting material:

CEDSSDocumentationForOpenABM20130717.zip

1 Introduction: Context and Overview of the CEDSS Model

CEDSS (Community Energy Demand Social Simulator) was designed and built as part of GILDED (http://gildedeu.hutton.ac.uk/), an EU Framework 7 multi-method social science project, investigating the determinants of domestic energy demand and covering five case-study areas, each consisting of a medium-sized city and its rural hinterland. The project involved theoretical work, desk study of energy governance and infrastructure, and both qualitative and quantitative surveys of residents of the case-study areas, in addition to agent-based social simulation. The latter focused on the Scottish case-study area, Aberdeen and Aberdeenshire. The original intention was that CEDSS should draw all its empirical data from the desk study and surveys making up the non-modelling work-packages of the project, but in fact, CEDSS required a great deal of data beyond that. Only those aspects of GILDED directly relevant to CEDSS will be described here: the model itself, parts of a questionnaire completed by households in the Scottish case-study area, the additional data-collection from publicly available sources required to calibrate and validate the model.

CEDSS models the direct domestic energy use of a community of households, conceived of as either a village or an urban neighbourhood. It is intended for use in forecasting how a range of possible economic conditions, technological changes, policy options, market and social network structures, and cultural factors, are likely to affect the dynamics of direct domestic energy use over the next several decades; but this paper concerns the collection and integration of data from the recent past to calibrate and validate the model, and the processes of calibration and validation themselves. The agents in CEDSS are the households, and the focus of the model is on household decisions to buy domestic energy-using and energy-saving equipment, and secondarily on the ways in which households may influence each other's decisions in this area. "Direct domestic energy use" covers the use of electricity, gas and oil within the home for space and water heating and electrical appliances. Lighting was not included because of the complexity of dealing with multiple light fittings and the relatively small proportion of domestic energy it consumes; other energy sources such as LPG and solid fuels were omitted because very few households in the case-study area use them.

Every empirical modeller, within and beyond social simulation, would like to work with an integrated dataset, preferably gathered for the purposes of calibrating and validating the model, and covering all the inputs it requires and enough of the outputs it produces to serve those purposes. In practice, many have to work with less than ideal data, often including processed data from multiple sources external to the project, without their raw precursors. Modelling may also be only one aspect of a larger project with multiple aims and methods, forcing compromise decisions on the data collected within the project. Moreover, what data will be required may not be clear at the start of the project: rather, the data requirements change as the model is developed. This paper describes in some detail the approach to dealing with these factors taken in one agent-based social simulation effort, recounts the main problems encountered, and presents the completed model together with an outline of the calibration and validation procedure used. While the paper is intended to be self-contained, the commented code, input and parameter files, and details of algorithms used in constructing some of these files are available from the library of agent-based models held by the OpenABM node: Network for Computational Modeling for SocioEcological Science (CoMSES Net), at http://www.openabm.org/model/3642/version/2/view. Our intention is a "warts and all" depiction of the complexities of developing and testing an empirically-based ABM, in sufficient detail to make replication possible; we hope others will be stimulated to undertake similar exercises. The discussion section draws together the most distinctive features of the way empirical data was collected, processed and used, and argues that the results of the calibration and validation undertaken indicate that the approach taken is sufficiently robust to underpin the model's purpose – to generate scenarios of domestic energy demand to 2050, and for its unusual aspects to be accepted for future use in similar cases.

The model is in part based on the psychological theory of 'goal frames' (Lindenberg and Steg 2007); households make decisions in one of three modes, depending on which goal frame is dominant: 'hedonistic', 'egoistic' (or 'gain') and 'biospheric' (or 'norm'). Which mode they choose depends on the current strength of their 'values': stored parameters representing 'hedonism', 'gain-orientation' and 'greenness'. Households must ensure they keep essential equipment running; otherwise, households' objectives depend on their currently dominant goal frame. If the currently-dominant goal-frame is hedonistic, a household will aim to buy as many of their desired appliances as they can afford; if egoistic, to save as much money as they can; if biospheric, to minimise their energy consumption. Households "visit" others with which they have social links, and these visits can affect both the strength of their values, and the specific appliances they decide to buy. In addition to buying energy-using appliances, insulation measures can be installed in the household's dwelling – this will not be done if the hedonistic goal-frame is currently dominant.

CEDSS is written in NetLogo (Wilensky 1999). The detailed design of CEDSS was influenced, although not determined, by a series of ontology elicitation exercises, in which non-modeller members of the project, and members of the Scottish team's "stakeholder advisory group", were asked what they would include in a model of domestic energy demand. These exercises led us to focus on electrical appliances to a greater extent than we had intended, by bringing out their prominence in the thoughts of a group with significant relevant expertise.

2 The CEDSS Model in Detail

A description of the model using ODD (Grimm et al. 2006, 2010), (Overview, Design concepts, and Details), has been made available in the OpenABM model library, but we felt that for the main text of this paper, ODD would constrain us to a description that would not be optimal**.** Aspects of the model not used in the runs described in this paper are not described here.

2.1 Outline of a single CEDSS time-step

The model is designed to carry out the following within each time step (a time step is 3 months in all the runs mentioned here, but this is a model parameter).

1. **Decide which owned appliances break down**. Each category of appliance is assigned a breakdown probability per time step; insulation does not break down.
2. **Each household then does the following** (sub-stages *e* to *i* are not strictly sequential in the code, as the cases where the goal-frame is or is not "hedonistic" are dealt with separately):
    a. **Choose goal frame**. The goal frame determines the household's algorithm for buying appliances and insulation measures. If it is "hedonistic", the household will tend to buy non-essential items, and will not install insulation. If it is "gain" or "norm" non-essential items will not be bought and insulation may be installed; the two differ in whether saving money or minimising energy use is prioritised. The goal-frame is determined probabilistically, with probabilities proportional to the current strengths of three household "values" parameters: hedonism, gain-orientation, and greenness, corresponding to the hedonistic, gain and norm frames.
    b. **Adjust goal frame**. Adjustment of the goal frame is done to implement a "habit" component of the model – the more a goal frame is used, the more likely it is to be used in future. The habit-adjustment-factor parameter (H) is used to make this adjustment: the larger this parameter, the more important the influence of past on future decisions. If T is the sum of all goal frame parameters, then let A be the parameter corresponding to the selected goal frame, and B and C be the other two. A is increased by H, and B and C decreased by H / 2. If the result causes A to be more than T, then adjustments are made to ensure that $A + B + C = T$, and that B and $C \geq 0$ as follows:

        $A = A + H$
        If $A > T$ Then $A = T$; $B = C = 0$
        Else
            $B = B – H/2$ $C = C – H/2$
            If $B < 0$ Then $C = T – A$; $B = 0$
            Else If $C < 0$ Then $B = T – A$; $C = 0$.

    We admit that while the influence of habit on consumer decision-making is well-established (Bamberg and Schmidt 2003, Carrus, Passafaro and

Bonnes 2008, Wood and Neal 2009), the specific algorithm used was chosen for simplicity and convenience of calculation, since we have no relevant empirical data on habitual influence in this specific context.

c. **Compute the total energy use for this step from using appliances and space/water heating**. For each appliance owned by the household, the step's fuel consumption and energy use is computed based on the consumption pattern associated with the household's type, the type of their dwelling, the usage mode, and the time of year.
d. **Compute financial situation**. The cost of running the appliances is deducted from the capital-reserve of the household, and the income for that step is added.
e. **Replace broken appliances**. If the appliance is essential and the household only had one of them before it broke, then a new item will be bought using a method relevant to the current goal frame of the household and the tenure of their dwelling.
    i. If the dwelling is rented, or the goal-frame is gain, the cheapest replacement available is chosen (and in the former case, the cost will not be charged to the household).
    ii. If the goal-frame is hedonistic, a random replacement is chosen (on the grounds that hedonistic choices are unpredictable).
    iii. If the goal-frame is norm, the replacement is chosen at random from among those with the lowest energy rating, or from among all those available if this is not supplied for the appliance category.
f. **Update wish list**. This stage is carried out only if the goal-frame is hedonistic. The wish list of the household is updated to contain items chosen in all of the following three ways (*M, N*, *V* and *T* are all model parameters):
    - Up to *M* appliances (not to do with heating) each belonging to a different new subcategory introduced in the last *N* steps.
    - One random item not already owned, "seen" during one of *V* visits to another household (see *i* below).
    - One random replacement for an item more than *T* steps old.
g. **Buy insulation**. This sub-stage is carried out only if the goal-frame is **not** hedonistic, and if the dwelling is owned by the household rather than rented. What insulation can be added, and the effect it has on energy demand for space heating, depends on the type of dwelling.
h. **Buy new appliances**. If the goal-frame is hedonistic, as many items from the current wish list as can be afforded will be bought (but no more than one from each category – appliance categories are described in 2.2). Otherwise, only one will be bought, and that only to replace a non-essential item that has broken.
i. **Adjust values relative to those of social neighbours and vice versa**. The household "visits" a number of their social neighbours – households to which they have social links – and (if a household "frame-adjustment

parameter" is greater than 0) adjusts the strength of the values determining the probabilities of the different goal frames being selected, in the direction of those of the visited household. A reciprocal adjustment will also occur if a model parameter "reciprocal-adjustment" is set to true. Each goal frame parameter *G* is adjusted in the following way: let *Gi* be the goal frame parameter of the household making the adjustment; let *Gj* be that of the other household; then:

$$Gi = Gi + F(Gj - Gi) ,$$

where *F* is the frame-adjustment parameter, set on the CEDSS interface. After this, if *Gi* is less than zero, *Gi* = 0. In the runs described here reciprocal-adjustment is always true, and the frame adjustment parameter for all households is set at 0.2, meaning the values are shifted by 0.2 of the difference between the two households. As with the influence of habit, the tendency toward alignment with the consensus values of a person's social milieu is well established (e.g. Haslam, Turner et al 1998), but the specific algorithm used was selected for simplicity and ease of calculation, in the absence of relevant empirical evidence in the specific context considered in the model. It is of course possible that contact with those with markedly different values will lead to enhanced differences between the participants; in the current model, however, social contacts are more likely between households having similar appliances, and such similarity is largely determined by a combination of household values and income, so we considered it unnecessary to complicate an already complex model further by allowing for this possibility, given that we had no empirical data in relation to it.

j. **Update social links**. With equal probability, the household either loses or gains a social link. (If the choice is made to lose a link, then this only happens if there is a link to lose; if the choice is made to gain a link, and the household already has the maximum number set by a model parameter, no link will be gained.) The choice of a link to lose will be made among the current social neighbours with the least similar set of appliances (used as a measure of general household similarity), and within that set, at random among those furthest away. If a new social link is to be made, it will be made with a randomly chosen household linked to an existing social neighbour with maximally similar set of appliances.

All runs discussed here cover a period of 10¾ years, from the start of 2000 through September 2010.

2.2 CEDSS Entities

Aside from Households, the entities modelled in CEDSS are as follows:

A. Dwellings. Each Household has a Dwelling, which may be owned or rented, and may be a house, a bungalow or a flat; subdivisions of these types are explained in 3.2. If a dwelling is rented, the household cannot change its insulation state (and it is assumed in the current model that the landlord does not do so), while the landlord is responsible for replacing essential appliances (the heating system, a cooker, refrigerator and washing machine) if these break down. The landlord, in these cases, always chooses the cheapest option.

B. Appliances. The categories of appliance included in the runs described here are heating systems, cookers, cold appliances (refrigerators, freezers and fridge-freezers), washing machines, dryers, dishwashers and televisions. Some categories are divided into sub-categories, and both subcategories and undivided categories usually include multiple specific models. Further details are given in section 3 below.
C. Insulations. Each type of insulation, in each type of dwelling to which it is applied, has a specified effect on the amount of space-heating energy required; they are described in 3.2.
D. Fuels. These have a cost per unit (kWh equivalent), which can vary over time.
E. Consumption patterns. These determine a household's use of appliances; there is only one available to households in the runs described.

Figure 1 is a UML (Unified Modeling Language, see http://www.omg.org/spec/UML/) diagram of CEDSS entities and relationships; Figure 2 is a screenshot of CEDSS in operation, showing a representation of the households' dwellings and social links, some of the parameters (mostly names of input files), and graphs of some of the outputs. NetLogo breeds of elements (turtles) are represented as classes, breeds of links as associations. Dashed lines around classes and their associated arrows represent reified relationships (in NetLogo terms, link breeds with their 'own' parameters).

2.3 CEDSS input files

Initialisation of CEDSS is achieved by loading a series of files, as described here.

Files encoding information that remains fixed throughout the run:

1. *Patch file*. This specifies the type of each patch in the NetLogo 2D space of the model.
2. *Fuel file*. This creates the fuels available, and initialises their type, the unit in which each type is measured, and kWh per unit (the equivalent of that unit in kWh – always 1 in the runs reported here).
3. *Maximum in category file.* This specifies, for each category of appliance, the maximum number of appliances that a household can own.
4. *Insulation file*. This contains data on the fuel use factor, used in calculating energy used in space heating, for each combination of insulation state and dwelling type.
5. *Insulation upgrade file*. This contains cost data used to create the links representing insulation upgrades.
6. *Household transition matrix file*. If used, this specifies the probabilities of households changing type each time step. To 'not use it', the matrix file can simply consist of an identity matrix indicating a probability of 1 for transitioning from each household type to itself, and a 0 for all other transitions.

Display information file:

7. *Patch legend file*. This specifies the colour to use for each type of patch.

Files encoding initial model state:

8. *Household initial appliances file*. This is used to create initial appliances owned by particular households, types of households, or households living in particular dwelling types.
9. *Social link matrix file.* If used, this file specifies the probability of making a social link between households and dwellings of different types.
10. *Dwellings file*. The dwellings file specifies the type of each dwelling, its tenure and its initial insulation state. After the dwellings file is loaded in, 'blocks' of dwellings are identified (e.g., Figure 2).

Files encoding initial model state plus time series information:

1. *Appliances file*. This initialises the name, category, subcategory, whether the appliance is essential, its cost list, energy rating, embodied energy, breakdown probability, and first and last step available of each appliance. The cost list specifies the price of the appliance in each time step for which it is available, and the first and last time step available are also time series data.
2. *Appliances fuel file*. This specifies the amount of fuel of each type each appliance uses per quarter.
3. *Appliances replacements file*. This specifies which specific appliances can replace which others in case of breakdown. Strictly speaking, this information is fixed throughout the run, but as appliances appear for sale during the course of the run, information in the file becomes relevant at different point, as for a time series.
4. *Households file*. This file initialises the identifier, type, income, capital-reserve, goal frame parameters, goal frame adjustment parameters, planning horizon and dwelling of the household. Income is time series data.
5. *Suppliers file.* This contains data about the suppliers for each type of fuel, and its price per unit at each time step.

Other files listed on the user interface have no significant role in the runs reported: they are either "null", or specify a single default value used in all runs (e.g. "household transition matrix file" would handle changes in household structure if these were being modelled).

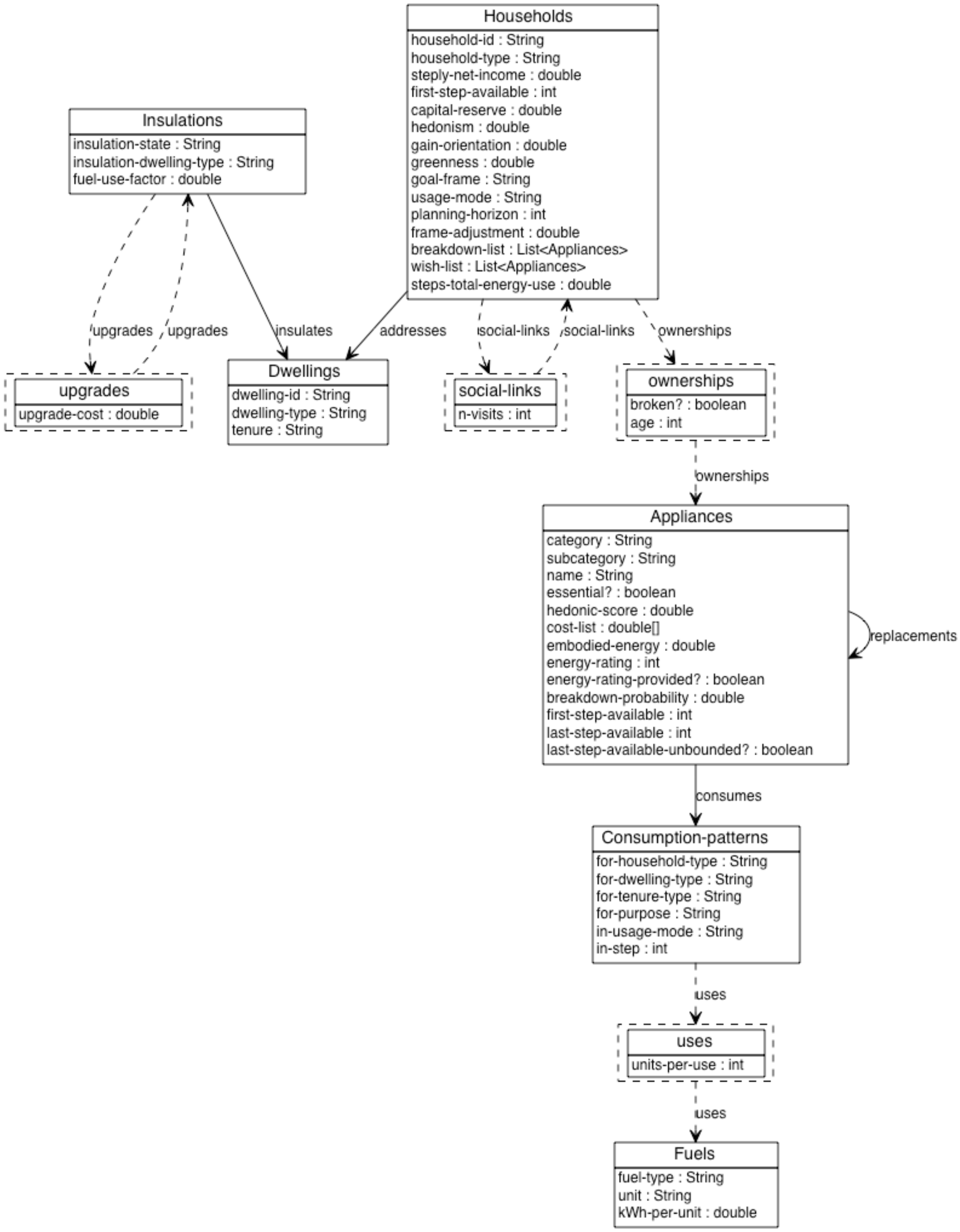

Figure 1: UML diagram of CEDSS entities and relationships.

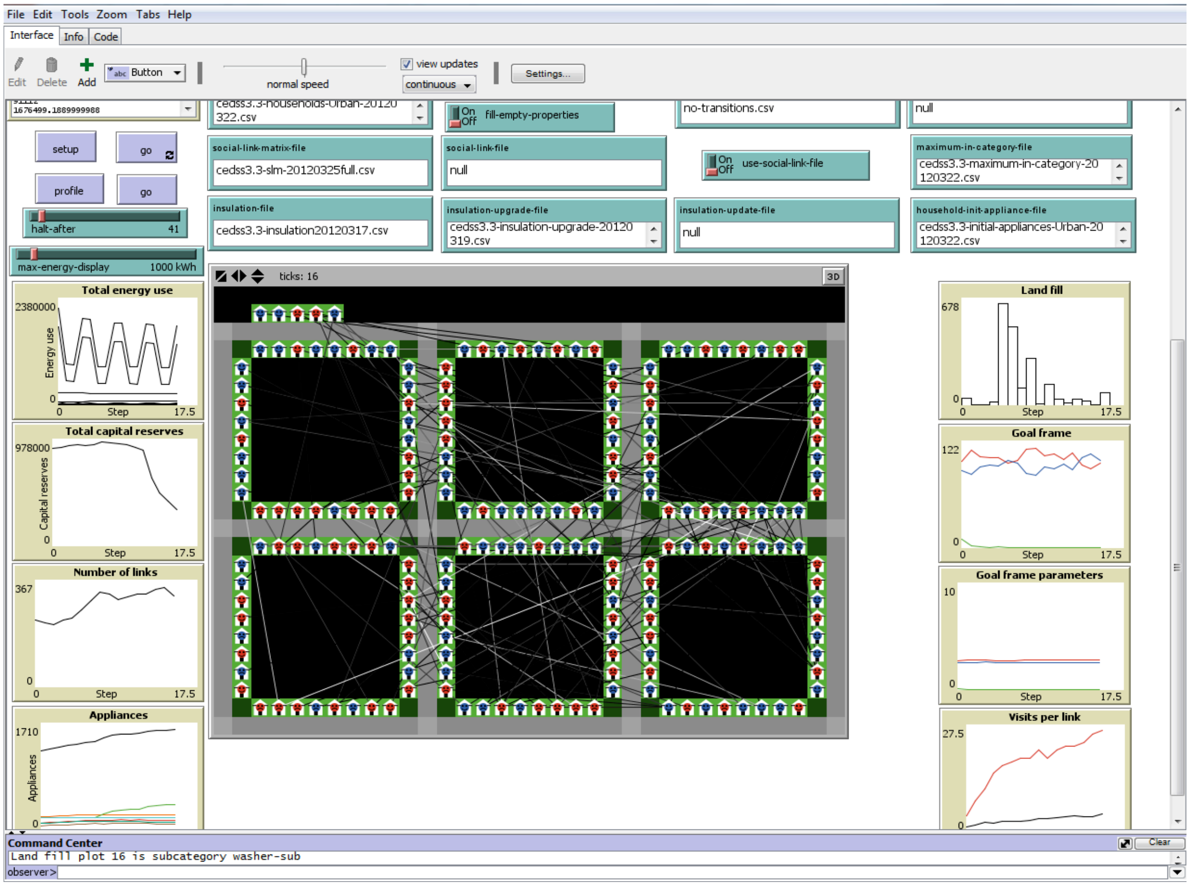

Figure 2: Screenshot of CEDSS, showing patches of homes around urban blocks, social links between households, and time series plots

3 Collecting and Processing Data for CEDSS

The necessary investment of effort in data collection for the agent-based model was considerably underestimated initially. So far as we know, no such model of household energy demand at community level has previously been designed and implemented, so we had no good precedents to draw on. We intended that most of the necessary data would be derived from the questionnaire and carbon calculator surveys undertaken, and these did indeed provide essential information. However, the need to keep these research tools to a length that subjects would be willing to complete, while satisfying the data requirements of non-modelling workpackages, limited the amount of data relevant to CEDSS that could be gathered. Moreover, the importance of issues relating to household appliances revealed by the knowledge elicitation exercises we undertook with non-modelling colleagues and stakeholders, necessitated gathering data about appliances that would not be available from the households themselves.

Since the model was intended to simulate the process of change in household energy demand over time, in scenarios reaching to 2050, we decided to test it by setting it up to represent the evolution of a village or urban neighbourhood over a period leading up to 2010, when the first survey, including a questionnaire and carbon calculator, was distributed, completed, and collected. However the questionnaire and carbon calculator mainly asked questions about current energy-using equipment and energy-conserving insulation (some questions were asked about the age of equipment, but these were asked purely in order to calculate likely current energy requirements). No questions were asked about how purchasing decisions were made, but such decisions were central to the model. We therefore decided to combine the information from the questionnaire and carbon calculator with data from a range of publicly available sources about changes over time in the availability and ownership of relevant equipment. The survey was distributed to a stratified random sample of 1099 households from Aberdeen city and Aberdeenshire. A member of each of 489 households completed the survey; these reflected the urban/rural balance and income distribution of the sampled area well, but single-person and single-parent households were under-represented. Almost equal numbers of women and men completed the form, although individuals with higher educational qualifications, and people over 60, were over-represented in relation to the total adult population of the area (we note that these groups are very likely to increase in share of the population over the next few decades). Once we excluded households which had not supplied pieces of information essential to the model, or which used primary forms of heating with only a few examples in the area (liquid petroleum gas or solid fuels), which the model did not cover, we were left with– 197 Aberdeen (urban) and 200 Aberdeenshire (rural) households. These two subsamples were modelled separately because possible differences between the populations of urban and rural areas were among the topics to be investigated and for the purposes of calibration and validation. This section focuses on the urban subsample, and the model parameters constructed using it as a basis – although many of the parameter files described were shared with the corresponding rural parameter set, and those that were not shared were constructed in a parallel fashion. The names of those parameter files that differ between the urban and rural models are followed in the subsection headings by "(urban)".

After a preliminary investigation of the available data sources, we decided that it was feasible to "retrodict" aspects of the survey households' dwellings and energy-using appliances as they might plausibly have been at the start of 2000. If running the model forward to 2010 then gave energy demands close to the figures derived from the survey, we could have sufficient confidence in the model to extend such runs to 2050 with the expectation of getting meaningful and useful results. The current section describes those aspects of the model that could be based, to varying extents, on the 2010 survey data, and a range of publicly available data sources; and how those sources were used. The most important of those used directly in constructing the CEDSS parameter files were as follows:

- UK Department of Energy and Climate Change (DECC) time series of prices for domestic electricity, gas and heating oil (taken from files qep413.xls, qep551.xls and qep591.xls, available from the DECC website http://www.decc.gov.uk/).
- United Kingdom Department of Energy and Climate Change's *Great Britain's Housing Energy Fact File 2011*. (Palmer and Cooper 2011).

- UK Office for National Statistics (ONS) "Family Spending" series (officially known first as the Family Expenditure Survey, then as the Expenditure and Food Survey, then as the Living Costs and Food Survey). These are available online from the ONS. These data were used for the estimates of spending on fuels, household appliances, and household maintenance and repair, by each gross income decile of the UK household income distribution, over the period 2000-2010; and the percentage of households with washing machines, tumble dryers and dishwashers in 2000 and 2010.
- The Institute for Fiscal Studies Working Paper 02/21, *The Distribution of Financial Wealth in the UK: Evidence from 2000 BHPS Data* (Banks, Smith and Wakefield 2002). This was used for figures on the net wealth of the UK population by income quintile in 2000.
- Argos catalogues, 2000-2010. Argos is a UK retailer, selling a wide variety of household appliances. CEDSS requires a list of appliances offered for sale, with prices and (where they exist) energy efficiency ratings, for each quarter-year covered by a run.

A summary of the relationship between the data sources, CEDSS files and model variables is included in the additional material uploaded to CoMSES Computational Model Library (http://www.openabm.org/model/3642/version/2/view).

Note that in this section, files are discussed in the order most convenient for exposition, rather than the order in which they are loaded during initialisation, which is followed in 2.3.

3.1 Households file (14 in 2.3) (urban)

This can be regarded as the key input file, in relation to which other files were constructed. It allocates initial households and their parameters to each dwelling. Each row after the first describes a household. The following columns are required: id, type, income, capital, hedonism, gain, norm, frame, planning, and dwelling. Of these, capital, hedonism, gain, norm, frame, and planning are numeric; income is expected to be a list of one or more numbers; dwelling contains the identifier of the dwelling belonging to the household and type is provided to allow for households to be assigned demographic characteristics (not currently used). Income is intended to represent quarterly household income available for spending on domestic energy, energy-using appliances, and in the case of owner-occupiers, replacement heating systems, and insulation, while capital represents the net monetary wealth available to a household at the start of a model run. The remaining fields represent decision-making characteristics of the household. The first three, "hedonism", "gain" and "norm" represent the extent to which three different types of value described in section 1 guide the household's decision-making: hedonistic values (focused on comfort and enjoyment), "egoistic" values (focused on gaining and keeping resources, and in this context, specifically saving money), and "biospheric" values (care for the environment). The "frame" field governs the extent to which these values are subject to change through social contacts, and the "planning" field the time horizon over which the household calculates savings of money or energy use when considering improving insulation or installing a new heating system.

The "id" field in each line identifies a specific (but anonymised) urban household in the dataset from the 2010 questionnaire and carbon calculator; details of dwelling type, insulation, appliance ownership, energy use, and income band were drawn from this dataset. Note, however, that these households did not in reality all live in the same neighbourhood.

In the work reported here, all households were treated as "average" households demographically for the purposes of calculating energy demand for water-heating, the only point in the model – and in the document used to calculate emissions in the 2010 and 2011 surveys of households in Aberdeen City and Aberdeenshire (Department of Energy and Climate Change 2009) – at which household size made a difference. For income figures over the entire period, we began with the questionnaire figures for "monthly household income after taxes", which divided the survey households into 11 bands. These bands corresponded reasonably well with the income deciles in Table A6 of the UK Office for National Statistics (ONS) 2010 Living Costs and Food Survey (Horsfield 2011), once the eighth and ninth questionnaire bands were amalgamated: the top row in Table 1 below. The correspondence is not exact, particularly given the different basis for the figures, but given the sources of uncertainty in both figures, it was considered good enough.

Table 1: Lower bounds of Horsefield (2011) 4-weekly gross income deciles compared with those of monthly household income after taxes from 2010 survey

ONS decile	1	2	3	4	5	6	7	8	9	10
ONS lower bound	0	640	952	1260	1652	2088	2604	3204	4060	5472
Survey lower bound	0	444	888	1332	1776	2220	2664	3109 3554	3998	4442

Tables in Horsfield (2011) and corresponding ONS reports for earlier years, back to 2000, provide the mean household expenditure on "electricity, gas and other fuels", "household appliances", "TV, videos and computers" and "maintenance and repair of dwelling" for each gross income decile. We assumed that the quarterly total of the first three of these four categories gave a reasonable estimate of the money that households in the corresponding survey income bands would have had to spend on domestic energy and energy-related equipment per quarter, for each calendar year of the period covered in the calibration runs (from the start of 2000 to midway through 2010) if renting their dwelling; and this amount plus the average quarterly spend on "maintenance and repair of dwelling" for owner-occupier households.

Figures for capital were drawn from an Institute for Fiscal Studies report on the distribution of financial wealth in 2000 (Banks, Smith and Wakefield 2002), which in

Table A4 gives figures for the distribution of net financial wealth in the UK for each quintile of the income distribution. Taking all the households in the urban subsample and grouping the deciles already defined into quintiles, 1/4 of them were assigned the Banks Smith and Wakefield (2002) 25th percentile of net wealth for the corresponding quintile, 1/2 were assigned the median figure, and 1/4 the 75th percentile.

For the remaining fields, we had in effect no real-world data: while we might have used some of the questions on values and attitudes to assign relative strengths to the "hedonism", "norm" and "gain" fields, the Scottish sample showed no statistically significant relationship between answers to these questions, and energy demand. Given the lack of real-world data, we tried a range of different possibilities for these fields, and for the "frame" and "planning" fields, as described below.

3.2 Dwellings file (6 in 2.3) (urban)

The dwellings file gives properties of the dwelling of each household. There is one row for each dwelling, where the entry in the “id” column corresponds to the dwelling-id in the patch file, and the remaining entries are “tenure”, “type” (of dwelling) and “insulation” (current insulation state). Entries in the insulation column should correspond to entries in the insulation file (see below).

The set of dwelling-types used was taken from those in the carbon calculator, and the types were assigned to individual households on the basis of their survey responses. The main types were bungalow (detached or semi-detached), house (detached, semi-detached, end-terrace or mid-terrace) and flat (top-floor or not). Each of these main types was subdivided according to the number of bedrooms (1, 2, 3, 4, 5, 6 or more), and by whether the external walls are solid, or have an internal cavity that is or could be filled to improve insulation. Tenure was either “owned” or “rented”, again taken from survey responses. The dwelling type and tenure were assumed to have remained the same since 2000.

The 12 possible insulation-states were constructed from three components: whether or not there was double-glazing, whether loft insulation was present and if so whether it was 100mm or 270mm thick, and whether there was wall insulation; flats other than top flats were assumed to be partially insulated from above by the flat above them, taken to be equivalent to 100mm of loft insulation. The combination of dwelling type and insulation state is used in the model to calculate “useful energy demand” for space heating.

With regard to insulation-state, it was not reasonable to assume that there had been no change since 2000; we knew that there has been considerable change both locally (Aberdeen City Council 2007) and nationally (Palmer and Cooper 2011) in home insulation. The method adopted was to compare national figures for changes in the penetration of the various types of insulation for 2000 and 2010 (taking the figures from Palmer and Cooper (2011)), and then assume that the same proportion of homes in the urban sample that had each type of insulation in 2010 would not have had it in 2000, as the national figures indicated would be the case for the whole population of UK households.

3.3 Patch file (1 in 2.3) (urban) and Patch legend file (7 in 2.3)

NetLogo divides space into square "patches". The patch file states the patch type of each patch. Currently only one type of patch has any direct effect on CEDSS: "dwelling". These are the patches on which dwellings may be located.

We decided not to use real-world street-networks as the basis of those used in CEDSS since the additional time required to do so could be more usefully spent in improving the model and collecting other types of data, as any specific street-layout used would not have corresponded to the locations in which the household surveys were undertaken. The two patch files (for the urban and rural subsamples) for the runs reported here were constructed, using a procedure able to generate a street-network to accommodate any desired number of dwelling-patches. Details are given in the accompanying material for CEDSS available in the OpenABM model library at http://www.openabm.org/model/3642/version/2/view/, and the result for the urban sample can be seen in Figure 2. Thirty-two dwelling-spaces make up a square block, eight on each side with a hollow centre. The facing rows of dwellings of an adjacent pair of blocks make up a street segment.

3.4 Insulation file (4 in 2.3)

The insulation file specifies the space heating energy demand for every permitted combination of insulation state and dwelling type, relative to an arbitrarily chosen standard combination, a two-bedroomed top floor flat with double glazing and 100mm of loft insulation, but no wall insulation. This factor is multiplied by a figure for the energy needed for space heating for a dwelling of that type and insulation state, for each type of heating system covered (see the "Appliances fuel file" below). The factors used are taken from tables in the document used to calculate CO_2 emissions in the 2010 survey (Department of Energy and Climate Change 2009).

3.5 Insulation upgrade file (5 in 2.3)

The insulation upgrade file is used to specify the insulation upgrades that are available, taking a dwelling from one insulation-state to another. There is one line for each possible upgrade for each dwelling type, giving the cost. The prices were taken from Cambridge Architectural Research et al. (2009), p.31.

3.6 Appliances file (11 in 2.3)

The appliances file gives properties of each energy-using appliance available for purchase by households in the model. The model currently covers eight categories of appliance: heating systems, cookers, refrigerators, freezers, washing machines, dryers, dishwashers and televisions. Four categories are divided into subcategories:

- heating-systems are divided by fuel (gas, electricity or oil – the few households using other fuels were excluded) and in the case of gas and oil, by whether the boiler was a standard or condensing boiler (standard boilers are no longer available after the second quarter of 2007, when it became compulsory to fit condensing boilers in new homes and when replacing an old heating system in Scotland);

- cookers are divided into electrical with a standard hob, electrical with a ceramic induction hob, gas, and dual fuel (electric oven and gas hob);
- refrigerators are divided into those with and without a freezer compartment;
- televisions are divided into cathode ray tube (CRT), liquid crystal display (LCD) and plasma.

The required details for an appliance are: name, category, subcategory, essential, hedonic-score, cost, energy-rating, embodied-energy, breakdown-probability, first-step-available, last-step-available. The name is a unique name for the appliance; category and subcategory are used in the process of determining what a household buys, while if essential is set to "true", households will replace the item immediately if it breaks down. Hedonic score and embodied-energy are not currently used. Cost is a list of purchase prices, one for each quarter during which the item was available, energy-rating is information about the energy consumption of the appliance given to consumers, with a higher score meaning better energy consumption (this is not available for all categories of appliance – for those for which it is not available, all appliances in the category are given the same score; the actual energy the model assumes are consumed by appliances of different categories, subcategories and energy ratings is given in the appliances fuel file.) The breakdown-probability is the probability, per time step, of the equipment breaking down. The first and last steps available are the numbers of the time steps in the model indicating when they are first and last available.

For heating systems, figures for energy use were calculated from Department of Energy and Climate Change (2009) figures on energy efficiency. Figures for heating system prices were taken from the file consumerissues.jobsandmoney.htm retrieved from http://www.guardian.co.uk/money/2005/apr/02/consumerissues.jobsandmoney/, and energy ratings corresponding to the boiler efficiencies from the website http://www.sedbuk.com/pages/bands.htm, which is linked to the UK government's Standard Assessment Procedure (SAP) for assessing energy efficiency of buildings. The remaining appliances listed in the file used in the calibration process are all taken from Argos catalogues of household appliances and other products. Argos is a large UK retailer, which publishes a catalogue every six months. It was judged impractical to include in the model the full range of household appliances available during the period 2000-2010, and indeed, accessing information about even a fraction of them proved challenging. Repeated requests to a number of retailers brought no positive responses as commercial organisations are understandably unwilling to release data that might reveal pricing strategies. Relevant pages of the catalogues from the second half of 2000 through 2007 were consulted at the Victoria and Albert Museum in London. Catalogues for Spring/Summer 2008, Autumn/Winter 2009, and Spring/Summer 2010 were obtained from colleagues. The contents of the catalogues limited the range of appliance categories it was feasible to cover. However, those included were estimated, from figures in Department of Energy and Climate Change (2009) to account for approximately 2/3 (to be precise, 65.4%) of domestic electricity use other than for space heating and hot water; a correction was applied when comparing figures derived from the carbon calculator results for appliance electricity use with those from the model.

An algorithm was used to select items from each subcategory (categories that were not subdivided were regarded as their own sole subcategory). If possible, three items from each subcategory were selected for each six-month period, with items selected for one period remaining available for the next period if found in the subsequent catalogue. The details of the algorithm are given in the additional material in the OpenABM model library.

Figures for breakdown probability of appliances (where "breakdown" means a failure so serious the appliance cannot be repaired or is not worth repairing) per year are not easy to find. In fact, breakdown probability varies over time, with older appliances and perhaps very new ones (which may have factory defects) more prone to breakdown, but attempting to replicate such effects was judged impractical. Survival curves for televisions and refrigerators are given by Gutierrez (2010): 50% of televisions have been discarded after about 200 months (66.67 quarters) while for refrigerators half are gone in 150 months (50 quarters). A quarterly failure rate of 0.014 for refrigerators will reproduce the latter result, and in the absence of other information this figure was used for other "white goods" (all the appliances included in the model other than heating systems and televisions); a quarterly failure rate of 0.010 for a television reproduces the figure for median failure time. Owen (2006, p.30) says that turnover of heating systems is 5% per annum, corresponding to a probability of 0.013 per quarter.

3.7 Fuel file (2 in 2.3)

The fuel file gives properties of each fuel used to supply an appliance. Most appliances will only use one type of fuel, but some cookers in the appliance file use two.

For the purposes of calibration, gas and electricity were subdivided according to whether their use was for space heating, water heating, or appliances; and oil according to whether its use was for space or water heating. All fuels were measured in kWhs (Department of Energy and Climate Change (2009)), the source for usage figures, gives all figures in kWh).

3.8 Suppliers file (15 in 2.3)

The suppliers file gives energy prices offered by different suppliers for each fuel type each step. There is no functionality at present to create a market for suppliers; fuel prices are instead exogenous time series, so there is little point in having more than one supplier for each fuel type. Data on prices was taken from the UK Department of Energy and Climate Change time series of prices for gas, electricity and oil, taken from files qep413.xls, qep551.xls and qep591.xls, all available online from DECC.

3.9 Appliances fuel file (12 in 2.3) (urban)

The appliances fuel file gives the fuel used by households for each use of an appliance (heating systems and cookers have more than one use) over a time-step. For each combination of household type, dwelling type, tenure, and the purpose for which the appliance is used, it gives the amount and type of fuel used in each quarter of the year (heating systems use more in the first and last quarters than in the others). Data was sourced from Department of Energy and Climate Change (2009). The urban and rural versions of the file differ only in the fuel requirements for water heating. The rural households in the 2010 survey had a slightly larger mean household size (2.41 as opposed to 2.34 for the urban subsample), and these figures were used in calculating those fuel requirements.

3.10 Appliances replacement file (13 in 2.3)

The appliance replacement file gives replacements for each appliance: the first item on a line can be replaced by any of the subsequent items on that line, but by nothing else. In the file used in calibration runs, any item can replace any other in the same subcategory. Additionally, condensing boilers can replace standard boilers of the same type, electric cookers with and without ceramic induction hobs can replace each other, gas and dual-fuel cookers can replace each other, LCD and plasma televisions can replace each other.

3.11 Maximum in category file (3 in 2.3)

The maximum in category file places limits on how many appliances of each category each type of household may possess (if an item is about to be added in excess of this limit, the oldest item in the category will be discarded first). There is one line for each type of household, with the first item on a line identifying the household type, and successive pairs of items identifying a category and setting the limit for that category (a limit of zero or below will cause an error). If no limit is set in this file for a household type-category pair, none is enforced. The limits used were taken from the maximum number of appliances of a category owned by any household in the 2010 survey.

3.12 Household initial appliance file (11 in 2.3) (urban)

The household initial appliance file assigns initial appliances to households. The first column is the name of the household, the remaining columns are appliance names.

The heating system supplied to a household at the start of 2000 was determined by the “primary” fuel that household reported using for heating in 2010 (where more than one fuel was listed as primary, gas was preferred to electricity and oil, electricity to oil). In the case of gas and oil using households, the heating system assigned for 2000 was less efficient than heating systems available in 2010. For other appliances, all appliances assigned were the middle one of the three items in a subcategory drawn from the Autumn/Winter 2000 Argos catalogue as described in 3.6. All households were assumed to have at the start of 2000 a cooker of the same subcategory as they possessed in 2010, a refrigerator which would have a freezer compartment if they had one in 2010, a washing machine, and one CRT television. All households with one or more freezers in 2010 were assigned one freezer in 2000. For dryers and dishwashers, which were the categories of appliance for which the change in prevalence between 2000 and 2010 was greatest, according to the Table A45 “Percentage of households with durable goods, 1970 to 2010 United Kingdom” of the 2010 Living Costs and Food Survey (Horsfield 2011), the same approach as for insulation states was taken: it was assumed that the proportion of households possessing such an item in 2010 who would not have possessed one in 2000, was the same as for UK households as a whole, and each household with such an item in 2010 was assigned such an item in 2000 with the appropriate probability.

4 Calibrating and Validating CEDSS

The input files described above were held constant throughout the calibration process, except for those aspects of the households file that were left unspecified in the preceding section, and the income figures in that file. Four rounds of calibration runs, covering the period from the start of 2000 to September2010, were undertaken to find values of these aspects of the households file, and of the remaining model parameters used in the work reported here, that gave the best match to the total usages of electricity, gas and oil for space heating, water heating, and non-heating appliances for the urban subsample in the 2010 survey. (Very few households reported using any other fuels, and these households were excluded from the subsample.) The resulting set of parameters is referred to as the "Urban 2000-2010 Model".

To validate CEDSS for the Scottish case study area, a second partial set of input files was created based on data from the rural (Aberdeenshire) subsample, and combined with the additional parameters selected in the calibration process to produce the "Rural 2000-2010 Model". We then verified that this model gave reasonably accurate results for the total usages of electricity, gas and oil for space heating, water heating, and non-heating appliances for the rural subsample in the 2010 survey.

4.1 Calibration Stage 1A

Keeping the parameter files described in section 3 fixed, CEDSS still has a considerable number of "free" parameters (parameters unconstrained by real-world data) to be specified. Calibration requires an exploration of a model's parameter space, experimenting with a range of combinations of parameter values, but even if using only two values per parameter, the number of possible combinations to be tried was too great to be explored simultaneously, even with the use of the "Behavior Space" facility available in NetLogo to perform multiple model runs across a range of parameters (this facility was indeed used, inside a Perl script "wrapper" which enabled us to save and subsequently explore output from the runs conveniently).

In calibrating any model, particularly one where the parameter space is too large for complete exploration to be feasible, the approach taken must be based on the purpose for which the model is being constructed. In the case of CEDSS, that purpose is the policy-relevant exploration of Scottish domestic energy demand scenarios stretching to 2050. Those using the model for this purpose will be primarily interested in the *total* use of different types of energy (primarily gas, oil and electricity) under a range of assumptions about factors such as energy price and income trends, technological change, and policy options such as subsidies for improving insulation and replacing inefficient boilers, or regulations to improve labelling or restrict the sale of inefficient appliances; in particular, they will be *more interested in absolute than in proportional errors in estimates of energy demand*. At the same time, if the model gets trends in these totals over the calibration period right but (for example) estimates energy use on appliances consistently much too high, compensating by getting figures for heating too low, that is less than satisfactory, both on general modelling principles, and because the ratio between these energy uses may change significantly over time, as indeed, it has done over the past decade (appliance energy use has increased, while that for heating has declined as efficient condensing boilers have become more widespread). The approach we have taken – by no means the only possibility – represents a compromise between these considerations, and one which was, in some respects, adapted as we proceeded, to take account of features of the model's performance that emerged during the process. We intend to explore a range of calibration and validation options in future work, and test multiple models on future scenarios to discover how much difference these options themselves make.

Much the largest component of domestic energy demand is for space heating, and this is likely to remain the case at least up to 2050 (most of the housing that will be in use then is already in use): it is thus most important that the model gets this right. We therefore decided to begin by varying those parameters considered most likely to affect this demand, while holding the rest constant (these parameters will also affect other aspects of demand indirectly). Calibration stage 1A performed single runs of the widest practicable range of possible combinations of these parameters, and singled out for further tests the 16 parameter combinations that gave the best *overall sum of absolute errors in the model's estimates of energy demand*. The overall sum of absolute errors was calculated as the sum of the absolute values of the differences between the energy demand calculated from the urban subsample in the 2010 survey and the corresponding model result, summed over the last four quarters of a run, for these eight amounts: electricity, gas and oil used for space heating; electricity, gas and oil used for water heating; and electricity and gas used for non-heating household appliances (the only gas appliances were gas cookers). This approach gives appropriate weight to the most important components of demand, while guarding to some extent against errors in opposite directions cancelling each other out.

Parameters varied in stage 1A (Experiment 5 in the parameter files available from the OpenABM model library) were as follows:

- *Households file*
    - *Income*. Because of the uncertainties inherent in the calculations of income levels, and the importance of this parameter, incomes uniformly 1.5 and 0.75 times those calculated as described in section 3.1 were substituted for those calculated.
    - *Value strength parameters* ('hedonism', 'gain-orientation' and 'greenness'). Because the 2010 Scottish survey indicated that expressed pro-environmental values did not have a significant effect on energy demand, which is consonant with the work of Kasser (2008), we made the default assumption that these values were weak relative to hedonic and egoistic values, at least when the purchasing decisions that CEDSS simulates are made. The default strengths assigned were hedonism 5, gain 5, norm 1. Alternative settings tried were 5:1:1, 5:5:5, 1:5:1.
    - *Planning horizon* parameter ('planning'), used in determining whether to adopt insulation measures, and how to replace a broken heating system. The default value was 20 time steps (5 years). An alternative value of 4 time steps (1 year) was tried. We considered it unlikely that many households would have a time horizon greater than 5 years, given uncertainties about both energy prices and life events over longer periods; a

time horizon of less than 1 year would almost never give a different outcome to one of 1 year.

- *habit-adjustment-factor*. This numerical parameter determines the maximum amount by which households adjust their value strength parameters in the direction of the value that has predominated in their decision-making in the current time step (the strengths have a floor of 0, and their sum never changes, so this maximum is not always reached). The default value was 0.1; alternative values of 0 and 0.5 were tried.
- *credit-multiple-limit*. When buying non-essential items, a household will not buy if the result would place them in debt (make their capital negative) by more than their current income multiplied by this number. The default value was 5; alternative values of 0 and 20 were tried. We considered that this covered the range of plausible values, given that we assign the same value for this limit to all households: Banks, Smith and Wakefield (2011) find that the poorest 10% of British households average just over £4,000 in debt, compared to the monthly income figures we used (recall that these represent income available for energy-related spending) ranging from £138 for the poorest in 2000 to £866 for the richest in 2010.
- *Social-link-matrix-file*. If two households have a social link, either can "visit" the other. As a result, their value strength parameters will move closer together, and if in hedonic goal-frame, the visitor may add an appliance which the host has to their "wish-list" of appliances they will consider buying. This file specifies the probability that a social link will exist between a pair of households at the start of the model run. The default social link matrix file allows the same probabilities for all pairs of households with dwellings on the same square of 0.1, and of all pairs of households anywhere of 0.05. There would be some initial assortment of social links by dwelling-type, as dwellings of the same type were placed close together. The alternative tried was to have no social links at all.

These ranges of possibilities gave a total of 3.4.2.3.3.2 = 432 possible combinations. The 16 giving the smallest sum of absolute errors were as shown in Table 2. For comparison, the total annual energy demand in kWh across all households and uses in the GILDED 2010 Scottish urban subsample was 4,775,091 kWh.

4.2 Calibration Stage 1B

The 16 best parameter combinations were next run 10 times each (Experiment 8 in the parameter files on Open ABM). The intention had been to take the version with the lowest mean sum of absolute errors as the basis for further parameter space exploration. However, a number of the model versions had a very similar mean sum of absolute errors, and a detailed examination of the different errors indicated that this might not be the best course of action. The relevant figures are given in Table 3. The survey urban subsample totals for appliance, space heating and water heating energy demand are 379,109kWh, 3,485,086kWh and 910,897kWh respectively, summing to 4,775,091 kWh as already noted (figures are rounded to the nearest kWh).

Table 2: The sixteen runs from calibration stage 1A giving the smallest sums of absolute errors in model estimates of energy demand in 2009-10

Identifier	Income multiple	Values parameters	Planning horizon	Habit adjustment factor	Credit multiple limit	Social links	Sum of absolute errors
1A:1	1	5:5:1	20	0.5	20	Yes	216562
1A:2	1	5:5:1	20	0.5	5	Yes	230931
1A:3	1	5:5:5	20	0.5	20	Yes	233209
1A:4	0.75	5:5:1	4	0	20	No	246743
1A:5	1	5:5:5	20	0.5	5	Yes	247642
1A:6	0.75	5:5:1	20	0.5	5	Yes	248262
1A:7	1	5:1:1	20	0	20	Yes	251139
1A:8	1.5	5:5:1	20	0.1	20	Yes	254533
1A:9	0.75	5:5:5	20	0.5	5	Yes	256755
1A:10	0.75	5:1:1	4	0	20	No	257008
1A:11	1.5	5:5:1	20	0.5	20	Yes	264376
1A:12	1.5	5:5:1	20	0.5	0	Yes	269621
1A:13	1.5	5:5:5	4	0.5	0	No	270567
1A:14	1.5	5:1:1	20	0	0	Yes	270585
1A:15	1	1:5:1	20	0	5	Yes	277378
1A:16	0.75	5:5:1	20	0.1	0	Yes	278119

All the models overestimate water heating energy demand and the overestimate is considerable. Model 1A:1 has the smallest magnitude mean net space heating energy demand error (the error for a run is calculated by adding the total space heating demand over all three fuels for the last four quarters of the run, then subtracting the corresponding value for the 2010 survey urban subpopulation, then taking the mean for this value over all 10 runs), and the third smallest magnitude mean appliance energy demand error (calculated in the corresponding way). It was decided that these would be the best basis for further exploration of parameter space. At the time of writing, the consistent positive errors in water heating energy demand remain unexplained, and further investigations are planned; we could easily get rid of them by reducing the mean size of household, but doing so without understanding their source would be unwise. A reviewer has pointed out to us that model 1A:1 actually has the smallest *Euclidean mean distance* from the survey figures among the models tested. This is calculated by summing the squares of the mean absolute errors in appliance, space-heating and water-heating energy demand, then taking the (positive) square root. (This last operation does not affect the ordering of the errors.)

Table 3: Results of runs during calibration stage 1B.

Identifier	Mean sum of absolute energy demand errors	Mean net appliance energy demand error	Mean net space heating energy demand error	Mean net water heating energy demand error
1A:1	260767	-4473	-28080	84624
1A:2	261620	-9170	-66346	82253
1A:3	322227	-8244	-157105	83156
1A:4	246424	-34856	-74153	78717
1A:5	298095	-8940	-134896	79298
1A:6	252522	-13959	-90127	80296
1A:7	357378	10667	-138881	81988
1A:8	340656	1280	-158158	79084
1A:9	302505	-19828	-149066	82281
1A:10	258170	-39233	-76481	82287
1A:11	252477	-1755	-39626	87595
1A:12	260186	-8119	-88242	77187
1A:13	276043	-83031	-72535	83102
1A:14	362093	6619	-157534	77888
1A:15	332007	-37700	-182152	74779
1A:16	297824	-18088	-154268	79986

4.3 Calibration Stage 2A

Calibration stages 2A and 2B (Experiments 9 and 10 in the parameter files on Open ABM) followed the same lines as stages 1A and 1B, but exploring changes in a different set of parameters. Because some of the best parameter sets in Stage 1B (1A:11 and 1A:12) had an increased income relative to the default, this parameter set was once again varied, using that of the model selected as the basis of further exploration (1A:1), along with 1.25 and 1.5 times that value. Apart from this, all the parameters explored in stage 1 kept the values of 1A:1 for all runs, but four parameters expected primarily to affect non-heating appliances were varied:

- *new-subcategory-appliances-per-step*. A number of appliances that belong to a recently introduced subcategory can be added to each household's wish list; this parameter specifies how many per time step. The default value (that used for 1A:1) is 2; alternative values of 1 and 4 were tried.
- *new-subcategory-steps*. This parameter specifies how long (for how many time steps) a subcategory is considered new. The default value is 4; an alternative of 8 was tried.
- *old-product-steps*. Even if appliances are not broken, the household may decide to replace them. This parameter specifies how many time steps an item must have been owned for before this may happen. The default is 4; an alternative of 8 was tried.

- *visits-per-step*. As explained above, when one household "visits" others, it may add an appliance it "sees" to its wish list. This parameter specifies how many visits a household may make per time step (but not how many items may be added, only the likelihood of some appliance it does not have being noticed on one of the visits). The default value for visits is 2; alternatives of 1 and 4 were tried.

These combinations of parameters produce 3 × 3 × 2 × 2 × 3 = 108 possibilities, each of which was run once. As for stage 1A, we list the best 16 in Table 4.

Table 4: The sixteen runs from calibration stage 2A giving smallest sums of absolute errors

Identifier	income multiple	new-subcategory-appliances-per-step	new-subcategory-steps	old-product-steps	visits-per-step	Sum of absolute energy demand errors
2A:1	1.5	1	8	8	1	170277
2A:2	1.5	2	8	4	2	180083
2A:3	1	1	8	4	1	184452
2A:4	1	4	8	4	2	190336
2A:5	1.5	1	4	4	4	193651
2A:6	1.5	1	4	4	2	195663
2A:7	1.25	4	4	4	2	195839
2A:8	1.5	1	8	4	1	197511
2A:9	1	4	8	4	1	198347
2A:10	1.5	4	4	8	1	199275
2A:11	1.5	2	8	4	1	200810
2A:12	1	4	8	8	1	202532
2A:13	1	4	4	4	4	203547
2A:14	1	2	8	8	1	203632
2A:15	1.25	2	4	4	1	205597
2A:16	1.25	4	8	4	2	206112

4.4 Calibration Stage 2B

As in stage 1, 10 runs of each of the best 16 versions of the model were performed.

On this occasion, as shown in Table 5, the version with the lowest mean sum of absolute energy demand errors, 2A:14, had the second lowest mean net appliance energy demand errors, and the fourth lowest mean net space heating energy demand errors; this was selected as the best version to validate, and if the validation was acceptable, to use for future scenario runs to 2049. (Had we focused on the mean Euclidean distance of the absolute values of net space-heating, water-heating and appliance energy demand from those of the survey, we would have selected the same version.) Figures 3 and 4 show more detailed mean results in graphical form. The meaning of the labels on the x-axis, and the figures from the 2010 Scottish urban subsample in relation to which energy demand errors are calculated are as follows:

Appliance electricity (A/E):	328,269 kWh
Appliance gas (A/G):	50,839 kWh
Space heating electricity (S/E):	159,740 kWh
Space heating gas (S/G):	3,307,148 kWh
Space heating oil (S/O):	18,198 kWh
Water heating electricity (W/E):	73,544 kWh
Water heating gas (W/G):	833,652 kWh
Water heating oil (W/O):	3,701 kWh
Total:	4,775,091 kWh

Table 5: results of runs during calibration stage 2B.

Identifier	Mean sum of absolute energy demand errors	Mean net appliance energy demand error	Mean net space heating energy demand error	Mean net water heating energy demand error
2A:1	238781	-17983	-59849	79658
2A:2	228647	-27075	-77018	87178
2A:3	238408	-37212	-46904	81201
2A:4	240802	-28492	-97324	77579
2A:5	264918	-22888	-125765	78889
2A:6	262452	-28500	-10592	82455
2A:7	244245	-25922	-93634	77262
2A:8	225661	-40441	-68200	75680
2A:9	228349	-38269	-57894	78805
2A:10	249586	-10592	-72245	79138
2A:11	238565	-37995	-62859	77503
2A:12	248063	-19289	-61198	80641
2A:13	229345	-20286	-88356	83328
2A:14	223354	-19453	-31127	84679
2A:15	230607	-34199	-46934	82812
2A:16	241632	-30091	-78228	86059

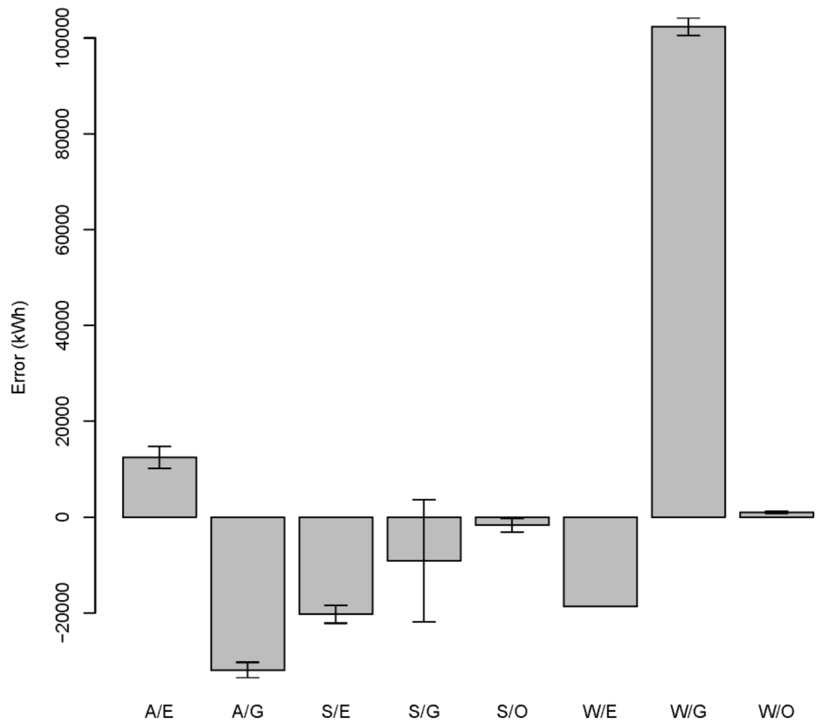

Figure 3: Mean net errors of CEDSS model 2a:14 on urban subsample, with 95% confidence intervals

As can be seen, all the net mean energy demand errors are small in relation to the total energy demand from the survey. The largest proportional error by far is for appliance gas, but this makes up only a little over 1% of total energy demand. The systematic overestimate of water heating gas demand has already been noted. It has emerged since the calibration and validation runs that the figures used for comparison with appliance electricity use in the model may well be somewhat too low, with the raw survey figures having been over-corrected in allowing for appliances not covered (home computers and related equipment, sound systems, radios, microwaves, kettles and others). However, all currently available figures for the proportions of demand assigned to different types of appliance are based on numerous assumptions.

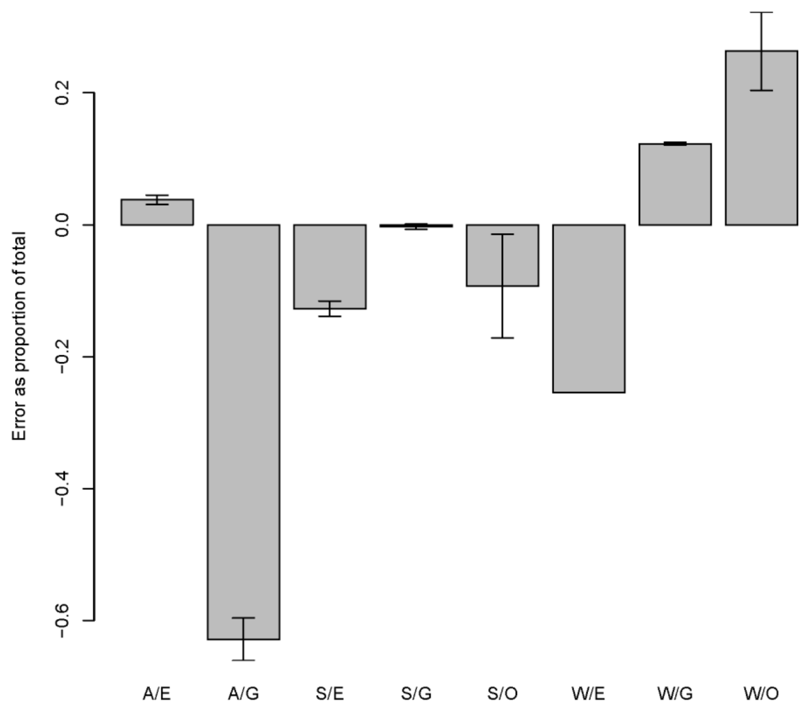

Figure 4: Mean proportional errors of CEDSS model 2A:14 on urban subsample, with 95% confidence intervals

4.5 Validation on the Rural Subsample

Validation was carried out by running model 2A:14 on the rural subsample of the 2010 Scottish survey ten times. The mean sum of absolute energy demand errors over ten runs was 294,830 kWh, compared with a total energy demand estimate of 6,272,414 kWh from the 2010 survey. Figures 5 and 6 show mean net energy demand error results in graphical form.

The figures from the GILDED 2010 Scottish rural subsample in relation to which energy demand errors are calculated are as follows:

Appliance electricity:	348,036 kWh
Appliance gas:	29,116 kWh
Space heating electricity:	469,836 kWh
Space-heating gas:	1,780,935 kWh
Space-heating oil:	2,751,044 kWh
Water-heating electricity:	365,088 kWh
Water-heating gas:	100,032 kWh
Water-heating oil:	428,407 kWh
Total:	6,272,494 kWh

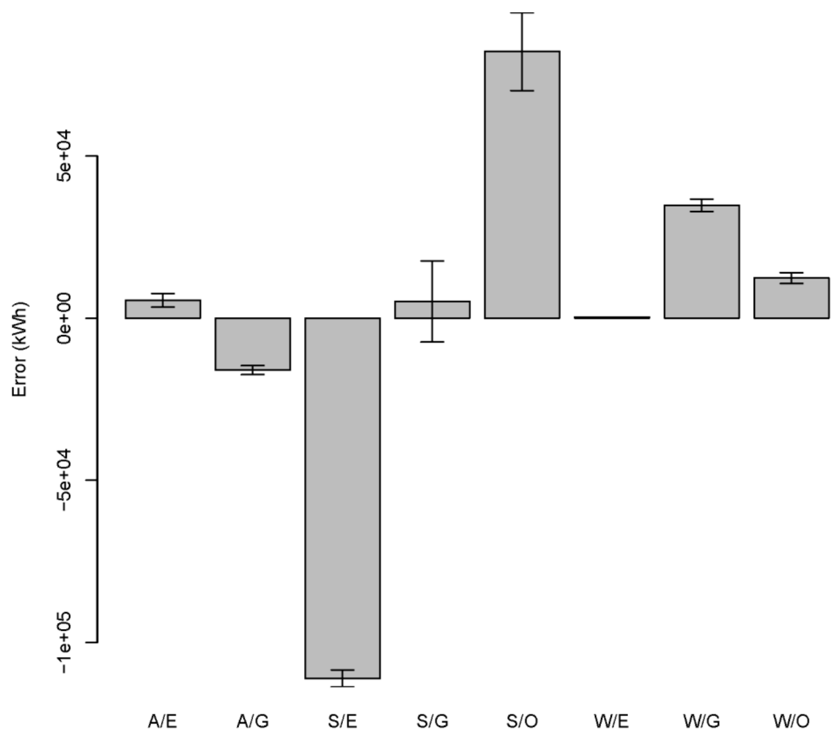

Figure 5: Mean net errors of CEDSS mode 2A:14 on rural subsample, with 95% confidence intervals

As can be seen there are two relatively large proportional mean net errors, on appliance gas, and to a lesser extent space heating electricity. However, the survey figure for appliance gas is less than 0.5% of the total, while the error on space heating electricity is almost balanced by that on space heating oil: it is possible that we have counted some households as using electricity for heating when in fact they use oil, or a mix of both, since if both electricity and oil were noted in the survey as “primary” fuels, we assumed they used oil for space (and water) heating.

Given that the total energy use for the rural subsample is nearly 1/3 larger than that for the urban subsample, and the balance of fuels is very different, with much more oil used by the rural subsample (many rural households in the sample are not supplied with gas from the mains), it was considered that the model was an acceptable basis for future scenarios.

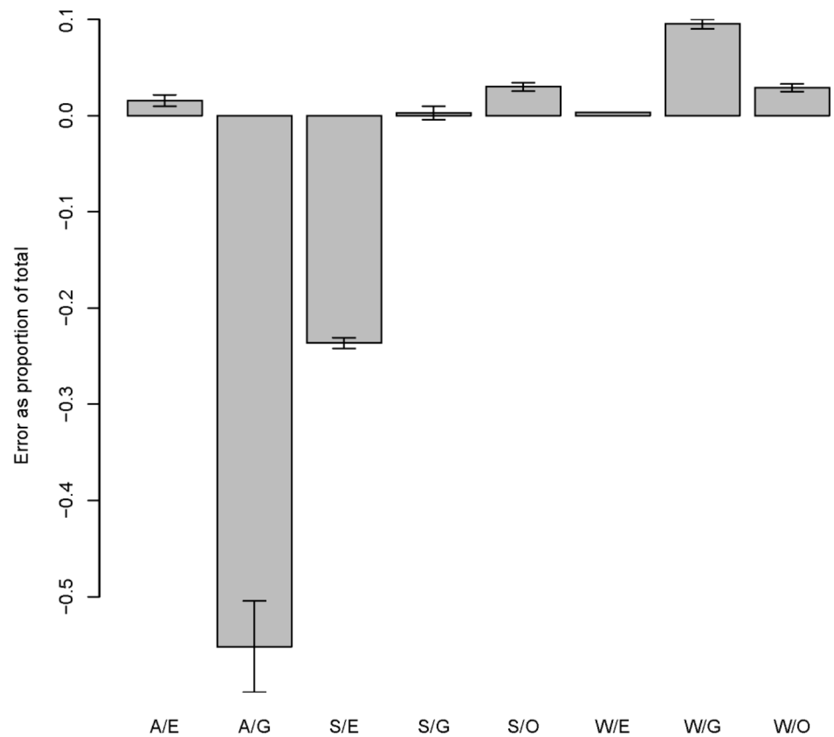

Figure 6: Mean proportional errors of CEDSS model 2A:14 on rural subsample, with 95% confidence intervals

5 Discussion

Heath et al. (2009), conducted a sample survey of ABMs described in the literature from 1998-2008. They classified them on a number of dimensions, of which those of interest here are:

- Purpose of the simulation. They distinguish three segments of a continuum: ABM as "Generator", "Mediator" and "Predictor", differing primarily in how well the system modelled is understood in advance of the modelling effort. When the real-world system is very well understood, the model is used "like a calculator to provide clear and concise predictions about the system": a "Predictor". When the state of understanding is intermediate, it "provides insight into the system, but is not a complete representation of how that system actually behaves" – acting as a "Mediator". When it is little understood, the model is used as a "Generator", i.e. to generate hypotheses about it. In these terms, CEDSS is a "Mediator" because the definition of a "Predictor" is so strict – and in fact, Heath et al. found no "Predictors" among the 279 models they surveyed.
- Validation techniques. Heath et al. (2009) start by stating that "the emphasis of simulation validation is ensuring the model is an appropriate representation of the real system of interest for a given set of objectives". They distinguish two "rounds" of validation: that of the conceptual model and that of the simulation

> output. The former takes place with respect to "system theories and assumptions", and will not be pursued here. Validation of simulation output, against real system results, Heath et al. (2009) partition into "statistical" (i.e., using formal statistical tests), and "non-statistical", using "more qualitative assessments such as expert opinion". In this regard, validation of CEDSS involved statistical tests, but nothing more sophisticated than the calculation of 95% confidence intervals. At any rate, the decision to accept the calibrated version of CEDSS as adequate for the purposes of scenario-building is based on the quantitative similarities between model output and real-world data, but there is no obvious objective way to specify how large the differences would have to be for it to be wrong to accept the model.

In our case, the "given set of objectives" is to use the model as a basis for running scenarios of direct domestic energy demand in the case-study area for the period 2010-2050. Ensuring the model is appropriate for this required that we test it by modelling an extended period of time, using data from the whole of that area if possible, data on sample households in the area or on larger geographical regions where necessary; and get a "good enough" quantitative match between the key outputs of the model – energy use related to different fuels and purposes – and the best energy demand data we had: that from the 2010 survey. What counts as "good enough" is a matter of judgement, but not wholly arbitrary. Year-on-year changes in total domestic energy use often exceed 5% and can exceed 10% according to Palmer and Cooper (2011); so the facts that the mean sum of absolute energy demand errors on the validation runs was within 5% of the sample total, while the corresponding sums for the two largest items making up the sum (electricity for appliances and gas for space heating) were considerably closer, give us confidence. Without further development, the model will allow us to vary trends in prices of both energy and equipment relative to income, a range of types of technical change (energy efficiency in appliances or insulation, new types of energy-hungry appliance), regulation of inefficient appliances, and quality of information about the energy use of appliances, under a range of assumptions about household behaviour and the effects of social interaction.

Turning to the *process* of model development and testing rather than the result, constructing the data files described in section 3 above, to represent the situation of the households in the model in 2000, clearly involved making a considerable number of assumptions. For example, the procedure for calculating incomes back to 2000 gives only a rough approximation, but in the absence of data on the actual income available for these areas of spending for the survey households, over the decade preceding the survey, is the best that could be done. Figures for capital are perhaps even rougher. Figures for breakdown probability of most types of appliances (where "breakdown" means a failure so serious the appliance cannot be repaired or is not worth repairing) per year could not be found, so we had to assume that broadly similar types of appliance would have roughly similar rates.

One of the most notable areas where we were obliged to do without empirical data is that of the strength of values parameters of households. As noted in section 3.1, no correlation was found in the Scottish sample of households between energy use and values as expressed in the answer to survey questions – although there were some correlations between these answers and other pro-environmental behaviours such as recycling. It may be that the differences in values do not translate into behavioural differences where the purchase and use of energy-using and energy-saving equipment is concerned, or that the carbon calculator results were not accurate or precise enough to pick up small effects. Our "value strength" parameters should be interpreted as the strength of values in the context of purchasing energy-using and energy-saving equipment. As described in section 4, we found that we got the best results when biospheric value strength ("greenness") was assumed to be low relative to hedonistic and egoistic values, which is in line with the lack of correlation noted.

All households retain their identity throughout the runs – and indeed, throughout the scenario runs, with the movement of households in and out of dwellings not being modelled. Obviously this is not realistic, but on the other hand, there is no reason to expect incoming households to differ in any particular direction from outgoing ones. One possible objection is that if a region is subject to greater turnover in home ownership with householders tending not to plan to stay for a particularly long time in a particular dwelling, then they might be less likely to invest in insulation, efficient boilers, and other energy-saving measures that stay with the building rather than moving with the owner.

Perhaps the most distinctive features of the way CEDSS uses empirical data are not captured by Heath et al.'s classification schemes, nor by any we know of. CEDSS was a part of an interdisciplinary project on household and community energy demand, and within that project had a specific role. This shaped the processes of data collection, calibration and validation described above. Specifically, the survey that was the main source of micro-level information -- which included a questionnaire covering household demographic characteristics, attitudes to energy and climate change issues, and a range of specific energy-related behaviours, along with a carbon calculator (derived from Department of Energy and Climate Change 2009) -- was a compromise between the needs of workpackages and research teams with differing requirements, and the need to limit the demands made on participants. It could not for that reason include, for example, specific questions about equipment purchasing decisions, which are central to the model. Furthermore, its samples of urban and rural households were designed to be representative of the Scottish case-study area, Aberdeen and Aberdeenshire, as a whole, so investigation of intra-sample social links was not possible, even if the resources to do this had been available. CEDSS' most distinctive features arose directly out of these limitations:

- The combination of data from different scales and types of source in constructing input files for the model: the survey of Aberdeen and Aberdeenshire households at the micro-scale; and at the macro-scale, the commercially produced Argos catalogues, along with data about UK energy prices, household incomes, capital reserves and spending, and possession of household appliances, from government sources. The closest parallel we are aware of is the Weaver model (Hare 1999).
- The construction of simulated communities from data on households that were not, in fact, members of the same real-world community. Smaigl et al. (2011) discuss the use of survey data to populate socio-ecological system models, but none of their cases correspond to the approach we needed to take.

- The need to retrodict aspects of the modelled households from 2010, when the survey data was gathered, to 2000, in order to set up test runs of the model for calibration and validation. Even without the limitations on the survey discussed above, we would have needed to run the model from a starting point before the beginning of the project to get a reasonable assessment of its ability to generate realistic results, and household memories of what equipment was owned at which points in the past cannot be expected to be very reliable, so some form of retrodiction would have been required even if we had been able to ask all the questions we would have liked.

We are encouraged by the results of the validation to think that the use of disparate sources of publicly available macro-level data, and the retrodiction approach we employed, are indeed sufficiently robust for their use to be recommended in future ABM work. We have already used the version of CEDSS described here in an exploratory set of scenarios running to 2049, the results of which will be described in a forthcoming paper. Nevertheless, given the many uncertainties in the data used in producing this version, we are currently developing an approach to calibration, validation, and scenario exploration which will produce and use a "flock" of CEDSS models with different parameter settings, allowing us to give ourselves and policy-makers a better understanding of the range of plausible futures.

Acknowledgements

Funding for the work reported was received from the European Commission under grant agreement SSH-CT-2008-225383 GILDED. The authors thank the members of the GILDED research team; and Mark Brewer, Jackie Potts and Betty Duff of Biomathematics and Statistics Scotland. They also thank the reviewers and the editor of *Structure and Dynamics* for their help in improving the paper.

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